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Tracking on an interactive pressure sensing floor

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Title: Tracking on an interactive pressure sensing floor

Abstract: Smart Sports Exercises is a project which uses data to support training and coaching in volleyball using an interactive pressure sensing floor and players wearing inertial motion units. The data from the floor and motion sensor units can be combined to analyse patterns in volleyball and the floor is capable of showing video. This opens up opportunities for new types of feedback, exercise and training. However, to allow these opportunities the location of players on the floor must be known. This thesis focuses on providing a three step system to localize players on an interactive pressure sensing floor.
The first step of this system provides a method to convert raw reading from the floor to weights. To do so measurements are made to provide a ground truth. With these measurements a calibration procedure is created to use when setting up the floor. The resulting calibration has an error of 2.57kg and a lowest detectable weight of 5kg.
The second step of this system looks for areas where players are active. This is done by placing sensors in a virtual graph. Connections between weights in this virtual graph are dropped by using a number of criteria. The graph will then split up into several connected sub-components which are areas where players are active.
The last step is to assign the players to areas and localize players within these active areas. If an area contains a single player the location of this player is a weighted mean. In the case of multiple players per area a more elaborate process is necessary. By using k-means the active area is divided into a number of groups (equal to the number of players assigned to this area), and then the location of players can be found.
A recommendation for this system is to use a number of frames to localize players as this reduces errors and provides additional information.

Keywords: Volleyball, pressure sensing floor, person localization

Preface

I present to you my master thesis: Tracking on an interactive pressure sensing floor. This document represents the end of my Master Interaction Technology and marks the start of a new chapter. In this preface I would like to express my gratitude for those who have helped me during my final graduation project.

I would like to thank Dennis and Fahim for being my supervisors, with the help of our meetings, discussions, and ultimately video-calls to make this thesis reach fruition.

I too with to thank Lara for all the support you gave me, sparring with me, listening to my ideas, for proofreading my thesis over and over again and for helping me calibrate the floor, by moving dumbbells from the rowing club to the design lab and moving the weights around.

I am grateful for my colleagues that they have helped me with ideation and problem solving with programming.

Finally I would like to thank my family for their unconditional support and for always being there for me when it mattered the most.

Bryan Oostra

Enschede, August 9, 2020

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1 Introduction

Data driven analysis in sports have been gaining popularity in the last decade. For endurance sports such as rowing and cycling this is often done by analyzing power output of an athlete over various durations. For volleyball a project exists called Smart Sports Exercises (SSE) which uses data provided by smart sensors to innovate within volleyball (Postma et al. 2019), this thesis is part of this project.

With the help of a smart training hall that has an interactive pressure sensing floor and has a number of wearable inertial motion units (IMU) for players, the projects tries to support training and coaching in volleyball with new insights.

The motion units can be used to detect which actions a volleyball player is performing (Salim et al. 2019). The quality of some of these movements can be assessed as well (Wang et al. 2018). The interactive floor provided by LedGO (see Figure 1) is able to display video. It could show the action radius of each player, as well as the area each player should cover. The ideal position of each player can be calculated and displayed. If a team is significantly stronger than the other team, the playing field of the weaker team can be reduced to even things out.

Figure 1. Interactive pressure sensing floor

Retrieved from https://www.weblogzwolle.nl/nieuws/67925/interactieve-sportvloer-onuitputtelijke-bron-van-informatie-voor-sporters-en-coaches.html

However, to execute these ideas the location of all players on the the floor must be known at all times. Preferably the identity of the found players as well. But to focus upon one task -tracking players- identifying players (which of the found players is Alice, Bob or Charlie?)

is out of the scope of this thesis. Hence this means the main research question of this thesis is: *To what extent can an interactive pressure sensing floor track movements of volleyball players?* The main research question can be divided into small sub-questions. By answering all sub-questions the main research question can be answered.
The first of three sub-questions is: *What movements exist in volleyball and how are they tracked?* This question is answered by briefly summarizing the sport volleyball and by looking into related work about tracking in volleyball.
The second sub-question is *What information does a pressure sensing floors provide and what are the characteristics of the provided floor?* This question is answered by looking up related work about pressure sensing floors in general. Subsequently, the floor provided by LedGO BV is analysed to gain more insight into the specifics of this pressure sensing floor.
The last sub-question is: *What methods are necessary to find players using data of the given interactive pressure sensing floor?* This question is answered by creating a system that is able to localize players on an interactive pressure sensing floor. This system consists out of three distinct steps that together are able to transform the raw data of the floor into locations of players. Each step (see Figure 2) is described and evaluated in its own chapter.

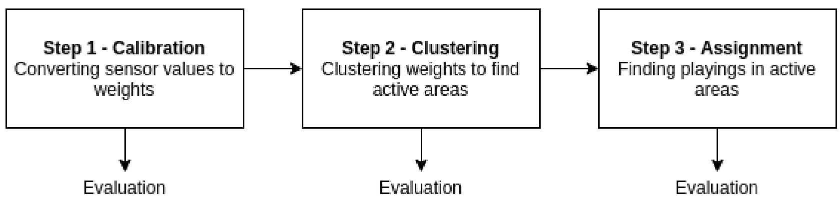


Figure 2. The three steps of the proposed system

These sub-questions provide structure for this thesis. The first sub-question is answered in section 2.2. The second sub-question has two parts, the first part about pressure sensing floors in general is answered in section 2.3, the second part about the specifics of the floor by LedGO is discussed in section 2.4. The last sub-question answered in the chapters about each step (Chapter 4, 5 and 6). The system is then discussed in Chapter 7 where recommendations for future work are also made. The conclusions are presented in Chapter 8.

2 Background

In this chapter context is provided about data driven analysis within sports, volleyball, pressure sensing floors and the specific pressure sensing floor used for the SSE project.

2.1 Data driven analysis

Data driven analysis has become more popular and available in the last few years. Smart watches can be used for a variety of sports (e.g. running, cycling, any other outdoor sport based on distance) and provide valuable metrics for the athletes. Speed can be viewed real time, allowing an athlete to pace their effort evenly. A heart rate monitor can show how hard an athlete is working at any given time. Heart rate can also be used to quantify training load, which can then be used to track fatigue, fitness and freshness. When there are interactions between athletes (e.g. soccer or hockey) these metrics are often less meaningful. The interactions between players (both teammates and opponents) are of greater importance as this defines the sport. The preferred tool to register these interactions is video analysis.

360SportsIntelligence (*360SportsIntelligence - Videoanalyse voor de hele club*) is an example of a company which uses video analysis to capture interesting actions happening in soccer, hockey, baseball, volleyball, basketball and tennis. It uses these fragments to generate a game-summary automatically. BallJames (*BallJames - Optical Football Tracking*), a subsidiary of SciSports, provides a tool which tracks all soccer players (and the ball) in 3d in real time using video. SciSports (*SciSports - Football Data Intelligence*) tracks soccer players (currently more than 300 000) and measures their performance and potential. The insight into the performance of players is often used for scouting and recruitment.

2.2 Tracking within volleyball

This section briefly summarizes the game of volleyball for those unfamiliar with the sport in section 2.2.1. Subsequently, section 2.2.2 lists a number of articles that have relevance to the topic of tracking within volleyball and lists a number of variables that could be relevant to track on an interactive pressure sensing floor.

2.2.1 Volleyball basics

Figure 3. A volleyball field with players

Retrieved from https://www.flovolleyball.tv/articles/5059785-volleyball-facts-and-dimensions

Volleyball is a team sport played with 12 people simultaneously (two teams of six people, usually with three substitutes) on a 18m by 9m court. A net divides the field into two areas of equal size, on which the teams play. The height of the net depends on the gender of the teams, females play with net height of 224cm, and males with a net height of 243cm. There are many differences in similar sport such as seated and beach volleyball. This thesis will focus upon regular volleyball.

A team can score points when the ball is ’in’ (touches the playing area of the opposing team), or via touché (the ball is out but was last touched by the opposing team). A team also receives a point when the opponent makes a mistake by placing the ball ’out’ (the ball lands outside of the playing area). The first team to obtain 25 points wins the set. First team to win 3 sets wins the match. There are many more rules involved, a complete explanation can be found on the Nevobo website (Nevobo 2018).

There are six basic skills in volleyball: serve, pass, set, attack, block and dig (Dearing 2018). All of them have unique characteristics and variations. When a team is trying to score a point, both teams participate in a ‘rally’. A rally can be seen as a set of complexes, starting with a serve. The first complex then consists of reception (pass), set and attack. The second complex (and all following complexes) start with block, followed by defence (dig), set and finished with an attack (Koch and Tilp 2009b). Every player has a different role in the game. The roles that exists are: setters, liberos, middle blockers, outside hitters and opposite hitters. Each role have a specific position on the playing field. Players usually specialize into a specific role, sometimes based on physical properties. The libero is often a bit shorter because he/she is specialized for defence, meaning its more convenient to be closer to the ground. Though, a smaller athlete is disadvantaged when attacking or blocking.

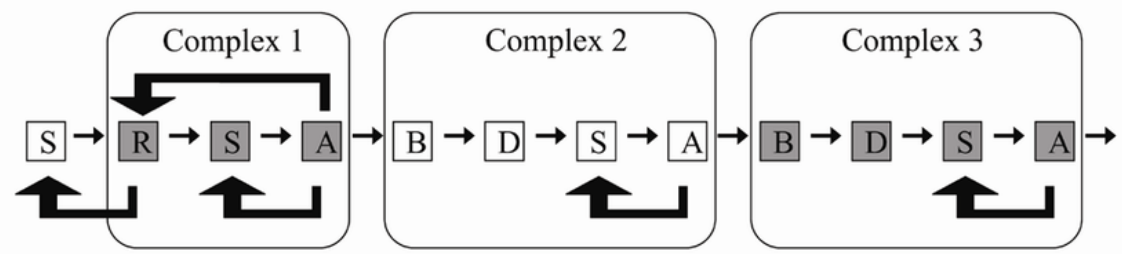


Figure 4. Visualization of a typical beach volleyball rally

The rally shows all possible actions (Serve (S), Reception (R), Setting(S), Attack (A), Block (B), Defence (D)). The white and shadowed boxes represent actions of the opposing team. Each sequence of actions within one team is often defined as complex (C1, C2, etc.). Arrows represent the dependency of actions on preceding actions.

Retrieved from Koch and Tilp 2009b.

2.2.2 Tracking techniques

To gain insight into the tracking techniques and tracked metrics for volleyball, research papers were sought using search terms as 'volleyball tracking' 'volleyball analysis' and 'volleyball performance' on Google Scholar during the Research Topics phase of this thesis. An initial collection of papers was found and studied. Then for the second iteration, additional papers were found by looking up other work by the authors of the original papers. These papers are listed in Table 1.

Authors	Aim	Sample or variables	Data provider	Statistic or method	Result
Wang et al. 2018	Demonstrate a system capable of assessing difference between elite, sub-elite and amateur volleyball players.	100 cross court spikes in total from 10 participants.	Wearable micro inertial measurement unit.	SVM, kNN, Naïve Bayes, PCA	Capable to assess difference with between players with an average accuracy of 94%.
Medeiros et al. 2014	Study the effect of age group and players role in beach volleyball.	94 sets of 47 games. 6 temporal variables and 6 physical variables.	Video analysis by a trained observer.	Log-likelihood, Schwarz Bayesian Criterion	Observed differences between variables age groups.
Chinchilla-Mira et al. 2012	Analyze the differences by gender of offensive zones in beach volleyball.	659 points from 8 matches. 6 zones.	Video recordings of 2 cameras, SportsCode v8 software.	Comparing means	A difference between offensive zones for men and women exists.
Trajković, Sporiš, and Krističević 2016	Assess the effects of a sand volleyball training program.	20 adolescent males.	Attack, block and standing broad jump tests.	T-test	Spike jump performance increased significantly.
Pérez-Turpin et al. 2014	Examine the effects of 6-week strength training with whole body vibration.	23 sub-elite males.	Squat jump, counter-movement squat jump, 1RM leg press tests.	Three factor ANOVA	Strength training with whole body vibration increases leg strength more.
Koch and Tilp 2009b	Analyze the differences by gender of six basic volleyball elements in beach volleyball.	15 matches from women, and 14 from men.	Video analysis using Statshot.	Chi-square test	Statistical differences were found for all basic elements.
Tilp and Rindler 2013	Establish a detailed representative record of landing techniques in beach volleyball	10 women and 10 men games were recorded.	Video analysis	Chi-square test	There is a difference of landing technique between men and women in indoor volleyball. Beach volleyball players land more often on 2 feet.
Pérez Turpin et al. 2009	Compare gross movement types and patterns in female professional beach volleyball	10 players in 4 games (1646 movements).	Video analysis using SportsCode	Chi-square test	Females use 59% of the time offensive movements patterns (41% defensive). 34% were placements, 50% attacking moves and 16% attack preparation moves
Mauthner et al. 2007	Tracking beach volleyball athletes using only a single camera	Ground truth provided by manual annotation of an expert	Single camera	Particle filter	The acquired position data revealed enough accuracy.
Koch and Tilp 2009a	Investigate sequences of typical beach volleyball actions	18 games containing 1645 action sequences	Video analysis annotated by beach volleyball players	Chi-square	The preceding reception did influence the quality of the attack (p<0.01).

Table 1. Overview of a selection of papers about tracking in volleyball

In Table 1 it can be seen that video analysis is the most popular method to gain insight into volleyball players as 7 out of 10 of the listed papers use video analysis. These seven papers use annotated videos (annotation performed by a human observer), often with help from spe-

cific software.
Metrics that are tracked are, including the location of, the six volleyball skills (Chinchilla-Mira et al. 2012; Koch and Tilp 2009b), as well as their quality (Wang et al. 2018). The sequence of actions is also investigated (Koch and Tilp 2009a). These studies provide sufficient ideas to use for a potential system that is able to track volleyball players on an interactive pressure sensing floor.

2.3 Pressure sensing floors in general

A pressure sensitive floor has not been used specifically for volleyball. Many applications exists such as gait recognition (Middleton et al. 2005), estimating weight of animals in farms automatically (Vaughan et al. 2017) and localization of humans, objects and robots (Andries, Simonin, and Charpillet 2015). For the detection of pressure, different technologies are used. The most common technique to detect pressure is a force sensitive resistor (FSR). This technique provides good precision by including a lot of sensors (at an increased cost), however sensory degradation is possible. Another method that was found was by using a camera and an infra-red projector (Bränzel et al. 2013). An advantage of this method is that the object very close to the floor can also be registered, as it measures proximity instead of weight. This technique could allow to track people hovering above the floor (during a dive or jump).
Even though there has not been done any specific work for volleyball and pressure sensing floors, there has been done a reasonable amount of work on pressure sensing floors. A list of papers, their aim and result can be found in Table 2.
In Table 2 it can be seen that the research papers working with a lower resolution floor try to estimate force and position. The higher resolution floors are used for person recognition and gesture recognition, because a higher resolution allows for more details.
If a sensor unit is about the same size as a human foot (1 feet or 30cm), the human can be tracked with fair accuracy, but tracking the location becomes unreliable when multiple humans walk closely to each other on the floor. This can be remedied by decreasing the size of a sensor unit, to be smaller than feet (e.g. down to 10 by 10cm per sensor). By being able to detect different feet, orientation can be tracked, without the use of temporal

data (where was the user, and where is the user now?). With separate feet, gait can also be studied by using features such as cadence, step size, and feet orientation. Gait can be used to differentiate between different users, possibly even across various sessions.
When increasing the resolution even more to 1 by 1cm per sensor, specifics about placing feet on the ground can be studied, providing significantly better gait recognition (for usage in biometric identification). The heel-to-toe ratio of the gait can be discovered (Middleton et al. 2005). Additionally, stances and gestures can be recognized, which can be beneficial for usage in volleyball.

Author	Aim	Sample or variables	Resolution	Method	Result
Vaughan et al. 2017	Develop a floor for frequent collection of animal weight and gait	20 weight scans		Polymer optical fiber	A 560-gram increase in weight is well distinguishable
Andries, Simonin, and Charpillet 2015	Localization, tracking and recognition of objects & humans.	2 scenarios (morning routine and receiving a visitor)	11.1 / m2	Strain gage load cells.	Average human localization error of 20cm.
Leusmann et al. 20113	Detect steps and falls to help the elderly & frail	545 steps performed	11.1 / m2	Piezo elements	72% of steps were detected
Murakita, Ikeda, and Ishiguro 2004	Human tracking system	30 samples of 10 people walking	30.8 / m2	VS-SS-F Info floor	Individual can be tracked perfectly. Two people need to maintain a gap of >80cm
Sousa et al. 2013	Human localization and identification.	398 events but only 55 with two or more persons.	32 / m2	Textile capacitive sensors arrays under floor + wearable.	Able to track up to three users walking in a narrow corridor.
Lombardi, Vezzani, and Cucchiara 2015	Detecting human movements without assuming a regular sensor grid	6 sequences with 1-7 persons	80 / m2	Florimage device	The proposed center of pressure model performed better on 5/6 sequences better than a pressure image model
Suutala, Fujinami, and Röning 2010	Person tracking.	8539 data frames from 70 walking sequences (2 male 1 female)	100 / m2 (binary)	Diode technology (VS-SF55 Info floor)	If persons are within 30 to 55cm the failure rate is between 8%.
Middleton et al. 2005	Person recognition using gait	15 subjects	1024 / m2	-	80% recognition rate
Pouyan et al. 2014	Classifying bed inclination	15 subjects	1480 / m2	-	Predicts bed inclination with 80.3% average accuracy
Srinivasan et al. 2005	Explore interactive media application of force sensing floors	-	9688 / m2	Force sensing resistors	(preliminary) the prototype was connected to a computer and shows data at enough rate to capture human foot movement
Zhang, Qian, and Kidanè 2009	Clustering, tracking and recognition footprints on a pressure sensing floor	399 frames from 1 subject	9688 / m2	Force sensing resistors	All 7 gestured can be detected reliably, recognized and tracked.

Table 2. Overview of a selection of papers about pressure sensing floors

2.4 Characteristics of the provided pressure sensing floor

This thesis uses an interactive pressure sensing floor provided by LedGO BV. To answer the latter part of the sub-question *What information does a pressure sensing floors provide and what are the characteristics of the provided floor?* the data the interactive pressure sensing floor is inspected, the physical properties of the floors are examined and the connection protocol is studied. With this information it can be confirmed whether localizing players on the floor is a feasible goal.

2.4.1 Initial analysis

The interactive pressure sensing floor consists out of 30 tiles in a 6 by 5 grid. Each tile is 50 by 50 centimeters, has a force sensor in every corner and is able to display an image. Every tile is linked to the 'next' tile and in the end connected to a controller. This method of linking tiles together causes that the tiles are ordered in a snake-type manner, with the benefit of shorter cables. A visual representation of the floor can be seen in Figure 5.

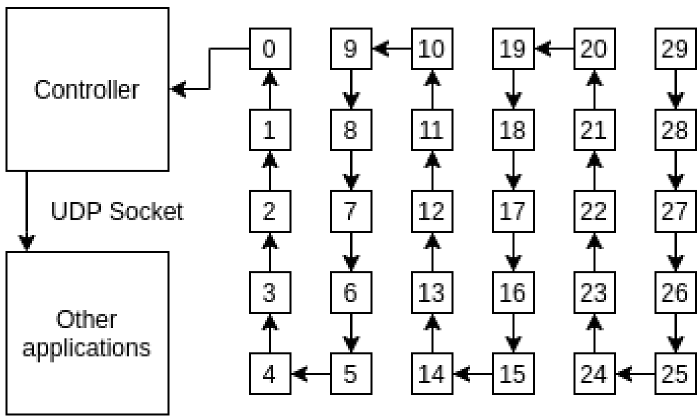


Figure 5. The flow of data of the pressure sensing floor

The data that the floor provides contains two main metrics: (1) pressure and (2) position. The knowledge of position of players on the floor is useful for volleyball and should be possible to infer from the data provided by the interactive pressure sensing floor.

A possible difficulty appears when looking closely at the floor. It can be seen that not all tiles are perfectly straight, most tiles are slightly leaning upon a single sensor. It is also possible to move the tile in a way so the weight is shifted towards a different sensor. This leaning likely causes different values to be reported by the force sensors when the floor is in an empty (nothing is on the floor) state, creating the need for a lowest detectable weight.
Another difficulty is that tiles are bigger than a foot. This introduces two scenarios to take into account:

- A single foot can be place on a junction of tiles, activating 4 tiles and distributing the weight.
- Multiple feet placed in proximity of one-another can cause a sensor to register weights of multiple feet.

This particular resolution causes an assignment problem at some point when trying to localize players: which weights belong to which person? Is this solvable?

The last difficulty lies in the connectivity of the floor. The controller is the main point of access. It can propagate a video signal and it broadcasts updates of the status of the floor over a network socket using the UDP. Data packets are available when connecting to the network socket using the correct port. A data packet contains the latest sensor values for all four sensors of a single tile. These packets can be used to construct the current status of the floor.
However, just the status provided by the floor is not directly useful for volleyball as raw sensor values have no meaning for volleyball. At a minimum the floor should be able to identify where players are approximately. With the knowledge of locations of players, they can be tracked and other metrics can be inferred such as distance, direction and speed. Thus an investigation in the reported sensor values in necessary.

2.4.2 Investigating sensor values

The initial analysis shows potential quirks of the interactive pressure sensing floor caused by physical properties. In this section the internals of the floor are explored. The pressure sensing floor provides, through a controller, updates of sensor values. However, these values cannot be used directly for volleyball. By converting these sensor values to weights, it is possible to locate areas of interest on the floor. These areas may hint at the whereabouts of a player.

Not all sensors are created equal. In the initial analysis it was hypothesized that there could be a difference in reported sensor values for identical weights. To confirm this hypothesis sensor values for 0kg and ~80kg were recorded for four sensors. The result of this test (for two sensors) can be seen in Figure 6 and Figure 7.

In each figure there are two peaks. The left peak shows sensor values when there is 0kg upon the sensor. The right peak is for 80kg. It can be seen that the left peak is located differently for the two sensors. The right peak is also at a different location, but it is hard to see with the naked eye. This effect is probably caused by the fact not all tiles are perfectly straight, lean onto one-another or variation in height of the mounted sensor. Other reasons could be wear and tear caused by usage, transport or age. For every reason the result is the same: every sensor needs to be calibrated individually.

Additionally, it was found that sensors report slight differences for the same weight on different days. This might be because of temperature differences as the sensors are quite sensitive (What is the temperature in the room? How long is the floor turned on?). However, this is not confirmed nor solved.

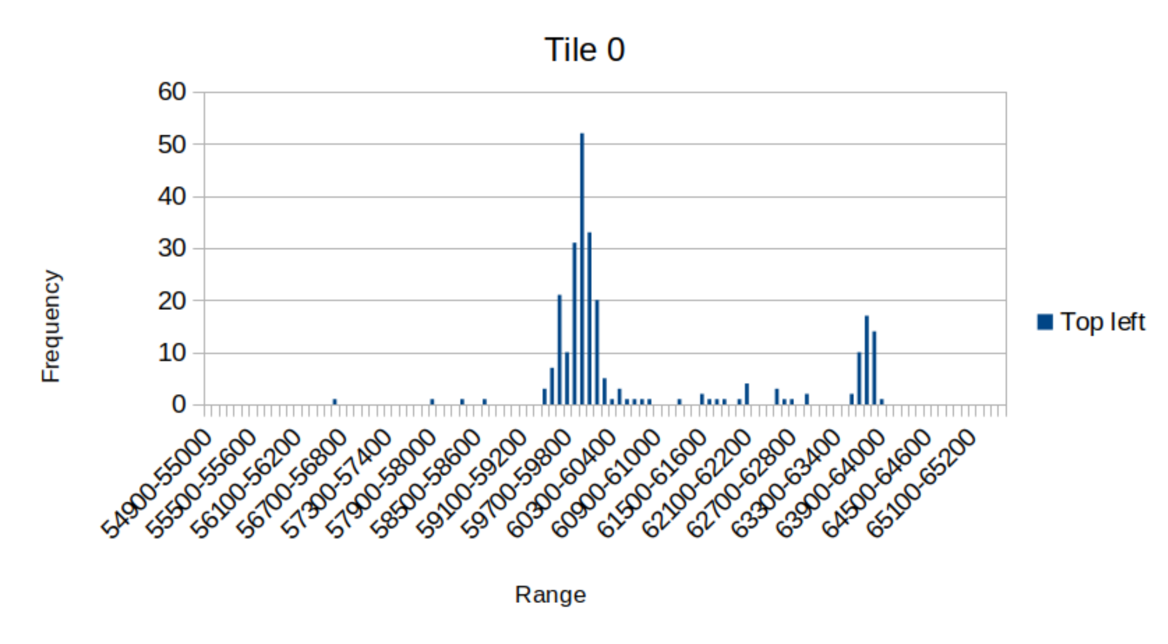


Figure 6. Histogram of sensor values for 0kg and 80kg

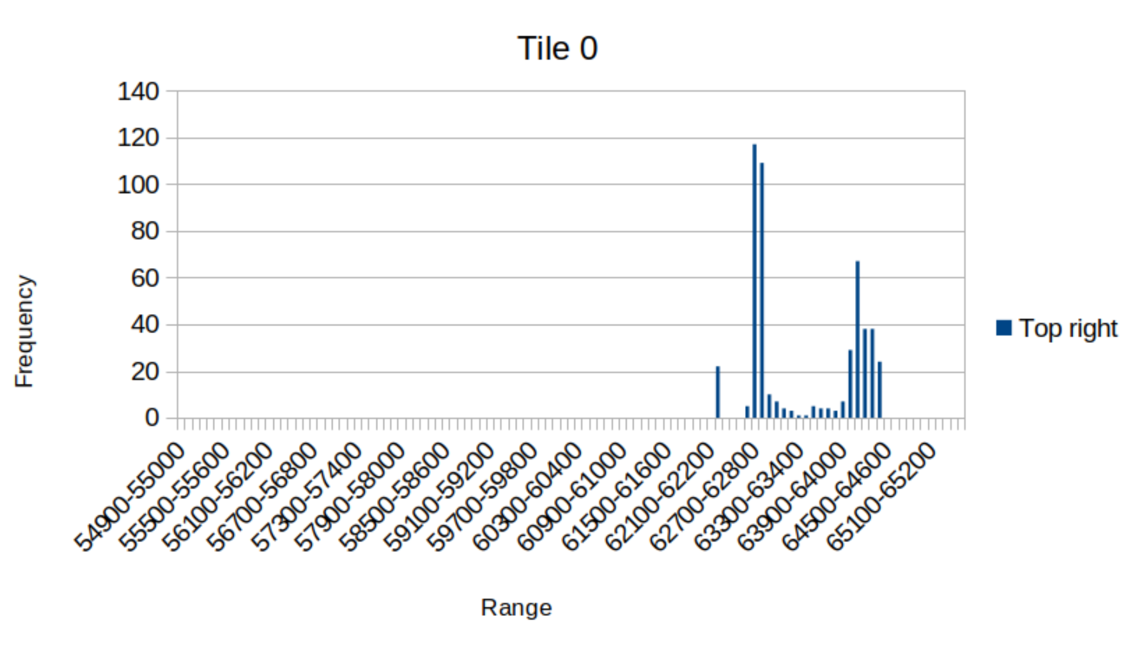


Figure 7. Histogram of sensor values for 0kg and 80kg

3 Overview of the overall architecture

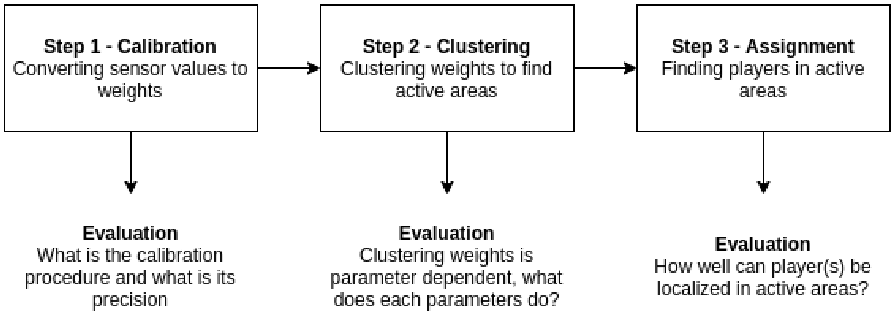


Figure 8. Technical approach & evaluations

In this chapter an overview is given on how data of the floor can be converted to player positions. The interactive pressure sensing floor provides raw pressure data. To use this data for further analysis a number of transformations are necessary to identify players at locations. The origin of these steps can be found in section 2.4. The order of the steps to transform raw data to players at locations can be seen in Figure 9.

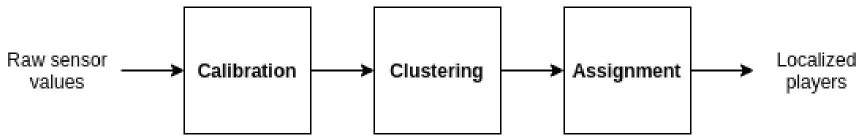


Figure 9. Steps to transform raw data to location data

Calibration

The calibration step provides a method to convert raw sensor values to weights. To do so a number of different weights will be applied to various sensor to find the relation between weight and reported sensor values. This relation can be used to fit a curve so that any sensor value can be converted to a weight.

Clustering

The clustering step tries to find areas of interest on the pressure sensing floor. This will be done by clustering nearby weights together. This results in group(s) of clusters which show where players are active. This means it is roughly known where players are.

Assignment

The assignment step takes all areas of interest of the floor and calculates how many players are active in each area by using the total weight of each cluster. Then this task will localize players by using a weighted mean or a more elaborate procedure in the case of multiple players per area of interest.

In this thesis each step has its own chapter and is structured similarly. After a brief introduction the problem is explained, a method to solve this problem is proposed. This potential solution is tried and its results are shown in the results section. Each chapter ends with an evaluation. Afterwards the entire system is evaluated while taking into account volleyball specifics in Chapter 7. Suggestions for future work are in Section 7.2.

4 Step 1: Converting sensor values to weights

In this chapter a method is created to provide a means to compare sensor values directly with one-another by converting sensor values to weights. As seen in Section 2.4 the signature of each sensor is unique and thus sensor values amongst different sensors cannot be compared. By calibrating each sensor individually the weight can be calculated and this can be used for comparison between sensors. To come up with a method to calibrate sensors four sensors are analyzed by applying ten different weights, so that a generalize pattern can be found and used for calibration. The result - a calibration procedure - is then used for the same four sensors so that the calibration procedure can be evaluated by comparing the error of the calibrated sensors with the known ten weights used for analysis.

4.1 Problem

The problem is that sensor values from sensor A cannot be compared to those of sensor B because they report different values for the same weight. By creating a calibration procedure sensor values can be converted to weights which then can be compared between sensors. To create this calibration procedure a number of problems have to be addressed.

Firstly, different weights will be placed upon sensors to provide a ground truth. However, every sensor reports its sensor values with some amount of noise. How can noise be dealt with?

Secondly, because a ground truth is necessary to evaluate a potential calibration procedure, a number sensor must be tested with a number of different weights. What is a proper method to do this?

Thirdly, it is known (see Section 2.4) that sensors report a broad range of values for low weights, and this range decreases in size when the weight increases (e.g. a reported sensor values of 0kg are within ~0-60000, and for 30kg ~64000-65000). This would make it impossible to create a fit function, so a minimum weight as a cutoff is needed. But what should this minimum activation value be?

Lastly, with clean data and ground truth the relation between sensor value and weight can be viewed. Thus a fit function can be generated, but how can this be done?

4.2 Methods

The following problems need to be addressed:

1. How can noise in sensor values be addressed?
2. How can a ground truth be provided?
3. How can a minimum activation value be chosen?
4. What kind of function is needed to create a fit for each sensor?

To keep this thesis more readable the specific method is explained within the result section of that problem.

4.3 Results

4.3.1 Noise removal

To calibrate sensors it is important to have clean data. If the data contains noise it is harder to calibrate sensors correctly. There is a natural deviation between readings for sensors on the same weight, but any peaks should be removed if possible. During the sensor values analysis two types of noise became visible:

1. Intermittent zeros: Occasionally the floor sends a sensor value of zero between 'regular' values, these can easily be filtered out by dropping the first (or more) zero value(s) after a non zero value.
2. Values with a high σ value: When recording sensor values for a specific weight the floor sometimes reports sensor values that are ~100 points from the average. These can be removed in a static setting (e.g. when calibrating the floor) by computing the average and standard deviation of that recording. However, when working on live data this needs more attention, but this is out of the scope of this thesis.

By removing this noise the data is suitable to use to provide a ground truth so the quality of the calibration procedure can be assessed.

4.3.2 Ground truth

To create a ground truth four sensors are calibrated individually. The weights used for this calibration were 5, 10, 15, 20, 25, 30, 35, 75, 85 and 95kg. The procedure is the following:

1. Clear the floor
2. Put weight directly above sensor
3. Record 100 sensor values

By plotting the recordings of 10 different weights the exponential nature of the relation between sensor value and weight became visible as can be seen in Figure 10. This means the function that will be used to generate a fit will be an exponential function.
Note that the plotted sensor values are relative to the sensor value for 0kg, this is because findings showed that the range of reported values for 0kg is from 0 to ~60000.

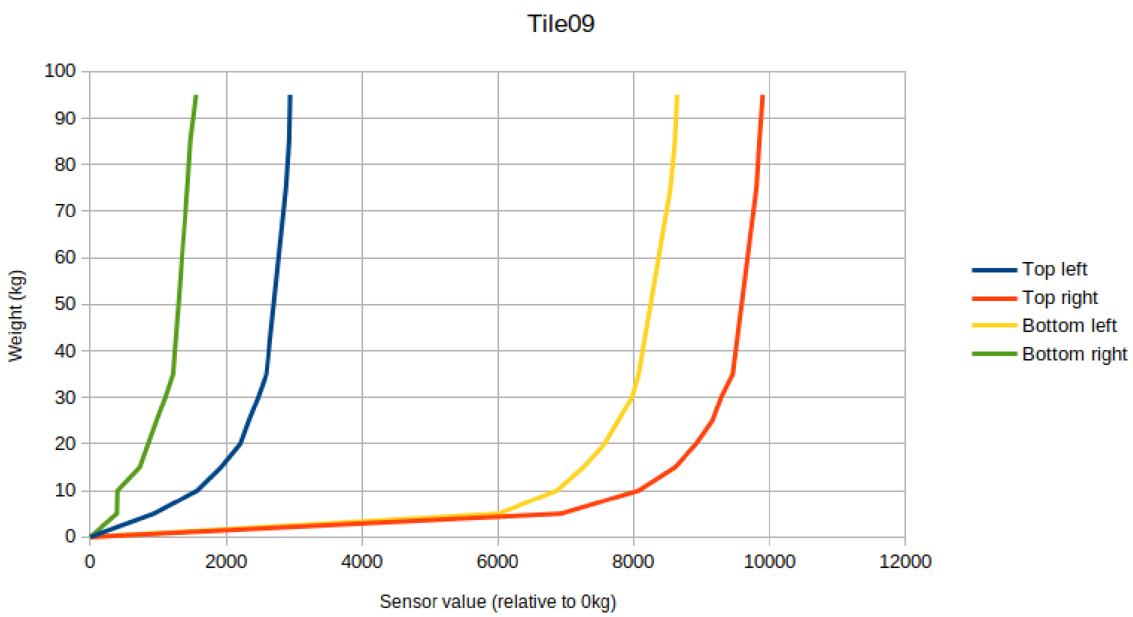


Figure 10. Sensor values and weights

4.3.3 Minimum activation value

A minimum activation is necessary to create a proper fit. To find a proper minimum activation value a small test is performed. In this test a number of low weights were placed on 4 sensors.

The weights that were used are 2.5kg, 5kg, 7.5kg, 10kg, and 12.5kg. For each weight 100 sensor readings were collected. The results are plotted in Figure 11 and Figure 12.
When looking at the average deviation in sensor values at the lower end of weights on a tile (see Figure 12) it can be seen that the deviation for 0kg is too high to use as a minimum activation value for calibration. The average deviation drops until 5kg, and then it varies by small amounts (but still trending downwards). Thus, it was decided to trim off all values lower than 5kg and take 5kg as a minimum activation value. This could potentially cause issues with players weighing less than 20kg (~5kg per sensor).

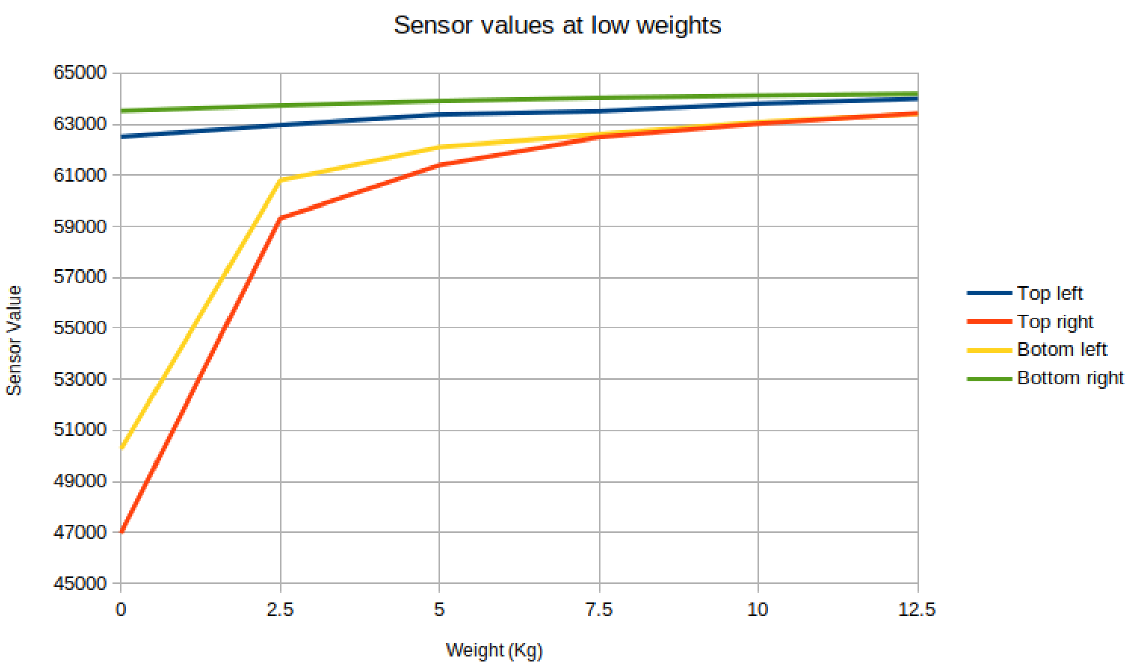


Figure 11. Sensor values at low weights

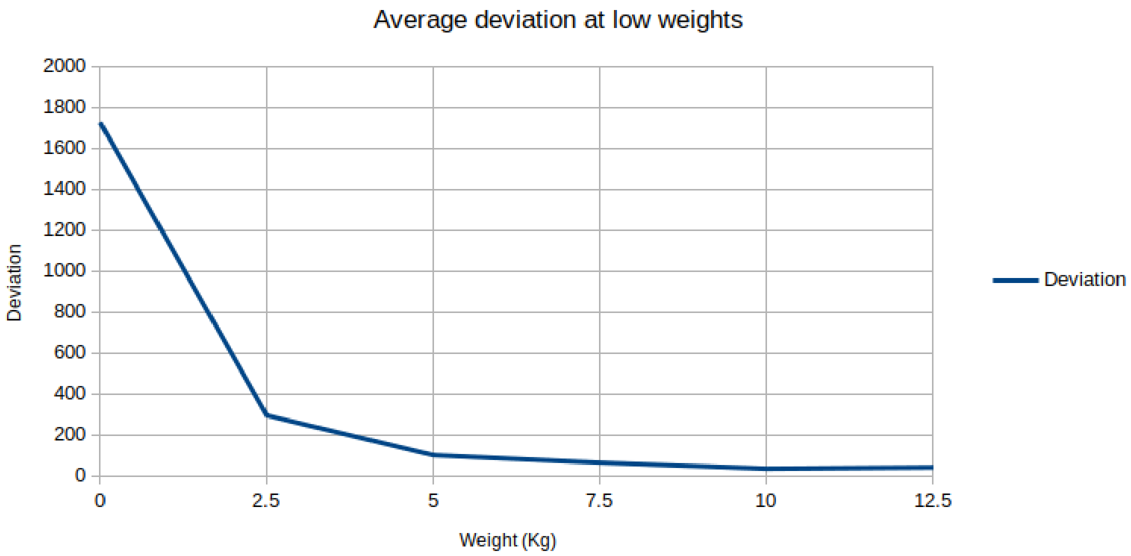


Figure 12. Deviation in sensor value at low weights

4.3.4 Generating a fit

To generate a fit, a function should be chosen, and a method to calculate a fit given some input data. It is clear that the sensor values follow an exponential trend when looking at Figure 10. Thus an exponential function will be used to create a fit.

An exponential fit is calculated by converting the relative (to the sensor value of 5kg) sensor values to logarithmic space, performing a linear fit (by minimizing the sum of squared errors) and then converting the parameters of the linear fit to an exponential space, creating a fitted curve. The formula used for this curve is this:

$$y = a \cdot e^{x \cdot b}$$

By taking into account the minimum activation value for 5kg the fit function transforms into:

$$weight(kg) = a \cdot e^{(x-c) \cdot b} + 5$$

a and b are fit specific values, c is the sensor value for 5kg (minimum activation value) and x is the reported sensor value.

Note that when the reported sensor value is lower than the minimum activation value the function will output 0kg by using an if statement. Omitting this statement would return 5kg for a reported sensor value below the minimum activation value.

4.4 Evaluation

In the previous sections a number of difficulties were solved regarding calibration. The noise removal step shows that the floor has some quirks. Intermittent zero's could be an indication that the floor tries to tell that there is a problem, or it could be an error in the controllers. Sudden changes in sensor values were also present. This shows that a number of sensor values should be collected before converting to weights.
When creating the ground truth dumbbells were used as weights, for heavier weights it was

more difficult to put the weight directly upon the sensor as the size of the dumbbell increased. It is likely that some weight has shifted upon the other sensors as well.
With all parts in order a calibration procedure can be drawn up. This procedure needs measurements of three different weights, each from a specific range. With these measurements any sensor value can be converted with an average error of 2.57kg. This error is not particularly small, but increasing the amount of weights used for calibration only marginally decreases the error.

4.5 Contribution - The calibration procedure

By combining the ground truth, using the minimum activation value and the method to generate a fit a calibration procedure can be drawn up. But first a set of weights to use for this calibration procedure must be chosen.
To find these weights all combinations of samples are used to generate a fit, then the best fit (lowest error) was chosen for 2, 3, 4, 5, 6, 7 and 8 samples. The error is averaged for each sensor and the result can be seen in Table 3. It can be seen that the average error drops significantly when using three samples instead of two. Increasing the number of weights after three samples only marginally decreases the average error. Thus the minimum number of weights needed to generate a proper fit is three.
The specific weights that were used for the best fits with 3 samples can be seen in Table 4. By diving the weights into three categories: low (10, 15 and 20kg), medium (25, 30 and 35kg) and high (75, 85 and 95kg) it can be seen that each category has four entries for a best fit and thus each category should be used when selecting weights for the calibration procedure. Suggested weights to use are 15kg, 35kg and 85kg.
This means the calibration procedure consists out the the following steps, to be performed on every sensor:

- For the 5kg (activation weight) place the weight in a corner of a tile.
  - For every corner of that tile:
    - Step in the specific corner.
    - Carefully move off the floor.

        * Take the average of 100 sensor values.

    – The activation value is then the average of the 4 readings.

- For all other weights (15, 35 and 85kg):

    – Place the weight firmly in the corner of a tile.
    – Record 100 sensor values.
    – The sensor value associated with the weight average of the 100 sensor values.

After taking all measurements a curve can be fitted for every sensor (see section 4.3.4), which can be used to convert any sensor value to a weight.

Number of samples	Average error in kg
2	4.07
3	2.57
4	2.39
5	2.34
6	2.29
7	2.28
8	2.27

Table 3. Average error of a fit generated by *n* weights

Weight	Frequency	Category
10	0	Low
15	4	Low
20	0	Low
25	2	Medium
30	0	Medium
35	2	Medium
75	1	High
85	2	High
95	1	High

Table 4. The frequency of weight used in the best fits with 3 samples

5 Step 2: Clustering weights to find active areas

In this chapter an action sequence is created to find areas where players are active. By converting all sensors to vertices and creating connections (edges) between all vertices a fully connected graph is created. A connection means that the vertices belong to the same active area. A number of criteria can be set up to reduce the number of connections within this graph. If the criteria are set up correctly the remainder - sub-components - indicate active areas. Too strict criteria (too many dropped connections) will result in players (in an area) being split into multiple sub-components. Too loose criteria will result in one big component where all players reside. Therefor the criteria are evaluated to find out if they are optimal.

5.1 Problem

Figure 13. Floor with three children

Retrieved from https://dpceventservices.com/dance-floors/dance-floor-led/

The problem is that a list of sensors reporting weights does not help to localise players. An initial step is to convert the list of weights reported by sensors to a graph, this adds location info to the available data. Then with this fully connected graph edges should be dropped so a small number (more or less equal to the the amount of players on the floor) of sub-components remain. What specific criteria should be used?

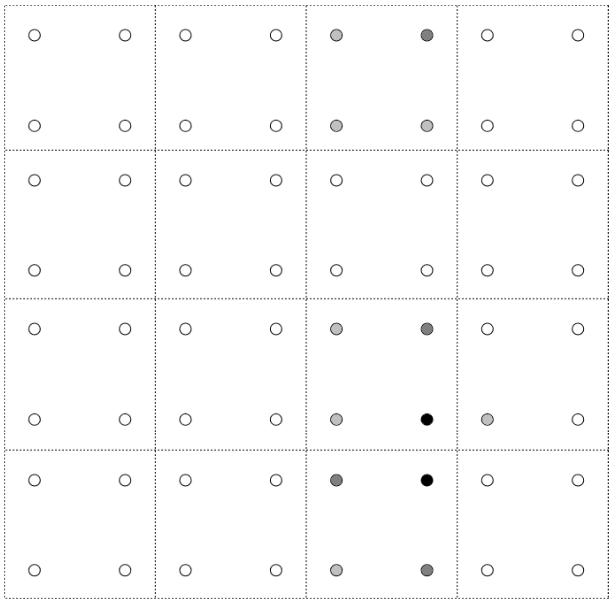


Figure 14. Possible weights reported by floor (outer tiles are cropped)

5.2 Method

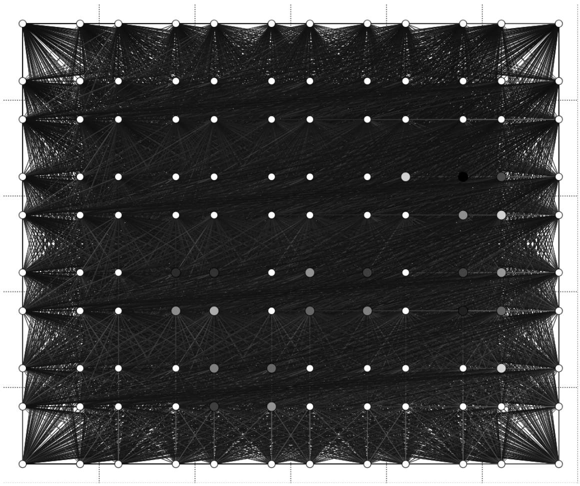
The two problems that need to be addressed are:

1. How can a list of weights be converted to a fully connected graph?
2. What criteria need to be set up so that a limited number of sub-components remain?

The first problem is rather straightforward. Each sensor has a physical location within the floor. This location will be used to give each a virtual location, but then 10cm from the top/bottom/left/right. By placing a sensor exactly in the corner of a tile would make them overlap with the sensors of neighbouring tiles. This results in the input for the second problem, a fully connected graph. The second problem will be solved in an empirical manner. By viewing the graph a number of connections can likely be dropped. By dropping them and plotting the graph again a number of sub-components should emerge. These criteria can be found in the next section.

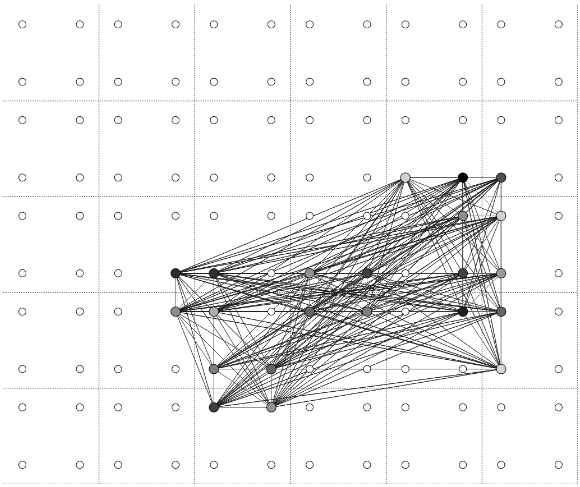
5.3 Result

In this section the action sequence to convert a fully connect graph with weights to a number of sub-components can be found.



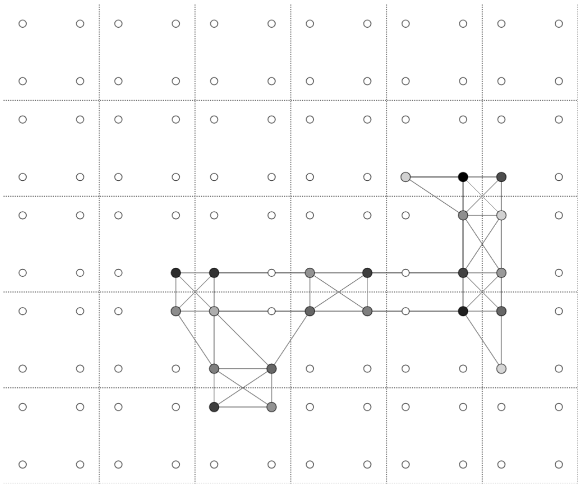
Initial graph

By converting sensor values to weights an unidirectional graph is constructed. Each vertex represents a sensor and has a weight. The length of an edge is equal to the distance of the connected vertices. Additionally each edge has a score equal to the cumulative weight of the vertices divided the the edge's length.

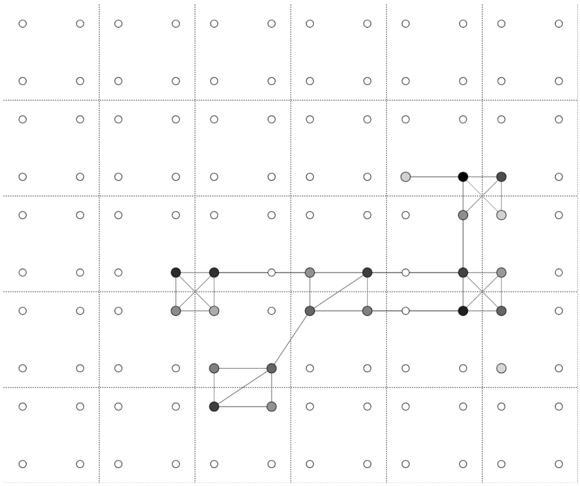


Removed 0kg vertices

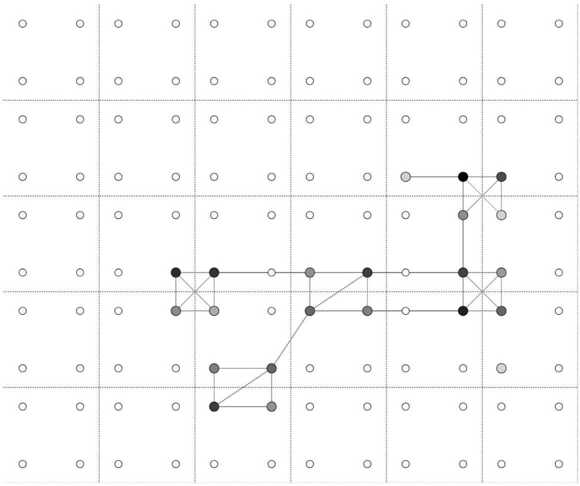
Zero weight vertices are removed because they are not used for to finding active areas. A sub graph emerges showing the active areas.



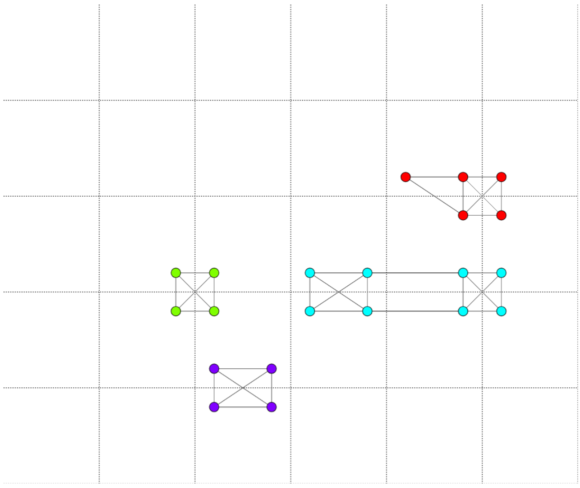
Removed edges longer than 50cm
Edges longer than 50 cm are removed. 50 cm was chosen because that is exactly 1 tile. A smaller cutoff would increase the probability of a persons feet being split into two sub components of weights. A longer cutoff increases the probability of multiple persons ending up in the same component.



Removed edges with a low weight / length ratio
For each edge the following value is calculated. The weights of each source & destination vertex is added together and divided by the length of the edge. If this value is 16 kg/cm or lower, the edge is removed.



Removed bridges
A bridge is a vertex which acts as a link between 2 sub components. All bridges, which do not link to a leaf (a vertex with a degree of 1), are removed.



Sub components
After removing all these edges and vertices a group of sub components can be found. This data is be used to assign players to these active areas.

After all the steps performed above, a list of sub components can be constructed. Each sub component represents an area of interest and is used in the next step: assign a number of players to locations.

5.4 Evaluation

The action sequence that was created contains a number of criteria that were used to split up the initial graph in sub-components that show active areas. In this section all criteria and their parameters are viewed to see if they have any (negative) consequences.

Removing 0kg vertices
This criteria removes all sensors not reporting weight. The threshold (0kg) could be increased, but given that a minimum activation value is already used to convert sensor values to weights this was deemed unnecessary. Note that this activation value is 5kg, so the threshold should higher than 5kg to have any effect.

Removing edges longer than 50cm
This criteria removes all connections longer than 50cm. 50 centimeters is a relatively small distance (European shoe size 40 is for feet of 25cm) between players. A neutral stance of a players is also ~50cm, meaning the parameter could be increased a bit. However, it is very likely that sensors between the feet of players are activated as placing your foot on a tile engages all four sensors. Increasing this parameter players standing close to each other end up in the same sub-component which is undesirable. The chosen distance allows

for connections within tiles and the direct neighbouring sensors, 50 cm still allows four additional sensors to remain connected see Figure 15. Because of the virtual positions of sensors there are limited number of distances between sensors (options are 20, 28, 30, 36, 50cm or more). Thus, slightly increasing or decreasing the distance parameter often has no effect.

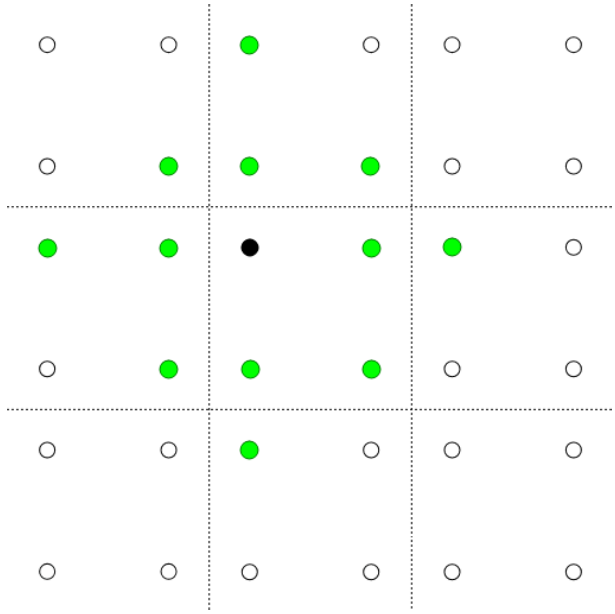


Figure 15. Sensors within 50cm of the primary sensor (black)

Removing edges with low weight/length ratio

This criteria removes connections between weights that are not so significant. There are four scenarios for connections:

1. Short connections with a low weight
2. Short connections with a high weight
3. Long connections with a low weight
4. Long connections with a high weight

By removing long connections with low weights, sub-components become less tangled. In the case there are short connections with low weights being removed, neighbouring sensors often still retain their connections. The threshold of 16 kg/cm was chosen empirically by viewing a number of test situations and increasing this value until all test situations have OK results (players not being split, while not ending up with a big active area).

Removing bridges

This criteria removes bridges. If a sub-component has two main parts, and these are only connected trough a single connection, it means the connection is a bridge. By removing these bridges loosely coupled sub-components become uncoupled. This criteria often acts as last resort, if other criteria were not quite able to split up a component.

6 Step 3: Finding players in active areas

In this chapter a method is explored to find the precise locations of players within active areas. This will be solved by assigning all players on the floor to active areas while maximizing the average weight of players (e.g. an active area with 200kg probably contains more players than an area with 100kg associated to it). Once this distribution is complete, players can be found using a weighted center of mass. In the case of more than one player per component a sub-step (assigning weights to players within an active area) must be performed. The method is evaluated by looking into situations where the method fails, so possible problems within volleyball can be explained at a later stage.

6.1 Problem

The problem is that the input of this step is a list of active areas, while the desired output is a list of players at locations. This means a number of transformations are in order to localise players within active areas. The initial problem to solve is to find out how many players there are in each area. By assigning a number of players to each area the next problem becomes a bit easier. Where are the players within active areas?

6.2 Method

The two problems that need to be addressed are:

1. How can players be assigned to active areas?
2. How can a number of players be localized within active areas?

The first problem can be solved by using an iterative algorithm which assigns players to the active area with the most weight. This results in a state where the weight of each player is maximized.

The second problem is solved by using a weighted average of weights associated with the active area. If there are multiple players assigned to the active area, the weights are first distributed between the number of players and then a weighted average is taken.

6.3 Result

Assigning players to active areas

The assignment of players to areas of interest follows a straightforward algorithm. The following step is executed repeatedly until the number of players to be assigned is reached: Assign a player to an area of interest with the most *weight per player*. So if there are 2 areas of interest and 3 players the following states are visited:

State	Area 1 (120kg)	Area 2 (180kg)
1	0 players	0 players
2	0 players	1 player (180kg)
3	1 player (120kg)	1 player (180kg)
4	1 player (120kg)	2 player (90kg each)

Table 5. Visited states when assigning 3 players to 2 areas of interest

Localising players within active areas

There are three scenarios which can occur when localising players within active areas:

- If there is no player assigned to an active area it is discarded.
- If there is a single player assigned to an active area, the player's location is a weighted average of all associated vertices.
- If there are more players a k-means clustering algorithm is used to position players. A k-means algorithm aims to partition n data points into k clusters. In this case: partition all weights (of a single active area) into k groups, a group then represents a player. The position of a player is then a weighted average of all associated weights.

A number of players assignments (for 4, 4 and 5 players respectively) can be seen in table 6.

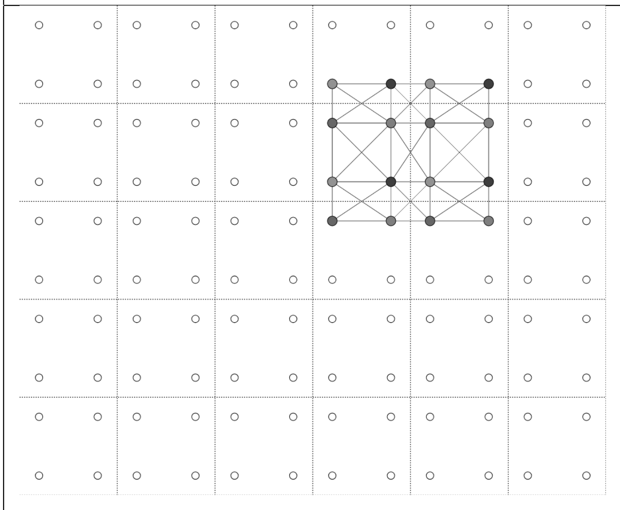
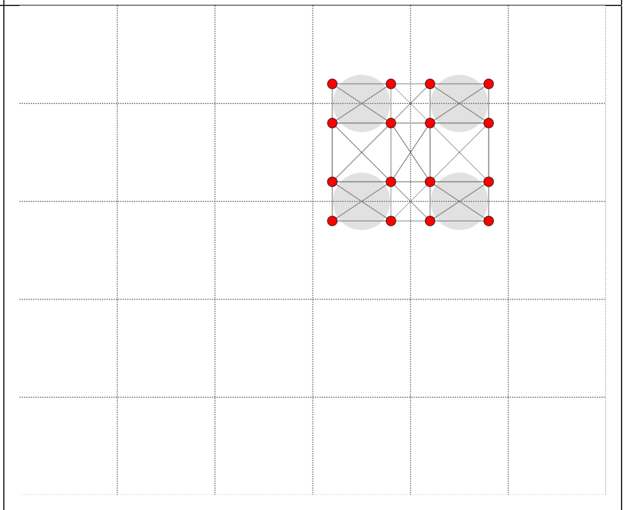
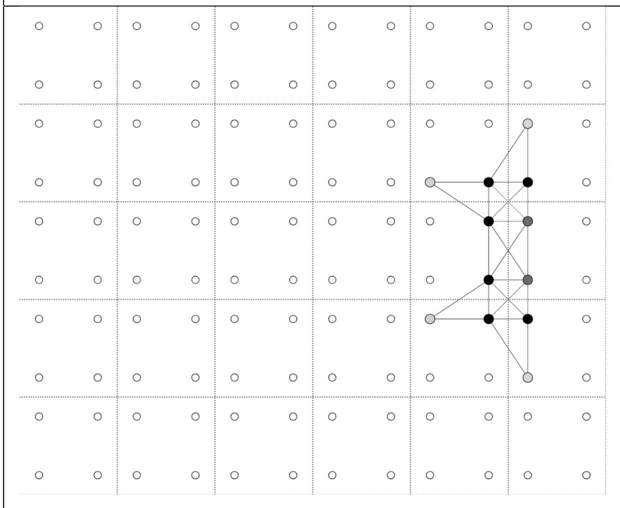
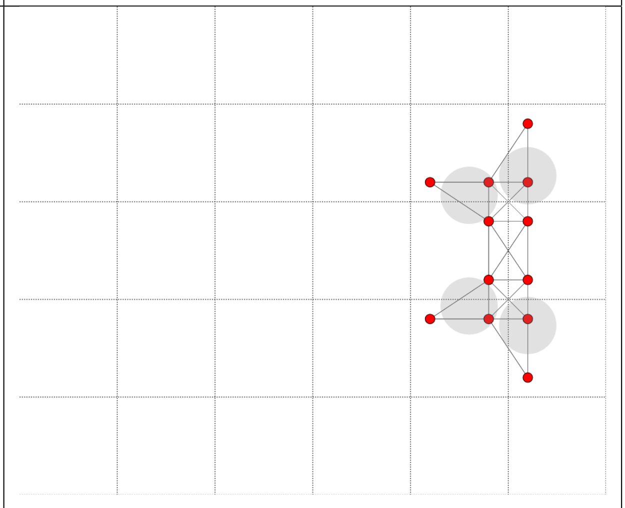
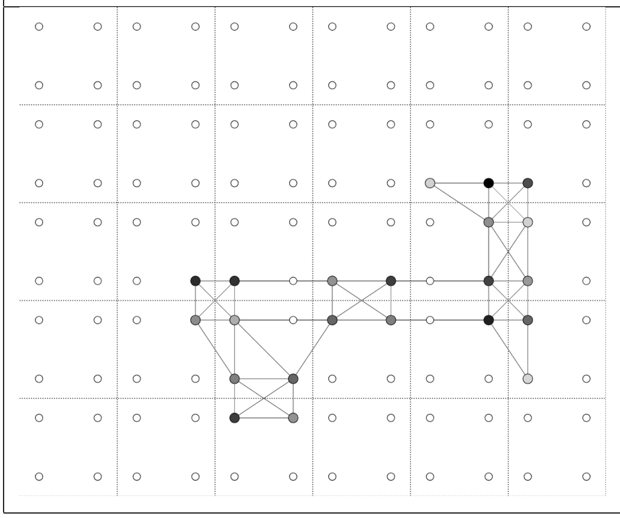
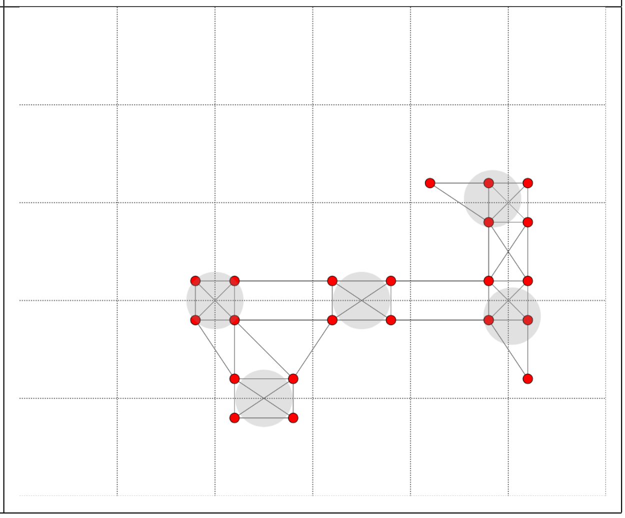
Input	Output
	
	
	

Table 6. Input & output of the assignment algorithm

6.4 Evaluation

Assigning players to active areas

Assignment of players to active areas follows a straightforward algorithm where it tries to maximise the average weight of every player. This works very good if all players are more or less the same weight. However, if large variance in weight of players occur this strategy may not be as suited. An example: a 100kg coach in one active area explaining an exercise to three children (30kg each) all in an other active area. In this example the algorithm will decide to put two players in each active area (two players of 50kg, two of 45kg).

Localising players within active areas

In the case of a single player in an active area The exact location is a weighted mean, this means that players position is shifted towards the foot a player is leaning the most upon. This reflects what is happening upon the floor, the center of gravity of a player shifts, and arguably the position as well. In the case of multiple players problems can occur when dividing the weights of the active area between players. Looking more specifically in the k-means algorithm shows five main disadvantages:

1. Choosing k manually.
2. Being dependent on initial values.
3. Clustering data of varying sizes and density.
4. Clustering outliers.
5. Scaling with number of dimensions.

Disadvantage 1 (the amount of players is known beforehand), 3 (the data always has the same size & density as the size of the floor does not change) and 5 (it will always be 2 dimensional data) are not applicable.

The clustering of outliers is not really a problem, because outliers are removed by the criteria during the clustering step.

The dependence on initial values can be troublesome. With a large number of data points a random selection of data points can function as the initial values, but given that e.g. two players activate 10 sensors this is not sensible. The initial values are provided by choosing n weights (for n players) where the distance between all weights is maximal. Selecting these weights for the initial values has a time complexity of O(n!), which means it does not scale well (see Table 7). For a small number of weights and a small number of players this is fine, but in the case there are many players in a single big active area this can be troublesome. The last scenario in Table 6 it the same as used in the clustering step, where it was attempted to cut up the component. The result of the clustering was four components (so there was a single component in which two players had to be localised).

Players	Weights	Combinations	Computation time (ms)
2	10	45	0.045
2	15	105	0.105
2	20	190	0.19
2	25	300	0.3
3	10	120	0.12
3	15	455	0.455
3	20	1140	1.14
3	25	2300	2.3
4	10	210	0.21
4	15	1365	1.365
4	20	4845	4.845
4	25	12650	12.65
5	10	252	0.252
5	15	3003	3.003
5	20	15504	15.504
5	25	53130	53.13
6	10	210	0.21
6	15	5005	5.005
6	20	38760	38.76
6	25	177100	177.1

Table 7. Computation time for k-means initial values (1 000 000 computations per second)

If the system would run at 60 frames per second, the computation time must be under 16ms.

7 Discussion

In this chapter there are two sections. In the first section the overall operation of the system is evaluated with respect to volleyball. If a step (calibration, clustering or assignment) has a weakness, is this a problem when tracking players for volleyball? In the last section a potential solution is explored where a number of frames is used for tracking, instead of a single moment.

7.1 Evaluation within the context of volleyball

In chapters 4, 5 and 6 a system is described which is able to transform data from the pressure sensing floor to a locations of players on that floor. Each step has strong and weak points. By looking into these weak points, and relating them to volleyball, their consequences can be evaluated.

7.1.1 Calibration

To transform raw sensor values to weights a calibration method was introduced. This creates a few limitations regarding the usability of the floor:

- The activation weight of a sensor is 5kg. This means players should weigh at least 20kg to activate all four sensors of a tile (though it is fine if players are a bit lighter and a portion of their weight disappears, the weight will be incorrect but the position is still quite okay). This means the floor is not as useful for tracking very young volleyball players.
- The average error of calculated weights is 2.57kg. This number may be high or low depending on the purpose. In the case of detecting players this error does not pose a problem. But in the likely case of distinguishing between players using weight this may prove troublesome. Because a players stand a small group of sensors this error can increase to up to 10kg (for four sensors). 10kg is definitely too much to be used to distinguish between volleyball players.

- The calibration procedure is quite labor intensive as every sensor must be calibrated individually with four weights (5kg - for the minimum activation value, 15kg, 35kg and 85kg). A volleyball field is 162m^2 which equals 648 tiles and thus has 2592 sensors. If each sensor takes 10 seconds (5 seconds to record 100 sensor values and 5 seconds to arrange the weights) it will take 7.2 hours to calibrate the floor. The floor is intended to be movable (hence its modular design), when the floor is moved it will need to be re-calibrated. It will be convenient to come up with some kind of automated method of calibration.

7.1.2 Clustering

When clustering weights to form active areas a number of criteria were used to drop connections between sensors. One of these criteria is that connections longer than 50 cm will be dropped. If a player is standing straight their feet will be close together, but when performing a dig it is often the case that the distance between feet increases significantly (see Figure 16). If feet are more than 70 cm from each other (a full tile is in between) the player will definitely be cut up into two components. A test is necessary to see how often this occurs to perhaps change the parameter (and other parameters as well).

Figure 16. A volleyball player performing a dig

Retrieved from https://www.pakmen.com/volleyball-dig/

7.1.3 Assignment

The step where players were assigned to active areas contained two steps.

- The first step assigns a number of players to each area. If all players are of similar weight this algorithm performs good, problems start to occur when the weight of a player is a factor 2 different than an other player). This could be the case when adults and youngsters are both on the floor. This could happen in a training context: a trainer demonstrates an exercise (and is on the floor) to young players. Another situation would be a casual volleyball game with mixed teams. A small female player (e.g. 50kg) versus a tall heavy male (e.g. 100kg) could produce spurious results.
- The second step localizes players within areas. Troubles would arise when there are multiple players within a big component (calculating the initial values for the k-means algorithm has a time complexity of *O(n!)*). This situation would occur when all volleyball players move to the same location, e.g. celebrating a goal or discussing tactics (typically happen after every rally). Or when a spike is set up, then there are 2-3 players of the offensive team and 2-3 players of the defending team (creating a block) in proximity (see Figure 17). Though, the teams can be split up (each team is restricted to their own playing field to reduce the number of players within a component) reducing the number of operations. A possible idea is to use a different method of calculating the initial values.

Figure 17. Three volleyball players blocking

Retrieved from https://www.fivb.com/en/volleyball/ioqt/2019/men-pool5/news/giant-leap-for-poland-on-road-to?id=87887

7.2 Recommendations

In this section a few ideas are recommended to improve the quality of usability of the system described in this thesis.

7.2.1 Identifying players

The system described in this thesis localized players on the floor. By tracking locations over time players can be tracked. However, it is unknown which player is who. Weights associated to that player (during the clustering) could be used to identify players, but the error (2.57kg) will likely prevent consistent results. A possible idea is to make players step onto the floor in a specific order. However, if the identity of a player is lost (when it is impossible to separate players from a cluster, or when players multiple accidentally leave the floor) it is hard to correctly identify them again. A possible solution for this problem is to introduce a linking procedure. Given that players will be wearing IMUs and it is known which player wears what specific IMUs this procedure can look as follows:

1. Alice wears IMUs on her forearms (IMU 1 and 2) and registers this in a system.
2. Alice steps onto the floor.
3. The system sees that a (new) player appears and asks the player (visually on the floor) to jump twice and clap hands.
4. The system now knows that the players that jumped twice wears IMUs 1 and 2 and is called Alice.

7.2.2 Sliding window

The system described in this thesis is focused on extracting information from a single frame provided by the pressure sensing floor. When using a number of frames (by using a sliding window see Figure 18) quite a few steps in the system change, but new information is gained as well.

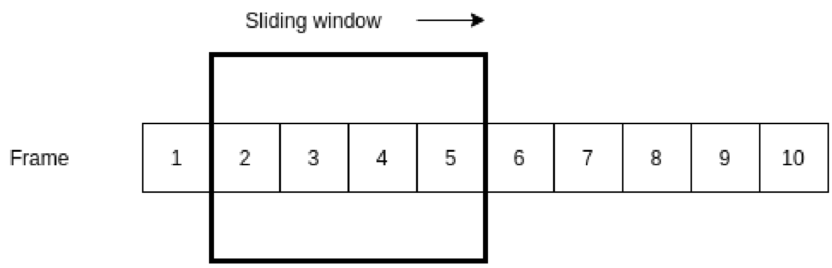


Figure 18. Example of a sliding window

Calibration

The calibration procedure would not change, but the sensor value used to convert to weight can be an average of this sliding window. This would remove some variances within sensor values. Additional information that could be used if the weight on the sensor is trending up or downwards. This could for example indicate whether the player starts jumping.

Clustering

In the case of grouping weights together a sliding window can function differently. Some initial components must be found (by using the existing techniques) and afterwards weights can be added or removed to components. If weights appear in an previously empty position a new component is created (this would occur when a new player steps onto the floor). If a weight appears near a component it can be appended to that component. By then tracking the directional and velocity of a component some situations where components are near to each each other can be resolved (not end up in the same component). An example would be a player standing still, and another running past. This does mean another method of dividing weights between components is necessary, because it is likely that weight of player A end up in the component of player B and vice-versa.

Assignment

Assigning players to components would remain the same when using a sliding window. An initial configuration use the same algorithm, but each window after that can use the previous configuration. If there are big differences the algorithm can be ran again. Localization of multiple players within a single component would occur less frequently. When it does occur the same strategy can be followed. An advantage could be that the initial setup for the k-means algorithm can use a previous configuration, meaning that the computational complexity is reduced and it would work fine for a bigger amount of players.

7.2.3 Transcending static frames

Another recommendation, though similar to the sliding window mentioned previously, is to move away from static frames. But in this case referring to the resulting locations of players. To track players their location must be known. That is the purpose of this thesis. By tracking players continuously a lot more information can be gained about them. Basic metrics such as distance travelled, velocity, acceleration and direction can easily be inferred. Possible metrics that can be inferred are the number of jumps, jump duration, steps, cadence, maybe in a controlled setting even ground reaction forces.

Moving towards volleyball, by tracking a player their action radius can be calculated. By doing this for a volleyball team on the field uncovered areas can be found. Combining this with the display function of the floor you can show which areas are not covered by the team.

8 Conclusion

This thesis aimed to provide a system to track volleyball players on an interactive pressure sensing floor. The system described in this thesis is able to localize multiple players on a pressure sensing floor. To come up with this system, a brief analysis of volleyball movements and the interactive pressure sensing floor was performed. With this knowledge a number of steps was drafted to convert the raw data of the pressure sensing floor into location data of players.

The initial step in this system was to calibrate each sensor. By measuring sensor values for various weights a pattern became visible and by using fitting a sensor values could be converted to a weight. To streamline this process a small side-step was taken to find out how many (and which) weights give good results. With just four weights a curve can be fitted with a reasonable error (2.57kg). With this result the next step, clustering, has the proper input to find areas where players are active.

In the second step each sensor is placed in a virtual graph to find these active areas. By using a number of criteria and techniques borrowed from graph theory connections within this graph are dropped. The criteria were drafted in an empirical manner and thus may still need to be tweaked further for volleyball specific situations. Nonetheless, the remainder of the graph has number of sub-components which indicate areas where players are active.

The last step in this system is then to find players within active areas. This consists out of two phases: assigning a number of players to each active area, and localising players within each area with more than one player. The first phase follows a straightforward algorithm which works in almost all cases, scenarios in which it fails are when the variance of weight between players is too big (e.g. when a player weighs twice as much as an other). The second phase localizes multiple players within a single active area works by using the k-means algorithm and is quite robust. K-means is quite dependent on the choice of the initial values, and the system currently looks for the best possible option (this means all combinations have to be checked and thus is quite computationally intensive).

However, a limitation of this system is that the identity of the found players is unknown. The weight associated with the found player could be used to identify individuals, but it is likely that the error (2.57kg) is too high to produce consistent results.

Further research for the system is to transcend from using static frames. What can be done with player location over time? Simple metrics such as distance, speed and acceleration can be inferred. After identifying players their location can be combined with data of the worn IMU. Actions can then be plotted on maps, actions can be rated for quality and this data can be used for future applications. An example of such an application is deciding what the action radius of a player is. Displaying this radius on the floor with players could be a very interesting experiment.

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