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Parametrization and Evaluation of Legible Motion for Human-Robot Interaction

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Abstract

This thesis provides a new understanding of how to design and evaluate legible motion in a spatial *human-robot interaction* context. Currently, *human-aware navigation* algorithms use minor adaptions of their trajectory when solving spatial conflicts with humans. However, this mode of trajectory adaption is not practical in deadlock situations and is generally thought to be of little effectiveness to communicate a robots status and intentions to a human observer. On a large scale this can harm the efficiency of many pedestrians and their acceptance of robots. The introduction of mobile robots in everyday contexts requires that they have a motion language that can easily be perceived, learned, and understood by pedestrians. This led to the conceptualization of *motion cues.* These are expressive movements that override the robots current planning algorithm. Motion cues should be legible, allowing for a quick and confident interpretation of an intent by the observer. In addition, the motion cues should be adaptable to different robots and scenarios. While such legible motion cues have been implemented in isolated studies, for a universal motion language their cross platform applicability and adaption to different robot types and scenarios should be demonstrated. Therefore, it is of particular interest how the motion parameters, such as a path travelled and velocity, have to be designed to be able to communicate a certain intent and how to measure the impact on human behavior. Previous studies of motion cues did not report this level of detail in parameters, nor did they demonstrate the transferability to different systems. In addition, existing work has not integrated the capabilities of observing motion and human movement analysis into this picture.

This thesis introduces robots' motion behavior when autonomous motion is applied (Chapter 1.1) and what ergonomic concepts to consider in spatial conflicts between humans and robots (Chapter 1.2). Subsequently, focus is brought on how other works have designed communicative motion and evaluated it (Chapter 1.3). Accordingly, research questions are derived (Chapter 1.4) and an innovative approach for designing and evaluating robotic motion cues is presented (Chapter 1.5). The process starts with an exploration phase (Chapter 2). Subsequently, it considers human perception, legibility evaluation and methods to measure the effect of a motion cue on human behavior (Chapter 3). Finally, the motion cue is parameterized to make it adaptable to differently sized robots and scenarios (Chapter 4). This thesis discusses the results and limitations of the published articles in relation to the design and evaluation process (Chapter 5.1), provides hands-on guidelines for developers (Chapter 5.2) and proposes how to implement the motion cue in a human-aware-navigation architecture (Chapter 5.3).

A retreating movement *back-off* proved to be feasible as the exemplary motion cue throughout the process. The results suggest that analysis of human motion behavior sheds insights into its legibility. For the parameterization, an interaction of design parameters such as back-off speed, length, and execution time appeared, where connections to the research domain *motion design* become apparent. Design guidelines are quantified as the Equations 5.1-5.4. On this basis, it is suggested that legible motion can be strategically designed and is adaptable to different robots and scenarios, using the presented methodology.

Zusammenfassung

Diese Dissertation zeigt eine neue Herangehensweise auf, wie lesbare Bewegung im Kontext der räumlichen *Mensch-Roboter-Interaktion* entworfen und bewertet werden sollen. In räumlichen Konflikten führen Algorithmen der *Human-Aware Navigation* zu kleinen Anpassungen der Trajektorie eines Roboters. Um einem Beobachter die Absichten eines Roboters mitzuteilen sind diese jedoch wenig effektiv. Die Effizienz vieler Fußgänger und deren Akzeptanz gegenüber Robotern ist somit beeinträchtigt. Die Einführung von mobilen Robotern in alltäglichen Anwendungen erfordert, dass sie über eine Bewegungssprache verfügen, die von Menschen leicht wahrgenommen, erlernt und verstanden werden kann. Dies führte zur Konzeptualisierung von *Motion Cues*. Das sind expressive Bewegungen, die der algorithmischen Bewegungsplanung des Roboters vorangestellt werden. Motion Cues sollten lesbar sein, um dem Beobachter eine schnelle und sichere Interpretation der Absicht des Roboters zu ermöglichen. Um als universelle Bewegungssprache zu gelten muss deren plattformübergreifende Anwendbarkeit und Adaption an verschiedene Robotertypen und Szenarien demonstriert werden. Daher ist es von besonderem Interesse, wie die Bewegungsparameter, wie z.B. ein zurückgelegter Weg und die Geschwindigkeit, parametriert sein müssen, um eine bestimmte Absicht zu kommunizieren und wie die Auswirkungen auf das menschliche Verhalten gemessen werden können. Bisherige Studien zu Motion Cues haben weder den beschriebenen Detaillierungsgrad der Parametergestaltung, noch die Übertragbarkeit auf verschiedene Systeme aufgezeigt. Darüber hinaus haben bisherige Arbeiten die Anforderungen an die menschliche Wahrnehmung und die menschliche Bewegungsanalyse nicht in dieses Bild integriert.

Zunächst wird das typische Bewegungsverhalten von Robotern bei autonomer Bewegung vorgestellt (Kapitel 1.1) und welche ergonomischen Konzepte bei räumlichen Konflikten zwischen Menschen und Robotern zu berücksichtigen sind (Kapitel 1.2). Anschließend wird der Fokus darauf gelegt, wie andere Arbeiten kommunikative Bewegungen entwerfen und evaluieren (Kapitel 1.3). Auf dieser Grundlage werden Forschungsfragen abgeleitet (Kapitel 1.4) und ein innovativer Ansatz für das Design und die Evaluierung von Motion Cues vorgestellt (Kapitel 1.5). Der Prozess beginnt mit einer Explorationsphase (Kapitel 2). Anschließend werden die menschliche Wahrnehmung, die Bewertung der Lesbarkeit und Methoden zur Messung der Wirkung eines Roboters auf das menschliche Verhalten betrachtet (Kapitel 3). Schließlich wird der Motion Cue parametrisiert, um ihn an Roboter unterschiedlicher Größe und Szenarien anzupassen (Kapitel 4). Ergebnisse und Einschränkungen der veröffentlichten Artikel werden in Bezug auf den Design- und Evaluationsprozess diskutiert (Kapitel 5.1). Entwickler von Robotern erhalten praktische Gestaltungsrichtlinien (Kapitel 5.2) und es wird vorgeschlagen, wie ein Motion Cue in die Software-Architektur autonomer Roboter eingebunden werden kann (Kapitel 5.3).

In diesem Prozess diente eine Rückzugsbewegung *Back-Off* als exemplarischer Motion Cue. Die Ergebnisse deuten darauf hin, dass die Analyse des menschlichen Bewegungsverhaltens Aufschluss über dessen Lesbarkeit gibt. Bei der Parametrisierung zeigte sich eine gemeinsame Wirkungsweise der Gestaltungsparameter Geschwindigkeit, Strecke und Ausführungszeit. Hier werden Parallelen zum Forschungsgebiet des *Motion Design* deutlich. Die Gestaltungsrichtlinien werden durch die Gleichungen 5.1-5.4 quantifiziert. Anhand der Erkenntnisse wird vorgeschlagen, dass lesbare Bewegungen mit der vorgestellten Methodik strategisch gestaltet werden können und an unterschiedliche Roboter und Szenarien anpassbar sind.

Nomenclature

DWA Dynamic Window Approach 4

HAN Human-Aware Navigation 2

HRCoex Human-Robot Coexistence 7

HRCollab Human-Robot Collaboration 7

HRCoop Human-Robot Cooperation 7

HRI Human-Robot Interaction 1

HRSI Human-Robot Spatial Interaction 2

IPS Information Process Space 8

RQ Research Question 23

RMP Robot Motion Planning 2

ROS Robot Operating System 41

SLAM Simultaneous Localization and Mapping 3

SFM Social Force Model 4

TEB Timed-Elastic Bands 4

Contents

Introduction

Robots have been used for several decades to perform useful tasks for humans. Since they can pose physical hazards to humans, it has usually been necessary to strictly segregate them. The development of lightweight robots enabled applications where humans and robots share the same spaces. However, the applications remained in the industrial context. These are very controlled and regulated spaces. New developments are bringing robots into unregulated private and public domains where existing rules for behavior among humans tend to be implicit. The implicit rules that exist are highly dependent on individual preferences, prior experience, context, and culture. Therefore, there is no basis for existing, transferable or generalizable communication strategies for robots.

Sales of service robots and industrial robots are increasing year by year. This process is even enhanced by the recent corona pandemic (International Federation of Robotics, 2020). New use cases such as delivering packages to the doorstep (Hoffmann & Prause, 2018) or assisting people in need of care in their home environment (Tröbinger et al., 2021) are coming into use. To achieve widespread acceptance among users, robots must not interfere with human efficiency and must enable intuitive interaction in these scenarios. Therefore, extensive research on Human-Robot Interaction (HRI) continues to be an important driver for the success of robotic applications. It is to the field of prospective ergonomics to act as strategist defining the future applications with future user needs in mind (Robert & Brangier, 2009).

To provide suitable interaction strategies for robots, *socially aware navigation* is often suggested (Lauckner, 2016; Rios-Martinez, Spalanzani, & Laugier, 2015; Lichtenthäler, 2014; Mavrogiannis, Hutchinson, Macdonald, Alves-Oliveira, & Knepper, 2019). It is defined as a robot-based strategy that follows social conventions to enable comfortable interaction with humans (Rios-Martinez et al., 2015). The state of human comfort can be easily achieved if there is enough space. A remaining problem is the resolution of deadlock and bottleneck scenarios. The communication of intentions from one actor to another is necessary to negotiate an order of passage through a bottleneck. At first it seems obvious to transfer proven concepts from interpersonal communication to interaction with robots (Keijsers & Bartneck, 2018; De Santis, Siciliano, De Luca, & Bicchi, 2008; Nass, Steuer, & Tauber, 1994). For example, robots could use explicit signals like speech to communicate intentions (Mehu & Scherer, 2012). While this approach offers potential for cooperative workplaces for single-human to single-robot interactions, a solution for communication with multiple actors is missing. Therefore, one design goal for autonomous robots is to increase their flexibility to operate in unforeseen situations. However, many current technical systems contain only a few mechanisms for communicating (Cha, Kim, Fong, & Mataric, 2018). For humans, a basic flexible communication mechanism is to actively use movements to tell others the own intentions, and to observe the movements of others to understand their next actions (Sebanz, Bekkering, & Knoblich, 2006).

On the technical side, path planning is a fundamental capability for autonomous mobile robots and deals with finding a path to a target destination in a given search space. This space is subject to constraints (e.g. collision avoidance, vehicle kinematics, social rules). Typically, path planning is broken down into global and local planning (Rimon, Kamon, & Canny, 1998). The global planner develops a plan from start to end point, taking into account a global map. The local planner tries to follow the given global trajectory while reacting to additional information (e.g. vehicle kinematics, dynamic objects and social rules). In order to combine path planning and socially aware navigation, algorithms have to be formulated that can follow social rules while moving the robot to its goal, resulting in what is called Human-Aware Navigation (HAN) (Fang, Shi, Qian, Zhou, & Gan, 2020).

There is a multitude of social spatial situations to be solved (Rios-Martinez et al., 2015; Babel, Kraus, & Baumann, 2020) and design as well as evaluation methods for expressive robot motion are sparse (Saerbeck & van Breemen, 2007). However, authors such as Ju (2015), Dragan, Lee, and Srinivasa (2013) see large potential in the usage of legible motion as a language to facilitate spatial conflicts. A motion language for robots is needed to resolve a variety of spatial conflicts. This language must meet the requirement of expressing intentions in different situations, mainly with the goal of helping both humans and robots navigate a shared environment. Robots need to be able to express different intentions, such as giving way to humans, setting their own priority, or simply communicating the status of waiting, each of which may require a specially designed motion cue. This thesis proposes a design and evaluation process for legible motion cues in HRI. In specific, a back-off motion cue is introduced to communicate the intent of yielding priority to humans. The requirements for its accurate parametrization and adaptation to different robots as well as the measurement of human reactions to such motion behavior are demonstrated.

The proposed approach is supported with the state-of-the-art in HAN. Furthermore, the cognitive and navigational considerations on the human side, as well as spatial constraints of interactions, are focused in the area of Human-Robot Spatial Interaction (HRSI). In addition, common design and evaluation methods and past implementations of legible motion are described. The main shortcomings and conclusions that emerged during the literature review are highlighted in gray boxes at the end of each chapter. For the scope of this thesis, the term mobile robot covers small mobile service robots (Reinhardt, Schmidtler, Körber, & Bengler, 2016) up to human-sized transport robots (Reinhardt & Bengler, 2021). The term industrial robot denotes robots with 6 degrees of freedom (Reinhardt, Pereira, Beckert, & Bengler, 2017; Moon, Parker, Croft, & Van der Loos, 2011), if not specified differently.

1.1 Human-aware robot navigation

The domain of mobile robotic research has dealt with the navigation in unstructured environments from the beginning (Latombe, 2012). An additional challenge came along when developers no longer had to find algorithms to autonomously navigate around merely static obstacles but also dynamic ones, namely humans. Algorithmic approaches that are used to deal with humans in an automated manner are bundled under the umbrella term HAN (Kruse, Pandey, Alami, & Kirsch, 2013). According to Kruse, Kirsch, Khambhaita, and Alami (2014), this is the intersection between the established engineering domain of Robot Motion Planning (RMP) (Latombe, 2012; Siciliano & Khatib, 2016) and a younger subdomain of robotics research that is HRI (Siciliano & Khatib, 2016; Fong, Nourbakhsh, & Dautenhahn, 2003; Goodrich & Schultz, 2008). This intersection has been increasingly researched in the past years. Thereby, particular emphasis has been placed on the design of efficiency, social behavior, and on the study of the interaction between navigating robots and humans (Mavrogiannis et al., 2019). HAN claims to implement social skills for robot navigation (Fang et al., 2020). However, this social behavior is often reduced to the superficial desire that robots should create a feeling of comfort, naturalness and acceptance in humans (Kruse et al., 2013; Chen, Zhang, & Zou, 2018; Kollmitz, Hsiao, Gaa, & Burgard, 2015). Detailed analysis of the perceptual process in interactions is sparse.

Being aware of humans is crucial for a social navigation strategy. Awareness must include perception, modeling and prediction of human positions and movements. Inspired by human motor control which is based on minimizing costs (Rosenbaum, 2009; Bitgood & Dukes, 2006), HAN planners are usually formed by means of a cost function optimization (Kruse et al., 2013).

Typically, a robot moves its base or arms resulting in base motion for mobile robots and arm motion for industrial robots (Kruse et al., 2013). The research area HAN is concerned with base motion, as this is the primary way of navigating a robot through its environment.

Algorithmic development in collision avoidance began with letting robots perceive static obstacles (Sisbot, Marin-Urias, Alami, & Simeon, 2007). Subsequently, humans were considered as dynamic obstacles (Kruse et al., 2013). Then, attempts at predicting humans were started (Kruse, Kirsch, Sisbot, & Alami, 2010), and reactive motion incorporated into robots (Kollmitz et al., 2015). Lastly, researchers implemented a robot behavior that affects human behavior (Cosgun, Sisbot, & Christensen, 2016) and handles navigation through large pedestrian groups (Fang et al., 2020).

However, from an ergonomics perspective, certain shortcomings with the publications in the field of HAN arise. They often lack clearly defined human-side research questions, sufficient sample sizes, and clear descriptions of experiments (Kruse et al., 2010; Kruse, Basili, Glasauer, & Kirsch, 2012; Sisbot et al., 2007; Kollmitz et al., 2015). Due to the fact that autonomous movements are not reproducible, the experimental behavior of the robot is not reproducible as well. This means that the experimental conditions vary from participant to participant and no controllable experimental setups can be achieved.

It is often claimed that the algorithms may improve human comfort (Khambhaita & Alami, 2017), acceptance and safety (Sisbot et al., 2007). However, often these concepts are not properly evaluated (Mavrogiannis et al., 2019). Evaluation focuses on robotic aspects, such as the time needed to calculate a trajectory (Sisbot et al., 2007; Fang et al., 2020) or the robots speed and travel time (Fiorini & Shiller, 1998; Molinos, Llamazares, & Ocaña, 2019). Actual distances that are kept to humans or human behavior are often not reported. Hence, HAN planning can be seen as the robot's view in HRI.

> The research on human-aware navigation may be seen as the robot's view in facilitating human-robot interaction. A prevailing problem is that experiments with autonomous robots are not well reproducible.

1.1.1 Common approaches

Path planning of robots is broken down into global and local planning (Rimon et al., 1998). Global planning aims to find a low-cost path based on prior knowledge of the surroundings. Hence, the robot needs a map of the environment. This can be created online while driving, using Simultaneous Localization and Mapping (SLAM) (Labbé & Michaud, 2018). The algorithm calculates a path to guide the robot through the environment and avoid collisions with the known static obstacles (Ravankar, Ravankar, Kobayashi, Hoshino, & Peng, 2018). A cost map allocates higher costs to places in the map that are occupied by an obstacle (Sisbot et al., 2007).

In global planning, robotic social behavior is usually calculated before the robot's ride is started, for example by assigning costs according to a human's static location in the room (Sisbot et al., 2007). One of the early HAN algorithms was proposed by Sisbot et al. (2007). Their motion planner maps a cost matrix to the area surrounding the robot based on two criteria. The first criterion is safety, which is operationalized via the distance to the human. The second criterion is visibility, which is operationalized via the human gaze direction. The path with the lowest cost is chosen for robot navigation. Dautenhahn et al. (2006) and Koay et al. (2007) argued that humans feel more comfortable if the robot is in their field of view. In agreement with this, the planner Sisbot et al. (2007) developed prevents the robot from choosing paths behind humans' backs. This HAN considers humans to stay at a fixed position. Therefore, Kruse et al. (2010) extended it with the ability to predict human walking. Kruse et al. (2012) present another extension. They proposed a strategy for compatible paths. Here, the robot searches for a path that crosses with the human in global planning. The authors argue that taking the shortest path to the goal for crossing scenarios appears to be the strategy that is most preferred and perceived as legible by humans in their experiments. In Kollmitz et al. (2015), the global planner for social robot navigation uses a layered cost map approach, where one layer includes static obstacles in the environment. It is overlapped with layers that include the predicted trajectories of humans. The combined costs of all the layers are considered in planning a trajectory. According to Cosgun et al. (2016), one shortcoming of HAN approaches has been that the human behavior is modeled as independent of the robot's motion. Their robot had the ability to anticipate human behavior by simulating human reactions during motion planning. To do this, they applied the the Social Force Model (SFM) (Cosgun et al., 2016). The SFM uses attractive and repulsive forces that are represented as vectors. Vector calculation leads to a summarized vector pointing in the direction to execute the robot's movement. Fang et al. (2020) propose a global path planning method that considers perception of many pedestrians and multi-layer cost-maps. This global planner is usable in larger crowds.

A global path is passed on to the local planner. The local planner calculates a trajectory based on the global path that avoids obstacles in the immediate surrounding of the robot. In local planning, the cost or objective function is changed or enriched with human-aware constraints (Khambhaita & Alami, 2017). Common strategies used in HAN are the avoidance of humans, avoiding of collisions, respecting personal spaces, minimal required obstacle distance (Sisbot et al., 2007), stop-and-wait behavior (Kruse et al., 2010) or spatial cooperation (Kruse et al., 2013). A local grid is calculated around the robot that includes information about whether a field in the grid is occupied or not. This is done via the sensor input that the robot perceives at its current location. The local occupancy grid covers a smaller region of the global occupancy grid and is able to detect objects, that are not known from the global occupancy grid before. After the local occupancy grid is created, the goal of the local planning algorithm is to determine commands for dynamic avoidance of static or moving obstacles in the near future. Therefore, local planning is also called *reactive planning* or *collision avoidance* (Kruse et al., 2013). Seder and Petrovic (2007) propose a solution to avoid humans via adaption of the Dynamic Window Approach (DWA). The movement of an obstacle is viewed as a moving occupied cells in the grid map. The predicted trajectory of the moving cell is used for the calculation of a possible collision with the robot trajectories. The algorithm requires the human's velocity vector and motion direction. Another widely used local planner is the Timed-Elastic Bands (TEB) planner which takes into account dynamic obstacles (Rösmann, Feiten, Wösch, Hoffmann, & Bertram, 2012). The inputs to this local planner are the position of the human in two-dimensional coordinates on the occupancy grid, and his or her linear and angular velocities. Due to smooth human circumvention, TEB has increased robot efficiency in HRI compared to DWA (Martins, Ferreira, Portugal, & Couceiro, 2019). While Seder and Petrovic (2007) and Rösmann et al. (2012) aim at avoiding pedestrians by navigating around them and/or adapting the robot velocity, other authors propose a *cooperative* HAN planner (Khambhaita & Alami, 2017). This planner allows trajectories to intersect. In order to plan this, the trajectories of the human must be known to the robot in advance. The robot does not entirely act reactive but it can also predict a path for the human. Based on the TEB optimization, a trajectory is predicted for each perceptible person. The social constraints in the robot's movement are set according to three criteria. A safety criterion ensures a minimum distance between the robot and the person. A time-to-collision criterion estimates the time frame in which a collision between the robot and the human could occur along the currently assumed trajectories. Direction of movement is incorporated according to Gockley, Forlizzi, and Simmons (2007).

To structure the research landscape on HAN and to aid implementation, Kruse et al. (2013) propose a framework. It distinguishes between deliberate software modules, that plan motion before execution, and reactive software modules, that make short-term adaptions to the robot's movements possible. An additional data flow from the sensors to the reactive software modules is suggested. In that, the framework is related to the sense-plan-act architecture paradigm which is a general state-of-the-art framework for mobile robots (Siegwart, Nourbakhsh, & Scaramuzza, 2011). Kruse et al. (2013) suggest that local planning can be extended to consider dynamic objects, such as humans, next to static objects in the environment. Reactive robot motion can be used to create motions that are adequate for humans. In this context, Trautman and Krause (2010) and Althoff, Wollherr, and Buss (2011) assume that humans are willing to cooperate with the robot and may give it space to pass. They develop approaches to identify and make use of immediate emerging path possibilities in local planning. Alternative HAN planners comprise the concept of legible motion (Kirsch, 2017), social conventions like tending to one side of a hallway (Kirby, Simmons, & Forlizzi, 2009), special emphasis on bypassing humans (Chen et al., 2018), or the modeling of activity spaces of groups of pedestrians (Marques, Gonçalves, Barata, & Santana, 2017). Mateus, Ribeiro, Miraldo, and Nascimento (2019) apply additional cost maps to represent standing, sitting and walking people. Cai, Wang, Li, Song, and Meng (2019) focus on modeling moving human crowds. In contrast to obstacle cost maps, Dondrup and Hanheide (2016) use velocity cost maps to model the mutual navigation intent between robot and human. Molinos et al. (2019) consider many possible trajectories at the same time in a tree-based structure, to find paths that do not intersect with the paths of humans. However, short-term and quick path adjustments are rather sparse in the algorithms studied, and instead, trajectory adjustments tend to be slow and give priority to driving forward. They tend to resemble a car-like strategy. What most HAN planners have in common is that they do not execute quick adaptive movements. This makes it difficult or impossible to implement unconventional avoidance strategies, such as moving sideways or backwards, in autonomous robot planning.

What these algorithms have in common is that they do not embed nor recommend the concept of quick adaptive movements, similar to the ones humans would use.

1.1.2 Solving spatial conflicts and bottlenecks

While the previous chapter introduced the general frameworks for HAN algorithms, this section takes a closer look at how these algorithms behave in bottlenecks to resolve spatial conflicts with humans. When a robot gets in the way of humans, an order of passage has to be arranged Reinhardt, Prasch, and Bengler (2021). Spatial conflicts arise especially in crowded or narrow spaces. If there was always a lot of room and a human and a robot could perceive each other in advance, there would most likely be no need for HAN because robots could make adaptions to their plans in advance and would never come into close interaction with humans. However, this is not the case in crowded spaces or when an immediate encounter happens behind a visual barrier. Hence, solving of bottlenecks is important in this work. First, they cannot always be prevented via a wide evasion or different global planning by the robot due to space restrictions or a lack of sensory perception by the robot. Second, efficiency evaluations for the robot's task make it lucrative to choose a direct encounter with a person over a trajectory planning where no encounter would occur. Hence, this thesis aims at how motion has to be executed in such bottlenecks. There is work that envisions a robot-side formalization that aims to reduce the necessary bypasses and instead allow for closer encounters between humans and robots (S. Liu et al., 2017). In addition, more attention needs to be paid to precise movement design and human-side evaluation.

Kollmitz et al. (2015) allow passing humans in frontal approaches in hallways by about 1 m distance. They handle crossing scenarios in an empty hall by reducing robot speed and letting the human pass first. When bottlenecks are too narrow to be solved dynamically, the robot maintains a stationary position until the human has passed the bottleneck. The paths created by their formalism exhibit decisions similar to those applied in human-human interaction. Polite pedestrian behaviors include waiting until another person has passed, not encroaching on another person's personal space, and moving out of the way when blocking another person's path. Kruse et al. (2010) consider two bottleneck situations. One situation is when a person occupies the space of the robot's goal. The second situation is if the path is too narrow for the robot to bypass the person, for example in a narrow corridor. Here, the cost function is changed on the spot. For example this can mean that the costs for moving in front of a pedestrian are increased. Khambhaita and Alami (2017) allow passing humans in bottlenecks by incorporating a time-to-collision metric into maneuver planning. The human trajectory is predicted and synchronized with the robot. If the situation cannot be solved, the robot stops and waits for the human to pass by. Other authors implement cooperative robot behavior by letting the robot accelerate (Lo, Yamane, & Sugiyama, 2019), decelerate (Kruse et al., 2010) or by dynamically responding to the predicted human path (Khambhaita & Alami, 2017). Many HAN planners do not consider humans in a way that is different from objects. In Rösmann, Hoffmann, and Bertram (2017), the robot circumvents the human with the same distance it keeps to all other obstacles. In terms of the appearance of these movements, efficient, fluid robot motions are characterized by a constant velocity and linear trajectories. Under this premise, mobile robots mostly move forward using path smoothing techniques (Ravankar et al., 2018) which is a behavior untypical for humans. Humans use complementary pointing gestures, backward steps, or evasive maneuvers to use their full-body motion to communicate with others. Under this premise, robot behavior consisting of decelerating, stopping, or linear trajectories is difficult to understand (Moon et al., 2011). This problem is especially expected in close proximity between humans and robots when local planning is applied.

Conflict resolution in HAN is characterized by the robot's tendency to move forward and make slight adjustments to their trajectory. It is hard for humans to understand the robot's intentions.

1.2 Human-robot spatial interaction

The research domain of HRSI rather takes the stance of the human. It can be termed the study of joint motion between robots and humans in a shared space and the social cues and signals that govern these interactions. The task for practitioners is to use and study models of the way humans and robots control their movements in close proximity to each other (Dondrup, Bellotto, Jovan, & Hanheide, 2015).

The design of robot behavior must take into account proximity to humans and intended or unintended interference with them. Hoc (2001) suggests that when humans and robots are engaged in a joint task that requires cooperation, this can be facilitated by precise control of interference. For this control, the human must understand the intention of the robot (Bengler, Zimmermann, Bortot, Kienle, & Damböck, 2012). Pedestrians who meet robots unintentionally, so called *bystanders* (Scholtz, 2003), have to get special attention to allow fluent interactions. These people may be unaware of obstacles and very focused on their own goal achievement. Plausible rules for robots should be found that have the potential to ensure safe and smooth navigation for all actors. Lam, Chou, Chiang, and Fu (2011) define rules to avoid collisions, refrain from encroaching on personal space, or waiting once a human's personal space is entered. Mere stop-and-wait behavior is impracticable in close encounters (Reinhardt, Prasch, & Bengler, 2021). Therefore, expressive and evasive movements can be an improvement to these rules.

The domain HRSI is a subdomain of HRI in which motion is focused. The way multiple pedestrians coordinate movements with each other is a complex topic involving stages of sensory processing and motor control (Karamouzas, Skinner, & Guy, 2014; Jungmann, Cox, & Fitzpatrick, 2014). It is assumed that for a complete understanding of the processes involved in HRSI, a similar level of detail including not only the perception process and motion planning on the robot's side is necessary, but also the feedback loop with the perception and response execution by humans. The mutual knowledge of both partners is a fundamental requirement for successful interaction (Bengler et al., 2012). Hence, findings from various fields of research such as human perception, motor control, cognition and classical HRI have to be addressed.

The research on human-robot spatial interaction reflects rather the human view in human-robot interaction and the management of motion in close proximity between humans and robots.

1.2.1 Classification of interaction and processing spaces

Definitions must be made to characterize the processes on both the robotic and human sides in an interaction. The umbrella term HRI is the research that investigates and designs mutual action of human and robot. It deals with the understanding, design and investigation of robotic systems used by, or with, humans (Goodrich & Schultz, 2008). Every change in a human's or robot's behavior as a consequence of the other's presence or action is an interaction (Kruse et al., 2013). In this context, HRSI is a more specified field dealing with those interactions where spatial conflicts have to be managed between one or multiple robots and humans.

Interaction implies a relationship between different actors that leads to a mutual or reciprocal influence (VandenBos, 2007). As an extension to this, cooperation is a joint execution of tasks, where it also depends on which actor the tasks are assigned to (Bengler et al., 2012). Schmidtler, Knott, Hölzel, and Bengler (2015) distinguished between Human-Robot Coexistence (HRCoex), Human-Robot Cooperation (HRCoop), and Human-Robot Collaboration (HRCollab). If there is a common workspace for human and robot and they act at the same time, the interaction can be labeled a HRCoex. In a HRCoop, humans and robots work on the same goal or on solving the same task. If physical contact is planned, the interaction can be labeled a HRCollab. This classification was best applied to industrial robots. A modification of this taxonomy for application to mobile robots was not sought by the authors. Due to the variations in distance and the intended or unintended interference of the two partners, movements have to be designed specifically for varying classifications (Reinhardt et al., 2017). People encounter robots in different scenarios. Also, the spectrum of possible tasks together or in the vicinity of robots is large and people have different prior knowledge about robots. To consider this, Scholtz (2003) suggest five different roles of humans in HRI. Humans can act as *supervisor*, *operator*, *mechanic*, *bystander* or *peer*. Bystanders are pedestrians who do not plan to encounter the robot. For example, pedestrians who occasionally manage bottlenecks with delivery robots on sidewalks would be called bystanders. Bystanders are the focus group of pedestrians addressed in this dissertation, as they are the ones who inadvertently cross the path of robots.

Besides the type of interaction, the spaces in which interaction happens have to be defined. Only then it is possible to apply valid and objective metrics for HRSI and to compare results between different experiments. Since the mutual action of both partners is focused, the domain of preferred personal spaces that is commonly researched in HRI (Walters et al., 2005; Syrdal, Dautenhahn, Woods, Walters, & Koay, 2006; Walters, Syrdal, Koay, Dautenhahn, & Te Boekhorst, 2008; Lauckner, Kobiela, & Manzey, 2014; Rossi, Staffa, Bove, Capasso, & Ercolano, 2017), has to be enhanced by the modeling of the dynamic human-robot system (Dondrup et al., 2015). For considerations of spatial formations between humans and robots, Rios-Martinez et al. (2015) and Leichtmann and Nitsch (2020), provide compelling overviews. The basis of this research area goes back to foundations of personal space and proxemics theory (Hall et al., 1968). Nguyen and Wachsmuth (2011) define an interaction space, in which cooperation takes place. In this space, the actions to claim more or to release spatial areas are performed. The model of this space is developed as an extension of *Kendon's F-formation system* (Jungmann et al., 2014). It is a concept of how people align themselves when communicating. In the interaction space, special attention is paid to posture and orientation between interaction partners. Kitazawa and Fujiyama (2010) introduce an Information Process Space (IPS) for pedestrian interpersonal interaction. The authors suggest that pedestrians perceive objects or other pedestrians as potential obstacles when they are in that space. The IPS is modeled as a cone-shaped area with an opening angle of 45°, a 4.5 m longitudinal length and a 0.5 m lateral width in front of a moving person. This space was applied in Reinhardt, Prasch, and Bengler (2021) as a result of a review of the interaction space literature. Other spatial process spaces include the egg-shaped model by Lam et al. (2011) or an elliptical model that Tomari, Kobayashi, and Kuno (2014) proposed as a human's sensitive area. Furthermore, Hayduk (1981) and Gérin-Lajoie, Richards, Fung, and McFadyen (2008) propose an asymmetric personal space. It is also important to examine the temporal component. The study of Rettenmaier, Dinkel, and Bengler (2021) classifies an approach phase and an interaction phase in which the order of passage through a bottleneck is negotiated between drivers and automated vehicles. Entering the interaction phase is triggered in human processing when a scenario-specific remaining time-to arrival is perceived.

The publications regarding classification in HRI and interaction spaces usually appear as isolated studies (Reinhardt, Prasch, & Bengler, 2021). An overview of interaction classification and interaction spaces both on human and robot's side has not yet been targeted. However, knowledge of such models is necessary to assess whether a robot's motion strategy can be observed by a human or to determine the size of the mutual interaction area that should be investigated. To design a HRSI experiment requires picking suitable models from the reviewed areas to be able to validate the experiment and to draw proper conclusions about the measured human behavior.

Appropriate interaction classifications and interaction spaces must be applied in study designs both on the human and the robot sides to assess motion perception, the spatial relationship between robots and humans, and the effect of robot behavior on humans.

1.2.2 Human perception of motion in a spatial interaction context

In the process of applying appropriate interaction models it is necessary to know about the human perceptual processes that are in use in spatial interactions. Humans rely on the ability to perceive what others are doing and to infer from gestures and expressions what others are intending to do (Blake & Shiffrar, 2007). They also show strong inter-individual differences in the way they master these perceptual skills. This is promoted by the fact that human actions can easily be misinterpreted. Although many advances have been made in the understanding of the visual, motoric and affective influences on perception of human actions, HRSI demands special consideration due to the different communication capabilities a robot possesses. In the sensory processing of movements, the execution of the movement and the functions of the human eye play the predominant role. After visual processing is successfully completed, the human derives knowledge about possible robot intentions and own reactions from his or her long-term memory. Subsequently, a feasible response is selected and executed through movement (Wickens, Hollands, Banbury, & Parasuraman, 2016). Ultimately, the process leads to a continuous feedback loop between human and robot.

An interaction can be classified as focused or unfocused (Rios-Martinez et al., 2015). Different spatial considerations and movement strategies apply to both. An exemplary scenario for focused interaction is when a robot approaches a human, for example to deliver an item. A scenario for unfocused interaction could be when a robot simply aims to avoid a pedestrian. Humans are looking out for different cues in such varying scenarios (Reinhardt, Schmidtler, & Bengler, 2018). This is related to research on awareness where it was found that people move in an environment without actually showing awareness of obstacles, yet they successfully avoid colliding (Harms, van Dijken, Brookhuis, & De Waard, 2019). Such findings need to be considered for robotic motion strategies as well.

First, any attempt by a robot to communicate with a human must be processable by the humans involved. Therefore, the focus in the following is on human sensory processing skills. There is a lot of information on visual perception like optical flow field (Lee, 1976) or the observer's visual world (Gibson, 1950). However, many of these traditional approaches are concerned with the perspective of a driver inside a car, where the world around him or her is moving. HRSI scenarios require to take the perspective of an observer who is either static or moving with his or her own motor capabilities and is observing motion of a moving autonomous object like a robot. Lee (1976) is primarily concerned with the locomotor optic flow field, which is determined only by the translatory movement of the eye relative to the environment. Humans can see a visual field measuring roughly 180° laterally and 150° vertically. This field is moved when the eyes move between different fixation points (Gibson, 1950).

Depth perception is the ability to perceive the volume of objects as well as their relative position in three-dimensional space (Watson & Enns, 2012). Depending on whether the viewing angle is in depth or lateral, the perception of motion is steered by dilation or contraction of the boundaries of an obstacle (Lee, 1976). A dilating image is seen when an observer faces an object's motion from the front. As the object approaches, the outer edges appear to move away from each other (Groeger, 2000).

Furthermore, vision is differentiated into foveal and peripheral vision. Foveal vision excels at high visual acuity, object identification and object tracking. However, this comes along with low photo sensitivity. Furthermore, humans can extract an exact trajectory using this mode of vision. The entire eye must be aimed at an object to enable to see it sharply. Two types of such eye movements can be distinguished. There are inspection saccades to explore the environment and target saccades for fixating a distinct object (Hagendorf, Krummenacher, Müller, & Schubert, 2011). Utilizing foveal vision is also associated with a certain amount of time to perceive the environment. To identify the rough location of an object, a minimum of 0.2 s are needed (Werner, 1935; Woyna, 2014). Afterwards, 0.2 s to 0.8 s are needed to fixate an object (Schweigert, 2003). To track moving objects, slow sequential eye movements are used (Rötting, 2001).

The peripheral vision excels at high photo sensitivity, motion detection, random detection taking into account the entire field of view, the simultaneous perception of several objects, and the orientation of the observer in space. However, this comes along with low visual acuity. Motion is mostly perceived via this mode of vision. Especially directions of movement and velocity can be derived (Gralla, 2007). The two modes of vision work in a co-existing way where the particular qualities are combined (Zaindl, 2018). When the distance between fixation points is large, head movements in the same direction as the eyes are applied. Most situations in everyday life actually require such additional head movements.

In order to translate movements to prediction metrics such as the time-to-collision, Lee (1976) suggested that a person can calculate a time-to-collision based on the perceived visual angle towards an object and its change over time. Carstengerdes (2005) noted that this ability is limited to small visual angles and constant speed of an approaching object. The rate at which the visual angle changes as an object approaches is called τ. The generalizability of this parameter has been questioned by Manser and Hancock (2007), Tresilian (1999), Clark, Perrone, and Isler (2013). A main concern is that adjusting the angle of view is always associated with a change in the distance to other objects that are used as cues by the observer (Clark et al., 2013). Savelsbergh, Whiting, and Bootsma (1991), Smeets, Brenner, Trebuchet, and Mestre (1996) changed only the visual angle and excluded any physical distance manipulation or velocity change of an object. The participants used other cues from the environment to estimate time-to-collision rather than estimating time-to-collision using the rate of the dilating visual angles. Therefore, it can be concluded that the parameter τ is involved in the perception of motion, but rather as one source of information among others (DeLucia, 2004; Cutting, Vishton, & Braren, 1995). These arguments have also been discussed in Reinhardt and Bengler (2021).

Spatial perception is also biased by action (Witt, Linkenauger, & Wickens, 2016). For example, objects appear closer, smaller, and faster when they are easier to reach. Visual illusions should be considered in the spatial interaction and relative motion between individuals and/or robots. The comparison of the speed perception of large moving objects with smaller moving objects showed that a size-speed illusion can be experienced by humans. It states that a large object is perceived to be moving slower than a small object that travels at the same speed (Clark et al., 2013; Leibowitz, 1985). In other words, observers underestimate the speed of large objects (Reinhardt & Bengler, 2021). The opposite phenomenon has been detected as the size-arrival effect. Here, observers underestimate the time-to arrival of large objects. This suggests that their speed is perceived as higher than the speed of smaller objects (Petzoldt, 2016; Beggiato, Witzlack, & Krems, 2017). There are some suggestions about the factors that contribute to these contradictory effects. For example, size-arrival considerations usually imply a frontal view of an object and movement is along the depth axis (Reinhardt & Bengler, 2021). In these scenarios, dilating images have to be used by the observer to judge speed, which is more difficult for small objects (Watson & Enns, 2012). Also, eye movement behavior of humans seems to be different when following the movements of small and large objects. In a study conducted by Clark, Perrone, Isler, and Charlton (2016), eye fixations were located further away from the front of large objects compared to small ones. In a virtual reality study environment, the size of robots and the expectations towards the robot's motion were indeed correlated (Reinhardt & Bengler, 2021).

Second to the ability to see motion, the intent behind a robot's action must be understood by a pedestrian. Hence, the focus in the following is on the way how humans derive information from observed movements. Färber (2015) emphasizes the importance of facial expression, eye contact and nonverbal communication such as gestures and body movement during the execution of a mutual task. Humans utilize the observation of motion as a communication principle. This is promoted by humans' way of processing it. Castelli, Happé, Frith, and Frith (2000) showed activation of mental state attribution in humans watching actions of computer animations. The authors suggest that humans have brain regions that form a network for processing information about intentions. In addition, they propose that the ability to make inferences about mental states is linked to the ability to make inferences about actions. According to Sebanz et al. (2006), motion and actions are not only visual properties. People also perceive movements with the inclusion of an assessment of the underlying goals of the action. Not only is it important to understand what others are doing, but additionally the ability to predict what they will do next. An observed action immediately activates an existing mental model of the expected next action and the intended goal. In fact, this activation does not necessarily require the occurrence of motion. Mental models are already activated when an object is recognized, before an action is performed. This means that in unambiguous situations with clear rules, such as traffic, the mere presence of a street sign activates mental models about how pedestrians are expected to move (Fuest, Sorokin, Bellem, & Bengler, 2017). Thus, situational context is a factor that influences the appropriateness of certain behaviors. Schubö, Vesper, Wiesbeck, and Stork (2007) declared that humans also have mental models of the robot in terms of how it wants to effectively resolve spatial conflicts. The mental model of what behavior is expected can also change over time and is determined by the amount of interactions experienced (Paetzel, Perugia, & Castellano, 2020). Gibson (1950) support this argument by discussing that familiarity with an object also plays a crucial role in motion estimates. The authors note that without prior knowledge of its shape, an object will naturally appear changed in size depending on the distance or viewpoint relative to the observer. This changes if the observer has an accurate mental model of the object. Although its location is changed an observer can perceive the object with constant size and shape because the observer inadvertently uses the existing mental model (Gibson, 1950).

The above descriptions depict the process of translating motion properties to motion perception. It becomes apparent that there is a difference between understanding an actor's intention, and fulfilling the observer's expectations. The first process deals with activating a mental model during motion observation. The second process happens when the observer has a mental model that complies with the observed action. This view is also supported by the work of Dragan et al. (2013), according to whom two distinct properties of motion exist: legibility and predictability. Legibility corresponds to the understanding of an intention. In Dragan et al. (2013), a movement is legible if an observer can infer the robot's goal from observing its movements. Other terms found in the literature that describe the same phenomenon are readable, understandable or anticipatory motion (Lichtenthäler & Kirsch, 2016). Predictability on the other hand corresponds to the fulfilment of expectations. A movement is predictable if it fulfils the observers expectations (Dragan et al., 2013). It is the property of a movement to reflect what an observer expects in this situation (Faria, Silva, Alves-Oliveira, Melo, & Paiva, 2017). It is the property of a movement to fit an already activated mental model. Legibility and Predictability are said to be contradictory properties. They only coincide if an observed movement fulfills the expectation of the observer and no further intentions could be communicated beyond that (Dragan et al., 2013). Lichtenthäler and Kirsch (2014) oppose the theory by Dragan et al. (2013) since the experiment was limited in that there was no actual HRI but participants were mere uninvolved observers. They claim that in physical interaction, legibility always coincides to some degree with predictability. Experimental conditions can play a large role in the notion of these two properties of motion. Despite the ongoing debates, the notion of legible movement as a concept in which movements should be designed to efficiently and accurately communicate intentions to the observer is a fundamental concept of this work.

After an actor's movement has been sensory processed correctly by an observer, it is legible if the intention underlying the movement is also comprehensible.

1.2.3 Human motion in a spatial interaction context

The execution of a particular robotic behavior should enable a pedestrian to confidently select as well as execute an associated response (Reinhardt, Prasch, & Bengler, 2021). The research domain HRSI deals with motion as a substantial component (Dondrup et al., 2015). In HRSI, the human's response can be measured quantitatively as a specific motion behavior. In order to interpret a human's behavior as a result to a robot's maneuver, it is important to understand human motor control and the variances of basic human motion (Carton, Olszowy, & Wollherr, 2016). This is also important for the application in robot control. For collision-free navigation, it is necessary that the robot can measure and understand human behavior. Lam et al. (2011) highlight that with more accurate tracking of human movements, robots could better infer people's intentions from their movements and feed this knowledge into robot navigation. This suggests that both technological advances and means of understanding behavioral outcomes are needed.

Research in the field of human movement behavior is a basis for the studies conducted in this dissertation. The characteristic values for walking speed, acceleration from a standing position or cornering strategies that humans use are a necessary information to analyze the data and discuss the results of measured human behavior. Humans aim to keep a set speed, which minimizes energy consumption (McNeill Alexander, 2002). Bohannon (1997) derived average walking velocities for women between 20 and 30 years of age of $M = 1.41$ m/s ($SD = 0.18$ m/s). Men of this age group walk at $M = 1.39$ m/s ($SD = 0.15$ m/s). Muir, Rietdyk, and Haddad (2014) find that 20-25 year old pedestrians reach usual gait speed about three steps after gait initiation. Derived from the studies of Jian, Winter, Ishac, and Gilchrist (1993), a typical step length is assumed to be 0.5 m. With these values, it is possible to calculate typical velocities at different points in a spatial scenario for humans and derive values for acceleration, as shown in Reinhardt, Prasch, and Bengler (2021). Humans typically prefer to adapt their trajectory in terms of curvature in order to evade spatial conflicts (McNeill Alexander, 2002). In cornering situations, Fino, Lockhart, and Fino (2015) found that humans apply walking speeds of $M = 1.27$ m/s ($SD = 0.26$m/s). Humans tend to cut the corners. With this behavior their lateral distance to the corner reaches a minimum approximately in the middle of the turn (Brogan & Johnson, 2003).

It is also necessary to investigate which behavioral concepts might be responsible for the shown human behavior. Human proxemics follows a pattern described by Hall et al. (1968), which assigns typical distances from each other to the social relationship between two interacting people, ranging from an intimate space (0.45 m) to public space (7.6 m). These spaces can be responsible for determining whether a person evades in a certain way. The space is deformed by the human walking speed. With increasing walking speed, pedestrians need an increasing amount of longitudinal space (Daamen & Hoogendoorn, 2003). Hayduk (1981) found that these spaces can be asymmetrical and Gérin-Lajoie et al. (2008) measured that the shape of personal space, modified by a person's dominant side, influences turn strategies and obstacle avoidance. The authors note that personal space is used to control navigation. Also, people follow distinct rules. In the case of opposing movement directions and overlapping trajectories most people evade to their right side (Bitgood & Dukes, 2006). To plan trajectories in crowded spaces, people estimate the time-to-collision with other pedestrians and use this information to re-plan their own movements (Karamouzas et al., 2014). As a result, the flow of pedestrian groups in bottlenecks can be modeled mathematically (Daamen & Hoogendoorn, 2003).

Compared to the level of detail found in the literature on human movement research, the way human movement is treated in current HRSI and HAN research is less multifaceted. Many studies in HRSI so far follow a too static approach (Reinhardt et al., 2016). Often only one of the two interacting partners moves (Morales, Kanda, & Hagita, 2014). State-of-the-art HAN algorithms frequently do not consider that humans also try to avoid colliding with the robot by adapting their own trajectories. Consequently, the resulting robot behavior is often over-reactive, or the planner fails to find a solution when a human is blocking the way (Khambhaita & Alami, 2017). Therefore, the study of human motion is important to consider how the robot should best adapt its own behavior.

In order to interpret a person's behavior in response to a robot's maneuver, it is important to understand the variances in human motion and its motivators.

1.3 Design, execution and evaluation of robot motion

HRI research shifts from controlled industrial environments to human inhabited public and private environments. In traditional ergonomic perspectives on human-machine interfaces, the operator is a highly trained individual, with expertise for automation errors and a machine's behavior. In comparison, a typical human bystander does not have this experience. This urges the question on how to design and evaluate efficient interactions for untrained users (Schubö et al., 2007). More expressive movements are necessary here. Most of the coordination between people in public space is realized by observing each other's movements (Ju, 2015; Hogan, 2003). The integration of robots in this context means that their movements must be legible as well. The design of motion for robots and other autonomous systems is an urgent matter. Once applied in public areas, robots will interact with humans who have no experience with robots (Reinhardt et al., 2018). As humans become increasingly familiar with robots, initial encounters largely determine future expectations of robot behavior (Paetzel et al., 2020). Motion behaviors should be designed to work for robots with different embodiment and in different scenarios (Saerbeck & van Breemen, 2007).

From a regulatory perspective, ISO standards are aimed at ensuring safety (Vysocky, Wada, Kinugawa, & Kosuge, 2019). ISO/TS 15066:2016 specifies safety requirements for collaborative industrial robot systems and the work environment (ISO, 2016). The standard applies to industrial robot systems. It does not apply to non-industrial robots, although the standard states that the safety principles can be useful to other areas of robotics. Accordingly, formulating a safety standard for the new service robots is essential so that close HRI may be permitted in the public and private domain (Virk, Moon, & Gelin, 2008). Recently, regulatory bodies have picked up on the specific need for standards of sidewalk robots (Grush, 2021). The draft of an international standard aims to provide a consistent and coherent framework from which entrepreneurs can innovate, cities can regulate, and advocacy groups can express preferences. What should be taken into account in this effort is the concept of legible behavior.

A key component of uniform regulations could be a standardized design procedure for legible robot motions. Standardization could ensure that the various robotic movements are designed according to consistent guidelines and evaluated using reproducible methods worldwide. The goal is to make robot behavior work for different cultural backgrounds, in different contexts, and for different application domains (Reinhardt et al., 2018). In addition to a thorough argument for using motions to create a robot language, this chapter explains three main components of motion design. Some publications propose to design movement using structured design methods. Practical implementation and executions of legible movements in empirical research are displayed by another group of authors. There is also a body of work for evaluation methods. So far, the three components are rather scattered in the literature reviewed.

In order to develop a universal robot motion language, legible motion should be designed according to consistent guidelines and evaluated with reproducible methods.

1.3.1 Legible motion cues can represent the language of robots

One might ask, why we don't implement speech in robots to unambiguously and clearly solve all conflicting situations that demand arrangement with humans: Although language is often used in research and mentioned as a possible modality for interaction, it is not appropriate in many situations. In areas with high noise levels, speech can be drowned out, and in other noise-sensitive areas such as schools or hospitals, it can be disturbing (Cha et al., 2018). Nonverbal communication on the other hand accounts for more than sixty percent of communication between two people or between a speaker and a group of listeners (Hogan, 2003). It is likely that this percentage may be even higher in places where verbal communication is impractical, such as noisy pedestrian areas. Due to the interference of sounds and their limited range, auditory feedback or explicit signals such as lights appear ineffective and inefficient in these scenarios. An increasing number of robots will move through crowded and noisy public spaces, where they will have to find cooperative navigation solutions with several pedestrians in a short time. Motion as mode of communication can be an alternative for robots to convey their intentions. Movement could evoke elegant ways to communicate and is visible to many observers, if observer viewpoints and the requirements for human perception are taken into account (Nikolaidis, Dragan, & Srinivasa, 2016).

As suggested by Kruse et al. (2012), it would theoretically be useful to enable robots to use strategies that allow them to never infer with humans. However, this approach requires planning algorithms that adjust a plan many times, resulting in very long detours (Kollmitz et al., 2015). In addition, in confined spaces such as corridors, corners or bottlenecks, there will always be situations where humans and robots meet unexpectedly. This is where legible behavior becomes especially important. For short-term and time-critical adjustments, the robot's motion language must be designed in a way that a specific intention becomes apparent (Dragan et al., 2013; Pacchierotti, Christensen, & Jensfelt, 2006; Cha et al., 2018; Ju, 2015). The review of human motion perception brought to light that humans use motion as a means to infer intent. This suggests that robots can also use this capability.

To differentiate the use of movements from other modalities such as lights, audio or displays, some authors divide communication in explicit or implicit communication Kruse et al. (2013). When observers infer an intention from an agent's movement, this would generally be called an implicit form of communication, whereas displays with a verbal message are more explicit forms of communication. Additionally, the terminology of formal versus informal communication can be found for the same distinction. In the studies of Dey and Terken (2017) and Rasouli, Kotseruba, and Tsotsos (2017), more than 90% of pedestrians solely communicated using informal communication like motion. Hence, it is reasonable that researchers call for the need of a body language of robots (Knight, Thielstrom, & Simmons, 2016).

To differentiate the intended communicative value, researchers use the terminology of legible and predictable motion (Dragan et al., 2013). Saulnier, Sharlin, and Greenberg (2011) state that a universal form of non-verbal communication, which is available to every robot, could be achieved via motion. While traditional algorithms for robot navigation focus on ensuring a collision-free trajectory, the resulting robot behavior can appear unpredictable, complicated, or unnatural to humans (De Santis et al., 2008; Dragan, 2015; Kruse et al., 2012; Pol & Murugan, 2015). To prevent this, the behavior of the robot must be legible for humans (Dragan et al., 2013; Kruse et al., 2012; Beetz et al., 2010). Legible motion is defined as a movement that allows an observer to quickly and confidently infer the intention of the robot (Dragan et al., 2013). If an observer can infer a robot's intention efficiently and confidently from observing movement, the motion is called legible (Lichtenthäler & Kirsch, 2016; Dragan et al., 2013). This applies to the unobstructed and undistorted human view of the movement (Nikolaidis et al., 2016). Predictable motion on the other hand is a movement that fulfills an observer's expectations given that the observer has a possible goal of the robot in mind (Dragan et al., 2013). Trajectories of driving straight-ahead and during cornering have been optimized for this purpose (Knight, Thielstrom, & Simmons, 2016; Dragan et al., 2013; Reinhardt et al., 2016). Studies in HRCoex suggest that straight-line movements of the robot improve human comfort and performance compared to curved movements (Bortot, Born, & Bengler, 2013) and appear to be more intuitive for humans (Huber, Rickert, Knoll, Brandt, & Glasauer, 2008). Given the debate of the two properties of motion, legibility and predictability, a focus has been to determine the individual contribution of each of them in HRI performance evaluation. For instance, Lichtenthäler and Kirsch (2014) conclude that predictability is the predominant correlating property of motion when the dependent variables safety, comfort and reliability are measured. Sudden and unexpected movements are usually excluded from the design of predictable movements, which makes humans feel safer, according to Lichtenthäler and Kirsch (2014). In contrast, Kirsch et al. (2010) claim that legible motion and perceived safety are strongly correlated. However, the design of legible motion usually involves exaggerated paths and short-term changes in direction.

The aforementioned research is primarily based on forward facing trajectories. However, it is assumed that forward trajectories are not an ideal way to resolve spatial conflicts. Inspired by the way humans coordinate actions, little tweaks like a hand gesture to give each other the right of way in front of a door, or a quick backward motion, have the potential for faster legible communication (Moon et al., 2011; Vassallo et al., 2018; Reinhardt et al., 2017). Humans have a large repertoire of movement possibilities due to a multitude of degrees of freedom made possible by joints and complex biomechanics. For example, a human arm has 7 degrees of freedom (Moon et al., 2011). This enables a variety of social cues such as gaze direction, pointing gestures, and postural cues (Sebanz et al., 2006). Many commercial robots do not have an anthropomorphic design due to their industrial origin (Hockstein, Gourin, Faust, & Terris, 2007; Venture & Kulić, 2019). A simple industrial (6 degrees of freedom) or mobile robot (2 degrees of freedom) is comparatively restricted in its freedom of movement. These robots have limited modalities for interaction, which makes defining unambiguous and legible interaction strategies a contemporary challenge (Bethel & Murphy, 2007; Harrison, Horstman, Hsieh, & Hudson, 2012). In cooperative tasks, people also show movement cues to indicate to the other actor in the cooperation that he or she is given priority. In such a context, a back-off movement with the hand could be observed (Moon, Parker, Croft, & Van der Loos, 2013). Robots do not have the same movement capabilities as humans, so such movement patterns must be adapted to their simpler form. It is unclear whether the little tweaks that work for humans could also be applied to robotics or how they have to be adapted to achieve comparable results.

While the efficacy of humanoid general purpose robots has yet to be proven (Sheridan, 2016), robots with a simple shape are more likely to be ubiquitous in the near future. Castelli et al. (2000) conducted a study in which participants watched silent computer animations. The figures in the animations were simple geometric shapes whose movement patterns triggered a mental state or action recognition in the observers. Moon et al. (2011) confirm that even when the human wrist trajectories were the only replicated components of the gestures in the robot motion compared to their human counterparts, the gestures could be successfully recognized by the participants. Already Heider and Simmel (1944) showed that even simple objects in motion can be manipulated to communicate intentions through small movements. In fact, robots that perform easy-to-automate tasks such as package delivery consist of simple geometric shapes like a box.

Even robots that have a simple geometric design should reflect human social norms and show a consistent set of behaviors (Bartneck & Forlizzi, 2004) that reflect common sense (Rios-Martinez et al., 2015; Barraquand & Crowley, 2008) and may also be inspired by human-human interaction (Schubö et al., 2007). Development of robot behavior to reflect what is common sense among humans requires to translate human social behavior to robot behaviors. Studies in HRI often lack a theoretical foundation based on models from psychology in human-human interaction (Leichtmann & Nitsch, 2020). In this domain, Mehu and Scherer (2012) adapted the terms social signals and social cues, which originated in ethological research, for the use in human-human interaction. Individuals need to use information from their environment in a way that helps them make adaptive decisions. In this context, social signals are behaviors or components that are intended exclusively for the communication of the social signal and are rather explicit forms of communication (Mehu & Scherer, 2012). Social cues are rather nonverbal (Rios-Martinez et al., 2015). Facial expressions, body posture, neuromuscular and physiological activities may not only be a response to a stimulus, but also represent communicative cues. Social cues are not built to be communicative units, however, to observers they provide a method to derive information (Mehu & Scherer, 2012). These are rather implicit forms of communication. This ethological metaphor can also be used to classify communication modalities of robots (Reinhardt et al., 2018).

Reinhardt et al. (2018) discussed that the ethological metaphor means that a signal is displayed via a device designed exclusively to communicate the signal. For example, a request to a pedestrian to stop, displayed on a screen attached to a robot, could be called a signal. Cues on the other hand make use of technical devices that exist primarily for other specific functions. A mobile robot consists of technical components (e.g. motors, wheels) that enables it to drive. These components' function primarily is to enable forward motion of the robot. If the movement of a robot is additionally used to communicate intentions, which is expressed in short-term movement variations, it can be called a motion cue. Motion cues potentially give humans insights into robot intention in cooperative situations, which can improve human performance in terms of time to completion and trust (Lasota & Shah, 2015; Reinhardt et al., 2017; Hancock, Billings, & Schaefer, 2011; Law, de Leeuw, & Long, 2020). Saerbeck and van Breemen (2007) and Knight, Thielstrom, and Simmons (2016) showed that with non-humanoid robots, intent can be expressed by varying the trajectory of motion.

To consider social norms in the context of scenarios when humans and robots share the same space, rules for establishing a social hierarchy must be identified (Rios-Martinez et al., 2015). For conventions such as the order of passage, rules similar to those observed between humans may be appropriate. In Vinciarelli, Pantic, Bourlard, and Pentland (2008), generic descriptions of social cues are summarized and linked to signals they are suited to represent. However, these descriptions are at too high a level to meet the requirements for a complete robot motion language (Reinhardt et al., 2018). Efficient and silent cooperation enabled by intent-expressive motion requires a correct application of motion properties. This can only be achieved by a prior consideration of the situation and profound knowledge of how people process and perceive movements given the constraints of the situations. It requires a situational decision whether a legible or a predictable motion is more appropriate. In the study by Faria et al. (2017), it was not clear which strategy works better in a scenario with multiple users encountering a robot. An improper application of either motion class may even complicate the cooperation. Empirical evidence can be found in Kruse et al. (2014), who studied navigation strategies of robots when crossing the path of a human. Even though the participants mainly focused on the trajectory behavior of the robot, they also perceived small changes in velocity that were not intended in the robot's trajectory. These unexpected velocity changes, even without any meaning, irritated the participants. It is therefore crucial to avoid accidentally creating misleading cues (Lichtenthäler & Kirsch, 2016).

Legible motion cues are a suitable way to solve situations that require cooperation, especially in crowded or noisy spaces where other modalities such as audio would be impractical or useless.

1.3.2 Design methods for legible motion

Although individual studies on stylization of robot movements already exist, a generalizable framework or collection of design features on motion sequences and their effect on humans is not yet established (LaViers & Egerstedt, 2012; Carton et al., 2016). Existing work examining the impact of motion on interaction with robots often uses different terms for what is essentially the same concept, legibility. The review by Lichtenthäler and Kirsch (2016) compares the findings of 32 different studies. The authors find that the different terms legibility, readability, anticipatory, predictability and human-likeness are often used interchangeable for intent-expressive motion. An appropriate use of this type of motion improves cooperation with robots and autonomous systems. Therefore, articles exploring the core concept underlying legibility are included in the following review, even if the term "legibility" is not used in the paper. This chapter first presents classifications of design methods before concrete design principles are presented.

Saerbeck and van Breemen (2007) distinguish three classes of methods to design expressive motion: *Trajectory design methods* are hand-crafted techniques such as scripted animations or key framed animations. *Motion editing methods* include signal processing and the blending of existing animations. *High level behavior design methods* include algorithms that create a certain behavior such as emotional reasoning and subsequent parameter variations. Venture and Kulić (2019) divide design methodologies into *implicit* ones that generate motion where the purpose of the movement is to solely convey an intention, and *formulated* methodologies that enable simultaneous generation of functional and expressive movement. Implicit approaches cover movements that are hand-coded or animation-inspired. Such an approach may take advantage of expert knowledge in motion design, however, the designed motion is hard to generalize to other movements or to integrate in an autonomous robot's navigation strategy. Such design was applied in the works of Bretan, Hoffman, and Weinberg (2015), Inderbitzin, Väljamäe, Calvo, Verschure, and Bernardet (2011), Takayama, Dooley, and Ju (2011), Faria, Costigliola, Alves-Oliveira, and Paiva (2016). Formulated approaches, on the other hand, are algorithmic methods that formalize motion into a mathematical model. The HAN algorithms usually fall under this framework and the formalized legibility functions by Dragan et al. (2013), Stulp, Grizou, Busch, and Lopes (2015), C. K. Liu, Hertzmann, and Popović (2005), Chakraborti, Kulkarni, Sreedharan, Smith, and Kambhampati (2019) are examples for this type of design methodology applied in a legibility design and assessment. In the *co-creation* method, participants are directly involved in the design process of an interaction. This is in contrast to classical ergonomics research, where the user is the subject (Sanders & Stappers, 2008). In this context, the human roles can vary. Depending on the level of expertise, passion, and creativity of the user/co-designer, different levels of manipulation by the participant can be achieved. Besides few examples like the study of Lauckner et al. (2014), an active inclusion of participants in the design process is sparse in HRI research.

Some guiding principles for the design of robot motion could be derived from the literature. *Complementary motion* is additional to the navigational movement (Basili et al., 2012; Nehaniv et al., 2005). Takayama et al. (2011) and Schulz, Torresen, and Herstad (2019) follow the specifications of *animation principles*. *Human-likeness* of motion generated from human motion data is the underlying principle in Beetz et al. (2010) and Kuz, Bützler, and Schlick (2014) and Fuest, Michalowski, Träris, Bellem, and Bengler (2018). Furthermore, *proxemics* (Lauckner et al., 2014), *stereotypical motion* (Beetz et al., 2010), *exaggerated trajectories* (Dragan et al., 2013), *the Laban Effort System* (Knight & Simmons, 2016), *the Uncanny Valley* (Piwek, McKay, & Pollick, 2014), and *animalistic motion* (Faria et al., 2016), serve as inputs for concrete designs. The following gives a closer look at the underlying research methods and results.

It is a commonly studied method to vary proximity in experiments to infer specific preferred motion design variations. In the experiments by Lauckner et al. (2014), stationary participants steered a robot remotely. The participants adjusted the stopping distance between them and an approaching robot via the push of a button. In addition, the lateral distance to a bypassing robot was set by the participants. The goal of the study was to derive minimum acceptable values for the distance with regard to proxemic rules (Mead & Matarić, 2016). Pacchierotti et al. (2006) studied a robot moving along a hallway with participants moving in the opposite direction. The lateral passing distance was varied. The participants rated the robot behavior according to perceived comfort.

Dragan et al. (2013) aimed to verify whether predictability and legibility were contradicting properties of motion. They exposed participants to video recordings of simple points, a robotic arm, and a human arm, that started to grasp one of two bottles. The movements were varied in two ways: One trajectory was calculated according to the authors' predictable formalism, the other one according to the legible formalism. As a dependent variable, subjects noted the time at which they were certain about the actor's target and which of the two bottles was chosen by the actor. Using these measurements, the authors created a combined score to evaluate the legibility of the trajectory. Legible trajectories were found to be those that showed strong evasive maneuvers towards the target early in the movement. Furthermore, the end effector turns towards the goal earlier in a legible movement in the condition that included a robot. This highlights the need to consider more than just the basic motion of a robot for legibility. In order to classify what movements are applicable to robots with respect to their embodiment, Venture and Kulić (2019) sort robots according to their degrees of freedom.

Authors in the automotive domain argued a need for balanced acceleration and deceleration profiles to communicate effectively with pedestrians (Zimmermann & Wettach, 2017; Fuest et al., 2018). Fuest et al. (2018) had participants drive a car with the task of either executing a maneuver that conveyed the intention to yield right-of-way to pedestrians or to claim their own right-of-way. The authors combined the recorded driving styles into an average recommended trajectory. Ackermann, Beggiato, Bluhm, Löw, and Krems (2019) used vehicle deceleration as motion cue. The authors varied movement parameters such as deceleration rate, onset of deceleration, vehicle size, and speed. They investigated the ability to detect yielding intentions using video-based simulations. Consequently, communicating yielding intent of automated vehicles to pedestrians should exhibit smooth and early deceleration. This is is further altered by vehicle speed and size.

Knight and Simmons (2014), LaViers and Egerstedt (2012), Sharma, Hildebrandt, Newman, Young, and Eskicioglu (2013), Knight and Simmons (2016) researched applications of the *Laban Effort System* in robot motion. Originated in the discipline of theater, it is a framework to classify how actors generate expressive motion. Four categories, time, weight, space, and flow, define the framework. According to this framework, efforts such as acceleration or focus can be combined along a trajectory in a way to reflect an actor's inner state. In an experiment by Knight and Simmons (2014), subjects moved an object between two points with the goal of evoking the different attributes, happy, sad, confident, shy, and rushed. The authors discovered principles that link movements to the expression of a state. Specifically, they concluded that communication of a shy attribution represents paths with hesitation and that timing is a primary design parameter for distinguishing movement patterns. Because of its origin in the description of motions performed by humans, the Laban Effort System is better suited for designing motions for humanoid robots than for simple service robots (Reinhardt & Bengler, 2021). Li et al. (2019) also used such a metaphor. Using concepts from improvisational theater, the authors examined movement styles in three scenarios. The robot was to either move laterally, approach, or move away. The movement was intended to communicate a robot's dominance status using only motion.

In an attempt to validate the *Uncanny Valley* hypothesis of Mori, MacDorman, and Kageki (2012) in respect to motion, Piwek et al. (2014) could not confirm a direct link between the optical and movement human-likeness of a character and the affinity that humans felt. However, the study of humanoid robots in terms of motion involves many dynamic features. Humanoid robots have many degrees of freedom that allow complex movements, and it is inevitable to exclude their complementary gestures, facial expressions, or general embodiment when trying to measure the effect of movement. Therefore, there is a risk of confounding effects in such experiments.

The computer animation discipline focused on the design of movements early on. To support this, Lasseter (1987) described fundamental principles for such motion design. For example, through *timing* the motion of an object in specific proportions, a communicative effect can be achieved. When robotic movements are also designed according to principles of motion design, correlations between physical properties such as geometric dimensions or color, with human perception of the motion are expected (Reinhardt & Bengler, 2021). Schulz, Torresen, and Herstad (2019) generalize a list of twelve animation techniques that are used in robotic motion design. A robot's movement design according to the animation principles *slow in* and *slow out* has been applied by Schulz, Holthaus, et al. (2019). Two velocity profiles, one of which was created using these principles and the other one as a standard linear profile, were applied in a robot. The dependent variable was the human's perception of the robot while working together on a task. They find no strong differences between the perception of the two strategies. The authors discuss whether they should have implemented multiple motion design principles in combination to achieve a stronger effect. In agreement with Venture and Kulić (2019), they argue that the inclusion of multiple body parts in addition to the use of base movement alone could improve the possibility of achieving a communicative effect via movement.

Schneider and Kummert (2020) find that humans wish to have an adaptive robot rather than one they can adapt themselves. Thus, a viable approach to the design of robotic behavior could aim at adapting robot movements to changes in the human behavior in real-time. However, in other studies, overly adaptive robot motion has led to additional confusion about what the robot wants to do (Kruse et al., 2014). Pacchierotti et al. (2006) also expressed concerns about a possible excessive degree of adaptivity. If the human's actions are tracked with too high a frequency and the robot's own behavior is constantly adjusted to match the human, the back-and-forth loop in resolving a spatial conflict can lead to human disengagement and distraction. Since the robot changes its trajectory frequently, a human cannot adapt to it precisely. To counteract this, predefined and consistent motion cues could be used with non-humanoid robots and simple embodiment as a nonverbal communication method. A motion cue should be scripted and remain as is so that humans can better anticipate robot behavior (Cha, Matarić, & Fong, 2016; Faria et al., 2016; Reinhardt et al., 2018; Reinhardt et al., 2017). The state-of-the-art applied HAN does not take into account scripted changes in direction and amplitude of movement

(Kruse et al., 2014). Also, the point of view that an observer has on the motion must be taken into account in the design. The effect and design implications of the viewpoint of the observer on the perception of the movement of a robot is discussed in the works of Nikolaidis et al. (2016), Schulz, Holthaus, et al. (2019). The theory behind this has already been evaluated in other domains. An example will illustrate why this is important: A linear motion is not perceived as linear if it is performed in an angular constellation with respect to the observer. Especially for distant motions the boundaries between depth perception of motion and a lateral perception become blurred (Gibson, 1950; Clark et al., 2013).

What most of the cited papers have in common is that the description of motion is not broken down to individual parameters. This is seen as a major research gap that this thesis aims to address. If motion is not broken down into its single components, a reproduction of the movement is not possible for other researchers. Transferring the effect of the motion to other embodiments of robots or implementing the motion cue in a different scenario may also be inhibited (Reinhardt & Bengler, 2021). Detailed investigations of the parameters that constitute movements are necessary in order to be able to design the movement that conveys an intention in the best way (Reinhardt, Prasch, & Bengler, 2021). For example, the descriptions of motion cues in the work of Vinciarelli et al. (2008) do not specify spatial representations of cues in terms of technical parameters such as *velocity* or *acceleration*. Therefore, there is a need for parametrization.

While the number of articles on the classification of design methods is considerable, reports on design according to specific motion parameters are rare.

1.3.3 Implementations

The following summarizes specific implementations of what was defined as a motion cue in Chapter 1.3.2. Several authors have designed motion cues and applied them in empirical user research. In this chapter, there is a focus on how they are designed by motion parameters, when it is possible to report them. It also discusses the intent they were designed to convey and how well they performed.

Moon et al. (2011) investigated the communicative capabilities that can be expressed in the trajectory characteristics of hesitant movements. In their video study, participants watched recordings of hesitation motions and rated whether they recognized this intent. Movements were performed by both a human and a robot. They extracted trajectory characteristics of such hesitation gestures. The results show evidence that hesitation gestures that are implemented in a robot arm can convey similar communicative value as such motion performed by humans. In addition, the gestures are composed of a characteristic acceleration profile. The authors report that they used only four out of six of the robot's joints. They considered retract-type, and pause-type hesitations. In pause-type hesitation, the hand or robot's end effector halts in midair until the spatial blockage is cleared. In retract-type hesitations, an additional backwards movement to the original position is performed. The authors provide acceleration values to describe the movements. They report peak accelerations of M = -1.40 cm/s^2 (SD = 0.12 cm/s^2) for humans who perform a retraction movement. Such human values could be translated into appropriate robot motions. Also other authors report on findings to a similar retraction cue. In Sadigh, Sastry, Seshia, and Dragan (2016), a back-off movement emerged from autonomous planning in a traffic scenario. The authors use machine learning methods that develop a back-off maneuver in self driving car scenarios.

Kaiser, Glatte, and Lauckner (2019) researched the effect of motion cues on people's self-reported appreciation and the legibility of a robot's motion. They show that participants have a higher appreciation for robots that perform a polite movement to the side compared to dominant robots that do not let participants pass. In social interactions, dominance has been shown to correlate with lower trust in a robot (Li, Ju, & Nass, 2015). Furthermore, people are less hesitating when the robot moves out of the way before it stops. The movement is performed to the side in a frontal encounter at a door and intended to communicate letting the person pass first. A participant and the robot simultaneously approached a bottleneck either side by side or from opposite sides. The robot performed three behaviors. It could move without any explicit cue, stop, or move aside and then stop. The authors found significant effects of the cues on the participants' appreciation and the legibility of the robot's motion. Another discovery was that the sideways movement allows more fluent motion of humans.

Kruse et al. (2014) test deceleration versus a change in direction with constant speed in a path-crossing scenario with humans. The participants rated deceleration without changing the direction of motion as more comfortable and easier to read compared to changing direction without changing speed. Here, the robot uses a path planner and thus generates slightly different trajectories each time it encounters a human.

Other examples of expressive motions include Müller, Stachniss, Arras, and Burgard (2008), who implement a robot behavior to shoo away people who block a narrow passage. The robot achieves this by accelerating towards the person. A similar concept is explored by Knight, Lee, Hallawell, and Ju (2017). They investigated how a robotic chair could convince people to let it pass in a bottleneck. To achieve this, it applies an effective forward-backward motion, as opposed to a subtle pause and side-to-side motion. However, they find that the effect of the motion decreases rapidly with the number of trials. This is an aspect that Fink et al. (2014) also discuss. Fink et al. (2014) apply a *wiggle* behavior in a robotic toy box. The movement can be described as turning from side to side and is intended to engage children to tidy up their room. Faria et al. (2016) tested a movement cue to convince participants to follow a robot by moving towards and away from a person. The authors experienced weakened results as the cues were confounded with other behaviors like nodding the head or flashing a light. Thus, a clear alignment of effect of the planned motion on the human response is not possible. In a study by Hoffman and Weinberg (2011) a marimba-playing robot used the animation principle of *slow in* and *slow out* to signal and better synchronize with the musicians playing along. Hetherington, Croft, and Van der Loos (2021) report findings on motion legibility cues, however, the authors use the term differently and instead of using the robot's body motion, they implement additional features such as projections and lights.

Motion designs in HRI studies have so far tended to focus on static scenarios in which rarely both interaction partners move (Morales et al., 2014). Furthermore, although human-like robotic motion has been assessed as crucial for human interpretive ability near robots (Carton, Turnwald, Olszowy, Buss, & Wollherr, 2014), robots in HRI studies typically move slower than usual human speeds (Butler & Agah, 2001; Hüttenrauch, Eklundh, Green, & Topp, 2006; Pacchierotti, Christensen, & Jensfelt, 2005). Such unnatural speeds lead to insufficient acceptance and inefficiency. In the experiment by Carton et al. (2016), a slow robot also caused interacting humans to slow down from their natural walking speed. When the problem is properly addressed, as demonstrated in an industrial robot, anthropomorphic velocity profiles in the motion led to a reduction in the time required for humans to predict the robot's motions (Kuz et al., 2014).

A problem that arises with the state of the art of motion cue applications is that some authors used autonomous robots in their experiment (Kruse et al., 2014). Experiments with an autonomous robot imply that the motion is never exactly reproduced. Therefore, the robot moves slightly differently each time it encounters a participant. Another issue is that motion is rarely reported in terms of its physical parameters such as path and speed over time (Kaiser et al., 2019; Fink et al., 2014; Knight et al., 2017). This lack of reporting inhibits reproducibility of the study.

The informative value of the reviewed motion cues suffers from confounded experimental designs or the use of autonomous robots instead of scripted movements and thus, insufficient reproducibility. In most cases, motion is not reported as description of physical parameters.

1.3.4 Evaluation methods for legible motion

This section provides an overview of evaluation methods that aim to measure the effect of intent communication on humans, in other words, legibility. There are studies that consider quantitative measures, and there is an overwhelming number of qualitative measures (Kruse et al., 2013). Some experiments also aim to combine qualitative and quantitative measures (Lichtenthäler & Kirsch, 2016).

As a basis for successful HRI, human trust in the system must be established (Hancock et al., 2011; Meyer & Lee, 2013). This construct combines reliance and compliance. Reliance describes the extent to which a person relies on the correctness of the behavior of a robot. Compliance is the extent to which a person follows the instructions given by a autonomous system (Meyer & Lee, 2013). Therefore, a robot's legible motion and the human's ability to interpret intentions play an important role in the decisions associated with trust (Hancock et al., 2011). Under this assumption, legibility and trust have been evaluated in combination (Reinhardt et al., 2017; Reinhardt, Boos, Bloier, & Bengler, 2020). Trust can be measured qualitatively through questionnaires and quantitatively through metrics such as the relative number of times a person agrees to an action recommended by a robot (Babel et al., 2020; Körber, 2018; Boos, Sax, & Reinhardt, 2020; Nunnally, 1994; Fuchs & Diamantopoulos, 2009).

Legibility is given when a movement conveys an intention efficiently and effectively. From the human perspective, this means that a movement is legible if the observer can quickly and confidently infer the goal (Dragan et al., 2013). This means that one component of legibility evaluation is time. In this context, a researcher would typically formulate the hypothesis that a movement is more legible if an intention can be inferred more quickly (Basili et al., 2012). It can also be compared to a traditional HRI-assessment metric, the time-to-completion (Steinfeld et al., 2006). Dragan et al. (2013) measured the time from the start of the robot's movement until the participant indicated which of two bottles the robot was going to pick by pausing the video. This measure was weighted by prediction accuracy to obtain a combined legibility score. This approach is also mentioned by Steinfeld et al. (2006) as a classification accuracy in perceptive measures. Similarly, in Gielniak and Thomaz (2011), participants were asked to indicate the time at which they were confident they could predict the robot's intention. After stopping the video at the click of a button, the screen changed to a blank screen with an empty prompt for typing the intention. In general, two variations of this method have been observed. The first of which is that participants are required to indicate the intention during interaction (Gielniak & Thomaz, 2011; Dragan et al., 2013). The second one is that participants indicate the intention at a predefined time (Takayama et al., 2011; Basili et al., 2012). Bodden, Rakita, Mutlu, and Gleicher (2016) mention three factors that the observer performance of intent-expressive motion depends on: The kinematic abilities of the robot, the viewpoint towards motion and the estimation time relative to the overall motion execution time of the robot.

There are purely quantitative evaluation metrics that are somewhat related to legibility such as human idle-time, minimal distance to the robot, walking speed changes, or path-change (Steinfeld et al., 2006). Metrics are often derived from the proxemics literature (Pacchierotti et al., 2006). These include human task performance metrics or motion tracking techniques to monitor human movement patterns. Carton et al. (2016) apply trajectory smoothness as a human-side metric. The authors' goal is to reduce the planning effort for both, human and robot by implementing human-like motion in an autonomous robot. Human responses to different behaviors of a path intruder, which was either a human or a robot, were evaluated in a probabilistic manner by applying confidence intervals to the trajectories executed by the participants. The authors conclude that they consider a trajectory to be more legible when the reactive human trajectory is mathematically smoother. A similar approach was used in Reinhardt et al. (2016). Here, the smoothness in the following behavior of a human behind a mobile robot is compared between different motion styles of the robot.

By some authors, qualitative legibility has been assessed by asking participants to rate their experience of the entire HRI in retrospect. In Dehais, Sisbot, Alami, and Causse (2011), participants were asked to rate legibility on a 9-point scale from very low to very high after being presented with each of three motions. Heerink, Krose, Evers, and Wielinga (2009) proposed a questionnaire for the investigation of socially accepted robot behavior, in which the subjective measures *perceived usefulness*, *perceived ease of use*, and *perceived enjoyment* were collected. It is important to have standardized metrics for evaluating the success of robots in order to compare and validate results between different implementations (Weiss & Bartneck, 2015). Therefore, another research tool that has become omnipresent to the HRI research field is the *Godspeed Questionnaire* (Weiss & Bartneck, 2015). Bartneck, Kulić, Croft, and Zoghbi (2009) designed this questionnaire to measure *anthropomorphism*, *animacy*, *likeability*, *perceived intelligence*, and *perceived safety* of robots. With a citation count of 1444 as of April 2021 according to google scholar, it is one of the most cited and reused evaluation tools in HRI. When reviewing articles in the field of participant studies, one can get the impression that this questionnaire is treated as a one-fits-all solution. However, Schulz, Holthaus, et al. (2019) find that the *Godspeed* does not have a sufficient item structure for measuring legibility, predictability, or safety. Therefore, using the Godspeed in conjunction with legibility should be done with caution.

A subjective measurement scale may not be sufficient for capturing people's perceptions (Schulz, Holthaus, et al., 2019; Winkle et al., 2019). Legibility is a complex construct. Therefore, an evaluation tailored to the experimental scenario is necessary. An example can be found in Kaiser et al. (2019), who examined the legibility of different motion cues. They captured the participants' responses to the statement: "The movement of the autonomous assistant is courteous" on a 5-point Likert scale. Specific to their study was the notion of courtesy, thus, the degree to which the intention of yielding priority could be communicated by each experimental condition. For each condition, this was assessed by asking "How did you perceive the movement of the autonomous assistant?". The responses to these six distinct items were given on a 5-point Likert-scale ranging from *courteous* to *discourteous*.

Some general guidance for experimental design, including legibility evaluation, can be summarized. Paetzel et al. (2020) point out that it is important to give participants time to interact with a robot before measuring their perception of the robot. In addition, confounding is an issue and experiments should be controlled to highlight the cue being evaluated. Faria et al. (2016) and Kruse et al. (2014) experienced weakened results by confounding the cues with other robot behavior, thus, a clear alignment of effect to the planned movement cue was not possible. It is not recommended to ask about legibility in retrospect as applied in Dehais et al. (2011). If we view this construct as Dragan et al. (2013) has defined it, namely as the quick and confident recognition of the robot's target, it is not possible to measure legibility in retrospect and by directly naming it a legibility measure. Rather indirect measurements are needed. It is important not to bias the evaluation by priming participants the intention behind a movement. Furthermore, the core components of legibility, efficient and effective communication must be measured, rather than asking directly if a movement appears legible.

It is promising to evaluate legibility through a combination of specifically designed questions, and measurement of the efficiency and effectiveness of intention-inference.

1.4 Research questions and contributions

This thesis aims to provide a new perspective on the design and evaluation of legible motion cues in HRI. There are some key characteristics and shortcomings with the existing approaches as follows. Many experiments are done with autonomous robots, which is not reproducible. Furthermore, research questions in the domain of HAN often lack human-centric research questions. Hence this field of research appears like a robot's view in HRI. The algorithms do not embed nor recommend the concept of quick adaptive movements, similar to the ones humans would use. Conflict resolution in HAN is characterized by the robot's tendency to move forward and make slight adjustments to their trajectory (Chapter 1.1).

The research on HRSI reflects rather the human view in HRI. What the definitions and classification section shows is that an exhaustive application of interaction classification and interaction spaces both on the human and robot's side have not yet been established in a pedestrian scenario. Motion is legible if an observer can infer the actor's intention from observing its movement. However, to measure this and to interpret a person's behavior as a result to a robot's maneuver, it is important to consider human perception of motion and his or her own execution of movements (Chapter 1.2).

Motion cues as a motion language for robots have been introduced by some authors as a suitable way to solve cooperative situations, especially in crowded or noisy spaces where other modalities such as audio would be impractical or useless. However, the concept of legibility is not extensively evaluated. No detailed design of cues according to motion parameters exists. A design process according to transferable guidelines and evaluation with reproducible qualitative and quantitative methods should be established. While the number of articles on the classification of design approaches on motion is growing, reports on design according to specific motion parameters are rare in the literature. The informative value of the reviewed motion cues suffers from confounded experimental designs or the use of autonomous robots instead of scripted movements and thus, insufficient reproducibility. In most cases, motion is not reported as descriptions of physical parameters. To successfully measure legibility, indirect measurement of the construct by measuring components, efficiency, and effectiveness is promising. In particular, the field of easing spatial conflicts at bottlenecks leaves out a promising back-off movement application (Chapter 1.3). Accordingly, the following main research questions are formulated:

Research question 1: How can we measure the human sensory processing of a motion cue and combine it with a legibility assessment?

The back-off serves as the research tool throughout the thesis providing an exemplary motion cue designed to communicate the intention of yielding priority to humans. As a basic requirement, movement cues have to be perceivable in regard to the human capabilities to process motion. Second, the intent behind a movement cue has to be understood effectively and efficiently, hence it must be legible. The back-off motion cue is first introduced in Chapter 2. Chapter 3 transfers the motion cue to an application in mobile robots and conducts a detailed qualitative and quantitative evaluation of Research Question (RQ) 1.

Research question 2: How does a motion cue affect the motion behavior and efficiency of humans in human-robot spatial interaction?

Chapter 3 applies a thorough analysis of human motion behavior in response to different robot motion behaviors. To this end, the back-off motion cue is applied in a mobile robot with two different design variants. In this publication, the RQ is broken down into sub-questions that aim to establish a relationship between higher legibility of a back-off motion cue and an expected improvement in human motion efficiency.

Research question 3: How must a motion cue be parameterized to achieve the legibility effect?

This RQ addresses the fact that a motion cue needs to be broken down to physical parameters and designed accordingly to make it reproducible and applicable in different contexts. In order to make a back-off motion legible in a wider variety of robots, this motion cue needs to be adapted to robots of different sizes and tailored for varying spatial constellations between humans and robots. To answer this RQ, it is also of interest to not only present participants with predefined variants of a motion cue, but to actively involve them in order to find the best adaptation of the motion parameters. This is pursued in Chapter 4.

1.5 The design process for a customizable legible robotic motion cue

The composition of RQs, the scope of design and evaluation variables and the application and implementations of the ideas in the articles that lead to this dissertation, can be organized in a design process structure (Figure 1.1). This structure can possibly be reused and adapted to different design problems and help developers as a guidance throughout the development process of robotic motion language. The design process is divided into three consecutive phases, *Exploration*, *Interaction analysis*, and *Parameterization*. This thesis presents a novel composition of variables in the design and evaluation of motion cues for HRSI. Figure 1.2 provides an overview of the design and evaluation variables covered in this dissertation. On the robot side, the approach is oriented towards the domain of implicit design methodology (Venture & Kulić, 2019). To concretize the movement, the process builds on the foundations of legibility research (Dragan et al., 2013), animation principles (Schulz, Torresen, & Herstad, 2019), and previous works with similar motion cues (Moon et al., 2011; Kaiser et al., 2019). On the human side, the concept of information processing is applied (Wickens et al., 2016), consisting of, sensory processing [vision (Gibson, 1950), information processing (Kitazawa & Fujiyama, 2010)], perception [awareness (Harms et al., 2019), interpreting action (Sebanz et al., 2006)], response selection [legibility measure (Dragan et al., 2013), compliance (Meyer & Lee, 2013)], and response execution [human motion (Muir et al., 2014), subjective evaluation (Lichtenthäler & Kirsch, 2016)].

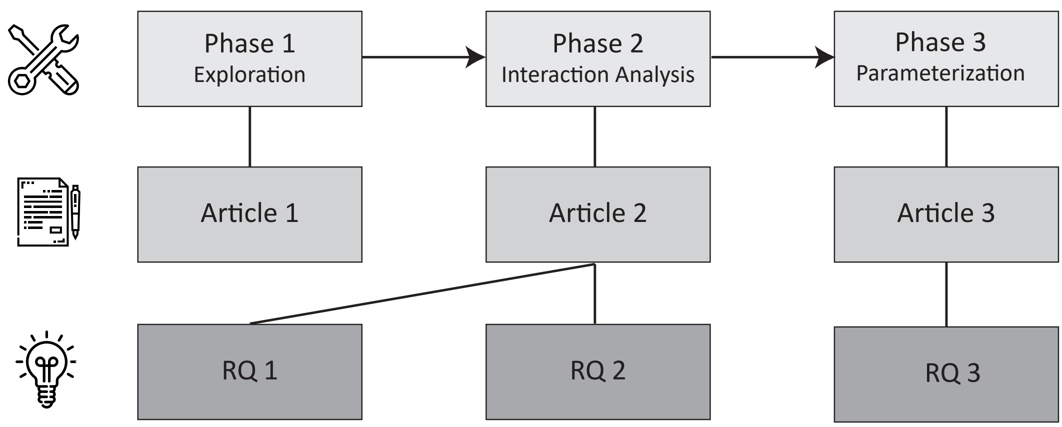

Figure 1.1: The design process structure for a customizable legible robotic movement cue shows the connection of three research questions, three articles, and the three design phases conducted in this dissertation.

1.5.1 Phase 1: Exploration

This phase of the design process is undertaken in Chapter 2. In a human-robot cooperation scenario, a particularly close interaction between the human and a cooperating robot takes place and provides the opportunity to explore multiple motion cues. In this proximity, efficient communication from the robot to the human co-worker is especially important.

The referenced work in Chapter 1.1 summarizes where autonomous robot research stands and what behaviors could be added to this area of currently applied motion. Furthermore, the referenced work in Chapter 1.3.2 can serve as a source for design methods of motion cues in the exploration phase. In this thesis, the back-off motion cue is established with an industrial robot. The spatial proximity between human and robot allows the assumption that the human is able to perceive the motion cue and thus the level of detail of the sensory processing investigation can be kept comparatively low. Instead, the focus can be on subjective evaluation in scales and qualitative comments about how the motion cue is perceived or understood.

At the end of this first stage, an idea for a motion cue is born. Researchers are able to have a good guess of how the motion cue is executed. In the example of back-off, it is clear at this point that it should be executed as a movement backwards along a robot's original trajectory when a collision with a human must be avoided or an order about who has priority needs to be arranged. Therefore, the researchers also know the intention they want to communicate with this cue: Giving priority to a cooperating human. After evaluating user comments and subjective analysis, the motion cue seems promising for successfully communicating this intent.

1.5.2 Phase 2: Interaction analysis

Being heavily focused on RQ 1 and RQ 2, the second phase first involves a thorough analysis of the legibility assumption set up in the previous step. This stage of design process is focused in Chapter 3. At this point, it has not yet been fully evaluated whether the motion cue can be sensory processed and whether it successfully communicates intent to a large proportion of the people observing the motion cue (RQ 1). Once this is achieved, the subsequent question becomes which variants of the motion design perform better or worse, and whether legibility leads to more efficient human motion behavior (RQ 2).

To enable this evaluation, a study design with uninformed users is needed. Ideally, none of the subjects has previously encountered a robot exhibiting the motion cue in question. To target RQ 1, the motion cue should be presented to a broad population. Showing videos of the targeted movement can be a viable method. Interviewees should be asked qualitative questions that focus first on sensory processing and then on the legibility of the motion cue. Procedures for evaluation at this phase can be derived from the referenced work in Chapter 1.3.4. In this work, subjects in public places were presented with different motion cues as videos that were intended to communicate the same intention of giving precedence. Participants were indirectly asked how they perceived the execution of the movement and what intention they derived from it.

Subsequently, a real encounter between human and robot enables the evaluation of quantitative motion data in an interaction analysis. Here, a motion cue should be designed in different variants that seem feasible to the experimenter or show the limits of what is feasible with the motion capabilities of the robotic system used. The design parameters serve as independent variables in the study. The range of possible physical motion parameters was explored in Chapters 1.3.2, and 1.3.3. Motion parameters to be varied include but are not limited to: *Distance to the human, path travelled, velocity, acceleration, execution time of the movement, smoothness of the trajectory, number of repetitions.* In this work, the motion cue is adapted to mobile robots for use in communicating the intent to yield the right-of-way to pedestrians at a bottleneck. The parameters *path travelled* and *execution time* have been used from the aforementioned list. The back-off is presented in two variants. Different back-off lengths d and back-off times t are applied.

At this stage, it is important to validate whether humans are able to perceive the movement. This could be done using models of human spatial perception and interaction spaces derived from the Chapters 1.2.1 and 1.2.2 In the application of this dissertation, human perception of motion by applying IPS is considered as a prerequisite. Human responses to motion can be studied using motion tracking techniques. The scope of evaluation metrics can be derived from the work of human motion analysis in Chapter 1.2.3 and the summary of evaluation methods specified for robot motion in Chapter 1.3.4. These include but are not limited to: *Interaction time, deceleration/speed reduction, acceleration, stopping or walking, idle time, trajectory energy, minimum distance to the robot.* In addition to a wide range of applied metrics, this work focused on *interaction time* when analyzing human movements to assess their fluency and efficiency.

At the end of this phase, researchers will know whether the motion cue has been qualitatively legible to a large group of people and quantitatively legible to a selected group of participants. The first group can be tested via interviews and the second in a controlled study using motion tracking techniques in a real encounter between humans and a robot that displays the motion cue. In this work, back-off with a short path and short execution time showed the most promising results and was able to improve human efficiency in the second encounter with the robot compared to a stop-only behavior.

1.5.3 Phase 3: Parametrization

Last, the focus is shifted to the design, parametrization, and customization of a motion cue (RQ 3). This phase of the design process is covered in Chapter 4. Up to this point, a motion cue has been tested in several design variants for its legibility in a specific human-robot encounter situation. Therefore, there is an understanding of the effect of these variants in the situation. The idea behind Phase 3 is to make the motion cue applicable to a variety of autonomous systems and situations. This means that it must be adaptable to other robot shapes and spatial constraints between humans and robots. This adaptation must be formalized by adopting modeled approaches to the key physical design parameters of the motion.

This work recommends involving participants directly in designing the parameters of the movement. This is motivated by the design methods of co-creation and participatory design (Chapter 1.3.2). Compared to classical user research, where the user is the subject, here the user is the co-designer. This approach is more practical than presenting many different design variants to the participants. Accordingly, independent and dependent variables must be selected for the design approach, which can be achieved by considering human perception (Chapter 1.2.2), interaction classifications (Chapter 1.2.1), and the set of existing design parameters from Phase 2. In this work, the literature on size-speed illusions and viewpoint-based legibility considerations seemed to have the biggest influence and served as the main drivers for independent variables in the experiment. For the dependent variables, d and v (cf. Figure 1.2) were chosen, as an extension to the previous Phase 2.

At the end of this phase, the motion cue can be adapted to a larger variety of robots and situations. Therefore, there is a model that tells developers how to adjust the motion parameters to adapt the motion to a different robot in a different context while achieving the same intent communication. In this work, the back-off can be scaled in length and velocity for robots of different sizes and for two different viewing angles that the human observer may have on the motion.

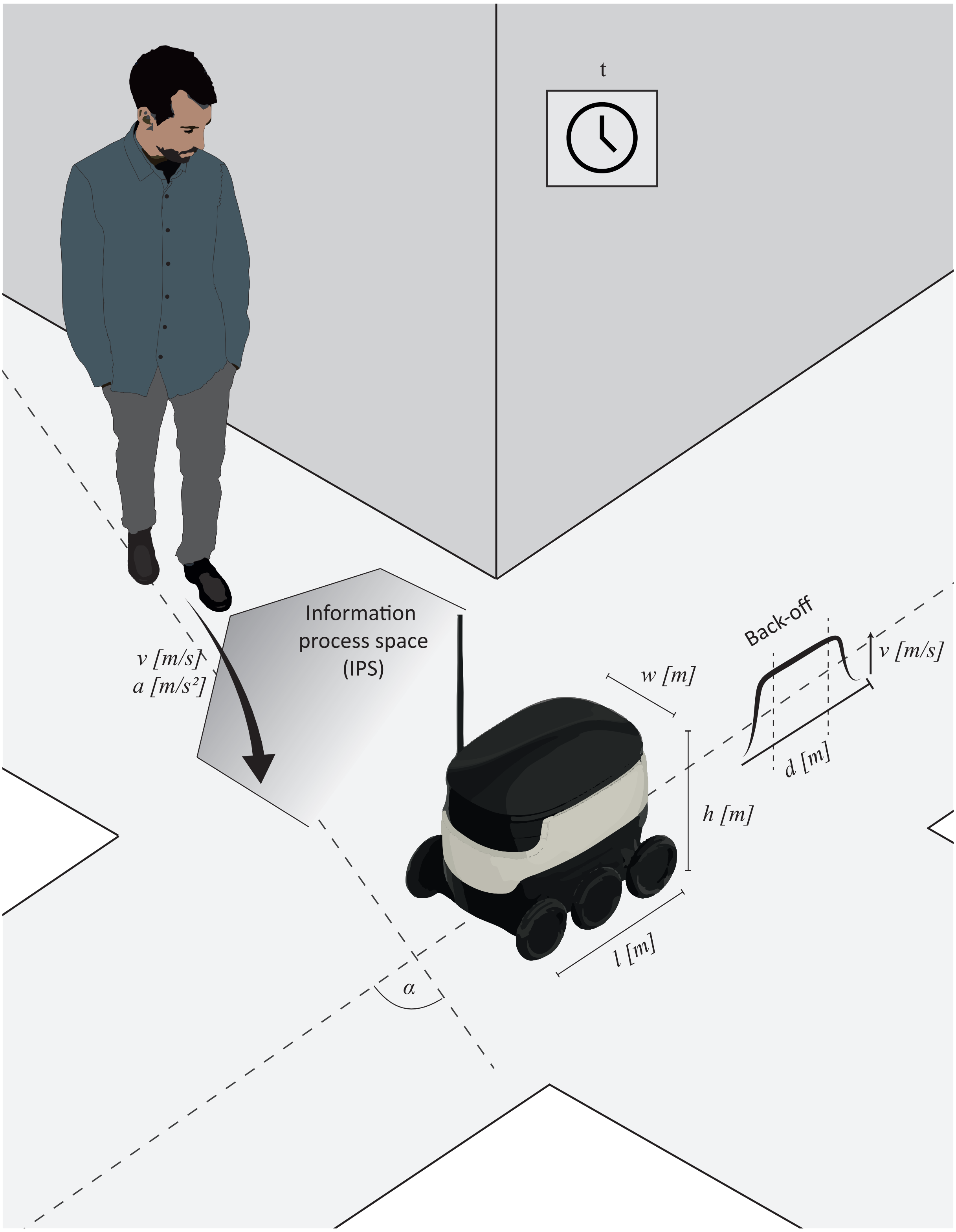

Figure 1.2: The figure illustrates the design and evaluation variables that contributed to this thesis. A back-off motion cue is varied according to the parameters d, v, t in a path crossing scenario and bottleneck. The human perception of the robot's motion is validated by applying the IPS to the orientation of the head. Movement analysis focuses on the parameters v, a, t. Two scenarios with different angles α of 90° and 180° are targeted resulting in lateral and frontal view of the robot's movement. The robot's size is varied according to l, h, w. The robot model is inspired by Starship Technologies' robot and was designed in a student project.

Article 1: Dominance and movement cues of robot motion: A user study on trust and predictability

Reinhardt, J., Pereira, A., Beckert, D., & Bengler, K. (2017). Dominance and movement cues of robot motion: A user study on trust and predictability. In 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC) *(pp. 1493–1498). IEEE*

Summary[1]

This article first introduced the concept of motion cues in this dissertation. The literature suggests that users have more confidence in autonomous systems when it is clear that the system is aware of them. The goal of this paper was to investigate which robot motion strategy outperforms in communicating intent and awareness during collision avoidance in a human-robot cooperation task. A short back-off motion was applied to grasping motions of an industrial robot in a shared workspace when the robot comes close to the human. The research question was whether a human-inspired back-off motion could communicate awareness and thereby increase trust and predictability. Robot motion was varied in two ways: By the presence or absence of the motion cue and by dominant or submissive behavior. This resulted in four motion strategies. Robot motion was characterized as dominant when the robot continued its task despite possible collision with the person, forcing the person to stop. It was called submissive when the robot interrupted its own motion and allowed the person to work on his or her task. The presence of the motion cue condition made the robot perform the back-off motion. The backward movement was always performed for a duration of 1 second. In the absent condition, it performed a simple stop. The hypotheses stated trust and predictability towards the system would differ between the four motion strategies. Twenty-five healthy volunteers took part in the study (40% female). The participants had to arrange small objects in a common workspace while working on the same product as the robot. Participants were instructed to perform the task quickly and accurately. While working on the task, the robot's strategies were applied in randomized order to avoid bias due to a learning effect. A validated questionnaire was used to measure trust and predictability on a 5-point Likert scale. In addition, human task completion time was captured for an exploratory analysis. The results showed that the submissive back-off movement strategy significantly enhances the users' trust compared to the dominant movement strategy without movement cue. The other strategies showed no significant differences in trust or predictability ratings. The study provided initial insights into the communicative qualities of a motion cue. The experiment also showed that some individuals would prefer the robot to act in a dominant manner. Quantitative metrics were not yet sought and the robot performed autonomous control, therefore participants didn't experience the same encounter situations.

[1] Author contributions: Aaron Pereira conceptualized the robot control and wrote parts of Chapter II. 3). Dario Beckert was involved in conducting the study and invited participants. Klaus Bengler provided overall comments. All other parts were written by the first author.

Article 2: Back-off: Evaluation of robot motion strategies to facilitate human-robot spatial interaction

Reinhardt, J., Prasch, L., & Bengler, K. (2021). Back-off: Evaluation of robot motion strategies to facilitate human-robot spatial interaction. ACM Transactions on Human-Robot Interaction*,* 10*(3)*

Summary[2]

Previous work suggested that standstill behavior by a mobile robot can be ineffective for a human's interpretation of a robot's intention and result in inefficient human-robot spatial interaction. In this article, a back-off movement was implemented in a mobile robot to communicate the intention of yielding priority to pedestrians at a bottleneck. To facilitate cooperation, robots can use motion to express intent. Such legible motion enables an observer to quickly and confidently infer the robot's goal. Uninformed pedestrians participated in order to evaluate intent-expressiveness with untrained persons. A focus of the study was on the human ability to perceive motion in a spatial interaction. As a prerequisite, the movement had to happen within a person's information process space. In a video-based preliminary study, the back-off was compared to three other motion strategies to evaluate human sensory perception and subjective legibility qualitatively. The interviews were conducted at the university and public spaces with $N = 167$ interviewees. The back-off movement provided the best results for legibility. Afterwards it was implemented in a real encounter between participants and the mobile robot *Beam*. The participants had to switch between two task inside the university's motion laboratory. On their way, they had to pass through a bottleneck where the robot appeared and an order of passage had to be established. They had to solve this situation in three trials involving the robot behavior in question. By applying the information process space, data analysis filtered out participants who were unaware of the motion cue and thus provided invalid measurements. The objective motion behavior of $N = 78$ participants as a reaction to a stop & wait strategy, and two versions of back-off (short and long path) showed that the pedestrians' efficiency was improved in the second encounter with the robot's short back-off version compared to a stop strategy. In the third encounter, interaction caused only a small time consumption. This residual duration is an order of magnitude that is always required by the cognitive process of perceiving an object in the visual field. Therefore, the legibility advantage of the motion cue was attenuated in the third trial of this study. Unlike previous studies in which participants were often only uninvolved observers, in this experiment participants actually interacted with a mobile robot. The article contributed to evaluation methods of legible motion strategies for human-robot spatial interaction. The results of this study also suggest that the design of kinematic parameters, back-off path, and time, influence human responses and should be investigated in a follow-up study.

[2]Author contributions: Lorenz Prasch wrote parts of Chapter 1.1, participated in the conceptualization of the data analysis method, and prepared Figure 1. Klaus Bengler wrote parts of Chapter 1.5 and provided overall comments. All other parts were written by the first author.

Article 3: Design of a hesitant movement gesture for mobile robots

Reinhardt, J. & Bengler, K. (2021). Design of a hesitant movement gesture for mobile robots. PLOS ONE*, 16(3)*

Summary[3]

In previous experiments, the back-off movement was introduced as a strategy of robots to facilitate the order of passage at bottlenecks. This article took a closer look at the appropriate design of the motion parameters to achieve legible motion. Insights from the field of human distance perception, size-speed illusions of moving objects, and viewpoint-based legibility optimization of robotic motion suggested that these variables have an impact on the parameterization. In particular, the literature suggests a relationship between the size of the robot and the observer's perspective on the expected execution of the backward motion. To allow the application in a variety of autonomous moving systems, the main research aim was how appropriate back-off design can be modeled and translated to different robots and observer's viewpoints. The experimental method was to integrate users into the design and involve them directly in the creation of the motion parameters, as suggested by the field of participatory design. In order to test a large number of variants, the experiment was conducted in a virtual reality environment. In this way, it was possible, for example, to vary the size of a robot from a length of 0.175 m to 1.204 m. The independent variables were the robot size, and the viewpoint of the back-off movement. As dependent variables, participants set the minimum required back-off length and the preferred back-off speed. Fifty participants took part in the study. Each participant experienced five different robots and set the back-off for each robot for a lateral and a frontal view in a sequential order. Back-off length and back-off speed were adjusted at the same time. The participants were asked to apply the minimum necessary back-off length, which is as small as possible but as large as necessary to be expressive. No additional information was provided for the back-off speed. In this analysis, additional focus was on idiosyncratic factors by applying a linear mixed effects model. Through a process of comparing models containing different intercepts and slopes, the best fitting model was identified. A significant relationship was found between increasing back-off lengths with increasing robot size. The model proposes to increase the back-off lengths by about 16% when the robot size is doubled. On the other hand, the influence of a certain point of view on the requirements of this movement was small. An exploratory analysis revealed that an execution time of $M = 1$ s might be a promising parameter to consider for the design of legible motions in general. As expected, the requirements for executing a movement in this experiment differed depending on the robot. However, only the assumptions associated with the *length* parameter were supported by the data set. Also, the effects found were rather weak. A follow-up question could be whether the motions can be trimmed to an optimized execution time while covering minimal distances.

[3]Author contributions: Klaus Bengler provided general supervision, wrote parts of Chapter 1 and general comments on the manuscript. All other parts were written by the first author.

Discussion

5.1 Results and additional experiments

This chapter summarizes the results of the articles and discusses them in a comparative manner. As the thesis contributes to the state of the art in design and evaluation methods of legible robot motion, the focus is on revisiting the experimental design, analysis, the presentation of guidelines and how to proceed with the results. Furthermore, this chapter includes some additional study results from experiments that were not included in the published articles.

5.1.1 Revisiting Article 1

In the results of the first article (Chapter 2), the submissive back-off motion cue ($M = 3.31$, $SD = 1.15$) was significantly prioritized in terms of trust compared to the dominant strategy without a motion cue ($M = 2.63$, $SD = 1.11$) ($p = 0.025$). The judgments towards other motion cues did not differ significantly. This finding was addressed in the following articles as the main motivation for further persecution of the back-off movement cue. The predictability scores showed no significant differences. It should be mentioned here that at this point in the course of the dissertation the term *predictability* was used differently. The underlying concept was treated more like legibility than predictability as defined as in Chapter 1.2.2. This means that the term was associated with intention inference rather than expected behavior. Another issue is the measurement of the construct. In the paper, predictability is assessed via the *Trust in Automation* questionnaire (Körber, Baseler, & Bengler, 2018) using the items: "The system state was always clear to me.", "I was able to understand why things happened.", "It's difficult to identify what the system will do next.", "The system reacts unpredictably.". What these items have in common is that the underlying concept of inferring an intention quickly and confidently is not evaluated. This is in contrast to the propositions put forward in this dissertation (Chapter 1.5).

Time was treated as a proxy for successful cooperation. The time to complete the task was calculated both for human and the robot (Steinfeld et al., 2006). There was no significant difference in the times that were achieved by the humans between the motion cues. However, regarding the conditions that included the motion cues, the robot stopped, resulting in significantly higher robot times, with an increase of about 55.6%. The combined efficiency of both actors in HRI was further deemed meaningful and followed up throughout the work.

At the end of the experiment, participants were asked about their preferred strategy and additional qualitative justifications for it. Opinions about the dominance and the submissiveness were mixed but for the group of interviewees that preferred submissive motion, comments like "The behavior of the robot is most natural and human-like when it backs off" were promising. Previous work had already suggested that humans prefer to complete their own task first and make the robot wait rather than let the robot go first (Li et al., 2015; Lasota & Shah, 2015). This could also be shown in the collected data set. Twenty-two of the participants, as opposed to three, chose to continue with their task when the robot stopped to yield priority to the humans. This indicated that humans were comfortable with a dominant role. In contrast, only three moved their hand or body back to allow the robot to continue.

The described use of qualitative feedback illustrates why this article serves as a suitable example of an exploration phase for motion cues as suggested by this dissertation (chapter 1.5). However, some shortcomings arise from the way it was conducted. The experiment lasted only about 20 minutes on average. In an industrial environment, the tasks of working with robots take more time. The motion strategy was changed after each of the four assembly tasks. This means that there was only one assembly task for each motion strategy, which took about 1-2 minutes. A higher number of trials with the same movement strategy could have resulted in more informed evaluations. In addition, the repeated measures design implied that each participant experienced each movement strategy in a short period of time. This may have made it more difficult for users to differentiate sharply in the ratings. In this experiment, an entry level microsoft kinect sensor was used so that only upper body motion velocities could be incorporated into the model as a proxy for human reachable areas according to ISO standards (ISO, 2010). More accurate motion tracking may have enabled more precise execution of motion strategies due to more accurate probabilistic modeling of human motion (Pereira & Althoff, 2017).

In a related experiment involving human-human interactions, we were able to observe the back-off movement cue in humans as well.[4] This investigation was done only after conducting the experiment of Article 1. In this cooperation task between two participants assembling Lego blocks, we observed that 54% of hesitation movements were *back-off and wait* movements, compared to 31% of *back-off and continue* movements and only 15% *stop and wait* strategies. As it is commonly used in human-human interaction, this finding supports the idea that submissive back-off is an appropriate movement strategy.

5.1.2 Revisiting Article 2

In the video study, the back-off was characterized by good legibility and was described correctly or correctly and only incompletely by the majority of interviewees. This indicated that it can be sensory perceived. Furthermore, the findings from the qualitative analysis regarding the legibility of a back-off from Article 1 were now transferred to a mobile robot. At this point, it could be concluded that back-off is also promising for mobile robots as a motion cue to communicate the right-of-way and thus promising for facilitating HRSI.

Subsequently, Article 2 addressed the implementation of the back-off motion cue as opposed to a stop-and-wait behavior in a real-world encounter between participants and a mobile robot. The back-off was presented in two versions, a short-path version and a long-path version. For the sample of 78 university students, the short back-off version was found to provide the fastest learning of an intention. The time improvement was approximately $M = 0.32$ s between participants' second encounter with the stop strategy and participants' second encounter with the back-off motion cue. In this setting, this corresponded to an increase in efficiency of 20%. Supported by an additional analysis of participants stopping their movement during interaction with the robot, Article 2 confirmed more fluid human movement with the robotic motion cue. This result is consistent with similar studies, for example, those by Kaiser et al. (2019).

Additional qualitative feedback from participants also confirmed that both back-off versions conveyed a stronger sense of communicating the right-of-way to people than the stop strategy. Here, legibility was measured with two questions. It is interesting that participants provided a lot more positive results regarding the question "The robot wanted to let me pass" than for the question "The robot made its intentions clear", where the responses were much more heterogeneous. This can be seen as a further indication that wording style is crucial in measuring legibility and rather an indirect measure is needed, as proposed in Chapter 1.5.

[4] Further information regarding this study can be found in the master theses of Berta Escude Lloveras, "Which back-off movements do humans do?", and Nicolas Barschkis, "Development of a machine learning algorithm for automatic hesitation recognition" conducted at the Chair of Ergonomics, at the Technical University of Munich in 2018

Intention recognition by older interviewees at public spaces was more heterogeneous in the video study of Article 2. The article suggested that a follow-up study could therefore target older pedestrian groups. This was implemented in an additional study at the Chair of Ergonomics and seniors' meeting points in the surroundings of the Technical University of Munich.[5] A sample of 25 participants ranging from 61-94 years and a mean age of $M = 74.28$ years ($SD = 8.90$ years) was compared to a sample of 35 19-29 year old participants ($M = 22.69$ years, $SD = 2.29$ years). Both groups experienced the back-off movement at a bottleneck in eight consecutive trials. The study confirms that older participants have more heterogeneous scores on their derived intentions. For example, the older group scores a possible intention *greeting* one point higher with $M = 2.9$ out of 5, than the younger group, which scores this possible intention with $M = 1.9$ on the five-point Likert scale. The correct intention *yielding* is scored with $M = 4.2$ for the young and $M = 4.9$ in the old and thus, high in both groups. A detailed analysis of the movement style was performed by manually reviewing the video recordings. Here, drastic differences between older and younger participants appeared. In the second encounter with the motion cue, 47% as opposed to 12% completely stopped their movement and observed the robot. Still in the seventh trial, 53% as opposed to 13 % noticeably slowed down their movement. At this stage the number of stoppers was drastically reduced in both groups. Interaction times were also derived from the video recordings and normalized to age using the reference values for natural walking speeds from Bohannon (1997). Although not statistically significant, a trend towards higher interaction times for the older group could be assumed. The data shows that mean times for the interaction in all eight trials were equal to or higher than the corresponding times for the younger group. In conclusion, qualitative feedback, gait analysis, and quantitative efficiency analysis show different results for the two age groups. Therefore, the assumptions about the effectiveness of a movement cue differ between different age groups.

The study design included a dominant robot movement. Although the second encounter with the back-off strategy occurred following the dominant robot behavior, a significant improvement in interaction time was observed. Therefore, the discussion of the Article 2 suggested that the back-off strategy resolves confusion after variable behavior. This hypothesis was focused in a follow-up study. The follow-up experiment investigated the effect of variable robot motion on human compliance (Reinhardt et al., 2020). The robot's behavior was varied in two ways. The robot could either perform a back-off movement at a bottleneck or the robot passed it, taking priority over the pedestrian. The objective compliance of a baseline group of participants that experienced consistent behavior, displayed by a robot that always performed back-off, was compared to a group that experienced variable robot behavior with both movement variations. Participants had the choice to either comply with the robot's behavior by moving through the bottleneck in front of the robot, as suggested by the back-off gesture, or behaving reactantly. Reactance is behavior in which a person does the opposite of what is asked of them (Meyer & Lee, 2013). In this case, that meant taking a detour or trying to move after the robot despite its yielding behavior. The results showed no significant differences in objective compliance. However, subjective trust, as measured by the trust subscale in Körber et al. (2018), decreased among participants. The results of this follow-up study render the aforementioned assumption of Article 2 rather provisional. The variable behavior is an important point because it will be the realistic behavior. Robots will sometimes need to communicate their dominance over humans, for example in the delivery of urgent goods. Therefore, variable behavior should be considered as an important co-research domain to those empirical studies where participants experience repetitive robot behavior.

In accordance with the studies of other authors, high-resolution motion tracking was used in this article (Carton et al., 2014). To achieve the level of detail of the motion data, a space

[5]For more information on this study, see the bachelor's thesis by Verena Hofmann, "Evaluating Movement Behavior of a Mobile Robot Regarding Legibility and Learning Behavior of Elderly" conducted at the Chair of Ergonomics, at the Technical University of Munich in 2019

stationary motion capture was used. With cameras placed in each corner of the room, it is possible for the robot to see what is behind a corner that the robot would not be able to see with only on-board sensors. This deplorable state shows in the implementation targeted in Chapter 5.3.

5.1.3 Revisiting Article 3

The central contribution of Article 3 is a model that predicts how the parameters for back-off length and back-off speed should be applied to robots of different sizes and two spatial formations in this interaction, a lateral and a frontal view by humans. There were only weak effects for applied back-off velocity. For back-off length, the results indicated a non-proportional increase in required back-off length with increasing robot size, confirming the expectation. The application of the model can be demonstrated with a computational example. For a spatial arrangement in the lateral view, doubling the robot size from a length of 0.5 m to 1.0 m results in a back-off length recommendation of 0.706 m instead of 0.606 m. This corresponds to an increase of 16.6%.

The idiosyncratic effect suggests that participants have individual preferences for motion design. A detailed analysis of the single coefficients of the linear mixed model fitted on required back-off length reveals that 11 out of 50 participants experience a decline of requested back-off length with increasing robot size instead of the model-predicted increase. This means that there are about 20% of individuals for whom the model might predict a wrong direction of back-off design. In this context, it does not seem plausible why participants would choose to reduce the back-off length for larger robots. One possible explanation could be that they are afraid of larger robots and want them to move less in their proximity. Another explanation could be that they were confused by the changing robots and therefore the study design was unfavorable for them. However, it has already been discussed in the article that the size differences between different robots were correctly perceived with a high accuracy. The size judgment is also a common HRI metric (Steinfeld et al., 2006). Similarly, 12 of 50 participants had a different prefix (plus instead of minus) for the model on estimated back-off speed. The variance of the idiosyncratic slopes does not exceed half the value of the axis intercepts in either model, indicating that the variance of the random slopes is within tolerable levels for model validity, according to Winter (2019).

The design approach of this article can be classified in the field of implicit models according to the review of motion design methodologies by Venture and Kulić (2019). This means that the design process offers actual parameters as a result of a hand-crafted movement, as opposed to formal algorithms. This is important from an ergonomics perspective. The physical parameters are what people can actually perceive and experience when interacting with a robot and should be reported as a result of ergonomic studies in HRSI. In comparison, the formal description of an algorithm cannot be perceived. For robot development and real-world applications, however, formalization is important because it provides a repeatable and planned behavioral description for robots. However, the presented modeling approach is intended to serve as an extension to the mere reporting of parameters of an implicit model. It can target the inadequacy of implicit models over formulated approaches by making the hand-designed back-off applicable to other robot sizes and spatial scenarios, thus incorporating a design formalism.

Through the additional exploratory analysis, the article concludes that an execution time of about 1 s could serve as a benchmark for designing various expressive movements. In this context, it should be noted that the two models exercised in the article show a slight contradiction. The required back-off length increases while the preferred back-off speed decreases. This leads to slightly longer (temporal) back-offs for larger robots. The duration of 1 s was also associated with legible movements of the short back-off in Article 2. Even the back-off applied in an industrial robot in Article 1 had about 1 s execution time. The recurring evaluation of the *timing* parameter and its importance as a design principle in animation and motion design make it useful to highlight its role in the HRSI in this dissertation. Thus, two perspectives can be unified. Timing is a design parameter in HRSI, or as Knight and Simmons (2014) put it, timing is a factor that helps people distinguish movements. In animation design and motion design, a communicative effect can be achieved by *timing* the movement of an object in certain proportions (Lasseter, 1987).

Another qualitative conclusion of the article could be the report of an optimal retreat maneuver selected from the data set. This process could start with the resulting mean values of the parameters back-off time, back-off length, and back-off speed, i.e. values generated by the empirical analysis. To select a maneuver from the data set, a hierarchy would need to be established for how well a designed back-off must meet these requirements. As an example, it might be useful to start the selection with time as the highest priority, speed as the second, and length as the lowest. Then, one would select the designed back-off that is similar to the mean values according to the hierarchy. The back-off designed by participant 30 in trial 3 in a frontal view best fits this process: it consisted of a back-off time of 1 s, a back-off speed of 1.1 m/s, and a back-off length of 1.35 m. Thus, this is a motion cue that is designed by a participant while meeting most of the population's requirements. However, the procedure would neglect the different robot sizes and the two viewpoints. This is further support for the recommendations discussed in the article that the study could be repeated with a smaller number of different robots. In that case, aforementioned qualitative selection process could be supported by a larger number of suitable data points. Fewer robot sizes and a higher number of repetitions for each robot could also reduce variance as participants become more familiar with each robot.

5.1.4 Limitations in the design process

The process for the design and evaluation of legible motion cues was introduced in Chapter 1.5. It is a methodology to create movements, measure their effect on humans and adapt them to different robots and scenarios. The process is made up of three consecutive steps, *Exploration*, *Interaction analysis*, and *Parameterization*. However, the implementation showed that there are some inconsistencies between Articles 1-3 in the sequential process of pursuing and developing the research idea. These are summarized below.

The short duration of the experiments and the few encounters with the robot were discussed in Article 1 and Article 2. These Articles focused on the measurement of legibility. Therefore, only a statement about the short-term effects can be made. In Article 3, participants were given comparatively more time to design the back-off. It is unclear whether the effect of a back-off movement cue continues to diminish after many encounters and increasingly learned behavior by humans (Paetzel et al., 2020). The temporal component in interaction related to motion perception was discussed in Article 2. There will be a residual time for interpretation, which a person will always need. It could be hypothesized that a stop-and-wait strategy could be equally useful once learned by humans. However, the inevitable occurrence of variable motion behavior (Reinhardt et al., 2020) supports the idea that the robot is on the safe side with a back-off rather than a stop-and-wait strategy to ensure that the human can interact intuitively and interpret the behavior efficiently.

As discussed in the previous chapters, a shift in the evaluation methodology for legibility between Article 1 and Article 2 has occurred. There are several approaches to assessing legible motion. There is the possibility of direct and indirect measurement of the construct (Chapter 1.3.4). Article 1 was able to derive rather qualitative assumptions about the legibility of the back-off through verbal feedback from participants, which aligns well with the developer's intention of an exploratory phase of motion design. Article 2 was able to provide detailed insight into the underlying concept of legibility by measuring motion perception and whether intention could be inferred quickly and confidently. Article 2 was further diversified in a qualitative interview-based approach in the preliminary study and a quantitative assessment based on motion analysis in the main study. The use of different assessment methods and the different conclusions that can be drawn from them show that it is important to have sound knowledge about the actual construct legibility. The articles were able to show that it is nevertheless possible to infer communicative quality of a back-off motion via different metrics and assessment methods.

There is a change in scenarios between Article 1, Article 2, and Article 3. Regarding the classifications made in Chapter 1.2.1, the HRI must be handled differently. In Article 1, the interaction between a human and an industrial robot is a cooperative assembly task where both actors aim for the same goal. Following Schmidtler et al. (2015), the interaction can be called HRCoop. In Article 2, a human and a mobile robot aim for the same goal by negotiating an order of passage through the bottleneck in an angular encounter. The HRCoop classification has not been created for mobile robots, hence the definition of HRSI is applied. Managing an order of priority via management of movement is in line with the definition made by Dondrup et al. (2015). The greater distance between humans and robots, and thus the different perception of motion in relation to Chapter 1.2.2, is a clear difference between Article 1 and Article 2. The angle of view of a motion affects how it can be perceived. In addition, the movements are performed by robots with different characteristics. The most effective motion design can vary depending on physical properties, as discussed in Chapter 1.3.1. In this context, the number of degrees of freedom a robot possesses (Venture & Kulić, 2019) or its optical human resemblance (Piwek et al., 2014) can be factors to consider for an appropriate motion design (Chapter 1.3.2). Similar to Article 2, in the Article 3 setting, human and robot strive to pass a bottleneck. The scenario is an intersection in an office environment. However, the formations at the encounter are not angular, but frontal and lateral. The participant study focused on movement design. A live interaction with mutual influence takes place only at the beginning of the experiment. The goal is to first teach the participants the robot's intention. In the later experiment, there is no real interaction when the static human sets the back-off parameters. Despite these differences, the three scenarios have in common that there is a conflict of goals between humans and robots, so that an order must be determined as to who has priority to achieve their goal. This fact was always taken into account when designing the experiments. While scenarios that vary from an assembly to a spatial bottleneck to an intersection situation can cause more variance in the measurement, this allowed testing the motion cue in more varied situations, expanding the scope of this work. It was also possible to transfer a motion cue between two very different looking robots, an industrial robot and mobile robot applications.

The design process can be described as moving from detail to abstraction or from the bottom up. In Article 2, only two variants of the back-off were applied, the design of which was supported by the results of the preliminary study. The results showed an advantage of the shorter back-off variant. It is unclear whether a hypothetical third variant could have altered the course of this dissertation. From this specific motion cue design, Article 3 moved to a more generalized view where an almost infinite set (limited only by the resolution of the virtual environment) of back-off designs were possible. A more in-depth comparison of the design variants developed in Article 3 with the design variants presented in Article 2 will clarify whether the bottom-up approach can be considered a viable method. The back-off length selected by participants in the study of Article 3 was in the range of the worse-performing longer back-off of the Article 2 study (Md = 0.57 m). This is an objection between the articles' experiments. Article 2 conducted a thorough analysis of stopping behavior. In the first encounter with the long back-off, all but one participant continue after a standing time of less than 1.9 s. In the following encounters, all of these observation times are lower than 1.8 s. This suggests that the proposal made in Article 3 to design motion cues with an execution time of 1 s could be extended with a maximum value of less than 1.8 s to limit the very inefficient behavior of participants waiting and watching the motion. For the shorter back-off in Article 2, all but one of the stoppers observe the motion cue for less than 0.9 s. It appears that the short back-off provides a sufficiently long backward motion. In Article 3, an execution time of about 1 s for motion cues was suggested as a result of the exploratory analysis. The fact that the parameters preferred and adjusted by the participants in

Article 3 were within the range of the two movements from Article 2 suggests that the proposed designs from Article 2 were not far from optimal.

The design and evaluation process is aimed at developing multiple motion cues to result in an exhaustive motion language for robots. The reviews of the published Articles 1-3, and the discussions with many collaborators and colleagues during the time working on this dissertation underpin that there is scientific value in this detailed process. However, repeating such a series of experiments for every remaining individual motion cue, which could be e.g. a two-digit number of motion cues needed to solve all scenarios in HRSI, poses a considerable amount of work. It is arguable that regulatory bodies, corporations, and even research institutions could refrain from the financial risks in conducting the creation of a complete motion language for robots. One possible countermeasure could be to include the use of large amounts of natural driving studies. There are already companies that collect large amounts of quantitative data from the environments that mobile robots perceive. Conducting experiments with different motion cues in addition to the everyday driving of these robots and using this data to clarify the hypothesis about the legibility of the motion cues could speed up the process. At the very least, the exploration phase of the design process could be facilitated by this idea, and perhaps even all three phases could eventually run in parallel with the normal operation of the robots.

5.2 Guidelines for design and evaluation of legible motion cues

A motion language is necessary to harmonize with humans if you want robotic applications to become commonplace in human-dominated domains (Chapter 1.3.1). To achieve that, you need not just a back-off, but several appropriate motion cues to solve all the different little things that we humans achieve through movements and gestures. In addition to yielding the right of way, these can include intentions such as denying something (shaking), greeting (waving), or to make an evasive maneuver to the side understandable (exaggerated side step). The goal of this thesis is to support the development of further motion cues. In addition to the process described in Chapter 1.5, this chapter derives practical recommendations. The process guidelines should be seen as help for the development of further motion cues (Chapter 5.2.1). They are motivated by conclusions drawn from the experiments and experience gained from the study designs. These guidelines are a general response to the research questions beyond the Articles 1-3. The back-off guidelines (Chapter 5.2.2) are derived from Articles 2-3 and relate specifically to the design of the back-off motion cue for mobile robots.

5.2.1 Process guidelines

Invent a new motion cue and compare it to other possible cues.

In Article 1, a bold step was taken. A back-off motion was designed and hypothesized to improve the status-quo, i.e., the stopping behavior of robots when an order of priority must be managed. Other motion cues could also have solved the same problem. Therefore, in Article 2, the motion cue was compared to other possibilities, such as turning in the direction of the person. In the beginning, a good guess about what might work seems like a feasible start. The initial design may be inspired, for example, by human-human interaction (Schubö et al., 2007; Leichtmann & Nitsch, 2020), animation techniques (Takayama et al., 2011; Schulz, Torresen, & Herstad, 2019), or animalistic motion (Bartneck et al., 2009; Faria et al., 2016) (Chapter 1.3.2).

The evaluation of the sensory processing of the robot movement is a prerequisite.

Previous research has shown that people are good at navigating around obstacles in their path without even being aware of them (Harms et al., 2019). In addition, the experiments conducted in this work were characterized by brief encounters. A very close interaction occurred in an assembly task in Article 1, where the interaction time during a motion cue was in the range of 1 s. In Article 2, the interaction is very sudden after the person passes a barrier and has to deal with the encounter with an emerging robot in front of the bottleneck. The studies were also characterized by distractors such as motion-tracking systems and the presence of experimenters in the same room. Therefore, it is deemed necessary to validate whether participants have processed the motion before legibility measures are evaluated. Suitable processing models can be derived from Chapter 1.2.1 and Chapter 1.2.2. For example, it is feasible to apply the IPS (Kitazawa & Fujiyama, 2010) to the human motion data in a real human-robot encounter to evaluate human awareness of the robot. The guideline can be viewed as an answer to the first part of RQ 1, which is, how a measurement of the human sensory processing of a motion cue can be obtained. The IPS represents a method for evaluating human sensory processing of robot movements.

To assess legibility, it is necessary to measure whether the intent underlying a motion cue can be inferred quickly and confidently.

Legibility assessment must be achieved through a combination of measurements that show whether humans are quick to infer a robot's intent while being accurate with their predictions (Dragan et al., 2013). Participant bias must be prevented. Naming the intention during the measurement or asking whether a movement is legible without considering the underlying concept would in this case be considered an invalid measurement (Dehais et al., 2011). In the video study of Article 2, the question "Why did the robot show this behavior?" was used to evaluate the accuracy of the prediction. In the main study of Article 2, interaction time with the robot was considered as the main proxy for evaluating whether intention could be inferred quickly. After reviewing this article, these measures can be recommended for further use in situations similar to the interview situation and the motion laboratory of the experiment in Article 2. The guideline can be viewed as an answer to the second part of RQ 1, which is, how a legibility assessment can be obtained.

Incorporate the motion cue into an experimental setup that allows quantification of the effect.

Assumed that a good idea about a useful movement cue has emerged and qualitative evaluations suggest that it is intent-expressive to many. At this stage, bring the motion cue into an experimental design that allows quantification of the effect. Compared to just measuring prediction time or qualitative readability, human motion analysis allows for greater insight. Human movement can be analyzed synchronously with the movement of the robot. The use of a high-end motion tracking system makes it possible to see all those little human quirks like stopping behavior, head turns, accelerations, decelerations (see Chapter 1.2.3) that would not be possible via pure video studies, stopwatches or qualitative interviews. In Article 2, RQ 2 of this dissertation was comprehensively verified in this way. In that, the article showed how a motion cue can affect the motion behavior and efficiency of humans. The motion cue promises a capability to facilitate spatial interaction, thus influencing human movement behavior and efficiency by reducing stopping behavior and increasing fluidity.

Robotics development can benefit from the application of a motion cue if there are rules on how to adapt motion to different contexts and different robots.

There is a wide variety of robots in terms of appearance, size, and movement capabilities (Venture & Kulić, 2019). This leads to the following questions: How useful are the conclusions that a motion cue of say 0.1 m evasive maneuver is legible by an observer 1 m away from a 0.5 m tall robot, when another developer wants to apply such a motion in his or her 2 m tall robot? Will this developer be satisfied with implementing the same motion, or will pedestrians interacting with the robot interpret the motion as mere vibration or erratic behavior? One way to approach this dilemma is through statistical modeling. A statistical model can predict the appropriate parameters for a different spatial constellation and size of the robot, provided the model is constructed from well-collected empirical data. However, one must be aware of how to discuss the results of a model. Revision has shown that a model can predict misleading design implications even for a minority of individuals (Chapter 5.1.3). Therefore, the tradeoff involving the pros and cons between standardization and personalized design in robotic motion is one of the most important cross-disciplinary issues in the coming years. The drivers, such as institutions or companies, that will determine such rules or standards in the future may have competing interests in this matter (Reinhardt et al., 2018). This guide shows that a discussion on how to parameterize a motion cue to achieve the desired effect needs to continue (RQ 3).

Consider different age groups.

In the preliminary study for Article 2 (Chapter 3), middle-aged interviewees showed more variability in the accuracy of the intentions they inferred from a motion cue compared to university students. This trend was reinforced in the study of elderly people in senior communities (Chapter 5.1.2). However, this dissertation draws most of its conclusions from studies conducted with young university students (main experiments in Article 1 - 3). Since the research topic targets the entire population, an important recommendation is to include different age groups in the study of legible movement. A consequence of this could be the development of different motion cues for different age groups.

5.2.2 Back-off guidelines

Execution time of the movement.

In Article 2, the successful short back-off motion uses an execution time of 1 s. Also, a median back-off time of 1 s is selected in Article 3 ($M = 1.04$ s; $SD = 0.52$ s; $Mdn = 1.00$ s). Accordingly, an execution time of 1 s can be recommended for back-off in various applications.

Maximum speed during the movement.

Participants chose a maximum speed of $M = 1.11$ m/s ($SD = 0.450$ m/s; $Mdn = 1.10$ m/s) in Article 3. The maximum speed was achieved via a cosine function. It is questionable whether a different type of acceleration to achieve this speed, such as a linear approach, would change the appearance of the motion and thus the participants' choice of maximum speed. However, as a starting point for developers, a maximum back-off speed of 1.1 m/s can be recommended when factors such as the robot size and the observer's viewpoint of the movement are neglected.

Length of the path traveled.

The more legible back-off in Article 1 covered a distance of 0.19 m. In Article 3, the required distance chosen by participants was $M = 0.64$ m ($SD = 0.34$ m; $Mdn = 0.57$ m). These values serve as a starting point when applying a back-off motion, but for a more specific application, the focus should shift to the following equations for adapting the back-off design depending on the viewing angle and robot size.

Adaption to different robots and viewpoints.

The following formulas are provided by Article 3. They calculate an estimate to adapt back-off length (d) and maximum back-off speed ($v_{\max}$) to different sized robots and observer viewpoints. The robot size is operationalized via the length of the robot (l). The viewing angles (α) are generalized to a lateral (90°) or frontal (180°) view (cf. Figure 1.2). Using these equations, developers responsible for robot motion find a hands-on method for applying the research findings from this dissertation to the HRSI scenario that is individual to their specific needs in terms of the robots they use and in terms of the angular formation in the encounter. Equation 5.1 estimates the needed back-off length for a lateral viewing angle to different robots.

$$d\ [m] \ = \ 0.51\ m \ + \ 0.20 \ \cdot \ l\ [m]. \tag{5.1}$$

Equation 5.2 estimates the needed back-off length for a frontal viewing angle to different robots.

$$d\ [m] \ = \ 0.41\ m \ + \ 0.34 \ \cdot \ l\ [m]. \tag{5.2}$$

Equation 5.3 estimates the preferred back-off speed for a lateral viewing angle to different robots.

$$v_{\max}\ [m/s] \ = \ 1.30\ [m/s] \ - 0.26\ [1/s] \ \cdot \ l\ [m]. \tag{5.3}$$

Equation 5.4 estimates the preferred back-off speed for a frontal viewing angle to different robots.

$$v_{\max}\ [m/s] \ = \ 1.28\ [m/s] \ - 0.26\ [1/s] \ \cdot \ l\ [m]. \tag{5.4}$$

5.3 Implementation of motion cues in human-aware navigation

The literature review shows that HAN planners can achieve motion planning characterized by the robot's tendency to move forward and make only slight adjustments to its trajectory (Chapter 1.1.2). Research on HRSI, on the other hand, suggests more expressive legible motion cues as a necessary motion mechanism (Chapter 1.3.1). Since formalized HAN planners are necessary to enable autonomous robot motion, there is a research gap on how to integrate motion cues into such algorithms. This chapter provides an overview of an implementation task that aimed to bridge this gap between HRSI and HAN by implementing the back-off motion cue in a general autonomous robot framework.[6]

Autonomous robots are usually realized by means of a two-stage architecture. Global planners plan the overall path from a start to a final destination and local planners generate the trajectories to overcome obstacles in the robot's immediate environment. Both global and local planners exist to consider HAN. That is, in this case, to treat circumvention measures differently when it is known that the obstacle is a human being. Various HAN planners were compared for their suitability to integrate motion cues.

5.3.1 Comparison of local and global planners

Lam et al. (2011) argue that robots should disrupt human pathways as little as possible. Therefore, global planners could be designed to avoid people at all costs. In this design case, however, the global planner must allow for both human-robot encounters and bottlenecks. In addition to the prospect of resolving spatial conflicts using the motion cues, this also has an efficiency aspect. A trajectory of a global planner that prevents robots from meeting humans can become very inefficient. It may be beneficial to re-plan and propose a trajectory that actually allows for an encounter, as was done by Cosgun et al. (2016). For this design task, six global planners were identified for comparison and subsequent selection. As a basic mechanism, the global planner of Sisbot et al. (2005), Kruse et al. (2010) and Kruse et al. (2012) is based on cost maps. Kollmitz et al. (2015) and Fang et al. (2020) extend the concept of cost maps to layered cost maps, which makes it possible to incorporate time in the planning. Cosgun et al. (2016) instead apply the SFM. The six global planner approaches are summarized below, with a focus on whether they are more likely to enable human-robot encounters or more likely to avoid them. In addition, the

[6] The implementation of this chapter can be found in the master thesis by Joana Haase, "Implementation of human-aware robot navigation with motion cues", conducted at the Chair of Ergonomics, at the Technical University of Munich in 2020

criteria according to which costs are assigned to cost maps and which are responsible for either promoting or neglecting encounters or corresponding social forces are mentioned.

Sisbot et al. (2005) aim to avoid people as much as possible. The planning criteria are safety, visibility and hidden zones. Kruse et al. (2010) enable meeting humans by relaxing the safety criterion of the cost function and lower the velocity in the proximity of humans. Kruse et al. (2012) add a compatibility criterion where an additional speed adjustment is performed to promote that the robot and the human can each stay on their paths without collisions. No implementation in the Robot Operating System (ROS) exists for this planner. Kollmitz et al. (2015) also aim to avoid humans as much as possible. They use human distance from the robot and movement execution time as criteria in the cost map. Likewise, Fang et al. (2020) try to avoid humans as far as possible. Here, path length, and human distance are the input to the cost maps. In Cosgun et al. (2016), the planner keeps a safe distance from humans or avoids them. Here, the human's motion is estimated based on social forces and the robot also uses the SFM for path generation. This vector approach must be treated differently from the other cost-based approaches. The HAN of Kruse et al. (2010), Kruse et al. (2012), and Cosgun et al. (2016) would enable encounters. Unfortunately, there are no implementations for any of these in ROS yet. A new implementation was deemed impractical. For example, Cosgun et al. (2016) does not fit into the cost map architecture provided by the operating system.

The local planner is the focus of this implementation, as it is responsible for unforeseen obstacles and the trajectories in the near vicinity of the human, as well as in bottlenecks (Kruse et al., 2013). Instead of integrating the back-off motion cue into the goal function of a planner, the design idea was to have the local planner pause during the execution of the motion cue and resume when the distance between the human and the robot grew to a certain level. A human's personal space was determined to be an appropriate threshold for deciding stopping behavior (Hall et al., 1968). Therefore, one requirement is that a local planner should be stoppable in bottleneck situations. However, the literature proposes to bypass humans or to find a cooperative trajectory via HAN (Chapter 1.1.1). For this design task, five local planners were identified for comparison and subsequent selection. The five local planner approaches are summarized below, with a focus on whether they are more likely to enable human-robot encounters or more likely to avoid them. In addition, the optimization criteria are stated, according to which the trajectory is altered in the near vicinity of humans.

Seder and Petrovic (2007) aim to avoid people using the DWA. When a pedestrian is detected, the path is re-planned globally rather than locally. However, the ROS navigation framework relies on a clear separation of global and local planners. Therefore, it is difficult to implement this planner. Molinos et al. (2019) also aim to avoid people using a DWA-based local planner. Rösmann et al. (2017) use TEB and deform the trajectories by predicting human velocity. Their planner rather avoids humans. The work is implemented in ROS. Due to the fact that this planner bases trajectories on human speed prediction, it was not possible to include proxemics as a threshold for initiating motion cues. This was limited by the capabilities of the sensors. Also Khambhaita and Alami (2020) uses TEB, which allows the inclusion of additional interaction concepts, such as legibility and cooperation at bottlenecks. Their planner is implemented in ROS. Such TEB-based local planners produce smooth trajectories. Fiorini and Shiller (1998) use a *velocity obstacles approach* that is based on neither DWA nor TEB. This algorithm rearranges the angle of motion and speed to avoid humans. No such planner has been implemented in ROS.

5.3.2 Implementation in a mobile robot

The hardware used for the implementation was the Turtlebot 2i platform. It has already been used in a number of research projects on mobile robotics (Xiong & Zhang, 2013; Koubâa et al., 2017; Ingabire, Kim, Lee, & Jang, 2019). The robot can move forward and backward at a speed of up to 0.7 m/s. The maximum rotational velocity is 180 °/s. It can carry loads of up to 2 kg and overcome obstacles of less than 0.012 m. It is equipped with an Intel NUC processor and Orbbec Astra RGB-D depth camera. Perceivable distances range from 0.4 m to 8.0 m. In addition, the Astra Body Tracking SDK was used to detect humans. All implementations on this platform are done with ROS.

Due to the unavailability of the global HAN planners in ROS, the search algorithm *Dijkstra* (without HAN) was used (Müller et al., 2008). The algorithm makes it possible to find a human-aware path, if the costs in the global cost map are assigned according to human-aware criteria. For local planning, the TEB-based planners create smooth circular trajectories and provoke wide evasions around obstacles and humans whereas DWA takes rather direct paths and evades at a comparatively short distance. Tests have shown that the circular movements of TEB make it difficult to realize human-robot encounters. The circular motion also prevents the camera from focusing on a single object or person for long periods of time. Human detection was more reliable for the comparatively straight trajectories produced by a DWA. Therefore, the DWA local planner was implemented in the prototype. For flexibility, a modular architecture was chosen, where planners can be changed in the future. To enable this, the navigation is designed to be started and stopped from an external package.

The back-off motion cue is integrated into this framework as follows. In normal driving mode, the global planner follows a path through the environment to navigate to different destinations. The local planner aims to optimize the robot trajectory around unforeseen obstacles using optimization criteria. Unforeseen obstacles can be, for example, a chair recently placed in a location in the office that is not noted on the robot's map. Once a person is near the robot, the person must first be detected via the camera image. Two inputs are used in conjunction to decide whether to trigger a back-off. One is that the distance between the human and the robot must decrease over a time window, i.e., an increasing proximity situation exists. The other is the remaining distance. This is a form of human trajectory prediction similar to Molinos et al. (2019), Rösmann et al. (2017), Khambhaita and Alami (2017). If personal space is violated, a back-off should be performed. A distance of less than 1.22 m around the person is considered personal space (Hall et al., 1968). Asymmetrical personal spaces (see Chapter 1.2.1) were not applicable because the robot cannot accurately measure human orientation with the implemented camera and body tracking. Tests showed that a larger trigger distance was required because robot planning was delayed by the sensors, software, and inertia. As a result, a trigger distance between human and robot of less than 1.6 m was realized. When this threshold is reached, global planning and the current local trajectory planning are stopped. The robot then starts to move backwards. During back-off execution, the robot checks whether the person is at a distance of less than 2.0 m from the robot. As soon as this evaluation is negative, the robot continues its global and local planning. Human-robot encounters can take place in different spatial formations. One of which is a 90°, or lateral, path crossing. This can be compared to the study of Lo et al. (2019), the human-robot encounter in Article 2 of this thesis, or the lateral view of robot motion in Article 3 of this thesis. Another scenario is a frontal encounter, which is, for example, the subject of Khambhaita and Alami (2020) or as implemented in the frontal view of robot motion in Article 3. The back-off has been implemented in a way that it is modifiable in terms of parameters such as triggering distance to human, execution time, back-off speed, or back-off distance via a graphical interface.

The implemented planning algorithm was tested on the third floor at the Chair of Ergonomics with the goal of evaluating navigation capabilities, performing back-off, and logging interaction-specific parameters. Therefore, a map of the surroundings was created using SLAM. The forward speed during normal drive was set to 0.2 m/s. The back-off was configured with a back-off time of 1 s at a velocity of -0.4 m/s. The robot was operated for four hours per day over a period of seven days. For frontal encounters, the Astra Body Tracking SDK was used to detect a person. Initially, a large number of false-positive back-off triggers occurred. In particular, doors and tables were recognized as people. Focusing on the lower extremities of pedestrians improved the situation but did not completely prevent false-positive results. The most reliable detection of humans was achieved between 1.3 m and 8.0 m distance. At smaller distances, joint placement was less accurate. A persons left knee is used for the tracking task, since humans tend to pass the robot on the right side (Daamen & Hoogendoorn, 2003; Bitgood & Dukes, 2006). Thus, the left knee is the last body part visible to the robot. In this way, the distance to the person is tracked as long as possible. Exceptions had to be made for side encounters. An evaluation of the camera's depth images is used for person detection during encounters in lateral formation. Assuming that a person moves in front of the robot camera from the side, sudden changes in the distance value of the pixels of the camera image are used to trigger a back-off. An approach distance is not available for lateral constellations. Manual video analysis was performed to detect valid, as well as both false-positives and false-negatives of back-off execution. A total of 424 back-offs were recorded. Of these, 54 could be considered valid back-offs, with 44 valid back-offs in a frontal formation and 10 valid back-offs in a lateral formation. False-positives accounted for 308 of the motion cues and false-negatives accounted for 62. True-negatives were not considered.

Some key findings arise from this field test. The presented approach is characterized by the fact that the motion cue is implemented as an external module and can thus be combined with variable motion planners. An exceptionally high number of false triggers occurred in the field test. During the evaluation to execute lateral back-off motion, human detection was based on pixel differences in depth images and not on reliable human body tracking data. To enable better perception of such lateral path crossings, additional cameras on the left and right sides of the robot could improve accuracy. Thus, advances in human recognition and human trajectory prediction have the potential to reduce errors as well as enable earlier and faster back-off execution in both frontal and lateral encounters. In addition, more comprehensive analysis of the environment could be implemented to execute movement cues in the right situations. The behavior of a robot must be executed in a legible way that takes into account the right timing in the right place.

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Appendix

Article 1

Article 2

Article 3