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Radio-based Position Tracking in Sports
Validation, Pattern Recognition and Performance Analysis

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Abstract

In recent years, the acquisition of positional data in sports competitions has established itself as an important part of performance analysis. Positional data contains valuable information about the movement of players and objects, allowing conclusions to be drawn about decision-making, load, technique and tactics. Until now, positional data in sports competitions has mostly been collected via video-based tracking systems as competition rules forbid the attachment of transmitters on players and objects, such as the ball in the sport of football. This restriction therefore prevented the use of radio-based systems in sports competitions. Recent studies have shown the potential of radio-based systems for player tracking as these systems allow to capture more accurate data with higher sampling rates than video-based systems. Current rule changes in football now allow players and objects to be equipped with transmitters in competitions.

This dissertation evaluates the quality and the potential, respective applications of radio-based tracking data in sports. It is based on three publications dedicated to system validation of radio-based football tracking and pattern recognition for the automated detection of performance-relevant sprint parameters in athletics. Results show that radio-based football tracking provides accurate information about ball position and speed and radio-based positional data can be used to automatically obtain accurate sprint parameters over the full course of a 100 m sprint. As data is available in real-time the application of radio-based tracking systems opens up new possibilities for performance analysis.

Zusammenfassung

Die Erfassung von Positionsdaten im Spitzensport ist mittlerweile ein fester Bestandteil der Wettkampfdiagnostik. Diese beinhalten Informationen über die Bewegung von Spielern und Spielobjekt und erlauben es, Rückschlüsse auf Entscheidungsfindung, Belastung, Technik und Taktik zu ziehen. Aktuell werden Positionsdaten hauptsächlich kamerabasiert erfasst, wobei der Einsatz von funkbasierten Ortungssystemen eine vielversprechende Alternative bietet. Durch aktuelle Regeländerungen, beispielsweise im Fußball, ist deren Einsatz im Wettkampf nun ebenfalls möglich.

Die vorliegende Dissertation untersucht die Qualität von funkbasierten Positionsdaten und potenzielle Anwendungen für die Leistungsdiagnostik. Der Dissertation liegen drei Veröffentlichungen zugrunde, die sich mit den Themen der Validierung des Balltrackings eines funkbasierten Ortungssystems im Fußball, sowie mit der Mustererkennung zur automatischen Detektion von Sprintparametern im 100 m Sprint auf Basis von funkbasierten Positionsdaten beschäftigt haben. Die Studien zeigen, dass funkbasierte Ortungssysteme es erlauben, Fußballposition und -geschwindigkeit genau zu erfassen sowie die automatische Detektion von Sprintparametern für jeden Schritt ermöglichen.

Die Verfügbarkeit von akkuraten, zeitlich hochaufgelösten, funkbasierten Positionsdaten in Echtzeit eröffnet somit neue Anwendungsmöglichkeiten für die Leistungsdiagnostik.

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Seidl, T., Völker, M., Witt, N., Poimann, D., Czyz, T., Franke, N., & Lochmann, M. (2016b). Evaluating the indoor football tracking accuracy of a radio-based real-time locating system. In P. Chung, A. Soltoggio, C. W. Dawson, Q. Meng, & M. Pain (Eds.), *Proceedings of the 10th International Symposium on Computer Science in Sports (ISCSS)*, volume 392 of *Advances in Intelligent Systems and Computing* (pp. 217–224). Cham: Springer.

Seidl, T., Czyz, T., Spandler, D., Franke, N., & Lochmann, M. (2016a). Validation of football's velocity provided by a radio-based tracking system. *Procedia Engineering*, *147*, 584–589.

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Chapter 1

Introduction

Figure 1.1: David Marsh Litho Print. "Some People Are on The Pitch. B. Charlton v F. Beckenbauer - 1966 World Cup Final". The red lines track Bobby Charlton throughout the game, the bold lines show possession of the ball. The black lines show Frank Beckenbauer's pitch positions. Image taken from Marsh (2010).

1.1 Player Tracking in Sports

Figure 1.1 shows the movements of Franz Beckenbauer and Bobby Charlton in the 1966 World Cup Final. This artwork, created by David Marsh, "has turned the 1966 World Cup Final into a series of prints interpreted through the medium of movement" (FourFourTwo, 2010). Art usually provides no utility. However, if one considers the technological developments in sports, these "artworks" are nowadays generated *automatically* by player tracking systems in every match for each player in the English Premier League, German Bundesliga or National Basketball Association. These "artworks" are called *spatio-temporal player tracking data*, *positional data* or *player trajectories*[1] and nowadays form the objective basis for the evaluation of sports performance. However, looking at Figure 1.1 it is hard to believe that one could actually deduce whether Beckenbauer or Charlton was the better player in the final by simply comparing their trajectories. Nowadays, computers are able to translate these "artworks" into insights about player performance and blur the boundaries between art and craft.

Data is collected everywhere. We are in the midst of a data revolution and according to Forbes, the amount of data we captured during the last two years makes up 90% of all data that has ever been collected (Marr, 2018). Accurate and objective data can now be gathered in activities such as training and matches that was not even possible ten years ago. The availability of player tracking data in competitions marks the beginning of a new era for sports science as new technologies allow the acquisition of more and better data on all aspects of sports. At its center lies spatio-temporal player tracking which provides information about the movement of players and ball[2] over time. In all major sports leagues player tracking data is currently recorded during competition:

- In the German Football Bundesliga, video-based player tracking data has been available since the 2011/2012 season and the data is shared with all clubs from 1. and 2. Bundesliga.
- The National Basketball Association (NBA) rolled out league-wide Stats SportVU video-based player tracking in 2013/14[3]. In addition, all NBA teams nowadays have their own analytics departments which try to make sense of this data by analyzing shooting and passing patterns.
- The National Football League (NFL) started to use the RFID-based tracking system Zebra MotionWorks in 2014 which integrates small radio transmitters into shoulder pads (Zebra, 2018).
- The National Hockey League (NHL) is about to introduce a hybrid tracking system (radio-based and video-based) in the 2019/2020 season (Lemire, 2017; Whyno, 2019).

More and more businesses are being built around its acquisition and analysis. The sports analytics market size was estimated to be $764.3m in 2016 and is anticipated to reach $15.5bn by 2023 (Wintergreen Research, 2017).
Tracking player and ball movements throughout a match creates massive amounts of usable data; a typical football match tracked by a video-based system creates more than 3 million data points[4]. Leagues and organizations are changing rules to permit the use of transmitter-based

[1] The terms "trajectories", "(spatio-temporal) player tracking data" and "positional data" will be used interchangeably, meaning xy(z) positions (and if available accelerations and velocities) over time.

[2] In this thesis the term *ball tracking* refers to tracking objects like a football, basketball, american football and ice hockey puck.

[3] Stats SportVU video-based tracking systems have been first installed in four arenas already in season 2010/11.

[4] If a standard camera with a frame rate of 25 Hz is used to simultaneously track 22 players and the ball (23 objects in total), assuming a football match to last 90 minutes, results in $3.105.000 = (25 \times 60 \times 90 \times 23)$ data points for one match.

systems in their respective competitions. In January 2014, the International Tennis Federation (ITF) introduced the Player Analysis Technology program (PAT) which aimed to provide an official testing procedure that new technologies have to undergo before being used in competition (ITF, 2018). During the 2018 Soccer World Cup in Russia, FIFA even allowed the use of electronic performance and tracking systems (EPTS) and the communication of results within matches to coaches (FIFA, 2018).
So, why are sports governing bodies such as FIFA in football changing their rules of the game to permit attaching transmitters to players and the communication of analysis results even within the game to coaches? Why is capturing movement and actions of players so important? This wealth of new information is key to better understand every aspect of the sport. This includes analysis of technique, tactics, decision making, player load and injuries within the game; it allows clubs to find players fitting to squads and helps to evaluate and improve player and team performance and to ultimately win championships.
Although player tracking systems have been introduced almost a decade ago, there are still ongoing discussions regarding the quality and usefulness of player tracking data. The former is based on the fact that early validation studies used questionable methods to establish reliability and validity of these systems (Di Salvo et al., 2006), which led people to think that all types of questions about performance can be answered by using a player tracking system. However, data quality back then was by no means comparable to today and technology was not mature enough and only allowed to provide rather simple performance indicators like covered distance or the creation of heat maps. Data and analysis tools were not able to answer more sophisticated sport-scientific questions.
With regards to the latter, Carling (2013) made clear that for practical purposes performance analysis findings are mostly not relevant, i.e. they fail to identify non-trivial performance indicators, prove significant but hardly relevant positional differences in athletic performance, and mostly fail to measure the degree of fatigue.

Hence, there are still two main questions related to positional player tracking that need to get addressed:

1. How accurate are player tracking systems?
2. How can spatio-temporal player tracking data be used to gain relevant insights for performance analysis?

This publication-based dissertation tries to get one step closer to answering these questions for *radio-based tracking systems*. The application of these systems is promising as those allow for higher accuracies and sampling rates and the availability of results in real-time.
Despite the issues mentioned above positional player tracking has become a fundamental part of performance analysis as well as training and exercise science in sports.

How player tracking can be related to topics within performance analysis is discussed in Section 1.2. The analysis of player tracking data can be structured in a hierarchical way which is presented in Section 1.3.

1.2 Player Tracking within Training & Exercise Science and Performance Analysis

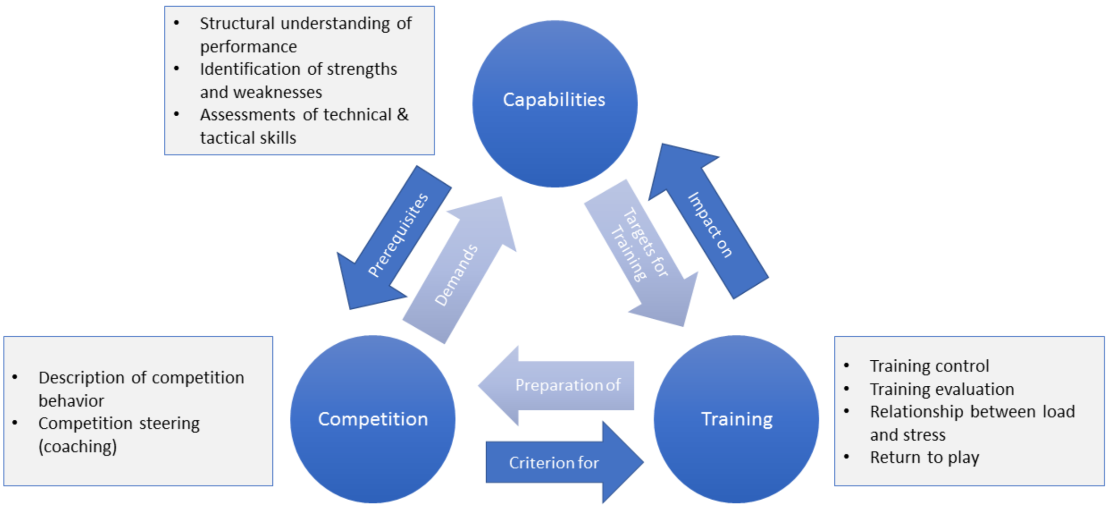


Figure 1.2: Subject areas of training and exercise science: capabilities, training and competition. Interactions between areas are shown. Based on Hohmann et al. (2010). Own translation. Possible applications of player tracking data within each subject area have been added.

This section provides a short introduction to *training and exercise science*[5], *performance analysis* and its relationship to positional player tracking. As will be shown the use of positional player tracking data can be beneficial in almost all subject areas of training and exercise science and performance analysis.

Training and Exercise Science & Performance Analysis

Hohmann et al. (2010) define *training and exercise science* as the discipline of sports science that deals with the scientific foundation of training and competition in application fields of sport from a holistic and applied perspective. At its core are the subject areas *capabilities*, *training*, *competition* and their interactions.

Capabilities, Training and Competition

> "The underlying assumptions of classic performance analysis are that the observed performances can be explained by the abilities and skills of the athletes. These abilities and skills are conceived of as being stable properties, properties that

[5]In this thesis *training and exercise science* refers to the German "Trainingswissenschaft" and performance analysis is thought to be a part of "Trainingswissenschaft".

> may only be influenced in time by special measures taken in training." (Lames & McGarry, 2007).

Hence, training and exercise science is not only studying its subject areas but also the interactions between them. Based on the current capabilities of an athlete a coach sets training targets. On the one hand, training will have a positive impact on the capabilities of an athlete. On the other hand capabilities are also prerequisites for competing against others and will determine results in competition, whereas competition poses requirements or norms on the capabilities of an athlete. Whether a coach did a "good" job is evaluated based on results within competition. Success in competition will therefore have implications on training. Figure 1.2 shows the three subject areas of training and exercise science, its interactions and possible applications of player tracking data within each subject area. The analysis of spatio-temporal data can be beneficial within all subject areas of training and exercise science.
Before possible applications of player tracking data are outlined, the terms *theoretical* and *practical performance analysis* are defined.

Theoretical and Practical Performance Analysis

Performance analysis can be defined as "an objective way of recording and interpreting sport performance using the latest technology so that key elements can be quantified in a valid and consistent manner" (Katz, 2014). It can be subdivided into theoretical and practical performance analysis (Lames & McGarry, 2007).
The task of *theoretical performance analysis* in training and exercise science is to structure athletic performance. This means in the first place prioritisation of the influencing variables and in the second place their internal order (Hohmann et al., 2010).
In order to attain general laws typical methods of behavioural basic research are taken. Large, representative samples are used to ensure to capture typical structures of the game. Within this context, dynamical systems theory has been shown to be a promising tool to better understand the nature of team sports (Davids et al., 2005; Lames & McGarry, 2007; Siegle & Lames, 2013; Walter et al., 2007).
As spatio-temporal player tracking allows to (automatically) capture and analyze large amounts of matches it, nowadays, builds a solid fundament for theoretical performance analysis.
In contrast, the task of *practical performance analysis* is to compare actual and target values, i.e. to identify strengths and weaknesses as well as to monitor training success (Hohmann et al., 2010).
One part of practical performance analysis is the assessment of physiological, technical or tactical demands on players within competition in order to steer training in a way such that training demands on players or athletes are similar to those present within competition. As an example Stevens et al. (2017) quantified in-season training load relative to match load in professional Dutch Eredivisie football using radio-based tracking data. Thus, the monitoring of player load can potentially be based on player tracking data. In practice, load monitoring is nowadays most often based on Global Positioning System (GPS) (de Silva et al., 2018). There are several challenges, however, associated with the comparison of data from GPS systems (Malone et al., 2017). Player tracking systems also allow to analyze actual and target values and can, therefore, help to identify strengths and weaknesses. Analysis of positional data can also be used for monitoring and steering of return to play after injuries (Hoppe et al., 2018b).

Another part of practical performance analysis comprises agility tests in training. Here, the possibility of tracking training material, like cones and poles, allows to automate these kind of agility tests. Grün et al. (2011) showed how radio-based tracking can be used to automate the "DFB-Testbatterie", which comprises standardized tests for the assessment of technomotorical skills of football players proposed by the German Football Association (DFB).
In this context, the application of radio-based tracking systems in particular seems to be promising as these systems allow for the same analyses as GPS-based systems but provide more accurate data with higher sampling rates. Hence, these systems can be used for automated monitoring of training. Since radio-based data does not need any post-processing it can even be used in real-time scenarios. This opens up new possibilities for feedback systems in training environments.
Therefore, positional player tracking can be regarded as a standard method within performance analysis.

Looking more closely on typical data analysis steps which are needed to obtain measures and metrics for performance analysis provides another perspective that eventually allows to position the publications related with this thesis within this data analytics framework.

1.3 Spatio-temporal Data Analytics

Obtaining positional data within competition provides spatial and temporal information about the movement of players and objects—typically position, speed and acceleration[6] over time.
However, information about player trajectories is only of limited use as it does not directly relate to quantities and concepts of performance analysis, e.g. tactical or technical performance. As shown in Figure 1.1 the result of "tracking" Bobby Charlton and Franz Beckenbauer throughout the World Cup Final 1966 is rather an artwork than something that can be directly used to analyze and evaluate their performances. Therefore, some sort of transformation, e.g. event detection or pattern recognition, is needed to obtain useful parameters like shots, passes and possession sequences in football or step parameters in athletics. An analysis built on these parameters can then be used to assess and understand player or team performance, e.g. tactical, technical or load analysis.
This motivates to look at the analysis of player tracking data from a more data analytical perspective which yields a hierarchical layer structure of data analytics—the *data analytics pyramid*. Typically, results of a particular layer can be used as input to a technique described in a higher layer[7].
This hierarchical structure is shown in Figure 1.3 and is best illustrated by an example.

[6]This can vary based on the method used. Most video-based systems provide only x,y (and possibly z) positions. Speed and acceleration can then be obtained by numerical differentiation.

[7]Modern deep learning techniques actually allow to skip the second layer and use trajectory data directly to learn a concept in the top layer (Knauf et al., 2016).

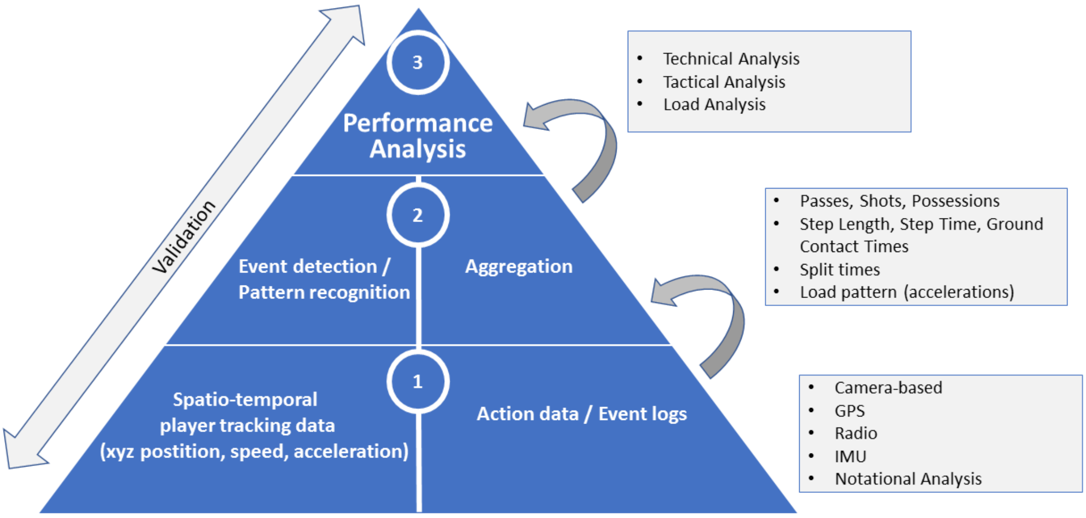


Figure 1.3: A hierarchy of positional data analytics in sports–*data analytics pyramid*. A common first step in data analytics is to capture spatio-temporal or event data in competition or training (layer 1). Based on player trajectories events, like passes and shots, are detected. Transformation and aggregation steps are needed for (manually captured) events or actions (layer 2). Results can then be used as basis for performance analysis (layer 3). The accuracy or quality of methods and parameters within each layer can (and should) be evaluated as errors will get propagated from lower to higher layers.

Example - Expected Goal Value Model in Football

Consider the tactical analysis task of understanding goal scoring in football[8]. This is usually done by training a machine learning algorithm to learn the (non-linear) relationship between scoring context and shot outcome, i.e. whether the shot resulted in a goal (Link et al., 2016; Lucey et al., 2015).

1. For this example, assume the model to be built on spatio-temporal player tracking data[9] (*layer 1*).

2. A training set holds examples of shots on goal which resulted in a goal and also examples that did not result in a goal. The data set also contains features that describe the context of the shot, e.g. distance and angle to goal, type of shot, etc. (*layer 2*).

3. Training a machine learning algorithm on many examples allows the algorithm to learn a model of the relationship between shot context and shot outcome. Model performance is evaluated on an unseen test set and it can then be used for performance analysis (*layer 3*) to (a) understand the most important features that influence whether a shot will result in a goal and (b) to evaluate new unseen shots by providing the probability of this shot resulting in a goal.

[8] In the literature, this type of analysis is commonly referred to as *expected goal value* (xG) model.
[9] xG models can also be trained on event data.

An example for the relationship between distance to goal and the likelihood of goal scoring is shown in Figure 1.4. Looking only on the distance from goal, and neglecting all other contextual features, indicates that shots taken from outside the penalty box are less likely to result in a goal.

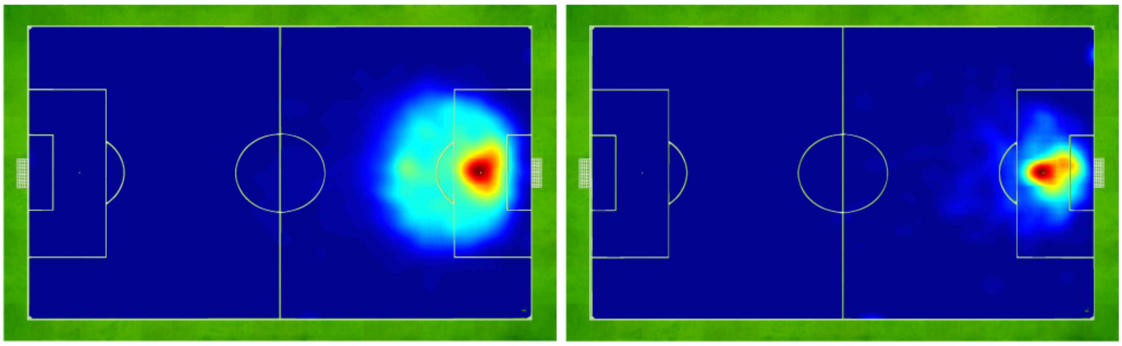


Figure 1.4: Expected goal value modeling in football. Distributions of shot location based on all shots (left) and locations based only on shots which resulted in a goal (right). It is more likely to score if the shot is taken from closer proximity to the goal. Taken from Lucey et al. (2015).

Layer 1 is concerned with data sources that comprise spatio-temporal and event data. Neither results from layer 1 and layer 2 are directly applicable to evaluate performance. Only further analyses associated with layer 3 will allow to gain performance insights.

Validation

The accuracy or quality of methods within each layer can (and should) be validated as errors will get propagated from lower to higher layers:

- In the first layer, these evaluations will be accuracy studies of player tracking systems assessing its capability to provide position, speed and acceleration. For notational analysis systems, for example, one can assess the reliability of two human observers to detect the same actions.
- Within the second layer, accuracy of algorithms to detect passes, shots or foot ground contacts are evaluated.
- In the third layer the accuracy of performance concepts, e.g. expected goal value model, are evaluated.

Horton (2018) describes a similar, but slightly more technical, layer structure when discussing the current state of the art in sports analysis. Similarly, a higher layer can build on the results of a lower layer, starting with trajectories or events as input[10].
The pyramid structure presented in Figure 1.3 now allows to discuss the current state of the art and to position the publications on which this dissertation is based.

[10]Horton's input layer also contains trajectory data as well as event logs and is succeeded by a data analytics layer. Finally, visualizations can be created based on results from the analytics layer.

Layer 1: Spatio-temporal Data

Information about the movement of players or athletes can be obtained by various means and an in depth analysis of tracking methods is presented in Chapter 2.
Most studies do not concentrate on the quality of the tracking data itself and will simply use this data to answer questions from layers 2 and 3. Buchheit & Simpson (2017) provided a good overview of player tracking systems and their use in football.
Since any kind of data analysis, like aggregation or transformation is part of layer 2 the main topic addressed by studies within layer 1 is the evaluation of *data quality* provided by player tracking systems. However, there are only a few studies that investigated the *accuracy* of player positions. Siegle et al. (2013) compared the positional accuracy of a radio- and video-based tracking system for the use in football. The authors used a laser measurement device as criterion instrument that is commonly used in biomechanics and allows an accurate estimation of a players position for linear runs. Linke et al. (2018) and Ogris et al. (2012) set up a whole motion capture system as criterion within a stadium environment and were able to come up with ground truth values even for small sided games. However, both studies only evaluated the accuracy of player tracking and excluded the football within their test setups.

The publication *Evaluating the Indoor Football Tracking Accuracy of a Radio-based Real-Time Locating System* evaluated the positional accuracy of radio-based football tracking by comparing positional estimates to ground truth positions derived by manually marked high speed camera footage (Seidl et al., 2016b).
The publication *Validation of Football's Velocity provided by a Radio-based Tracking System* extended this analysis by investigating the capability of radio-based football tracking to estimate (mean) football speed (Seidl et al., 2016a).
Both publications deal with system validation and can therefore be assigned to layer 1.

Layer 2: Event Detection and Pattern Recognition

For spatio-temporal data the second layer involves some sort of event detection to extract events or recurring patterns, like shots and passes in football. For event data, this step involves aggregation and transformations of the data. Typically, developing a new method for event detection should also involve a thorough validation, e.g. how good does an algorithm for the detection of shots in football work?
Exemplary studies are the detection of individual ball possession in football (Link & Hoernig, 2017) or the detection of step parameters, like step length and step time, based on video (Dunn & Kelley, 2015) or IMUs (Bichler et al., 2012; Schmidt et al., 2016). Choppin et al. (2018) used Hawkeye's tennis ball tracking data to analyze differences in drag between new and old balls in tennis. Since this study calculates a new parameter (drag) based on spatio-temporal ball tracking data it can also be assigned to layer 2.

The publication *Estimation and Validation of Spatio-temporal Parameters for Sprint Running using a Radio-based Tracking System* developed and validated an algorithm to detect ground contacts and estimate step length, step time and ground contact time from radio-based tracking data (Seidl et al., 2017). Hence, it can be assigned to layer 2.

Layer 3: Performance Analysis

Within the third layer, analyses of results obtained by methods from the second layer allows to come up with parameters or constructs that are relevant for performance analysis. Nowadays many of these studies will be based on machine learning techniques.
Similar to the goal scoring example mentioned before, methods and studies within this layer often rely on supervised learning techniques and include the development of expected goal value models in football (Link et al., 2016; Lucey et al., 2015) or expected goal assist models in ice hockey (Stimson & Cane, 2017) which allows to better understand goal scoring and passing, respectively.
But also the application of unsupervised learning techniques can be beneficial to enhance our understanding of sports. In tennis, Kovalchik & Reid (2018) applied techniques from unsupervised learning to obtain a taxonomy of shots for elite tennis players using tracking data from multiple years of men's and women's matches at the Australian Open. Hobbs et al. (2018) recently applied trajectory clustering to quantify the value of transitions in football.
Besides using techniques from machine learning, the application of methods such as network analysis can be used to compare passing behaviour across team sports (Korte & Lames, 2018). Due to high accuracy and sampling rates application of radio-based tracking, for example, enabled the analysis of intra-cyclic speed in 100 m sprint. The analysis of intra-cyclic speed has been shown to be useful for performance analysis in other cyclic sports like swimming but only the investigation of positional player tracking data allowed to observe fine-grained speed cycles over the full course of a 100 m sprint (Seidl et al., 2019). These studies clearly constitute to theoretical and practical performance analysis and can be seen as layer 3 studies. Within this hierarchical analysis structure also methods overviews for the analysis of spatio-temporal data (Gudmundsson & Horton, 2017; Horton, 2018) and reviews of tactical performance analyses in soccer using positional data (Memmert et al., 2017) are thought to be parts of layer 3.

The present work is organized as follows: this section, namely Chapter 1, **"Introduction"**, presents the topic of this publication-based thesis and outlines the major questions concerning (radio-based) positional player tracking in sports.
Chapter 2, **"Methods"**, provides an overview of commonly used player tracking technologies and methods in sports. As all publications have used the radio-based Local Positioning System RedFIR its functioning is discussed in detail.
In Chapter 3, **"Articles"**, summaries of the underlying publications are presented and personal contributions of the studies are mentioned.
Chapter 4, **"Discussion"**, comments on important topics, such as deficiencies of current validation studies for player (and ball) tracking systems, challenges related to transferability of obtained parameters between multiple systems and to the analysis of spatio-temporal player tracking data.
Chapter 5, **"Conclusion and Outlook"**, summarizes the results of this thesis, presents promising approaches and further possibilities for research related to positional player tracking in sports.
The publications on which this dissertation is based can be found in the **"Appendix"**.

Chapter 2

Methods

What gets measured gets managed.

Peter Drucker

Positional player tracking systems are nowadays common in training and competition and there are a multitude of technologies that allow the acquisition of positional data in sports. Systems differ with regard to localization methodology, the potential need for transmitters or manual post-processing, system's applicability in training or competition, in indoor or outdoor scenarios, spatial and temporal resolution, as well as accuracy and level of detail of the obtained positional data.
This chapter provides an overview of the most common methods for position tracking in sports today.

- **Motion capture systems (MOCAP)** track reflective markers attached to an athlete based on images obtained from multiple synchronized high-speed infrared cameras. These systems are known to be accurate within millimeters and by attaching multiple markers allow to capture fine-grained motion details like the movement of body segments. MOCAP systems are most commonly used in biomechanics laboratories.

- **Video-based time-motion analysis (VBT)** is based on the manual observation and annotation of videos to obtain activity patterns. It has a long tradition in sports but is no longer used due to the tedious and time-consuming annotation process.

- **Global positioning systems (GPS)** are nowadays widely used in training. Systems only need a player to wear a GPS receiver. Accuracy (within meters) and level of detail are low compared to other methods.

- **Inertial measurement units (IMU)** also need to be attached to players and typically measure accelerations. The use of multiple IMUs allows to track the movement of body segments. However, IMU systems cannot be used as a standalone solution for positional player tracking, but are often integrated in GPS or LPS transmitters.

- **Semi-automatic video-based systems** use computer vision algorithms to automate the task of tracking players and objects in RGB videos. Fully automated systems are not yet available as obtained positional data still needs a considerable amount of manual post processing. *Video-based player tracking systems*, which are used for tracking all players within a football match for example, are known to be more accurate than GPS systems (with positional errors less than one meter). For very specific applications, like line calling in tennis or goal line technology in football, *referee aid systems* have been shown to be accurate within centimeters. The level of detail is nowadays still low as objects are mostly approximated by two-dimensional points on the football pitch or tennis court.

- **Local positioning systems (LPS)** work similar to GPS and also need transmitters which have to be worn by players or have to be integrated into objects, like football or ice hockey pucks. In contrast to GPS, LPS systems rely on a dedicated local infrastructure of receiving antennas around the sporting ground, allow to track many transmitters with higher update rates and are known to be more accurate than video-based player tracking systems. Depending on the system attaching multiple transmitters to a player can allow to capture the movement of body parts.

Functioning principles of these methods are explained and respective strengths and weaknesses are discussed in the following.
Additionally, because all of the studies presented within this thesis used the radio-based tracking system RedFIR[11] which was developed by Fraunhofer Institute for Integrated Circuits, the functioning principles behind the RedFIR system are also described in detail in Section 2.3.

Before an overview of tracking methods are presented it makes sense to discuss how the *position of player* can be defined.

2.1 Assessing a Player's Position

In general the human body has a shape and volume and consists of different body segments like arms, legs or head. Hence, the question arises how to define the *position* of a player (or human body). Since measuring every single point[12] belonging to a person's volume is not possible an *approximation* of the human body is needed.
The most sensible solution is the *(body) center of mass* (COM). In biomechanics, it is defined as the unique point where the weighted relative position of the distributed mass of the object sums to zero and "the entire mass of the body can be considered as concentrated in the center of mass." (Kingma et al., 1995). It is, therefore, common to assume that an object behaves as if it were a point mass located at the COM rather than a distributed mass (Winter, 2009). The COM can, thus, be used to effectively represent a football player for example.
However, *estimating* the COM is a non-trivial task and typically requires a motion capture system and multiple markers (59 when using Vicon Plug-in Gait for example (Judson et al., 2018)) directly attached to the human body. Given estimated body segment positions, the position of the COM can then be calculated using a mathematical model of the human body (Hanavan, 1964; Hatze, 1980). This approach is widely used in biomechanics laboratories. As this process is very time consuming, even in biomechanics less complex alternatives, such as the attachment of only one marker to the sacrum, are often used to minimize the effort required

[11] The latest version of the system is called "jogmo".
[12] This *point* can be, for example, a pixel in a $2d$-image or a voxel in a $3d$-image.

Figure 2.1: "Moving dots" are the result of the application of player tracking systems. This example shows the camera-based Stats SportVU tracking system for basketball. Image taken from Stats (2019).

to determine the COM (Gard et al., 2004). In sports practice, training and competition, the estimation of COM based on a full body model and motion capture system is simply not possible and the results of tracking multiple players in sports are typically "moving dots" on the pitch or court, which are rough approximations of their respective COMs. An example for video-based player tracking in basketball resulting in "moving dots" is shown in Figure 2.1. How the COM is approximated depends heavily on the tracking method and there are various, mostly technical, reasons why most (LPS and GPS) transmitters are attached between the shoulders rather than to the sacrum. These include the positioning of receiving antennas for Local Positioning Systems (LPS), line of sight between GPS receiver and satellites or other difficulties when attaching transmitters to an athlete. However, deviating from the theoretically optimal position of COM has severe implications for the interpretation and comparison of derived tracking variables like covered total and sprinting distance (Linke & Lames, 2018). Figure 2.2 shows the result of attaching markers to pelvis and scapulae. The former is typical when using transmitter-based methods, e.g. GPS or LPS, whereas the latter position is a more realistic representation of COM for video-based systems[13].

An estimate of a player's or object's position is then given by the three- or two-dimensional position of the estimated COM on the playing field. *Tracking* a player then means to follow

[13]How the center of mass will be estimated depends on the tracking method: in vision-based systems the midpoint of a rectangle surrounding a player is commonly used, whereas for transmitter-based systems the position of the transmitter on the human body will be used as a representation of the COM.

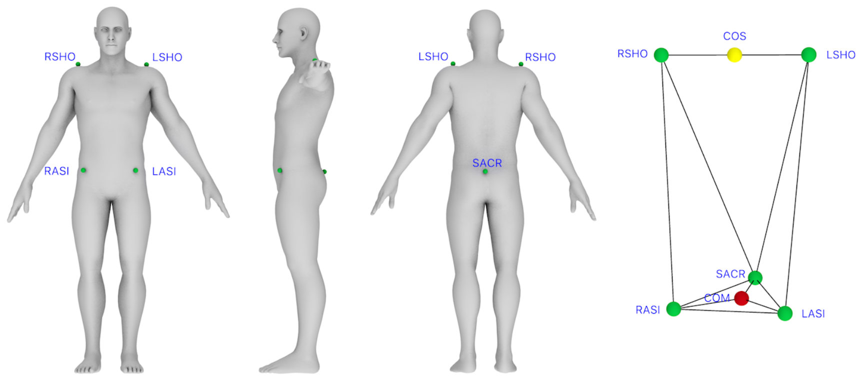


Figure 2.2: Approximating a player's position: the center of mass. Estimation of the COM depends heavily on the placement of multiple markers/transmitters on the human body and is based on mathematical equations (Hanavan, 1964; Hatze, 1980). Center of pelvis (COP) in red and center of scapulae (COS) in yellow are calculated based on markers attached to pelvis and scapulae. Sacral marker (SACR) is shown in green. Derived covered distance and sprinting distance varies strongly based on the used marker positions. Taken from Linke & Lames (2018).

the player over time, e.g. (x, y, t) where (x, y) corresponds to the two-dimensional position of the object at a time stamp t, relating position to a moment in time. Besides knowing position, clearly information about the kinematics of objects like speed and acceleration hold valuable information.

Nowadays, many different methods to track players and athletes in sports are available and an overview of current methods is given in the following.

2.2 Tracking Methods in Sports

There are multiple methods to obtain positional data in sports and this section provides an overview of most common tracking technologies.
Tracking systems vary with regards to the level of detail at which the movement of a player can be captured. A graphical comparison of tracking methods mentioned in the introduction of this chapter is shown in Figure 2.3[14]. The comparison is based on level of detail (LoD) and positional accuracy. LoD measures a system's ability to track details of the human body. It ranges from systems summarizing the body as point mass ("moving dots") over tracking of body segments to systems capable of tracking a full body model. System accuracy is shown on the x-axis. Accuracy increases from left to right and, therefore, a system that provides highly accurate and detailed positional data can be found in the upper right corner.
In the lower left corner video-based time motion analysis (VBT) and GPS systems are positioned as these systems allow only rough position estimates (errors larger than 1 m) and low level of

[14] Note that this figure only represents a schematic overview and accuracies of systems based on the same method can vary widely. As it is almost impossible to compare results from accuracy studies for different tracking systems this figure is thought to provide a rough overview and should be interpreted with caution.

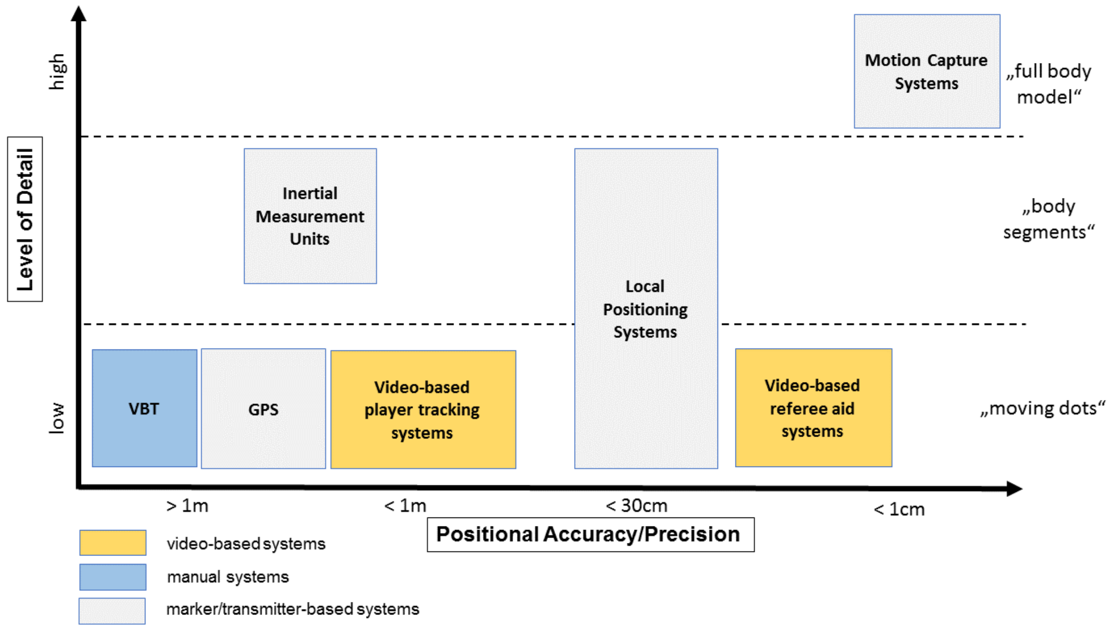


Figure 2.3: Tracking technologies in sports are compared based on positional accuracy (x-axis) and tracking level of detail (y-axis). With typical accuracies of more than one meter video-based time motion analysis (VBT) and GPS are known to be not very accurate and only provide a low level representation of the human body as “moving dot”. The use of multiple IMUs enables the tracking of body segments, but there is in no IMU-based system available that provides accurate positional data. The accuracy of video-based tracking system varies strongly based on its application (tracking all 22 players in football or monitoring of small regions, like court lines or goal line, for aiding referee decisions). Local Positioning Systems (LPS) can vary based on the systems’ capabilities to track multiple transmitter per player. Based on the overall frequency of the system, this might enable tracking of body parts. This is reflected by the LPS box ranging from “moving dots” to “body segments” with respect to tracking level of detail. Therefore, LPS can be positioned in between low level video-based tracking and high level motion capture system used within biomechanics which allow for tracking of a full body model with high accuracy[14].

detail , i.e. “moving dots”. Attaching multiple inertial measurement units (IMUs) to an athlete allows the tracking of body parts. However, due to position drift, IMUs are not very accurate to provide player positions over a longer period of time. The accuracy of video-based tracking systems depends on its application; player tracking systems monitoring the entire football pitch and all players achieve accuracies ranging from 50 cm to 1 m. Video-based referee aid systems are almost as accurate as motion capture system but currently allow only for a low level representation of the human body[15]. Radio-based tracking systems (LPS) are known to be accurate within 30 cm. But, there are differences between commercially available systems with regards to tracking multiple transmitters per player. Dependent on the overall frequency

[15]Recent advantages in Computer Vision actually allow to fit body pose models which enable the tracking of body segments (Felsen & Lucey, 2017). Today, however, no commercially-available video-based tracking system currently allows for such a level of detail. Section 5 provides more details about the detection of body pose within videos and its application to sports.

of the system, this might enable the tracking of body parts. Therefore, LPS can be positioned in between low level video-based tracking and high level motion capture system used within biomechanics. Motion capture systems show the highest accuracy and achieve a very high tracking level of detail by attaching many markers to the human body.
In the following the player tracking methods shown in Figure 2.3 are described in more detail.

Motion Capture Systems

Motion capture systems are based on the detection of reflective markers in infrared images. Corresponding real world $3d$ positions are then estimated based on triangulation of marker positions from multiple camera images (Leser & Roemer, 2014, pp. 87–89). Due to the extensive setup MOCAP systems are typically installed in biomechanics laboratories and are known to be accurate within millimeters for a small volume of a few meters (van der Kruk & Reijne, 2018; Windolf et al., 2008). Attaching multiple markers allows to track body segments and even to obtain full body models. This is especially useful for technical analysis in sports like for the analysis of golf swing or tennis serve which is based on the analysis of body segment angles and movements. MOCAP systems are nowadays the gold standard for tracking moving objects in a small volume.
Drawbacks are the high cost, the need to attach markers and the limited applicability to track multiple players. These make motion capture system impractical for the use in training[16] or competition.
Examples of MOCAP systems employed in sports research include VICON, Motion Analysis Corporation and Qualisys.

Video-based Time–Motion Analysis Systems

A traditional method for player tracking which has been most prevalent even before the rise of computers and digital video is commonly referred to as *video-based time motion analysis* (VBT) (Bangsbo et al., 1991; Mohr et al., 2003) which is part of Notational Analysis (Hughes & Franks, 2004). The manual or computerized analysis of video recordings of the sporting competition allows, for example, the schematic recording of player and ball movements during a rally in tennis (Talbert & Old, 1983) or to manually record an attacking play in football (Winterbottom, 1959). Activity patterns, like time spent and covered distance within different locomotor categories (standing, walking, low-intensity and high-speed running) is based on "time for the player to pass pre-markers in the grass, the centre circle and other known distances was used to calculate the speed for each activity of locomotion." (Mohr et al., 2003, p. 520)
Based on its non-invasive nature and since it only needs a human observer watching a match[17] similar observational techniques from notational analysis are nowadays still widely used to record *events* within competition, e.g. passes, shots (and corresponding locations), corner kicks or yellow cards. However, a fair amount of practice is still required for a human observer to accurately record events as they happen. No information about distances and speed of players which are not directly involved in attacking sequences is contained in event data. Notational Analysis is still widely used in competition. VBT, however, is no longer used due to its tedious

[16] Except for the before mentioned analysis of technique.
[17] This can be done while sitting within a football stadium or by watching the broadcast.

and time-consuming process. An automated alternative, that is nowadays commonly used in training, is based on Global Positioning System.

Global Positioning Systems

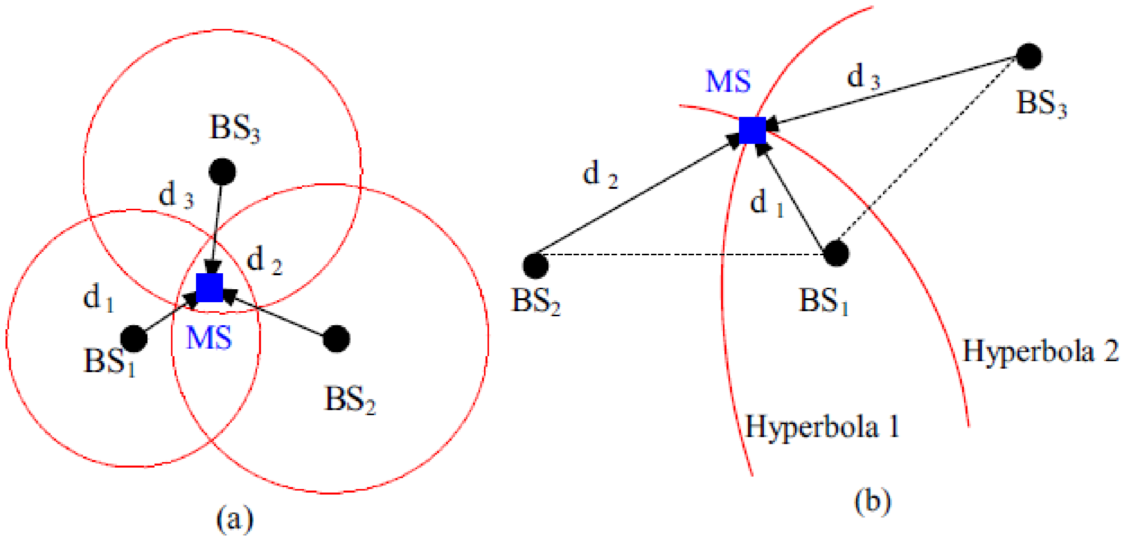


Figure 2.4: Graphical comparison of positioning principles used in GPS and LPS. GPS positioning is typically based on lateration of Time of Arrival (ToA) values (a) whereas LPS systems locate objects based on Time Difference of Arrival (TDoA) values (b). ToA positioning implies the object (MS) to be located within the intersection of all circles around base stations (BS). TDoA positioning implies the object to be located at the intersection of hyperboles. Figure taken from Zaidi et al. (2010).

Global Positioning Systems (GPS) are widely used in outdoor training environments. GPS systems only require line of sight between a GPS receiver—typically worn by athletes—and GPS satellites which makes these systems especially well-suited for the use in training. A player's position is estimated by lateration of GPS signals between multiple satellites and GPS receiver. Multiplying the time of arrival (ToA) of the incoming signal with the speed of light yields the estimated distance d_{rs} between receiver r and satellite s. In case of two-dimensional localization, this enforces the receiver's location to lie on a circle[18] with radius d_{rs} around the satellite (lateration). Intersecting measurements from at least three satellites allows to determine the $2d$ position of the object[19]. Another possibility for localization is based on the time differences of arrival (TDoA) between a pair of satellites and the GPS receiver to obtain the position of the object. A graphical comparison of ToA- and TDoA-based positioning for the two-dimensional case is depicted in Figure 2.4. Lateration of ToA values as in GPS (Figure 2.4(a)) implies the object to be located at the intersection of circles around the GPS satellites

[18] This is only true in two dimensions. In three dimensions the receiver's location is determined to lie on a *ball* of radius d_{rs} around the satellite.

[19] Due to small measurement errors, there is actually no guarantee that circles intersect at exactly one point. In practice, the positioning task boils down to solving a least squares optimization problem. This can be done efficiently, e.g. by the method of Levenberg (1944) and Marquardt (1963).

whereas LPS systems commonly rely on hyperbolic positioning based of TDoA values which implies the object to be located at the intersection of hyperboles (Figure 2.4(b)).
Update rates (ranging from 1 Hz to 15 Hz) and positional accuracy are rather low with typical errors greater than one meter (Linke et al., 2018). Tracking quality is strongly influenced by varying weather conditions and line of sight between receiver and GPS satellites. This prohibits the application of GPS systems in indoor scenarios.
However, due to easy application, system mobility and low cost, GPS systems are most commonly used for load monitoring in outdoor training. Commercial systems include Catapult, Polar and GPSports.

Inertial Measurement Unit

An inertial measurement unit (IMU) is an electronic device that combines accelerometers, gyroscopes and sometimes also magnetometers. Unlike GPS, IMUs do not need any (satellite) infrastructure to work and are known to provide accurate information about accelerations with high update rates (up to 2000 Hz). The low cost and its applicability in indoor and outdoor environments make them especially useful in settings where GPS signals are not available. However, as positional estimates can only be obtained by double numerical integration of the measured accelerations this results in a *position drift error*, meaning that the estimated position drifts away from the actual position due to an accumulation of integration errors over time (Leser et al., 2011; Taborri et al., 2016). Also, the necessary synchronization and communication of all IMUs across an entire football field, for example, makes the development of such systems challenging and, as a consequence, there are currently no commercial player tracking systems available that rely solely on IMUs. Most promising is the combination with other tracking methods like GPS or LPS (Bichler et al., 2012; Braysy et al., 2010).
A main drawback of attaching transmitters or IMUs to players is that data will only be available for players actually wearing a transmitter. This way, in competition no information about opponents can be provided. Using video allows to circumvent this issue as is permits to obtain information for all players present in the image or video.

Semi-automatic Video-based Systems

Modern video-based systems are most commonly used in competition in team sports, such as football or basketball, and can rely on a fixed installation of multiple synchronized cameras or the use of broadcast videos from one camera. There are basically two types of video-based systems:

- Referee aid systems
- Player tracking systems

Hawkeye's line calling system in tennis and goal line technology (GLT) system in football[20] are typical examples of *referee aid systems*. These systems rely on a fixed installation of synchronized (high resolution and high speed) cameras within a sport stadium and monitor only a small part of the tennis court (court lines) or football pitch (goal area). In this small

[20] An alternative RFID-based approach to GLT has been certified by FIFA and is described by Psiuk et al. (2014).

area systems record the position of a tennis ball or football with very high accuracy[21]. Systems are used to *aid* the referee in deciding whether a ball has crossed the goal line in football or touched the court line in tennis.
Player tracking systems on the other hand do not necessarily have to be based on a fixed installation of cameras in the stadium but can also work on broadcast videos. Usually much cheaper HD cameras (25 Hz) are used. These systems typically monitor the entire football pitch (or large portions in case of broadcast videos) and track all players and the football within this larger area. Due to the wider setting tracking accuracy is not nearly as good as for referee aid systems. Examples for player tracking systems include Stats SportVU, ChyronHego's Tracab and Second Spectrum.

Regardless of the application, semi-automatic tracking of players in sport videos is commonly based on multiple preprocessing steps, like play field detection, player detection, occlusion resolution and appearance modelling as described by Manafifard et al. (2017). This is shown in Figure 2.5.

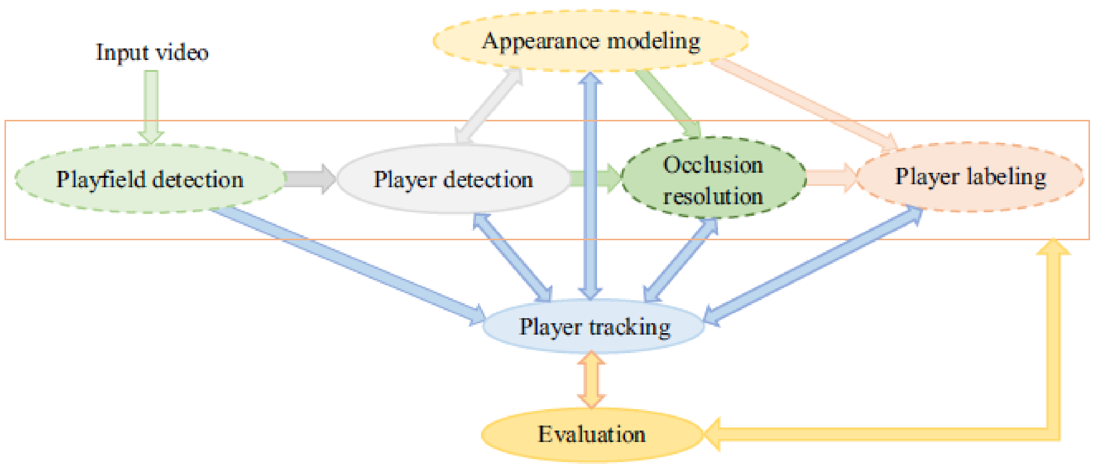
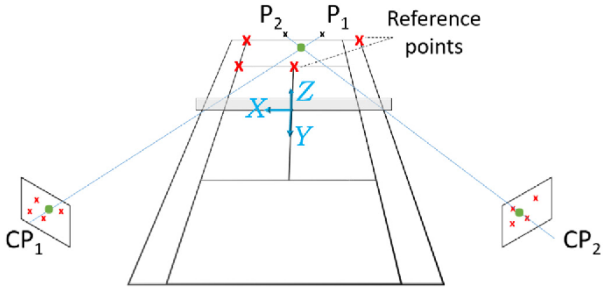


Figure 2.5: Flowchart for video-based player tracking systems. Figure taken from Manafifard et al. (2017).

All of these steps aid the tracking of players and eventually provide real world player locations on the football pitch or tennis court for example. *Playfield detection* eliminates the spectator region from an image and, therefore, decreases the possibility for false detections. *Player detection* is needed for initialisation of the subsequent tracking task and results in an approximation of a player by a rectangular bounding box. A player's location is then typically determined by the position of the feet. *Player labeling* assigns each player to a team. Since results of the previous steps still lack information about the temporal relationship between frames, this information is added by application of Kalman or Particle Filters or the Meanshift algorithm in the *player tracking* step. This step is similar to how LPS systems integrate temporal information into positioning algorithms. Another problem are occlusions, as stated in Manafifard et al. (2017):

[21]For a goal line technology system installation to be certified by FIFA it needs to pass a testing procedure that assures an accuracy of ±1.5 cm. The Hawkeye GLT system, for example, uses images from seven cameras per goal that are installed as high as possible within the stadium structure.

(a) Result of player detection and labeling steps for tracking football players. Bounding boxes, coloured by team identity, are drawn around players. Figure taken from Beetz et al. (2006).



(b) Camera calibration allows to map image pixels (CP_1 and CP_2) to corresponding real world locations (green dot). In tennis, usually line markings on the tennis court are used for camera calibration. Figure taken from Renò et al. (2017).

Figure 2.6: Player detection and real-world position. Results of player detection in football and mapping image pixel to real world locations in tennis.

> "Occlusions occur when some players are located in front of the others along the optical axis of the camera, and thus backward players are hided partially or completely."

Therefore, *occlusion resolution* is probably the most severe challenge for video-based player tracking systems. Each of these steps needs to be *evaluated* separately.
Exemplary results for football player tracking and labeling are shown in Figure 2.6a. Bounding boxes for players are drawn in the image and coloured by team identity. Pitch markings are used for camera calibration and allow to map player pixels in the image to real world coordinates on the football pitch (Beetz et al., 2006) or tennis court (Renò et al., 2017) with the result being "moving dots" (green dot) as shown in Figure 2.6b.
Although video-based tracking in sports has a relatively long tradition (Beetz et al., 2005) only recent advances in the field of computer vision—related to the use of Deep Convolutional Neural Networks (CNN)—in particular improved the state-of-the-art for detection algorithms. Nowadays, these networks allow to automatically track players and objects in sports with unprecedented quality. Large amounts of labeled images for training combined with a deep network structure allow the network to correctly detect and classify objects in an image (Goodfellow et al., 2016; Lee et al., 2009). Figure 2.7 shows how deep CNNs can learn more complex features (e.g. object parts) which built on low-level features (e.g. corners or edges) from earlier layers.

Despite these advances, challenges for video-based player tracking systems are still changing environmental conditions, like weather and light, and most importantly occlusions between players (and ball) which lead to swapping of player identities. Resulting drawbacks are the

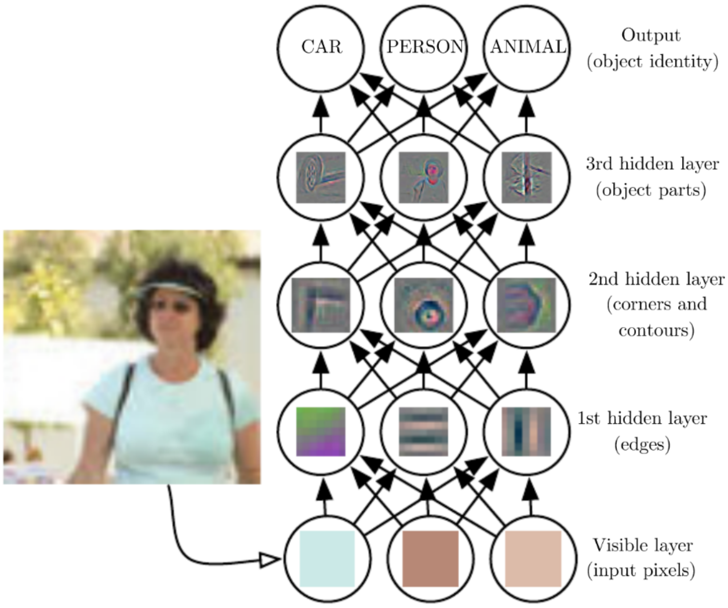


Figure 2.7: Convolutional Neural Networks for object detection. The deep network structure, comprising multiple layers, allows the network to build on low level features, like edges (first layer) in earlier layers and learn more complex features, like object parts (layer 3), in deeper layers. Image taken from Goodfellow et al. (2016).

limited accuracy (in particular for ball tracking), the low level of detail ("moving dots") and the need for manual post-processing (Barris & Button, 2008). This together with the need of cameras being installed at a certain height shows why video-based tracking systems are mainly used in competition.

Local Positioning Systems

Local Positioning Systems (LPS) circumvent all of these challenges as systems locate objects based on analyzing *radio signals* emitted from transmitters to receiving antennas. Therefore, these systems are commonly referred to as *radio-based systems*. A radio transmitter has to be worn or attached to an athlete and enables a consistent assignment of player identities—even in case of visual occlusions—by using a certain bandwidth within the frequency spectrum. Hence, there is no need for manual post-processing of player tracking data. Figure 2.8 shows the frequency spectrum for a range of communication and localization methods, e.g. Global Navigation Satellite System (GNSS), Global System for Mobile Communications (GSM), WLAN, Bluetooth and Ultra-Wideband (UWB)[22]. Frequencies used by commercially-available LPS tracking systems for sports applications are also shown.
In contrast to GPS, localization of objects relies on a dedicated local infrastructure of receiving antennas around the sporting ground. When LPS systems are installed in stadiums for live

[22]Emitted radio wave belongs to UWB if either the bandwidth exceeds 500 MHz or 20% of the carrier frequency. In order to avoid interference with other radio services, the Federal Communications Commission (FCC) in the USA has limited the unlicensed use of UWB to an equivalent isotropically radiated power density of -41.3 dBm/MHz and restricted the frequency band to 3.1 GHz - 10.6 GHz (respectively 6.0 GHz - 8.5 GHz in accordance to the European Communications Committee (ECC))(Mautz, 2012).

measurements interference between the tracking system and other services like WLAN can become an issue.

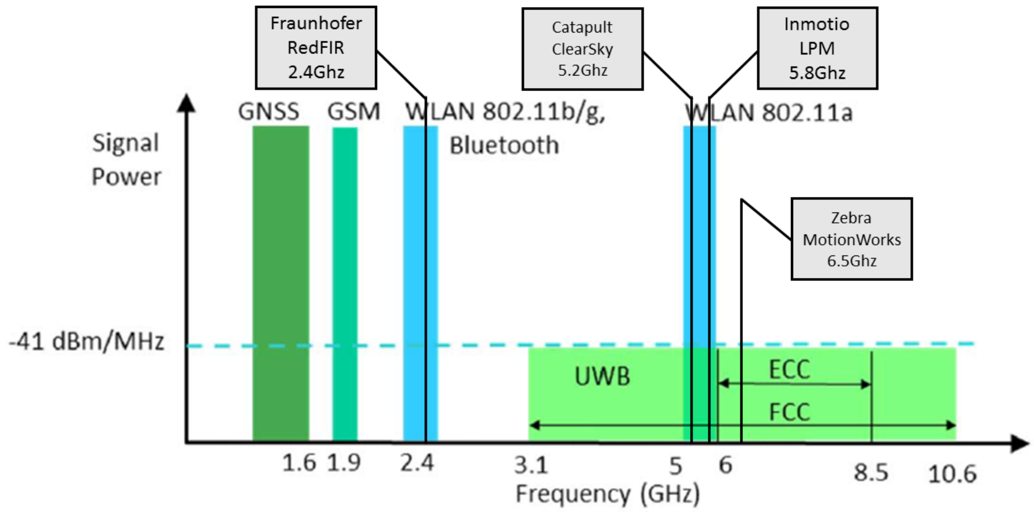


Figure 2.8: Frequencies of Local Positioning Systems and frequency spectrum for a range of communication and localization methods. Image taken from (Mautz, 2012, p. 69). Frequencies used by LPS player tracking systems Zebra MotionWorks, Inmotio LPM, Catapult ClearSky and Fraunhofer RedFIR have been added. Most LPS systems, with the exception of RedFIR, are UWB systems. RedFIR, Catapult ClearSky and LPM use frequencies that are also used by WLAN which can be an issue when systems are used in a stadium during competition. No information about the frequency bands used by Kinexon were found.

High update rates, the ability to track many transmitters simultaneously and the potential for cm-level accuracy makes these systems convenient for precise ranging and positioning in indoor and outdoor environments (Mautz, 2012). Therefore, these systems are especially well-suited for sports applications. Drawbacks are the high cost, the need to attach transmitters to athletes and the need for a dedicated receiver infrastructure around the sporting ground.

> "From a mathematical point-of-view, the position calculation (. . .) is similar to the methods used in the GPS, as there are satellites with known positions and a receiver with an unknown position and a time offset due to a missing synchronization between the receiver and satellites." (Stelzer et al., 2004, p. 2665)

The underlying functional principles for most LPS systems are similar as those typically rely on multi-lateration (hyperbolic positioning) of TDoA values of the radio signal between a transmitter and multiple receivers[23] rather than using ToA values (like GPS). This allows to estimate the position even in absence of synchronisation between transmitter and receiver. In addition, LPS systems are usually calibrated based on reference transmitters placed at known positions (Grün et al., 2011; Stelzer et al., 2004). As overall update rates are distributed over

[23]In two dimensions a hyperbolic curve describes the possible location of a transmitter between a pair of receiving antennas for one known TDoA value (Figure 2.4).

all active transmitters the frame rate per transmitter (and, therefore, player) decreases as the total number of transmitters increases. For example, to obtain information about player heading a second transmitter per player is necessary which further decreases update rates per transmitter[24].
As positional estimates based on hyperbolic positioning can still be noisy, LPS systems often rely on an additional filtering step like a Kalman Filter (Kalman, 1960). Filtering increases positional accuracy by denoising raw positional estimates and also allows to estimate velocity and position simultaneously[25].

Main differences between systems can be found with regards to update rates, used frequency bands, different number, size and weight of transmitters, the possibility of integrating transmitter into objects, like football, basketball or ice hockey puck, and the option for a mobile system. Table 2.1[26] shows a comparison of commercially available LPS systems for sports applications Fraunhofer RedFIR, Inmotio LPM, Kinexon, Catapult ClearSky and Zebra MotionWorks.

System	Company	Method	Frequency (GHz)	Frame Rate (Hz)	Transmitter (mm^3)	Ball Tracking	Mobile
RedFIR	Fraunhofer	Radio	2.4	$50,000$	$61 \times 38 \times 7$(15 g)	yes	no
LPM	Inmotio	UWB	5.8	$1,000$	$92 \times 57 \times 15$(60 g)	no	yes
Kinexon	Kinexon	UWB	$3.5 - 6.5$	$1,000$	$47 \times 33 \times 7.5$(15 g)	yes	yes
ClearSky	Catapult	UWB	5.2	$1,200$	$40 \times 52 \times 14$(28 g)	no	no
MotionWorks	Zebra	UWB	6.5	$3,500$	22.7×10(7 g)	yes	no

Table 2.1: Summary of Local Positioning Systems for sports applications. Differences between systems based on localization method, used frequency bands, frame rate, transmitter size and weight, the possibility of ball tracking and system mobility is shown. All systems, except for the Zebra system use rectangular transmitters, whereas Zebra uses round transmitters. For the latter transmitter column contains radius × height.

LPS systems use miniaturized lightweight transmitters—typically weighting less than 60 g—and most of the systems are based on UWB. As transmitters are actively sending signals, these need to be charged. Battery life times can range between a couple of hours (RedFIR, LPM, Kinexon and ClearSky) to years (Zebra MotionWorks)[27]. The integration of transmitters into a football, basketball or ice hockey puck, is challenging as transmitters have to be integrated

[24] This can be useful to distinguish between a player jogging forward or backwards (O'Donoghue, 2015). Using an LPS system with an overall frame rate of 1000 Hz for tracking 22 players in a football match, leads to a maximal frame rate of 45.45 Hz ($= \frac{1000\,\text{Hz}}{22}$) for each player.
[25] The alternative would be to numerically differentiate positional estimates which will possibly result in unrealistic velocities without further filtering or smoothing.
[26] Information is based on offical web pages from tracking providers or published web articles. Since this might not be a reliable source, this table should be read with caution. The difficulty to obtain this kind of information, however, is a good example for the current challenges when dealing with player tracking systems.
[27] Battery life time depends heavily on update rate. The life time given by Zebra MotionWorks is based on transmitter with a frame rate of 1 Hz.

seamlessly—rules do not allow any modification of ball weight, size and flight characteristics if the object is to be used in an official match. That such a seamless integration is possible for a football was shown by the magnetic-field based goal line technology system “GoalRef” which integrated copper coils into a football to determine the moment when a ball crosses the goal line. GoalRef was officially certified by FIFA for use in official matches (Psiuk et al., 2014). LPS transmitters have been succesfully intregrated into a football (RedFIR, Kinexon), handball and volleyball (Kinexon), an american football (Zebra) and ice hockey puck (RedFIR). By integrating a transmitter into the object LPS systems can provide a consistent and accurate ball tracking without the need for manual post-processing.
Commercial radio-based LPS systems include Fraunhofer’s RedFIR/jogmo, Inmotio’s LPM, Kinexon, Catapult’s Clearsky and Zebra’s MotionWorks.

As all publications have used the RedFIR LPS system, details about the system’s functioning are presented in the following.

2.3 Functioning of Radio-based Tracking System RedFIR

The following description of a RedFIR system is based on the system installation in the football stadium in Nuremberg, Germany (Grün et al., 2011; Mutschler et al., 2013; Seidl et al., 2016b). The localization process is illustrated in Figure 2.9.
Like other LPS systems, the RedFIR Real-Time Locating System (RTLS) is based on time-of-flight measurements, where small transmitter integrated circuits emit burst signals. Twelve antennas around the pitch receive these signals and send them to a centralized unit which processes them and extracts time of arrival (ToA) values. Based on time difference of arrival (TDoA) values between pairs of receiving antennas raw estimates for the three-dimensional position of a player or ball are obtained. The application of a Kalman Filter provides realistic estimates for position, speed and acceleration by the combination of a motion model with raw position measurements. The RedFIR system operates in the globally license-free ISM (industrial, scientific, and medical) band of 2.4 GHz and uses the available bandwidth of around 80 MHz. Miniaturized transmitters generate short broadband signal bursts containing identification sequences. The locating system is able to receive and process an overall of $50,000$ of those signal bursts per second. This specific installation provides 12 antennas that receive signals from up to 144 different transmitters. Balls emit around $2,000$ tracking bursts per second whereas the remaining transmitters ($61\,\text{mm} \times 38\,\text{mm} \times 7\,\text{mm}$, 15 g) emit around 200 tracking bursts per second. The miniature transmitters themselves are splash-proof (in case of the player transmitters) or integrated into the football.
Besides providing kinematics for players and ball the RedFIR system also incorporates a middleware to detect events, like passes or shots, based on positional data in real time.
Compared to other LPS systems, the high overall sampling rate of 50.000 Hz allows the potential use of multiple transmitters per player with update rates beyond 200 Hz which enables the tracking of body segments (Figure 2.3). The real-time availability of kinematic data and subsequent events makes this system in particular useful for potential feedback applications in training.

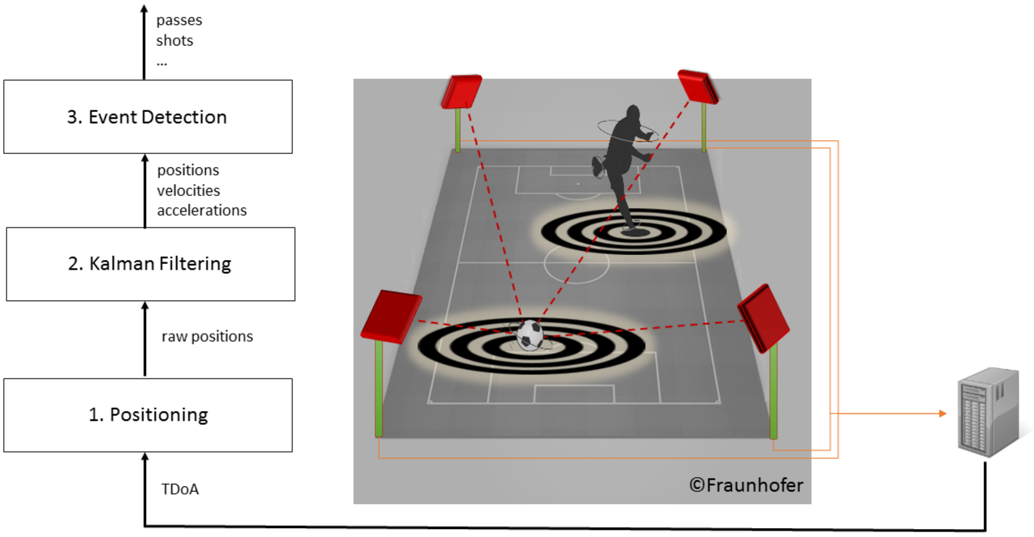


Figure 2.9: Functioning of the RedFIR system. Transmitters can be attached to players, training material or integrated into a football. Position, speed and acceleration are derived from time difference of arrival values between transmitters and receiving antennas (1. Positioning) and subsequent filtering (2. Kalman Filtering). The system also provides a middleware to detect events based on this positional data (3. Event Detection). With permission.

As discussed before, Kalman Filtering not only allows to increase the accuracy of player positions but also provides estimates for velocity and acceleration. However, in certain situations, like fast changes in direction, this process can lead to tracking artefacts. Therefore, the principles behind Kalman Filtering and its implications for capturing sport-specific motion is discussed in the following.

Kalman Filtering — Principles

Estimation of positions solely based on multi-lateration of TDoA values results in relatively accurate positions, where errors are usually less than one meter. To obtain cm-level accuracy LPS (and video-based) systems typically incorporate additional information about the temporal relationship between subsequent measurements into positioning. This is commonly done by applying a *Kalman Filter* (Kalman, 1960).
On a high level, a *Kalman Filter* allows to combine actual measurements and an underlying motion model into a single *state* estimate, which typically contains position and speed. The improvement of positional estimates is based on a two-step process where the position of a player is *predicted* based on an underlying motion model ("time update") and this prediction gets *updated* based on observed measurements ("measurement update"). For more details on mathematical principles behind the Kalman Filter see Perse et al. (2005) who applied a Kalman Filter to obtain smooth player positions for video-based tracking.

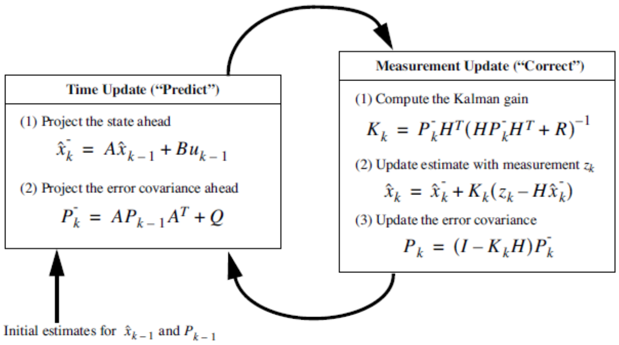


Figure 2.10: Fundamentals of Kalman Filtering. A Kalman Filter consists of two steps: time update step *predicts* the next state of a player $\hat{x}_k^-$ based on a motion model. The measurement update step *updates* the predicted position by incorporating the current measurement z_k. Figure taken from Welch & Bishop (1995).

The interplay between update and prediction steps is shown in Figure 2.10. The time update step *predicts* the movement of the player and process covariance P_k^- based on the underlying motion model. To *correct* the prediction based on observed measurements the *Kalman Gain* $K_k = P_k^- H^T(HP_k^- H^T + R)^{-1}$ is calculated. It works like a gate for how much correction is applied and is strongly influenced by the process noise Q and measurement noise R. If R gets large, i.e. measurement is very noisy, Kalman Gain goes to zero.
Based on the Kalman Gain the estimated state $\hat{x}_k^-$ is updated based on the observed measurement z_k as $\hat{x}_k = \hat{x}_k^- + K_k(z_k - H_k\hat{x}_k^-)$. K_k corresponds to a weighting of *innovations* $z_k - H_k\hat{x}_k^-$, .i.e. how much confidence should be put on the measurement compared to the prediction based on the motion model. Large K_k tend to put more weight on measurements, whereas small values of K_k put more emphasis on the prediction.
State covariance will then be updated as $P_k = (I - K_kH)P_k^-$, i.e., covariance gets smaller when $K_k > 0$, i.e. if measurement helps to improve the prediction. This process is then repeated for all measurements.
This way the Kalman Filter allows to improve the positioning of LPS systems based on underlying motion and measurement models.
However, the filter is also responsible for motion artefacts when dealing with fast changes of direction. This will be discussed based on two real-world examples.

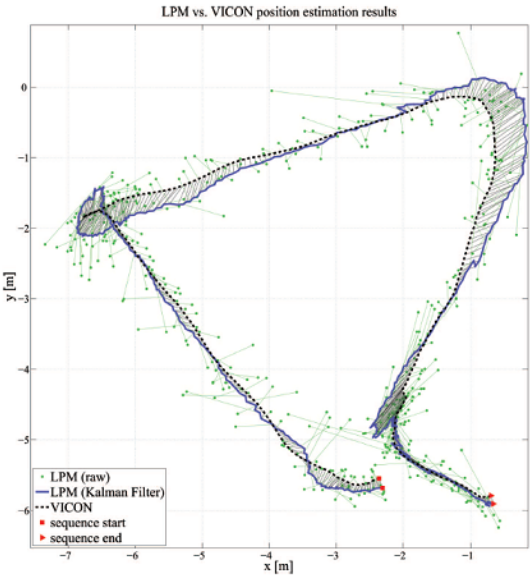
Kalman Filtering — Examples

As was shown, the application of a Kalman Filter allows to come up with realistic player motions the majority of the time. However, this process is also responsible for motion artefacts when dealing with fast changes of direction—which are typical for football. It is not fully understood where these artefacts come from as there are two possible sources of error:

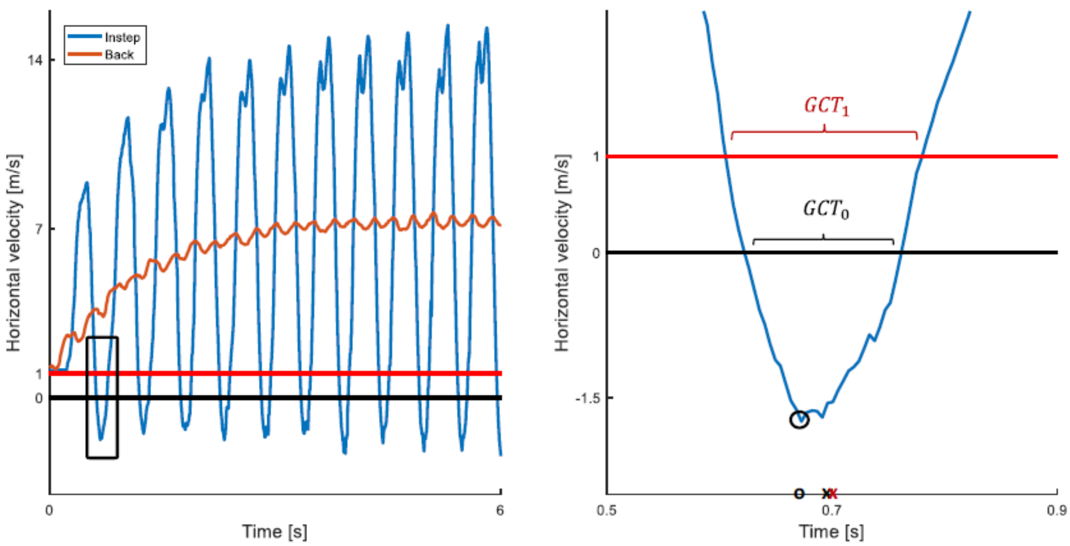
(a) Measurement errors. The measured phase values overestimate the average speed, which is why a compensation process (undershoot) takes place. So errors are caused by measured values. The same can result for the ToA measurements, because these have even larger measurement errors.

(b) Model errors. The *constant acceleration* motion model acts like a low-pass filter, smoothing out jerky movements. Relaxing the constant acceleration assumption to a *constant velocity* model might result in smaller filter effects.

Regardless of the error origin, filtering leads to unrealistic results and to errors in player or ball positions when dealing with sports-specific movements.
Figure 2.11a shows the effect of Kalman Filtering raw positional estimates for the movement of a football player tracked by Inmotio's LPM system (Ogris et al., 2012). Kalman Filtering (solid blue line) clearly improves raw positioning estimates (green dots) as can be seen by observing deviations from ground truth positions (dotted black line). Deviations of filtered positions and ground truth estimates are rather small during straight runs but increase when the player changes direction.
A similar effect can be observed when attaching a RedFIR transmitter to the shoe of an athlete during sprinting. High decelerations of the foot before ground contact and high accelerations after ground contact (in movement direction) lead to unrealistic negative velocities as shown in Figure 2.11b.
To circumvent these issues a threshold-based method was applied to determine ground contacts based on LPS data. This allowed to compensate for movement artefacts through the Kalman Filter (Seidl et al., 2017). Another possibility would be the development of a more realistic model for moments when fast changes in direction happen.



(a) Fast changes of direction in football captured by a radio-based position tracking system. Green dots correspond to raw position estimates based on multi-lateration of TDoA values. Kalman filtered positions are shown as solid blue line. Comparing both estimates to ground truth positions obtained by a motion capture system (black dotted line) shows the difficulties of capturing changes in direction. Figure taken from Ogris et al. (2012).



(b) Application of radio-based tracking in 100 m sprint. Velocity of a transmitter attached to the shoe of an athlete during 100 m sprint is shown (blue line). Unrealistic negative velocities are observed that could be caused by Kalman Filtering. As a consequence finding an optimal threshold for the detection of ground contacts was needed to compensate for filtering artefacts. Figure taken from Seidl et al. (2017).

Figure 2.11: Kalman Filtering artefacts for LPS systems based on fast change of direction in football and for ground contacts of the foot during 100 m sprint.

Chapter 3

Articles

In this chapter, a summary of the articles submitted for this thesis is presented and the personal contributions of the author are mentioned.

3.1 Evaluating the Indoor Football Tracking Accuracy of a Radio-based Real-Time Locating System

Seidl, T., Völker, M., Witt, N., Poimann, D., Czyz, T., Franke, N., & Lochmann, M. (2016b). Evaluating the indoor football tracking accuracy of a radio-based real-time locating system. In P. Chung, A. Soltoggio, C. W. Dawson, Q. Meng, & M. Pain (Eds.), *Proceedings of the 10th International Symposium on Computer Science in Sports (ISCSS)*, volume 392 of *Advances in Intelligent Systems and Computing* (pp. 217–224). Cham: Springer.
DOI: https://doi.org/10.1007/978-3-319-24560-7_28

Contribution

The author's contributions to this paper were the literature review, development of test methodology, data analysis, writing of the Section Introduction, the Section Methods, and the Section Results. Data acquisition and writing the Sections Discussion and Conclusion was done together with the co-authors.

Summary

Nowadays, many tracking systems in football provide positional data of players but only a few systems provide reliable data of the ball. Video-based systems are commonly used to track players and ball in competition.
However, the tracking quality of video-based systems suffers from high ball velocities up to 120 km h^{-1} and from the occlusion of both the players and the ball. To the best of our knowledge, there are actually no studies dealing with the positional accuracy of ball tracking. The use of radio-based local positioning systems for tracking in sports is promising as these systems allow for higher update rates and, theoretically, higher accuracy. Player transmitters are tracked with 200 Hz whereas the football transmitter even achieves update rates of 2000 Hz. These systems use transmitters integrated in the ball and located on the players' back or near

the shoes to avoid before mentioned issues.
This paper tried to close this gap by using the RedFIR radio-based locating system together with a ball shooting machine to repeatedly simulate realistic situations with different velocities in an indoor environment. As criterion a calibrated high speed camera with a frame rate of 1000 Hz was used and the position of the football was manually marked in the images by fitting a circle around the ball throughout 30 video sequences.
Positional accuracy of the ball tracking was evaluated by means of root mean square error (RMSE) and Bland-Altman analysis. On average a RMSE of 12.5 cm with 95 %-CI of [−21.1 cm, −1.9 cm] was observed.
Results showed the applicability of radio-based local positioning systems for tracking a football with a high accuracy.

3.2 Validation of Football's Velocity provided by a Radio-based Tracking System

Seidl, T., Czyz, T., Spandler, D., Franke, N., & Lochmann, M. (2016a). Validation of football's velocity provided by a radio-based tracking system. *Procedia Engineering*, *147*, 584–589.
DOI: https://doi.org/10.1016/j.proeng.2016.06.244

Contribution

The author's contributions to this paper were the literature review, data analysis, writing of the Section Methods, and main parts of the Section Discussion. Data acquisition and writing the Sections Introduction, Discussion and Conclusion was done together with the co-authors.

Summary

Building on the results of the previous study, dealing with the positional accuracy of radio-based ball tracking, the capability of radio-based football tracking to provide accurate football speed was investigated. As the previously used test setup did not allow to investigate the effect of largely varying ball speeds a slightly different setup was used. This study was, therefore, the first to consider the accuracy of ball speed estimates for radio-based football tracking.
To assess the accuracy of the football's velocity provided by the radio-based tracking system RedFIR, again, a ball shooting machine was used to repeatedly simulate realistic situations at different velocities in an indoor environment. The new setup (with no shooting wall) allowed to capture 50 shots at a much wider range of ball velocities ranging from $7.9\,\mathrm{m\,s^{-1}}$ to $22.3\,\mathrm{m\,s^{-1}}$. Obtained football speed values were compared to criterion speed values derived from light gates by way of mean percentage error (MPE) and Bland-Altman analysis.
Results showed a systematic bias of 2.6 % which indicates that the football's speed provided by the RedFIR system slightly overestimated the football's mean speed. Limits of agreement of 9.6 % ($1.9\,\mathrm{m\,s^{-1}}$) and the fact that 92 % of analyses had an absolute error of less than 6 % prove RedFIR's ball speed to be accurate within 10 % for velocities ranging from $7.9\,\mathrm{m\,s^{-1}}$ to $22.3\,\mathrm{m\,s^{-1}}$.
This study demonstrated the applicability of the RedFIR ball tracking to measure (mean) ball speed. This can be used to provide speed information about passes and shots, and combined

with information about the ball position allows to quantitatively assess technomotorical skills of football players like ball handling, passing and shooting behaviour that is fundamental for a quantitative evaluation of football players.

3.3 Estimation and Validation of Spatio-temporal Parameters for Sprint Running using a Radio-based Tracking System

Seidl, T., Linke, D., & Lames, M. (2017). Estimation and validation of spatio-temporal parameters for sprint running using a radio-based tracking system. *Journal of Biomechanics*, *65*, 89–95.
DOI: https://doi.org/10.1016/j.jbiomech.2017.10.003

Contribution

The author's contributions were the ideation, development and implementation of the algorithm for ground contact detection and the calculation of sprint parameters, literature research as well as writing of the Section Methods. Data collection concept for the evaluation of sprint parameters and data acquisition as well as writing of the Sections Introduction, Results and Discussion was done together with the co-authors.

Summary

Spatio-temporal parameters like step length, step frequency and ground contact time are directly related to sprinting performance. There is still a lack of knowledge, however, on how these parameters interact.
Recently, various algorithms for the automatic detection of step parameters during sprint running have been presented which have been based on data from motion capture systems, video cameras, optoelectronic systems or inertial measurement units.
However, all of these methods suffer from at least one of the following shortcomings: they are (a) not applicable for more than one sprinter simultaneously, (b) only capable of capturing a small volume or (c) do not provide accurate spatial parameters. To circumvent these issues, the radio-based local position measurement system RedFIR can be used to obtain spatio-temporal information during sprinting based on lightweight transmitters attached to the athletes.
To assess and optimize the accuracy of these parameters nineteen 100 m sprints of twelve young elite athletes (age: 16.5 ± 2.3 years) were recorded by a radio-based tracking system and an opto-electronic reference instrument. An algorithm to automatically detect spatio-temporal parameters was developed and optimal filter parameters for the step detection algorithm were obtained based on RMSE differences between estimates and reference values on an unseen test set. Attaching a transmitter above the ankle showed the best results.
Bland-Altman analysis yielded 95 % limits of agreement of [−14.65 cm, 15.05 cm] for step length, [−0.016 s, 0.016 s] for step time and [−0.020 s, 0.028 s] for ground contact time, respectively. RMS errors smaller than 2 % for step length and step time show the applicability of radio-based tracking systems to provide spatio-temporal parameters.

This creates new opportunities for performance analysis that can be applied for any running discipline taking place within a stadium. Since analysis for multiple athletes is available in real-time this allows immediate feedback to coaches, athletes and media.

Chapter 4

Discussion

Essentially, all models are wrong,
but some are useful.

George Box

All publications dealt with radio-based positional data in sports; two studies aimed to validate kinematic data obtained by radio-based football tracking whereas the third study investigated the development and validation of an algorithm for the detection of fine-grained motion details such as ground contacts. Due to limited space the following three topics related to the validation and use of positional player tracking data could not be addressed in the publications but are discussed in more detail below.

- System validation
- Interchangeability of results between tracking systems
- Deriving insights from spatio-temporal player tracking data

4.1 System Validation

Two of the publications on which this dissertation is based are validation studies of radio-based football tracking and to the best of the author's knowledge, there are still no other studies dealing with the positional accuracy of (radio-based) ball tracking. In addition, the topic of positional accuracy of player tracking is still not satisfactorily dealt with in the literature. This is due to the challenges that validation studies of player and especially ball tracking systems pose to test design which are discussed in the following.

To test the accuracy of a player tracking system for a specific sport typical movements—and, therefore, player positions or parameters like covered distance—are simultaneously recorded with the system under test and a criterion system. The criterion system is known to allow a valid measurement of the parameter(s) of interest, e.g. player position, with known accuracy. Challenges associated with the choice of criterion system concern external validity as this system has to validly capture *sport-specific motion* in a *sport-specific setting*. As a rule of thumb, it should be at least one order of magnitude more accurate than the system under test,

i.e., when validating a system that is assumed to be accurate within 10 cm the criterion should be accurate within 1 cm. As most tracking systems nowadays achieve positional accuracies of less than one meter (Figure 2.3) potential criterion systems have to be accurate within centimeters or even millimeters.
Moreover, the validation study should be performed in a *sport-specific setting*. For football the study should be done within a football stadium or at least on a football pitch. A study that aims to validate player or ball tracking in tennis has to be done on a tennis court under typical match or at least training conditions. At best, test protocols should incorporate drills and actual match play to be able to infer the validity for the system's use in competition.
In addition, the criterion system must also be able to capture *sport-specific movement* like fast changes of direction in football. This additionally requires high sampling rates. For example a high-speed high-definition camera might be used as criterion measurement to capture the movement of a player (or of his body parts). However, the same system might not be accurate enough to be used as a reference system for ball tracking as a too high speed of the ball can lead to a motion blur in the image[28]. This would render the method useless as a reference system. This narrows down the range of possible criterion systems for positional validation studies to motion capture and high speed camera systems with high resolutions which are very expensive and only available to large research institutions.
As a consequence, the majority of validation studies investigated derived parameters like covered distance and high-intensity runs instead of x,y positions, and used reference systems like a trundle wheel for covered distance or timing gates for measuring mean speed (Castillo et al., 2018; Frencken et al., 2010; Hoppe et al., 2018a; Sathyan et al., 2012).
Based on the hierarchical structure shown in Figure 1.3 in Chapter 1, however, this is highly problematic as any errors inherent in player positions (layer 1) get propagated to higher layers and, therefore, influence estimated performance parameters. This fact makes the validation of *positional accuracy* a central issue which was already noted by Siegle et al. (2013) a few years ago:

> "Distances and velocities are calculated based on raw positional data, the x,y position of a player over time, [...] studies so far have neglected to test this basic capability of dynamic x,y position measurement of position detection systems."

However, even in studies that use a reference system that potentially allows positions, velocities and accelerations to be analyzed, studies fail to also investigate the effect of errors in positional data on derived parameters (Linke et al., 2018; Luteberget et al., 2018; Ogris et al., 2012). This kind of sensitivity analysis is common in numerics for example, and allows the influence of changes in system inputs (here: positional data) and outputs (here: velocities, accelerations or covered distance) to be systematically investigated (Nocedal & Wright, 2006). This is not limited to quantities which are directly derived from positional data, like covered distance but might also be beneficial when detecting events, e.g. passes, shots or possessions based on positional data (Link & Hoernig, 2017).
The main question is not how accurate positional data is, but rather how accurate can the performance parameter of interest be estimated *based on the error in the underlying positional data*. However, knowledge about the sensitivity of parameters and positional data would be

[28]High speed cameras typically allow to change shutter time to cope with these issues. As a consequence, additional light might be needed.

beneficial when a decision about the use of a particular tracking system for a given application is to be made.

The design of *validation studies for football tracking* is even more challenging. The high speeds a football can reach combined with the fact that in camera images the ball is often occluded by players makes video-based ball tracking an extremely challenging problem, and thus a vivid research topic within computer vision. Despite this positive fact, it is particularly difficult to transfer results from computer vision studies to actual sports; evaluation metrics for tracking algorithms in computer vision are in most cases only based on detection rates rather than positional accuracy, i.e. the percentage of frames a ball has been detected correctly (Gomez et al., 2014; Kamble et al., 2017; Reno et al., 2018). However, a correct detection rate of 98 % does not yield any information about the *positional* accuracy on the football pitch for example, which also depends on camera calibration to determine the correspondence of image pixels and real world locations[29]. Hence, differences in evaluation metrics make computer vision studies not directly applicable to evaluate their usefulness in sport practice.
Unfortunately, there is actually no gold standard to be used for tracking the position of a football under match or at least training conditions. Based on accuracies and sampling rates, motion capture systems would be the criterion systems of choice, but fail due to the need to attach reflective markers to the ball itself.

However, there seems to be a encouraging trend. After the International Football Association Board (IFAB) allowed the use of electronical player tracking systems (EPTS) in competition in March 2015, FIFA began to develop a testing procedure for EPTS which player tracking systems have to pass before being used in competition (FIFA, 2015). Having every tracking provider to undergo the same testing protocols performed by an independent test institute would be a promising basis which would allow a fair comparison of different tracking systems[30]. Besides validation, the transferability of results between different tracking systems is an important topic which is addressed in the next section.

4.2 Interchangeability of Results between Tracking Systems

A professional football club usually deploys many different tracking systems and it is not uncommon, in practice, to obtain player tracking data from a video-based system for league matches and from GPS or LPS systems for trainings (Buchheit et al., 2014). If the aim is to evaluate player load for a given player over a season one needs to ensure that the way player load is measured by video-, GPS- and LPS-based systems is actually the same.
Based on the interactions between capabilities, training and competition (Figure 1.2) performance demands on a player in competition are the primary source for identifying the required levels of an athlete's capabilities. Since those act as targets for training the comparability

[29] However, a precision of only 60 % does yield valuable information as it would render the tracking algorithm to be useless for practical applications.

[30] Currently, such a comparison of results from different validation studies is almost impossible as studies are usually based on different test protocols, as well as varying reference systems. This even makes comparisons between studies of the same tracking system difficult.

of load measurements in training and competition is a prerequisite for the development of competition-specific training and thus for practical performance analysis.
Hence, the comparison of performance parameters, like covered distance and number of high intensity runs, is based on the assumption that parameters obtained from different player tracking systems are (a) based on the same definition, e.g. high intensity run ($\geq 14.4\,\mathrm{km\,h^{-1}}$) and (b) that each system is valid and reliable when measuring the parameter of interest.
To solve this issue, Buchheit et al. (2014) proposed the use of regression equations to transfer results between tracking systems. Regression coefficients were derived based on the comparison of player activity during training and match, that was recorded simultaneously with GPS, LPS and video-based systems. The study showed that it is possible to develop such calibration equations. However, large typical errors of the estimate for the regression were observed and led the authors to develop multiple equations for different areas of the football pitch which makes results at least questionable for the use in practice. Although these regression equations allow to transfer parameters between measurement systems it would be advisable to eventually transfer them to a gold standard system.
Another issue that is often overlooked is the effect of attaching transmitters to different body parts. Even small changes in the positioning of a transmitter on the human body will effect derived parameters. Linke & Lames (2018) used a motion capture system to track football players during football-specific drills and small sided games in a stadium environment. Reflective markers were placed to simulate typical positions for transmitter-based systems (center of scapulae – COS) and video-based systems (center of pelvis – COP). The authors showed that differences between COP and COS depended on the underlying movement characteristic and COS sprinting distance was on average 44.65 % ($p < .001$) lower in comparison to COP. This is an alarming result as these differences are solely based on different marker/transmitter positions. In practice, these differences are probably a lower bound when comparing estimates between transmitter-based and video-based systems.
The transferability of parameter estimates between tracking systems has been insufficiently investigated in the literature. However, the above mentioned studies clearly show common challenges when using player tracking systems in practice. Care should be taken when comparing parameters from different transmitter positions or when transferring results between tracking systems.

Even in absence of transferability issues between systems the main challenge is how to derive performance insights from positional tracking data.

4.3 Deriving Insights from Spatio-temporal Player Tracking Data

The last years have seen a large increase in the amount of collected data in sports. But as was mentioned by Pratas et al. (2018)

> “it is not always clear how these data should be processed with a view to providing coaches, match analysts and players with relevant information.”

However, only processing and analysis of spatio-temporal data can actually create insights about the underlying mechanisms of performance. This is clearly challenging as player and

team behaviour in sports is usually complex in nature due to the interaction between opponents and team mates which gives rise to non-linear systems (Lames & McGarry, 2007). Making sense of positional data is in particular challenging as there is no guarantee that a *closed form solution*[31] for a given problem in sports actually exists[32]. However, modern machine learning algorithms make it possible to *learn* those (non-linear) relationships based on examples.
The need for machine learning for the analysis of spatio-temporal player tracking data is best illustrated by the following example. Over a decade ago Beetz et al. (2005) developed a Football Interaction and Process Model (FIPM) based on first-order predicate logic. Logical rules governing equations were created by investigation of player tracking data and an example rule is shown in equation 4.1.

$$\forall sit. \Big(scoringAngle(sit) \geq 35.6° \wedge distance(sit) \leq 16.38 \xrightarrow{86\%} ScoringOpportunity(sit) \Big) \tag{4.1}$$

This logical rule states that

> "game situations [*sit*] in which the offensive player with the ball is less than 16.38 m away from the goal, and in which the largest angle to the goal not blocked by a defensive player is at least 35.6°, constitutes a scoring opportunity with a probability of 86 %." (Beetz et al., 2005)

The main advantage of the proposed method is that derived rules are easily understandable (once you understand first-order predicate logic). However, these rules are too specific to the situation to be useful for *understanding* goal scoring as basis for performance analysis. This is due to the missing option to investigate the effect of altering parameters on goal scoring probability, e.g. what happens if the player has the chance to get 5 m closer to the goal or what if the scoring angle is 180° instead of 35.6°?
In contrast, by using machine learning methods, one can train a model to learn the non-linear relationship between game context, e.g. scoring angle and distance in the example above, and the result of the shot. This approach allows to generalize to new unseen situations and to investigate for example the effect of changing distance to the goal on the probability of goal scoring (Link et al., 2016; Lucey et al., 2015) which, in turn, allows to answer the kind of "what if"–questions mentioned above. The application of machine learning can, therefore, enhance our understanding of performance concepts, like goal scoring, in unprecedented ways.
Even the development of an algorithm for the detection of ground contacts for 100 m sprint involved the machine learning concept of cross-validation to obtain an optimal velocity threshold (Seidl et al., 2017).
These examples clearly show the benefit and necessity of machine learning for the analysis of positional data in sport.

[31] An equation is said to be a *closed-form solution* if it solves a given problem in terms of functions and mathematical operations from a given generally-accepted set.

[32] Even for physical phenomena that can be modelled by governing partial differential equations, e.g. heat or wave equation, a closed form solution exists only in the simplest cases. Most real world problems can only be solved approximately, for example by computer simulation. It is therefore unrealistic to assume to find such a solution for complex phenomena like team sports.

Chapter 5

Conclusion and Outlook

Prediction is difficult,
especially about the future.

Yogi Berra

5.1 Conclusion

Despite the long-term availability of positional data in almost all major sports such as football or basketball, the question of the quality of positional data—especially the acquisition of the kinematics of objects such as a football or a basketball—has not been sufficiently investigated. One still has to rely on the statements of manufacturers. This dissertation presented test setups based on high speed camera footage and light gates that allowed to investigate the accuracy of ball position and speed for a radio-based tracking system in football. As test design was not specific to football it can be applied to other sports.

Furthermore, the usability of positional data for performance analysis is still controversial (Carling, 2013). However, it could be demonstrated that fine-grained motion details like ground contacts of the feet can be detected within radio-based positional data. The algorithm which was developed for the analysis of 100 m sprint allowed the automatic and continuous recording of performance-relevant step parameters, such as step length and step time, over the entire run. As the algorithm is not limited to straight runs it is also applicable to analyze step characteristics in team sports, showing the potential for technical analysis based on radio-based tracking.

These studies have shown the potential of radio-based tracking systems for applications in sports which provide more accurate data with higher sampling rates than video-based systems which nowadays are primarily used in competition due to competition rules. In addition, as data does not require a high level of manual post-processing, data available in real time is of the same quality as data after the competition. In many sports, there are clear tendencies for competition rules to change, to thus allow athletes and players to wear transmitters during competition (FIFA, 2015), and to provide tracking data and analysis results to analysts and coaches within the match (FIFA, 2018).

The present work gave an overview of the state of the art in system validation and analysis of positional data and attempted to classify it within the framework of training and exercise science and performance analysis as well as from a data analytics perspective. In addition, current methods for the acquisition of positional data were presented, and topics such as system validation, transferability of derived parameters between different systems, and the benefits of machine learning for profitable analysis were discussed.

This thesis led to promising first results but further research with regards to system validation and pattern recognition for performance analysis is necessary. However, technological innovations and advances in computer science will lead to various improvements in the ways spatio-temporal data is *gathered*, *analyzed* and *how results will be used in practice*. The following Outlook discusses these topics.

5.2 Outlook

Currently, there are various technological innovations and promising approaches in computer science which might help to improve our understanding of sports performance. This section gives an outlook on applications that might change the way data is collected, analyzed and integrated into sports practice. Based on the current literature, and the personal opinion of the author, major innovations can be expected in the following areas:

(1) Computer Vision

(2) Wearables

(3) Deep Learning & Predictive Analytics

(4) Integration of insights into practice

Within each subject area promising methods will be presented in the following.

(1) Computer Vision

Object detection and tracking is a vivid research area within computer vision. Further breakthroughs in computer vision research related to applications in other sectors, like autonomous driving, can possibly be applied to applications in sports as well.
As was seen in Chapter 2 “moving dots” are a vast simplification of the real world and valuable information is currently missing, which is, however, contained in other sources like broadcast videos. For example, there is currently no information on “the aspect (direction) faced by a player [contained in the tracking data]. A player moving a $4\,\mathrm{m\,s^{-1}}$ might be jogging forward, rapidly shuffling backwards or skipping sideways” (O’Donoghue, 2015). Figure 5.1 shows how information about body pose, derived from broadcast video, can help to better understand the current situation (Felsen et al., 2018). Looking only at spatio-temporal player tracking data (top) this appears to be a very high-percentage shot opportunity. However, the broadcast view (bottom) shows the pose of the player and reveals an off-balance shooter recovering from a poorly placed pass.
Also, advances in camera hardware and software will be beneficial for video-based tracking systems. Increasing video resolutions from HD (1920×1080) to 4k UHD (3840×2160) will facilitate the detection and tracking of players and objects. A larger number of pixels

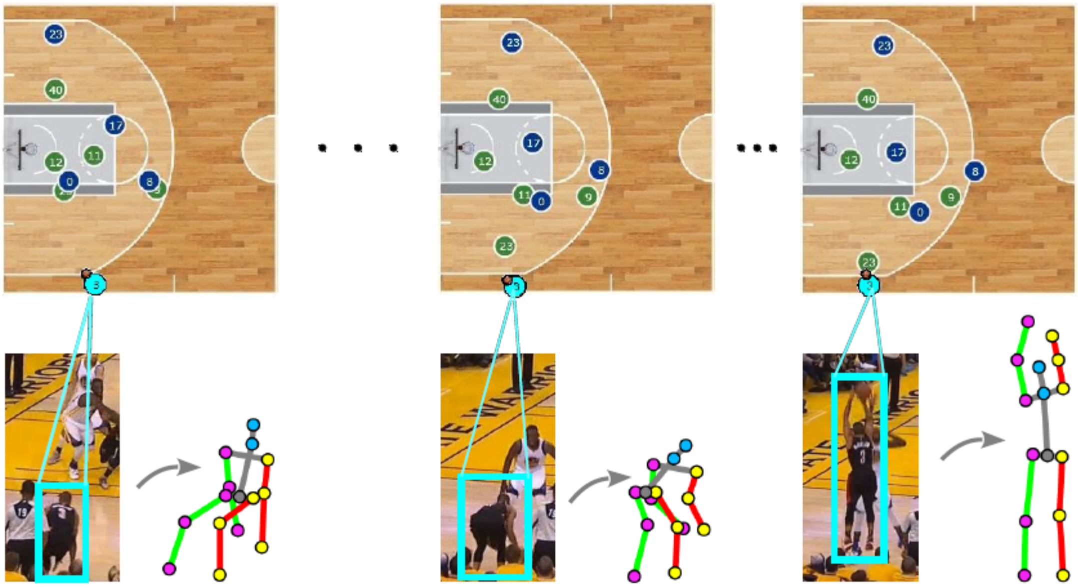


Figure 5.1: Beyond "Moving dots": body pose from video. From SportVU data (top), this appears to be a very high-percentage shot opportunity. However, the broadcast view (bottom) shows the pose of the player and reveals an off-balance shooter recovering from a poorly placed pass. Figure taken from Felsen & Lucey (2017).

corresponding to an object will enable, for example, a better assignment of player identities by recognition of jersey numbers. This will lead to the development of more stable tracking algorithms that will better cope with occlusions and, eventually, to "full automatic vision based player tracking in team sports (...) in the next 10 to 15 years" (Leser & Roemer, 2014, p. 98).

(2) Wearables

In contrast to video, wearables (including LPS systems) are intrusive as athletes need to be equipped with transmitters or sensors. However, wearables allow to make measurements "at" the object/player and therefore are deemed to be more accurate and reliable than non-invasive video technologies. Nowadays, wearables are already heavily used within training. In addition, further miniaturization of transmitters will eventually allow integration into clothes, shoulder pads (Zebra, 2018), objects (football, basketball or ice hockey puck) (Grün et al., 2011) or tennis rackets (Keaney & Reid, 2018) to overcome the before mentioned intrusiveness. This will then allow to obtain information about object kinematics like speed, acceleration and rotation. In baseball the use of a wearable sleeve integrating IMUs has been shown to be beneficial for the analysis of pitchers' performances. The Motus SleevePro, for example, has five integrated IMU sensors to analyze the technique of a pitcher in baseball. Only a few years ago, this type of technical analysis was limited to biomechanics labs but the wearable actually allows to be used during competition. 27 of the 30 major league baseball clubs were supposed to use the sleeve in 2016 (New York Times, 2016).
The greatest potential of wearables are the capacity to directly measure vital parameters like heart rate and breath rate which is not possible by using cameras. This information might be

especially useful when measuring load and fatigue.

In particular the combination of camera- and radio-based player tracking and wearables has the potential to open up completely new possibilities for performance analysis, injury prevention and to the media[33].

(3) Deep Learning & Predictive Analytics

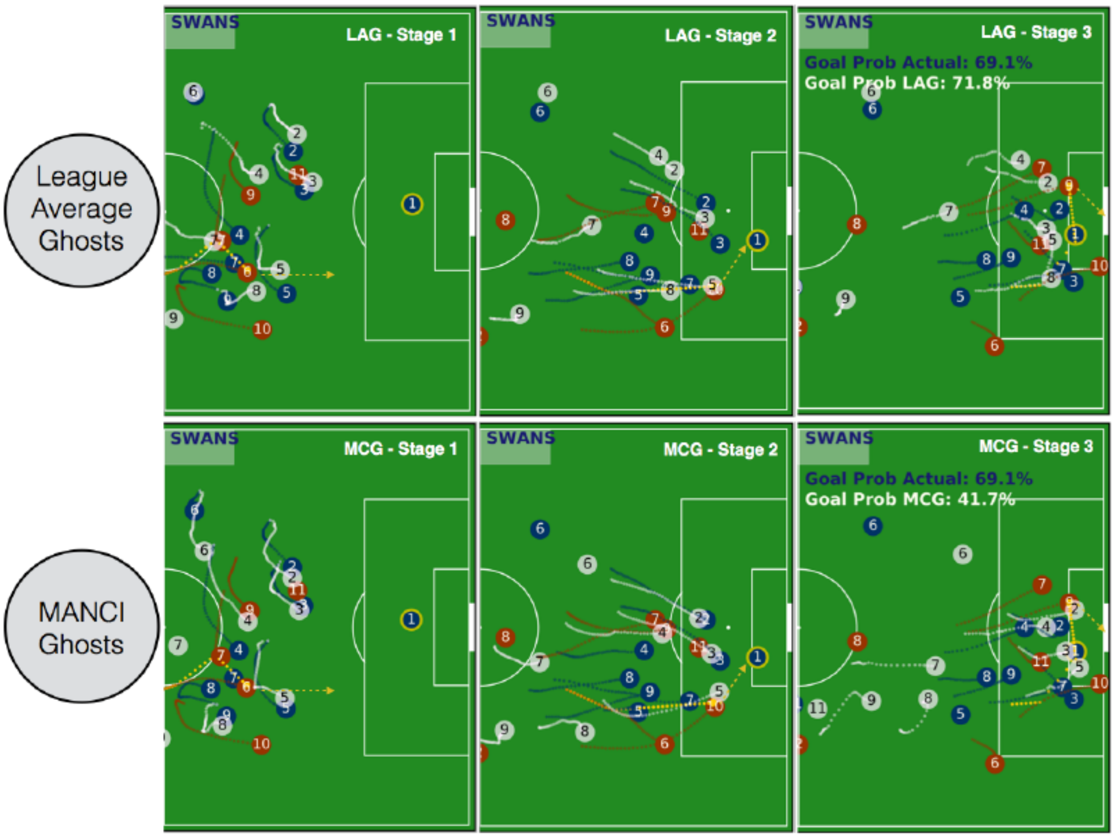


Figure 5.2: Data-Driven Ghosting in Football. Large amounts of player tracking data allow to develop deep learning algorithms that can learn realistic defensive behaviour for different teams in football. The model allows to predict and evaluate a team's defensive behaviour in situations which they never experienced in reality. Attacking team is shown in red, actual defensive team in blue and ghost defense in white. Models trained on sequences from good defensive teams (Manchester City, botton row) result in better defensive models (lower expected goal value). In contrast to a league average ghost (top, white circles) defender with jersey number 2 of Manchester City (bottom, white circles) manages to get between the striker (jersey number 9) and goal which results in a lower expected goal value (41.7 %) compared to the league average ghosts (71.8 %) and the actual defensive team (69.1 %). Figure taken from Le et al. (2017).

Besides the possibilities to get more detailed data from video or wearables, the main challenge remains how to gain insights for performance analysis.

[33]Especially for sports like ice hockey where tracking is even more challenging (Lemire, 2017).

The application of *Deep Learning* (LeCun et al., 2015) to sports applications is in particular promising as *deep neural networks*—in contrast to other machine learning methods—allow to leverage the vast amount of data as accuracy further increases as more data is provided to the deep neural network. Given enough examples deep learning models are capable to learn even complex sports behaviour. These models can then be used to *predict* most likely actions even in scenarios that teams or players have never faced in reality (Felsen et al., 2018; Wei et al., 2016). An example for the potential use of predictive analytics is data-driven *Ghosting*[34] where spatio-temporal player tracking data of a full season from the English Premier League was used to train deep neural networks to learn the defensive behaviour of football teams (Le et al., 2017). These ghosting models are built on the same principles and methods that allowed computer program AlphaGo to beat the best human Go players (Silver et al., 2017). These models have potential applications in scouting, match analysis and in media reporting. Figure 5.2 shows the comparison of the same attacking sequence run against a mean league model (top) and against a very good defensive team (bottom). Models trained on examples of good defensive teams, like Manchester City in this particular season, learned better defensive behaviour.
These developments are very promising for performance analysis applications. However, the question remains how analyses and models can find their way into practice.

(4) Integration of Insights into Practice

The challenge coming with more and better data (possibly from various sources) and better analytics is eventually how to integrate findings into practice.

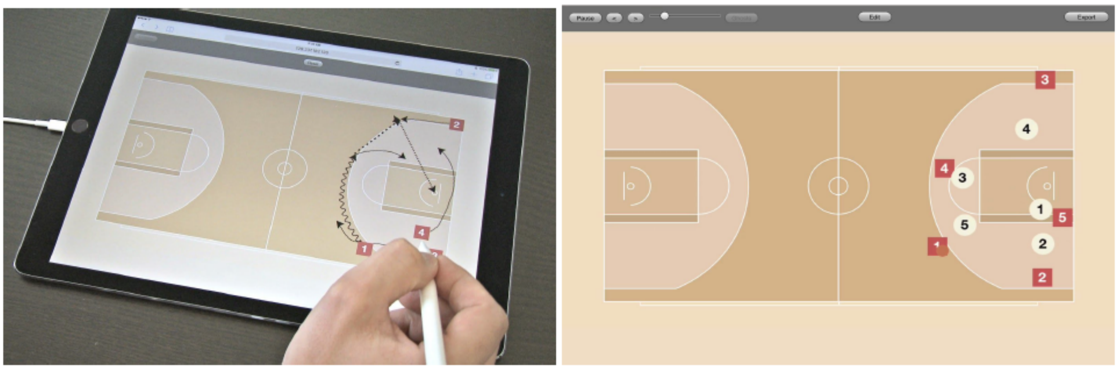


Figure 5.3: Bhostgusters: Intuitive iPad tool for tactical analysis in basketball: (left) interactive sketching, and (right) frame from corresponding synthesized tracking data with "ghost" players shown as white circles. Figure taken from Seidl et al. (2018).

Hence, there is a need for developing tools which are intuitive and easy to use by non-technical experts. As data will potentially be available in real-time, new tools will be developed that help coaches and staff to gain match insights and even assist with in-game decision making (Seidl et al., 2018). Figure 5.3 shows an iPad tool that allows NBA coaches to sketch offensive plays the same way they would do it on a white board. However, the tool then allows to translate the

[34]Ghosting refers to a concept developed by the Toronto Raptors. "Ghost players [...] are doing what Toronto's coaching staff and analytics team believe the players *should have done* on this play" (Lowe, 2013).

sketch into realistic animation, and simulates the defensive reaction on that play for different teams. The underlying ghosting models are similar to the before-mentioned example in football (Le et al., 2017) but also allow to adjust context variables, like simulating player fatigue or the effect of the number of fouls committed. Although the tool is based on sophisticated machine learning models its use does not rely on any expert knowledge related to machine learning. This shows a possible way how very complex systems could be integrated into practice.
Another possible way to bring insights into training could be to design tools that automatically provide some sort of feedback to coaches and players as soon as measured values reach or exceed certain target thresholds.
Future player tracking systems, which possibly combine multiple approaches like video- and radio-based player tracking systems, will allow to quantitatively assess technical and tactical performance of players in training or the monitoring of on-field rehabilitation after injuries (Hoppe et al., 2018b). Kemeth et al. (2014) presented such a feedback application to prevent collision of visually-impaired runners. However, similar methods could be used to provide feedback to athletes to optimize behaviour in training (and competition).

All of the above mentioned themes get facilitated by rule changes in sports that will allow their use in competition to capture, analyze *and* communicate results to coaches and media. Usability of new technologies and analytics in practice, however, does not only refer to mediation media and presentation, but will also require own studies to evaluate the use and reception of these new possibilities in practice as research objects.

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Appendix

The Appendix contains full paper versions for all publications related to this dissertation and written permission for its use, respectively. Since the paper *Validation of football's velocity provided by a radio-based tracking system* was published as open access article no permission statement is attached in this case.

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Estimation and validation of spatio-temporal parameters for sprint running using a radio-based tracking system

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ABSTRACT

Spatio-temporal parameters like step length, step frequency and ground contact time are directly related to sprinting performance. There is still a lack of knowledge, however, on how these parameters interact.

Recently, various algorithms for the automatic detection of step parameters during sprint running have been presented which have been based on data from motion capture systems, video cameras, opto-electronic systems or Inertial measurement units. However, all of these methods suffer from at least one of the following shortcomings: they are (a) not applicable for more than one sprinter simultaneously, (b) only capable of capturing a small volume or (c) do not provide accurate spatial parameters. To circumvent these issues, the radio-based local position measurement system RedFIR could be used to obtain spatio-temporal information during sprinting based on lightweight transmitters attached to the athletes. To assess and optimize the accuracy of these parameters 19 100 m sprints of twelve young elite athletes (age: 16.5 ± 2.3 years) were recorded by a radio-based tracking system and a opto-electronic reference instrument. Optimal filter parameters for the step detection algorithm were obtained based on RMSE differences between estimates and reference values on an unseen test set. Attaching a transmitter above the ankle showed the best results.

Bland-Altman analysis yielded 95% limits of agreement of [−14.65 cm, 15.05 cm] for step length [−0.016 s, 0.016 s] for step time and [−0.020 s, 0.028 s] for ground contact time, respectively. RMS errors smaller than 2% for step length and step time show the applicability of radio-based tracking systems to provide spatio-temporal parameters. This creates new opportunities for performance analysis that can be applied for any running discipline taking place within a stadium. Since analysis for multiple athletes is available in real-time this allows immediate feedback to coaches, athletes and media.

1. Introduction

Spatio-temporal parameters like step length, step time and ground contact time are related to running speed and thus sprinting performance. There is still a lack of knowledge, however, on how these parameters interact. Different studies reported contradicting results (Debaere et al., 2013; Hunter et al., 2004).

One main reason is the procedure by which these parameters are typically obtained—manual examination of video footage—which is very time-consuming, prone to errors and yields only mean values for different sections of the running track. Hence, their significance depends heavily on the length of the underlying intervals (Hanon and Gajer, 2009). The shorter these intervals the higher the impact of the related performance and competition analysis (Letzelter et al., 2005). Since there is a lower limit for the error of manual recording of ground contacts from video footage, the relative error increases when intervals are diminished. This procedure is therefore limited in its ability to obtain accurate estimates.

In recent years, several studies have been published on the automated acquisition of step-by-step parameters in sprint running. Different procedures based on motion capture (Nagahara et al., 2014), video (Dunn and Kelley, 2015), and photoelectric or IMU-based systems (Bichler et al., 2012; Schmidt et al., 2016) have been proposed. All of these methods suffer from at least one of the following shortcomings: they are (a) not applicable for more than one sprinter simultaneously, (b) only capable of capturing a small volume and are not applicable for events over 200 m long, or (c) do not provide accurate spatial parameters. Motion capture systems are very accurate and permit a detailed analysis of sprint kinematics (spatio-temporal parameters, movement and velocities of body

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segments and COM). Their multi-camera setup, the small volume which can be captured, the time-intensive post-processing as well as the need for attaching reflective markers to the athlete make their use impractical for training and prohibits their use in competition. Dunn and Kelley (2015) developed a video-based system which is unobtrusive as it does not need markers to be attached to an athlete's body. However, one camera captures only a range of 10 m. Therefore, to use this system for the analysis for 100 m sprints, the installation of a multi-camera network would be required. The analysis of running disciplines like 200 m, 400 m and 800 m would be even more demanding. To this extent video-based tracking suffers from certain shortcomings like occlusions—as athletes can be occluded by other athletes—and varying weather conditions. Hence their application for more than one sprinter simultaneously becomes impractical. Inertial measurement units (IMUs) seem to be a promising approach for detecting temporal parameters during sprinting as their application is not limited to a certain area and they are relatively inexpensive. Schmidt et al. (2016) developed an algorithm for the automated detection of ground contact time using IMUs and compared their estimates to the opto-electronic OptoJumpNext. However, the estimation of spatial parameters (e.g., step length) is challenging as the implementation of the double integration procedure suffers from error accumulation over time (Qi et al., 2016). To the best of the authors' knowledge there is no IMU-based system that is capable to provide accurate spatial parameters for a distance of 100 m and longer. For a review of gait partitioning methods see (Taborri et al., 2016). Based on the completeness and accuracy of data, photoelectric systems like OptoGait (Microgate, Bolzano, Italy) seem to be the method of choice as they provide accurate spatial (step length) as well as temporal (step frequency and ground contact time) parameters which are readily available after the sprint. However, these systems are only applicable for one athlete, limited to straight runs and need to be placed directly on the running track. This prohibits their use in competition and for runs including curved sections, i.e., that are longer than 100 m.

To circumvent these issues, the radio-based local position measurement system RedFIR (which has been developed for use in soccer) (Grün et al., 2011) could be used to obtain spatio-temporal information during sprinting based on lightweight transmitters attached to the athletes. The aim of the present study was, therefore, to apply this technology to the sprinting context and to develop a methodology able to automatically provide step length, step time and ground contact time during sprinting. Different transmitter positions were tested and the accuracy of the derived spatio-temporal parameters was evaluated by comparing them to an opto-electronic system.

2. Methods

2.1. The RedFIR Real-Time Locating System

The RedFIR Real-Time Locating System (RTLS) (Grün et al., 2011) is based on time-of-flight measurements, where small transmitter integrated circuits emit burst signals. Antennas around the stadium receive these signals and send them to a centralized unit which processes them and extracts time of arrival (ToA) values. ToA values are the basis for time difference of arrival (TDoA) values, from which x, y, and z coordinates, corresponding velocities and accelerations are derived using hyperbolic triangulation and by Kalman filtering assuming a movement with constant velocity. The RedFIR system operates in the globally license-free ISM (industrial, scientific, and medical) band of 2.4 GHz and uses the available bandwidth of around 80 MHz. Miniaturized (61 mm × 38 mm × 7 mm, 15 g) transmitters generate short broadband signal bursts together with identification sequences. The locating system is able to receive 50,000 of those signal bursts per second. The installation provides 12 antennas that receive signals from up to 144 different transmitters. Using a channel multiple access system allows to track multiple objects at the same time Transmitters typically emit around 200 tracking bursts per second. The miniature transmitters themselves are splash-proof. For a more detailed description of the RedFIR system and the generated data streams see Mutschler et al. (2013).

2.2. Test setup

Our experiments were conducted on the athletics track in the Grundig Stadion in Nuremberg—the official soccer Bundesliga stadium of 1.FC Nürnberg—where a RedFIR system is installed. Since this soccer stadium contains a 400 m running track it is often a venue for national athletics competitions and therefore was a good place to conduct our experiments. Twelve young elite athletes from various regional clubs (age: 16.5 ± 2.3 years) performed 48 sprints in total. The sample consisted of seven female and five male athletes. Subjects were tested one-by-one after a 20-min warm up that was chosen individually. Each athlete performed four sprints: two 50 m sprints and two 100 m sprints. Transmitters were attached to the athletes' insteps by tape, above both ankles and on the upper back by specially designed compression tubes/compression shirts providing a bag for transmitters, which have been developed for use in soccer. This was done to investigate spatio-temporal parameters from transmitters attached to different body parts. The chosen fixations have different intrusiveness and acceptance in sports practice. The work has been approved by the ethical committees of Technical University Munich and subjects gave informed consent.

Each sprint was simultaneously recorded by RedFIR and the photoelectric measurement system OptoGait (Microgate, Bolzano, Italy/OJ) that covered a range of 50 m and provided reference values for step length, step time and ground contact time with a measurement rate of 1000 Hz. All athletes were tracked simultaneously by the radio-based tracking system, but since the reference instrument allowed only one athlete at a time we had to restrict ourselves to test them one after the other.

The OptoGait system is comprised of 1 m modules which can be attached to each other to cover a larger volume. Each bar was 100 × 8 cm long and contained 96 light diodes that were located 3 mm above floor level and approximately 1 cm apart. Lienhard et al. (2013) reported 95% limits of agreement of [−1.0 cm, 1.8 cm] for step length, [−0.007 s, 0.023 s] for cycle time and 7.7% for ground contact time which met our demands for using it as a reference instrument.

To capture the entirety of a 100 m sprint the location of our reference instrument was changed during testing. Each athlete performed four sprints. For the first two sprints the opto-electronic system was placed to capture the first 50 m of the sprint. The system's location was then changed to capture the second 50 m of the track for the remaining two sprints. A similar approach was used by Debaere et al. (2013) to capture a 60 m sprint when only 40 m of OptoGait system was available.

2.3. Data analysis

The basis for the estimation of sprint-specific parameters is the detection of ground contacts of the foot. The following definitions for the detection of a ground contact are based on the horizontal velocity in running direction of a transmitter attached to an athlete. A ground contact is detected if the horizontal velocity (i) reaches a local minimum or (ii) falls below a given threshold. Ground contact time is defined to be the length of the interval when the horizontal velocity stays below a given threshold. Its centre corresponds to the moment of the ground contact t_i. Fig.1 illustrates the two definitions for a ground contact. Looking at the velocity of the back transmitter it becomes clear that there is no global threshold that would allow to obtain ground contact time in this case.

Step length, step time and ground contact time for a single leg are given by the following equations

$$step\ length_i = X(t_{i+1}) - X(t_i)$$

$$step\ time_i = t_{i+1} - t_i$$

$$gct_i = t_i^b - t_i^a$$

where t_i corresponds to the timestamp of the i-th ground contact, X to the position in the moving direction and t_i^a, t_i^b to the first and last timestamps when the horizontal velocity is below a given threshold. If thresholding is applied t_i will be the mean of the interval [t_i^a, t_i^b] or the timestamp where the horizontal velocity reaches a local minimum between two maximal values for the minimum-based approach.

2.4. Study design

The test setup described in Section 2.2 was applied to validate the accuracy of the obtained parameters and reference values were used to optimize several filter parameters (e.g., velocity thresholds, filter methods and window sizes) for the underlying step detection algorithms. The estimation of these parameters was based on splitting the data in separate training and test sets. We optimized (trained) the parameters on a separate training set of 60% of the samples. The remaining 40% of samples were used to evaluate the fit on an unseen test set. A similar method has been used by Miller (2009) to circumvent overfitting and to ensure generalizability of result. The parameter optimization scheme is illustrated in Fig. 2.

To differentiate between unfiltered raw estimates and estimates based on optimal filter parameters we define the following terms:

1. Raw/unfiltered estimate: An estimate for a parameter that is directly obtained by applying a thresholding of 1 m/s to the horizontal velocities for ankle and instep position. For the back position the raw estimate is based on finding the local minimum of the horizontal velocity.
2. Filtered estimate: An estimate for a parameter after using 'optimal' settings for threshold and filter. Optimal parameters consist of a threshold for ground contact detection (1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0 m/s), filter type (moving average, loess, lowess, savitzky-golay, robust loess, robust lowess) and filter window size (5%, 15%, 30%, 50%, 60% or 1–5 frames). Optimal parameters are found by minimizing the RMSE difference between estimated parameters and ground truth parameters.

To compare radio-based estimates and photoelectric ground truth values a Bland-Altman analysis (Bland and Altman, 1986) was performed, which is typically used to investigate differences between two measurement systems. The corresponding Root Mean Square Errors were calculated:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i^{rf} - p_i^{og})^2}$$

where p_i^{rf} and p_i^{og} denote the estimates of the parameters for RedFIR and OptoGait (i.e., step length, step time or ground contact time) at the i -th step, and N equals the total number of steps for all runs.

3. Results

Since each athlete had five transmitters attached during each of the 48 runs, a total of 240 'sensor runs' (48 runs $*$ 5 sensors) have been recorded. For 32 of these 240 sensor runs (13.3%) one of the

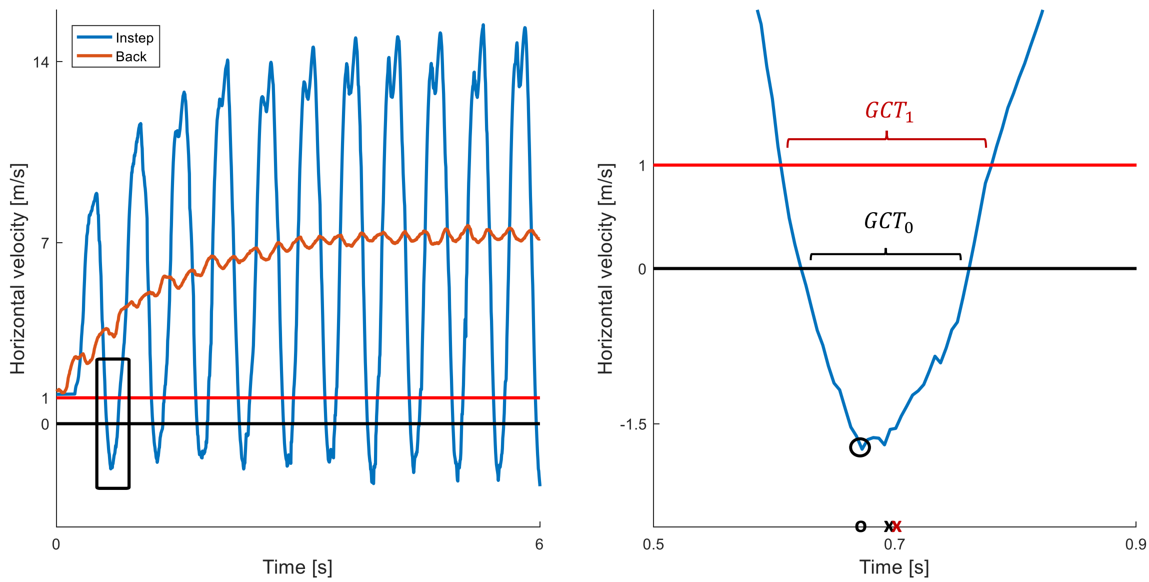

Fig. 1. The left plot shows the horizontal velocities for transmitters attached to the instep (blue) and back (red). Since velocities are based on Kalman filtering, unrealistic values lower than zero can be observed. The right plot shows a close-up of the red rectangle in the left plot explaining the two approaches to finding ground contacts: For minimum-based ground contact detection, a ground contact is detected if the horizontal velocity reaches a local minimum (black circle) between two maxima. For threshold-based ground contact detection, a ground contact period is detected if the horizontal velocity falls below a given velocity threshold (red and green line). The mean value of this interval corresponds to the moment of the ground contact whereas the duration of this interval is defined to be the ground contact time. Minimum- and threshold-based approaches provide slightly different estimates of the moment of the ground contact (black circle, red and green cross). Different thresholds result in different ground contact times as well. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

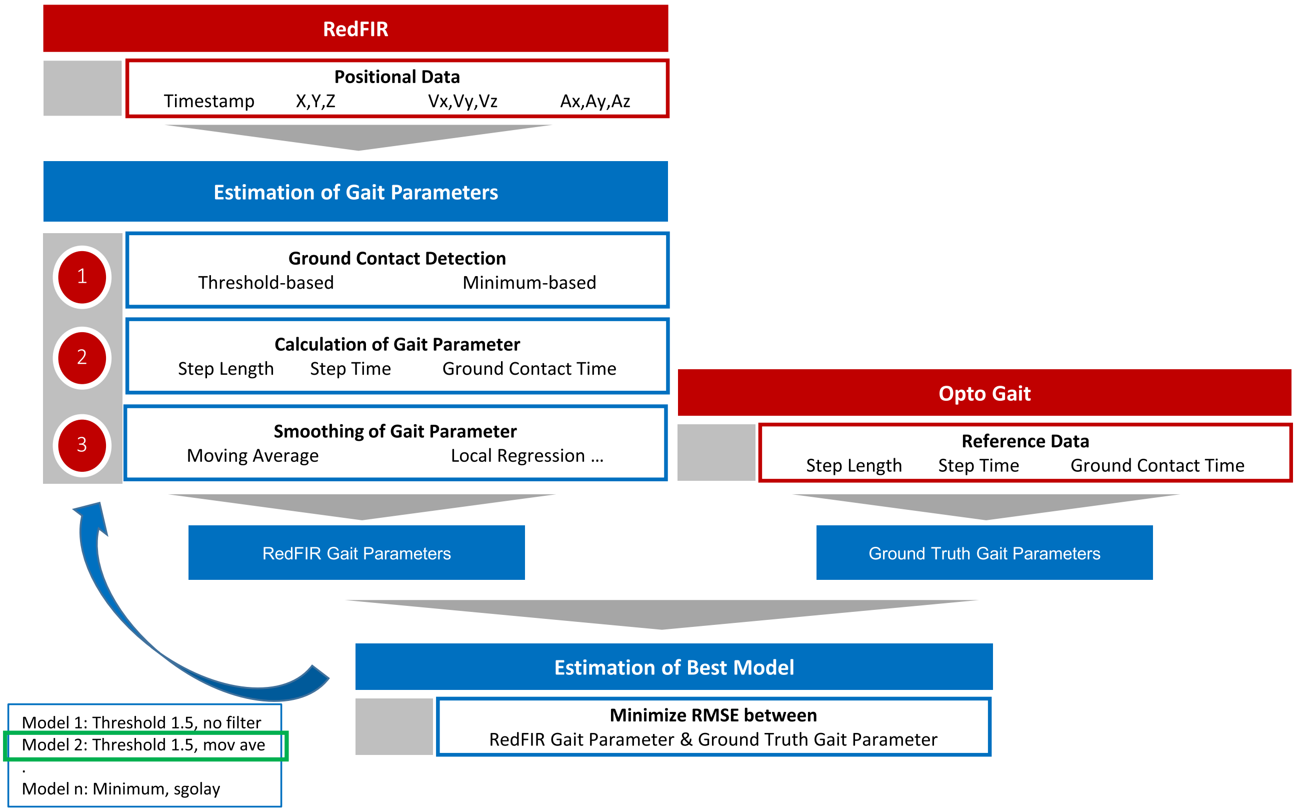

Fig. 2. Parameter optimization scheme: Based on the RMSE difference between estimated and reference step length, step time or ground contact time every possible combination of threshold, filter type and window size is evaluated and the best model (green rectangle) on the test set will be selected. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

five transmitters did not provide data continuously throughout data acquisition. This resulted in a total of 19 runs where data for all five transmitters was available. Since this study aimed at comparing different transmitter positions, analysis was restricted to these 19 (11 for 1–50 m, 8 for 51–100 m) runs yielding 508 ground contacts. By our definition there are no parameters for the last ground contacts of a sprint because parameters are based on differences between two consecutive ground contacts, so these 508 ground contacts yielded 470 parameters sets for step length and step time, respectively (508 ground contacts − 19 runs $*$ 2 legs = 470 parameters).

3.1. Effect of filtering & transmitter positions

Differences between raw and filtered parameters obtained from attaching transmitters to the instep, above the ankle and to the back have been investigated. Table 1 shows RMS errors for raw and filtered settings and the corresponding 95% limits of agreement. The raw RMS errors for step length, step time and ground contact time based on the instep were found to be 9.6 cm, 0.008 s, 0.016 s, based on the ankle 6.5 cm, 0.0075 s, 0.0047 s and based on back 17.2 cm, 0.023 s-since thresholding wasn't possible for the back (see Fig. 1) no ground contact time could be estimated. Applying the above-mentioned filtering resulted in similar results for instep and ankle positions whereas estimates based on a transmitter on the back showed slightly inferior results. Transmitters attached above the ankle showed slightly better estimates for step length (RMSE ankle: 5.85 cm; instep 7.4 cm) and step time (RMSE ankle: 0.0068 s; instep 0.007 s) whereas estimates for ground contact time (RMSE ankle: 0.01 s; instep: 0.009 s) was slightly better for the instep transmitter.

Normalizing error estimates by their respective means yielded percentage RMS errors of 1.6%, 1.3% and 7.6% for step length, step time and ground contact time respectively based on filtered estimates for a transmitter attached above the ankle.

Fig. 3 shows the effect of filtering for step length, step time and ground contact time based on a transmitter attached above the left ankle. Optimizing filter parameters helped to decrease the variance of errors compared to the raw parameters. The step time plot in Fig. 3 shows spikes at step 6 and step 7. Those are clearly observable within the reference data and (slightly less pronounced) within the raw RedFIR data. By filtering the raw estimate of step time the overall RMSE decreases but this fine-grained behavior—spikes at step 6 and step 7—is no longer observable.

3.2. Bland-Altman analysis

Fig. 4 shows a Bland-Altman plot based on filtered parameters for a transmitter attached above the ankle. Radio-based estimates were similar to the reference measurements of parameters: 95% limits of agreements were [−14.65 cm, 15.05 cm] for step length, [−0.016 s, 0.016 s] for step time and [−0.020 s, 0.028 s] for ground contact time.

Smaller step lengths at the start show larger errors compared to estimates based on the second 50 m of the track. No differences in errors have been found between first and second halves of the track for step time. Estimates for ground contact time, however, were systematically lower for the first 50 m whereas estimates were systematically higher for the second 50 m.

4. Discussion

We were the first to apply a radio-based tracking system to automatically obtain spatio-temporal parameters for sprint running. RMS errors smaller than 2% for step length and step time

Table 1
Absolute and percentage errors of spatio-temporal parameters obtained by RedFIR: Mean values based on the reference system, RMSE [absolute and percentage] on test set before and after filtering, and 95% levels of agreement after filtering [absolute and percentage] are shown for each transmitter position. Since thresholding wasn't possible for the back transmitter, no ground contact time could be estimated.

Transmitter position	Gait parameter	Mean (reference)	RMSE (unfiltered)	RMSE (filtered)	95% Limits of agreement (filtered)
Instep	Step length (cm)	375	9.6 (2.6%)	7.4 (2.0%)	[−17.88, 14.84] ([−4.8%, 4.0%])
	Step time (s)	0.504	0.008 (1.6%)	0.007 (1.4%)	[−0.0155, 0.0145] ([−3.1%, 2.9%])
	Ground contact time (s)	0.131	0.016 (12.2%)	0.009 (6.9%)	[−0.0222, 0.0218] ([−16.9%, 16.6%])
Ankle	Step length (cm)	375	6.54 (1.7%)	5.85 (1.6%)	[−14.55, 15.05] ([−3.9%, 4.0%])
	Step time (s)	0.504	0.0075 (1.5%)	0.0068 (1.3%)	[−0.0166, 0.0154] ([−3.3%, 3.1%])
	Ground contact time (s)	0.131	0.047 (35.9%)	0.01 (7.6%)	[−0.02, 0.028] ([−15.3%, 21.4%])
Back	Step length (cm)	375	17.2 (4.6%)	10.7 (2.8%)	[−23.44, 17.48] ([−6.3%, 4.7%])
	Step time (s)	0.504	0.023 (4.6%)	0.012 (2.5%)	[−0.05, 0.048] ([−9.9%, 9.6%])
	Ground contact time (s)	0.131	–	–	–

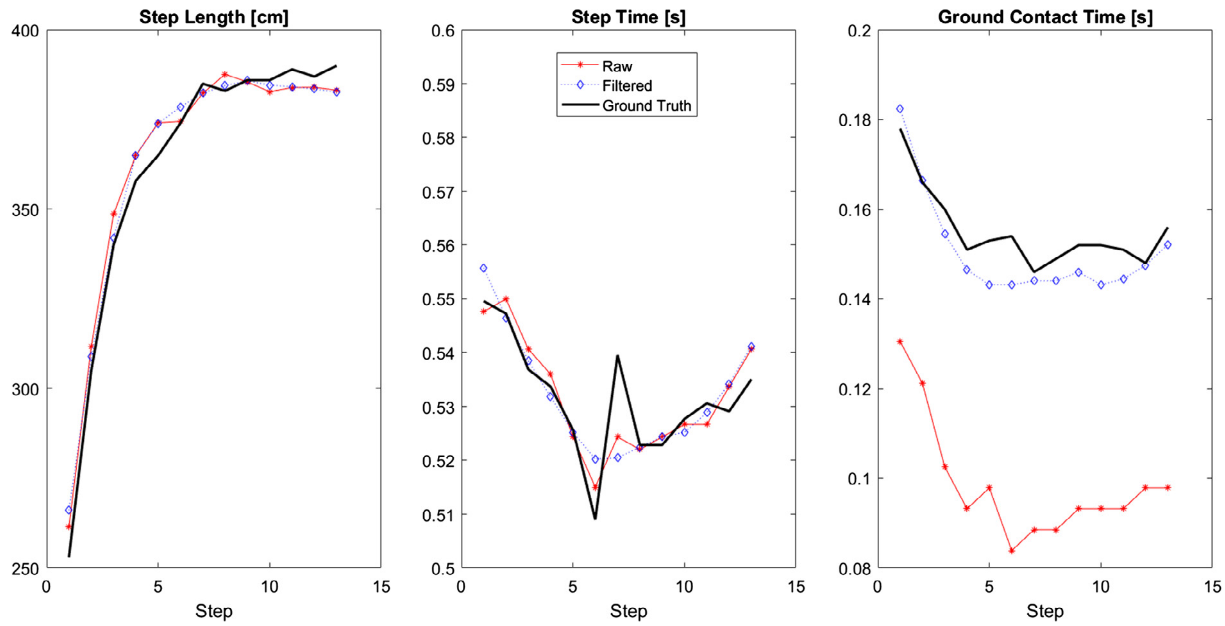

Fig. 3. Step length (left), step time (middle) and ground contact time (right) for one athlete over the first 50 m. Radio-based estimates are shown in red (raw data) and blue (based on best parameters for filtering) whereas ground truth trajectories are depicted in black. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

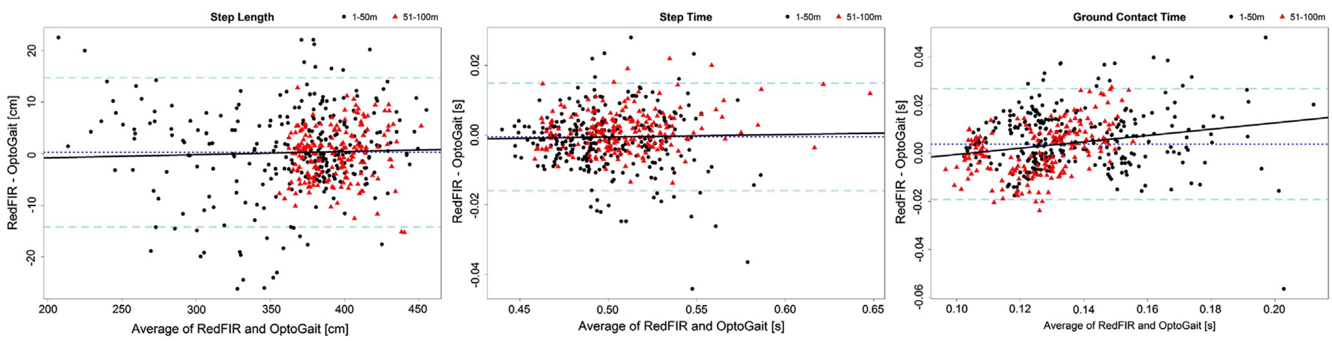

Fig. 4. Bland Altman plots based on optimal filter parameters for step length (left), step time (middle) and ground contact time (right): x-axis shows the mean of the radio-based estimate and ground truth. Y-axis shows the difference between radio-based and ground truth parameters. The dotted and dashed lines are the mean of the differences and the 95% limits of agreement, respectively. The solid black line shows the corresponding regression line. Circles and triangles correspond to the different sections of the track.

showed the validity of these measurements in general. Although our system is capable of tracking multiple athletes simultaneously around the entire track—Mutschler et al. (2013) have done this during a soccer match and have published their data—we only measured one athlete at a time on the straight part of the track due to the limitations of our reference instrument.

We also aimed to find an optimal sensor placement for a set of transmitter positions which varied in their intrusiveness, signal quality and acceptance in sports practice. The influence of different transmitter positions on the accuracy of the step detection algorithm was evaluated and we found similar results when placing the transmitter on the instep and above the ankle and slightly less accurate results when attaching the transmitter to an athlete's back. In competition, where the perceived intrusiveness of the attachment to an athlete plays a major role, one could work with the least intrusive setup by attaching only one transmitter to the back. However, attaching two transmitters above the ankles or on the insteps provides additional information about foot contact position, foot velocities and ground contact times, which are also relevant for performance analysis. It must also be noted that for some runs it was not possible to reliably detect each ground contact using the back transmitter. Hence, attaching transmitters above the ankles has been shown to be a good compromise between intrusiveness and accuracy of the estimation.

We demonstrated a way to increase the accuracy of the step detection algorithm based on reference data. However, the thresholds and filter methods found to work best for our setting might not be optimal when analyzing top athletes with different running styles. As our study was limited to young athletes it is recommended to redo this experiment with a sample of top athletes.

Due to the limited area captured by the reference instrument we were not able to obtain ground truth values for the full 100 m track. Hence, we split the 100 m track into two 50 m parts that could be captured by the reference instrument. Since filtering is typically applied to data on a full 100 m sprint, filter parameters would have to be adapted accordingly.

As described in Section 3, our analysis is based on only 19 out of 48 possible runs. The reason for this is threefold: (i) the radio-based tracking system is—like every other tracking system—not perfect and there will always be tracking artefacts from time to time based on environmental conditions. (ii) There was a big metallic bench—that is used for substitutes in soccer matches—on the track close to where the athletes performed the sprints. (iii) Our criterion for using a sprint for analysis was very strict: we disregarded a run even if the data from four out of five transmitters was perfect and only a small fraction for one transmitter was corrupted. Nonetheless, we ended up comparing 508 ground contacts yielded 470 parameter sets which is still more data than for comparable studies (Bergamini et al., 2012; Dunn and Kelley, 2015; Schmidt et al., 2016).

The errors we reported are slightly lower than the ones reported for a video-based step detection method presented by Dunn and Kelley (2015): they evaluated its performance by comparing estimates to manually marked ground contact positions for 10 m sprints and reported limits of agreements of [−182.6 mm, 172.8 mm] for step length and [−0.03 s, 0.03 s] for step time errors. As mentioned in the introduction this method presents the same challenges that are inherent in all camera-based systems: occlusions between athletes and changing weather and light conditions. In addition, their system did not provide estimates for ground contact time.

IMUs have been shown to provide accurate temporal parameters. However, the estimation of spatial parameters (e.g., step length) is challenging because the implementation of the double integration procedure suffers from error accumulation over time (Qi et al., 2016). Similar to the results reported here, Bergamini et al. (2012) reported errors of [−20 ms, 30 ms] for ground contact time based on one IMU attached to the lower back. Schmidt et al. (2016) recently developed an IMU-based system for detecting ground contact times in sprint running. They reported limits of agreement of [7.1 ms, 12.1 ms] for ground contact times, which are better than the ones found in our study. This is not surprising since IMUs allow for high update rates and direct measurements of accelerations whereas the local positioning system derives estimates for velocity and acceleration using Kalman filtering, which in turn assumes that the transmitter moves at a constant velocity—this is clearly violated when it is attached to a shoe or leg during sprint running. However, neither of these studies provided estimates for step time and step length or compared different transmitter positions, which clearly effects the ground contact detection.

Therefore, the combination of IMU and positioning systems as in radio-based or video-based systems seems to be a promising approach (Bichler et al., 2012, Qi et al., 2014). Another viable option would be to develop a more realistic sprint model for the Kalman filter.

5. Conclusion

We showed the applicability of a radio-based position tracking system for the automatic estimation of continuous spatio-temporal parameters in sprint running. Comparing parameter estimates for step length, step time and ground contact time to ground truth values obtained from a photoelectric system we found 95% limits of agreement of [−14.65 cm, 15.05 cm] for step length, [−0.016 s, 0.016 s] for step time and [−0.020 s, 0.028 s] for ground contact time, respectively. We compared the different transmitter positions—on the instep, above the ankle and on the upper back—and found that each position can be used to obtain accurate step parameters. RMS errors smaller than 2% for step length and step time show the potential of our approach for applications in performance analysis. Placing a transmitter slightly above the ankle was shown to be the best position for measuring step length and time. However, we were not able to detect ground contact time with comparable results to those that are possible when using IMUs. Therefore, the combination of local position measurement systems and IMUs seems to be a promising approach to provide in-depth analyses even beyond step length and step time.

This was the first study to present a method to automatically obtain accurate spatio-temporal parameters for each step during sprint running using a radio-based tracking system. Results are applicable to every running and jumping discipline that takes place in the interior of a stadium and are in principle available in real-time. This creates new possibilities for performance analysis and coaching which can benefit coaches, athletes and media.

Conflict of interest statement

The authors do not have any conflicts of interest or personal relationships with other people or organizations that could inappropriately influence this work.

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The authors declare that they do not have any financial interest or benefit arising from the direct applications of their research.

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Evaluating the Indoor Football Tracking Accuracy of a Radio-Based Real-Time Locating System

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Abstract. Nowadays, many tracking systems in football provide positional data of players but only a few systems provide reliable data of the ball. The tracking quality of many available systems suffers from high ball velocities up to 120km/h and from the occlusion of both the players and the ball.

Radio-based local positioning systems use sensors integrated in the ball and located on the players' back or near the shoes to avoid such issues. However, a qualitative evaluation of the tracking precision of radio-based systems is often not available and to the best of our knowledge there are actually no studies that deal with the positional accuracy of ball tracking.

In this paper we close this gap and use the RedFIR radio-based locating system together with a ball shooting machine to repeatedly simulate realistic situations with different velocities in an indoor environment. We compare the derived positions from high speed camera footage to the positions provided by the RedFIR system by means of root mean square error (RMSE) and Bland-Altman analysis.

We found an overall positional RMSE of 12.5cm for different ball velocities ranging from 45km/h to 61km/h. There was a systematic bias of 11.5cm between positions obtained by RedFIR and positions obtained by the high speed camera. Bland-Altman analysis showed 95% limits of agreement of [21.1cm, 1.9cm]. Taking the ball diameter of 22cm into account these results indicate that RedFIR is a valid tool for kinematic, tactical and time-motion analysis of ball movements in football.

1 Introduction

Positional data of football player movements helps to analyze the players' physiological demands during matches, to analyze tactical movements of opponents, and to show additional information about the performance of players to spectators. Nowadays, there are different tracking systems available that provide positional data of players. In official matches camera-based systems are used frequently as rules do not yet permit GPS- and radio-based systems that need to

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integrate sensors into the ball or to attach them to players. Hence, sensor-based systems are more common in training environments [18].
However, the tracking performance of camera-based systems suffers from considerable shortcomings: ball velocities of up to 120km/h, instantaneous movements, changing weather and illumination conditions and the occlusion of both the players and the ball are common challenges for these systems [14].
Several researchers have tried to evaluate the performance of different player tracking systems. See [2] for an overview how player tracking data has been used in research in the last few years. Positional data forms the basis for further statistical analyses, e.g. covered distances, runs with different intensities, analysis of tactical patterns. Thus the evaluation of the accuracy of positional data should be an integral part of the evaluation of a tracking system.
However, there are only a few studies that evaluated the positional accuracy of tracking systems [16, 18] rather than assessing the quality of a system by evaluating parameters directly, that are typically derived from positional data, e.g. covered distances and mean velocities [6,8]. This is mainly imposed by the lack of reference systems that precisely determine the position of fast moving objects.
These studies have in common that they are limited to player tracking as no study tested the positional accuracy of ball tracking so far.
Although ball tracking in sport is a vivid research area within Computer Vision (Football [13] , Baseball [11], Tennis [17], Basketball [3], Volleyball [4, 9]) the performance of tracking algorithms is typically measured by means of identification rates or pixel differences whereas resulting differences in $2D$ or $3D$ positions to a gold standard should be considered.
Kelley et al. validated an automated ball velocity and spin rate estimator that works on images from a high speed camera and compared it to velocities found with the help of light gates [12].
However, to find a correct estimate for the position of fast moving objects is significantly more challenging. Choppin et al. provided a set-up for obtaining precise three-dimensional positions of fast moving objects using two synchronized high speed cameras that has been applied in tennis matches for analyzing ball and racket speeds [5].
We use a similar approach based on one high speed camera (HSC) to provide ground truth values for the position of football shots that were simultaneously tracked by the RedFIR system. The RedFIR radio-based local positioning system uses sensors integrated in the ball and located near the players' shoes to provide positional, velocity and acceleration data on the players and the ball.
We organized the remainder of the paper as follows: Section 2 explains the functional principle of the RedFIR Real-time Locating System used for the experiments we describe in Section 3. We present results in Section 4, provide a discussion in Section 5 and summarize our conclusions in Section 6.

2 The RedFIR Real-Time Locating System

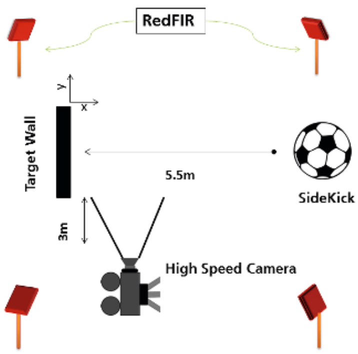
The RedFIR Real-Time Locating System (RTLS) is based on time-of-flight measurements, where small transmitter integrated circuits emit burst signals. Antennas around the pitch receive these signals and send them to a centralized unit which processes them and extracts time of arrival (ToA) values. ToA values are the basis for time difference of arrival (TDoA) values, from which x, y, and z coordinates, three-dimensional velocity and acceleration are derived using hyperbolic triangulation.
The RedFIR system operates in the globally license-free ISM (industrial, scientific, and medical) band of 2.4GHz and uses the available bandwidth of around 80MHz. Miniaturized transmitters generate short broadband signal bursts together with identification sequences. The locating system is able to receive an overall of $50,000$ of those signal bursts per second. The installation provides 12 antennas that receive signals from up to 144 different transmitters. Balls emit around $2,000$ tracking bursts per second whereas the remaining transmitters ($61\text{mm} \times 38\text{mm} \times 7\text{mm}$) emit around 200 tracking bursts per second. The miniature transmitters themselves are splash-proof (in case of the player transmitters) or integrated into the football. Figure 1b shows a glass model of a ball transmitter. For a more detailed description of the RedFIR system and the generated data streams see von der Grün et al. [10] and Mutschler et al. [15].

3 Methods

3.1 Hardware Setup

We conducted our experiments in the Fraunhofer Test and Application Center L.I.N.K. in Nuremberg, where -within an area of $30\text{m} \times 20\text{m} \times 10\text{m}$- a RedFIR system (version 1.1) is installed [7]. We placed a Seattle Sport Sciences SideKick ball shooting machine at a distance of 5.5m from a target wall and shot thirty times with speed levels 3 (4, 5), i.e., with approximately 45km/h (53km/h, 61km/h). For better readability we will refer to these velocities as 'slow', 'medium' and 'fast'. We only activated the ball's transmitter and two reference transmitter to minimize biasing side effects. Twelve receivers were active during our tests.
To map the coordinates of the ball to its real coordinates we used a Weinberger G2 high speed camera with a resolution of 1536×1024 @ $1,000$fps and a shutter time of 992μs. The camera was adjusted to aim at the target wall, as shown in figure 1a. Additional flicker-free light ensured that distortion or blurring effects in the images were avoided. The camera was triggered as soon as the ball became visible in the images of our reference system.

To calibrate the camera we used multiple checkerboard images together with the freely available camera calibration and digitization software Check2D (www.check2d.co.uk) and manually marked the ball in the images (Reprojection error 0.112 pixel). As a result we obtained real world coordinates of the ball in the direction of motion for each image frame.
We investigated the accuracy of the high speed camera data by digitizing known



(a) Hardware setup for test measurements.

(b) A glass model of the ball's transmitter and inductive charger.

Fig. 1: Test setup and glass model of a ball transmitter.

coordinates of a grid painted on a panel (residuals: 0.5mm $\pm$ 0.2mm) and by placing the ball at known positions (residuals: 11mm $\pm$ 6.8mm) in front of the camera. As we assume RedFIR's position errors to be a magnitude higher this suffices our requirements.

3.2 Synchronization

To synchronize the data of the RedFIR system with the camera data we applied the following procedure:
RedFIR provides approximately twice as much positions compared to the high speed camera recordings (2000 per second). We identify the frame that shows the ball deflecting by the target wall in the high speed camera images and in the RedFIR data. Since we know the time period of the ball being visible in the camera images we can cut the corresponding RedFIR data around the identified moment of deflection. We then interpolate RedFIR and high speed camera data to 2000Hz and correlate that position with the current frame provided by the camera.
In order to specify a common coordinate system for the high speed camera data we used a grid printed on a panel in line with known coordinates in the RedFIR coordinate system. The axes of the high speed camera coordinate system were chosen to point parallel to the RedFIR coordinate system. Hence, we can transform the data points with a simple translation (and mirroring of the axes), and align the data of the high speed camera to the RedFIR coordinate system and vice versa.

3.3 Data Analysis

We analyzed thirty shots at three different velocities (ten trials each). To minimize biasing effects we restricted our analyses to one sequence before impact with the target wall. The sequence starts when the ball becomes visible in the

image and ends 2.5ms before impact. Due to the deformation of the ball at impact it is difficult to mark the ball by fitting a circle around it.
We then calculated differences between the positions of the RedFIR system and the positions provided by the high speed camera and summarized them by means of root-mean-square error (RMSE) and 95% limits of agreement (LOA) for the shot in moving direction.
The RMSE is a measure of the deviation between the RedFIR data and the data provided by the camera and is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i}^{N}(X_{rf}^{i} - X_{hsc}^{i})^2}, \tag{1}$$

where X_{rf}^{i} and X_{hsc}^{i} denote the i-th sample, i.e. the position provided by RedFIR and the high speed camera. N equals the total number of samples.

4 Results

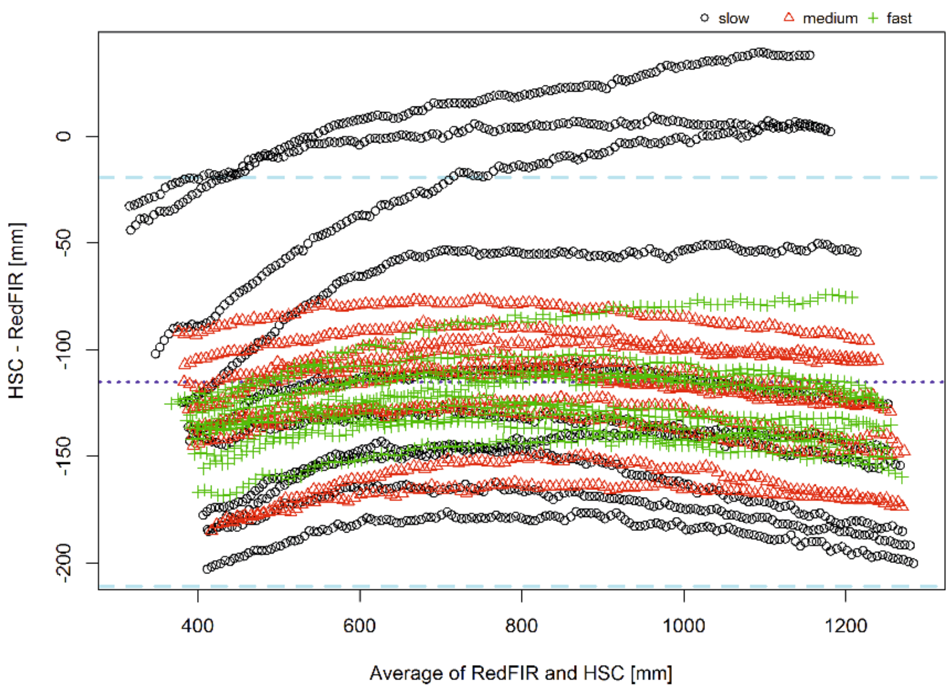


Fig. 2: Bland-Altman plot: The x-axis corresponds to the mean of RedFIR and HSC position in the direction of movement, whereas the y-axis shows the difference between the two systems. The dotted and dashed lines are the mean of the differences and the 95% limits of agreement, respectively. Circles, triangles and pluses correspond to slow, medium and fast velocities.

We were able to analyze all thirty shots. The RedFIR system provided continuously data throughout the experiments. There were no outliers in the data and we ended up comparing 3614 positions. The mean duration of the measurement interval was 0.065s.
For the comparison of the two systems we used the method by Bland and Altman [1]. Figure 2 shows the corresponding Bland-Altman plot.
Ball positions provided by RedFIR showed a systematic bias of −11.5cm. However, the overall standard deviation was 4.9cm and therefore quite low. The lower and upper 95% limits of agreement were −21.1cm and −1.9cm. The results show only a 1mm difference in RMS errors between slow, medium and fast shots. The maximum deviation between the two systems was found at lowest speed with an error of 20.3cm. The correlation between the positions obtained by the two systems was 98.1%. Table 1 summarizes the results for the different velocities.

Table 1: Positional errors obtained for different velocities: mean, standard deviation, RMSE, 95% LOA and maximum error are shown in cm.

Velocity	μ(cm)	σ(cm)	RMSE	95%-CI	Max. error(cm)
slow	-10.2	7.1	12.4	[-24.1, 3.7]	20.3
medium	-12.2	2.6	12.5	[-17.2, -7.0]	18.5
fast	-12.4	1.8	12.5	[-15.9, -9.0]	16.8
∅	-11.5	4.9	12.5	[-21.1, -1.9]	20.3

5 Discussion

Our studies show that the RedFIR system is able to accurately track the position of a football.
Its positional accuracy is better than the ones reported in previous studies for player tracking by Siegle et al. [18] and Ogris et al. [16].
For applications of positional data for kinematic and tactical analyses the estimation error of tracking systems should be below the diameter of the human's body when dealing with player data. Considering a ball diameter of 22cm the results indicate that the system is applicable in these domains for the analysis of ball movement. However, the system is not suited for applications like goal detection where only a maximal error of 1.5cm is allowed.
By using only one camera, we have limited our study to only focus on the main direction of motion. By using two synchronized cameras we could measure the tracking precision in much greater detail. However, the ball does not move much in y-direction and a comparison of the accuracy in x- and y-direction at the same

time results in imprecise conclusions. Instead, we propose to rotate the set-up by 90 degrees to investigate the system's accuracy in y-direction separately. The errors are expected to be similar to the errors described in this paper. The tracking accuracy was higher for lower velocities. RMS errors for the tested range of velocities were similar. Small differences between trials prove the robustness of the RedFIR ball tracking.

The experimental design may have had an influence on the results as the position of the integrated chip, suspended in the middle of the ball, is affected by its deformation when the ball hits the target wall. The moment of deflection identified in the images corresponds to the frame when the ball visually changes its direction whereas the moment identified in the RedFIR data corresponds to the moment when the integrated chip changes its direction. These estimates do not have to agree perfectly and this could have led to an imperfect synchronization. The setup was chosen to minimize biasing effects for the high speed camera and the RedFIR system. The camera system is able to provide a very accurate estimate of the ball position for a small volume in front of the target wall and a short time interval (1m and 0.15s in this setup), whereas the RedFIR system is applicable for the full size of a football pitch.

6 Conclusion

We conclude that the RedFIR system (version 1.1) installed indoors in the Test and Application Center L.I.N.K. is able to reliably track the movement of the ball with an RMSE of less than 13cm. This shows the applicability of RedFIR's football tracking for kinematic, tactical and time-motion analyses. Since the ball is the main object of interest in football, knowledge about its movement forms the basis for an automated detection of ball possession, passes and every tactical analysis that involves the ball.

As the system was developed for outdoor applications we expect the systems accuracy to be better than the one presented here, and aim on redoing the tests with a system that is installed outdoors in future work. Since the range of velocities was only between 45km/h and 61km/h we aim on doing a more thorough testing of the accuracy for lower and higher velocities. As a football can typically reach a speed of up to 120km/h it will be interesting to see how the accuracy changes for these high velocities.

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Validation of football's velocity provided by a radio-based tracking system

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Abstract

Nowadays, many tracking systems in football provide positional data of players but only a few systems provide reliable data of the ball itself. The tracking quality of many available systems suffers from high ball velocities of up to 34 ms^{-1} and from the occlusion of both the players and the ball. Knowledge about the position and velocity of the football can yield valuable information for players, coaches and the media.
To assess the accuracy of the football's velocity provided by the radio-based tracking system RedFIR, we used a ball shooting machine to repeatedly simulate realistic situations at different velocities ranging from 7.9 ms^{-1} to 22.3 ms^{-1} in an indoor environment. We then compared velocity estimates for 50 shots at five speed levels with ground truth values derived from light gates by way of mean percentage error (MPE) and Bland-Altman analysis. The speed values had an MPE of 2.6% (-0.49 ms^{-1}).
These results suggest that RedFIR is capable of providing accurate information about the kinematics of a football.

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Keywords: RTLS; Football Tracking; Accuracy; Speed

1. Introduction

Nowadays, there are different tracking systems available that provide positional and velocity data of football players and the ball. In official matches camera-based systems are used frequently as game rules do not yet permit GPS- and radio-based systems that need to integrate sensors into the ball or to attach them to players. Hence, the latter are more common in training environments [1]. However, the tracking performance of camera-based systems suffers from considerable shortcomings: ball velocities of up to 34 ms^{-1}, instantaneous movements, changing weather and illumination conditions and the occlusion of both the players and the ball are common challenges for these systems [2]. The RedFIR radio-based local positioning system uses sensors integrated into the ball and located near the players' shoes to avoid such issues and provides positional, velocity and acceleration data on the players and the ball with high update rates and high precision that could be used in training and match play.

Knowledge about the movements (position and velocity) of players and playing objects (e.g.; a tennis ball or football) allows for assessing tactical and technomotorical skills quantitatively and qualitatively without the need of subjective expert ratings and forms an important part of performance analysis. Kinematic data of football player movements can also help to analyze the players' physiological demands during matches and to show additional information about the performance of players to spectators. In game sports, like football or tennis, the target or goal for each party is to handle the ball in such a way to score a goal (or point) and simultaneously prevent the opponent from scoring [3]. Hence, knowledge about the movement and speed of the playing object is of utmost importance to analyze tactical performance in game sports.

Moreover, it can also be helpful when analyzing technomotorical skills: In sports like baseball, exerting force directly onto the ball is crucial for pitchers in order to accelerate it to high speeds which is an important factor of pitching performance [4,5]. Typically, technique-related studies have been conducted in laboratory scenarios on volleyball serves [6,7] as well as ball speed in table tennis [8] and football [9].

In a match or training environment some investigations based on ball speed have been carried out using radar guns, such as in football [10], tennis [11] or handball [12], others have used light gates and/or (high speed) cameras in tennis [13] and baseball

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[14]. Nevertheless, none of these methods provides an easy way to obtain ball speed that is applicable for every pass and shot on the whole football pitch: a radar gun just gives the closing speed between the moving object and the radar gun and is thus limited to goal shots when being placed behind a goal. Light gates require a fixed setup and the ball to intercept both light beams which makes their use non-practical in training and prohibits their use in actual match play. Obtaining ball speed from video cameras is possible in training and match play with the before mentioned shortcomings.

However, there is a lack of scientific research regarding the validity of methods for acquiring kinematic data of the football that are applicable in training and match situations since there are almost no studies concerned with the accuracy of ball speed estimates in sport. Kelley et al. [13] validated an automated software tool based on high-speed video for estimating ball speed and spin rate in tennis. They assessed its accuracy by comparing speed obtained by the software to the ones based on light gates. For this study we adapted their setup to football.

This study aims at validating the estimate of football speed obtained by the radio-based locating system RedFIR. See Seidl et al. [15] for a validation study dealing with the positional accuracy of the ball tracking. Hence the current study complements the validation of kinematic data of a football obtained by a radio-based tracking system.

2. Methods

2.1. The RedFIR Real-Time Locating System

The RedFIR Real-Time Locating System (RTLS) is based on time-of-flight measurements, where small transmitter integrated circuits emit burst signals. Antennas around the pitch receive these signals and send them to a centralized unit which processes them and extracts time of arrival (ToA) values. ToA values are the basis for time difference of arrival (TDoA) values, from which x, y, and z coordinates, (and subsequently three-dimensional velocity and acceleration) are derived using hyperbolic triangulation.

The RedFIR system operates in the globally license-free ISM (industrial, scientific, and medical) band of 2.4 GHz and uses the available bandwidth of around 80 MHz. Miniaturized transmitters generate short broadband signal bursts together with identification sequences. The locating system is able to receive an overall of 50,000 of those signal bursts per second. An installation typically provides 12 antennas that receive signals from up to 144 different transmitters. Balls emit around 2,000 tracking bursts per second whereas the remaining transmitters (61 mm × 38 mm × 7 mm) emit around 200 tracking bursts per second. The miniature transmitters themselves are splash-proof (in case of the player transmitters) or integrated into the football. Figure 1b) shows a glass model of a ball transmitter. For a more detailed description of the RedFIR system and the generated data streams see von der Grün et al. [16] and Mutschler et al. [17].

2.2. Hardware setup

We conducted our experiments in the Fraunhofer Test and Application Center L.I.N.K. in Nuremberg, where – within an area of 30 m × 20 m × 10 m – a RedFIR system is installed [18]. To repeatedly simulate realistic shots we placed a ball shooting machine (Seattle Sport Sciences, Inc., Redmond, WA, USA) in front of two light gates (Tag Heuer, Chronoprinter CP505) at known distances to obtain ground truth values for mean velocity. Since different speed levels resulted in slightly different ball trajectories we had to adjust the position of the second light gate to guarantee that the ball would interrupt both light gates and to increase the accuracy of the reference system based on rounding errors as outlined in 2.3.

We shot the ball ten times at each speed level 0 (2, 4, 6, 10), i.e., with approximately 7.93 ms^{-1} (9.75 ms^{-1}, 15.04 ms^{-1}, 20.17 ms^{-1}, 22.32 ms^{-1}) resulting in a total of 50 shots. Only the ball's transmitter and two reference transmitters were activated. Twelve receivers were active during our tests. Figure 1a) shows the setup detailing the placement of the ball shooting machine and light gates.

Fig. 1. (a) hardware setup for test measurements; (b) a glass model of the ball's transmitter and inductive charger.

2.3. Data analysis

To assess the accuracy of the ball velocity obtained by the RedFIR system we compared it to mean velocities based on the light gates. Knowing the distance between the gates one easily obtains mean velocities by dividing the distance between the gates by the time it took the ball to interrupt both light beams.

Based on ground markings in the test center we knew the positions of the light gates within the RedFIR coordinate system and restricted the corresponding ball data accordingly, thus resulting in comparable mean velocities. To assess the differences between these two estimates statistically the method of Bland and Altman [19] was used. We used the percentage error (PE) for our analysis since it is more meaningful than the mean squared error in this case. It is defined as the difference between the two estimates normalized by the ground truth value given by the light gate:

$$PE = \frac{v_{light\ gate} - v_{redfir}}{v_{light\ gate}}$$

The light gates were capable of measuring time with a precision of 10 milliseconds. We therefore placed the gates as far away as possible to minimize rounding errors but close enough for the ball to interrupt both light gates to provide valid measurements: Assume it took the ball 0.56 s to cover a distance of 5.5 m between the two light gates which results in a mean speed of 9.82 ms^{-1}. Since the time is rounded to two digits this will be the case for every value in the range from 0.555 s (which get rounded up to 0.56 s) to 0.564 s (which gets rounded down to 0.56 s) resulting in 'true' speeds between 9.75 ms^{-1} to 9.91 ms^{-1}. Hence, neglecting other possible sources of error, the light gates, in this example, are capable of providing ground truth values with an expected maximal measurement error based on rounding of ~1.0% $= (9.91\ ms^{-1} - 9.82\ ms^{-1})/9.82\ ms^{-1}$. An analogous calculation yields an expected maximal error ~1.2% at highest speed level 10 (22.32 ms^{-1}). However, this should suffice our requirements for using the velocity obtained by the light gates as ground truth.

3. Results

We were able to analyze 49 shots since for one shot the battery of the ball's transmitter was afterwards found to be empty. The RedFIR system provided data continuously throughout the experiments, there were no outliers in the data and we ended up comparing a total of 49 shots at five different speed levels. For the comparison of the two systems we used the method by Bland and Altman [19] that is typically used to investigate differences between two measurement systems. Figure 2 shows the corresponding Bland-Altman plot: Ball speeds provided by RedFIR showed a systematic bias (or Mean Percentage Error) of -2.6% (-0.49 ms^{-1}). In most cases RedFIR slightly overestimated the ball's velocity. However, the overall standard deviation of 2.4% showed a low variation between measurements. The lower and upper limits of agreement (LOA) were -7.4% (-1.44 ms^{-1}) and 2.16% (0.47 ms^{-1}) providing indication where one would expect the difference between the estimates to be the majority (95%) of time. The results show an increase in error at higher velocities. The maximum deviation between the two systems was found at speed level 6 (20.17 ms^{-1}) with an error of -8.1% (-1.98 ms^{-1}).

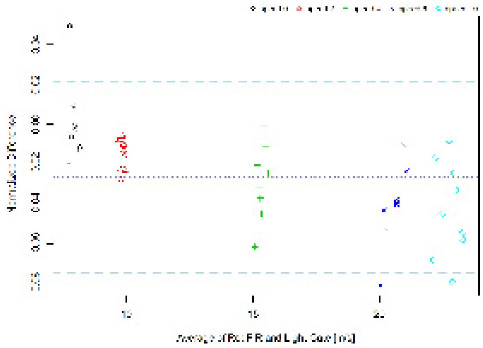

Fig. 2. Bland-Altman plot: The x-axis corresponds to the average of the velocities based on the light gates and RedFIR, whereas the y-axis shows the percentage difference between the two systems' estimates. The dotted and dashed lines are the mean of the differences (MPE) and the limits of agreement, respectively. Circles, triangles, pluses, crosses and diamonds correspond to the different speed levels.

Table 1 summarizes the results showing speed level, mean speed (based on light gates), mean percentage error, standard deviation, limits of agreement and maximum absolute error for different speed levels. The magnitude of the MPE increases with increasing velocity for speed levels 0-6 but decreases at highest speed level 10. An inspection of the cumulative density function showed that 92% of the analyses had an absolute error of less than 6%.

Table 1. Percentage errors of football speeds obtained by light gates and RedFIR: speed level, mean speed based on light gates, MPE, standard deviation, LOA and maximum absolute error in %.

Speed level	Mean speed *(ms^{-1})*	MPE *(%)*	Std *(%)*	LOA *(%)*	Max. abs. error *(%)*
0	7.93	0.1	2.0	[-3.8, 4.0]	4.9
2	9.75	-1.5	0.8	[-3.0,0.0]	2.9
4	15.04	-3.2	1.9	[-6.9,0.5]	6.2
6	20.17	-3.9	2.0	[-7.8,0.0]	8.1
10	22.32	-2.4	2.3	[-9.0,0.0]	7.9
Ø		-2.6	2.4	[-7.4,2.2]	8.1

4. Discussion

This study was the first to consider the accuracy of ball speed estimates for a radio-based tracking system. We found a systematic bias of 2.6% which indicates that the football's speed provided by the RedFIR system is slightly overestimating the football's mean speed. Limits of agreement of 9.6% (1.9 ms^{-1}) and the fact that 92% of analyses had an absolute error of less than 6% prove RedFIR's ball speed to be accurate within 10% for velocities ranging from 7.9 ms^{-1} to 22.3 ms^{-1}. The system was found to be more accurate at lower speeds (< 10 ms^{-1}) while the error increases at higher speeds. However, this could not be found to be true for velocities between 15 ms^{-1} and 22.3 ms^{-1}.

For their video-based software tool for automatically measuring tennis ball speed Kelley et al. [13] reported an MPE of 4.47% (1.08ms^{-1}) and 91% of analysis had an error less than 10% and concluded its applicability for ball speed within the tested range with an error to be expected within 10%.

Hence our results demonstrate the applicability of the RedFIR ball tracking to measure ball velocities. This could be used to provide speed information about passes and shots, and together with information about the ball position makes it possible to quantitatively assess technomotorical skills of football players like ball handling, passing and shooting behavior that is fundamental for a quantitative evaluation of football players.

However, the fastest shot in football was measured at 34 ms^{-1}. Since the ball shooting machine only provided shots up to 22.3 ms^{-1} one would need to use a more powerful ball shooting machine to test at these high velocities. We were forced to change the light gate positions during the tests to ensure the ball to pass both light gates and to minimize the effects of rounding errors for our reference system. It would be advantageous to use light gates with a higher precision that would allow keeping the test setting constant for all velocities.

Due to the lack of a reference system for continuous dynamic ball movement the current analysis had to be restricted to compare mean velocities over a straight line without spin. In match situations the ball will change direction and speed rapidly and will be kicked with different types of spin resulting in curved trajectories. With the RedFIR system providing continuous data about the kinematics of the football 2,000 times per second, this allows a much more detailed analysis. Figure 3 shows the ball speed for one trial and the corresponding radio-based and light gates-based estimates for the mean speed of the football in more detail. Having continuous information on the ball and player positions, also long ball velocity sequences, especially consecutive passes, could easily be analyzed, even if the number of passes, directions and passing lengths are initially unknown (as it is in match settings).

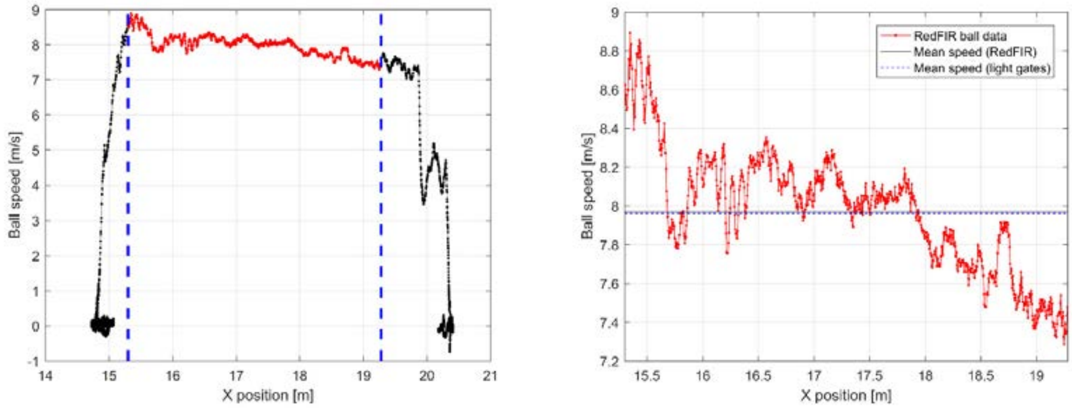

Fig. 3. A more detailed look at ball speed provided by the RedFIR system: The left side shows the ball speed for one recording with the dashed vertical lines indicating the positions of the two light gates. The right side shows a zoomed in version where the ball speed between the light gates is shown that was used for the evaluation of the ball speed accuracy.

5. Conclusion

Radio-based tracking systems are promising for the future of sports science since they allow for higher update rates, high precision without being affected by environmental conditions and occlusions by players.

This was the first study to assess the accuracy of football speed estimates provided by a radio-based tracking system. We conclude that ball speed obtained by the RedFIR system installed indoors in the Test and Application Center L.I.N.K. can be used interchangeably with the ball speed measured by light gates for velocities ranging from 7.9 ms^{-1} to 22.3 ms^{-1} in applications where an error of 10% is acceptable. This information can be provided in real-time and can be used for every shot on the whole pitch with no need to set up any additional material (provided a RedFIR system is installed) in training and official matches.

In conjunction with the positional accuracy of 13 cm reported previously [15] we postulate that RedFIR provides accurate information about a football's kinematics in real-time that can help players, coaches and the media.

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