TUM School of Engineering and Design
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Failure Detection and Isolation of Event-driven Binary Sensors in Ambient Assisted Living

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Vollständiger Abdruck der von der TUM School of Engineering and Design der Technischen Universität München zur Erlangung des akademischen Grades einer

Doktorin der Ingenieurwissenschaften (Dr.-Ing.)

genehmigten Dissertation.

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Die Dissertation wurde am 23.09.2021 bei der Technischen Universität München eingereicht und durch die TUM School of Engineering and Design am 08.12.2021 angenommen.

I dedicate this thesis to my family.
It is all because of you and for you.

Acknowledgements

I would like to express my deepest gratitude to my supervisors Prof. Veit Senner and Prof. Stephan Jonas. This dissertation would not have been possible without their guidance, support, understanding and encouragement. I'm forever indebted to them for believing in me and giving me the chance to pursue my studies.

Also, I would like to sincerely thank my former supervisor Prof. Julien Provost for his support, insights and guidance. He was very considerate, pushed me to achieve the work-family balance and made me feel at ease to bring my cranky baby girl to our meetings.

I'm grateful to my former colleagues Canlong Ma, Claudius Jordan and Laurin Prenzel for supporting me and for the good times I had at SES. Also, I would like to thank Maximilian Kapsecker, Jens Klinker and Lara Marie Reimer for their assistance. I want to pay my special thanks to Ms. Simona Chiritescu-Kretsch for her kindness and continuous help in the administrative issues.

This journey was quite tough and I would not have made it this far without the support of my family and friends. To my parents, thank you for never giving up on me when I was about to give up on myself. You never cease to amaze me by your persistence, faith in god and liveliness. Thank you for always giving me the strength to go on and restore my peace. To my brothers, I'm grateful for your unconditional love, support and encouragement. Thank you for all the laughter and for being extraordinary loving uncles. To my husband, I wouldn't have done it without your care, advice, help and support. Thank you for accompanying me on this journey, for the memorable excursions that we have gone on and for being a great father. To my daughter, Kenzy, you brought joy into my life, brightened my darkest days and gave me a reason to keep going, I have been blessed with you. My aunts, thank you for your sincere love, I know you will always have my back. To my dearest friends, Reem, Zeina, Aya and Yara, thank you for caring, listening, supporting and encouraging me when I needed it the most. I'm so grateful for having you guys in my life. To my lovely neighbour, Christina, I've been overwhelmed by your heart-warming kindness and thoughtfulness, thank you so much for everything.

I would like to express my love and gratitude to the ones I lost along the journey. To my dearest grandma, Duha, your encouragement and our talks were priceless, you are terribly missed and you are always on my mind. To my dear godfather in engineering, Prof. Ahmed Hussein, your academic and personal support was invaluable, your loss is heartbreaking. To my dear uncle, Salah, you showed me the meaning of beautiful patience, may your kind soul rest in peace.

Abstract

Ageing of populations is an alarming phenomenon that already has been encountered in many countries in the last decade and will hit even more countries in the upcoming decades. This would require a significant expansion in the social and health sectors to deal with higher capacities. However, investing in developing Ambient Assisted Living environments would be a cost effective way out to reduce the pressure on the social and health sectors.

Ambient Assisted Living (AAL) aims to exploit the advancement in information and communication technologies to help the older adults to age healthy, stay active, remain socially connected and live independently at their preferred place of residence. The key component of AAL environments is monitoring the activities of the resident. Monitoring of activities would enable implementing more AAL services to detect early signs of health deterioration, provide assistance when needed and help the residents to perform their daily activities or routine autonomously. In order to address the privacy and acceptability concerns of most older adults about monitoring, installing non-intrusive ambient sensors in AAL environments is required. Most of the research works that are concerned with developing AAL services assume that the sensors are fault-free. However, in practice most of the non-intrusive ambient sensors are low-cost binary sensors that are prone to failures, and thus can threaten the reliability of the AAL services. Sensor failures detection in AAL is challenging, especially in the presence of the non-deterministic human behaviour.

This thesis proposes a sensor failure detection and isolation system for AAL environments equipped with event-driven, ambient, binary sensors. First, an extensive literature review of research works was conducted, where research works were analyzed and categorized. Then, the feasibility of extracting sensor correlations using the association rule mining technique was studied. Finally, a sensor failure detection and isolation system was developed based on the extracted correlations. Guidelines for selecting the values of the parameters of the system were also presented. The proposed approach was evaluated on two publicly available datasets. In the experimental work, the datasets were injected with fail-stop, obstructed-view and moved-location failures. The results show that the proposed approach is capable of detecting and isolating failures in the event-driven, ambient, binary sensors of the AAL environments. Detecting and isolating failures would enhance the dependability of the AAL environments in practice.

Zusammenfassung

Die Alterung der Bevölkerung ist ein alarmierendes Phänomen, das in den letzten Jahrzehnten bereits in vielen Ländern zu beobachten war und in den kommenden Jahrzehnten noch mehr Länder treffen wird. Dies würde eine erhebliche Expansion des Sozial- und Gesundheitssektors erfordern, um die dadurch notwendigen höheren Kapazitäten zu ermöglichen. Investitionen in die Entwicklung von Umgebungsunterstütztem Leben (Ambient Assisted Living) wären jedoch ein kosteneffektiver Ausweg, um den Druck auf den Sozial- und Gesundheitssektor zu verringern.

Ambient Assisted Living (AAL) zielt darauf ab, die Fortschritte der Informations- und Kommunikationstechnologien zu nutzen, um älteren Menschen zu helfen, gesund und aktiv zu bleiben, soziale Kontakte zu pflegen und unabhängig an ihrem bevorzugten Wohnort zu leben. Die Schlüsselkomponente von AAL-Umgebungen ist die Überwachung der Aktivitäten der Bewohner. Diese würde es ermöglichen, mehr AAL-Dienste zu implementieren, um frühzeitige Anzeichen für Gesundheitsverschlechterungen zu erkennen, bei Bedarf Hilfe zu leisten und den Bewohnern zu helfen, ihre täglichen Aktivitäten oder Routinen selbstständig durchzuführen. Um die Bedenken der meisten älteren Menschen in Bezug auf Privatsphäre auszuräumen und die Akzeptanz der Überwachung zu erhöhen, ist die Installation von nicht-intrusiven Umgebungssensoren im AAL-System erforderlich. Die meisten Forschungsarbeiten, die sich mit der Entwicklung von AAL-Diensten befassen, gehen davon aus, dass die Sensoren fehlerfrei sind. In der Praxis handelt es sich bei den meisten nicht-intrusiven Umgebungssensoren jedoch um kostengünstige binäre Sensoren, die anfällig für Ausfälle sind und somit die Zuverlässigkeit der AAL-Dienste gefährden können. Die Erkennung von Sensorausfällen im AAL-System ist – vor allem in Verbindung mit dem nicht-deterministischen menschlichen Verhalten – eine Herausforderung.

Diese Arbeit entwickelt ein System zur Erkennung und Isolierung von Sensorausfällen in AAL-Umgebungen, das mit ereignisgesteuerten, umgebungsabhängigen, binären Sensoren ausgestattet ist. Zuerst wird ein detaillierter Überblick über die Literatur durchgeführt, bei dem die Forschungsarbeiten analysiert und kategorisiert werden. Anschließend wird die Machbarkeit der Extraktion von Sensorkorrelationen mit Hilfe der Assoziationsregeln-Technik untersucht. Schließlich wird auf Basis der extrahierten Korrelationen ein System zur Erkennung und Isolierung von Sensorausfällen entwickelt. Es werden auch Richtlinien für die Auswahl der Parameterwerte des Systems vorgestellt. Der vorgeschlagene Ansatz wird an zwei öffentlich zugänglichen Datensätzen evaluiert. In den Experimenten werden die Datensätze mit Fail-Stop, Sichtbehinderung und verschobener Position injiziert. Die Ergebnisse zeigen, dass der vorgeschlagene Ansatz in der Lage ist, Fehler in den ereignisgesteuerten, umgebenden, binären Sensoren der AAL-Umgebungen zu erkennen und zu isolieren. Die Erkennung und Isolierung von Fehlern würde die Zuverlässigkeit der AAL-Umgebungen in der Praxis verbessern.

Contents

List of Figures

List of Tables

Acronyms

AAL	Ambient assisted living.
AD	Activities discovery.
ADL	Activities of daily living.
ADLQ	Activities of daily living questionnaire.
AmI	Ambient intelligence.
AP	Activities prediction.
AR	Activities recognition.
ARM	Association rule mining.
AUC	Area under curve.
BADL	Basic activities of daily living.
BI	Barthel Index.
CBLOF	Cluster-based local outlier factor.
CCA	Canonical correlation analysis.
DBSCAN	Density-based spatial clustering of applications with noise.
DD	Detection of deviations.
EM	Expectation maximization.
FD	Fault detection.
FDI	Fault detection and isolation.
FDII	Fault detection, isolation and identification.
FN	False negatives.
FP	False positives.
FPR	False positive rate.
GMM	Gaussian mixture model.
HMM	Hidden Markov model.
IADL	Instrumental activities of daily living.
ICT	Information and communication technologies.
IHL	Indoor human localization.

IR	Infrared.
LCS	Least common subsumer.
MCM	Markov chain model.
NB	Naive Bayes.
PCA	Principle component analysis.
PIR	Passive infrared.
ROC	Receiver Operating Characteristic.
SMART	Simultaneous multi-classifier activity recognition technique.
TBM	Transferable belief model.
TFR	Total fertility rate.
TN	True negatives.
TP	True positives.
TPR	True positive rate.
UML	Unified modeling language.
UN	United nations.
WSN	Wireless sensor networks.

Glossary

False negatives	are the data points reported as negative while they are actually positive.
False positives	are the data points reported as positive while they are actually negative.
True negatives	are the data points are reported as negative while they are negative.
True positives	are the data points reported as positive when they actually are positive.
Accuracy	measures the percentage of true positives and negatives from the data.
Precision	measures the percentage of true positives from the total points reported as positive.
Recall	measures the percentage of true positives from the actual positive points.

1 Introduction

1.1 Addressed Problem and Scope of this Thesis

Ageing of populations is an alarming phenomenon that already has been encountered in many countries in the last decade and will hit even more countries in the upcoming decades. The global number of older adults aged 60 years and older is expected to exceed the number of young people aged between 15 and 24 years by 2050 [1]. Therefore, a significant expansion in the social and health sectors to deal with higher capacities is needed. The impact of the ageing population phenomenon can be transformed from being negative to positive by maintaining the older adult's health, social participation and independency. This could be achieved by investing in developing Ambient Assisted Living environments which would be the cost effective way out to reduce the pressure on the social and health sectors.

Ambient Assisted Living (AAL) aims to exploit the advancement in information and communication technologies to help the older adults to age healthy, stay active, remain socially connected and live independently at their preferred place of residence. The key component of AAL environments is monitoring the activities of the resident. Monitoring of activities would enable implementing more AAL services to detect early signs of health deterioration, provide assistance when needed and help the residents to perform their daily activities or routine autonomously. In order to address the privacy and acceptability concerns of most older adults about monitoring, installing non-intrusive ambient sensors (e.g., motion detectors) in AAL environments is required. Most of the research works that are concerned with developing AAL services assume that the sensors are fault-free. However, in practice most of the non-intrusive ambient sensors are low-cost binary sensors that are prone to failures, and thus can threaten the reliability of the AAL services.

Sensor failures detection in AAL is challenging, especially in the presence of the non-deterministic human behaviour. Two types of sensor failures can be encountered; fail-stop failures, where the sensor completely stop responding, and non-fail-stop failures, where the sensor is still reporting but it gives false information about their environment [2]. The traditional fault detection techniques for wireless sensor networks were mainly developed to deal with homogeneous, time-driven and continuous-valued sensors. However, the sensors installed in the non-intrusive AAL environments are mostly heterogeneous, event-driven and binary sensors. This thesis proposes a sensor failure detection and isolation system for AAL environments equipped with event-driven, ambient, binary sensors.

1.2 Thesis Outline

- Chapter 2: provides background knowledge for the presented research and an overview of the related literature.
- Chapter 3: presents an overview of the research methodology.
- Chapter 4: presents an extensive literature review of sensor failure detection and fault tolerance in AAL environments, it discusses the pros and cons of the approaches found in literature and highlights the research gaps.
- Chapter 5: introduces the use of association rule mining to find correlations between sensors, discusses the evaluation metrics of the rules and experiment the rules extraction using two sets of metrics.
- Chapter 6: proposes sensor failure detection and isolation system based on exploiting the rules extracted from the association rule mining. The approach was evaluated in a case study.
- Chapter 7: presents the effect of adding time features as well as modifying the data processing of contact sensors on the performance of failure detection. In addition, a second case study to verify the feasibility of the proposed approach was presented.
- Chapter 8: discusses the results of the thesis, and provides conclusion and directions for future work.

2 Background and Current State of Research

2.1 Ageing Population

The world is experiencing a distressful change in its population structure. The number of persons aged 60 years and older was 382 million in 1980, 900 million in 2015, and is expected to rise in fast pace to reach 2 billion in 2050 [3]. The percentage of people aged over 60 to the global population is expected to rise from 12% in 2015 to 22% in 2050 [4]. This demographic shift is known as Ageing population. This shift varies in its intensity from one region to another, some regions will be affected the most, e.g., China, Germany and Canada. Figures 2.1a and 2.1b show the percentage of ageing population of each country in 2015 and 2050, respectively. The decreased fertility rates along with the increased longevity of persons are the most influential factors that has lead to population ageing.

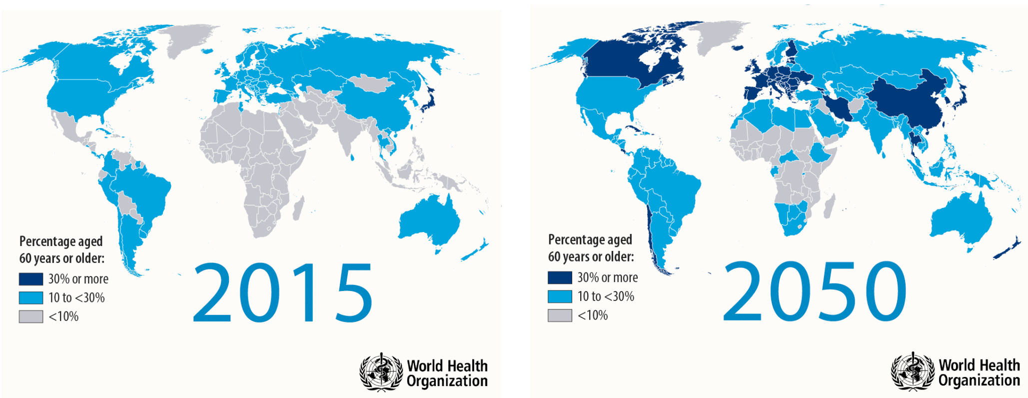

Figure 2.1: Percentage aged 60 years and older in each country in (**a**) 2015. (**b**) 2050 [5].

The global life expectancy at birth has increased by 7.7 years (12%) from 1990-1995 to 2015-2020, and is expected to further increase by 4.5 years (6%) from 2015-2020 to 2045-2050. The life expectancy at the age of 65 years, i.e., the average number of years that is expected to be lived beyond 65, globally was 17 years in 2015-2020. It was the highest in Australia and New Zealand (21 years) followed by Europe and Northen America (19 years). An increase in life expectancy is foreseeable in all regions between 2015-2020 and

2045-2050. Total fertility rate (TFR) is the average number of live births that a woman would give over a lifetime [6]. The global TFR has dropped from 3.2 in 1990 to 2.5 in 2019, and is expected to further drop to 2.2 in 2050. A TFR threshold of 2.1 has to be met in order to replace the population of a specific region. The TFR varies greatly from one region to another, the lowest TFR in 2019 was in Europe and North America with a value of 1.7, while the highest TFR in 2019 was in Sub-saharan Africa with a value of 4.6 [7]. In 2018, the people over 65 years old has outnumbered the children under 5 years old for the first time in history [8].

Although, population ageing has initially started in high-income countries, by 2050 the low- and middle-income countries are expected to have 80% of the older people of the world [4], which will make it even harder for those countries to deal with the ageing population phenomenon. The effects of the ageing population will be reflected on the dependency ratio, which is the ratio between the older and the working age. Globally the ratio of the persons having 65 years or above, per 100 persons aged 20 to 64 years is expected to rise from 20 in 2019 to 33 in 2050 [9]. Regionally in 2019, the highest dependency ratio was in Europe and North America with a ratio of 30 per 100, and the second highest was in Australia with a ratio of 27 per 100. Those numbers are expected to rise steeply by 2050 to reach 49 per 100 in Europe and North America, and 42 per 100 in Australia. Moreover, more Asian countries and other areas are expected to be on the top ten dependency ratio list by 2050 [6]. Europe's projected dependency ratio of 2050 implies that there would be 2 working-age persons for each person over 65 years old, meanwhile in 2010 there were 4 working-age persons for each person aged over 65 [10]. The population pyramid worldwide has been changing greatly, with the most alarming and significant pyramid change is in Europe as can be seen in Figure 2.2.

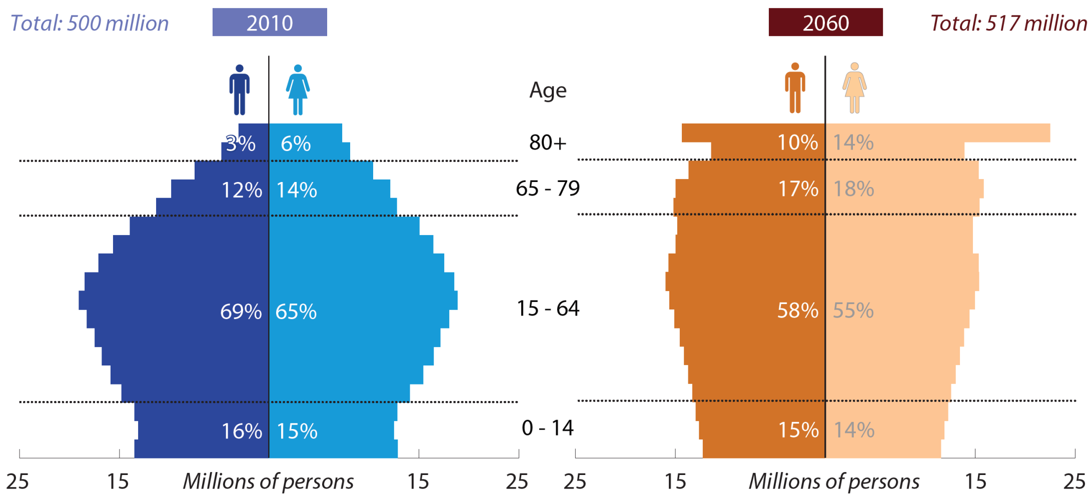

Figure 2.2: EU27 population pyramid for the years 2010 and 2060 [10].

Living independently, i.e., person living alone or with a spouse or partner only, is preferred by most older adults as it offers them more privacy and control over their household. Figure 2.3 shows that high proportion of older adults lived independently between 2006 and 2015, the percentage is higher in the more developed regions, and globally females were twice as likely to be living alone than men [11]. Unfortunately, ageing is often accompanied with physical and cognitive decline. The most significant challenges induced on governments by the ageing population are expanding the health care system as well as the social system to deal with the higher capacities. Moreover, the economic growth of countries will be affected due to the decreased work force and the increased financial expenditure on health and social systems to support the older adults. However, the impacts of the ageing population can be mitigated by promoting healthy ageing. When healthy and active, the older people can definitely have significant participation economically and socially [12].

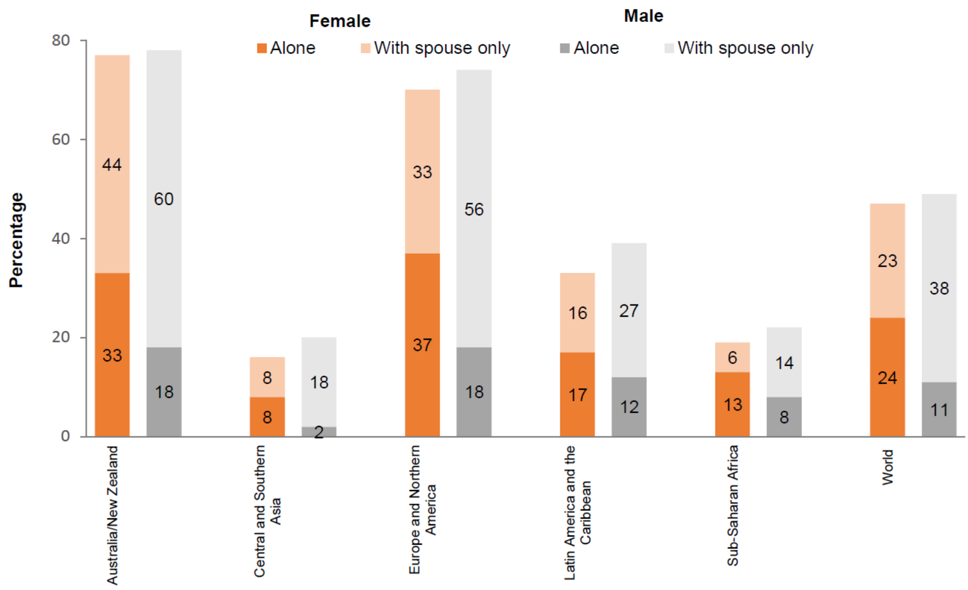

Figure 2.3: Regional percentages of males and females over 65 years old living alone or with spouse between 2006 and 2015 [11].

2.2 Healthy Ageing

Healthy ageing is "the process of developing and maintaining the functional ability that enables well-being in older age" [13]. The functional ability refers to the physical and mental abilities (i.e., intrinsic capacity) of a person, the surrounding environment and his interaction with it. The ability of a person to do the things that they value can be enhanced by providing an enabling environment, despite the weakening of his intrinsic capacities. The most crucial five domains of functional ability to the older adults are mobility, autonomy (i.e., independence in meeting their own basic needs), building and maintaining relationships, contributing to the community and personal growth [14].

The United nations (UN) has declared the upcoming decade from 2021 to 2030 as the "Decade of Healthy Ageing". This initiative is a wake-up action call to bring together the governments, organisations, researchers, private sector and communities to collaborate together to transform the ageing population from being a challenge to an opportunity through improving the lives of older adults. Delaying or even preventing many of the non-communicable diseases that hit the older people is possible by encouraging healthy life style, and creating supportive environments that can stimulate their functional ability and enable them to continue doing what they value [12].

Possible strategies for promoting Healthy Ageing across the life time of an individual is shown in Figure 2.4. The suggested strategies at the stage of high intrinsic capacity focuses on building and maintaining the capacity for the longest time possible through early detection of diseases and early intervention, as well as through promoting healthy behaviour of individuals and healthy environments. The strategies mainly focus on long-term care for the older adults whether they are at high risk or already suffer from significant decline in capacity. The long-term care aims to maintain an optimal trajectory for the intrinsic capacity and to enable the older adults to meet their needs as independently as possible [14].

A change of the place of residence of older adults who have decline in their internal capacity is often needed to provide them with a more supportive environment. However, most older adults are reluctant to relocate as they have a sense of connection to their homes, and relocating makes them feel of a loss of identity, autonomy and security. Therefore, the ageing in place policy is recommended, which refers to the ability of older adult to continue living in their homes safely, independently and comfortably regardless of their internal capacity. Ageing in place would have a positive impact on the well-being of older adults and will eventually decrease the health care costs on governments. Ageing in place would be more achievable in the future via implementing Ambient Assisted Living environments [14].

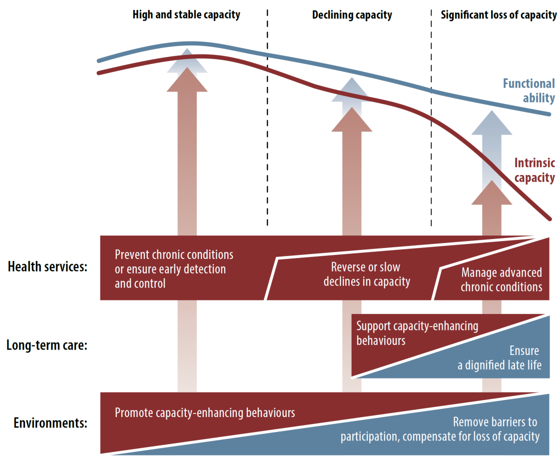

Figure 2.4: A public-health action framework for Healthy Ageing along the life course of an individual [14].

2.3 Ambient Assisted Living

The emergence of the ageing population phenomenon, along with the vast development in information and communication technology (ICT) over the past decades, has encouraged the researchers to develop Ambient Assisted Living environments (AAL) [15]. The AAL is based on the ambient intelligence (AmI) concept. AmI is about surrounding people with embedded intelligent devices that unobtrusively perceive their status, predict and respond to their needs [16]. Ambient Assisted Living can be defined as "the use of information and communication technologies (ICT) in a person's daily living and working environment to enable them to stay active longer, remain socially connected and live independently into old age" [17]. It is a multidisciplinary field that integrates information and communication technology, sociological sciences and medical research [15].

Assistive technology refers to the technology used to increase, maintain or improve functional capabilities of a person [18]. The assistive technology that support the independent living of older adults has evolved over three generations until it progressed into AAL [19]. The first generation included low-tech devices that respond to the older adult in emergency, like wearing pendant which the older adult would press its button in case of a fall to generate an alarm that would alert the informal or formal caregivers. Such technology has been beneficial in emergency situations, however, it required that the older adult is capable of initiating requesting assistance at the first place. The second generation included the instalment of sensors at the older adult's place of residence to automatically detect and respond to emergency situations, and also to detect potential hazards, e.g., gas leakage, and producing alerts. The third generation is about developing AAL systems that embeds technology in the surroundings of the older adults to unobtrusively monitor and provide support in all aspects of their daily living.

AAL is built on the top of the smart home services, providing advanced monitoring and assistive services to support the older adults [20]. Examples of the AAL functional services are health monitoring, wandering prevention, activities of daily living (ADL) assistance, fall detection and cognitive orthotics [21]. Health monitoring refers to the unobtrusive monitoring of the older adult health. The wandering prevention tools aims to prevent the wandering behaviour of the dementia patients. Assistance of the older adults to perform their daily activities is another crucial service. As older adults are more vulnerable to falls, it is critical to detect such falls, ensure their safety and provide the needed assistance. Cognitive orthotics tools are useful to help the older adults that have cognitive decline. The services could be categorized into assistance, autonomy enhancement and comfort services. Figure 2.5 shows an overview of the concept of AAL systems. The early research projects for building AAL environments have focused on safety and assistance in case of emergency situations, e.g., producing an alarm when a fall is detected [22]. Later, the focus expanded to be on providing sophisticated services for their daily living. AAL tools are supported by algorithms and computational techniques, e.g., activity recognition, context modeling and location identification, which act as the components of the AAL system [23]. The aim of AAL is to enable the older adults to live independently in their preferred environment safer and for longer, improve their quality of lives, and hence decrease the costs on the social and health sectors [24].

In order to fulfil this aim, most AAL applications need to first detect and classify the activities being performed by the resident. The activities of daily living (ADL) is "a term used to collectively describe fundamental skills that are required to independently care for oneself such as eating, bathing, and mobility" [25]. The ADL reflect the behavioural routine of older adults. It may be classified into basic activities of daily living (BADL) and instrumental activities of daily living (IADL). The BADL refers to the necessary self-care activities, e.g., eating, toileting and dressing, while the IADL refers to the more advanced or leisure activities, e.g., housekeeping, watching television and preparing meals [26]. The ADL of the older adults can be monitored to track their health status and anticipate any forthcoming risks [27]. The ability to complete ADL, how and with which pace they are being performed, can give an indication about the functional health status of a person. Assessment of ADL by healthcare providers helps in spotting deterioration of the health status of a person and deciding on the type of further diagnosis, assistance and/or medications needed. Examples of the conventional assessment methods are Barthel Index (BI) [28], Katz Index [29] and Activities of Daily Living Questionnaire (ADLQ) [30]. Hence in AAL environments, detection of ADL performed by older adults via his interaction with the surrounding environment would enable automatic analysing of his health status. In the last decade, the main focus of research in ADL has been on activities discovery (AD), activities recognition (AR), detection of deviations (DD) and activities prediction (AP) [31]. Activities discovery means building a model of activities for the monitored person, while activity recognition is the process of detecting which activity is performed by the inhabitant in real-time. Detection of deviation refers to analysing the behaviour of resident and identifying the deviations in his behaviour, meanwhile activities prediction refers to predicting the upcoming activity based on his previous ones. Additionally, indoor location tracking has been the focus of many research works to help in detecting activities, as many activities are location dependant [32].

The essential requirements of AAL systems that need to be met are adaptability, acceptability, usability, low-cost and dependability [15, 24, 33]. Adaptability refers to the ability of the system to adapt to various situations and person capabilities. Acceptability is the extent to which the persons are willing to integrate it into their life [34]. The AAL systems should be unobtrusive, i.e., do not interfer with the person daily living or cause inconvenience, in order to reach high acceptability. Usability refers to the ease of use. In order to improve the usability of systems, the services should be easily accessible. As AAL systems are primarily implemented for older adults who are mostly retired, providing a low-cost system that is affordable should be taken into consideration. Dependability refers to the reliability, maintainability, safety and privacy of the system [34]. Reliability is achieved when the system continues to provide its services correctly. Dependability of AAL systems is crucial to gain the trust of the older adults. Yet, it has received little attention in research and need to be tackled more [32].

Figure 2.5: Overview of the Ambient Assisted Living (AAL) systems [35].

2.4 Sensors in AAL

AAL relies on continuous and mostly real-time monitoring of the older adult's behaviour, health and surrounding environment, to trigger assistance via an event based system [22]. In order to provide AAL services, contextual information about the activities of the older adult need to be gathered in real time via sensor network. Sensors deployed in AAL environments can be categorised into intrusive sensors and non-intrusive sensors [31]. The intrusive sensors are those based on audio and visual sensing, e.g., cameras and microphones. Those sensors provide high level information that makes it easier to deduce the activities of the monitored person, detect falls or any crucial events. Cameras can be used to produce images or videos from which the activities can be extracted precisely but at a computational expense. Microphones can be used to detect voice and other sounds in the environment, e.g., sound of dishes, water or hits, that would ease the recognition of activities. Research works in the field of AAL commonly focus on the environments equipped with audio and visual sensors. However, in practice such intrusive sensors face privacy issues and are not widely accepted by older adults as most of the people have the feeling of being watched [36]. The non-intrusive sensors are either ambient (environmental) or wearable sensors. Most of the ambient sensors in AAL are binary that have two states, e.g., motion sensors and contact switches, or even continuous that can be perceived as binary using a threshold, e.g., water flow sensors and pressure pad sensors

[31]. To be able to efficiently monitor the activities of the older adult, various types of ambient sensors are deployed in the AAL environment [37]. Table 2.1 lists the most common non-intrusive sensors installed in the AAL environments. Passive infrared (PIR) motion sensors detect changes in the infrared emission that occurred due to a movement in its field of view. They are typically installed on ceilings and walls. The data collected from motion sensors can be used to interpret various features, e.g., presence, degree of activity, falls, location, sleeping patterns and gait velocity [38]. Contact switches are installed on objects, e.g., door, drawer and cabinet, to deduce interactions. Magnetic contact switches consist of a magnet mounted to the moveable object and a reed switch mounted to the frame. The electric circuit is completed by getting the magnet in contact with the reed switch, changing the state of the sensor. Pressure sensors are installed on flat surfaces, e.g., chairs, beds and door mats, to detect interaction between the resident and the contact surface. Tactile pressure sensors are often used in AAL and the outputted force or pressure distribution is compared to a threshold to detect the interaction [39].

The non-intrusive ambient sensors have low cost and are easy to install. Usually the wearable sensors are used to monitor the physiological signals of the person, e.g., heart rate and blood pressure, while the ambient sensors are used to monitor his activities. The main drawback of the wearable sensors are that wearing them for extended periods at home often bring discomfort to users, thus the non-intrusive ambient sensors are preferred and can even be used in the future to monitor some physiological signals like heart rate [38]. However, the reliability of the non-intrusive ambient sensors must be assured.

In AAL environments, the deployment of non-intrusive ambient sensors reduces the costs and acquires only low level information from the resident's surrounding environment. Sharing this low level information is usually more acceptable by older adults than the high level information gathered by the intrusive sensors. On the other hand, inferring the activities and behaviour of the monitored older adult from low level data would require advanced techniques. In addition, such sensors are more prone to errors. Flöck has reported some of the observed sensors malfunctions that affected activity monitoring in AAL environments, e.g., spurious signals and faulty activation of motion sensors by sunlight [40]. Moreover, the researchers in the university of Virginia have investigated in practice the challenges of the sensing systems deployed in 20 homes over several years for monitoring the activities of daily living [41]. They have found that high failure rates of sensors occur, around one sensor failure per day. In addition to the power loss and poor network connectivity, it was reported that the human interference is an alarming source of failure. The sensors installed on objects, e.g., mircowaves and faucets, are dislodged during normal use by residents, guests and cleaning services, and hereafter get remounted wrongly. Moreover, moving the furniture that has sensors installed on it leads to reporting incorrect data. Also, the sensors sometimes get hidden behind objects or furniture causing its view obstruction. Sensor failures in non-intrusive AAL environments can be classified as fail-stop and non-fail-stop failures [2]. When the sensor completely stops responding, it is denoted as fail-stop failure. While non-fail-stop failure is when the sensor continues to report but the reported data is not representative of what is really

Table 2.1: Typical non-intrusive sensors in AAL environments [38].

Sensor	Type	Function	Signal
PIR motion sensor	Ambient	Detect motion or movement	Binary
Magnetic contact switch	Ambient	Detect opening and closing of doors, cabinets, drawers, etc.	Binary
Pressure sensor pad	Ambient	Measure applied pressure on beds, chairs, door mat, etc.	Continuous
Water flow sensor	Ambient	Measure water flow in faucets	Continuous
Smoke sensor	Ambient	Detect smoke or fire	Binary
Biosensor	Wearable	Monitor human vital signs	Continuous
Home electric appliances	Ambient	Detect switching of appliances	Binary
Float sensor	Ambient	Detect toilet flush	Binary

occurring in the monitored environment. Examples of the non-fail-stop failures are the moved-location and obstructed-view failures.

2.5 Fault Detection

2.5.1 Background

The dependability of systems can be improved via enhancing the reliability and quality of its individual components, e.g., sensors, actuators, etc., yet a fault-free operation still can not be guaranteed [42]. Accordingly, fault diagnosis became an essential part of any system design. The main goals of fault diagnosis are fault detection, isolation and identification. Fault detection refers to determining that a fault has occured in the system, fault isolation is about finding out the location of fault, i.e., the faulty component, and fault identification refers to determining the type of the fault [43]. The fault diagnosis system can be referred to as fault detection (FD) system, fault detection and isolation (FDI) system and Fault detection, isolation and identification (FDII) system, according to its functionality.

A classification of fault diagnosis techniques was presented in [42], where the techniques have been divided into hardware redundancy, signal processing, plausibility test and software/analytical redundancy based techniques. Hardware redundancy is about installing extra redundant hardware for each component, and comparing the output of each component with its redundant one to detect a fault occurrence. Despite having the advantage of direct fault isolation, this technique suffers from high implementation costs. Signal processing based techniques rely on detecting significant changes or deviation in the signals (readings) that is considered as a symptom of the fault using suitable signal processing, e.g., limit values, mean values and trends. Plausibility test is based on checking that some physical laws that governs the component and will be affected by the fault remain valid. Software/analytical redundancy is about constructing a model of the system, and comparing the output signals with its estimated value from model, i.e., residual generation.

As wireless sensor networks (WSN) became widely used in many applications, e.g., industrial monitoring, surveillance and health monitoring, developing fault detection techniques for wireless sensor networks has received the attention of many researchers. Wireless sensor networks are “interconnected sensor nodes that communicate wirelessly to collect data about the surrounding environment” [44]. The sensor nodes may fail due to various reasons, e.g., poor connection, hardware faults, low battery, weather or environmental conditions [45]. In wireless sensor networks, the fault detection techniques can be classified as centralized and distributed approaches [46, 47]. In the centralized approach, a base station constantly sends queries to the sensors to check on their status. The distributed approach is mainly implemented via node self-detection, neighbour coordination and clustering approach. The node self-detection is based on comparing the output of the sensor nodes to predefined fault models. The neighbour coordination where the sensor nodes coordinate with their neighbouring nodes to identify the failure, where a node is suspected to be faulty when sensor readings differs greatly from its neighbours. The clustering approach first group the sensor nodes into clusters and then apply the most suitable fault detection technique to each cluster.

The traditional fault detection techniques are mainly used to tackle wireless sensor networks that have homogeneous, time-driven and continuous-valued sensors. However, the non-intrusive ambient sensors installed in the AAL environments are mostly heterogeneous, event-driven and binary sensors. Detecting faults in such environments is a challenge especially in the presence of the non-deterministic human behaviour.

2.5.2 Related Work

In the last decade, developing sensor failure detection systems for AAL environments equipped with non-intrusive ambient sensors has gained the interest of researchers. A comprehensive literature review has been proposed in Chapter 4, where the approaches of the reviewed sensor failure detection systems were classified into model-based and correlation-based. An overview of the related work is presented in this section.

The model-based approaches rely on checking if the deduced location of the resident using a model [48, 49] or localization hardware [50, 51] is consistent with the location estimated based on the triggered binary sensor, and if not then the binary sensors are expected to be faulty. The surveyed model-based sensor failure detection techniques either suffer from using a non-realistic generic mobility model of the resident, e.g., random walk model, that does not take into account the previous locations and speed of the person, or depend on installing extra localization hardware that would subsequently increase the faults likelihood and the cost of implementation. Modeling the human behavior or mobility is very challenging as humans are characterized by having a non-deterministic nature. Also, since the AAL systems are targeting older adults who are mostly retired, the cost of the system is one of the important aspects that need to be considered. Fault detection frameworks have been proposed that are based on modelling either the physical effects that are expected to occur due to the activation of actuators [52, 53] or the causal relationships in predefined assistance user scenarios [54] to deduce the expected sensors readings and comparing it with the actual readings. However, those methods can only detect failures in the sensors that are involved in tasks that have sensor-actuator feedback. Therefore, in this thesis adopting a model-based approach was avoided as it seems less promising for our application compared to the correlation-based (data-driven) approaches.

The correlation-based sensor failure detection approaches found in literature rely on using historical data to deduce correlations that form the basis for the detection of sensor failures. The correlation-based approaches can be classified as works that exploit the sensor-appliance [55], sensor-activity [56] and sensor-sensor [57, 58, 59, 2, 60] correlations. In [55], a motion sensor is flagged as faulty when the monitored interval between triggering a motion sensor after and/or before turning on/off an electrical appliance deviates from the regular interval patterns learnt from the training data. The distribution of each of the after and before interval of every sensor-appliance pair is represented using Gaussian mixture model, where the model is composed of one or more normally distributed components reflecting all the regular interval(s) of the sensor-appliance pair. The Gaussian mixture model is parametrized by the mixture component weights, means and covariances, which are estimated using the Expectation maximization algorithm [61] that is based on initially assigning random values for the parameters, and then iterating and updating the parameters until convergence occurs. This approach is based on the assumption that the person has to be physically around the electrical appliance to turn it on/off and accordingly the motion sensors covered by that area will be triggered. The sensor-appliance correlation-based approach has the drawback that its hypothesis may not always hold especially with the spread of using advanced remote controlled technology, e.g., voice controlled electrical devices. Kodeswaran et al. [56] have proposed detecting sensor failures via exploiting the functional redundancy of sensors per activity, where the sensors that are typically triggered with each activity are extracted using an activity labeled training dataset. At run-time, failure alerts are generated according to the recognition of a performed activity along with the absence of one of its sensors. The limitation of this approach is that it needs activity labeled training data, which are costly and hard to obtain. Moreover, it assumes that the performed activity has been correctly identified by the activity recognition system. Hence, basing our failure detection system on sensor-appliance and sensor-activity correlations has been avoided.

Exploiting the sensor-sensor correlations to detect sensor failures in AAL environments has been tackled by researchers. Ye et al. [57] aimed to detect missing sensor events using the temporal correlations and time-series analysis. The temporal correlations between sensors are generated using the mutual information technique, while the non-linear time-series analysis is used to represent the firing pattern of each sensor. A missing sensor event is reported when a sensor does not trigger although it was supposed to be triggered according to temporal correlations and/or the non-linear time-series. The authors have stated that their proposed approach could not be evaluated properly in the experiments due to using a dataset with a small number of sensors and short duration. Same authors have proposed using a clustering based outlier detection technique to detect non-fail-stop sensor failures [58, 59]. The sensor events are clustered according to their time stamp, object to which the sensor is attached to, its location and the user triggering that event. A clustering based local outlier factor (CBLOF) is assigned to each event which is function in the size of the cluster to which it belongs, the distance from the closest large cluster and the historic abnormal behavior of the triggered sensor. The drawback of this approach is that sensor events must be collected first and then the approach is applied offline to detect abnormal binary sensor events. Kapitanova et al. have proposed sensor failure detection system based on using the classification technique [2]. Mutliple classifier instances are trained for each sensor failure by excluding this sensor out of training set to mimic the failure. At run-time, sensor failure is flagged via assessing the relative performance between the classifiers which did not have that sensor in their training set and the classifiers which had it. This approach requires excessive training effort, which proportionally increases as the number of deployed sensors increases. Choi et al. [60] extract the correlations between sensors represented as sensor state sets (groups), and find the transitional probabilities across the sensor groups as well as between the sensor groups and the actuators. At run-time, a failure is detected either when there is one sensor state difference between the incoming events and the correlation, or when a group of sensors fires despite having a zero transitional probability with the previous group of triggered sensors or actuators and vice versa. In this approach, any group of triggered sensors is considered as a correlation that the system can use for failure detection, even if it has occurred once in the precomputation phase. As a result, there is a high possibility of including correlations that may be unreliable for failure detection, and the computational effort would be high especially when more sensors are deployed in the environment.

2.6 Motivation

Most of the research works that focus on developing services for AAL environments equipped with non-intrusive ambient sensors, assume that the sensors are fault-free. Nevertheless, those sensors are likely to fail in practice. In AAL environments, a failure in one of the sensors may induce misleading result in the activity recognition, location tracking, or in any of the subsystems and services of AAL. Sensor failure has been acknowledged as one of the significant challenges that affects inferring the activities of daily living in AAL [62]. Location tracking was significantly impacted when sensor failures were imposed in a case study [49]. Detecting failures in the event-driven binary sensors of the AAL environments is challenging especially in the presence of the non-deterministic human behaviour.

This thesis aims to propose a sensor failure detection and isolation system in the AAL environments equipped with event-driven, ambient, binary sensors. The approach also aims to overcome the previously mentioned shortcomings of the related works, e.g., high cost, need of labelled datasets and lack of scalability.

In order to reach our aim, the following reasearch questions have been formulated:

RQ1 What are the existing failure detection solutions of event-driven, binary, ambient sensors installed in AAL environments?

RQ2 What are the limitations of the existing solutions?

RQ3 Is using association rule mining (ARM) to find sensors correlations in AAL environments feasible?

RQ4 Which data preprocessing and metrics are suitable to find sensors correlations using association rule mining?

RQ5 How to exploit the sensors correlations to detect and isolate sensor failure?

RQ6 How to choose the values of the set parameters of the proposed sensor failure detection and isolation system?

RQ7 Is the proposed solution effective in detecting and isolating sensor failures?

3 Methodology

This chapter gives an overview of the thesis methodology. Figure 3.1 provides an illustration of the steps performed in order to answer the previously mentioned research questions of Section 2.6.

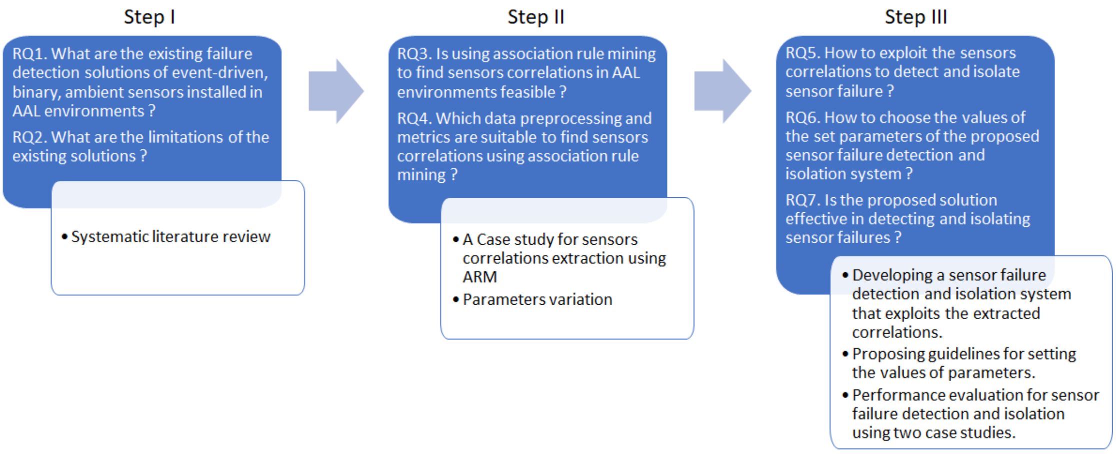

Figure 3.1: Methodology overview

3.1 Step I: Literature Review

As illustrated in Figure 3.1, to answer RQ1 and RQ2 an extensive literature review was conducted and presented in Chapter 4 to explore the state-of-the-art for the sensor failure detection systems and fault tolerance methods in the presence of sensor failures in AAL systems equipped with non-intrusive, binary, event-driven, ambient sensors.

In order to conduct the literature survey, the title, abstract and keywords fields were searched in Scopus, IEEExplore, Web of knowledge and ACM databases for the following combination of terms; ("fault detection" OR "sensor failure") AND ("smart home" OR "ambient assisted living"). Scopus and Web of knowledge databases produced the largest number of relevant articles. The search was then extended on Scopus and Web of knowledge to include more combinations of the keywords shown in Table 3.1, so that the combination is as follows; ((Group A AND Group C) OR Group D) AND Group B. The years field was not constrained, yet it was observed that the papers found were all published between 2008 and 2017. Only the papers concerned with non-intrusive ambient binary sensors were included in the survey.

Table 3.1: Search keywords.[1]

Group A	Group B	Group C	Group D
"sensor*"	"smart home"	"fault detection"	"sensor* error"
	"ambient assisted living"	"failure detection"	"sensor* failure*"
	"AAL"	"fault toleran*"	"sensor* fault*"
	"location tracking"	"fault identification"	"sensor reliab*"
	"actvity recognition"	"failure identification"	"faulty sensor*"
	"activity monitoring"	"fault diagnosis"	"*reliable sensor"
	"activity detection"	"FDI"	"uncertain sensor"
	"home* based care"	"fault isolation"	"sensor diagnos*"
	"indoor localization"	"fault prevention"	"sensor node fail*"
		"fault prediction"	"fail* sensor*"
		"fault recover*"	"anomal*" AND "binary sensor*"
		"self-check*"	
		"self-heal*"	
		"dependable"	
		"failure management"	

The research works were categorized into five categories according to the function of the proposed systems and the approach that their methods are based on. The categories were correlation-based fault detection, model-based fault detection, fault-tolerant location tracking, fault-tolerant activity recognition, and fault detection and diagnosis framework for AAL. An overview of the method, algorithm, experiments conducted, datasets used and performance metrics of each of the research works was given. The limitations of the works were also discussed.

The model-based fault detection techniques found in literature rely on deducing the location of the resident using the triggered sensors due to his movement or his performed activities. Then, this deduced location is compared with the location predicted either by his model of mobility or by a localisation system. The proposed model-based sensor failure detection approaches are not promising as they either use unrealistic models of resident motion that do not take into consideration previous locations and speed or install extra hardware that increases the cost as well as the chances of errors. Moreover, the fault detection and diagnosis frameworks that rely on modelling the sensors' and actuators' activation due to various user scenarios can only detect failures in sensors that are involved in tasks that have sensor-actuator feedback. Thus this thesis favoured adopting a correlation-based approach over a model-based approach.

Correlation refers to the relation or dependency between variables. If a correlation that has already been applicable during nominal operation, has been defied then this may indicate the presence of a fault. The surveyed correlation-based (data-driven) techniques

[1] * replaces any number of characters, i.e., sensor* will search for sensor, sensors, sensory, etc.

can be classified as methods based on exploiting sensor-appliance correlations, sensor-activity correlations and sensor-sensor correlations. The sensor-appliance approaches rely on assuming that there will be correlations between the activation of the electrical appliance and the triggering of the motion sensors in the areas leading to it, which is becoming less common in smart homes as most appliances can be switched on remotely. Meanwhile, failure detection using sensor-activity correlations found in literature requires obtaining labelled data of performed activities to correlate the activities to the sensors during the training phase and relies on the accuracy of the activity recognition system at run-time to detect sensor failures. The proposed sensor failure detection and isolation system approach that will be presented in the next chapters focuses on sensor-sensor correlations rather than sensor-appliance and sensor-activity correlations.

3.2 Step II: Correlations Extraction using ARM

Finding the strong correlations between the employed sensors could form the base for developing a sensor failure detection system. In step II, the use of association rule mining to find the highly correlated sensors from an unlabelled recorded dataset was investigated. The obtained rules could then be used for sensor failure detection in such a way that if the sensor(s) of the antecedent part of rule got triggered while the sensor(s) of the consequent part of rule did not within a specific time, then the sensor(s) can be suspected to be faulty.

Association rule mining [63] is a data mining technique that was primarily developed to find correlations between items in large transactional databases. It aims to find the frequently occurring correlations in categorical data, the outputted correlations takes the form of a set of rules. Each rule consists of antescedent and consequent, it implies that if the item(s) of the antescedent is (are) found in a transaction, then it is likely that the item(s) of the consequent will be found. Its most famous application is the market basket analysis, where the association rule mining is applied to find which Y product(s) is (are) likely to be bought when X product(s) is (are) purchased.

A formal representation of the association rule mining problem is as follows. Let $I = \{I_1, I_2, .., I_m\}$ be a set of binary features denoted as items. Let the dataset T consist of a set of transactions $T = \{T_1, T_2, .., T_n\}$, where each transaction is a binary vector of items, e.g., if transaction T_1 contains only two items I_1 and I_3, then T_1 will have $T_1[1] = 1$, $T_1[3] = 1$ and the rest of T_1 vector are zeros. An association rule has the form of $X \rightarrow Y$, where the antecedent $X \subset I$, the consequent $Y \subset I$ and $X \cap Y = \phi$. The most commonly used evaluation metrics (interest measures) of a rule are its support and confidence. The support of a rule is defined as "the fraction of transactions in T that satisfy the union of items in the consequent and antecedent of the rule", while the confidence of a rule is defined as "the fraction of transactions that satisfy the antecedent X also satisfy the consequent Y " [63]. The support reflects the statistical significance while the confidence reflects the strength of a rule. A rule's support and confidence must exceed a minimum threshold value so that a rule is considered interesting and worth consideration. One of the widely used algorithms for association rule mining is the Apriori algorithm, in which the dataset is first scanned to find 1-itemsets (itemsets of length 1) that satisfy the minimum support, then from those frequent 1-itemsets, 2-itemsets will be generated and checked against the minimum support value, and so on [64].

In order to answer RQ3 and RQ4, a case study was conducted in Chapter 5, where using association rule mining to find correlations between the event-driven binary sensors installed in AAL environments was examined. In a market basket analysis, transactional datasets are analysed to discover which products are likely to be bought together. However in AAL, we would like to know which sensors are likely to be ON simultaneously in addition to knowing which sensors are usually triggered within a few seconds from each other, i.e., temporal correlations, due to performing various activities by resident. Therefore, a sliding window is used in the data preprocessing stage described in the next paragraphs to account for the temporal correlations.

The log obtained from AAL environments equipped with non-intrusive sensors consists of a series of sensor events. Each event has a time stamp, sensor ID and the corresponding sensor event trigger. In order to extract correlations using association rule mining, the transformation of the time-stamped sensor event triggers dataset into the set of transactions of our interest takes place over a couple of steps. The first step consists of creating a multivariate time-series, where the value of each sensor is logged at every time stamp of the dataset in a separate sensor signal variable. Formally, let $s_{i,t} \in \{0, 1\}$ be the value of the i-th sensor at timestamp $t \in T$. The set T is the set of timestamps of the log. For n sensors, concatenation produces the multivariate time-series S.

$$S = \{(s_{1,t}, s_{2,t}, ..., s_{n,t})\}_{t \in T} \tag{3.1}$$

Next, removal of all-zero rows is done. Formally, it corresponds to removing all-zero row vectors from the time-series S.

$$V := S \setminus \{(0_{1,t}, 0_{2,t}, ..., 0_{n,t})\}_{t \in T} \tag{3.2}$$

Figure 3.2a shows an example for a multivariate time-series created from an AAL log. At each row, a sliding window is used to group the sensors that have a signal value of 1 within the size w seconds of the sliding window via logical ORing. The output of the window will be a single transaction that has the time stamp of the start of the window. Formally, the value of the i-th sensor in the transaction computes to:

$$d_{i,t} = sgn(\sum_{j \in [t, t+w]} v_{i,j}) \tag{3.3}$$

The sliding window is run over the multivariate time-series data to output a transactional database as illustrated in Figure 3.2, where each transaction presents the sensors that appear to be ON within w seconds from each other. The obtained sensors transactional database will be used in the upcoming correlations extraction step.

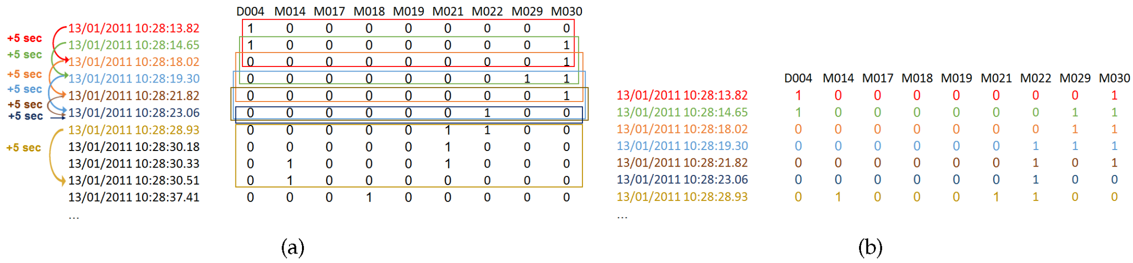

Figure 3.2: (**a**) Sliding window of size $w = 5$ s, is run over the multivariate time-series data. (**b**) Transactional database.

In our AAL application there may be uneven usage of the different areas of an apartment. A living room may be used by an older adult resident more often than the office room, leading to scarcity of the triggers of the office's sensors in the dataset. In such cases, the support of the rule that has the less often triggered sensors may not exceed the minimum support value that was preset in the Apriori algorithm, and thus will not appear in the extracted set of rules. To overcome this limitation, a metric was defined as relative support to be used in the Apriori algorithm instead of the support for rules extraction. Support compares the number of transactions containing all items of X & items of Y to the total number of transactions present in the database as shown in Equation (3.4). While relative support is defined by Equation (3.6), it compares the number of transactions containing all items of X & items of Y to the minimum number of transactions that contain any of the individual items of X or Y.

$$\text{Sup}(X \rightarrow Y) = \frac{|\text{Transactions containing X\&Y}|}{|\text{Transactions}|} = P(X \cap Y) \tag{3.4}$$

$$\text{Conf}(X \rightarrow Y) = \frac{|\text{Transactions containing X\&Y}|}{|\text{Transactions containing X}|} = P(Y|X) \tag{3.5}$$

$$\text{Rel. Sup}(X \rightarrow Y) = \frac{|\text{Transactions containing X\&Y}|}{\text{Min}(|\text{Transactions for each item in X or Y}|)} \tag{3.6}$$

In an attempt to find the interesting correlations between sensors, the use of association rule mining was investigated in a case study in Chapter 5 where two techniques were considered; the first used support and confidence as the interest measures, while the second used relative support and confidence. The two techniques were applied on a publicly available dataset collected from a single resident apartment. A systematic variation of the parameters of each was conducted. The number of association rules obtained from each experiment, the number of the sensors present in the consequent part of those rules (consequent sensors) and the ratio of sensors present in the consequent part to the number of extracted rules were plotted. The experiments analysed which parameters and values extract the most meaningful association rules. It is meant by meaningful association rules that the rules represent useful and interesting relations, that have as many sensors as possible in the consequent part of rules while avoiding redundancy. The sensors that do not appear as consequent to the activation of other sensor(s) in the apartment cannot be checked for failure because the obtained rules would then be used for sensor failure detection in such a way that if the sensor(s) of the antecedent part of rule got triggered while the sensor(s) of the consequent part of rule did not within a specific time (sliding window size), then the sensor(s) can ben suspected to be faulty. The ratio of consequent sensors to the number of rules indicates the redundancy of the extracted rules using the chosen values for the set parameters, i.e., whether the increase in the number of association rules is useful in extracting new interesting rules that covers more sensors in its consequent part.

It was observed that the relative support experiment permits to extract more consequent sensors within less number of functionally redundant rules than the standard support experiment. This shows that using the relevant support of rule is more beneficial for our application. This can be explained by the fact that the AAL datasets are usually unbalanced: some sensors are triggered much more often than others; yet, infrequent triggered sensors may be highly correlated.

By checking the extracted association rules and the apartment layout, logically correct correlations could be obtained between the different sensors. It was concluded that it is promising to design a sensor failure detection for Ambient Assisted Living that relies on those rules to flag a sensor failure.

3.3 Step III: Sensor Failure Detection

3.3.1 Sensor failure detection and isolation system

Attempting to answer RQ5, a sensor failure detection and isolation system was proposed in Chapter 6 that is based on exploiting the rules extracted from the ARM. The proposed sensor failure detection and isolation system consists of two stages: an offline stage and an online stage. During the offline stage, the fault-free sensor correlations are extracted from previously collected sensor dataset at the resident's home during nominal behaviour. Meanwhile online, the fulfilment of correlations are checked as sensor events are triggered by the resident and accordingly failure of sensors is determined. An overview of the proposed system is shown in Figure 3.3.

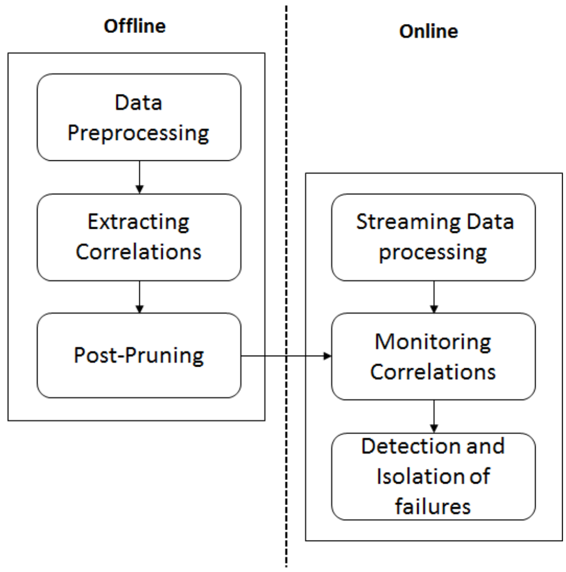

Figure 3.3: An overview of the proposed system.

3.3.1.1 Offline Stage

First, preprocessing of training data is done, followed by rules extraction using association rule mining as described in the previous section. In order to exploit the extracted association rules to detect and isolate sensor failures, the mined set of rules that have already exceeded the minimum values for the relative support and confidence still needs further post-pruning to eliminate the redundant and/or less useful rules. Thus, the extracted rules undergoes post-pruning as follows; Since our proposed sensor failure detection method relies on the following hypothesis; if a rule has all of its antecedent sensors active during run-time, while its consequent sensors(s) did not become active within the specified sliding window size, then the sensors can be suspected to be faulty. Accordingly, we aim to have most of the sensors installed in the resident's home appear in consequent part of rules so that they could be checked for being faulty in the monitoring stage. Hence, the rules are grouped for each sensor in consequent, i.e., if there are 20 sensors that appear in the consequent parts of rules, then we will have 20 groups. From each group, the rule with highest confidence, the rule with highest support and the two top trade-off rules between confidence and support, are selected. In our opinion, the former would be the most interesting rules to our application. To obtain the trade-off rules, confidence and support of the rules within each group are normalised, then are summed with weights 1:1, and the rules with the top two highest sums, i.e., trade-off scores, are selected.

3.3.1.2 Online Stage

The pruned set of rules are the most interesting correlations that will be monitored online; they are stored using bitmap arrays [65]. The health status of each sensor, which is the probability that a sensor is healthy, will be computed according to the fulfilment of these correlations.

Every time a sensor trigger *event* occurs, the data is processed and the corresponding sliding window is prepared similar to Section 3.2, where the sensor signal value is updated and the sliding window logically OR the sensors' signals within the sliding window size of w seconds. A UML (Unified Modeling Language) diagram that describes the main workflow for the health status update is shown in Figure 3.4. The pseudocode in Algorithm A1 illustrates in details the health status update of sensors due to monitoring the pruned set of rules. Two satisfaction states of rules are possible: satisfaction and unsatisfaction. If the sliding window contains active sensors that satisfy a rule antecedent as well as its consequent, then this correlation is fully satisfied and the health status of these sensors are updated according to the satisfaction set of equations in Algorithm A2. It is assumed that only one sensor failure can occur at a time (single-sensor failure). Hence, if the sliding window contains active sensors that satisfy a rule antecedent but it fulfils the rule consequent except for one sensor, then this rule is unsatisfied. If this unsatisfied rule has already been satisfied in the previous sliding window or if it will be satisfied in the upcoming sliding window, then the health status will not be updated. In addition, if this rule has been unsatisfied in the previous sliding window then health will not be updated. Otherwise, the health status of this rule's sensors are going to be updated according to the unsatisfaction set of equations in Algorithm A3. The joint probabilities between sensors that are included in the equations can already be obtained from the intermediate calculations of the Apriori algorithm while scanning the training data for finding the frequent itemsets, hence no extra computation is needed. Whenever the health status of a sensor falls below the preset health threshold, failure of this sensor will then be flagged. Figure 3.5 shows a UML analysis object model of the online stage of our system.

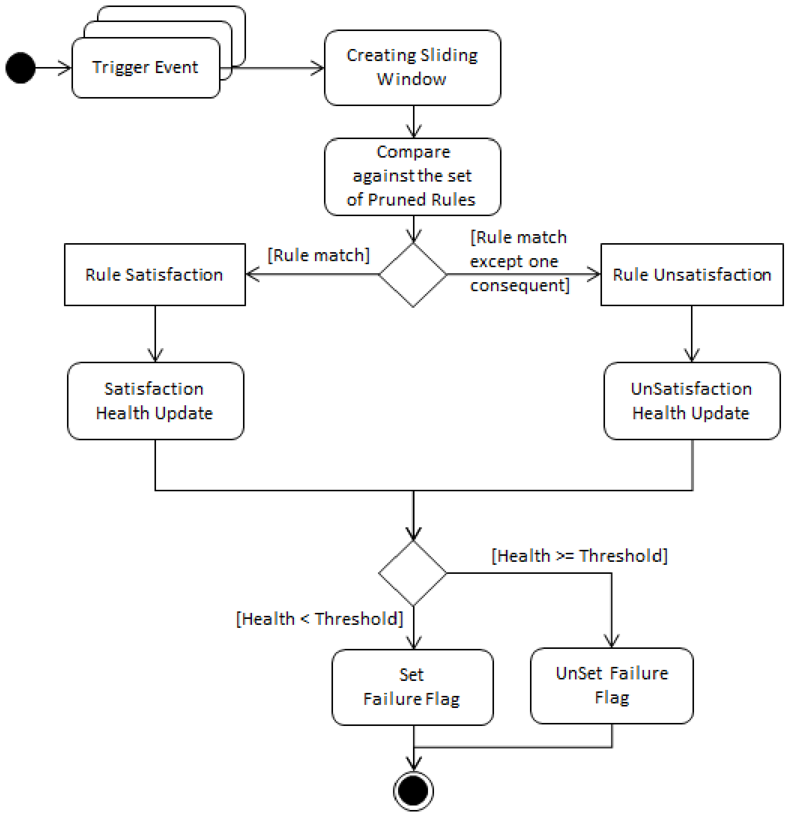

Figure 3.4: UML activity diagram of the health status update.

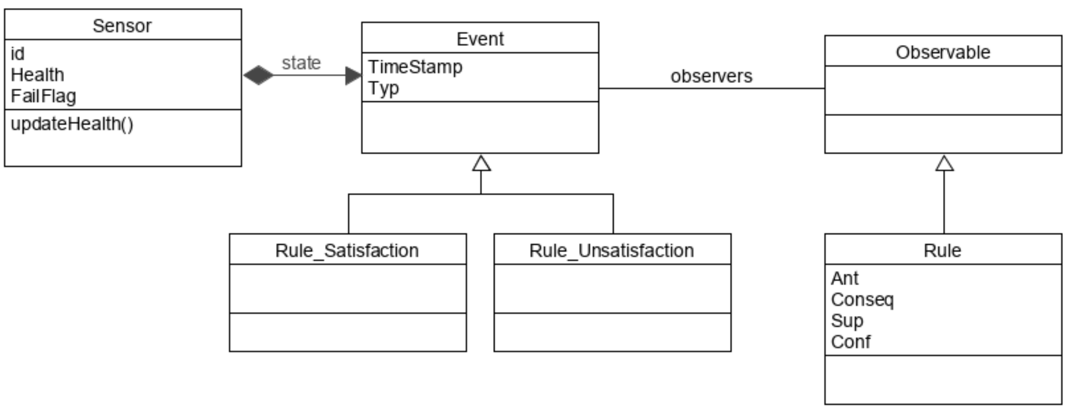

Figure 3.5: UML analysis object model of the online stage of the failure detection system.

3.3.2 Setting Parameters

To achieve high performance for the sensor failure detection and isolation system, optimum values for four parameters need to be selected. Those parameters are the sliding window size, minimum relative support, minimum confidence and health threshold. To better understand the effect of each parameter independently on the extracted rules and the performance of the system, changing the value of a parameter while keeping the rest at the same values was studied using a publicly available dataset.

In order to select the best combination of values for the sliding window size, minimum relative support, minimum confidence and health threshold, which would enable failure detection and isolation of as many sensors as possible with high precision and recall, a set of guidelines that aids in the parameters selection process was formulated and presented in Chapter 6 tackling RQ6.

3.3.3 Evaluation

The proposed approach for sensor failure detection and isolation was evaluated in Chapters 6 and 7 using two publicly available datasets (Aruba and HH122 datasets) in attempt to answer RQ7. To obtain the training and testing data, a split ratio of 50/50 was used. The training data was used for extracting the offline correlations, while the testing data was processed sequentially to simulate the run-time online processing using MATLAB 2019b software. Three types of failures were injected in the testing dataset; fail-stop, obstructed-view and moved-location failures. The following metrics are used for evaluating the sensor failure detection and isolation system: precision, recall and F1-measure. Precision is the percentage of true positives from the total number of sliding windows reported as positive, while recall is the percentage of true positives from the actual positive sliding windows. Receiver Operating Characteristic (ROC) curve [66] and the area under its curve (AUC) were also used to evaluate the performance of failure detection. The ROC curve shows the trade-off between the true positive rate (TPR) and the false positive rate (FPR) as the health threshold value is varied from 0 to 1. An overview of the evaluation metrics are presented in the Background section of Chapter 4. Moreover, in Chapter 7 two modifications in the approach were investigated on the Aruba dataset, which are adding time features in the correlations and modifying the data preprocessing of the contact sensors.

4 Paper A

A Systematic Survey on Sensor Failure Detection and Fault-Tolerance in Ambient Assisted Living [1]

ElHady, N.E.; Provost, J. A Systematic Survey on Sensor Failure Detection and Fault-Tolerance in Ambient Assisted Living. Sensors 2018, 18, 1991.
https://doi.org/10.3390/s18071991

Summary

Ambient assisted living environments equipped with non-intrusive ambient sensors is the key to gain acceptability by older adults. However, reliability should be ensured to provide a dependable system and gain the users trust. As failures of sensors are inevitable, sensor failure detection and fault tolerance in AAL systems are crucial. This research paper reviews the work done in sensor failure detection and fault tolerance in the presence of sensor failures in AAL environments equipped with non-intrusive binary sensors. The different types of failures found in the sensors of the AAL environments were discussed, and an overview of the publicly available datasets that were used in works concerned with fault detection or tolerance in AAL were presented. The surveyed works were classified into correlation-based fault detection, model-based fault detection, fault tolerant location tracking, fault tolerant activity recognition and fault diagnosis frameworks. The methodology, experimental work, results and evaluation criteria of each of the works were highlighted. A discussion of the surveyed works was presented, along with highlighting their pros and cons. Research gaps in the field were identified and discussed.

[1] The author of this thesis contributed to the conceptualization and design of the study, carried on the literature survey, investigation, and wrote and edited the original draft of the manuscript. The co-author has contributed to the conceptualization, supervision, and manuscript editing and revision. All authors have read and agreed to the published version of the manuscript.

sensors

MDPI

Review

A Systematic Survey on Sensor Failure Detection and Fault-Tolerance in Ambient Assisted Living

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Received: 13 April 2018; Accepted: 20 June 2018; Published: 21 June 2018

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Abstract: Ambient Assisted Living (AAL) systems aim to enable the elderly people to stay active and live independently into older age by monitoring their behaviour, provide the needed assistance and detect early signs of health status deterioration. Non-intrusive sensors are preferred by the elderly to be used for the monitoring purposes. However, false positive or negative triggers of those sensors could lead to a misleading interpretation of the status of the elderlies. This paper presents a systematic literature review of the sensor failure detection and fault tolerance in AAL equipped with *non-intrusive*, *event-driven*, *binary* sensors. The existing works are discussed, and the limitations and research gaps are highlighted.

Keywords: ambient assisted living; sensor failure; fault detection; fault tolerance; smart home

1. Introduction

According to the World Health Organization, the world's population percentage of people aged over 60 is expected to double in the next decades to increase from 12% in 2015 to 22% in 2050. This phenomenon, known as Ageing Population, can be already witnessed in high-income countries. This demographic shift will induce new challenges to the countries, e.g., preparing the health care and social systems to deal with higher capacities [1]. Focusing on healthy ageing is an essential investment for facing that shift. Taking care of the elderlies would decrease the chance of further complications to their health status. This can be achieved by providing care in nursing homes or hospitals. However, it is costly and the costs increase greatly if the person needs specialized care due to immobilization or other health problems. A cost-effective alternative is using technology for independent living of the elderlies [2].

Ambient assisted living (AAL) is defined as "the use of information and communication technologies (ICT) in a person's daily living and working environment to enable them to stay active longer, remain socially connected and live independently into old age" [3]. AAL technologies can monitor the behavior of elderly people at home and provide support whenever required, and hence, improve the quality of life [4]. This would cast some burden away from the family members of the elderlies, decrease the need for qualified caregivers and have a positive impact on the psychological status of the elderlies, as they would live independently at their homes longer and safer [5].

Smart homes and *ambient assisted living* (AAL) terms were found to be interchangeably used in scientific articles, however, AAL is a special form of a smart home. AAL tools range between health and activity monitoring tools, wandering prevention tools, and cognitive orthotics tools [6]. The technology of those tools are based on ambient intelligence, a paradigm that integrates technology in people's environment to help them in their everyday lives by learning and adaptively responding to their behaviour [7]. Researchers are interested in investigating approaches to track the location and the activities of the residents, prompting the residents, discovering the abnormal behavior, and predicting the future activities [8]. Integrating sensors in an unobtrusive intelligent way in the residents' homes, allow monitoring their activities of daily living (ADL) to track their health status, and to detect early signs of diseases [9].

The sensors used to monitor and locate the resident can be classified into intrusive sensors (e.g., camera, microphone) and non-intrusive sensors (e.g., motion detectors, pressure sensors). In practice, the sensors installed in the inhabitant's place of residence may produce wrong output, e.g., false positives or negatives. A failure in one of the sensors of the AAL could lead to misleading result in activity recognition, or in location tracking. This can have dramatic consequences to the health of the inhabitant [10].

This survey paper aims to review the research work done in the sensor failure detection and fault tolerance in the presence of sensor failures in AAL systems equipped with non-intrusive binary sensors. The paper is organized as follows; Section 2 provides an overview of sensor failures, Section 3 presents an overview of the typical publicly available datasets used in the reviewed works, Section 4 outlines the methodology used to conduct the literature survey, Section 5 presents the research work found in the survey, Section 6 discusses the reviewed works and Section 7 discusses the status of research and highlights the gaps.

2. Background on Sensors Failures in Smart homes and AAL

A *fault* can be defined as an abnormal event that can cause an element or an item to fail, while a *failure* is the termination of the ability of an element to perform a function as required [11]. A fault may or may not lead to failure.

For sensor networks in general, two perspectives for fault type classification in sensor networks was proposed by [12]:

1. Data-centric viewpoint, which is based on the characteristics of sensor readings, e.g., stuck-at and spike.
2. System-centric viewpoint, which describes faults causing the malfunction of sensor, e.g., low battery and calibration.

The authors in [13] have presented another three perspectives for classification:

1. Fault-tolerant distributed system viewpoint, that is based on the behaviour of the failed sensor, e.g., crash and omission.
2. Duration viewpoint that classifies faults based on their duration e.g., permanent and intermittent.
3. Components viewpoint, e.g., functional and informational faults.

Several fault detection techniques have been developed for sensor networks. However, the techniques were mainly designed for *time-driven*, *continuous-valued* and *homogeneous* sensors, e.g., temperature sensors. Thus, those techniques are not suitable for the *event-driven*, *binary* and *heterogeneous* nature of sensors that are needed for the ambient assisted living, e.g., motion detectors, contact sensors, etc. [14].

In an AAL system, a sensor failure is considered to be a fault from the perspective of the whole AAL system. There are two main categories of sensor failures in the AAL terminology:

- A *fail-stop failure* means that the sensor has stopped responding.
- A *non-fail-stop failure* indicates that the sensor is still responding, however, the reported values are no longer representative of the measured variable, nor the occurring events in the surrounding environment that are intended to be detected.

Sensor failures can also be classified as single-sensor failures and mutliple-sensor failures. In research works considering single-sensor failures, it is assumed that only one sensor can fail at a time [14].

In the field of AAL, Flöck has presented an overview of the binary sensors malfunctions that were observed during practical AAL implementation, e.g., faulty activation of motion detectors by sunlight, bouncing of contact sensors, and switch-off delays of motion sensors [15]. Also, Rahal et al. have reasoned the false information sent by binary sensors to be either due to an intrinsic error, e.g., the sensor's error rate, or due to an external error, e.g., an air draft or a pet may close the door triggering false events [16]. Different types of non-fail-stop failures have been stated in the research papers. Examples of the non-fail-stop failures are:

- *Moved-location failure*, which occurs due to moving furniture that have sensors installed on it to a different area or re-mounting in the wrong location.
- *Obstructed-view failure* that occurs due to covering the sensors or its dislodgement that may result from regular use, cleaning, other non-residents, etc. [17,18].

A set of guidelines and principles for the deployment of large-scale residential sensing systems was proposed in [19], summarizing the experience gained from installing over 1200 sensors in over 20 homes to monitor human activity. The main failure modes were examined to identify the longest acceptable time interval of inactivity for each sensor. For each periodic sensor, the interval is set to 5 times the sampling period, while for event-driven sensors, it is set to 36 h. The root cause of failure is identified based on the set of simultaneous sensor failures, where the considered causes of failure are wireless link loss, dead battery, disconnected plug, sensor sub-system down, internet-down, power outage, and gateway down. The described failure detection and classification approach was applied on four deployments for seven months. The analysis of the results showed that sensors are 2.3 times more likely to fail due to being unplugged than to dead battery and that wireless link loss is a less cause of failure than the other sources of sensor down time. Failure of an entire sensor sub-system appeared to be the most common cause of failure. This performed failure analysis enabled the authors to present guidelines that could avoid some of the pitfalls and failures observed in the deployments. However, a fault detection and diagnosis system still needs to be implemented to deal efficiently with sensor failures.

The following is the most common terminology found in the surveyed literature for the evaluation of various systems;

- *true positives* (*TP*) are the data points reported as positive when they actually are positive
- *false positives* (*FP*) are the data points reported as positive while they are actually negative
- *false negatives* (*FN*) are the data points reported as negative while they are actually positive
- *true negatives* (*TN*) are the data points are reported as negative while they are negative
- *precision* measures the percentage of true positives from the total points reported as positive ($TP/(TP + FP)$)
- *recall* measures the percentage of true positives from the actual positive points ($TP/(TP + FN)$)
- *accuracy* measures the percentage of true positives and negatives from the data ($(TP + TN)/(TP + TN + FP + FN)$)
- *failure detection latency* is the amount of time taken to detect a sensor failure after its occurrence.

Figure 1 elaborates the terminology with respect to sensor failure detection systems, where the *accuracy*, *precision* and *recall* values are 85%, 72% and 88%, respectively. The *accuracy* would still be relatively high if the system does not report as many sensor failures as before (lower *TP* and higher *FN*), however, the *precision* and *recall* would significantly drop. Thus, only using the *accuracy* for evaluating the system performance is insufficient. The *precision* indicates the ratio of the correctly reported sensor failures to all the positively reported sensor failures, while the recall indicates the ratio of correctly reported sensor failures to the positive sensor failures ground truth.

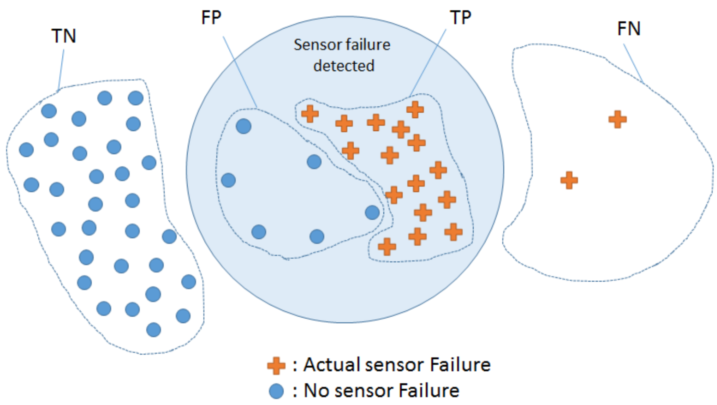

Figure 1. Evaluation metrics terminology for sensor failure detection system.

3. Datasets

This section presents an overview of the publicly available datasets that were used in a number of the reviewed research works. Other publicly available datasets exist for ambient assisted living, but they have not been used in research papers that focus on fault detection nor fault tolerance. It is worth noting that to the best of our knowledge, all the public datasets do not include any labels of the faulty sensors data.

3.1. Kasteren Datasets

Tim van Kasteren has collected benchmark datasets (called house A, B and C) [20] from three single-resident apartments which were collected over 14, 23 and 19 days, respectively. Wireless sensors that gives binary output were installed; reed switches for the doors and cupboards, pressure mats for couches and beds, mercury contacts for drawers, passive infrared (PIR) sensors to detect motion of resident in different areas of the apartments and float sensors for toilet flushing detection. The number of sensors installed in the three apartments (A, B and C) are 14, 23 and 21, respectively. During the collection of data, the resident performed his daily routine freely in an unscripted manner (i.e., the resident was not told what to do or which activity to perform). Annotation of the start and end of activities was performed by the resident using handwritten activity diary or a bluetooth headset [21]. The following data is recorded in the dataset files; start and end date/time of sensor activation, sensor ID, start and end date/time of activity and activity label.

3.2. CASAS Datasets

The CASAS research group in Washington State University (WSU) has made 64 datasets publicly available [22]. The recorded datasets were either collected from the WSU smart apartment equipped with around 90 sensors, residential apartments that has a number of sensors that ranges between 30 to 50 sensors or SHib partner lab equipped with 25 sensors, for a duration ranging from hours to years, for single- or two-resident apartments. Some of the experiments were scripted, e.g., adlnormal data and adlinterweave data, and others were unscripted, e.g., aruba data and kyoto data. Examples of sensors installed in the apartments are motion sensors, magnetic sensors, water flow sensors, item presence sensor, stove burner sensor and temperature sensors. The following data is recorded in the datasets files; data/time, sensor ID, sensor value/status. Some of the datasets have labels for the start and end of the performed activities.

3.3. Placelab Datasets

Three datasets (PLIA1, PLIA2 and PLCouple1) were collected from Placelab living lab [23] (note that the Placelab dataset website has been down for months). The living lab is an apartment where volunteers live during the data collection process. Two datasets were collected from single residents for 4 h who were asked to perform a set of activities, and the third one was collected from a couple who lived freely there performing their own daily routines for 10 weeks. The datasets were annotated with the performed activities using video recordings. The apartment is equipped with around 400 sensors that range between reed switches, light sensors, motion detection sensors, water flow sensors, temperature sensors, humidity sensors, electrical current flow sensors, gas sensors, etc. [24].

3.4. Tapia Datasets

Emmanuel Munguia Tapia has conducted experiments for two weeks in two single-resident apartments (subject 1 and subject 2) equipped with 77 and 84 sensors, respectively. The sensors are reed switches attached to the everyday objects, e.g., drawers, doors, containers, refrigerator, etc. The residents carried out their daily activities without any scripts [25]. The following data is recorded in the datasets; activity label, start and end date/time of activity, sensor ID, start and end date/time of sensor activation.

4. Literature Survey Methodology

In order to conduct the literature survey, the title, abstract and keywords fields were searched in Scopus, IEEExplore, Web of knowledge and ACM databases for the following combination of terms; ("fault detection" OR "sensor failure") AND ("smart home" OR "ambient assisted living"). Scopus and Web of knowledge databases produced the largest number of relevant articles. The search was then extended on Scopus and Web of knowledge to include more combinations of the keywords shown in Table 1, so that the combination is as follows; ((Group A AND Group C) OR Group D) AND Group B. Only the papers concerned with non-intrusive ambient binary sensors were included in the survey. The obtained articles were cross-referenced, and a total of 30 papers were selected for the review. It was observed that these 30 papers were all published between 2008 and 2017.

Table 1. Search keywords.

Group A [1]	Group B	Group C	Group D
"sensor*"	"smart home"	"fault detection"	"sensor* error"
	"ambient assisted living"	"failure detection"	"sensor* failure*"
	"AAL"	"fault toleran*"	"sensor* fault*"
	"location tracking"	"fault identification"	"sensor reliab*"
	"actvity recognition"	"failure identification"	"faulty sensor*"
	"activity monitoring"	"fault diagnosis"	"*reliable sensor"
	"activity detection"	"FDI"	"uncertain sensor"
	"home* based care"	"fault isolation"	"sensor diagnos*"
	"indoor localization"	"fault prevention"	"sensor node fail*"
		"fault prediction"	"fail* sensor*"
		"fault recover*"	"anomal*" AND "binary sensor*"
		"self-check*"	
		"self-heal*"	
		"dependable"	
		"failure management"	

[1] * replaces any number of characters, i.e., sensor* will search for sensor, sensors, sensory, etc.

The main focus of the research works can be mainly categorized as works concerned with:

- sensor failure detection in AAL
- fault-tolerant ADL recognition
- fault-tolerant abnormal behavior detection
- fault-tolerant indoor localization system/location tracking
- maintenance scheduling/management
- fault detection and diagnosis framework for AAL

The reviewed papers classification is shown in Table 2. These papers are presented and analyzed in detail in the next section.

Table 2. Main focus of the research works.

Focus	Research Work
Sensor failure detection	[10,14,17,18,26–36]
Maintenance scheduling/management	[14,27,30]
Fault-tolerant ADL recognition	[14,27,30,37–45]
Fault-tolerant abnormal behavior detection	[37]
Fault-tolerant indoor localization system/location tracking	[16,46,47]

5. Literature Survey Results

This section provides a state-of-the-art review for the sensor failure detection systems and fault tolerance methods in the presence of sensor failures in AAL systems equipped with *non-intrusive*, *binary*, *event-driven* sensors. The research works are categorized according to the function of the proposed systems as well as the approach that their methods are based on: correlation-based fault detection, model-based fault detection, fault-tolerant location tracking, fault-tolerant activity recognition or fault detection and diagnosis framework for AAL, respectively. A glossary of the technical terms can be found at the end of this paper.

5.1. Correlation-Based Fault Detection

The following research papers proposed sensor failure detection systems based on either sensor-appliance, sensor-sensor or sensor-activity correlations.

FailureSense [17] was presented by Munir and Stankovic to detect fail-stop and non-fail stop mutliple-sensor failures. It is based on exploiting the correlation between the trigger of motion sensors and the activation/deactivation of electrical appliances. The correlation is represented by the smallest interval of sensor firing after and before a turn on/off event within 5 min, denoted by I_A and I_B, respectively. The distribution of I_A and I_B is modelled by Gaussian mixture model (GMM), whose parameters are estimated from the training data using the expectation maximization (EM) algorithm. Online failure detection takes place by monitoring the sensor appliance behaviour represented by I_A and I_B. A failure is reported when a deviation occurs in the distribution beyond predefined thresholds for each sensor-appliance pair. The thresholds are computed using the training dataset. Evaluation was performed on three real-home datasets with around two thirds of the dataset used for training and one third for testing. Fail-stop failure was simulated by removing all the readings of a sensor after its randomly assumed day of failure. For the obstructed-view failure, simulation took place for two of the homes by randomly removing a 10-day period during which sensor view is considered to be obstructed, and for the third home, physical obstruction of the view of 5 motion sensors was done during the data collection phase. Simulation of the moved-location failure was done by replacing the readings of failed sensor with the readings recorded by the sensor at the newly moved location. The evaluation metrics used are the precision and recall of failure detection, where they represent the percentage of the true failure alerts from the total observed failure alerts, and the percentage of the true failure alerts from the sensor failures, respectively. Experiments of the fail-stop, obstructed-view and moved-location failures produced approximately 82.8%, 90.5% and 86.8% average precision, with an average recall of 92.86%, 84.4% and 89%, respectively. The effect of increasing the number of sensors that experience fail-stop failures on the percentage of failure detection has been also examined, showing an average of 86.6% sensor failure detection. On the other hand, a limitation of the proposed approach is that the average median failure detection latency is 22.08 h.

Ye, Stevenson and Dobson presented a technique to detect missing data in event-driven sensors based on temporal correlation and time-series analysis [26]. Temporal correlation relationship is defined to indicate if two sensors fire within a preset time interval. A missing data is reported when one of two highly correlated sensors fires without the other. For each sensor, the next firing time is predicted using non-linear time analysis technique, and if it does not fire at the predicted time, then it is considered as missing data. Evaluation is carried on Kasteren dataset [20] (house A), in which randomly chosen sensors events were removed from the testing data, using precision and recall metrics for each of the temporal correlation and time series approaches independently, then combined. The effect of changing predefined parameters of the algorithm on the performance was also examined. Moreover, the relation of increasing the error rate percentage (percentage of data removed) in the testing set on precision and recall was plotted along with increasing the percentage of training set. The results on the examined dataset have shown that the performance of using the temporal correlations for detecting missing events is better than using the time-series analysis. Also, it was observed from the results that using both temporal correlation and time-series analysis simultaneously for failure detection had a very low impact on the performance improvement. Using temporal correlation with data split by half for training and testing sets, the precision was nearly 70% and the recall decreased from around 80% to 40% with increasing the error rate from 10% to 90%. Increasing the training data to 90%, has made the precision to be around 78% and the recall to decrease from 85% to 75%. The authors stated that the proposed approaches could not be sufficiently evaluated on the chosen dataset, as it has few sensors and is collected over a short duration.

Kodeswaran et al. aimed to propose a system called Idea, for monitoring the activities of daily living while preserving a reduced maintenance overhead [27]. It is based on the assumption that there are redundant heterogeneous sensors installed for detecting each activity. Maintenance is scheduled according to the impact of a sensor failure on the performance of the system to detect ADL. The main components of Idea are; ADL signature Extraction, ADL detection, Impact estimation, Sensor Failure detection and Maintenance scheduling. Frequent itemset mining algorithm is used to form a rule-base containing the frequently occurring subsets of sensors for each ADL, and then the most probable time of day of occurrence and duration of activity are calculated from the training dataset. The critical sensors are identified based on their impact on detecting the ADL, which depends on the redundancy level per ADL using the training dataset. For critical event-driven sensors, a failure alert is flagged if the time elapsed since the last detection of ADL exceeded a threshold. For non-critical sensors, a rarity score is computed as the probability that a sensor has not been triggered while certain ADL, that should involve this sensor, has occurred. Experiments were conducted on Kasteren [20] (house A, B and C) and CASAS [22] datasets (aruba, twor9-10, twor2009, tworsmr and adlnormal) using 80% of the dataset for training. The accuracy of ADL detection was investigated in the presence of fail-stop sensor failures, emulated by discarding all the events of the failed sensor, and compared to Naive Bayes classifier (NB) and Hidden Markov model (HMM) algorithms. The maintenance efficiency was also evaluated in terms of the number of maintenance visits and per-home maintenance inter-arrival times. Across all the datasets, the ADL detection accuracy is reduced in average by approximately 0.5%, 1% and 3% in the presence of 1, 3 and 7 failed sensors.

Dealing with sensor faults in smart homes using data-driven approach was proposed by Monekosso and Remagnnino [28]. The proposed method aimed to detect sensor faults, mask it, and differentiate between anomalous activities and sensor deviation by combining reconciliation with failure detection techniques. The approach has two components; one component deals with random measurement fluctuations using data reconciliation, while the other component deals with systematic deviations due to sensor failures or anomalous activities. Models of sensors correlations are built using historical data via principle component analysis (PCA) and canonical correlation analysis (CCA). The models are refined continuously and can deal with heterogeneous sensors types to be used for detecting sensor faults. Experiments were carried out using Kasteren dataset [20] (house A). Two case studies were implemented by injecting intermittent and permanent faults into the dataset. A permanent fault was simulated on a sensor by removing its readings from the testing dataset after the assumed failure point of time. A transient sensor fault was injected by corrupting random instances of sensor readings with wrong values.

An approach for data-driven failure detection based on clustering was proposed by Ye, Stevenson and Dobson. They address non-fail-stop sensor failures as a clustering-based outlier detection problem [18,29]. DBSCAN clustering based outlier detection algorithm is used. The similarity between binary sensor events is calculated using least common subsumer (LCS) based on their semantic features; time stamp, the object to which a sensor is attached, location and user. Data points are clustered into groups and then the groups are sorted by their size in descending order. Shoulder-location method is used to select the threshold below which a cluster is considered small. To each data point, a cluster-based local outlier factor (CBLOF) is assigned which is a function in the size of the cluster to which this point belongs, the similarity between the point and the closest large cluster, and the historic faulty sensor behaviour. A point is considered as an outlier if its CBLOF is below a threshold defined by the shoulder location method. The technique was evaluated on Placelab [23] (PLCouple1), Kasteren [20] (house A and B) and CASAS [22] (adlinterweave) datasets with injecting random and systematic anomalies. Random abnormal events were injected into the datasets by randomly creating new sensors events within randomly selected time slots. While systematic abnormal events are injected by selecting random sensors and creating an event for each of the selected sensors within each time slot of the testing data. Plots of the precision and recall against the injection rate of abnormal events were presented.

In another attempt, detection of sensor failures was tackled using classification. Kapitanova et al. proposed simultaneous multi-classifier activity recognition technique (SMART) [14,30], which uses top-down application level semantics to detect non-fail-stop single-sensor failures. Furthermore, the research work addresses schedule maintenance according to failure severity and improvement of activity recognition accuracy in the presence of failures. Multiple classifier instances are trained offline by excluding each time a sensor out of the training set resembling a sensor failure, and one time with all sensors present in the set. Online detection of a fault is achieved by assessing the relative performance of the classifiers that has a missing sensor versus the one trained with all sensors, thus a fault is detected and identified. Severity analysis is performed to evaluate the impact of sensor failure on the accuracy of activity detection. As the level of sensor redundancy increases per activity, the urgency of repairing a faulty sensor decreases. Fault-tolerance of the activity recognition is achieved by updating the classifier ensemble with the classifiers that were previously trained to deal with a particular sensor failure. The system was evaluated using CASAS [22] and Kasteren [20] (house A and B) datasets considering only prepare breakfast, lunch and dinner activities. NB and HMM classifiers were used. Stuck-at failures and misplacement failures were introduced manually to the datasets. To simulate stuck-at failure, the value of the failed sensor is set to 1. For simulating misplacement failure, the data of failed sensor is replaced with the sensor in its new location. The results showed that this approach could decrease the number of maintenance dispatches by 55%, identifies non-fail stop failures by 85% accuracy, and improve activity recognition accuracy in presence of sensor failures by 15%.

5.2. Model-Based Fault Detection

The following researchers have used model-based fault detection based on localization systems. An indoor human localization (IHL) system with fault detection focusing on hardware as well as human-made single faults was presented by Veronese et al. [31]. The IHL system consists of three main components; an RF-based localization subsystem, an off-the-shelf modular wireless home automation subsystem and a fault detection subsystem. The types of sensors chosen for home automation were contact sensors and passive infrared (PIR) sensors. A model-based fault detection approach was applied based on the concept proposed by Isermann [48] which states that a fault can be detected using the dependencies between different measured signals. The activation of the home automation sensors and its features were used to estimate the resident's location. Also, the position of the resident is estimated independently with the localization subsystem. The fault detection subsystem compares the two estimated location areas, and flag a fault whenever there is no intersection between the two areas. Experimental work was done, where 19 fixed LAURA anchors and 7 Z-wave devices were fixed across the rooms of the university building. Two fault scenarios were considered; forgotten worn device and blinded PIR motion detector. The results showed that the faults could be detected using the proposed approach. As a continuation of the work, multi-user simulation was conducted using three virtual users trajectories, the faults could be detected in the presence of multiple users with specificity and sensitivity above 90% [32].

Danancher proposed model-based location tracking of single as well as multiple inhabitants in smart homes [10]. He treated the location tracking of inhabitants as a problem of discrete event system modeling. Finite automata was used to model the observable motion of inhabitant, where each state represents a zone in the apartment, each event represents the rising or falling edge of binary sensor, and each transition is the observable location change. A case study was presented for an apartment equipped with motion detectors and door barrier sensors. The impact of sensor faults on the performance of location tracking was discussed. The applicability of three model-based fault detection and isolation (FDI) approaches; diagnoser, template and residual approaches, were investigated for fault-tolerant location tracking. An adaptation to the residual-based approach was applied to a case study of tracking a single inhabitant. Three fault scenarios were considered; spurious activation of a motion sensor, failure of power supply of door barrier sensor and a failure of motion detector sensor. The approach could not detect nor isolate faulty sensors in the proposed faulty scenarios. The author concluded that the industrial FDI approaches are not suitable for sensor faults in smart home and that a new FDI approach designed specifically for smart homes should be developed.

Another discrete event system approach for location tracking was proposed by Wu et al. [49]. The motion of the resident is modeled using an automaton model and the observations of motion events from sensor signals are described using the state tree of Graph theory. An Observer is then used to estimate the location of the inhabitant. Dealing with transient sensor faults is performed by adding a reset procedure to the state tree and the observer so that they return to the initial state whenever blocking occurs due to missing or disordering of a sensor event. This ensures that the location tracking returns to output correct estimation results after deviating due to the transient sensor fault. However, false location estimation still occurs. A scenario of the motion of inhabitant in the presence of a missing sensor event was presented.

Amri et al. have proposed fault detection approach for indoor localization based on set-membership fault detection using the q-relaxed intersection method [36]. The random walk model is used as the mobility model of the resident. The PIR sensor activation leads to the activation of a box representing its coverage area. At one second time step, the measurement boxes are observed and the predicted boxes are deduced using the mobility model. The q-intersection method deduces the location zone of the resident using these boxes. Outlier detection takes place by comparing the solution set obtained and the measurements. Experiments were conducted in a living lab equipped with PIR sensors.

5.3. Fault-Tolerant Location Tracking

A fault-tolerant location tracking system was presented by Rahal, Pigot and Mabilleau, which aims to localize single inhabitant using the already installed sensors in smart home [16]. The authors aimed to provide a reliable location tracking system that can estimate the location of inhabitant accurately despite the false trigger of sensors that may occur due to various factors. The adopted approach is based on sensor fusion, in which particle filters approach is used to estimate the new inhabitant's location using the last known position and the last sensor event. To evaluate the system, experiments were conducted in the DOMUS apartment, where non-intrusive unobtrusive sensors (infrared (IR) presence sensors, tactile carpets, smart light switches, contact sensors and pressure detectors) are installed. A daily routine scenario was performed by 14 subjects, one subject each time, and the results showed an accuracy in location tracking above 85%. The system performance was also investigated with respect to the inhabitant's profile, sensor configuration, inhabitant's dynamics and in the presence of noise. The results showed that the accuracy of the system is profile-independent. The accuracy of localization when using only infrared sensors is similar to using all the sensors. However, the IR sensors are more prone to false triggers, thus, the authors recommended the usage of at least one other type with IR sensors. The system accuracy remained at 84% when 2.5% and 5% noise were applied to the collected data.

A similar system was proposed by Ballardini et al. that is based on estimating the resident location in the presence of false positive or false negative sensor readings via Bayes filtering [46]. The system uses a probabilistic model of the sensors and a motion model of the inhabitant. The proposed approach was tested on two noisy datasets that use PIR sensors (observed frequent false triggering of a motion sensor when no person is moving, and trigger of atrium's motion sensor when motion occurs in the dining room), producing 5% and 9% error rates in localization.

A fuzzy set-based approach for localization tolerating sensor failures was proposed by Ahvar et al. [47]. The approach relies on using several functionally redundant sensors at specific nodes. The system is composed of sensor nodes and context broker based on the fuzzy set theory. The apartment is divided into zones and equipped with various types of ambient sensors. The sensors send context information, then the membership values for each zone is computed. The highest value indicates the user location. A case study was presented and simulated using the DPWsim simulator with different sensor error rates. However, the system was not verified using a real dataset.

5.4. Fault-Tolerant Activity Recognition

In addition to the fault-tolerant activity recognition implemented by SMART system [14,30] and Idea system [27], a framework of fault-tolerant activity recognition was addressed by Hong et al. [38–40]. First, the effect of sensor failures on the accuracy of activity recognition was investigated. Only binary sensors were considered for monitoring the ADL in smart homes. Sensor evidence reasoning network was designed based on activity hierarchy of ontology for activity recognition while tolerating uncertainty in the sensors' measurements. The discounting values depend on the manufacturer statics on the sensors. To validate the proposed approach, a case scenario was presented. In addition, sensors data recordings were collected from smart laboratory environment of a kitchen area for four weeks, and then, offline analysis was performed to verify the sensor data with video recordings. The sensor data was fed to the evidential reasoning network that is based on the Dempster-Shafer theory. The performance of activity recognition was assessed with respect to the number and combinations of sensor failures. Mckeever et al. [41] have extended the evidence of theory to incorporate temporal features and evaluated their proposed framework on Kasteren dataset [20] (house A). A limitation of the approach is that expert knowledge is needed for the sensor mass functions and sensor quality. Also, knowledge from users is used to get information about the temporal features of activities.

Liao et al. [42–44] have proposed an activity recognition framework that deals with uncertainty in sensor measurements based on Dempster-Shafer theory of evidence while considering the effect of historical information and activity patterns. This is implemented through a framework with a lattice structure, which has a context layer that includes combinations of sensors derived from the historical data of inhabitant. Two types of uncertainty sources were considered; sensor hardware and context uncertainty due to the variability in human activities. A case study was presented in addition to applying the proposed approach to a publicly available dataset (Tapia dataset, subject 1) [25] collected from an apartment equipped with binary sensors. The performance was evaluated using precision, recall and F-measure metrics for activity recognition.

A Weighted Dempster-Shafer theory was presented by Javadi, Moshiri and Yazdi [45], where a weight for each sensor is assigned based on the historical data and activity patterns of the resident. In the training phase, 10 models are built for each sensor, and then in the testing phase, a weight for each sensor is calculated based on the membership degree of each sensor signal to the sensor's models. The proposed method is applied to a dataset (Tapia dataset, subject 1) [25] and evaluated through the accuracy detection rate of toileting activity. A drawback in the experiments is that, sensor faults were not injected to the dataset.

Abnormal behaviour recognition in the presence of sensor failures/uncertainties was addressed by Marhic et al., it is based on the evidential approach using transferable belief model (TBM) [37]. It is assumed that there are three or more heterogeneous redundant sensors per each monitored activity. The system consists of Sensor FDI and the Abnormal behaviour detection modules. The Sensor FDI analyses the conflict between the heterogeneous redundant sensors using sensor fusion calculated by the Smet's operator and two experts. Abnormal behaviour is then detected by comparing the normal behaviour of inhabitant represented by the Markov chain model (MCM) and the detected/predicted behaviour within the TBM framework. Experiments were conducted on datasets collected from performing sitting, lying and standing activities with various single sensor failures, during which pressure sensor, omni-directional vision sensor and an accelerometer were used. The authors showed the ability of the system to detect abnormal behaviour in presence of sensor failures (unplugging sensor for a period of time) and highlighted some limitations that could be addressed in the future.

Methods for fault tolerance in Ambient Assisted Living were suggested by Ahvar et al. [50]. Data from binary sensors, e.g., movement sensors, may be corrected using a model of the inhabitant behaviour. While fault tolerance for analog data from sensors, e.g., temperature sensors, may be implemented using sensor fusion. However, the system was not verified against faults in a case study.

5.5. Fault Detection and Diagnosis Framework for AAL

A fault detection and diagnosis framework for Ambient Intelligent systems was presented by Mohamed, Jacquet and Bellik [33,34], however, it is concerned only with the tasks performed by the systems through the actuators. The approach is based on modeling the physical phenomena that are supposed to occur in the environment due to the activation of a particular actuator. The system then automatically creates links between actuators and sensors at run-time using the models. It predicts the expected sensor reading due to the activation of an actuator and compares it with the actual sensor reading to detect if a fault has occurred. Simulations were performed to illustrate the operation of the system and show the ability of the system to discover new components at run-time. The basic idea of the diagnoser model was presented without details.

A self-diagnosis framework was proposed by Oliveira et al. [35], where a Bayesian network construction algorithm is used to create a Bayesian network for each scenario that is supposed to be fulfilled by the AAL system to assist the user. The algorithm takes as inputs the rules file that specifies the causal relations between variables, and the scenario description file that specifies the required assistance and the home description. Conditional probability distribution is calculated for each child node. The real values are then compared with the predicted ones and a fault is flagged if the readings are different. Using the causality relations and conditional rules, a diagnostic is reached. A case study was investigated to show the ability of the proposed framework to detect and diagnose faults. However, like the previous system [34], the framework would only work fine for the tasks that involve a sensor-actuator feedback.

6. Discussion

6.1. Correlation-Based Fault Detection Systems

Next, we discuss the pros and cons of the correlation-based fault detection approaches.

FailureSense [17] has good average precision and recall for the examined fail-stop, obstructed-view and moved-location failures. Also, the experiments show consistent performance for failure detection with increasing the number of sensors that had fail-stop failures. However, the method does not work well if the failed sensor is not associated with any electrical appliance. In addition, its average failure detection latency is not suitable for emergency situations. Another limitation of the system is that, it is based on the assumption that the resident has to be physically beside the appliance to turn it on.

In addition, the system performance depends on the behaviour of residents (i.e., the residents turn on/off electrical appliances remotely or their behaviour pattern in using electrical appliances).

Using temporal correlations and/or time-series analysis in [26] only relies on sensors firing to detect missing sensor events. The temporal correlation method achieves better results than using time-series analysis. However, the average precision and recall on the examined dataset with random non-fail-stop failures are not as good when increasing the error rate percentage, except when the training data percentage was increased to 90% . This makes the performance of the proposed method still questionable and needs to be evaluated on other larger datasets.

The approach of the Idea system [27] is designed to suit homes equipped with functionally redundant sensors per activity of daily living. Otherwise, it will not work as expected. In this work, only fail-stop failures were considered. The reduction in the ADL detection accuracy in the presence of sensor failures is relatively low. Thus, an efficient fault tolerant activity recognition seems to be promising using the proposed approach. However, the effect of monitoring multiple ADLs to detect sensor failures on the failure latency detection, and the effect of rarity threshold on the false positive alerts were the only assessments used for the sensor failure detection subsystem. Those assessments are not enough to be able to see the efficiency of the sensor failure detection. Also, non-fail-stop failures need to be considered in the experiments. In our opinion, detecting failures using time elapsed is not an efficient solution and using the rarity score assumes that the system has not misclassified the activity. Similarly, the detection of sensor failures using the proposed approach in [28] was not thoroughly evaluated. The experiments were only concerned with the ability of the system to detect and isolate a faulty sensor, without any quantitative evaluation of the performance. Another drawback is that the injected faults in the experiments were applied on only a single sensor.

The advantage of using clustering approach as in [18,29], is that no training phase is required. However, the proposed method aims to detect false sensor triggers, but it can not detect missing sensor data. Another limitation is that the failure detection takes place in a post-processing step on the collected data. Also, the false positive trigger is less likely to be detected if it is associated with a sensor that has similar features to other correctly working sensors. Using multiple classifier instances [14,30] produced promising results for sensor failure detection and fault-tolerant activity recognition. However, the disadvantage of this approach is that the training effort is large and it increases proportionally with the number of installed sensors, thus the system is non-scalable.

6.2. Model-Based Fault Detection Systems

The reviewed model-based fault detection systems do not seem to provide better results than the correlation-based fault detection systems. The approaches mainly rely on checking if the sensor trigger is consistent with the predicted location of the resident. The method proposed in [31] that uses RF-based localization system in addition to the environmental binary sensors installed at home, can not identify if the fault source is the localization system or the installed sensors. In another research work [10], applying residual-based fault detection to the location tracking finite automata model of an inhabitant could not detect nor isolate the faulty sensors. Only preventing the transient sensor faults from blocking the discrete event location tracking model was proposed in [49]; however, it was not even capable of tolerating those faults. In [36], comparing the motion sensors triggers with the random walk mobility model is not reliable, since this mobility model can produce unrealistic patterns as it does not keep track of the past locations and speed.

6.3. Fault-Tolerant Location Tracking Systems

The fault-tolerant location tracking systems reviewed are based on attempting to estimate the location of the resident under uncertainty of sensors whether through sensor fusion [16,46] or fuzzy theory [47]. The results seem promising, however, the systems need to be investigated more thoroughly in real-time experiments.

6.4. Fault-Tolerant Activity Recognition Systems

In addition to the SMART [14,30] and Idea [27] systems discussed before for proposing sensor failure detection and fault-tolerant activity recognition, fault-tolerant activity recognition based on recognizing activities under sensors uncertainty were reviewed. The works that used the evidence theory [37–45] have the disadvantage of requiring lots of expert knowledge.

6.5. Fault Detection and Diagnosis Framework

The reviewed fault detection and diagnosis frameworks [33–35] were designed to only suit AAL systems involved with sensor-actuator feedback.

7. Conclusions

In the last 10 years, an increasing interest in tackling sensor failures/faults in AAL has been observed. However, there is still much to be done in this area to offer a dependable system for the users.

Tables 3 and 4 summarize the work reviewed in Section 5. For each research work; the contributed system, its method, algorithm(s), experiments conducted and performance metrics used are listed in this table.

The overall general limitations of the existing works can be categorized as follows:

Limitations regarding the approaches:

- Most of the existing works have developed their approaches considering only single failures. However, it may happen that more than one sensor fail simultaneously.
- The majority of the developed algorithms use parameters or thresholds that need to be chosen by an expert rather than being deduced automatically.
- Differentiating between failed sensors and anomalies in human behaviour is still a challenge that needs to be addressed.

Limitations regarding the datasets:

- The public datasets used for the training and testing phases are limited to short duration, low sensor node redundancy and single resident apartments.
- Also, the data in the publicly available datasets was originally collected for activity detection with labelled activities, thus, failures or anomalies were not labelled. Instead, sensor failures were manually injected and simulated by the researchers, which may not be representative of real-home sensor failures rate and percentage.

Limitations regarding the experimental methodology:

- It is difficult to compare between the efficiency of the presented approaches because not all the authors use the same evaluation criteria and same testing data. Thus, there is a need for standardized evaluation criteria.
- Beside the accuracy, precision and recall, the sensor failure detection latency is an important criterion to be considered.
- Real-time online evaluation of the algorithms was not carried out, instead the data collected from previous experiments or datasets were fed to the algorithms.
- The proposed approaches should additionally be evaluated on data collected from elderlies with physical and/or cognitive deficiencies.

Table 3. Summary of the reviewed work in Sections 5.1 and 5.2.

Source	Contribution	Method	Algorithm	Experiments		Performance Metrics
				Data	Failure Type	
[17]	sensor fault detection	sensor-appliance correlations	GMM & EM	custom datasets	injecting fail-stop and non-fail-stop (obstructed-view and moved-location) failures	precision, recall & failure detection latency
[26]	sensor fault detection	sensors correlations	mutual information and non-linear time series analysis techniques	publicly available dataset (Kasteren, house A)	injecting non-fail-stop failures (removing random sensors events)	precision & recall
[27]	sensor fault detection, fault-tolerant activity recognition & maintenance scheduling	sensor-activity correlations	frequent itemset mining algorithm & rarity score calculation	publicly available datasets (Kasteren; house A, B & C, and CASAS; aruba, twor9-10, twor2009, tworsmr & adlnormal)	injecting fail-stop failures	sensor failure false alert rate, failure latency detection & reduction in ADL detection accuracy in presence of failures
[28]	sensor fault detection and masking	sensors correlations	PCA & CCA	publicly available dataset (Kasteren, house A)	injecting permanent and intermittent faults (i.e., fail-stop and non-fail-stop)	ability to detect faults
[18,29]	sensor fault detection	clustering-based outlier detection	DBSCAN clustering algorithm	publicly available datasets (Placelab, PLCouple1, and Kasteren; house A and B, and CASAS, adlinterweave)	injecting random and systematic false positive sensor triggers (non-fail-stop)	precision & recall
[14,30]	sensor fault detection, fault-tolerant activity recognition & maintenance scheduling	simultaneous use of multiple classifiers	NB, HMM, hidden semi-Markov model (HSMM) & decision trees	publicly available datasets (Kasteren, house A and B, and CASAS (not specified))	injecting non-fail-stop failures (stuck-at and moved-location)	failure detection accuracy & failure latency detection
[31,32]	indoor localization system with fault detection	model-based fault detection using RF-based localization & home automation subsystems	estimating the location using the activation of home automation sensors and the RF-based localization subsystem	custom dataset	collected with blinded PIR sensor and forgotten worn device	sensitivity & specificity
[10]	location tracking with sensor fault detection	model-based fault detection using a model of the observed motion of the inhabitant	finite automata & residual calculation	scenario of motion of inhabitant	in the presence of fail-stop and non-fail-stop failures	ability to detect faults
[49]	location tracking dealing with transient faults	state estimation with reset procedure	automaton model & state tree of graph theory	scenario of motion of inhabitant	scenario of the presence of missing sensor event (non-fail-stop)	location estimation in presence of transient sensor faults (non-fail-stop)
[36]	localization system with sensor fault detection	model-based fault detection using the random walk model of inhabitant	set-membership fault detection using the q-relaxed intersection method	custom data collected from Living lab	not specified	ability to detect faults (outliers)

Table 4. Summary of the reviewed work in Sections 5.3–5.5.

Source	Contribution	Method	Algorithm	Experiments		Performance Metrics
				Data	Failure Type	
[16]	fault-tolerant localization system	state estimation based on sensor fusion	particle filters approach	custom data collected	injecting random sensor noise (non-fail-stop)	localization accuracy & mean belief
[46]	fault-tolerant localization system	state estimation	bayes filtering	custom dataset	data collected in presence of noise	localization error rate
[47]	fault-tolerant localization system	fuzzy-based approach using various types of ambient binary sensors	fuzzy-set theory	scenario and simulation of motion of inhabitant on DPWsim simulator	in the presence of sensor node failure fail-stop and non-fail-stop	localization accuracy
[38–40]	fault-tolerant activity recognition framework	evidential approach for reasoning under uncertainty	sensor evidence reasoning network & dempster-shafer theory	scenario and custom data collected	injecting different combinations of sensor failures	belief in activity inference
[41]	fault-tolerant activity recognition framework	evidential approach for reasoning under uncertainty	temporal evidence theory & dempster-shafer theory	publicly available dataset (Kasteren, house A)	no faults injected	activity recognition precision, recall & F-measure
[42–44]	fault-tolerant activity recognition framework	evidential approach for reasoning under uncertainty	evidential lattice structure considering historical information and activity patterns & dempster-shafer theory	scenario and publicly available dataset (Tapia, subject 1)	no faults injected	activity recognition precision, recall and F-measure of activity recognition
[45]	fault-tolerant activity recognition framework	evidential approach for reasoning under uncertainty	weighted dempster-shafer theory & fast fourier transform	publicly available dataset (Tapia, subject 1)	no faults injected	activity recognition accuracy
[37]	fault-tolerant abnormal behaviour detection	evidential approach for reasoning under uncertainty in the presence of heterogeneous redundancy per activity	sensor fusion based on Smet's operator, experts, TBM & MCM	custom data	collected with inducing non-fail-stop sensor failure	ability to detect abnormal behaviour and/or failed sensor
[33,34]	fault detection and diagnosis framework for AAL	modeling the physical phenomena that are supposed to be detected by sensor due to the activation of an actuator	not applicable	simulating a scenario in presence of sensor failure	not specified	ability to detect system fault
[35]	self-diagnosis framework for AAL	Bayesian network for each scenario that is supposed to be fulfilled by the AAL system to assist the user	bayesian network construction algorithm	scenario of inhabitant in the presence of sensor failure	fail-stop	ability to detect system fault

As illustrated by the number and importance of the limitations of the existing works, fault-tolerance in AAL is still in its early phase. Thus, intensive research work is still needed to tackle them. The research topics to be addressed can be grouped in the three following research questions:

- Can novel machine learning techniques tackle the problem of sensor failure detection in AAL without the need for expert knowledge?
- Should the research priority be directed towards enhancing the accuracy of binary sensors or instead towards dealing with the faulty sensors data through fault-tolerant systems?
- Would differentiating between behaviour anomalies of residents and sensor anomalies be possible?

As a conclusion, as highlighted by this systematic literature review, methods for fault-tolerant Ambient Assisted Living are still in their infancy stage. Also, intensive research works would be needed to ensure the development and implementation of a robust sensor fault detection and diagnosis system for Ambient Assisted Living in a near future.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AAL	Ambient assisted living
ICT	Information and communication technologies
ADL	Activities of daily living
GMM	Gaussian mixture model
EM	Expectation maximization
NB	Naive Bayes
HMM	Hidden Markov model
PCA	Principle component analysis
CCA	Canonical correlation analysis
DBSCAN	Density-based spatial clustering of applications with noise
LCS	Least common subsumer
CBLOF	Cluster-based local outlier factor
SMART	Simultaneous multi-classifier activity recognition technique
IHL	Indoor human localization
PIR	Passive infrared
FDI	Fault detection and isolation
IR	Infrared
TBM	Transferable belief model
MCM	Markov chain model
HSMM	Hidden semi-Markov model

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5 Paper B

Towards Sensor Failure Detection in Ambient Assisted Living: Sensors Correlations [1]

https://doi.org/10.1109/COASE.2018.8560367

Summary

Sensor failures can have significant effect on the ability to provide reliable AAL services. The model-based fault detection techniques for AAL found in literature were not promising due to the non-deterministic human behaviour. Finding fault-free sensor correlations can be the first step towards a data-driven fault detection approach. This paper proposed extracting correlations between event-driven binary sensors from unlabelled dataset using the association rule mining technique. Data preprocessing steps were described, which included the use of a time-based sliding window to take into account temporal correlations between the sensors and form a set of transactions. Evaluation metrics are used to measure the strength of a rule, and only those rules that exceed minimum values of the metrics would be on the list of the extracted rules that perceive the sensors correlations. In addition to using the typical evaluation metrics, support and confidence, a refined metric denoted as relative support is examined to better suit our application. The two techniques, one using support and the other using relative support, were applied on a publicly available dataset collected from a single resident apartment. The experiments aimed to check which parameters and values would extract the most meaningful association rules that have as many sensors as possible in the consequent part of rules. The existence of the sensor as a consequent in a rule, would make it possible later to detect

[1] The author of this thesis contributed to the conceptualization, methodology, investigation, software, validation and wrote and edited the original draft of the manuscript. The co-author has contributed to the conceptualization, methodology, supervision, and manuscript editing and revision. All authors have read and agreed to the published version of the manuscript.

its failure. The effect of varying the parameters; sliding window size, minimum support, minimum confidence and minimum relative support, on the number of extracted association rules, the number of consequent sensors and the ratio of consequent sensors to the number of rules, was studied. The results have shown that using the relative support allows extracting more consequent sensors within less number of redundant rules. Moreover, the extracted rules were logically correct when compared to the sensor layout within the apartment. It was concluded that the extracted rules are promising to form the basis of failure detection in event-driven binary sensors.

2018 IEEE 14th International Conference on Automation Science and Engineering (CASE)
Munich, Germany, August 20-24, 2018

Towards Sensor Failure Detection in Ambient Assisted Living: Sensors Correlations

Nancy E. ElHady and Julien Provost

***Abstract*— Ambient Assisted Living promotes healthy independent ageing of the elderly at their homes by monitoring their behaviour, and support medical assistance whenever needed. For privacy and acceptance issues, non-intrusive sensors are preferably used. However, such sensors are more prone to produce false positive or negative data. Faulty sensor data could be automatically detected if correlations between sensors can be identified. This paper aims to propose the use of association rule mining to find correlations between binary event-driven sensors installed for monitoring purposes in an apartment. A case study was carried out to validate the approach and investigate the effect of different data mining parameters on the quality of obtained association rules. The results show that correlations could be successfully deduced from unlabelled datasets with no prior expert knowledge on the sensors topology.**

I. INTRODUCTION

The Ageing population phenomenon is affecting countries all over the world, with an expectancy of multiplying by two the number of people aged over 60 years by 2050. Several countries will have more than 30% of its population over 60 years old, like Germany, France, China, Canada and others [1]. To be able to face this demographic shift, an increasing numbers of research works are investigating the development of approaches and tools for Ambient Assisted Living (AAL). Ambient Assisted Living promotes healthy ageing in the elderly's place of residence by using information and communication technologies to monitor their Activities of Daily living (ADL), detect deviation of their behaviour, predict their future activities, and provide help whenever needed.

Sensors used to monitor the behaviour of elderly people at their homes are either intrusive sensors, e.g., cameras and microphones, or non-intrusive sensors, e.g., motion sensors and contact sensors. The systems equipped with intrusive sensors are not highly accepted by the population due to privacy and security concerns. Consequently, in the last decade, a stronger focus in research was directed towards the use of non-intrusive sensors in AAL. However, such sensors often suffer from false positive or negative triggers that can affect the performance of the system.

Two types of sensor failures could be encountered; fail-stop failures, where the sensors completely stop responding, and non-fail-stop failures, where the sensors are still working but give false information about their environment. The typical non-fail-stop sensors malfunctions that were reported by Flöck [2] during practical implementation of AAL include spurious signals of motion sensors at night, faulty activation of motions sensors by sunlight, bouncing of door contact sensors for several minutes, and switch-off delays of motion sensors after the last observed activity. Other sources for non-stop-failures could be moved-location failure when the sensor gets remounted by the resident to another location, and obstructed-view failure where the sensor gets blocked by furniture [3].

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Various fault detection techniques have been developed for wireless sensor networks that consist of homogeneous, time-driven and continuous-valued sensors, e.g., majority voting scheme and time-series analysis. However, the non-intrusive sensors used in AAL are heterogeneous, event-driven and binary sensors.

Sensor failure detection in Ambient Assisted Living equipped with non-intrusive ambient sensors has been approached previously in a few works.

SMART [3] used classification technique in which the classifier instances are trained with one sensor left out of the training dataset to replicate a sensor failure. This approach deals only with single sensor failure and lacks scalability due to the significantly increasing training effort required.

FailureSense [4] exploited the correlation between the turn on/off of electrical appliances and the sensors trigger events based on Gaussian mixture model. However, it assumes that the person has to be physically beside the electrical appliance to turn it on/off and the average failure detection latency is approximately 22 hours. A clustering based outlier detection was proposed in [5], that can only deal with false positives sensor triggers but not false negatives.

Amri et al. [6] used q-relaxed intersection technique to detect faulty sensors via comparing the estimated location of the resident from the activation of motion sensors with the location estimated from the random walk model. Nevertheless, the random walk model is not accurate enough to model the resident behaviour.

Idea's [7] approach to detect failures is based on the assumption that there are functional redundant sensors for ADL recognition. A sensor failure is flagged when the probability that a certain activity has been detected while the sensor was not triggered exceeds a certain threshold. This approach relies on accurate ADL recognition which can not be guaranteed in presence of sensor failures, in addition it needs labelled dataset for the training phase.

Ye et al. [8] have attempted to detect missing sensor data by finding correlations between sensors using mutual information technique along with predicting the trigger time using non-liner time series analysis techniques. However, the authors could not prove the effectiveness of their approach due to the limited duration of the testing dataset and the low number of used sensors beside its biased distribution across the flat under test.

As highlighted in the previous paragraph, sensor failures detection in AAL is still challenging, especially in the presence of the non-deterministic human behaviour that made model-based fault detection unable to guarantee good results. This paper aims to find correlations between non-intrusive binary sensors using a data-driven approach, specifically association rule mining. A refinement to the association rule mining method is proposed and a comparison of the results obtained for different parameters is done in order to evaluate the feasibility of extraction correlations. Those sensors correlations could be utilized in the future for the detection of fail-stop and non-fail-stop sensor failures in AAL.

II. BACKGROUND

In order to detect sensor failures in AAL, large sensors datasets have, first, to be thoroughly analysed to detect the fault-free sensors correlations during the nominal behavior of the resident. Association rule mining is a data mining technique that was introduced by Agrawal et al. [9] to find associations between items in large datasets. Association rule mining was successfully used in various fields, with its most common application is the market basket analysis [10].

The items in the datasets are the set of binary features denoted as I = {I1,I2,..,Im}. The dataset consists of a number of transactions T = {T1,T2,..,Tn}, where each transaction contains a subset of the items I; T $\subseteq$ I. The association rule is in the form of X $\rightarrow$ Y, where X $\subset$ I, Y $\subset$ I and X $\cap$ Y = ϕ. X and Y are the itemsets called the *antecedent* and *consequent* of a rule, respectively. An association rule X $\rightarrow$ Y means that "IF the item(s) X occured THEN the item(s) Y occured as well". There are two important evaluation metrics for each rule, which are the support and confidence of this rule, defined as follows:

$$\text{Support}(X \rightarrow Y) = \frac{|\text{Transactions containing X\&Y}|}{|\text{Transactions}|} \quad (1)$$

$$\text{Confidence}(X \rightarrow Y) = \frac{|\text{Transactions containing X\&Y}|}{|\text{Trasactions containing X}|} \quad (2)$$

To find the association rules of interest from a dataset, minimum support and confidence are predefined by the user for the association rule mining. The support reflects how likely it is to find the items of X and Y together in the transactions of a dataset, while the confidence reflects how frequent the items of Y in the transactions that contains items of X.

One of the widely used algorithms for association rule mining is the Apriori algorithm, in which the dataset is first scanned to find 1-itemsets (itemsets of length 1) that satisfy the minimum support, then from those frequent 1-itemsets, 2-itemsets will be generated and checked against the minimum support value, and so on [11]. Only the association rules that satisfy the minimum support and minimum confidence will be extracted. Another evaluation metric for association rules is the lift, which confirms the correlation between the antecedent and consequent items of rules if its value is greater than 1. The lift of an association rule is defined as follows:

$$\text{Lift}(X \rightarrow Y) = \frac{|\text{Transactions containing X\&Y}|}{|\text{Transactions containing X}| * |\text{Transactions containing Y}|} \quad (3)$$

```
04/11/2010 19:48:25.951116 M015 ON
04/11/2010 19:48:27.158853 M019 ON
04/11/2010 19:48:29.096358 M018 ON
04/11/2010 19:48:30.887026 M021 ON
04/11/2010 19:48:30.966912 M019 OFF
04/11/2010 19:48:32.33508  M022 ON
04/11/2010 19:48:33.314738 M015 OFF
04/11/2010 19:48:33.383733 M018 OFF
04/11/2010 19:48:33.843558 M023 ON
....
```

Fig. 1. Sample of the sensors dataset

III. APPROACH

An essential step towards developing a sensor failure detection system is to find strong correlations between the employed sensors. In this paper, we investigate the use of association rule mining to find the highly correlated sensors from an unlabelled recorded dataset. The obtained rules could then be used for sensor failure detection in such a way that if the sensor(s) of the antecedent part of rule got triggered while the sensor(s) of the consequent part of rule did not within a specific time, then the sensor(s) can be suspected to be faulty. The higher the correlation, the higher the confidence in the sensor failure detection and the shorter the time to detection.

A. Data Preprocessing

As the association rule mining was primarily designed for transactional databases, some modifications had to be done so that this method would better suit our application whose dataset consists of timestamped sensor *event* triggers as depicted in Fig. 1, e.g., On 2010-11-4 at 19:48:25.951116, the sensor M015 got switched ON. The first step is to reformat the data in a more usable form. First, the dataset is converted to a set of binary time series, a series for each sensor. At each time stamp of the dataset, the signal value (0/1) of each sensor is calculated, based on its previous value and the current event. Thus, the dataset is converted from an event-based to a signal-based dataset. Then, all-zeros rows were deleted as we are interested in the relation between positively triggered sensors. The resulted transformation can be seen on Fig. 2(a).

In a market basket analysis, transactional datasets are analysed to discover which items are likely to be bought together. Similarly, in AAL, we would like to know which sensors are likely to be ON simultaneously. Even in single-resident homes, simultaneously ON sensors in different locations can

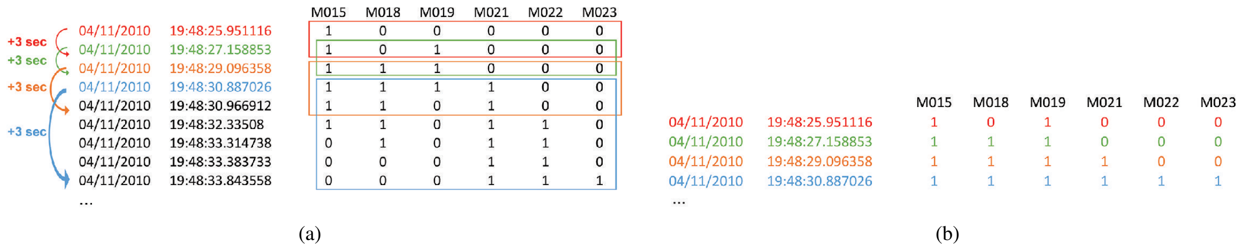

Fig. 2. Data aggregation using sliding window of size 3 seconds

be observed due to the switch-off delay time of motion sensors or due to the overlapping detection areas of those sensors. We are also interested to know which sensors are usually triggered within a few seconds from each other. To take into account the temporal correlations, we consider that if a sensor is ON within t seconds from another sensor then they are considered as happening simultaneously. Thus, a time-based *sliding window* is then used to aggregate the sensor data into a set of transactions as in Fig. 2(b).

B. Association Rules Mining

In an attempt to find the strong association rules that reflects the correlations between sensors, the use of rule mining with different measures were investigated. The first technique uses the typical measures for association rule mining which are the support and confidence of a rule. The minimum support and minimum confidence values should be determined by the designer to control the quality of the obtained association rules. The support calculates the probability of finding two or more simultaneous positively triggered sensors.

As the use of different areas in the apartment may not be equally distributed, some sensors may be triggered much less often than others, consequently their support will be relatively low in comparison to others, and thus, they will not appear in the extracted rules as they did not exceed the minimum support value. Consequently, a new measure termed *relative support* is calculated as defined in equation 4. The second technique investigate the use of the relative support and confidence as evaluation metrics for the association rules mining.

$$\text{Rel. Support}(X \to Y) = \frac{|\text{Transactions containing X\&Y}|}{\text{Min}(|\text{Transactions for each item in X or Y}|)} \tag{4}$$

For example, the relative support of the rule M4,M5 $\to$ M7, is calculated as follows:

$$\text{Rel. Support}(M4, M5 \to M7) = \frac{\text{Trans}_{4,5\&7}}{\text{Min}(\text{Trans}_4,\text{Trans}_5,\text{Trans}_7)} \tag{5}$$

where $\text{Trans}_{4,5\&7}$ is the number of transactions in which the sensors M4, M5 and M7 appear together, and Trans_4, Trans_5 and Trans_7 are the number of transactions containing M4, M5 and M7, respectively.

IV. CASE STUDY

A. Dataset

The proposed approach has been evaluated on the publicly available Aruba CASAS dataset [12], which was collected from a single-resident apartment for 6 months. The apartment is equipped with 31 motion sensors, 4 contact door sensors and 5 temperature sensors. However, only the motion and contact sensors were included in our experiments. Also, there is one door contact sensor that never triggered any event in the recorded dataset. Thus, in total we have used the data from 31 motion sensors and 3 contact sensors which results in a dataset of 1316981 sensor triggers. The training data used for finding the correlations is 50% of the dataset. The other 50% of the data is left to be used for the validation of a sensor failure detection system based on the extracted correlations; however, this is not addressed in this paper. Also, it is assumed that the recorded dataset does not have faulty sensors triggers.

B. Experiments

In order to evaluate the techniques proposed in the previous section, two experiments were conducted using MATLAB 2017b software. Standard support experiment (Experiment A) uses the first technique which implements association rule mining with minimum support values of 0.5%, 1% and 1.5%, minimum confidence values of 60%,

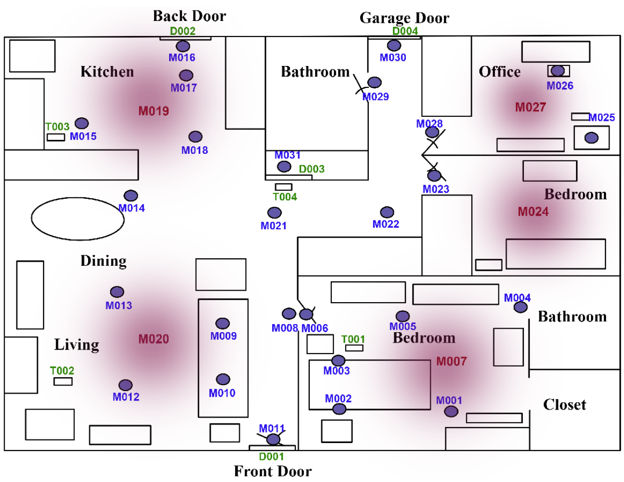

Fig. 3. Aruba CASAS floor plan [12]

80%, 90% and 100%, and sliding window sizes of 3, 5, 8, 10, 15, 30 and 45 seconds. Relative support experiment (Experiment B) uses the second technique which depends on the minimum relative support instead of the minimum support and experimented with the values of 15%, 20%, 25%, 35% and 45%, and the same minimum confidence and sliding window parameters.

The objective of these experiments is to extract meaningful association rules that have as many as possible of the employed sensors appearing in at least one of the consequent parts of the extracted rules so that most sensors could be checked for faulty behaviour. An example of the outputted association rules is as follows: M6, M8 $\rightarrow$ M20 (Support: 4.5942%, Confidence: 92.9159%). This rule means that, according to the given dataset, 92.9159% of the times the sensors M6 and M8 were active, the sensor M20 was also active. From a fault detection perspective, it would also means that, if during a real-time monitoring, the sensors M6 and M8 are active and the sensor M20 is not activated within the size of sliding window used in the data preprocessing, then it is highly probable that any of these sensors is faulty.

In the next subsection, several combinations of the above-mentioned parameters will be evaluated and compared with respect to the number of extracted rules, the number of sensors present in the consequent part and the ratio of sensors present in the consequent part to the number of extracted rules.

C. Results

The number of association rules obtained from each experiment, the number of the sensors present in the consequent part of those rules and the ratio of sensors present in the consequent part to the number of extracted rules were plotted on Fig. 4, Fig. 5 and Fig. 6, respectively.

First, as shown in Fig. 4, in all experiments the number of obtained rules increases roughly linearly as the sliding window size is increased from 3 to 10 seconds included, then afterwards the number increases exponentially even more drastically. On the other hand, as shown in Fig. 5, after 10 seconds the number of sensors in the consequent part of rules does not increase in the same rate of increase of number of rules. However, as shown in Fig. 6, for a sliding window larger than 10 seconds, a dramatic drop occurs in the ratio of the number of sensors to the number of rules. As a first result, it can be concluded that for a sliding window larger than 10 seconds, the drastic increase in the number of association rules is not useful as it does not permit to extract more new rules that covers the sensors that have been missing in the consequent parts.

In the standard support experiment, the graphs plotted in Fig. 4 clearly show that the trend is almost consistent within the sub-experiments; at each specific minimum support, the number of rules and consequent sensors increase for each value of minimum confidence as the sliding window size increase. The trend is also consistent on the global view of the sub-experiments; as the minimum support decreases, the number of association rules increase (see Fig. 4) as well as the number of sensors in consequent part (see Fig. 5). However, the latter one is increasing less rapidly, as depicted in Fig. 6, where the ratio of sensors to rules decreases as the minimum support decreases.

Similarly to the standard support experiment, in the relative support experiment as the minimum support decreases the number of association rules and consequent sensors

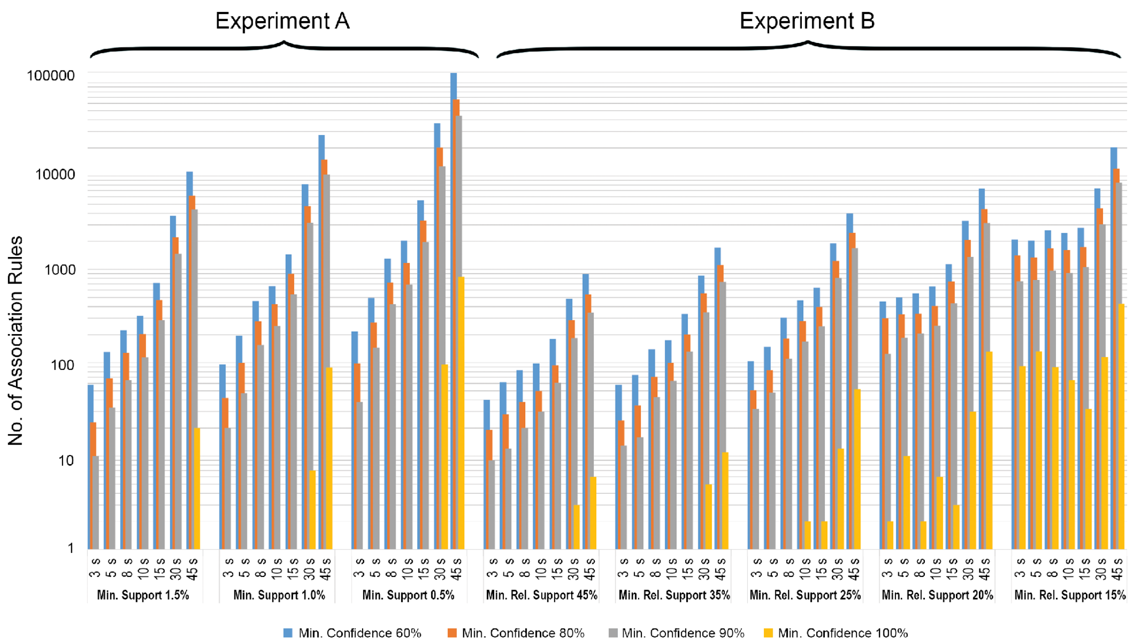

Fig. 4. Number of association rules w.r.t. minimum support/relative support, minimum confidence and sliding window size

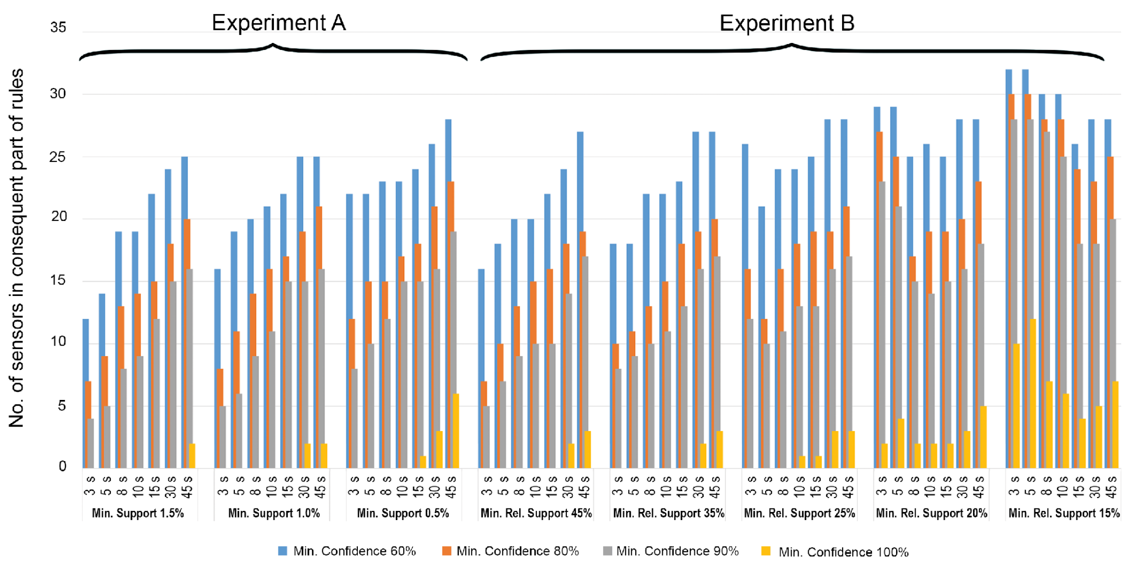

Fig. 5. Number of sensors in the consequent part of association rules

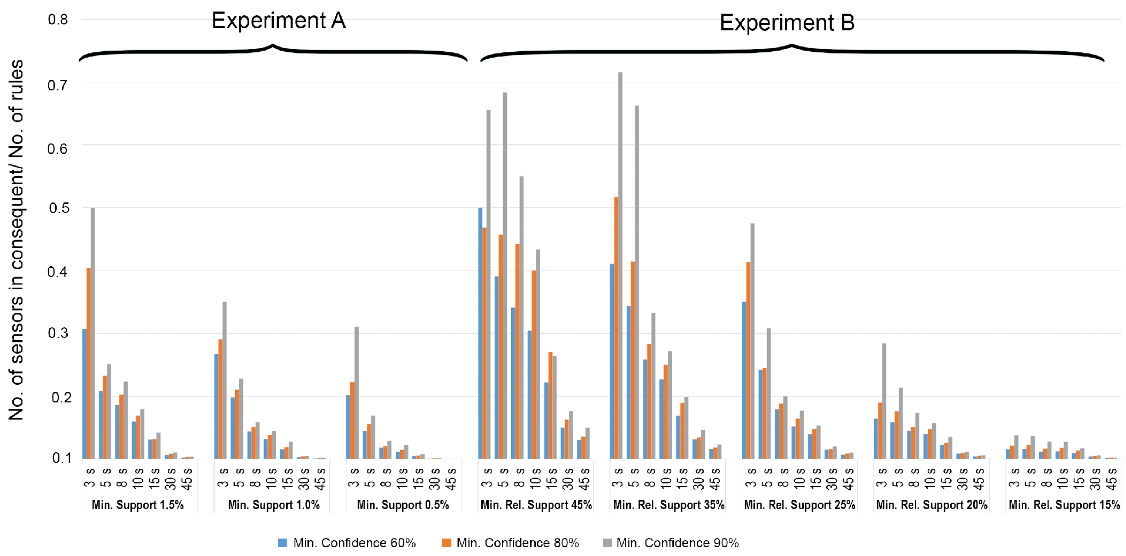

Fig. 6. Ratio of the number of sensors in the consequent part of association rules to the number of rules

increase. However, the plots of the relative support experiment show that the trend within the sub-experiments is inconsistent, for example, at minimum relative support of 20% the number of consequent sensors at a sliding window size of 10 seconds that have a confidence of 100% is greater than that at 8 seconds, while at minimum relative support of 15% the same parameter is less at 10 seconds than that at 8 seconds (see Fig. 5). This could be due to the fact that each of the numerator and denominator of the relative support equation increases in different rates according to the switch-off delays of motion sensors and the resident's behaviour, changing the relative support of each itemset.

As observed in Fig. 6, the ratio of consequent sensors to the number of rules that have a confidence of 90% or more is always the highest in all sub-experiments compared to the other minimum confidence values. By setting the minimum relative support to 35%, sliding window size to 3 seconds and minimum confidence to 90%, the resulted ratio of consequent sensors to rules is 0.615. However, the number of consequent sensors is only 8. Therefore, such rules are not sufficient to discover faulty sensors in an apartment that deploys 34 sensors. As illustrated, judging the best parameters for achieving good results in association rules from investigating either one or two of Fig. 4, 5 and 6 is not

Rule	(Support, Confidence, Lift)
M4,M5 -> M7	(1.8598%, 99.7798%, 7.0076)
M27,M28 -> M26	(0.44116%, 97.0335%, 24.9976)
M7,M8 -> M6	(2.2994%, 77.7066%, 13.104)
M28,M31 -> M29	(0.13819%, 96.5847%, 63.3015)
M10,M13 -> M9	(1.8377%, 76.0495%, 3.7885)
M15,M16 -> M19	(1.318%, 96.5078%, 3.8882)
M5 -> M7	(5.7343%, 94.9325%, 6.6672)
M6,M8 -> M20	(4.5942%, 92.9159%, 3.0962)
M10,M12,M13 -> M20	(1.2897%, 92.0608%, 3.0677)
M4,M7 -> M5	(1.8598%, 64.6531%, 10.7034)
D4,M29 -> M30	(0.59519%, 91.4964%, 50.4254)
M21,M23 -> M22	(1.4179%, 90.5279%, 13.6379)
D2,M19 -> M16	(0.11063%, 90.4153%, 20.0021)
D1,M11 -> M20	(0.15969%, 78.7091%, 2.6228)
M29,M30 -> D4	(0.59519%, 68.4423%, 45.958)
...	

Fig. 7. Sample of the obtained rules at 25% min. relative support, 60% min. confidence and sliding window size of 3 seconds

sufficient, the three figures should be considered together to determine the best trade-off among the parameters, as will be discussed in the next section.

D. Discussion

Overall, the relative support experiment permits to extract more consequent sensors within less number of functionally redundant rules than the standard support experiment. This shows that using the relevant support of rule is more beneficial for our application. This can be explained by the fact that the AAL datasets are usually unbalanced: some sensors are triggered much more often than others; yet, infrequent triggered sensors may be highly correlated.

Pursuing a trade-off between the number of meaningful association rules and consequent sensors, a minimum relative support of 25%, combined with a sliding window size of 3 seconds and a minimum confidence of 60% appear to be the best values for extracting strong correlations between sensors that could be used to detect sensor failures. Those parameters produce 104 rules that contains 26 different sensors in the consequent part of the association rules. 32 out of the 104 rules have a confidence of 90% or more; 12 sensors out of the 26 consequent sensors are included in those 90% confidence rules. In general, this means that for some sensors it would be easy to extract relations with a few rules, but others may require many more rules or are even impossible to correlate for a given configuration of these sensors positioning in an apartment. A sample of the obtained rules is shown in Fig. 7, the lift value for all the rules is always greater than 1.

By checking the extracted association rules and the apartment layout, logically correct correlations could be obtained between the different sensors. As a consequence, a sensor failure detection for Ambient Assisted Living could rely on those rules to flag a fail-stop or non-fail-stop sensor failure. Those rules could be exploited to build a probabilistic model for sensors' triggers which can be used for fault detection. As the number of rules with 100% confidence is relatively small, it is not possible, after a positive/negative trigger observation of a sensor, to guarantee with certitude whether the sensor is faulty or not. Yet, after a sequence of highly probable unexpected events (confidence >80%), the confidence in the diagnostic can be increased.

V. Conclusion and Future Work

This paper proposed the use of association rule mining to find the correlations between binary event-triggered sensors deployed in Ambient Assisted living environment. Two techniques were implemented, one using support and the other using relative support, and compared on a case study. The criteria for obtaining the association rules of interest were discussed. The proposed approach, using the relative support of a rule, permits to obtain interesting correlations between sensors from an unlabelled dataset, with no need for prior expert knowledge.

As future work, those correlations could be used for the detection of fail-stop and non-fail-stop sensor failures and/or fault tolerance in Ambient Assisted Living. A limitation for the proposed system is that some of the deployed sensors do not have rules that enable us to check on their faulty behaviour. This point will be considered in the future work, especially in relation to existing works on automatic placement of sensors for ADL recognition [13]. Also, a sensor failure detection system will be developed based on the obtained rules and real-time experiments will be conducted with injecting various types of failures to evaluate the performance of detecting failures.

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6 Paper C

Sensor Failure Detection in Ambient Assisted Living Using Association Rule Mining [1]

ElHady, N.E.; Jonas, S.; Provost, J.; Senner, V. Sensor Failure Detection in Ambient Assisted Living Using Association Rule Mining. Sensors 2020, 20, 6760.
https://doi.org/10.3390/s20236760

Summary

Sensors failures in AAL environments are either fail-stop or non-fail-stop failures. Fail-stop failures may occur due to hardware breakdown and power loss, while non-fail-stop failures may exist due to remounting the sensor in a wrong place after its dislodgment and obstructing its view by furniture. Sensors installed in non-intrusive AAL environments are mostly event-driven, heterogeneous and binary sensors, which made it challenging to detect its failure. Several fault detection techniques were developed for wireless sensor networks, however, they mainly tackle the networks that have homogeneous, time-driven and continuous sensors. This paper proposed a sensor failure detection and isolation system for AAL environments equipped with event-driven, ambient binary sensors. The system consists of an offline stage and an online stage. In the offline stage, the fault-free correlations between sensors are extracted via association rule mining using relative support and confidence as the evaluation metrics. The extracted rules undergo further post-pruning to obtain the most interesting correlations for our failure detection system. At run-time, every time a resident triggers a sensor, the set of correlations are checked for satisfaction/unsatisfaction and accordingly the health status variables of the sensors are computed. Whenever the health status of a sensor drops below a predefined threshold, the sensor will be flagged as faulty. The effect of the system's parameters; sliding window size, minimum relative support, minimum confidence and health threshold, on the

[1] The author of this thesis contributed to the conceptualization, methodology, investigation, software, validation and wrote and edited the original draft of the manuscript. Prof. Stephan Jonas has contributed to the conceptualization, supervision, and manuscript editing and revision. Prof. Julien Provost has contributed to the conceptualization and manuscript revision. Prof. Veit Senner has contributed to the conceptualization and supervision. All authors have read and agreed to the published version of the manuscript.

performance of the system was experimented. Guidelines for selecting the values of the parameters were proposed. Moreover, our approach was evaluated on a publicly available dataset injected with fail-stop, obstructed-view and moved-location failures. The results show that our system was able to detect and isolate failures.

sensors

MDPI

Article

Sensor Failure Detection in Ambient Assisted Living Using Association Rule Mining

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Received: 20 October 2020; Accepted: 22 November 2020; Published: 26 November 2020

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Abstract: Ambient Assisted Living (AAL) is becoming crucial to help governments face the consequences of the emerging ageing population. It aims to motivate independent living of older adults at their place of residence by monitoring their activities in an unobtrusive way. However, challenges are still faced to develop a practical AAL system. One of those challenges is detecting failures in non-intrusive sensors in the presence of the non-deterministic human behaviour. This paper proposes sensor failure detection and isolation system in the AAL environments equipped with event-driven, ambient binary sensors. Association Rule mining is used to extract fault-free correlations between sensors during the nominal behaviour of the resident. Pruning is then applied to obtain a non-redundant set of rules that captures the strongest correlations between sensors. The pruned rules are then monitored in real-time to update the health status of each sensor according to the satisfaction and/or unsatisfaction of rules. A sensor is flagged as faulty when its health status falls below a certain threshold. The results show that detection and isolation of sensors using the proposed method could be achieved using unlabelled datasets and without prior knowledge of the sensors' topology.

Keywords: ambient assisted living; enhanced living environments; sensor failure; fault detection; fault isolation; smart home; non-intrusive sensors; binary sensors; event-driven sensors

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1. Introduction

The ageing population phenomenon is one of the toughest challenges of this century. In 2019, 1 in 11 people around the globe was over 65 years old. This number of aged people is expected to rise to 1 in 6 people by 2050. The old-age dependency ratio is the ratio of the people over 65 to people between 20 and 64 years old. Some regions will witness this demographic shift the most, e.g., Europe and North America, will have an old-age dependency ratio of 49 per 100 by 2050 [1]. This demographic shift will induce challenges to governments as well as individuals [2]. The increasing ratio of retired persons to workers requires increasing the capacity of the social system. Moreover, as people grow into older age the chances of having age-related impairments and diseases increase, which if not monitored closely could lead to much worse health complications. Thus, the health-care costs are expected to increase as the population ages as well as the need for more care-givers. Stress would also be imposed on informal caregivers, e.g., family members. In order to decrease the burden on governments and individuals, promoting healthy ageing and independent living is becoming a priority. Exploiting the vast development of the information and communication technologies (ICT) and the emergence of ambient intelligence (AmI) is the key to providing such independence to older adults.

As a result, there has been an increasing interest in establishing Ambient Assisted Living (AAL) environments [2]. One of the definitions proposed for Ambient Assisted Living is "the use of information and communication technologies (ICT) in a person's daily living and working environment to enable them to stay active longer, remain socially connected and live independently into old age" [3]. It is a multidisciplinary field that involves information and communication technologies, sociological sciences and medical research [4]. The AAL tools could be mainly categorised into health and activity monitoring tools, wandering prevention tools and cognitive orthotics tools [2]. The health and activity monitoring tools aim to monitor the activities of daily living (ADL) in an unobtrusive way, either to ensure the safety of the monitored person, or the completion of his activities, or to detect the deterioration in his cognitive and physical abilities. Wandering prevention tools were developed mainly to aid people suffering from dementia, while cognitive orthotics tools are used to aid people with cognitive decline. The AAL tools would cast some burden away from the family members of the older adults, decrease the need for qualified caregivers and have a positive impact on the psychological status of older adults as they would live independently at their homes for longer and more safely. To achieve the goals of the AAL systems, the following requirements need to be fulfilled; adaptability, interoperability, acceptability, usability and dependability [4].

Health or mobility related sensors are widely used for the monitoring purposes and represent the heart of the AAL environments [4]. Most of the sensors that are used for monitoring are event-driven binary sensors, for example the PIR sensor produces high output when motion is detected, otherwise it produces low output. Such sensors provide low level information, unlike the sophisticated information from cameras or microphones, and thus is more difficult to interpret and more prone to errors [5]. The failures that are encountered in such sensors are either fail-stop failures, where the sensor stops reporting values, or non-fail-stop failures, where the sensor reports values that do not reflect the occurring *events* that were supposed to be captured by it. Examples of the reported non-fail-stop failures that occur in AAL environments include sensors that get blocked by furniture, get remounted by the user in wrong locations, get stuck at a value or get spurious signals due to air drafts, sunlight rays or pets [6,7]. The traditional fault diagnosis methods for wireless sensor networks [8–10] are designed to deal with homogeneous, time-driven and continuous-valued sensors. However, such methods do not suit the nature of sensors installed in non-intrusive AAL environments, which are often heterogeneous, event-driven and binary sensors. This work aims to propose a sensor failure detection and isolation system for AAL environments equipped with event-driven, ambient binary sensors.

2. Related Work

A comprehensive literature review was presented by the authors of this article in [11], which focuses on the works concerned with detecting sensor failures, as well as tolerating its resulted faults, in AAL environments equipped with binary, event-driven sensors. The surveyed fault-tolerant systems focus mainly on location tracking [7,12,13] and activity recognition [6,14,15]. The sensor failure detection systems found in literature may be classified as model-based and correlation-based approaches [11]. The model-based techniques rely on deducing the location of the resident using the triggered sensors due to his movement or his performed activities. Then, this deduced location is compared with the location predicted either by his model of mobility, e.g., in [16,17] or by a localisation system, e.g., in [18,19]. The proposed model-based sensor failure detection approaches are not promising as they either use unrealistic models of resident motion that do not take into consideration previous locations and speed or install extra hardware that increases cost as well as the chances of errors. Fault detection and diagnosis frameworks that rely on modelling the sensors' and actuators' activation due to various user scenarios were presented in [20–22]. However, it can only detect failures in sensors that are involved in tasks that have sensor-actuator feedback.

The surveyed correlation-based techniques can be classified as methods based on exploiting sensor-appliance correlations, sensor-activity correlations and sensor-sensor correlations [11]. FailureSense [23] monitors the interval between motion sensor triggers and electrical appliances. Sensor failure is flagged during run-time when the monitored interval deviates from the previously learnt patterns from training datasets. The drawback of this method is that the assumption that the resident has to be physically beside the appliance to turn it on does not always hold. Idea system [24] first extracts the sensors that are triggered with each activity of daily living using an activity labelled dataset. In order to detect sensor failures, activity recognition is done, and whenever an activity is recognised while one of its sensors did not trigger, a rarity score is computed. Sensor failure alert is raised when the rarity score falls below a set threshold. The limitation of this approach is that it assumes that the activity has been correctly recognised in the first place. In addition, it requires labelled datasets for training. Following are the works based on the sensor-sensor correlations techniques. An approach based on temporal correlation and nonlinear time series analysis was investigated by Ye, Stevenson and Dobson; however, the experimental data was not enough to prove the effectiveness of this approach [25]. Same authors have proposed the use of density based clustering to detect outlier sensor triggers [26,27]. However, clustering occurs as a postprocess step on the collected data. SMART system uses simultaneous multiple classifiers, a classifier for each sensor failure. It detects a sensor failure by analysing the relative performance of these classifiers [6,28]. This approach lacks scalability and needs excessive training effort. DICE [29] extracts correlations and transitional probabilities among sensors and actuators offline. Failure is detected either when a sensor is missing from a predefined correlation or when a group of sensors fires despite having a zero transitional probability with the previous group of triggered sensors. The drawback of this approach is considering any group of triggered sensors as a correlation, even if it has only appeared once, thus questioning the reliability of correlations and making the approach more computationally complex especially when the number of installed sensors increases.

Our research work favoured adopting a correlation-based approach over a model-based approach, to avoid the disadvantages of relying on generic human mobility models, like in [16], that may not be accurate nor personalised to reflect the behaviour of the monitored person. In addition, adding extra hardware, as in [18,19], was avoided in order not to increase the implementation cost. Our proposed sensor failure detection and isolation system approach focused on sensor-sensor correlations rather than sensor-appliance and sensor-activity correlations. Sensor-appliance approaches [23] rely on assuming that there will be correlations between the activation of the electrical appliance and the triggering of the motion sensors in the areas leading to it, which is becoming less common in smart homes as most appliances can be switched on remotely. Meanwhile, failure detection using sensor-activity correlations [24] requires obtaining labelled data of performed activities to correlate the activities to the sensors during the training phase and relies on the accuracy of the activity recognition system at run-time to detect sensor failures. Our method does not need labelled datasets of sensor failures nor performed activities. It is based on extracting the nominal correlations between the installed sensors with no prior knowledge on the topology using unlabelled datasets. The association rule mining [30] technique is used to extract correlations. Unlike the approach presented in [29] that considers any proceeding triggers between sensors as a correlation, association rule mining extracts strong correlations that meet minimum relative support and confidence, which would ensure more reliability for failure detection. Association rule mining is characterised by its simplicity and good interpretability of results. There are works that have based their fault detection system on association rule mining; however, they were used to detect faults in time-series, continuous-valued data, e.g., [31,32]. Association rule mining has also been used for fault diagnosis using datasets that are already labelled with various system faults to associate which sensor signal values are responsible for corresponding system faults, e.g., [33]. In this paper, we propose a failure detection and isolation system for binary, event-driven sensors that is based on association rule mining. Association rule mining is refined to better suit our application. Postpruning is applied to get the most interesting correlations that the sensor failure detection and isolation system can rely on. The extracted correlations appear as a set of IF-THEN rules that indicate the sensors that trigger within a few seconds from each other. At run-time the set of rules are monitored and then the health status of each sensor is updated according to the satisfaction/unsatisfaction of the correlations. A sensor is flagged as faulty when its health status falls below a predefined threshold. Guidelines for the selection of the values of the parameters of association rule mining algorithm and the health status threshold are presented in Section 4.3.2. Failure detection and isolation take place at run-time; this is contrary to the approach in [26,27] that detects failure in precollected data. The approach presented in this paper is scalable; therefore, it overcomes this shortcoming found in the SMART system [6,28] which needs a large training effort to train a classifier for each sensor failure.

3. Sensor Failure Detection and Isolation System

Our sensor failure detection and isolation system consists of two stages: an offline stage and an online stage. During the offline stage, the fault-free sensor correlations are extracted from previously collected sensor dataset at the resident's home during his nominal behaviour. Meanwhile online, the fulfilment of correlations are checked as sensor *events* are triggered by the resident and accordingly failure of sensors is determined. An overview of the proposed system is shown in Figure 1.

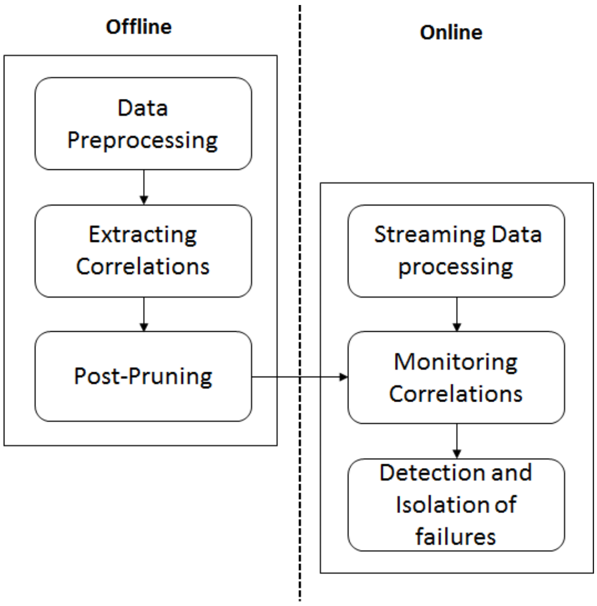


Figure 1. An overview of the proposed system.

3.1. Sensor Correlations Extraction

First, preprocessing of training data is done, followed by rules extraction using association rule mining. Afterwards, the extracted rules are further pruned to obtain the most interesting sensor correlations.

3.1.1. Data Preprocessing

The log obtained from AAL environments equipped with non-intrusive sensors consists of a series of *events*. Each *event* has a time stamp, sensor ID and the corresponding sensor *event* trigger. An example of a sensor *event* is 13 January 2011 10:28:14.65 M030 ON, which implies that sensor M030 has been positively triggered at the given time stamp. In order to extract correlations using association rule mining, the transformation of the time-stamped sensor *event* triggers dataset into a set of transactions takes place over a couple of steps. The first step consists of creating a multivariate time-series, where the value of each sensor is logged at every time stamp of the dataset in a separate sensor signal variable. Formally, let $s_{i,t} \in \{0,1\}$ be the value of the i-th sensor at timestamp $t \in T$. The set T is the set of timestamps of the log. For n sensors, concatenation produces the multivariate time-series S.

$$S = \{(s_{1,t}, s_{2,t}, ..., s_{n,t})\}_{t \in T} \quad (1)$$

Next, removal of all-zero rows is done. Formally, it corresponds to removing all-zero row vectors from the time-series S.

$$V := S \setminus \{(0_{1,t}, 0_{2,t}, ..., 0_{n,t})\}_{t \in T} \tag{2}$$

Figure 2a shows an example for a multivariate time-series created from an AAL log. At each row, a sliding window is used to group the sensors that have a signal value of 1 within the size w seconds of the sliding window via logical ORing. The output of the window will be a single transaction that has the time stamp of the start of the window. Formally, the value of the i-th sensor in the transaction computes to:

$$d_{i,t} = sgn\Big(\sum_{j \in [t, t+w]} v_{i,j}\Big) \tag{3}$$

The sliding window is run over the multivariate time-series data to output a transactional database as illustrated in Figure 2, where each transaction presents the sensors that appear to be ON within w seconds from each other. The obtained sensors transactional database will be used in the upcoming correlations extraction step.

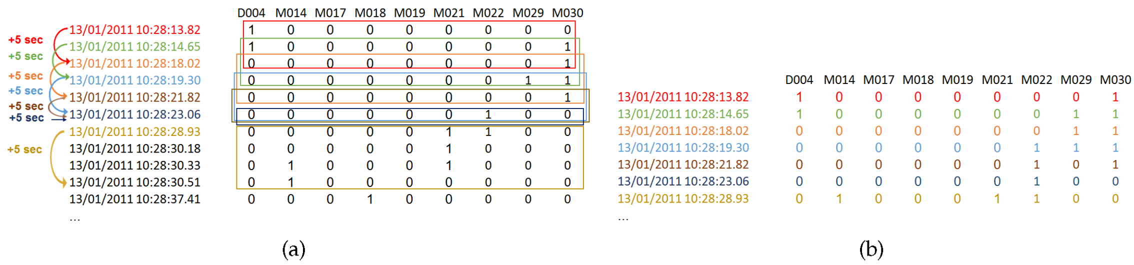


Figure 2. (**a**) Sliding window of size $w = 5$ s, is run over the multivariate time-series data. (**b**) Transactional database.

3.1.2. Extracting Correlations

Correlations between fault-free sensors are extracted using the association rule mining technique. It is a data mining technique that was introduced by Agrawal et al. [30] and is commonly used on large transactional databases to find correlations between its items. Its most famous application is the market basket analysis, where the transactions of a supermarket are analysed to find which items are usually bought together by customers. Similarly, we aim to detect which sensors are most likely to be simultaneously active implying strong correlations.

A formal representation of the association rule mining problem is as follows. Let $I = \{I_1, I_2, .., I_m\}$ be a set of binary features denoted as items. Let the dataset T consist of a set of transactions $T = \{T_1, T_2, .., T_n\}$, where each transaction is a binary vector of items, e.g., if transaction T_1 contains only two items I_1 and I_3, then T_1 will have $T_1[1] = 1$, $T_1[3] = 1$ and the rest of T_1 vector are zeros. An association rule has the form of $X \rightarrow Y$, where the antecedent $X \subset I$, the consequent $Y \subset I$ and $X \cap Y = \phi$. The confidence of a rule denotes how likely it is to find item(s) of Y when item(s) of X occur(s), while the support of a rule is how frequent items of X and Y appear together in the dataset. Support and confidence, defined by Equations (4) and (5) respectively, are the most commonly used evaluation metrics that assess how strong the association rule is. The Apriori algorithm [34] is used to extract the association rules from transactional datasets. Minimum values for support and confidence have to be satisfied to avoid extracting meaningless rules. These minimum values need to be set by the designer. Lift is a metric used to confirm the dependency between the rule's antecedent and consequent as shown in Equation (6), a value of 1 indicates independency, while greater than 1 indicates dependency. The higher the lift value, the greater is the dependency.

$$\text{Sup}(X \rightarrow Y) = \frac{|\,\text{Transactions containing X\&Y}\,|}{|\,\text{Transactions}\,|} = P(X \cap Y) \tag{4}$$

$$\text{Conf}(X \rightarrow Y) = \frac{\mid \text{Transactions containing X\&Y} \mid}{\mid \text{Transactions containing X} \mid} = P(Y|X) \quad (5)$$

$$\text{Lift}(X \rightarrow Y) = \frac{\mid \text{Transactions containing X\&Y} \mid}{\mid \text{Transactions containing X} \mid * \mid \text{Transactions containing Y} \mid} = \frac{P(X \cap Y)}{P(X)P(Y)} \quad (6)$$

In the market basket analysis application, the items are the supermarket products, e.g., butter, bread, and a transaction contains the items that have been simultaneously bought by a customer in this transaction. In our AAL application, the items of the transactional database are the sensors installed in the AAL environment. However, a transaction contains the sensors that are ON simultaneously in an instant of time, as well as those sensors that are ON within its sliding window of size w seconds. This is because we are concerned to capture the temporal correlations between sensors within few seconds due to performing various activities by resident. The transactional database has been prepared in the preprocessing stage. Another concern in the AAL application is the uneven usage of the different areas of an apartment. A living room may be used by an older adult resident more often than the office room, leading to scarcity of the triggers of the office's sensors in the dataset. In such cases, the support of the rule that has the less often triggered sensors may not exceed the minimum support value that was preset in the Apriori algorithm, and thus will not appear in the extracted set of rules. To overcome this limitation, we define a metric as relative support to be used in the Apriori algorithm instead of the support for rules extraction. Support compares the number of transactions containing all items of X & items of Y to the total number of transactions present in the database as shown in Equation (4). While relative support is defined by Equation (7), it compares the number of transactions containing all items of X & items of Y to the minimum number of transactions that contain any of the individual items of X or Y.

$$\text{Rel. Sup}(X \rightarrow Y) = \frac{\mid \text{Transactions containing X\&Y} \mid}{\text{Min}(\mid \text{Transactions for each item in X or Y} \mid)} \quad (7)$$

3.1.3. Post-Pruning of Correlations

The mined set of rules that have already exceeded the minimum values for the relative support and confidence still needs further post-pruning to eliminate the redundant and/or less useful rules. Our proposed sensor failure detection method relies on the following hypothesis; if a rule has all of its antecedent sensors active during run-time, while its consequent sensors(s) did not become active within the specified sliding window size, then the sensors can be suspected to be faulty. Accordingly, we aim to have most of the sensors installed in the resident's home appear in consequent part of rules so that they could be checked for being faulty in the monitoring stage. Hence, the rules are grouped for each sensor in consequent, i.e., if there are 20 sensors that appear in the consequent parts of rules, then we will have 20 groups. From each group, the rule with highest confidence, the rule with highest support and the two top trade-off rules between confidence and support, are selected. In our opinion, the former would be the most interesting rules to our application. To obtain the trade-off rules, confidence and support of the rules within each group are normalised, then are summed with weights 1:1, and the rules with the top two highest sums, i.e., trade-off scores, are selected. For example, to prune the rules of sensor M012, the rules that have M012 as a consequent are grouped, and then those rules which have the highest confidence, highest support and the two top trade-off scores are selected to be on the final set of rules that will be used in the monitoring stage, while the rest of the rules that have M012 as a consequent are eliminated.

3.2. Sensor Correlations Monitoring

The pruned set of rules are the most interesting correlations that will be monitored online; they are stored using bitmap arrays [35]. The health status of each sensor, which is the probability that a sensor is healthy, will be computed according to the fulfilment of these correlations.

Every time a sensor trigger *event* occurs, the data is processed and the corresponding sliding window is prepared similar to Section 3.1.1, where the sensor signal value is updated and the sliding window logically OR the sensors' signals within the sliding window size of w seconds. A UML (Unified Modeling Language) diagram that describes the main workflow for the health status update is shown in Figure 3. The pseudocode in Algorithm A1 illustrates in details the health status update of sensors due to monitoring the pruned set of rules. Two satisfaction states of rules are possible: satisfaction and unsatisfaction. If the sliding window contains active sensors that satisfy a rule antecedent as well as its consequent, then this correlation is fully satisfied and the health status of these sensors are updated according to the satisfaction set of equations in Algorithm A2. It is assumed that only one sensor failure can occur at a time (single-sensor failure). Hence, if the sliding window contains active sensors that satisfy a rule antecedent but it fulfils the rule consequent except for one sensor, then this rule is unsatisfied. If this unsatisfied rule has already been satisfied in the previous sliding window or if it will be satisfied in the upcoming sliding window, then the health status will not be updated. In addition, if this rule has been unsatisfied in the previous sliding window then health will not be updated. Otherwise, the health status of this rule's sensors are going to be updated according to the unsatisfaction set of equations in Algorithm A3. The joint probabilities between sensors that are included in the equations can already be obtained from the intermediate calculations of the Apriori algorithm while scanning the training data for finding the frequent itemsets, hence no extra computation is needed. Whenever the health status of a sensor falls below the preset health threshold, failure of this sensor will then be flagged. Figure 4 shows a UML analysis object model of the online stage of our system.

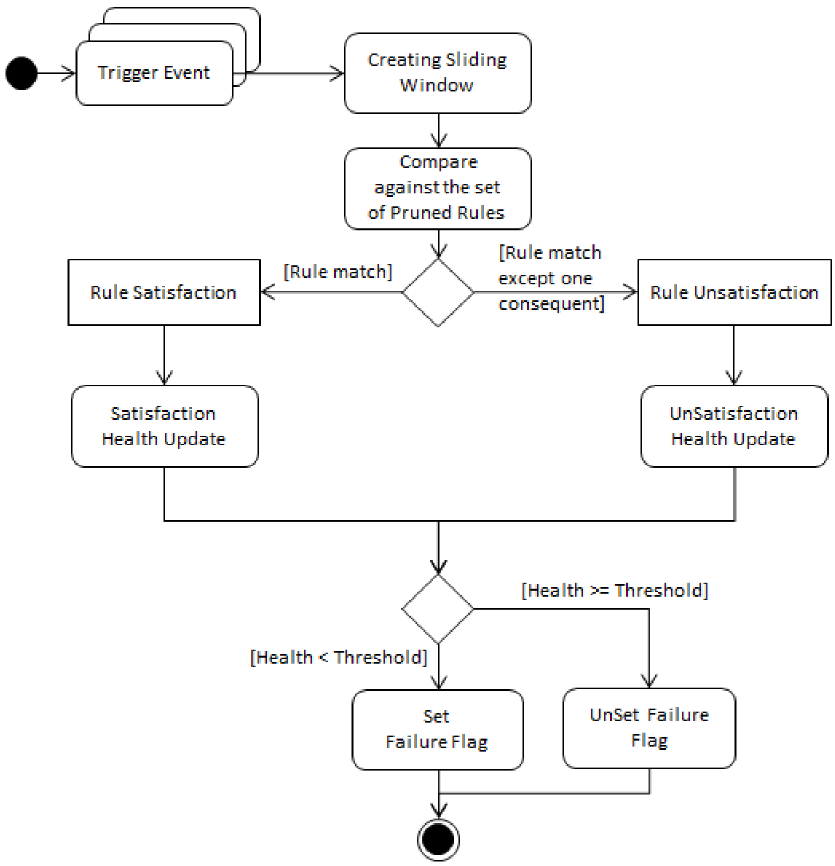


Figure 3. UML activity diagram of the health status update.

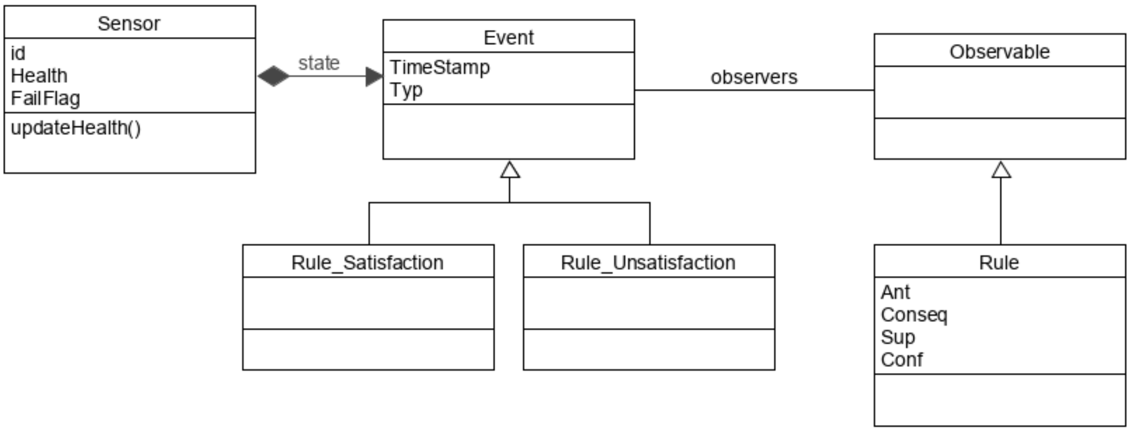


Figure 4. UML analysis object model of the online stage of the failure detection system.

4. Experimental Work and Results

Our proposed approach for sensor failure detection and isolation was evaluated using a publicly available dataset. In this section, the methodology of the experimental work and the results will be presented.

4.1. Dataset

The publicly available Aruba CASAS dataset [36] was used to evaluate the proposed approach for failure detection and isolation of non-intrusive sensors installed in AAL. The dataset was collected over a duration of 6 months from a single-resident elderly's home equipped with 31 motion sensors, 4 door contact sensors and 4 temperature sensors. As our approach is concerned with finding failure in event-driven binary sensors, temperature sensors were not included in the evaluation. In addition, the contact sensor D003, installed on a door located within the apartment as shown in Figure 5, does not have any triggers in the dataset. Thus in total, we have 34 sensors under investigation. The dataset was found to have some instances at which all of the sensors of the apartment get triggered at fractions of a second and all remain active for some time, thus filtering was done to remove such instances. To obtain the training and testing data, a split ratio of 50/50 was used. The training data was used for extracting the offline correlations, while the testing data was processed sequentially to simulate the run-time online processing using MATLAB 2019b software.

4.2. Evaluation Method

The following metrics are used for evaluating the sensor failure detection and isolation system: precision, recall and F1-measure. Precision is the percentage of true positives from the total number of sliding windows reported as positive, while recall is the percentage of true positives from the actual positive sliding windows. The testing dataset was divided into 6 segments, where the segment is approximately 2 weeks in length. Precision, recall and F1-measure are averaged over the segments.

In order to compute the true positives (TP) and false negatives (FN), the segments were duplicated and injected with failure. Failure is injected in each segment on each of the sensors that appear in the consequent parts of the extracted rules. Whenever a sliding window is reported to have a failure from our algorithm, the ground truth is compared with the report to determine whether it is a true positive or not. The start of sensor failure is chosen to be the first timestamp at which the sensor gets triggered in the segment. The faultless segments were used to count the false positives (FP) and true negatives (TN). Receiver Operating Characteristic (ROC) curve and the area under its curve (AUC) were also used to evaluate the performance of failure detection. The ROC curve shows the tradeoff between the true positive rate (TPR) and the false positive rate (FPR) as the health threshold value is varied from 0 to 1. The closer the curve to the left top corner of the plot, the better the performance of failure detection is, implying higher quality of rules that govern the failure detection. A diagonal ROC indicates that it is sort of random classification of failures.

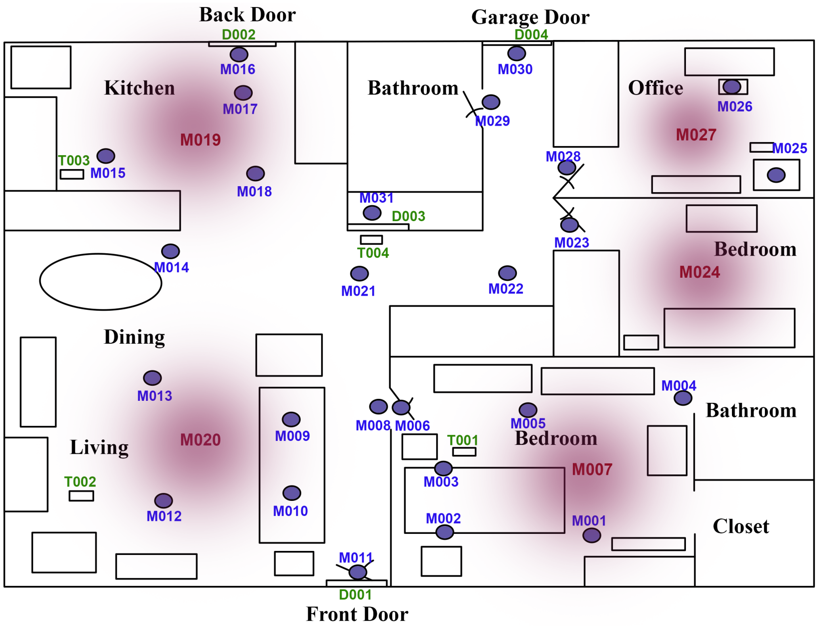


Figure 5. Aruba CASAS floor plan.

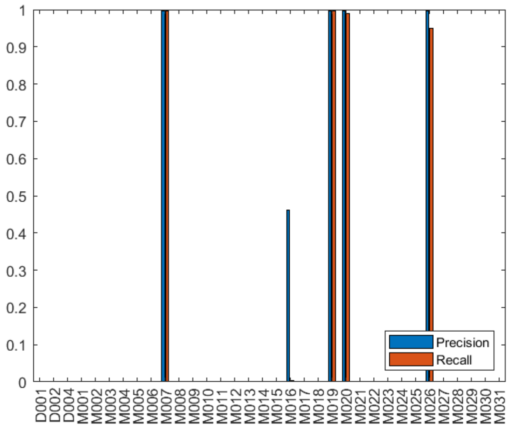
4.3. Parameters of the Correlations Extraction

To achieve high performance for the sensor failure detection and isolation system, optimum values for four parameters need to be selected. These parameters are the sliding window size, minimum relative support, minimum confidence and health threshold. The optimum parameters would output the best set of correlations and thus the best failure detection and isolation performance. During the selection of parameters, thresholds setting dataset is used. The thresholds setting dataset contains 4-week data (2 segments) of the testing dataset.

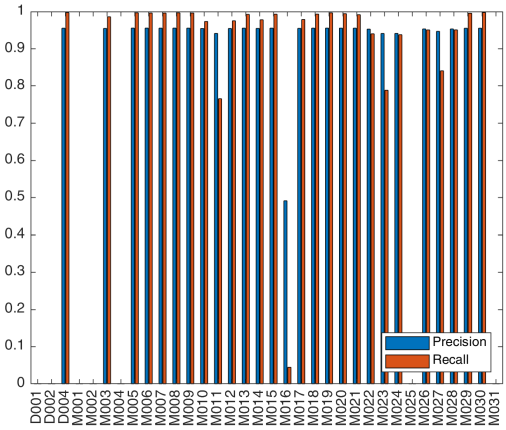
4.3.1. Parameter Effect

Before the selection phase, we wanted to study the effect of each parameter independently on the extracted rules and the performance of the system. Using the training dataset, we set the parameters and extract the correlations as described in Section 3.1. Then, the effect of the extracted rules on the performance of the failure detection system is evaluated on the threshold setting dataset that was injected with fail-stop failures. Fail-stop failure was injected for each of the sensors found in the consequent part of the extracted rules.

Increasing the size of the sliding window from 0 to 60 s, while keeping the minimum relative support at 45%, minimum confidence at 60% and health threshold at 0.4, was studied. It was observed that increasing the size of the sliding window increases the total number of sensors in the consequent parts of rules and increases the complexity of rules as well, i.e., more items/sensors per rule. Figure 6a,b plot the precision and recall of failure detection with the parameters set to the former values when the sensor ID of the x-axis is injected with fail-stop failure. For example, in Figure 6a the columns at sensor M007 show the values of precision and recall of failure detection when M007 was injected with fail-stop failure. High failure detection precision and recall can be observed in most of the cases of failed sensors. Note that the sensors with nonempty bar data in the figures are the consequent sensors of the extracted rules at the indicated values of parameters. Failure detection of only the consequent sensors were evaluated, i.e., in Figure 6a there are only 5 sensors that have bar data, denoting that only those sensors were present in the consequent parts of the rules extracted using 0 s sliding window, minimum support of 45% and minimum confidence of 60%, and failure was injected in each of those sensors and failure detection was evaluated then.



(a)



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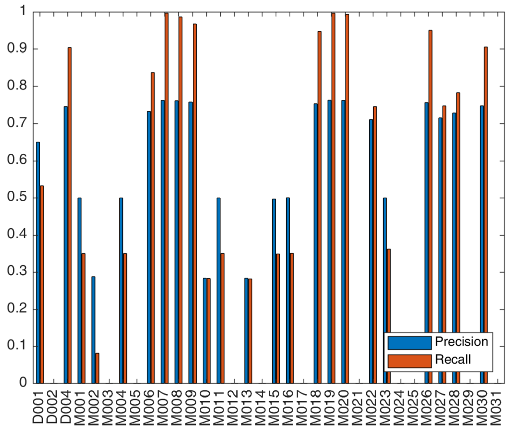
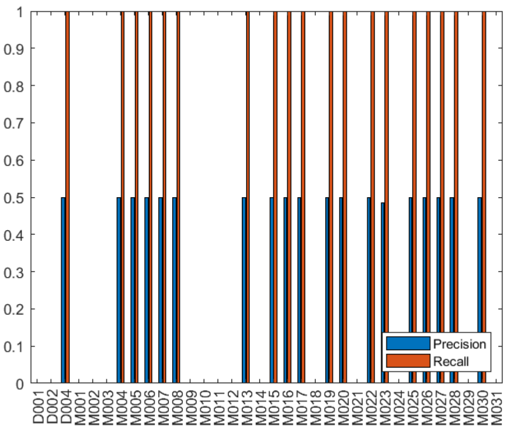


(c)



(d)

Figure 6. Precision and recall of failure detection when a sensor has fail-stop failure, at health threshold 0.4, (**a**) sliding window 0 s, minimum relative support 45%, and minimum confidence 60%. (**b**) sliding window 60 s, minimum relative support 45%, and minimum confidence 60%. (**c**) sliding window 0 s, minimum relative support 2%, and minimum confidence 60%. (**d**) sliding window 0 s, minimum relative support 45%, and minimum confidence 10%.

Figures 6a,c show the precision and recall of detecting failures with setting the minimum relative support at 45% and 2%, respectively, while maintaining the size of the sliding window at 0 s, minimum confidence at 60% and health threshold at 0.4. Observing the effect of decreasing the minimum relative support, it was found that the number of sensors in consequent part of rules increases but nearly half of them have low failure detection precision and recall. The low precision and recall are due to the low relative support of the rules that govern those sensors. Such sensors are the source of false positives, their governing rules seems to be spatially unrealistic, e.g., M001, M023 $\rightarrow$ M010, that was obtained using a sliding window of 0 s, implying that they are supposed to be ON simultaneously which cannot happen from a single resident even with the switch-off delays of motion sensors. The performance of the other sensors was also affected; the high false positives of the system have reduced their failure detection precision while maintaining their high recall. The complexity of the extracted rules has increased due to lowering the minimum relative support. Some sensors appeared in the consequent of rules when the sliding window has been increased but not when the relative support has been decreased, and vice versa. From Figure 6a–c, it is observed that D001, M001 and M002 have appeared in the consequent of rules, when relative support decreased from 45% to 2% and thus can be checked for being faulty, but they were not part of any rule's consequent when the sliding window was increased from 0 to 60 s.

Lowering the minimum confidence from 60% to 10%, while keeping the sliding window at 0 s and the minimum relative support at 45%, is presented in Figure 6a,d. More sensors appeared in the consequent part of rules, and the complexity of rules did not change when the minimum confidence was lowered. The low confidence rules imposed high number of false positives for its sensors, which has deteriorated the performance of the system. The false positives induced when the minimum confidence was decreased to 10% (average false positives of 84,178) are much greater than those induced when the minimum relative support was lowered to 2% (average false positives of 29,493). This is because some of the extracted low confidence rules have high support, thus their sensors will be triggered a lot by the user.

4.3.2. Setting Parameters

We aim to select the best combination of values for the sliding window size, minimum relative support, minimum confidence and health threshold, which would enable failure detection and isolation of as many sensors as possible with high precision and recall. The thresholds setting dataset is used to validate the selection. A set of guidelines that aids in the parameters selection process was formulated and is presented as follows:

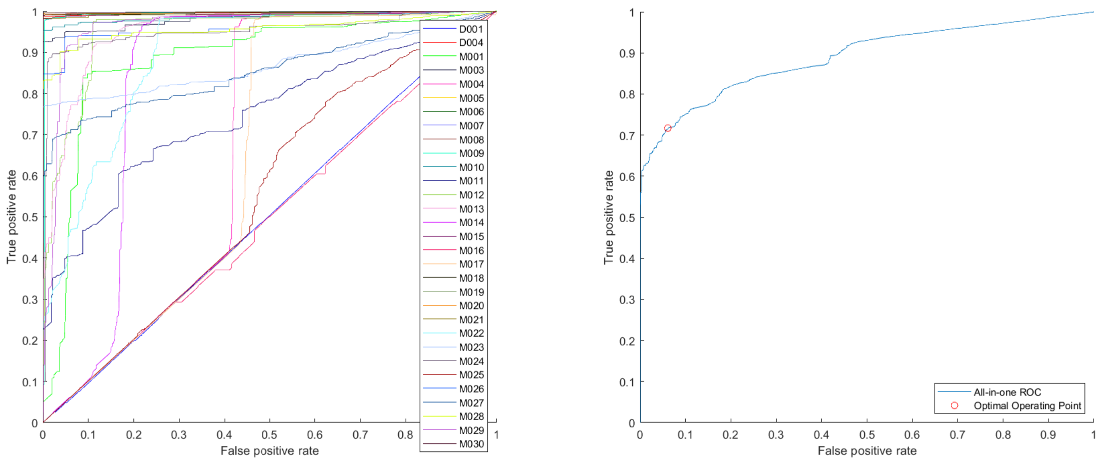
1. First, extract the association rules for various combinations of values from wide range of sliding window size, minimum relative support and confidence > = 50%, while maintaining a single preliminary threshold value, using the training dataset.
2. Then, sort the combinations of parameters according to the total number of sensors in consequent part of their extracted rules in descending order.
3. Select the top-most set of parameters, which produces rules with the highest number of consequent sensors, then prune this set of rules as illustrated in Section 3.1.3.
4. Use the pruned rules to detect failure when each of the consequent sensors is injected with fail-stop failure in the thresholds setting dataset. Afterwards, plot the all-in-one ROC curve of failure detection, that is plotted with aggregating all the sensor failure cases. Furthermore, plot the individual ROC curves of failure detection when each sensor has failed to have more insights about the performance.
5. Find the optimal operating point and the AUC of the all-in-one ROC curve.
6. If the all-in-one ROC curve shows poor performance, i.e., optimal TPR is low (<0.8), optimal FPR is high (>0.02) and AUC is low (<0.9), then delete this set of parameters entry from the sorted combinations and repeat Steps 3–6 with the next highest number of consequent sensors. Otherwise, the selection process of parameters is done successfully, recording the corresponding sliding window size, minimum relative support and minimum confidence.
7. Record the health threshold value that corresponds to the optimal operating point of the all-in-one ROC curve.

The exclusion of the values of confidence that are below 50% in Step 1 is necessary, as when we experimented with below 50% confidence, its ROC curves had always showed poor performance with optimal TPR below 0.8 and/or optimal FPR above 0.02 and/or AUC below 0.9. In addition, the logic in Algorithm A2 which our calculations for failure detection rely upon in the case of rule satisfaction is sustained while using > = 50% confidence. If we used a low confidence rule, e.g., 10%, and it is satisfied then the probability that the sensors of the satisfied rule are faulty would be 90%, which would make rule satisfaction useless to confirm that its sensors are nonfaulty due to fulfilling the correlation.

To select the parameters for our case study, the proposed guidelines were followed. In Step 1, the set of values we used for the sliding window size was [0, 3, 5, 8, 10, 15, 20, 25, 30, 45, 60] s, the minimum relative support set was [2, 5, 10, 15, 20, 25, 30, 35, 45] %, and the minimum confidence set was [50, 60, 70, 80, 90, 100] %. Note that the number of sensor events of the dataset can be divided by its collection duration to get an estimate about the rate of sensors triggering and accordingly choose the range of set values of the sliding window size. The preliminary health threshold value was chosen to be 0.4. The highest number of consequent sensors that could be obtained using the various combinations of the sets was 31 sensors. However, the values of the parameters that yield 31 consequent sensors produce bad failure detection performance that is reflected on its ROC curves. Figure 7 shows the ROC curves that were plotted from setting the sliding window size to 60 s, minimum relative support to 5% and minimum confidence to 50%, this setting yields rules with 31 consequent sensors. The all-in-one ROC curve has an optimal TPR of 0.7169, optimal FPR of 0.06104 and AUC of 0.8903. Iterating back between Steps 3–6, until good ROC curves in Figure 8 are reached from setting the sliding window size to 30 s, minimum relative support to 15% and minimum confidence to 60%. These finally selected values of parameters could detect failures for 28 sensors. Its all-in-one ROC curve has an optimal TPR of 0.8773, optimal FPR of 0.01593 and AUC of 0.9419. The health threshold value that corresponds to the optimal operating point is 0.3591. Note that it may happen that multiple combinations of parameters for the same number of consequent sensors would produce similar overall performance but with one sensor performing better than the other, and vice versa. In our case study, the previously mentioned selected values for parameters produced close performance to that of using sliding window of 45 s, minimum relative support of 20% and minimum confidence of 60%. However, we favoured our selection because less computational effort during the monitoring stage is needed for the smaller sliding window size.

4.4. Experiments

Three types of failures were injected in the testing dataset; fail-stop, obstructed-view and moved-location failures. Each consequent sensor was injected with failure, and the failure detection as well as isolation was evaluated. The initial values of all health status of sensors were set to 1. The sliding window size, minimum relative support, minimum confidence and health threshold were set to 30 s, 15%, 60% and 0.3591, respectively, according to the selection of parameters conducted in Section 4.3.2. The following sensors, D001, D002, M002, M004, M025 and M031, were not checked for failure, as they did not appear in the consequent part of any rule.



(a) (b)

Figure 7. Using sliding window size of 60 s, minimum relative support 5% and minimum confidence of 50%: (**a**) ROC curves of failure detection when each consequent sensor has fail-stop failure. (**b**) All-in-one ROC curve.

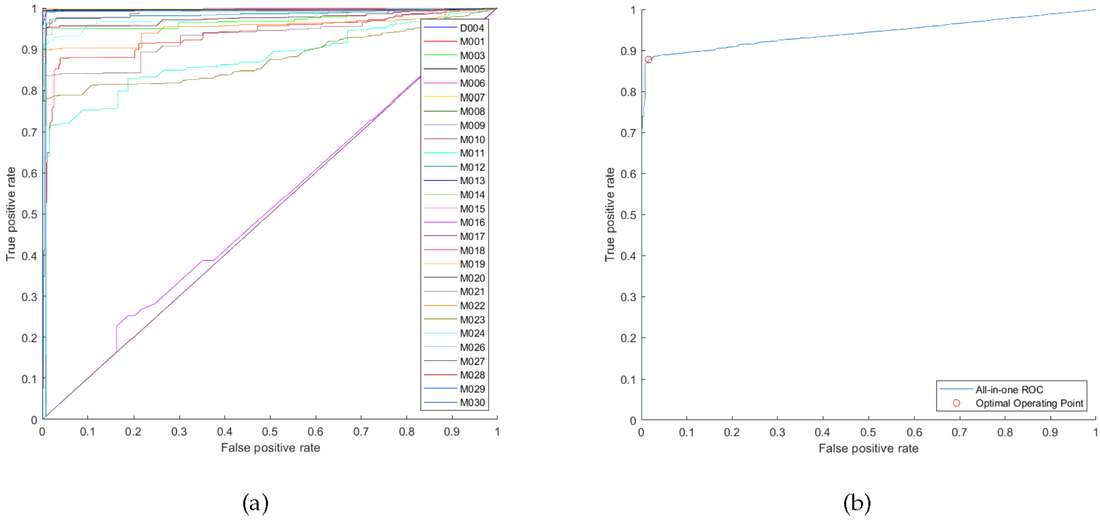
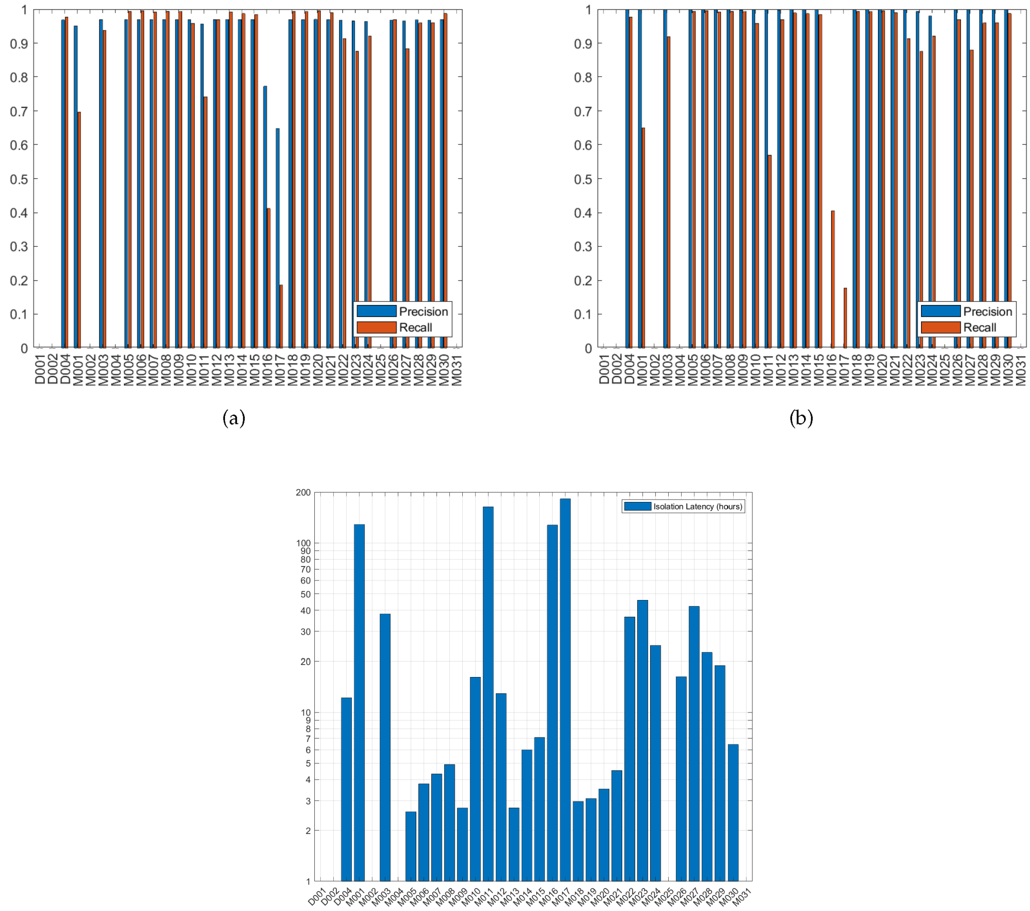


Figure 8. Using sliding window size of 30 s, minimum relative support 15% and minimum confidence of 60%: (**a**) ROC curves of failure detection when each consequent sensor has fail-stop failure. (**b**) All-in-one ROC curve.

4.4.1. Fail-Stop Failure

Fail-stop failure was injected by replacing the readings of the sensor under test by zeros after its point of failure. Fail-stop failure was injected individually on each of the sensors that appeared in the consequent part of rules. The precision and recall of detecting fail-stop failure when failure is injected in each of those sensors is shown in Figure 9a. Meanwhile, the precision and recall for isolating the faulty sensor is shown in Figure 9b. The precision and recall metrics were computed as described in Section 4.2. On the x-axis of Figure 9 lie the IDs of all the event-driven sensors of the apartment shown in Figure 5. The figures are interpreted as follows, the bar columns at sensor D004 in Figure 9a are the precision and recall values of detecting that a failure has occurred when D004 was injected with fail-stop failure. While in Figure 9b, the columns at D004 show the precision and recall of identifying that D004 has failed. No columns were plotted at D001, D002, M002, M004, M025 and M031, as those sensors were not injected with failure nor evaluated as they did not appear as a consequent in the rules. Most of the consequent sensors have high precision and recall for its detection and isolation. There are 26 sensors that when injected with fail-stop failure cause failure detection precision ≥ 0.95, and 24 sensors that cause a recall ≥ 0.87. Isolation precision is ≥ 0.97 for 26 sensors, while the isolation recall is ≥ 0.87 for 24 sensors. The isolation latency was plotted in Figure 9c. The isolation latency is between 2 and 7 h in 13 sensors, 12 and 24 h in 6 sensors and 24 and 48 h in 5 sensors. There are 4 sensors (M001, M011, M016 and M017) that reported very high isolation latency ≥ 120 h. The higher the rate at which the sensor is triggered by the user, i.e., higher support, the shorter the time needed for isolation. It is observed that the sensors which have high isolation precision but along with low isolation recall and high latency, e.g., M001 and M011, are those governed by rules of low support. D002 appears as an antecedent in all the governing rules of M016 and M017, e.g., D002, M019 -> M016. In the first two segments of the testing data, D002 did not have any triggers. Thus, the rules that have M016 and M017 as consequent were never initiated in the first two segments. As a result, M016 and M017 have undefined isolation precision in Figure 9b because of the zero true positives of those two segments. Those segments that have undefined isolation precision were excluded when calculating the average isolation latency for each sensor plotted in Figure 9c. M016 and M017 have high trigger rates but their rules have low support, because one of its antecedent sensors, D002, has a low trigger rate. To calculate the average precision and recall of failure detection and isolation among the examined sensors of the experiment, the two segments of M016 and M017 that had undefined isolation precision were excluded. The average precision and recall of failure detection are 0.9493 and 0.9018, respectively, while the average failure isolation precision and recall are 0.9987 and 0.9116, respectively.



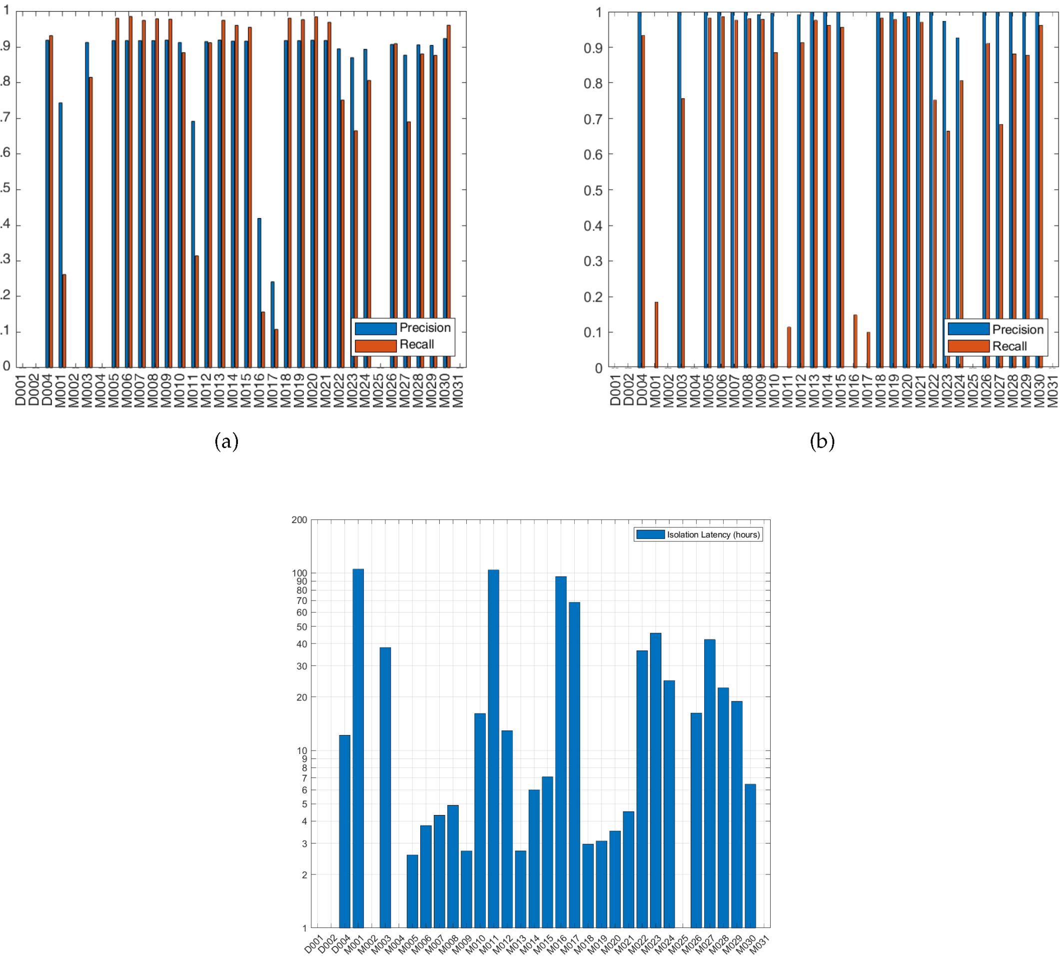
(a) (b)

(c)

Figure 9. Fail-Stop Failure: (**a**) Precision and recall of failure detection. (**b**) Precision and recall of failure isolation. (**c**) Failure isolation latency.

4.4.2. Obstructed-View Failure

Obstructed-view failure is the failure at which the sensor view is obstructed, e.g., its view gets blocked by furniture. It was simulated by replacing the sensor readings by zeros along the duration at which the sensor view was obstructed. The obstruction duration was set to 5 days. Figure 10a shows the precision and recall of detecting 5 days of obstructed-view failure. The precision and recall for isolating the faulty sensor and its isolation latency are shown in Figure 10b,c, respectively. Similar to the fail-stop failures, detecting and isolating most consequent sensors show high detection and isolation performance except for M001, M011, M016 and M017. There are 20 sensors that when injected with obstructed-view failure cause failure detection precision ≥ 0.9, and 4 sensors between 0.8 and 0.9. Meanwhile, 24 sensors can be isolated with precision ≥ 0.92, and 19 sensors can be isolated with recall ≥ 0.87. The average failure detection precision and recall among examined sensors are 0.8563 and 0.8089, respectively. The average failure isolation precision and recall are 0.9954 and 0.8285, respectively. The isolation latency for the sensors injected with obstructed-view failure is almost the same as when injected with fail-stop failure.



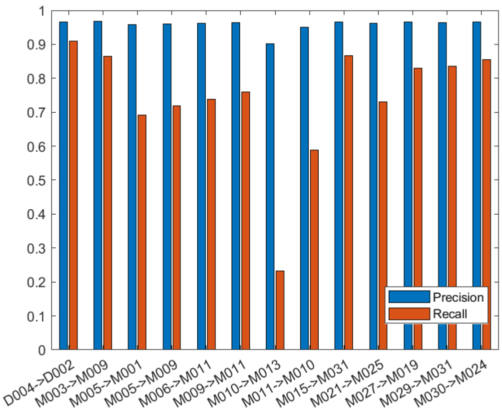
(a) (b)

(c)

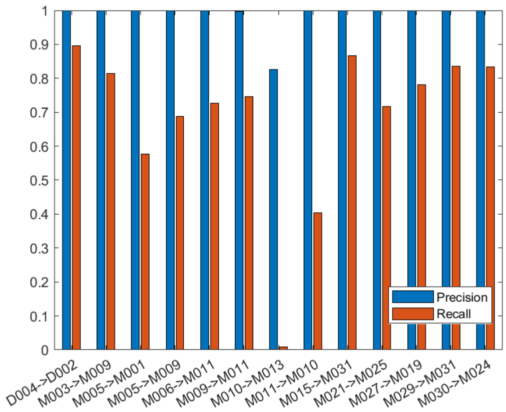
Figure 10. Obstructed-View (5 days) Failure: (**a**) Precision and recall of failure detection. (**b**) Precision and recall of failure isolation. (**c**) Failure isolation latency.

4.4.3. Moved-Location Failure

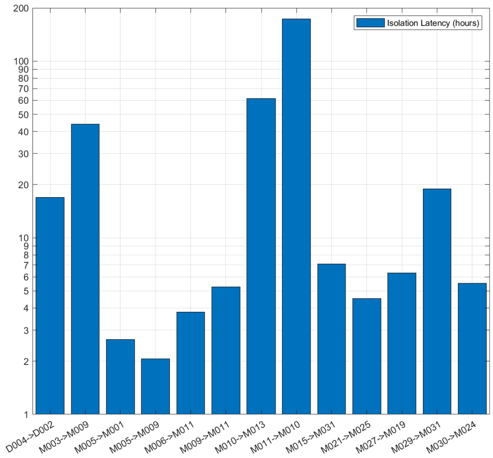
Moved-location failure means that a sensor's location has changed, this may happen when a sensor gets remounted by the user in the wrong location or when it is mounted on a piece of furniture that has been moved to another location. This type of failure was simulated by changing the readings of the sensor after its point of failure by readings of its newly moved location. Figure 11 shows the performance of detecting and isolating the moved-location of some of the consequent sensors. The x-axis of Figure 11 describes the moved-location case, e.g., D004 -> D002, means that the sensor D004 has moved to the location of sensor D002. Figure 11a plots the precision and recall of detecting failure, and Figure 11b shows the precision and recall of identifying that the moved sensor has failed, i.e., the failed sensor is D004 in our previous example. The precision of failure detection in the presented 13 moved-location cases are $\geq$0.9, and the precision of the failure isolation is $\geq$0.99 in the presented cases except for M010 -> M013 is 0.83. On the other hand, the recall of failure detection is $\geq$0.82 for 6 cases, between 0.7 and 0.8 for 5 cases, and $\leq$ 0.6 for 2 cases. Meanwhile, the recall of failure isolation is $\geq$0.8 for 5 cases, between 0.68 and 0.8 for 5 cases, and $\leq$0.6 for 3 cases. The average failure detection precision and recall among the presented cases are 0.9580 and 0.74, respectively, while the average failure isolation precision and recall are 0.9863 and 0.6839, respectively. The isolation latency is $\leq$7 h in 8 cases, between 16 and 19 h in 2 cases, and $\geq$42 h in 3 cases. The distance of the new location from the old one is not what dominates the precision or recall of detecting the moved-location failure. Moving a sensor within the same room could be detected with higher recall when M005 was moved to the location of M001 within the bedroom than that of moving M010 to M013 within the living room. Similarly, moving a sensor to another room could be detected with higher recall when D004 was moved from the garage door to replace the D002 at the kitchen back door than that of moving M005 from the bedroom to M009 in living room.



(a)



(b)



(c)

Figure 11. Moved-Location Failure: (**a**) Precision and recall of failure detection. (**b**) Precision and recall of failure isolation. (**c**) Failure isolation latency.

5. Discussion

Our proposed failure detection and isolation system is distinguished by its low computational effort and high interpretability, in addition to its use of unlabelled datasets. The results show that the consequent sensors that were injected with fail-stop and obstructed-view failures could be detected and isolated with high precision and recall. The isolation latency is highly dependable on the behaviour of the resident as well as the start time of failure with respect to his behaviour. The more frequent the usage of the area of an apartment that has the failed sensor is, the shorter the time to isolate this sensor failure. In addition, the start time of the failure affects the isolation latency, i.e., if the sensor failure has occurred just before the resident goes to bed at night, then the failure will not be isolated before the next morning by any means. Detecting moving a sensor to another place can be achieved with high precision and recall only when this newly moved location has minimal correlation to the old location. This is on contrary to the fail-stop and obstructed-view failures, where the sensor failure detection performance is proportional to its correlation to other sensors.

A summary table of the related work was presented in our survey paper [11]. Although the results are not directly comparable due to the use of different datasets, design of experiments and evaluation methodology, the benefits of our proposed system over the other relevant state of the art was presented in Section 2. The limitation of our approach is that the sensors that do not appear as consequent to the activation of other sensor(s) in the apartment cannot be checked for failure. However, our approach can be used to determine these sensors, and thus can help to highlight the needed reconfiguration of sensors' positioning in the apartment to obtain a fully functional sensor failure detection and isolation system.

As for future work, the use of variable size sliding window for detecting failures may further improve the system performance, especially for the moved-location failures. Rules will be extracted for the consequent sensors that have strong rules using shorter duration sliding window during the correlations extraction stage, and only those sensors that did not appear will be extracted over a longer duration sliding window. However, this should be weighed against its computational complexity during the real-time correlations monitoring stage. Furthermore, the use of an auxiliary system to detect failure for those sensors that did not appear as consequent could be investigated. This auxiliary system may exploit the following features for those sensors; its trigger day, trigger time and duration of activation.

6. Conclusions

This paper proposed a failure detection and isolation system for binary event-driven sensors deployed in the AAL environment. Correlations between sensors were extracted with no prior knowledge of the sensor placement on the floor plan and using unlabelled datasets. Guidelines for the selection of the user defined parameters for correlations extraction were presented. The correlations are monitored during run-time to detect sensor failures. The proposed approach was evaluated using publicly available dataset injected with fail-stop, obstructed-view and moved-location failures. The system was able to detect and isolate the various types of failures. The results show that fail-stop failures could be detected with an average precision and recall of 0.9493 and 0.9018, and isolated with average precision and recall of 0.9987 and 0.9116, respectively. Obstructed-view failures were detected with average precision of 0.8563 and recall of 0.8089, and isolated with average precision of 0.9954 and recall of 0.8285. Meanwhile, the moved-location failures were detected at 0.9580 average precision and at 0.74 average recall and isolated at 0.9863 average precision and 0.6839 average recall.

Author Contributions: Conceptualization, N.E.E., S.J., J.P. and V.S.; Methodology, N.E.E.; Investigation, N.E.E.; Validation, N.E.E.; Writing—original draft preparation, N.E.E.; Writing—review and editing, S.J. and J.P.; Supervision, S.J. and V.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research paper is part of a Ph.D. Thesis granted by the Ministry of Higher Education of Egypt.

Acknowledgments: The authors acknowledge the Technical University of Munich for supporting the publication in the framework of the Open Access Publishing Program. Furthermore, the authors would like to thank Maximilian Kapsecker, Jens Klinker and Lara Marie Reimer for their technical assistance during the revision stage of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AAL	Ambient assisted living
ICT	Information and communication technologies
AmI	Ambient intelligence
ADL	Activities of daily living
PIR	Passive infrared sensor
TP	True positives
FN	False negatives
FP	False positives

TN	True negatives
ROC	Receiver operating characteristic
AUC	Area under curve
TPR	True positive rate
FPR	False positive rate

Appendix A

Algorithm A1 Failure detection.

Input:

$DataStream$: the stream of the AAL sensors *events*

Sen: the set of sensors represented by tuples $\{(id, Health, FailFlag)\}$, where id is the sensor's id number, $Health$ is the health status of sensor, and $FailFlag$ is the failure flag of sensor

R: the set of rules represented by tuples $\{(Ant, Conseq, Sup, Conf)\}$, where Ant contains the sensors in the rule antescedent, $Conseq$ contains the sensors in the rule consequent, Sup is the support of rule, and $Conf$ is the rule's confidence

$SatRulHist$: the set of rules that were satisfied in the previous sliding window $SwNum - 1$, where $SwNum$ is the sliding window's running number

$UnSatRulHist$: the set of rules that were unsatisfied, i.e., has one missing sensor in the rule consequent, in the previous sliding window $SwNum - 1$

$FutSw$: the set of sensors that are active in the next sliding window $SwNum + 1$

$HealthThresh$: the threshold value for the health status of sensors

Output:

Sen: updated $Health$ and $FailFlag$ of the set of sensors

while $CurrSW =$ ProcessSW($DataStream$) **do**
    // $CurrSw$ is the set of active sensors in the current sliding window $SwNum$
    for each $Rul \in R \wedge Rul.Ant \subseteq CurrSw$ **do**
        if $Rul.Conseq \subset CurrSw$ **then**
            $Sen.Health \leftarrow$ SatisfHealthUpdate(Rul, $CurrSw$, Sen)
            $SatRulHist \leftarrow Rul$
        else if $|Rul.Conseq - CurrSw| = 1$ **then**
            if $Rul \notin SatRulHist \wedge |(Rul.Ant \cup Rul.Conseq) - FutSw| \neq \phi$ **then**
                if $Rul \notin UnSatRulHist$ **then**
                    $Sen.Health \leftarrow$ UnSatisfHealthUpdate(Rul,$CurrSw$,Sen)
                end if
                $UnSatRulHist \leftarrow Rul$
            end if
        end if
    end for
    for each $s \in Sen$ **do**
        if $s.Health < HealthThresh$ **then**
            $s.FailFlag \leftarrow 1$
        else
            $s.FailFlag \leftarrow 0$
        end if
    end for
end while

Algorithm A2 Health Status Update due to Rule Satisfaction.

```
SatisfHealthUpdate {Rul, CurrSw, Sen}
for each s ∈ Sen, s.id ∈ (Rul.Ant ∪ Rul.Conseq) do
    PrF ← 1 − Rul.Conf // PrF is the probability that the sensor is faulty
    s.Health ← 0.1 × (1 − PrF) + 0.9 × s.Health
end for
return Sen.Health
```

Algorithm A3 Health Status Update due to Rule UnSatisfaction.

UnSatisfHealthUpdate $\{Rul, CurrSw, Sen\}$

for each $s \in Sen, s.id \in Rul.Ant$ **do**

  if $|Rul.Conseq| = 1 \wedge |Rul.Ant| = 1$ **then**

    $PrF \leftarrow 1 - P(s)$

  else

    $PrF \leftarrow 1 - \dfrac{P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq)\}} x)}{P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq))|x \neq s\}} x)}$

  end if

  $s.Health \leftarrow 0.1 \times (1 - PrF) + 0.9 \times s.Health$

end for

for each $s \in Sen, s.id \in Rul.Conseq$ **do**

  if $s.id \in CurrSW$ **then**

    $PrF \leftarrow 1 + \dfrac{Rul.Sup - P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq))\}} x)}{P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq))|x \neq s\}} x) - P(\bigcap_{\{x \in (Rul.Ant \cup Rul.Conseq)|x \neq s\}} x)}$

  else

    $PrF \leftarrow \dfrac{Rul.Sup}{P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq))\}} x)}$

  end if

  $s.Health \leftarrow 0.1 \times (1 - PrF) + 0.9 \times s.Health$

end for

return $Sen.Health$

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7 Supplementary Work

In this chapter, further enhancement of the proposed approach for sensor failure detection and isolation was considered. Two modifications in the approach were investigated on the Aruba dataset, which are adding time features in the correlations and modifying the data processing of contact sensors. Moreover in this chapter, the proposed approach was evaluated in a second case study on the HH122 dataset.

7.1 Further work on the Aruba dataset

7.1.1 Time features

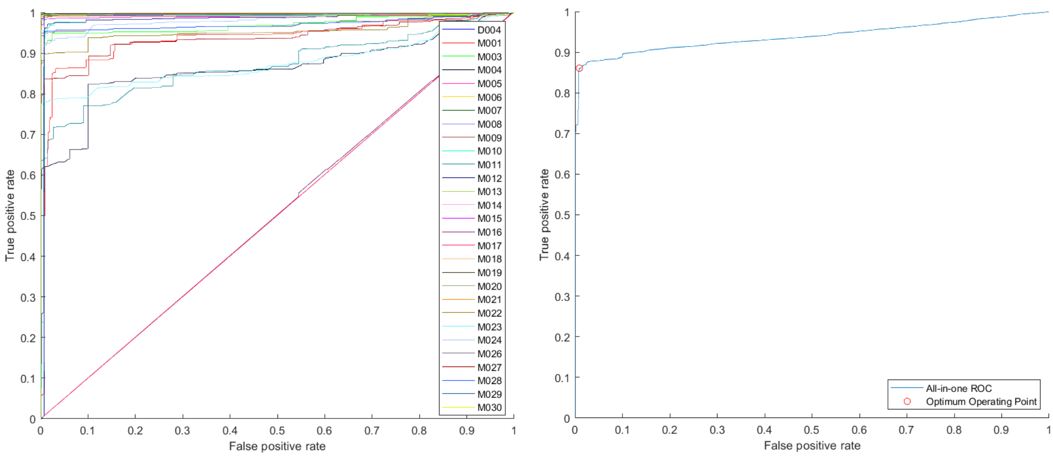
Sensors may be correlated to one another as well to time. Association rule mining can be used to discover the sensor-sensor correlations and sensor correlation with respect to time by incorporating categorical time features in its items. Following is an experiment conducted on the Aruba CASAS dataset [70] incorporating time features. In the data preprocessing, the items of the transactional database has been extended by adding 11 time features representing the hours range of the timestamp of the start of sliding window. The categorical time features are EarlyMorning, Morning, LateMorning, EarlyAfternoon, Afternoon, LateAfternoon, EarlyEvening, Evening, LateEvening, EarlyNight and LateNight. For example, EarlyMorning is given a value of 1 if the time stamp of the start of sliding window is between 6 am and 8 am, otherwise 0. Next, the association rules were re-extracted using the values of the parameters that have been previously set according to the selection of parameters conducted in Chapter 6; sliding window size 30 s, minimum relative support 15% and minimum confidence 60%.

The extracted rules have been found to contain some rules that have a time feature in its antecedent part. Such rules are often present also without time feature in the extracted set of rules, however the rules that have time item in its antescedent have lower support and sometimes higher confidence, than the same rule without the time feature as can be seen in Table7.1. Compared to the rules previously extracted without incorporating time features using the same dataset and set parameters, an additional sensor has appeared as consequent, which is M004. Post-pruning of the extracted rules has been performed, and then the detection of fail-stop failures of each consequent sensor has been experimented using the thresholds setting dataset. Figure 7.1 shows the obtained ROC curves as a result of incorporating the time features while using the former values for the set parameters.

The all-in-one ROC curve has an optimal TPR of 0.8608, optimal FPR of 0.009308 and AUC of 0.9391.

Table 7.1: Sample of the rules that appeared with extra time feature item.

Rule	Support, Confidence, Lift
M002,EarlyNight → M003	0.36455%, 91.3793%, 12.1931
M002,LateNight → M003	0.19181%, 83.5616%, 11.1499
M002 → M003	1.3352%, 73.2823%, 9.7783
M025,M026,LateAfternoon → M027	0.29439%, 96.2725%, 25.459
M025,M026 → M027	1.3733%, 94.1906%, 24.9084
M025,M026,EarlyAfternoon → M027	0.23504%, 92.2128%, 24.3854
M004,M005,LateNight → M007	0.17392%, 100%, 4.8615
M004,M005,LateMorning → M007	1.4839%, 99.9868%, 4.8608
M004,M005 → M007	6.5426%, 99.985%, 4.8607
M018,M020,EarlyEvening → M014	2.3974%, 77.8345%, 3.0862
M018,M020 → M014	11.1265%, 66.6341%, 2.6421

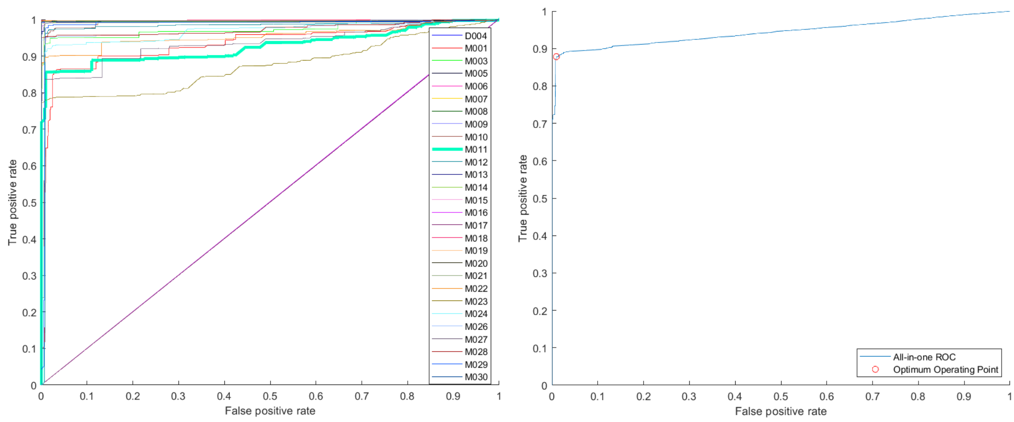


(a) (b)

Figure 7.1: Incorporating time features while using sliding window of 30 seconds, minimum relative support 15% and minimum confidence of 60% (**a**) ROC curve for fail-stop failure detection of each consequent sensor (**b**) All-in-one ROC curve

7.1.2 Contact Sensors

As illustrated in Chapter 6, the data preprocessing includes converting the sensors events to signals. Thus, the correlations are extracted between the sensors that are ON within the size of the sliding window regardless the type of the sensor. In this section, treating the contact sensors somewhat differently is considered. Contact sensors have different nature than the motion sensors. When an ON event of a motion sensor is encountered, it indicates that a movement has triggered this sensor. The sensors remains triggered as long as the movement continues in its field of view. When the movement stops, an OFF event of the motion sensor is perceived. On the other hand, when an ON event of a contact sensor occurs, it indicates that the sensor has been triggered by an interaction on an object and this interaction has stopped, however no event has been perceived because of the contact sensor's latching nature. The next OFF event of that contact sensor would indicate another interaction. Thus, extracting rules based on the edge triggers of contact sensors might be more effective.



(a) (b)

Figure 7.2: Processing contact sensors based on edge trigger and motion sensors based on latch trigger while using sliding window of 30 seconds, minimum relative support 15% and minimum confidence of 60% (**a**) ROC curve for fail-stop failure detection of each consequent sensor (**b**) All-in-one ROC curve

Accordingly, modifying data preprocessing for the Aruba CASAS dataset has been performed, where the values of the variables of contact sensors have been set to 1 only when an ON/OFF event of those sensors is perceived and 0 otherwise. The association rules were re-extracted using sliding window size 30 s, minimum relative support 15% and minimum confidence 60%. Each of the consequent sensors was injected with fail-stop failure in the thresholds setting dataset and the ROC curves of failure detection were plotted in Figure 7.2. A significant improvement in the ROC curve of detecting failure when M011 was injected with fail-stop failure has been observed compared to the corresponding ROC curve plotted in Chapter 6 for the same parameters setting. This is due to the increase of the confidence of the rule D001 $\rightarrow$ M011 from 74.1 % to 99.8 %. Investigating the training data, it has been found that there are instances that M011 gets triggered then D001 is opened, M011 stops triggering and D001 remains opened for some time before being closed again, and then M011 triggers again. This explains the lower confidence when D001 has been treated similar to motion sensors, i.e. setting its variable value to 1 during the elapsed time between its ON and OFF events. The plotted all-in-one ROC curve in Figure 7.2b has an optimal TPR of 0.8781, optimal FPR of 0.009578 and AUC of 0.9434.

7.2 Case study on the HH122 dataset

In this section, the failure detection and isolation approach presented in Chapter 6 is being evaluated on a second publicly available dataset, HH122 CASAS dataset [70]. The dataset was collected from a single-resident home that is equipped with 24 infrared motion/light sensors, 4 contact sensors and 5 temperature sensors [71]. The available activity-annotated data was collected over a duration of one month and do not have any triggers from the contact sensors. The ambient light and temperature readings were excluded from our experiments as the proposed approach is concerned with finding failure in event-driven binary sensors. As a result, only the 24 motion sensors were under investigation. A split ratio of 50/50 was used to obtain the training and testing data.

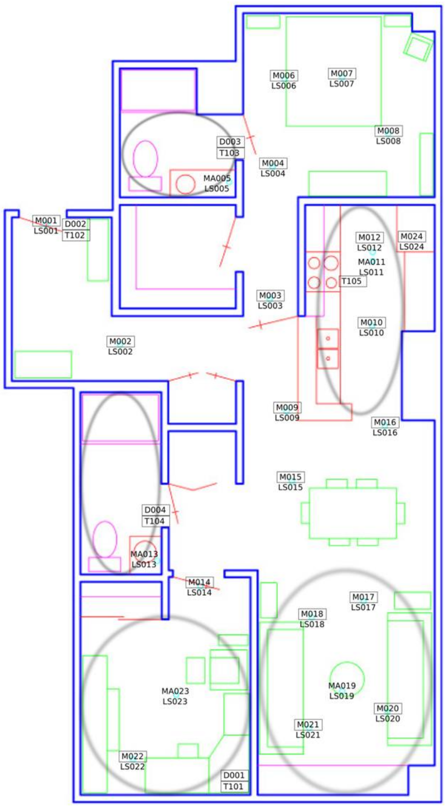
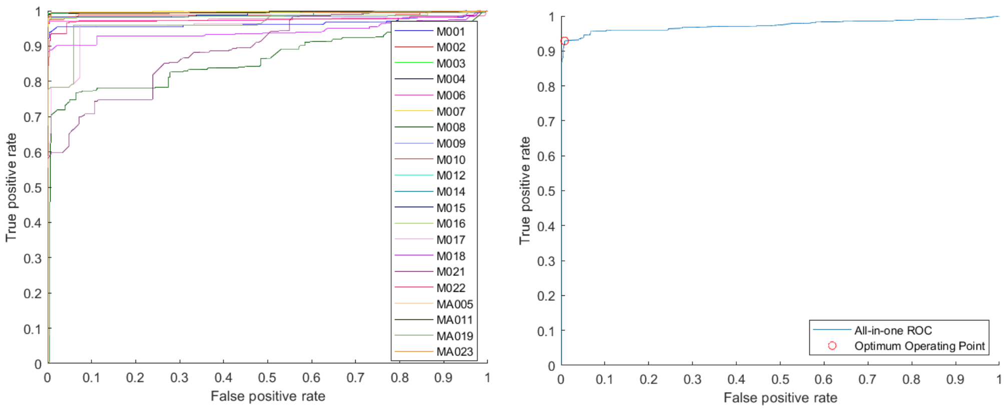


Figure 7.3: HH122 CASAS floor plan [70].

The data was preprocessed and the guidelines for setting the values of the parameters were followed. The association rules were extracted using the training data, while the thresholds setting dataset that contains 1-week data of the testing data was used to validate the selection of parameters. Accordingly, the values of the parameters were selected to be 60 s sliding window size, 25% minimum relative support and 60% minimum confidence. Those values enable failure detection and isolation of the 21 sensors that appear as consequent in the rules, where MA013, M020 and M024 did not appear as consequent. The ROC curves using the former values of parameters are plotted in Figure 7.4. The all-in-one ROC curve has an optimal TPR of 0.9288, optimal FPR of 0.008148 and AUC of 0.9739. The health threshold value that corresponds to the optimal operating point is 0.4497.



(a) (b)

Figure 7.4: HH122: Using sliding window of 60 seconds, minimum relative support 25% and minimum confidence of 60% (**a**) ROC curve for fail-stop failure detection of each consequent sensor (**b**) All-in-one ROC curve

Evaluation of failure detection and isolation was conducted when each of the consequent sensors was injected with fail-stop, obstructed-view and moved-location failure. Fail-stop failure was injected individually on each of the consequent sensors, then failure detection and isolation was evaluated. The precision and recall of detecting failure and isolating the faulty sensor are shown in Figures 7.5a and 7.5b, respectively. All of the 21 consequent sensors when injected with fail-stop failure cause failure detection precision ≥ 0.9, 16 sensors cause a recall ≥ 0.95 and 5 sensors result in a recall between 0.8 and 0.9. Isolation precision ≥ 0.99 for 18 sensors, while isolation recall is ≥ 0.96 for 16 sensors. MA013, M020 and M024 were not injected with failure nor evaluated as they were missing from the consequent of all rules, and thus empty columns appear at their labels in all plots. The isolation latency plotted in Figure 7.5c, shows that the latency is ≤ 2.2 h for 13 sensors, between 8 and 14 h for 4 sensors, and between 28 and 55 h for 4 sensors. The average precision and recall of failure detection are 0.926 and 0.962 respectively, while the average failure isolation precision and recall are 0.995 and 0.961, respectively.

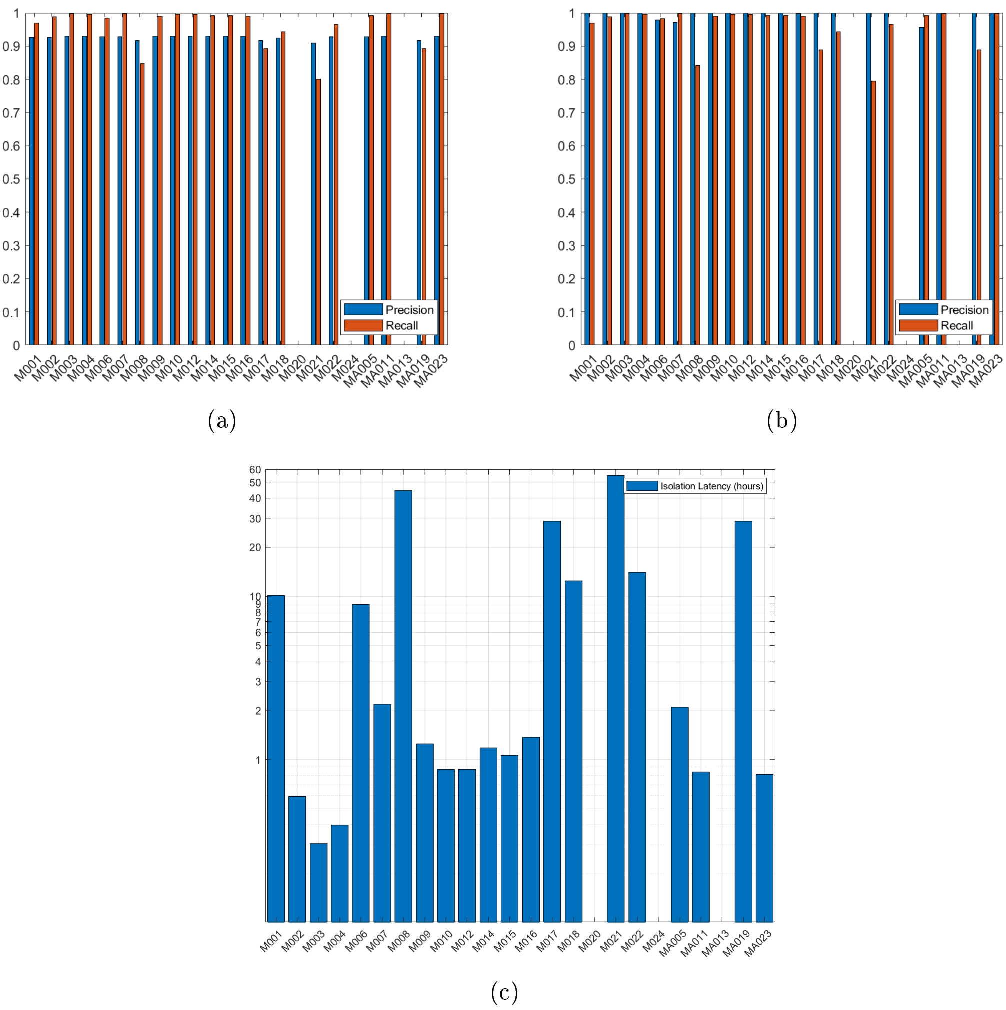


Figure 7.5: HH122 injected with fail-Stop failure: (**a**) Precision and recall of failure detection (**b**) Precision and recall of failure isolation (**c**) Failure isolation latency

Obstructed-view failure was injected in each of the consequent sensors for 5 days. Figure 7.6a shows the precision and recall of detecting the failure, while Figures 7.6b and 7.6c the precision and recall for isolating the faulty sensor, and the corresponding isolation latency, respectively. There are 19 sensors that when injected with the obstructed-view failure cause detection precision ≥ 0.8, and 16 sensors lead to a recall ≥ 0.92. Meanwhile, all of the 21 consequent sensors can be isolated with precision ≥ 0.9 and 16 sensors can be isolated recall ≥ 0.9. The isolation latency for the sensors injected with obstructed-view failure is similar to as when injected with fail-stop failure. The average failure detection precision and recall among the examined sensors are 0.836 and 0.916, respectively, while the average failure isolation precision and recall are 0.990 and 0.913, respectively.

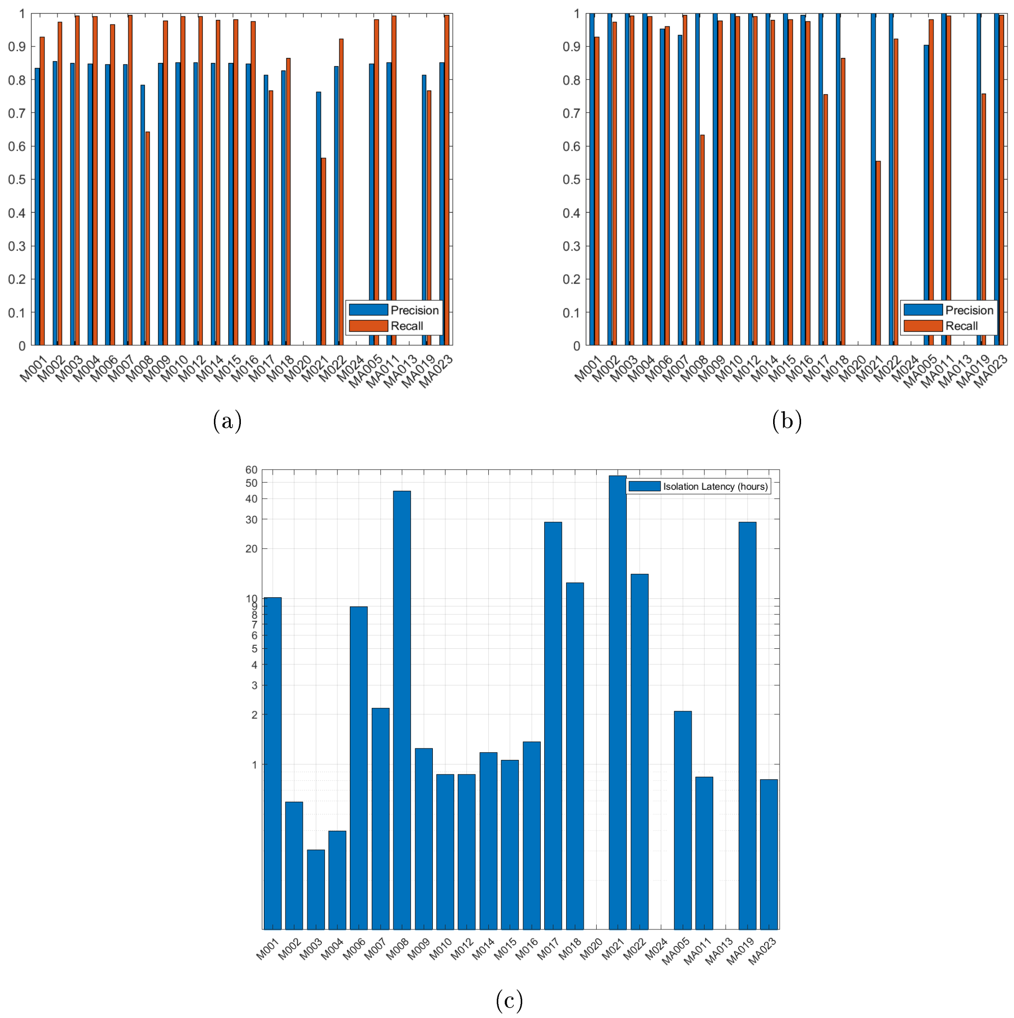
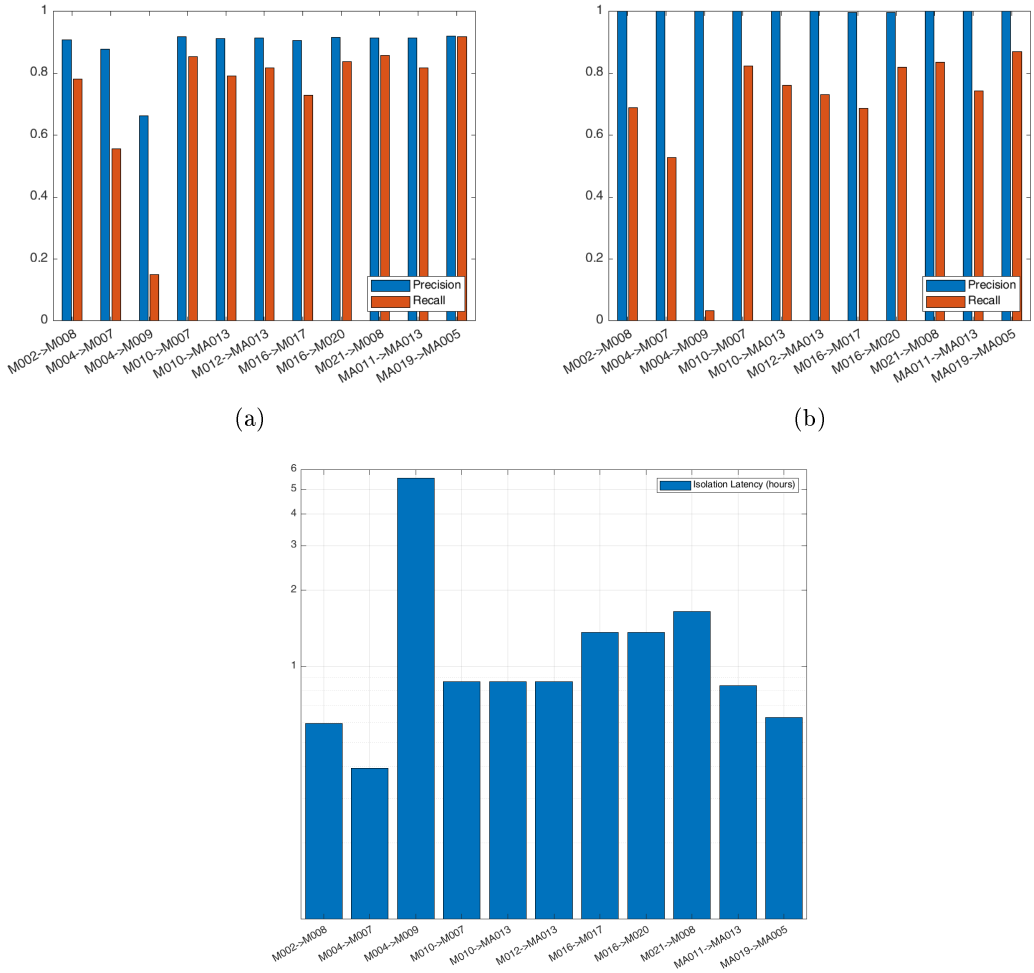


Figure 7.6: HH122 injected with Obstructed-View (5 days) failure: (**a**) Precision and recall of failure detection (**b**) Precision and recall of failure isolation (**c**) Failure isolation latency

Moved-location failure was simulated on some of the consequent sensors, and the detection and isolation of the moved sensors were evaluated. The 11 moved-location cases are described with an arrow relation, where the left part of the arrow is the original sensor location, and the right part of the arrow is the new location to where the sensor has been moved. Figure 7.7a shows the precision and recall of detecting failure, while Figure 7.7b shows the precision and recall of identifying that the moved sensor has failed. The precision of failure detection is ≥ 0.88 for all cases except for the M004 $\rightarrow$ M009 it is equal to 0.66, while the precision of the failure isolation is ≥ 0.99 for all the 11 presented cases. On the other hand, the recall of failure detection is ≥ 0.81 for 6 cases, between 0.7 and 0.8 for 3 cases and < 0.6 for 2 cases. The recall of failure isolation is

≥ 0.82 for 4 cases, between 0.7 and 0.8 for 3 cases and ≤ 0.69 for 4 cases. The average failure detection precision and recall are 0.8880 and 0.7374, respectively. Meanwhile, the average failure isolation precision and recall are 0.9994 and 0.6841, respectively. As observed in Figure7.7c, the isolation latency is < 1 h for 7 cases, between 1 and 2 h for 3 cases and equals to 5.55 h in 1 case.



(a) (b) (c)

Figure 7.7: HH122 injected with Moved-location failure: (**a**) Precision and recall of failure detection (**b**) Precision and recall of failure isolation (**c**) Failure isolation latency

8 Discussion, Conclusion and Future Work

Ambient Assisted Living environments are the way to transform the challenges imposed by the ageing population phenomenon into opportunities. Monitoring the older adults at their place of residence, spotting early signs of health deterioration and providing assistance when needed, would help in providing them with independence, safety, early intervention, and sustained activity. Acceptability and dependability are two of the most essential requirements to make the older adults willing to live in an AAL environment. The use of non-intrusive ambient sensors would help in gaining more acceptability. However, failure in non-intrusive ambient sensors is an obstacle that can hinder the success of the AAL environments. Enhancing the reliability of the AAL systems would increase the dependability and strengthen the trust of the older adults in the systems. This thesis explored the works done to deal with sensor failures in AAL environments equipped with non-intrusive ambient sensors, and presented a sensor failure detection and isolation system for the non-intrusive, event-driven, binary sensors.

8.1 Discussion

A comprehensive literature review was presented in Chapter 4, which gives an overview of the sensor failures in AAL and the publicly used datasets in the conducted case studies, in addition to reviewing the works concerned with detecting sensor failures as well as providing fault-tolerant services in AAL environments equipped with event-driven binary sensors.

Chapter 5 has investigated extracting correlations between event-driven binary sensors using association rule mining. For extracting the correlations, the use of the relative support metric instead of the support metric was proposed in order to overcome the problem of the scarcity of some sensors' triggering imposed by the uneven usage of the apartment areas by the resident. The experiments conducted on the Aruba dataset showed that using the relative support metric allows extracting more consequent sensors within less number of functionally redundant rules than using the support metric. The effect of varying the values of the parameters of the correlations extraction; sliding window size, minimum relative support and minimum confidence, on the number of extracted association rules, the number of sensors present in the consequent part of the rules and the ratio of consequent sensors to number of extracted rules were plotted and investigated. It was concluded that setting the values of those parameters to obtain meaningful rules that have large number of consequent sensors, may be possible via investigating the three former plots in order to choose the values that would achieve a trade-off between the number of association rules and consequent sensors. The rules obtained were found to be logically correct when compared to the sensors topology in the apartment layout which made it promising to pursue in the direction of using it to detect sensor failures. The extracted rules can later serve as a foundation for sensor failure detection using the following hypothesis; if the sensor(s) of the antecedent part of rule got triggered while the sensor(s) of the consequent part of rule did not within window size time, then the sensors can be suspected to be faulty. However, as only few portion of the rules have 100% confidence, i.e., every single time the antecedent occurs the consequent occurs as well, thus using the rules to decide on the sensor failure still have some uncertainty. Hence, the probability that a sensor has failed due to fulfilling/unfulfilling the rules should be deduced.

A sensor failure detection and isolation system that exploits the extracted rules was presented in Chapter 6. Fault-free correlations between sensors are extracted offline using data collected from the resident's home. Then, post-pruning is applied to further reduce the number of the redundant rules that can have negative impact (increasing the processing time) on the performance of the failure detection system. Storing the rules as bitmap arrays has decreased the processing time in pruning as well as during the correlations monitoring. The pruned set of rules represents the most interesting correlations that are monitored online to detect sensor failure. During the correlations monitoring stage, the health status of a sensor, which is the probability that a sensor is healthy, is updated according to the satisfaction or unsatisfaction (missing one consequent sensor) of any of its correlations. Moreover in Chapter 6, the effect of changing the values of the parameters of the correlation extraction stage has been extended to include the effect on the number of consequent sensors, the complexity of the pruned rules, and the precision and recall of failure detection and was investigated with the aid of the Aruba dataset. Guidelines for setting the values of the correlation extraction parameters along with the health threshold value were presented. The guidelines aim to aid in selecting the values that enables failure detection and isolation of as many sensors as possible with high precision and recall. If more than one set of values show similar overall performance, the set of values having the smaller size of sliding window is preferred to be selected in order to decrease the computational effort during the monitoring stage.

As the presence of fault-free data during the training stage is important, the matlab code in [72] has been adapted to implement a graphical user interface for visualizing the daily sensors triggers in the dataset of our Aruba case study. By inspecting the visualized data, it has been found that there are a couple of days that have instances at which nearly all the sensors of the apartment got triggered simultaneously and remained active for some time[1], e.g., on 16 Nov. 2010 all the motion sensors got triggered at around 1:09

[1]One possible explanation for those instances, according to the CASAS research group, is that there might have been several power outages during that period due to a storm and that when the sensors

and remained active until 2:23, such behaviour has been repeated multiple times until around 8:09. Such instances were excluded from the training data in the experiments conducted in Chapter 6. However, in Chapter 5 the presence of those instances in the data was not discovered yet, and it has lead to extracting more correlations for the same values of the set parameters during the extracting correlations stage.

In the proposed Aruba case study of Chapter 6, the chosen values for the parameters yields rules having 28 sensors present in the consequent part of the rules out of the 34 sensors of the apartment. However, those missing sensors from the consequent appeared as antecedents which means that when one of those sensors get triggered, other sensor(s) will consequently appear within its sliding window, but not vice versa. Injecting fail-stop, obstructed-view and moved-location failures in each of the 28 consequent sensors was simulated, and the failure detection and isolation were assessed. The performance of the proposed system was evaluated by computing the precision and recall of failure detection as well as failure isolation of each consequent sensor in addition to the failure isolation latency. High precision and recall for detecting and isolating fail-stop and obstructed-view failures were observed. The isolation latency decreases as the resident's usage of the areas that have the failed sensor and its correlated sensors increases. Moreover, the time of the day at which the failure has started affects the isolation latency, e.g., a failure that occurs just before the resident leaves the apartment can not be detected before he gets back. Thus, the isolation latency depends greatly on the behaviour of the resident and the start time of failure with respect to his behaviour. The performance of detection and isolation of fail-stop and obstructed-view failures increases as the correlation of the failed sensor to the other sensors increases. On contrary, the performance of the detection and isolation of moved-location failures increases when the sensor at the newly moved location has minimal direct or indirect correlation to its old location. On the other hand, the distance between the old and newly-moved location do not affect the performance. To further examine the approach proposed in Chapter 6, an additional case study was presented in Chapter 7 using another dataset (HH122 dataset). The results of the case study was found to be aligned with the above conclusions drawn from the Aruba case study.

A limitation of the approach proposed in this thesis for sensor failure detection and isolation is that the sensors that do not appear as consequent to the activation of other sensor(s) cannot be checked for failure. This is because the antecedent of a rule must be satisfied in order to update the health status of the sensors of the rule. If a sensor is not present as a consequent in our set of rules it means that there is no strong correlation that indicate that this sensor should have been active as a consequence to the activation of other sensors. Hence, in practice if a sensor that does not appear in the consequent part in the set of rules failed, then we will not be able detect its failure by relying on its correlation with other sensor(s). However, the proposed approach can be used to help in identifying the needed modification in the sensors layout to overcome the former

(electricity-powered) first turn ON after each power outage they are stuck at 1 during warming up, and the next power outage occurs before they finish warming up and thus no OFF event has been sent to the server that is still running on battery.

limitation and obtain a fully functional sensor failure detection and isolation system, where all the sensors in the apartment appear as consequent and hence can be checked for failure. Seeking another way to overcome the limitation by correlating the sensors to time in addition to correlating it to the other sensors has also been considered. The Aruba case study was extended in Chapter 7, where 11 time features for the timestamp of the start of sliding window were added in the data preprocessing stage. Only one consequent that was previously missing from the consequent part of rules has appeared when time features were added. However, when fail-stop failure detection experiment was carried on using the pruned set of rules that includes the time items, a sort of similar overall performance to the previously conducted experiment without the time features in Chapter 6 was observed. Even detecting and isolating that newly appearing consequent sensor has shown poor performance. Thus, adding time features in the association rule mining to enrich the sensors correlations was not helpful in improving the system's performance. Nevertheless, it is useful in getting knowledge about whether a correlation usually occurs in specific range of time along the day or not. Additionally in Chapter 7, modifying the data preprocessing for the contact sensors to be based on its edge trigger rather than its latch values was considered, and has shown a positive impact on the results. Basing the data processing of the contact sensors on its edge trigger means that the values of the variables of contact sensors have been set to 1 only when an ON/OFF event of those sensors is perceived and 0 otherwise. This is on contrary to basing the data processing on its latch values, where the values of the variables of contact sensors have been set to 1 when an ON event of those sensors is perceived and stay at 1 until the next OFF event is perceived it would be then set to 0. The positive impact on the results that was observed when the data processing of contact sensors was based on the edge trigger was due to the increase of the confidence of the rules that has the contact sensor as antecedent and the motion sensor as consequent, i.e., how frequent the motion sensor is in the transactions that contains the contact sensor, as the contact sensor are installed on doors/windows that may be left open for some time while no motion is being detected.

8.2 Conclusion

In this thesis, a failure detection and isolation system for event-driven, binary, ambient sensors deployed in the AAL environments was proposed. Sensors correlations were extracted based on the association rule mining technique. At run-time, the correlations are monitored and accordingly failure is detected. Guidelines to set the values of the parameters of the proposed approach were presented. Experiments were conducted on two datasets injected with fail-stop, obstructed-view and moved-location failures. The results show that detection and isolation of the sensor failures using the proposed method could be achieved.

The proposed sensor failure detection and isolation system is of low cost, as it does not need installing extra hardware, on contrary to [50, 51], nor deploying redundant sensors. The system is data-driven and thus is tailored to capture the sensors correlations triggered by the resident, instead of relying on generic human behavioural model, as in [48, 49], or predefined user case scenarios or tasks, like in [54, 52, 53]. Moreover, it is characterized by its good interpretability of results because of the interpretable association rules. No prior knowledge on the topology of the installed sensors, unlike [58, 59], nor labelled data with activities, as in [56], or failures is needed. On contrary to [2, 60], the proposed approach is scalable, i.e., increasing the number of deployed sensors will not have a drastic effect on the training effort nor on the number of monitored correlations used for failure detection. Moreover, unlike the approach presented in [60], the used correlations must meet minimum evaluation metrics that indicate its strength, thus this ensures its reliability to be used for detecting sensor failures.

Living in AAL environments equipped with non-intrusive sensors is usually more acceptable by the older adults yet non-intrusive sensors are more prone to failures than intrusive sensors. Detecting and isolating failures in non-intrusive, binary, event-driven, ambient sensors, as proposed in this thesis, would ensure that the AAL subsystems or services do not produce spurious results due to sensor failure. Therefore, the acceptability and dependability of AAL environments would be improved encouraging the older adults to live in such environments that would enable them to live independently in their place of residence, maintain their functional abilities and well-being in addition to decreasing the burden on governments.

8.3 Future Work

There are several directions to expand this research to further improve and investigate the proposed approach for sensor failure detection and isolation. In the following, future work directions are highlighted in respect to methodology and experimental work.

The first direction for future work would be working on overcoming the limitation that was previously discussed, which is that it is not possible to check failure for the sensors that did not appear as a consequent to the activation other sensor(s) in the set of correlations. Investigations should be done on the use of our approach to identify those sensors, and to accordingly modify the sensors layout to ensure that all of the sensors in the apartment can be checked for failure. Alternatively, an auxiliary system to detect failures for those missing consequent sensors that rely on features other than sensor-sensor correlations, e.g., trigger frequency, time and duration of activation, might be considered.

Additionally, the approach might be extended to correlate the binary sensors to the continuous valued sensors as well. The continuous valued sensors, e.g., temperature sensors and light sensors, could be discretized or thresholded for specific significant values or changes in their values. This would increase the chance that the sensors that was previously missing from being a consequent to the binary sensors may then appear as a consequent to the continuous valued sensors.

To further enhance the performance of the proposed approach for failure detection and isolation, the use of variable size time-based sliding window might be considered. The correlations for the consequent sensors that can have strong rules within a shorter duration sliding window will be first extracted, and then a longer duration sliding window can be used to extract correlations for the remaining sensors. This could be beneficial for improving the system performance especially in detecting and isolating the moved-location failures. However, the impact of dealing with multiple sliding window sizes on the computational complexity during the real-time correlations monitoring should be then inspected.

Investigating the performance of the proposed approach in various settings could be performed to ensure its adaptability. The sensors of the datasets used in the experimental work of this research were mostly motion sensors along with few contact sensors. Case studies on datasets that have more diverse sensors installed in the apartment, e.g., float sensors and pressure sensors, could be considered. Also in the experimental work, datasets collected from two-resident apartments could be used as it is common that the older adult would be living with spouse at older age. Moreover, datasets collected from an apartment inhabited by an older adult with physical and/or cognitive deficiencies might be considered.

Future research might investigate how often it is that two or more sensors would fail simultaneously in AAL environments, and then further expand the proposed approach to deal with multiple failures. Furthermore, experimental studies should be carried on to further examine in-depth the non-fail-stop failures that occur in AAL environments. Investigating the performance of our approach while injecting other forms of non-fail-stop failures, e.g., stuck-at failures, in the datasets may be explored.

In future work, investigating the effect of seasons on the extracted correlations, i.e., whether specific sensors stop correlating to each other due to seasonal variations or new correlations appear, might prove important to check if re-extracting the sensors correlations offline need to be carried on when seasons change. Similarly, investigations should be done to identify whether the behavioural deviation of the resident due to an emerging physical or cognitive decline would require re-extracting the sensors correlations.

Future research might consider implementing and evaluating the proposed sensor failure detection and isolation system in an older adult's apartment to validate the system in real world setting. Moreover, it will be interesting to explore in the future how a fault-tolerance framework for AAL services could be built based on exploiting the proposed failure detection system.

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A Appendix

Algorithm A1 Failure detection.

Input:

$DataStream$: the stream of the AAL sensors *events*

Sen: the set of sensors represented by tuples $\{(id, Health, FailFlag)\}$, where id is the sensor's id number, $Health$ is the health status of sensor, and $FailFlag$ is the failure flag of sensor

R: the set of rules represented by tuples $\{(Ant, Conseq, Sup, Conf)\}$, where Ant contains the sensors in the rule antecedent, $Conseq$ contains the sensors in the rule consequent, Sup is the support of rule, and $Conf$ is the rule's confidence

$SatRulHist$: the set of rules that were satisfied in the previous sliding window $SwNum - 1$, where $SwNum$ is the sliding window's running number

$UnSatRulHist$: the set of rules that were unsatisfied, i.e., has one missing sensor in the rule consequent, in the previous sliding window $SwNum - 1$

$FutSw$: the set of sensors that are active in the next sliding window $SwNum + 1$

$HealthThresh$: the threshold value for the health status of sensors

Output:

Sen: updated $Health$ and $FailFlag$ of the set of sensors

while $CurrSW$ = ProcessSW($DataStream$) **do**
  // $CurrSw$ is the set of active sensors in the current sliding window $SwNum$
  for each $Rul \in R \wedge Rul.Ant \subseteq CurrSw$ **do**
    if $Rul.Conseq \subset CurrSw$ **then**
      $Sen.Health \leftarrow$ SatisfHealthUpdate(Rul, $CurrSw$, Sen)
      $SatRulHist \leftarrow Rul$
    else if $|Rul.Conseq - CurrSw| = 1$ **then**
      if $Rul \notin SatRulHist \wedge |(Rul.Ant \cup Rul.Conseq) - FutSw| \neq \phi$ **then**
        if $Rul \notin UnSatRulHist$ **then**
          $Sen.Health \leftarrow$ UnSatisfHealthUpdate(Rul,$CurrSw$,Sen)
        end if
        $UnSatRulHist \leftarrow Rul$
      end if
    end if
  end for
  for each $s \in Sen$ **do**
    if $s.Health < HealthThresh$ **then**
      $s.FailFlag \leftarrow 1$
    else
      $s.FailFlag \leftarrow 0$
    end if
  end for
end while

Algorithm A2 Health Status Update due to Rule Satisfaction.

SatisfHealthUpdate $\{Rul, CurrSw, Sen\}$
for each $s \in Sen$, $s.id \in (Rul.Ant \cup Rul.Conseq)$ **do**
  $PrF \leftarrow 1 - Rul.Conf$ // PrF is the probability that the sensor is faulty
  $s.Health \leftarrow 0.1 \times (1 - PrF) + 0.9 \times s.Health$
end for
return $Sen.Health$

Algorithm A3 Health Status Update due to Rule UnSatisfaction.

UnSatisfHealthUpdate $\{Rul, CurrSw, Sen\}$
for each $s \in Sen$, $s.id \in Rul.Ant$ **do**
  if $|Rul.Conseq| = 1 \wedge |Rul.Ant| = 1$ **then**
    $PrF \leftarrow 1 - P(s)$
  else
    $PrF \leftarrow 1 - \dfrac{P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq)\}} x)}{P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq)) | x \neq s\}} x)}$
  end if
  $s.Health \leftarrow 0.1 \times (1 - PrF) + 0.9 \times s.Health$
end for
for each $s \in Sen$, $s.id \in Rul.Conseq$ **do**
  if $s.id \in CurrSW$ **then**
    $PrF \leftarrow 1 + \dfrac{Rul.Sup - P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq))\}} x)}{P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq)) | x \neq s\}} x) - P(\bigcap_{\{x \in (Rul.Ant \cup Rul.Conseq) | x \neq s\}} x)}$
  else
    $PrF \leftarrow \dfrac{Rul.Sup}{P(\bigcap_{\{x \in (CurrSW \cap (Rul.Ant \cup Rul.Conseq))\}} x)}$
  end if
  $s.Health \leftarrow 0.1 \times (1 - PrF) + 0.9 \times s.Health$
end for
return $Sen.Health$