The discriminating factors of winning and losing in elite level wheelchair tennis

Timo Dinkelberg

TU Delft

The discriminating factors of winning and losing in elite wheelchair tennis

By

T.S. Dinkelberg

in partial fulfilment of the requirements for the degree of

Master of Science
in Mechanical engineering

at the Delft University of Technology,
to be defended publicly on Tuesday, July the 2nd 2019

Thesis committee:

Chairman:	Prof. dr. H.E.J. Veeger
External member:	Assistant prof. T. Huysmans
Project supervisor:	Dr. D.J.J. Bregman

TU Delft

Preface

The topic for my master thesis was chosen with my own passion for sports in general. I asked Daan Bregman at the Sports Engineering institute in Delft if there were any possible thesis subjects for me I was introduced to Rienk van der Slikke from the Haagse Hogeschool and his wheelchair research. Inertial measurement units (IMUs) were used to do measurements in wheelchair basketball and wheelchair rugby. These measurements allowed to analyse the movements of the athletes and give them some feedback regarding their movements. To broaden the scope of the research Rienk asked me to setup a protocol for tennis measurements. For my internship I developed a measuring method that can be used to measure the mobilities of athletes during tennis matches. During my internship I also obtained a large amount of data during the measurements of the ABN AMRO tennis tournament. This research will be about analysing this data and determining the differences between winning and losing a match.

I hope you enjoy reading my thesis.

Timo Dinkelberg 12-04-2019

Acknowledgements

Finishing my thesis was a long and tough road to me, mainly due to the unfinished business with regards to some left open courses, I pulled through in the end, but I couldn't have done it alone. I would like to thank Daan Bregman and Rienk van der Slikke as my main supervisors. Daan has supported and guided me through writing my thesis and finishing my last few courses. He has not only been a professional support but also been a great mental support. Rienk has introduced me to the usage of IMUs and helped me get the hang of how to measure with them. He has been the greatest help during the measurements at the ABN AMRO tournament.

I would also like to thank my main friends at university who always supported me and whom I spent most my time with during my study. Johnny and Kenny, even tough they already graduated long before me they kept supporting me and helped me get there in the end.

Lastly but most important, my parents and sister for their patience and continued support during my time studying.

Thanks again to all of you!

Timo Dinkelberg 12-04-2019

Contents

List of figures

List of tables

List of abbreviations

Accel.	Acceleration
Avg.	Average
IMU	Inertial measurement unit
Max.	Maximum
Rot.	Rotational
Vel.	Velocity
WMP	Wheelchair mobility performance

Abstract

Technology is being used more and more to aid elite athletes in improving their performance. Recently there have been promising developments in the research using IMUs regarding wheelchair rugby and basketball. Applying this same measurement setup to wheelchair tennis could give better insight in the wheelchair mobility of wheelchair tennis athletes. This knowledge could aid the athletes in causing less sport related injuries, altering the focus of their training or even training entirely new aspects of the sport. This is why this research will be answering the research question: **"What is/are the most influential factor(s) regarding the mobility of wheelchair tennis athletes to discriminate between the winning and losing player?"**. We define the wheelchair mobility performance as all the measurable parameters related to the movements of the athlete. These mainly consist of the velocities and accelerations reached by the athletes.

Measurements were done during the wheelchair event of the ABN AMRO tournament. For this study 11 athletes competing in the male single matches were measured. Measurements were taken by three different means, by using IMUs, by using tagging data and by using video material. The IMUs were attached to the wheelchairs and made recordings of the accelerations and velocities during the match. Tagging data is information regarding the tennis match that is linked to every point played, for example, who won the point, who was serving and what the duration was of the point played.

The measurements resulted in three different ways to output variables. Match statistics, these include information about the distance travelled, turns made and points played during the match. This was chosen to give general insight into the match. The wheelchair mobility performance (WMP), shows information about the velocities and accelerations during the match. This was chosen to compare the velocities and accelerations of athletes, they are plotted against the average value of the entire database of all measurements, this will be a standardized baseline to compare the results to. Lastly the speed zone plots, the plots give an indication of how long the athlete has been driving within a certain velocity range. To give better insight in the dynamic of the match all outputs also includes the constraints of winning/losing and serving/receiving. It is therefore possible to compare the differences between won and lost points and served and received points. There was also experimented with the possibility of making a plot that shows the location of the athlete on the field as a heatmap. However, because the IMUs only record accelerations the cumulative error to distance had to be manually adjusted for, therefore this was only done for one match as a pilot case.

The match statistics, WMP plots and speed zone plots showed no significant differences between winning and losing points. Therefore, this study found that the mobility performance has no deciding effect on the outcome of a tennis match. The technique used to hit the ball and place it on the right spot in the field will probably be the determining factor here. This said, the mobility does however have to be above a certain threshold for the player to compete at a certain level of play, so neglecting it completely is not recommended, however the focus should be on the technique that involves hitting the ball.

The heatmap case shows that the winning player plays more aggressive, but whether he is playing aggressive because he is winning or winning because he is playing aggressive cannot be concluded by this research. There is however a lot of potential in the heatmap concept, because this position on the field tracking could also be combined with the wheelchair mobility performance to determine for example on what position on the field the peak velocities are reached. This might give insight in the playstyles that are effective or not for a specific match and/or player.

1 Introduction

In sports at the highest level the smallest change in technique or strength can make the difference between victory or defeat. With modern day technology more and more parameters can be quantified to potentially give athletes insight in where they are most likely to get the edge over their opponents to secure victory. This edge can be found in different aspects of the sport such as improvement to give feedback to the athletes so they can improve their personal technique but there are also other aspects. A research done regarding 15 different sports shows that on average 13.8 injuries occur per player per 1000 games played and 4.0 injuries per player per 1000 practices attended (Hootman, Dick, & Agel, 2007). These numbers do not seem alarming, however with elite athletes training at least once per day this would mean on average every athlete will have more than one injury each year. Depending on how severe the injury is, the athlete cannot train or not train optimally which hampers their progress and might cause them to miss crucial events, this makes injury prevention a big topic among elite athletes and coaches. Another insight that can be offered by modern technology is to give extra information important aspects of the sport and guide athletes in their training methods. This information will be different for every sport, but a wide arrange of sensors is already available to analyse gait in athletics, foot/knee angle during cycling and to give an indication of how fatigued athletes are during, for example a soccer match (Mendes, Vieira, Pires, & Stevan, 2016).

Paralympic sports are very suited for research regarding their performance and especially regarding injury prevention. Paralympic athletes have a disability which means their body is not functioning optimally, this means their body must compensate for the disability which might put extra strain on the able parts of the body. Research during the London 2012 summer Olympics and Paralympics shows an injury rate of 130 injuries per 100 athletes for the Olympics while at the Paralympics 169 injuries per 1000 athletes were reported (Derman et al., 2013; Engebretsen et al., 2013), so this number was significantly higher for Paralympic athletes. There also is the fact that in Paralympic sports the athletes frequently rely on orthosis or prothesis, this means there is not just the interaction of the athlete with the sport itself, but also the interaction of the athlete with this material. A clear example of this is the interaction of a wheelchair athlete with their wheelchair, this research will also be focussing on wheelchair sports.

There are already some methods that are especially suited to quantify velocity and accelerations in the wheelchair sport. An example of these technologies is using inertial measurement units, the viability and reliability of this measurement method has already been tested by comparing it to an indoor tracking system (van der Slikke, Mason, Berger, & Goosey-Tolfrey, 2017) . This measurement technique that uses IMUs has already been used to conduct a variety of researches in other wheelchair related sports like wheelchair rugby and wheelchair basketball (van der Slikke, Berger, Bregman, & Veeger, 2016). This research focussed on the so-called mobility performance, which gives an indication of the athlete his capabilities to manoeuver around the court with the wheelchair. Because these sports are very mobility driven they were a logical first step in conducting research focused on the mobility of wheelchair athletes. Mobility performance and classification are known to be strongly related in wheelchair tennis and wheelchair rugby (Rhodes, Mason, Malone, & Goosey-Tolfrey, 2015; Sarro et al., 2008; Usma-Alvarez, Chua, Fuss, Subic, & Burton, 2010; van der Slikke et al., 2016). This relation could be explained because these sports are very driven by sprints, the person who gets to the ‘goal’ first will have better odds to score.

Wheelchair tennis is a different kind of sport than wheelchair rugby or wheelchair basketball. In rugby and basketball mobility is used to acquire a favourable position on the field and increase the amount of opportunities and likeliness to score, however in tennis the mobility is used to reach the ball in time to not lose a point and acquire more time to place the next shot. There is also the fact that your opponent plays a big role in the mobility that is required to reach the ball, the further away it is hit from your current location, the more mobile you have to be to actually reach the ball. Because of this reason measuring a single athlete in a tennis setting would not make sense, this means both athletes participating in a match have to participate in the measurements to give sensible results. The setting for this research will therefore be the ABN AMRO tennis tournament, this has given the opportunity to measure the difference within a specific match and the difference within the entire tournament.

In the field of wheelchair tennis the focus has been on research regarding shoulder injuries and physiological demands (Croft, Dybrus, Lenton, & Tolfrey-Goosey, 2010; Goosey-Tolfrey & Leicht, 2013; Warner et al., 2018). However, little is known regarding mobility performance in wheelchair tennis. Therefore, this research has focused on the wheelchair tennis sport. Because tennis is a different sport compared to rugby and basketball, where generally the fastest player always wins, a different approach is required.

Considering mobility there already has been done research in the field of able-bodied tennis players using a tracking system. This research concluded that losers of games tend to cover less distance, travel quicker and spend more time in the defensive zones of the field and less time in the offensive zones of the field. Because of these results it was concluded that the winning player simply dominated the losing player (Martínez-Gallego et al., 2013). The question is if these parameters will carry over to the wheelchair variant of the sport or if the different dynamics will change the results.

Because just using the wheelchair mobility performance as a measure doesn’t take into account a lot of interaction between the athletes. This is why it is necessary to also take into account other measures such as, who won the point, the duration of the point, who was serving during the point and so on. These data are manually tracked and are called tagging data. These tagging data were used in combination with the wheelchair mobility performance to create a more complete view of the match played. This enabled the comparison of won and lost points by using a combination of the wheelchair mobility performance and tagging data. These are very valuable data because at the end of the day the athlete’s main goal is to win his match.

Another aspect is the effort an athlete puts into a specific match, because if one player is obviously better than the other player it is expected for the athlete to put in less effort but still win the match. The amount of effort put in is very hard to measure with the wheelchair mobility performance, because the wheelchair mobility performance doesn’t clearly show whether the athlete is just not able to reach the velocities and accelerations or that he just doesn’t need to put in the effort to win the match. To get a better measure of this speed, speed zones were used, which show for what duration the athlete is in certain velocity ranges (van der Slikke et al., 2017). A majority of the duration in higher speed zones indicates more effort, while being in the lower speed zones indicate less effort.

This research will answer the question: "What wheelchair mobility performance measures discriminate between winning and losing in elite level wheelchair tennis?".
We define the wheelchair mobility performance as all the measurable parameters related to the movements of the athlete. These will mainly consist of the velocities and accelerations reached by the athletes.

The expectation is that the main difference between winning and losing a point was made in short accelerations because most of the movements in wheelchair tennis require short sprints to get to the ball as fast as possible, this should be seen in the wheelchair mobility performance. It is also expected that the losing player of a match will put in more effort and still lose because he is slightly inferior to the other player and tries to compensate this by putting in more effort, this should be seen in the speed zones.

2 Method

2.1 Participants

The research was conducted during the ABN AMRO tennis tournament from 13 to 19 February 2017. The participants were all participating in the men's wheelchair tournament. Prior to the research all participants received an info letter and were asked to sign an informed consent, in which also was clarified that all the results that would be published would not be retraceable back to the athlete, a copy of the info letter and informed consent can be found in the appendix. This research was also approved by the human research ethics department of TU Delft.

The participant pool consisted of 12 participants, who are all males and were at the time seeded in the top 25 of the world rankings (ITF, 2017). Five of the participants have once been number one in the rankings while 9 out of the 12 participants have once reached the top 10 in their career. Two of the participants are left-handed players while the other 10 are right-handed players. The youngest participant had an age of 17 while the oldest participant was 46 years old, the average age was 27 with a standard deviation of 8.5 years (ABN, 2017).

The tournament consisted of 11 matches in a knockout system the schedule was partially decided by a random draw, but the player seeded first and second instantly got a BYE for the first round. Of the 11 matches four matches were the first round, while four players received a BYE in the first round, four of the matches were quarterfinals, two of the matches were semi-finals and there was one deciding final. an overview of the tournament if shown in figure 1.

Six of the matches were measured successfully, in four of the matches the IMUs on one of the wheelchairs failed to measure correctly, so these data will be not taken into consideration and the data of one match were lost due to software failure. Due to the lost data, data of 11 out of the 12 participants were successfully collected.

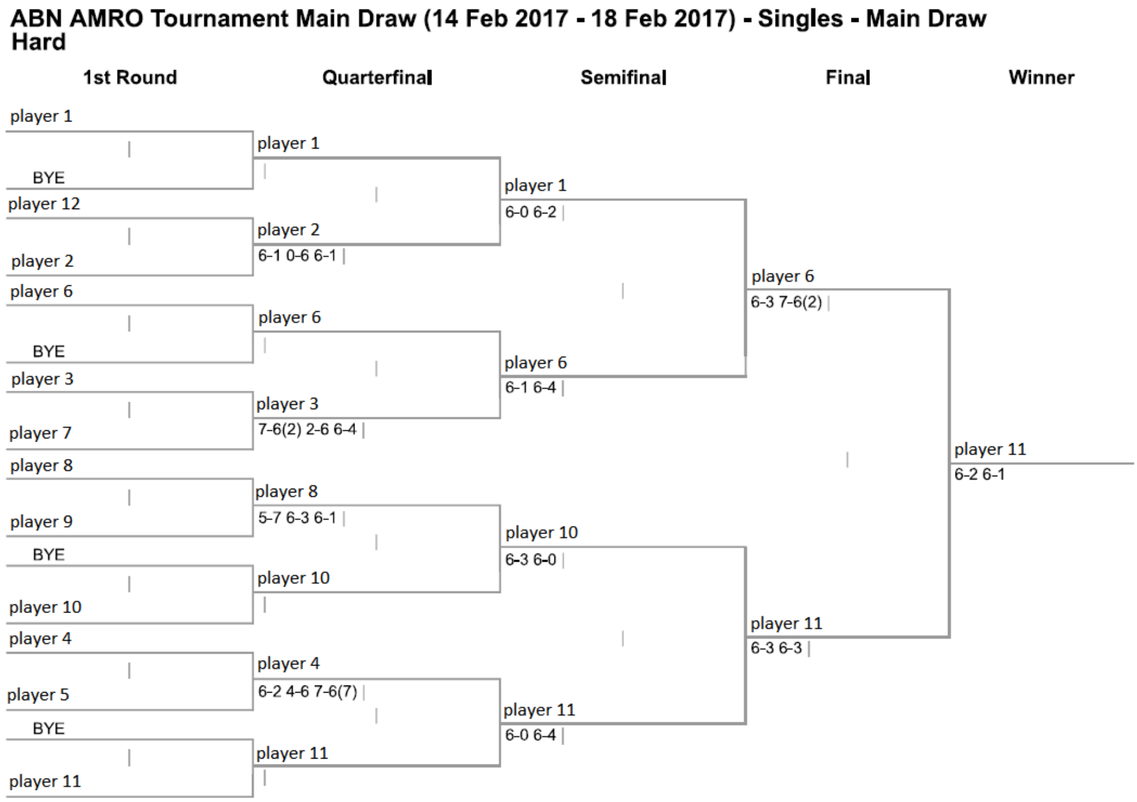


Figure 1: The tournament draw of the ABN AMRO tournament
(ITF, 2017)

2.2 Measuring procedure

During each match measurements were recorded using two sets of sensors, video material and by manual tagging.

2.2.1 Inertial measurement units (IMUs)

The sensors used for all the measurements are Shimmers, a brand of IMUs (Shimmer, 2017). Three IMUs are placed on every measured wheelchair, one on the frame and one in every wheel, the ones in the wheels will also rotate at the same rate as the wheel does (van der Slikke et al., 2017). The exact locations of the IMUs are shown in figure 2. The outputs used in this research are the accelerations given by the inertial sensors and the rotations given by the gyroscopes, also available in the IMU. The gyroscope data from the wheel- and frame sensors will be used to determine the speed and rotational speeds of the wheelchair while the inertial data of the frame sensor will be used to determine the accelerations.

The measurements were conducted by using the SD-cards located in the IMUs. This means the IMUs were prepared and started measuring before the start of the match and stopped measuring after the match, after which the measurements are uploaded to a laptop and removed from the SD cards.

During every match the procedure was the same. Before every match the IMUs were configured to have all required sensors on and to save their collected data on the SD-card. After this was done they could be switched on manually, this was done approximately 20 minutes before the start of the match. All six IMUs that are required for the match were rotated in an especially designed box, so they would all rotate in the same orientation, these rotations are later used in the data processing phase to make sure the timelines of all six the IMUs are synchronised. After the synchronised rotations were done the sensors are firmly attached in the specified locations shown in figure 2. When the match is done the IMUs are removed from the wheelchair rotated in synch again and powered off. During every step of activating the IMUs and during the match, timestamps were taken manually to correct in case something would go wrong in synchronisation or in any other step. After the IMUs are powered off they are ready to be connected to a laptop and for the data to be removed from the SD-cards and saved on the laptop. A detailed roadmap to help during the measurements is added in the appendix.

Figure 2: IMU placement on the wheelchair

2.2.2 Tagging and video data

During every match video, cameras were used to make video recordings of the match. This camera was stationed perpendicular to the baseline, parallel to the centre serve line while just being off the court on a higher position. This position gives a nice overview of the entire court.

The video material taken during the match was used to ‘tag’ the data this means that for every point certain info is stored in a database. The following tagged events were used during the ABN AMRO tournament:

- The number of the point
- Timestamp at the beginning of a point
- Timestamp at the end of a point
- The set number
- The current score
- If the point was a breakpoint
- Court side of the server
- The person serving
- 1st or 2nd serve
- Service direction
- The winner of the point
- The way the point was won/lost

All these data were saved in an Excel file and subsequently processed in Excel or Matlab. This means the data could be synchronised with the IMU data, this could facilitate in determining the differences between, for example won/lost and serve/received points.

2.3 Data processing & Synchronisation

The IMU data and tagging data were processed as one big data set. This makes the data more viable, because we mainly want to look at what happens during the points played and we do not really want to take into account the action that happens between the points, because this does not affect the outcome of the match. The timestamps in the tagging data are perfectly suited for this approach.

Both the datasets were synchronised to match the timestamps of the IMUs and the timestamps of the tagging data. The synchronising process was performed manually. The four sources of information we had were:

1. The video data, with timeline.
2. The timestamps manually made during the match.
3. Timestamps that are embedded in the tagging data.
4. The outputs given by the IMU, also with their own embedded timestamps.

The synching process is as follows, first there was looked at the video data (1) in combination with the manually made timestamps (2), with both these values a roughly estimate could be made at what time the match started in the IMU output (4). With this rough estimation there was looked at the actual IMU velocity data (4), this data was used to pinpoint the actual start of the point. For synchronisation purpose there was always looked at the player that is serving, because at the moment a player is serving his velocity will always be 0 or close to 0. Because both IMU sets were synchronised with each other, the receiving player’s data were automatically synchronised with the help of a Matlab function. If the synchronisation point was chosen and altered in a way that it synchronises with the tagging data timestamps (3), the beginning and ending of every point is plotted with vertical lines ((begin=red, end=green), this is shown in figure 3. This plot was used to manually check the synchronisation, the first five points and last five points of every match are manually checked by comparing the plots shown in figure 3 and video data. If clear inconsistencies were found the synchronisation process will be repeated and altered until the inconsistencies are no longer there.

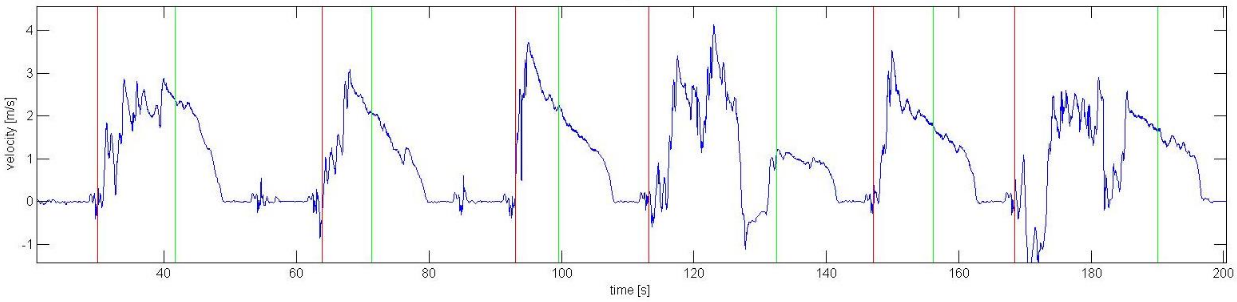


Figure 3: IMU velocity data used for synchronisation with begin and end of point (red=begin, green=end)

To minimize human errors, a software check was programmed in Matlab. These human errors could occur at two points in the process. First, these human errors could be in the timestamps of the tagging data, like there was said before this is also done manually. Secondly, the human error could be in the synchronisation process. To minimize both these errors and make the results as consistent as possible there is also done an automatic correction with a Matlab function. This function takes into account only the serving player and for the start of every point there is made sure that the starting velocity is below 0.1 m/s. If this is not the case, the function will search for a time closest to the manually chosen time, where this is the case, this time will be chosen as the new starting time of the point. Similar to the manual synchronisation the timeline of the receiving player is also automatically altered with the help of a Matlab function.

2.4 Calculation of output variables

2.4.1 Match statistics

Before using advanced plots, the first step in the research was to examine if there are obvious differences between just some raw data of data that seems very trivial, like distance travelled, points played, amount of turns made by the athlete and so on. There is not just the fact that this data is easy to output from our data, but there is also the fact that this data has never been looked at before, so it might give a different view on the whole matter. Statistical tests were used to determine if there is a significant change between players and between different constraints. For all cases an independent samples t-test is used with a significance level of $\alpha=0.05$. These tests were used to test significant differences in as well the statistical data as in the WMP plots. The significant differences found are discussed in the results.

2.4.1.1 Distance

The first parameter that comes to mind is the distance, there are some ways to interpret this value, four different interpretations are looked at in this research. Firstly, looking at the whole match without any cuts, so this means the entirety of travelled distance while players are on the court. Secondly, an average value of this per point was calculated, since this value is comparable over different matches. For the last two distance values the data gathered between the points is cut out using the timestamps of the tagging data, so again the total distance during the entire match is calculated, but only the distance travelled during the points is considered. This value is also averaged over the number of points played to make an easier comparison between matches.

2.4.1.2 Turns

The amount of turns the player made during the match was calculated by analysing the summation of all the rotations made. A turn is defined as a turn of at least 180 degrees, turns that are less than 180 degrees will not be considered for this value. There is also a distinction between left and right turns, to avoid confusion figure 4. shows the definition of both right and left turns. The amount of turns shown in the match statistics is only the amount of turns taken while playing points, the turns taken in between the points will not be considered, not considering the turn in between points is again done by using the timestamps of the tagging data.

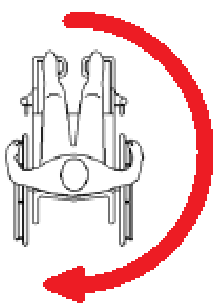


Figure 4a: the definition of a right turn

Figure 4b: the definition of a left turn

2.4.1.3 Time and number of points played

The calculations regarding the playtime are similar to the calculations done for the distance parameter. The time was considered a continues timeline, so without any cuts. Just like we did with the distance the time is also averaged over the amount of points played. Then the tagging data timestamps were used again to disregard the time between the points and only consider the time the players were actually playing a point. This 'playing' time was also averaged over the points to make it into a more comparable value. Lastly the amount of points played was also kept track of.

2.4.2 Wheelchair mobility performance

To give a better overall indication of the way the athletes manoeuver themselves around the field, the WMP (wheelchair mobility performance) is used. This indicator has already been used in previous research done in wheelchair rugby and wheelchair basketball (van der Slikke, 2016). The WMP is shown a spin plot, with values that give an insight in the mobility of the athlete like velocity and acceleration. All the values in the plot will be discussed later in this section. The values are the same as the ones used in the wheelchair basketball and wheelchair rugby research. The values are shown in comparison to the average values of our database, this will be indicated with a red dotted circle. The database consists of the ABN AMRO tournament and the Dutch national tournament (both men and woman). This way the plot indicates if and where there are significant differences between the mobility of the athletes.

The spin shows a total of 16 values, they are listed below:

- Avg. Vel.
- Max. Vel.
- Avg. Accel.
- Avg. Accel. over 2m
- Max. Accel. over 2m
- Avg. Rot. Vel.
- Max. Rot. Vel.
- Avg. Rot. Vel. in a turn
- Max. Rot. Vel. in a turn
- Avg. Rot. Vel. in a curve
- Max. Rot. Vel. in a curve
- Avg. Rot. Accel.
- Avg. Rot. Accel. in a turn
- Avg. Rot. Accel. in a curve
- Avg. Rot. Accel. over at least 60 degrees
- Max. Rot. Accel. over at least 60 degrees

(avg. = average; max. = maximum; vel. = velocity; accel. = acceleration; rot. = rotational)

First the data was cut using the timestamps of the tagging data to disregard all the data between the points. This means only the data that was collected during the points is considered for this analysis. To calculate the values first the values that are under a certain threshold were taken out of the dataset, because we do not want to include the time where the athlete is standing still, because this would delude the average values. The threshold for the linear velocity is 0.1 m/s and the threshold value for the rotations is 10 degrees/s. To filter the data even more only the movements that were of a duration of 0.5 seconds or more were included, because movements less than this were caused by measurement errors or were not significant enough to be included.

There were also some other constraints specific to the value, these will now be explained. The over 2m constraint means the values are only considered if the distance where over is accelerated was equal or longer than 2m. The over at least 60 degrees constraint means that the values were only included if the angle size where over is accelerated is equal or larger than 60 degrees. There were also the turn and curve constraints for rotational movements, these constraints determine whether the rotational movement is the only movement, so if the player was below a 1.5 m/s threshold it counted as a turn and if the player was above this threshold it counted as a curve. The average values were calculated by averaging all the values that fell under the criteria for that value. The maximum values were calculated by taking the five peak values within the criteria and averaging these, five values were used to average out outliers.

Similar to what was done with the match statistics, the tagging data also allowed us to add extra constraints to the values shown. For the WMP four different constraints were used, points won, points lost, serving point and receiving points. This means there are three different WMP plots to look at, the unconstrained one, one with lost versus won points and one with serving versus receiving points.

2.4.3 Speed zones

To give a better indication of how much efforts athletes use during the matches there can be looked at the speed zones (van der Slikke et al., 2017). Comparing these speed zone plot between athletes could give an indication about whether one athlete is having an easy match because he is spending more time in lower speed zones for example.

The speed zones are plotted in a spider plot similar to the WMP, but instead of values each sector gives an indication of how long the athlete has been driving within a certain velocity range. The speed zones were plotted in two different ways, the first one is done with absolute velocity values, these zones are pretty similar to the ones in the research where they were originally used. The second method uses relative values, this means it uses the maximum velocity value of the athlete during the whole tournament. This maximum velocity is determined by taking all the matches played and selecting the top 5% of all velocities during playtime, averaging this 5% gives the value used for the relative calculations. The absolute method is used to get a feel of what the exact differences are absolute the athletes, while the relative method was used to give an indication about how much effort an athlete is putting in. Below is shown how the speed zones are exactly divided.

Absolute:	Relative:
z1 = 0-0.1 m/s	z1 = 0-5%
z2 = 0.1-0.5 m/s	z2 = 5-20%
z3 = 0.5-1.5 m/s	z3 = 20-40%
z4 = 1.5-2.5 m/s	z4 = 40-60%
z5 = 2.5-3.5 m/s	z5 = 60-80%
z6 = 3.5+ m/s	z6 = 80+%

Similar to what was done with the Match statistics, the tagging data also allows us here to add extra constraints to the values shown. For the speed zones four different constraints were used, points won, points lost, serving point and receiving points and there also is a comparison between the winning and losing player. This means there are four different speed zone plots to look at, the unconstrained one, one with lost versus won points, one with serving versus receiving points and one with the winning versus the losing player.

2.4.3 Location on the field (Heatmap)

Location on the field is a very powerful tool to give insight in the playstyle and strong points of a tennis player. Graphically showing the position on the field is generally done with the use of a heatmap. These heatmaps give a colour indication of where the player has been during the match, warm colours for the locations where the player spent the most amount of time and cold colours where the player spent the least amount of time. Combining this with the tagging data could give a lot of insight in where the player is on the field during point that are won and points that are lost and this could be used to alter the playstyle of the player to develop a more winning or less losing playstyle.

IMUs do not give a certain position on the field, but rather a velocity and acceleration at a certain point in time. This makes the realisation of a heatmap a very tricky endeavour, there is the fact that the IMUs don't have a 100% accuracy and small perturbations could cause measurement errors in the final heatmap, this cannot be easily solved because there is a lack of set points that the position can be calibrated on reliably. So, for this research the calibration of the position was done manually. Because this is a very labour-intensive process it could not be done for the entire tournament, instead it is done for one match and seen as a case-study.

The raw position plot can vary depending on how the measurements went, because very slight errors get integrated and become very large error. There seem to be two main measurement errors, firstly there seems to be a slight offset in the rotational velocity, which could cause slightly more turns to one side, which over the course of a whole match is a problem. Another error could be a 'random' error which happens by unforeseen circumstances during the match, for example a IMU might be touched slightly by the player and turn a bit, this could cause major deviations in the final plot. Two examples of unadjusted plots are shown in figure 5. Figure 5a requires a lot more manual adjustment to be viable than figure 5b.

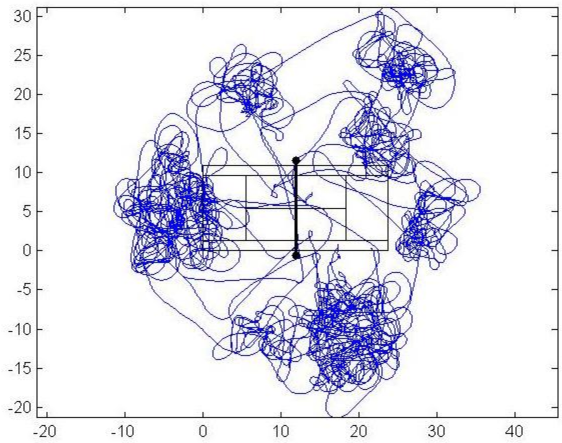


Figure 5a: The raw position plot of a player that requires significant manual adjustment

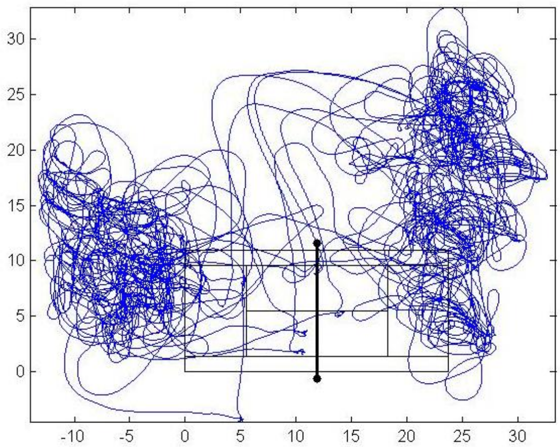


Figure 5b: The raw position plot of a player that requires slight manual adjustment

The manual process was done mainly by looking at every time the players switch sides of the field, because the players tend to travel along the same line to get past the net, due to this fact it can be used as a reference. Every moment before the side change the position and angle is altered manually in Matlab and is tweaked until the line is approximately overlapping with the previous side switch. This is done by alternating between the Matlab file and the plot up until just after the side switch. An example of an alteration of the plot with Matlab changes is shown in figure 6.

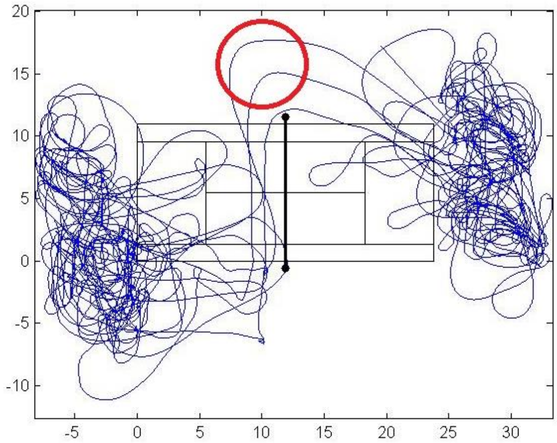


Figure 6a: The position plot up to just after a side switch before manual correction

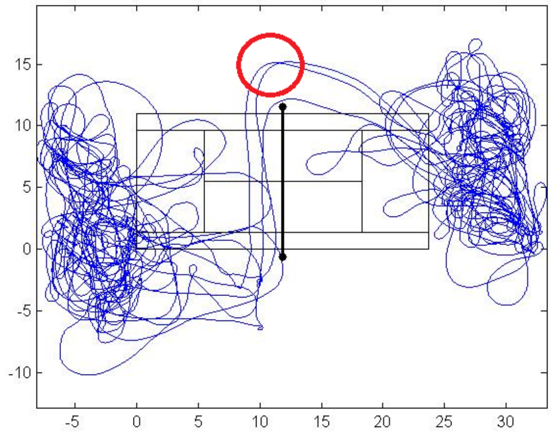


Figure 6b: The position plot up to just after a side switch after manual correction of 10 degrees

Because the heatmap in itself is not enough to give a proper insight it is again combined with the tagging data to add extra constraints. For the heatmaps four different constraints were used, points won, points lost, serving point and receiving points. This means there are five different heatmaps to look at, the unconstrained one, one with won points, one with lost points, one with serving points and one with receiving points.

3 Results

3.1 Match statistics

The match statics are the most general result measure resulting from the data collection, these include values of the amount of distance travelled and the amount of turns made during the match. This data will be compared for winning and losing and differences will be used to examine if there are any general differences between winning and losing a point.

Looking at the match statistics of a single match with the data of the winning player shown in table 1 and the data of the losing player shown in table 2. For overview purposes, first the values measured in a single match are discussed and after that comments are made on the similarities seen over all matches.

Table 1: Match statistics of a winning player of a generic match (not averaged). In red is highlighted the suspected difference in left and right turns per point depending on the dominant hand. In yellow is highlighted the suspected difference between distance travelled while winning and losing a point.

	TOTAL	WIN	LOSS	SERVE	RECEIVE
distance (m)	2069	1411	657,8	1048	1021
distance/point (m)	18,98	21,38	15,30	20,54	17,61
right turns	80	54	25	40	40
left turns	36	21	15	19	16
right turns/point	0,7339	0,8182	0,5814	0,7843	0,6897
left turns/point	0,3302	0,3182	0,3488	0,3725	0,2759
points	109	66	43	51	58

Table 2: Match statistics losing player of a generic match (not averaged). In red is highlighted the suspected difference in left and right turns per point depending on the dominant hand. In yellow is highlighted the suspected difference between distance travelled while winning and losing a point.

	TOTAL	WIN	LOSS	SERVE	RECEIVE
distance (m)	1460	524,3	935,3	737,9	721,8
distance/point (m)	13,39	12,19	14,17	12,72	14,15
right turns	32	14	19	16	16
left turns	52	18	34	23	29
right turns/point	0,2936	0,3256	0,2879	0,2759	0,3137
left turns/point	0,4771	0,4186	0,5152	0,3966	0,5686
points	109	43	66	58	51

The two things that stand out are highlighted, firstly the turns made, highlighted in red. Every player seemed to have a preferred side to turn to, upon further inspection it was noticed that the left handed-players have more right turns in a match, while right-handed players have more left turns during a match. Comparing right turns per point and left turns per point using t-tests reinforces this claim, for right-handed players as well as left handed players the t-tests show a significant difference with a chance larger than 95% ($p_{left\text{-}handed}$=0.0057, $p_{right\text{-}handed}$=0.0063). In the case in tables 1 and 2 the winning player was left handed while the losing player was righthanded. This rule applied to all players except for one, this player had approximately the same amount of turns to the positive and negative side. Secondly there is the distance/point which is highlighted in yellow, for most of the matches the average distance travelled per point during won points is higher than the distance during lost points, but only if they win the match. If the player loses the match this does not occur as much. When the player won the match, the statement is true for 7 out of 9 cases, but if the player lost the match, the statement is only true 4 out of 8 cases. In tables 1 and 2 there can be seen that in this case the statement is only true for the winning player. However t-tests show no significant differences for neither winning, losing or all players ($p_{winning}$=0.6268, p_{losing}=0.9563, p_{all}=0.9018).

If all the data are averaged, we get the values shown in tables 3a and 3b. We can see highlighted in yellow that despite the fact that most of the cases we looked at travelled more distance per point if the point was won compared to lost points, the averaged value is almost equal. The t-test indicated that the probability that this difference was based on erroneous observation was (marginally) larger than 5% (p=0.0513). Highlighted in red we do see that the average amount of left turns is higher than the amount of right turns, this supports the previous observation that right-handed players take more negative turns, because 9 of the 11 players measured where right-handed. Highlighted in green we can also see that the distance travelled per point while serving is also significantly higher than the distance travelled while receiving. Besides these things no significant differences were observed.

Table 3a: The mean ± standard deviation values of the match statistics of all the point, the lost points and the won points

	TOTAL		WIN		LOSS	
distance (m)	2530	± 1246	1298	± 628,9	1233	± 687,8
distance/point (m)	18,18	± 4,183	18,25	± 4,499	18,11	± 4,528
right turns	64,39	± 37,25	33,78	± 20,21	30,44	± 18,46
left turns	85,28	± 66,26	41,50	± 31,25	44,06	± 37,82
right turns/point	0,489	± 0,2198	0,5029	± 0,2209	0,4736	± 0,2394
left turns/point	0,6488	± 0,2562	0,6179	± 0,2297	0,6854	± 0,3127
points	131,4	± 48,19	67,17	± 23,69	64,28	± 28,13

Table 3b: The mean ± standard deviation values of the match statistics of the served points and the received points

	SERVE		RECEIVE	
distance (m)	1329	± 689,5	1201	± 655,1
distance/point (m)	19,21	± 4,907	17,16	± 5,761
right turns	32,00	± 14,79	32,22	± 25,06
left turns	43,33	± 38,40	41,94	± 33,81
right turns/point	0,4898	± 0,1908	0,4874	± 0,2906
left turns/point	0,6633	± 0,3350	0,6345	± 0,2934
points	65,33	± 23,35	66,11	± 26,02

3.2 Wheelchair mobility performance

The wheelchair mobility performance (WMP) is given by a plot that analyses the mobility of a specific athlete compared to the average values of an existing database. The athlete is evaluated on velocity and acceleration in linear motions as well as in rotational motions. For these velocity and acceleration values there are also distinction made between average and maximum values. This way of evaluating will highlight the stronger and weaker aspects of players and could possibly assist in determining what is required to be the winning player.

In figures 8a, 8b and 8c three mobility performance plots of a single player, playing different matches are shown. There can be seen that the shape is similar for every match. There of course are differences between the matches, but if an athlete performs above average or performs below average on a certain aspect it seems like he is likely to have a similar performance the match after. This behaviour is not just noticed for this certain player but also for the other players that were measured multiple matches during the tournament. The most varying aspect seems to be the maximum linear acceleration.

In figures 7a and 7b two comparisons are made, the comparison between won and lost point and the comparison between points where the player is serving and points where the player is receiving. Both these plots show the average of all matches measured during the entire tournament. These comparisons show little to no difference between lost and won points, the same is true for the difference between receiving and serving points.

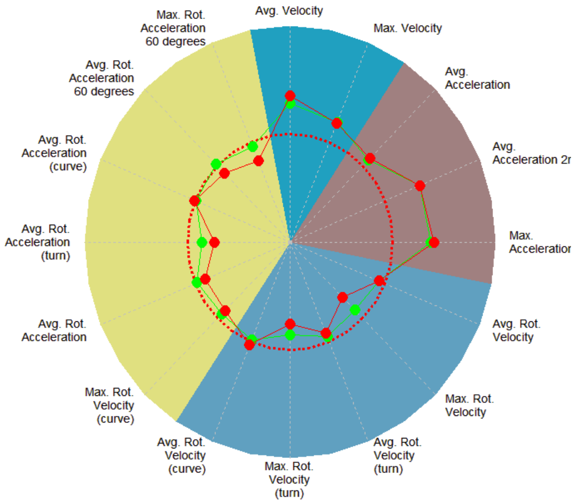


Figure 7a: The averaged Wheelchair Mobility Performance of won and lost points. Green: points won, Red: points lost.

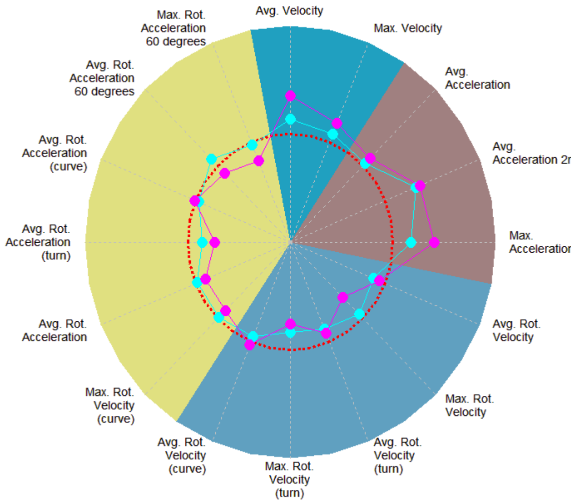


Figure 7b: The averaged Wheelchair Mobility Performance of served and received points. Cyan: points served, Magenta: points received.

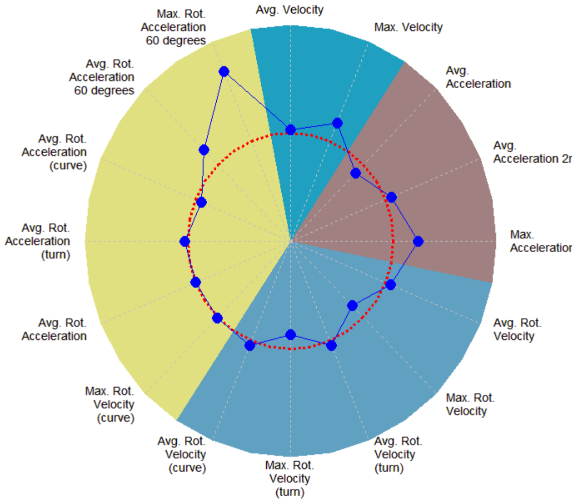


Figure 8a: The Wheelchair Mobility Performance of the first match of a player

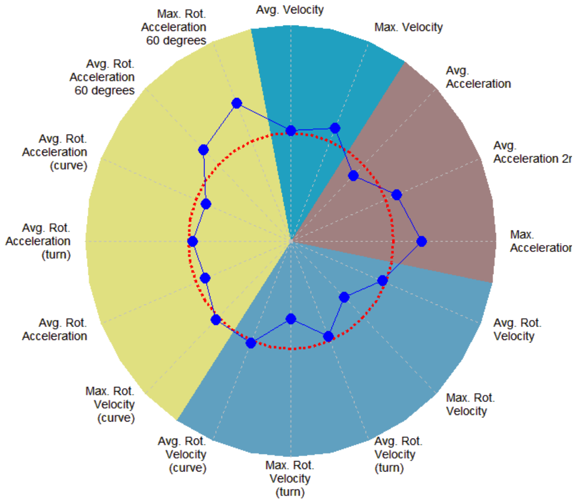


Figure 8b: The Wheelchair Mobility Performance of the second match of a player

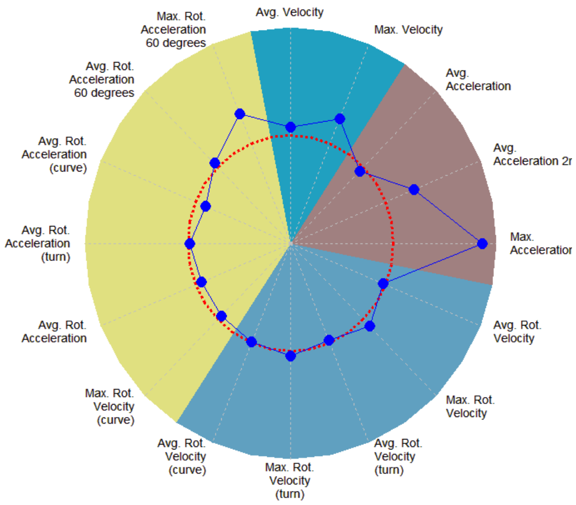


Figure 8c: The Wheelchair Mobility Performance of the third match of a player

3.3 Speed zones

Speed zones are plots that illustrate in what velocity range the athlete has travelled during the match. In what speed zone the athlete travels dominantly gives information about how much effort the athlete is putting in. The plots can be made on the principle of absolute speed zones to compare the absolute velocities between velocity, but relative speed zones can also be made to correct for the difference in maximum potential velocity between the player. These plots might give insight in the difference in effort put in between lost and won points or difference in quality between players.

3.3.1 Absolute Speed zones

In figures 9a and 9b the two absolute speed zones of both players of a single match are shown next to each other. There can be seen that the speed zones are very similar to each other, this similarity can be seen in every match. So, this basically means the shape of the speed zone plot is determined by the match and not by the player.

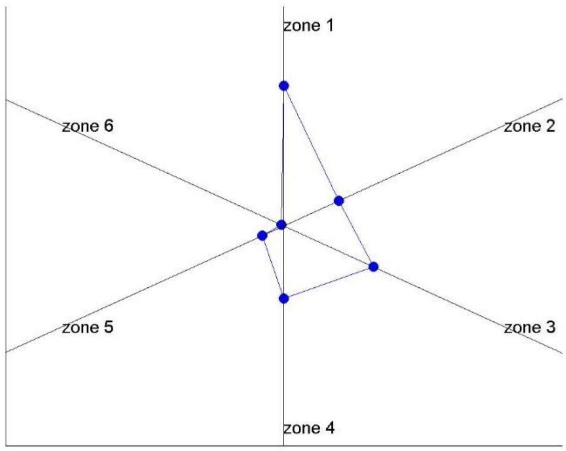


Figure 9a: The absolute speed zone of player 1 in a generic match

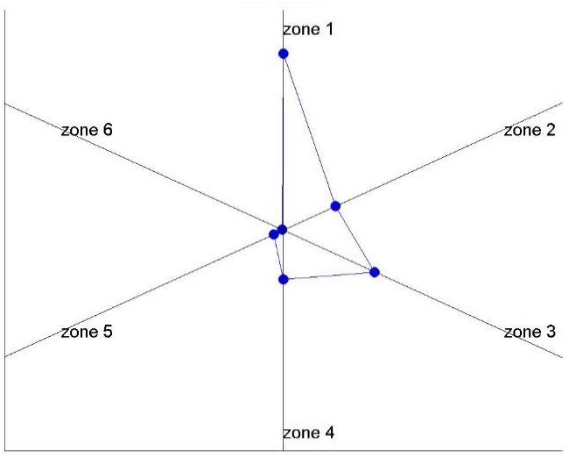


Figure 9b: The absolute speed zone of player 2 in a generic match

In figure 10 The average of all matches is shown. There is seen that a lot of time is spend traveling at a very low speed or standing still, while very little time is spent in the higher speed zones where athletes are close to their maximum speed.

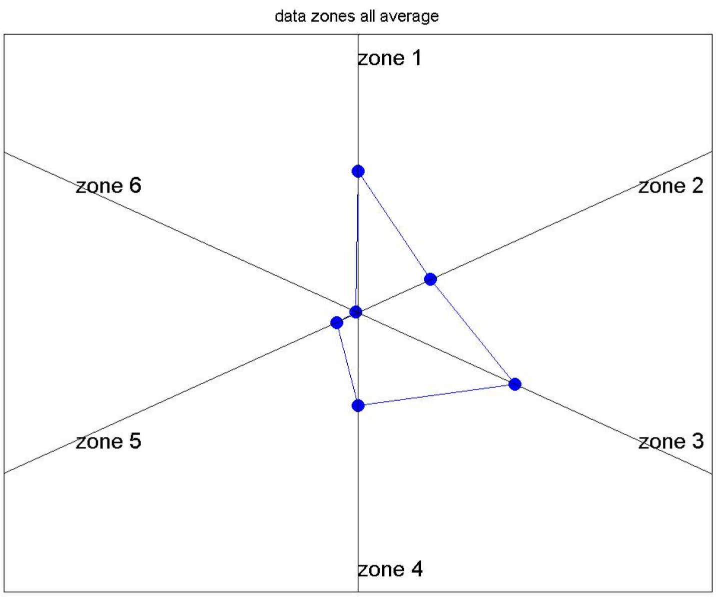


Figure 10: The average absolute speed zone of all the players measured during the tournament

In figure 11 the comparison is made between won and lost points, served and received points and won and lost matches, for these comparisons all values are used and averaged. All comparisons show little to no difference between the different constraints. To clarify, the overview plots made of singular matches showed more difference than the average plots, but the differences were still not significant enough to mention.

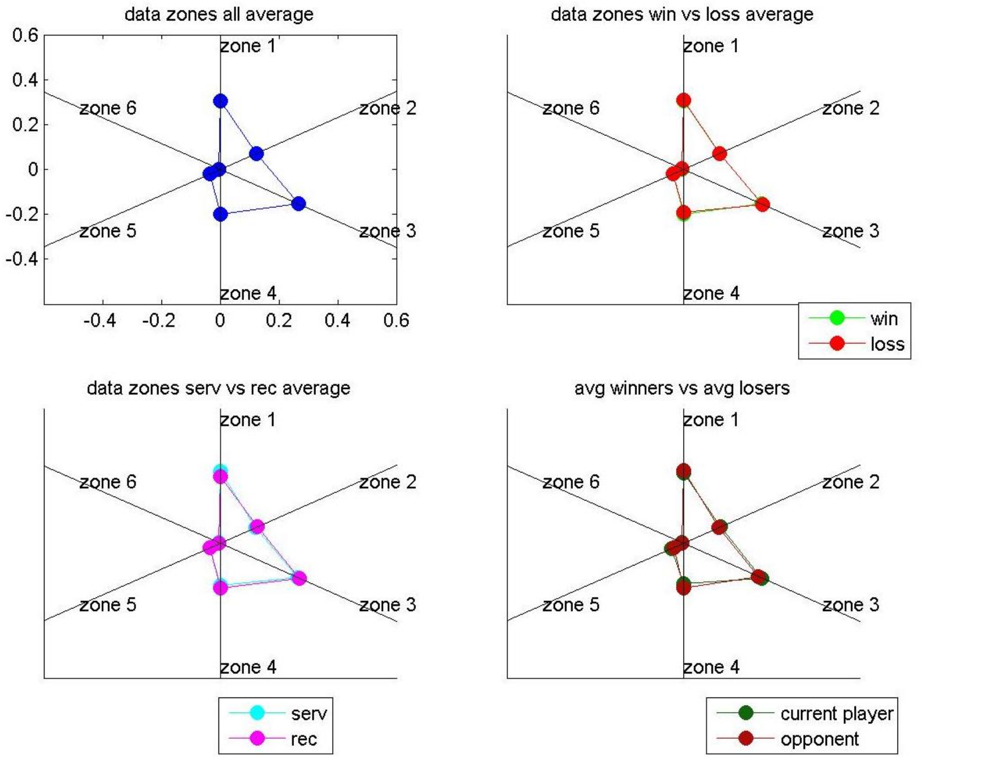


Figure 11: An overview of all comparisons made by using the averaged absolute speed zones

3.3.2 Relative Speed zones

In figures 12a and 12b the two relative speed zones of both players of a single match are shown next to each other. There can be seen that the speed zones are very similar to each other, this similarity can be seen in every match. So, this basically means the shape of the speed zone plot is determined by the match and not by the player.

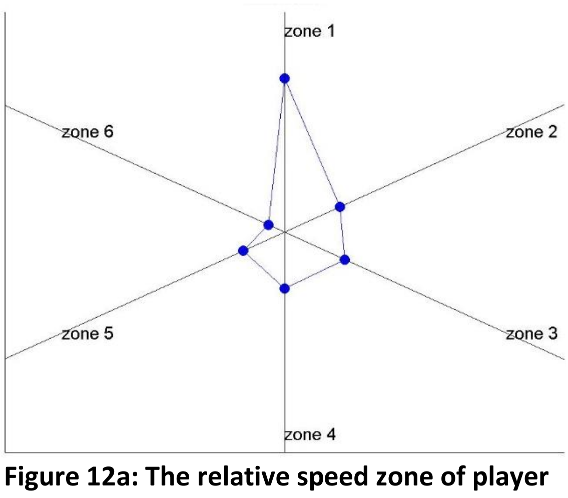


Figure 12a: The relative speed zone of player 1 in a generic match

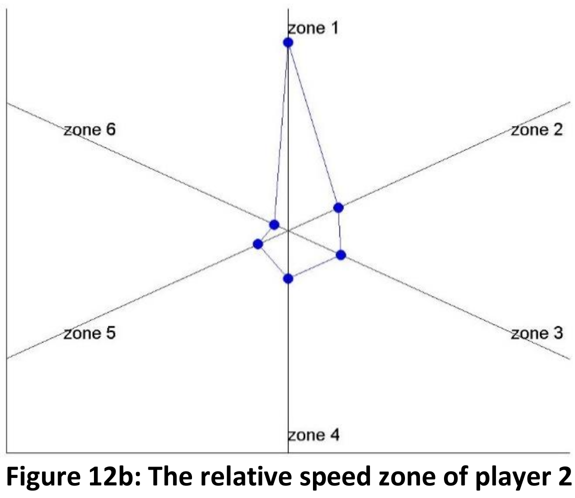


Figure 12b: The relative speed zone of player 2 in a generic match

In figure 13 the average of all matches is shown. There is seen that a lot of time is spent traveling at a very low speed or standing still, while the time spent in the higher zones is still less than the time spent in lower zones, the distribution is already more even than in the absolute plot.

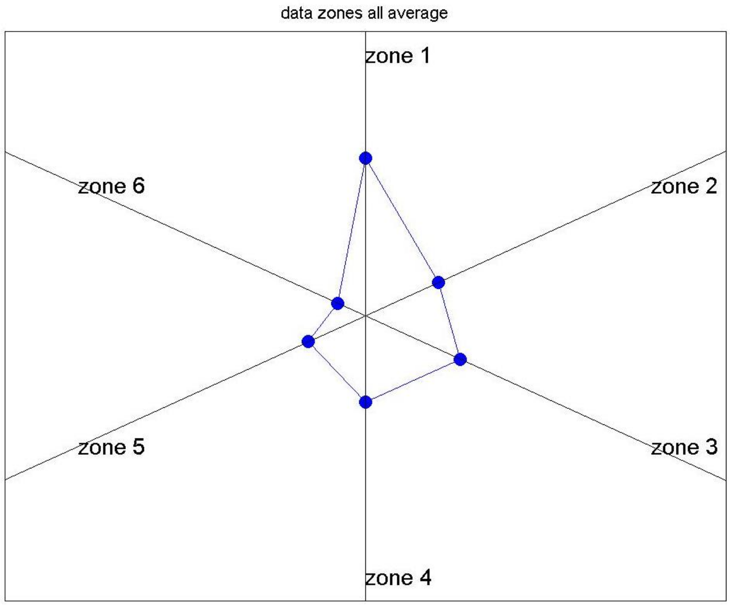


Figure 13: The average relative speed zone of all the players measured during the tournament

In figure 14 the comparison is made between won and lost points, served and received points and won and lost matches, for these comparisons all values are used and averaged. All comparisons show little to no difference between the different constraints. To clarify, the overview plots made of singular matches showed more difference than the average plots, but the differences were still not significant enough to mention.

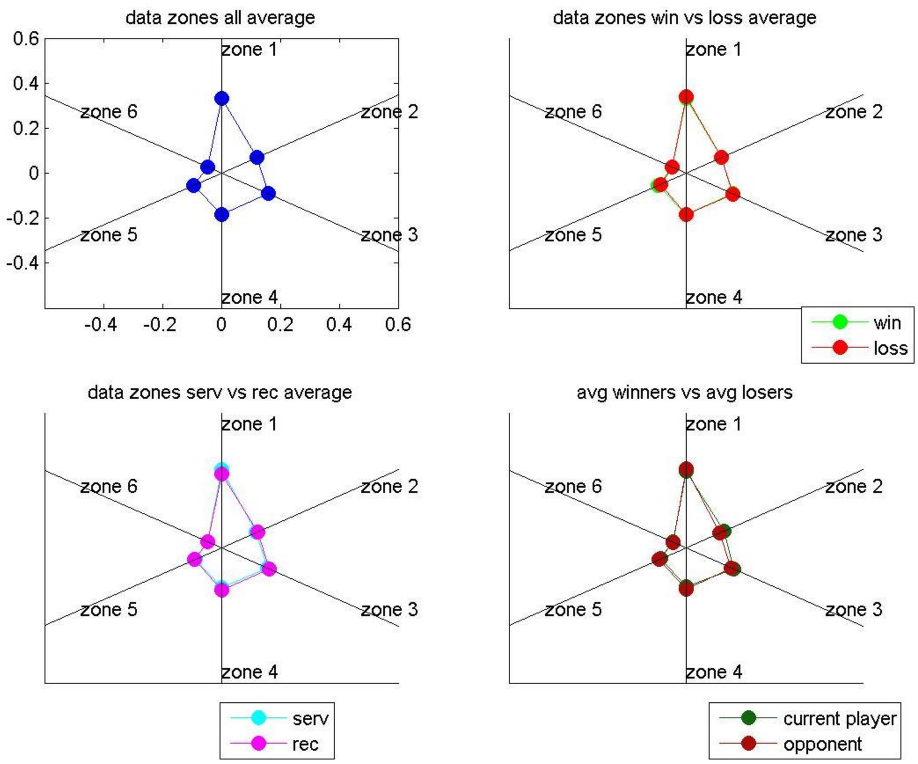


Figure 14: An overview of all comparisons made by using the averaged relative speed zones

3.4 Heatmap case study

Heatmaps are colour-based plots where the colour indicates how much time was spent at every position of the field. These plots will therefore can also be used to determine where the player is on the field when he is winning and when he is losing points, this could possibly give better tactical insight into the game.

Firstly, the coordinate plots used to produce the heatmaps are shown in figures 15a and 15b, there can be clearly seen that the plots are adjusted by using the path the players take past the net here.

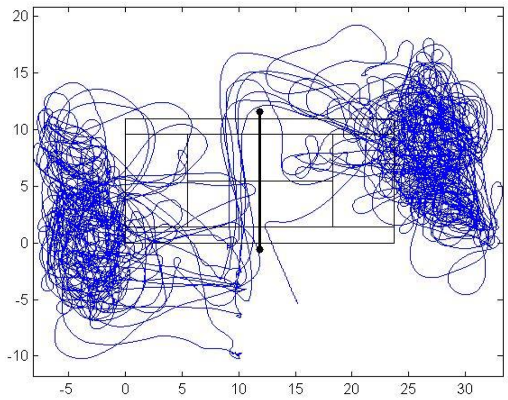


Figure 15a: The coordinate plot of player 1 used for the heatmap case.

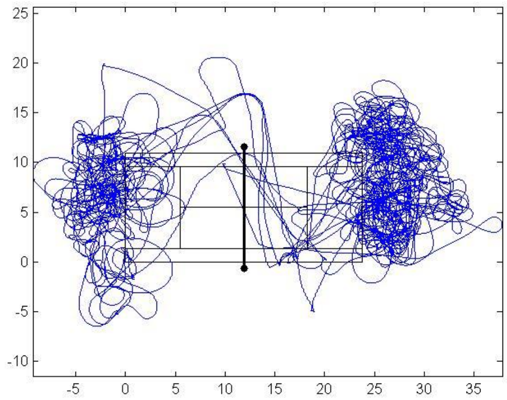


Figure 15b: The coordinate plot of player 2 used for the heatmap case.

The heatmaps made as a result are shown in figures 16a and 16b. In as well the coordinate plots as the heatmap can be seen that the heatmap of player 1 is more refined and probably more accurate as a result. This is shown by some random lines in the coordinate plot of player 2 and also the less defined heatmap for player 2. In the heatmaps is seen most of the time the players spend during their match is spent around the base line.

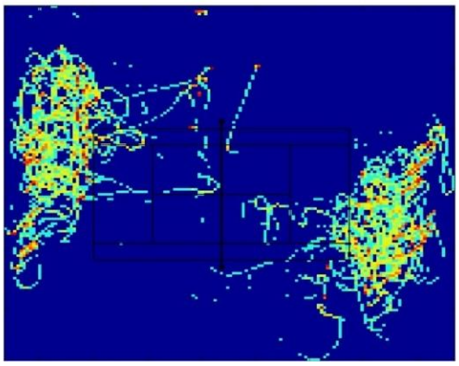


Figure 16a: The full heatmap of player 1.

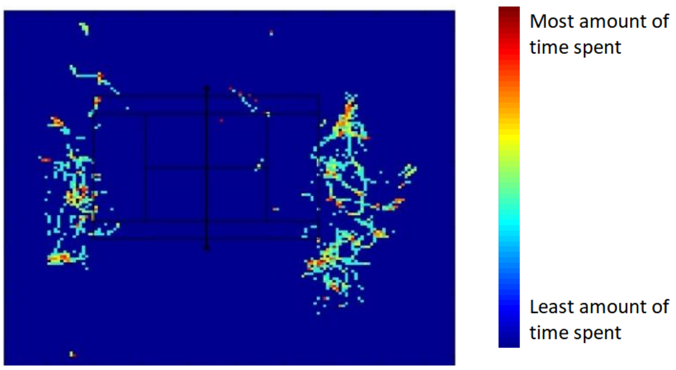


Figure 16b: The full heatmap of player 2

Now using the constraints for winning/losing we get the heatmaps shown in figures 17a, 17b, 17c and 17d. There can be seen that the points that are won have more movement towards the net, while the lost points have more movements towards the sides and back of the field. This also means that while winning point the curves made will have a smaller radius, on the other hand the curves in the lost points will have a bigger radius, however the losing points will also involve sharper 180 degree turns.

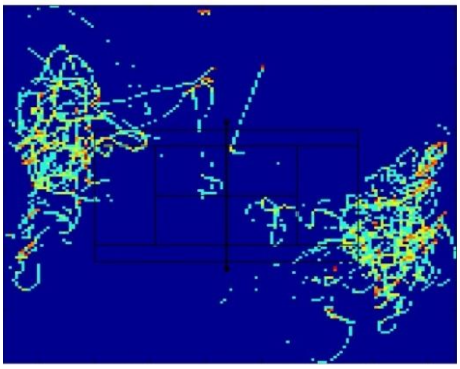


Figure 17a: The won heatmap of player 1

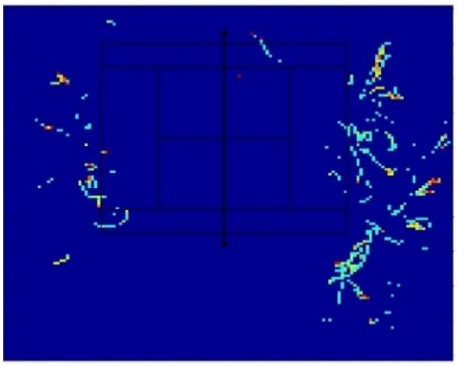
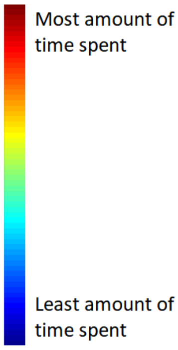


Figure 17b: The won heatmap of player 2



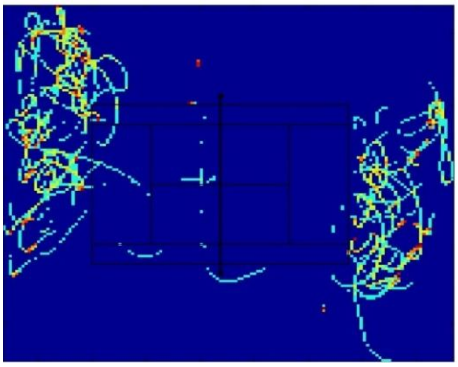


Figure 17c: The lost heatmap of player 1

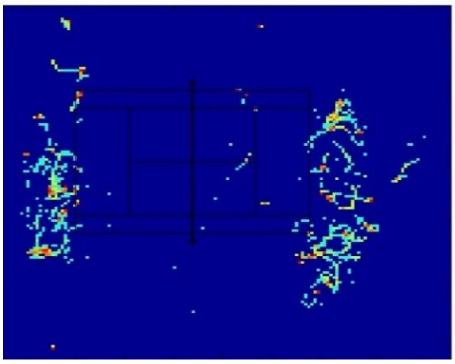
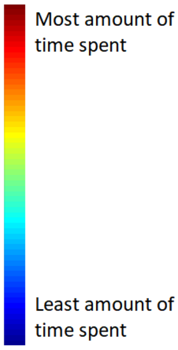


Figure 17d: The lost heatmap of player 2



Now using the constraints for serving/receiving we get the heatmaps shown in figure 18a, 18b, 18c and 18d. There can be seen that while serving the player tends to use a smaller area around the baseline, so not use the sides of the field as much and move more forwards, on the other hand, while receiving the player uses almost the entire width of the field and not move forward as much as while he is serving. Similar to the comparison for won and lost points this will also mean that curves while serving will have a smaller radius than the curves made while receiving, however the return points will involve more 180 degrees sharp turns.

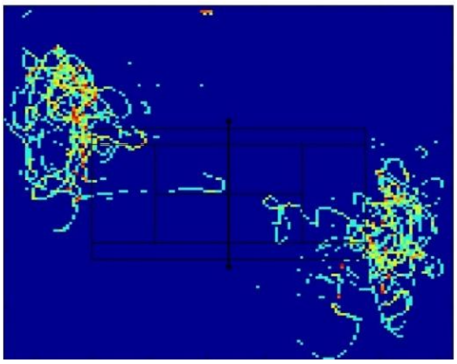


Figure 18a: The serve heatmap of player 1

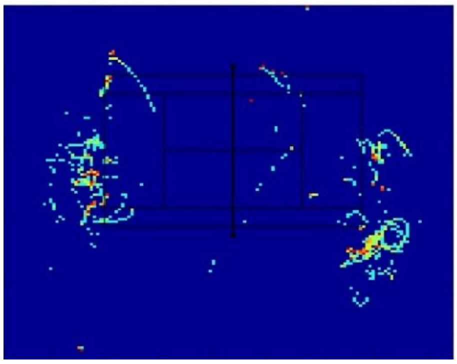
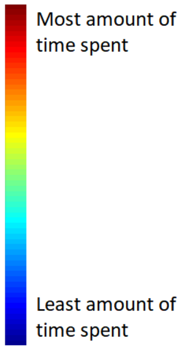


Figure 18b: The serve heatmap of player 2



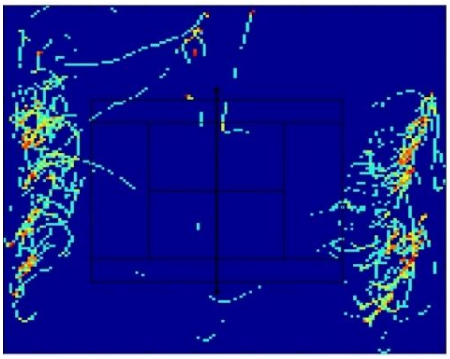


Figure 18c: The receive heatmap of player 1

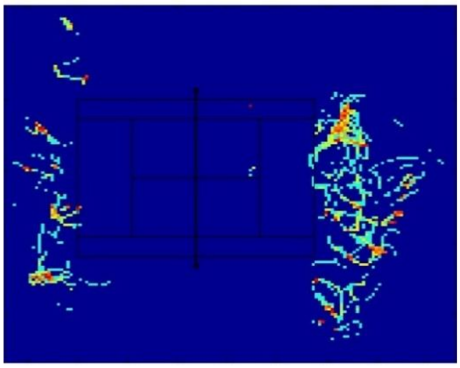
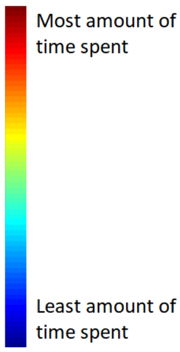


Figure 18d: The receive heatmap of player 2



4. Discussion and Conclusion

The question which was answered with this research is: **"What is/are the most influential factor(s) regarding the mobility of wheelchair tennis athletes to discriminate between the winning and losing player?"**.

The results from the wheelchair mobility performance show slight differences between players in their mobility, each player have factors which he will be slightly stronger or weaker in. However, the comparison between won and lost points show that these differences don't play a significant role in whether a point is won or lost. This would mean that at this level the mobility of the athletes does not play a significant role in the outcome on the match. The reason for this outcome is assumed to be that all the athletes are in good shape and are above a certain threshold that the mobility does not matter anymore. At lower levels of play the mobility could actually play a role. Research regarding talent scouting in football also claims that technique and skill should be the deciding factor while recruiting (Meylan, Cronin, Oliver, & Hughes, 2010).

For the speed zones the results show that the speed zone plots, absolute or relative does not say anything about the player his capabilities but only about the match. This would mean that speed zones could be used to determine the kind of match which is in turn determined by the combination of playstyles of both the players. Besides the playstyle it could also give an indication of the intensity of the match, because the speed zones plot could be seen as an indication to how much effort was put in during a match. Currently all the research regarding the intensity of a tennis match focusses on oxygen consumption and lactate measurements (Fernandez, Mendez-Villanueva, & Pluim, 2006; Smekal et al., 2004). Combining this knowledge with the speed zones might lead to new insights in the intensity of a match. The intensity of a match could be a discriminating factor because fatigue does significantly increase the performance of tennis athletes (Mulazimoglu, Yanar, Celikbilek, Kizilkaya, & Cetin, 2015).

The heatmaps basically show that a winning player plays more aggressive, which means more forward instead of to the sides of the field, while a losing player plays more to the sides of the field around the baseline. It also shows a similar pattern for serve and receive, with serve having a more aggressive pattern compared to receive, this means that the serve accommodates more aggressive play than the receive. However, whether a player is playing aggressive because he is winning, or a player is winning because he is playing aggressive can simply not be concluded from this research. There is potential for further research here, however the method using IMUs is not ideal for making heatmaps, it is very error sensitive and will not have a high success rate or require a lot of manual labour. Ultra-wideband tracking is an alternative method that might be better suited for creating heatmaps, because this method directly tracks the players location instead of accelerations. While this method is more suited, it does require a larger amount of equipment that has to be installed on the court beforehand (Leser, Schleindlhuber, Lyons, & Baca, 2014).

There are a few critical points that can affect the validity of the measurements done. Firstly, the synching process was very crucial in this research, because being a few seconds off in the synching process would mean selecting a time frame that is off a few seconds every point, this would heavily affect the results. The errors could occur in the manual moments of the process namely, while tagging the data, while writing down timestamps during the match and while selecting the synch point. The measures that were taken to ensure the accuracy of the results were the double checking of the manually assigned synching points by visualization in Matlab and also using Matlab to ensure the serving player was standing still every time the point starts. These measures should ensure the accuracy of the synching process.

There is also the fact that not all matches were successfully measured, this could potentially bias the averages or affect the trends that could be seen. Because the matches that were not measured successfully didn't have a very similar factor that could bias the averages, this will probably not be the case. The trends that were spotted, or not spotted were also very clear over all matches, so a few missed measurements will not change these conclusions.

To validate the use of WMP as a tool of evaluating the mobility, firstly we can refer to previous research done regarding the WMP where it was used to compare the mobility of different athletes in the wheelchair basketball and rugby sport (van der Slikke et al., 2016). To validate the fact that WMP can also be used to compare different athletes in wheelchair tennis, data from the pilot measurements prior to the ABN tournament is used, these are shown in figure 19. These show the average WMP plot of the women during the Dutch national championships (cyan line), this includes the measurements of four women that were at the time seeded top 10 of the world. The women's averaged WMP was compared to the averages of the values obtained at the ABN tournament (red dotted line). This comparison shows that women score significantly lower on parameters where they are expected to score lower, mainly the maximum (rotational) acceleration and max velocity, these are highlighted in red. The parameters where the women score above average could be explained by the fact that they are average rotational values. Compared to men's tennis, women's tennis has longer rallies, therefore it might be a slower game compared to the men's game (O'Donoghue & Ingram, 2001). This slower game might enable the women to rotate more in between hitting the ball, in this time they could be for example looking at the location of the ball.

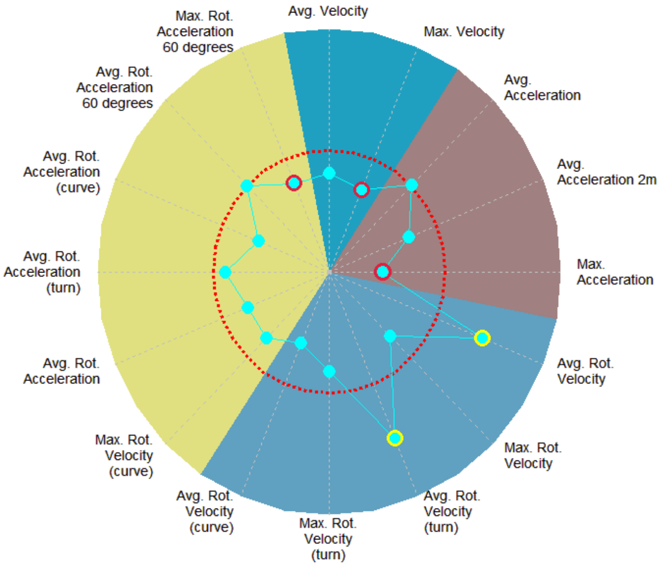


Figure 19: The average WMP plot of the women during the Dutch national championships (cyan line) compared to the average of the ABN tournament (red dotted line)

In this study was found that the mobility performance of the players does not have a deciding effect on the results of the match. The expected reason for this is the high level all these athletes compete at, because all the athletes are world class athletes, with all of them being in the top 25 of the world during the measurements. The expectation is that the difference between winning and losing is not determined by the mobility of the athlete but rather by other aspects, like insight in the game and placement of the ball. Figure 20. shows the different levels of competition (Gulbin, Weissensteiner, Oldenziel, & Gagné, 2013), this research shows that at the peak of the competition the difference in measured WMP is so slight that it is not a discriminating factor between winning or losing, however it is expected that in less competitive environments the difference in WMP will increase and play a bigger role because athletes are generally less trained and their play is less optimized.

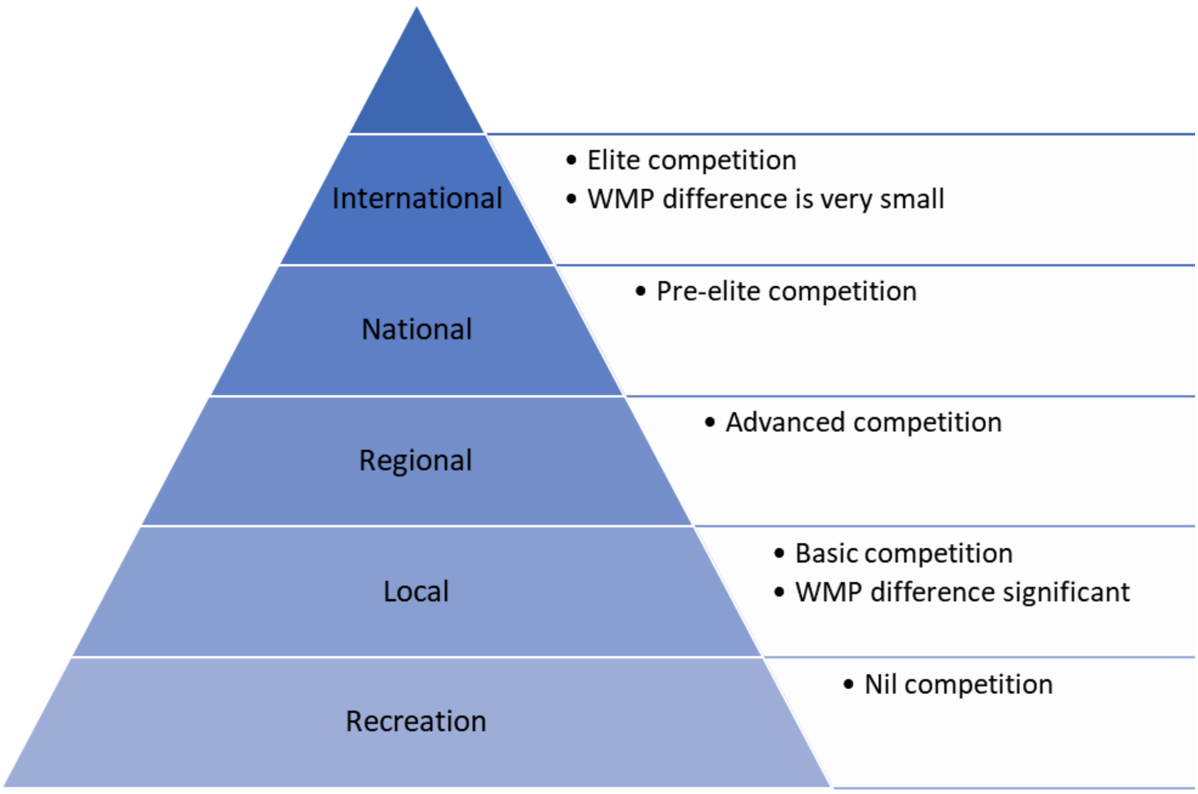


Figure 20: The different levels of competitions and relative the effect of WMP

The heatmap case shows that the winning player plays more aggressive, but whether he is playing aggressive because he is winning or winning because he is playing aggressive cannot be concluded by this research. There is however a lot of potential in the heatmap concept, because this position on the field tracking could also be combined with the wheelchair mobility performance to determine for example on what position on the field the peak velocities are reached. This might give insight in the playstyles that are effective or not for a specific match and/or player. Because there was concluded that the mobility is not the discriminating factor between winning or losing a match, the insight in tactics and playstyle of players becomes an even more important factor to take into account.

Comparing able bodied tennis to wheelchair tennis, no difference is found in the rally length, however able-bodied athletes have a significantly faster serve. At the Australian Open of able bodied athletes in 2019, 71% of the points played in matches were decided in the first 4 shots (short rally). But, only 19% of the points were decided in 5-8 shots (mid-long rally) and only 10% of the points were decided in 9+ shots (long rallies) (ATP, 2019a). This is similar to the findings of a study analysing wheelchair tennis where 70% of the points where decided under 5 seconds (short rallies), 23% of the point were decided between 5 and 10 seconds and 7% of the points were decided in over 10 seconds (Filipčič & Filipčič, 2009). The world record for fastest recorded serve in able bodied tennis is recorded at 263km/h by Samuel Groth, while the world's fastest wheelchair tennis serve is recorded around 170km/h (ATP, 2019b). With this information it is safe to assume that the serve is less important in wheelchair tennis than it is in able bodied tennis. However, this would mean that it is more reasonable to look at mid-long rallies of able-bodied athletes because the service has such a great impact on the short rallies. Looking at the match between Wawrinka and Federer at the 2017 Indian Wells final Federer got most of his advantage in the mid-long rallies, a summary of this is shown in table 4. Another statistic of this match is that Federer came to the net 22 times and won 82% of these points. With the assumption that wheelchair tennis is best compared to mid-long rallies of able-bodied athletes this would mean that coming forward and being able to play close to the net is a very important skill in wheelchair tennis, which matches with the findings in the heatmap case.

Table 4: A summary of the number of short/mid/long rallies played and won at the 2017 Indian Wells final, highlighted in yellow the big difference in won point at mid long rallies (ATP, 2019a)

	Total	Won by Wawrinka	Won by Federer
0-4 shots (short rally)	75	38	37
5-9 shots (mid rally)	46	16	30
10+ shots (long rally)	6	2	4

A recommendation to coaches and elite athletes would be to focus their training regimen on other aspects than their mobility. Other aspects like positioning on the field, game insight and technique used to hit the ball and place it on the right spot in the field will probably be the determining factor here. This said, the mobility does however have to be above a certain threshold for the player to compete at a certain level of play, so neglecting it completely is not recommended, however the focus should be on the other aspects of the game. Previous research regarding team sports has also shown that game-based training offer an effective alternative for traditional conditioning activities (Gabbett, Jenkins, & Abernethy, 2009), which further supports the statement of focusing on skills in the game. This would also mean that focusing on alternative aspects of the game still enhance the mobility athletes enough to be able to compete at the highest level.

This research concludes that in high level wheelchair tennis the wheelchair mobility performance does not have a significant impact on the eventual outcome of the match. However, there should be noted that the athletes measured are already well-trained and world class athletes. With this in mind, the advice to coaches would be to focus the training around other aspects like tactics, positioning on the field and ball control rather than focusing on a better wheelchair mobility. However, the mobility performance should never be completely dismissed and kept above a threshold to be able to compete, because moving around the field is the foundation to perform all other actions during a tennis match.

Appendix A: info letter

Scientific research during the ABN

Abstract

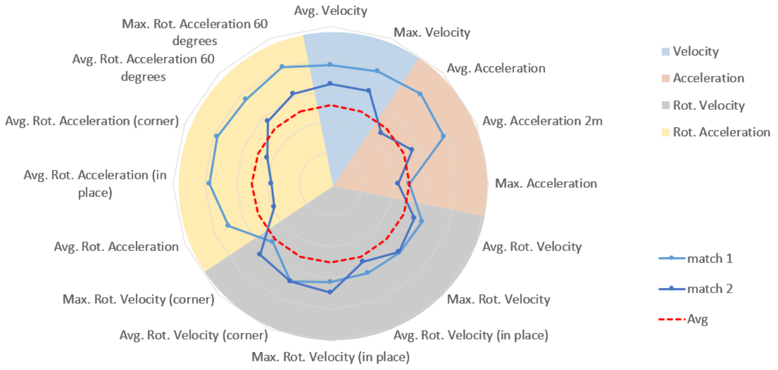
This research is conducted by a collaboration of de Haagse Hogeschool and the TU Delft. The main goal of the research is to optimize the performance of athletes by providing them a quantified measure of their *mobility performance* during their matches. This will give insight in the weak and strong aspects of the athlete. An individual overview of the *mobility performance* will be sent to every athlete, so every athlete will only receive his own data. Further use of the data will also be fully anonymous and the data won't be trackable to the athlete in question. The only 'inconvenience' the research will cause is the attachment and detachment of the sensors which will take only a few minutes of time with the wheelchair, during the match the sensors will not even be noticed due to their small size and weight. Signing up can simply be done by writing down your signature and e-mail address on the distributed form.

Why is this research being conducted?

The research is being conducted by a collaboration of de Haagse Hogeschool and the TU Delft. The ultimate goal of the research is to optimize the performance of the athletes. This could be done by simply watching the match and giving pointers, but with these measurements a graph with the so called *mobility performance* can be produced to actually quantify the performance of the athlete. Coupling this *mobility performance* to the points won and the points lost, will give an insight in the weak and strong point of the athlete and will help him to cover for his weaker aspects and enhance his strong aspects.

What is in it for me?

After the tournament has ended you will be send personal graphs regarding the *mobility performance*. These graphs will include your *mobility performance* off all the matches you played in the tournament. The graphs will only include your personal data however, to enable the players to athletes to determine how they performed relative to the other contenders a red dotted line with the average off all athletes will be added. A brief legend will be added to explain the more technical terminology to make sure the graph will be readable by everyone. An analysis regarding your strong and weak points will however not be done, this will be left up to you and your coach. An example of the mobility performance graph is shown below.



Mobility performance graph

What happens with my data?

Besides the personal *mobility performance* graphs that you will receive after the tournament, the data collected will be used for further scientific research regarding the performance improvement of athletes. All published data will be made fully anonymous and there will not be a possibility to track this data back to the athlete it belongs to. We can't emphasize enough that trackable personal data will only be made available to the athlete and its coach.

What does it mean in practice?

We can't emphasise enough that the measurement equipment won't hinder the athletes during their match. The exact same measurements have already been conducted during the Dutch national championships and not a single athlete complained about any discomforts. Before the match 3 small sensors will be attached to the wheelchair, 2 of the wheels and 1 on the frame. Attaching the sensors takes a few minutes and can be done at any time before the match. The sensors weigh about 30g and the athletes won't even notice the sensors are attached. After the match the sensors will be removed again and that is all there is to it.

Attaching sensors during Dutch national championships

How do I Sign up?

A form will be distributed, this form has to be signed to agree to the conducted research. To be able to receive the obtained graphs when the tournament is finished, there also has to be provided an e-mail address, the personal *mobility performance* graph will be send to this e-mail address only.

Appendix B: Informed consent copy

INFORMED CONSENT

Title program: The Perfect Wheelchair
Title research: Wheelchair Tennis Measurements during ABN AMRO World Tennis Tournament.
Principal investigators: Daan Bregman & Rienk van der Slikke

Particpant

- I have been informed about the objective of the investigation and my role in it and the responsible researcher has answered all my questions.
- I had sufficient time to consider my participation in this investigation and I am aware that it is completely voluntarily.
- The potential risks associated with my participation in this investigation and the anticipated benefits have been discussed with me.
- I realize that I may decide to refuse participation or stop participation at any time.
- I understand and agree that data about me will be collected and processed, either manually or by computer, by the responsible researcher and other researchers in the project
- I understand and agree that data collected about me will be stored fully de-identified
- I understand that I am entitled to access the personal information collected about me and to have inaccuracies corrected.
- I know that all data that will be collected in this investigation will be stored for at least 5 years.
- I agree to participate as a volunteer in this investigation.

________________	____________	____________
Name	Signature	Date

Responsible Researcher

- I have answered all questions about the research project and discussed the meaning and scope of this informed consent and signed it in the presence of the volunteer

________________	____________	____________
Name	Signature	Date

Appendix C: Roadmap measurements

Roadmap measurements:

Preperation:

1. Charge all the shimmers in docking station.
2. Power shimmers on.
3. Clear previous measurements of shimmers.
4. Synchronise all shimmers.
5. Enter session name of measurements.
6. Check all measurement settings on shimmer.
7. Remove shimmers from docking station.

Before the game:

1. Starting measurement:
    a. Start measurement on shimmers. (orange button)
    b. Start stopwatch.
    c. Calibrate shimmers in designated box. (note time)
2. Mounting on wheelchair:
    a. Get the wheelchair measurements (if it is the first time for this wheelchair).
    b. Mount the shimmers on the wheelchair.
    c. Let the wheelchair stand still for 1 minute. (note time)
3. Infosheet invullen:
    a. General match info.
    b. Wheelchair data.
    c. Shimmer set info.

During the game:

1. Note times:
    a. Begin set.
    b. End set.
    c. Calivration moments. (if any)

After the game:

1. Ending measurements:
    a. Let the wheelchair stand still for 1 minute. (note time)
    b. Dismount the shimmers.
    c. Calibrate shimmers in designated box. (note time)
    d. Ending measurement on shimmer. (orange button)
2. Importing the measurement data.
    a. Mount the shimmers in the docking station.
    b. Export measurement data to Consensys.
    c. Export measurement data to laptop.
    d. Power shimmers off
    e. Remove shimmers from docking station.

References

ABN. (2017). 46e ABN AMRO World Tennis Tournament - Spelers. Retrieved May 20, 2018, from https://www.abnamrowtt.nl/spelers

ATP. (2019a). ATP statistics. Retrieved June 21, 2019, from https://www.atptour.com/en/news/news-filter-results/all/on-court/brain-game/all/all/?page=3&requestedPage=3

ATP. (2019b). groth fast serve _ ATP Tour _ Tennis. Retrieved June 21, 2019, from https://www.atptour.com/en/news/groth-fast-serve

Croft, L., Dybrus, S., Lenton, J., & Tolfrey-Goosey, V. (2010). A comparison of the physiological demands of wheelchair basketball and wheelchair tennis. *International Journal of Sports Physiology and Performance*, *5*(3), 301–315. https://doi.org/10.1123/ijspp.5.3.301

Derman, W., Schwellnus, M., Jordaan, E., Blauwet, C. A., Emery, C., Pit-Grosheide, P., … Willick, S. E. (2013). Illness and injury in athletes during the competition period at the London 2012 Paralympic Games: Development and implementation of a web-based surveillance system (WEB-IISS) for team medical staff. *British Journal of Sports Medicine*, *47*(7), 420–425. https://doi.org/10.1136/bjsports-2013-092375

Engebretsen, L., Soligard, T., Steffen, K., Alonso, J. M., Aubry, M., Budgett, R., … Renström, P. A. (2013). Sports injuries and illnesses during the London Summer Olympic Games 2012. *British Journal of Sports Medicine*, *47*(7), 407–414. https://doi.org/10.1136/bjsports-2013-092380

Fernandez, J., Mendez-Villanueva, A., & Pluim, B. M. (2006). Intensity of tennis match play. *British Journal of Sports Medicine*, *40*(5), 387–391. https://doi.org/10.1136/bjsm.2005.023168

Filipčič, T., & Filipčič, A. (2009). TIME CHARACTERISTICS IN WHEELCHAIR, *41*, 67–75.

Gabbett, T., Jenkins, D., & Abernethy, B. (2009). Game-Based Training for Improving Skill and Physical Fitness in Team Sport Athletes. *International Journal of Sports Science & Coaching*, *4*(2), 273–283. https://doi.org/10.1260/174795409788549553

Goosey-Tolfrey, V. L., & Leicht, C. A. (2013). Field-based physiological testing of wheelchair athletes. *Sports Medicine*, *43*(2), 77–91. https://doi.org/10.1007/s40279-012-0009-6

Gulbin, J., Weissensteiner, J., Oldenziel, K., & Gagné, F. (2013). Patterns of performance development in elite athletes, (November). https://doi.org/10.1080/17461391.2012.756542

Hootman, J. M., Dick, R., & Agel, J. (2007). Epidemiology of Collegiate Injuries for 15 Sports: Summary and Recommendations for Injury Prevention Initiatives. *Journal of Athletic Training*, *42*(2), 311–319.

ITF. (2017). ITF Tennis - WHEELCHAIR - Search Current Rankings.

Leser, R., Schleindlhuber, A., Lyons, K., & Baca, A. (2014). Accuracy of an UWB-based position tracking system used for time-motion analyses in game sports. *European Journal of Sport Science*, *14*(7), 635–642. https://doi.org/10.1080/17461391.2014.884167

Martínez-Gallego, R., Guzmán Luján, J. F., James, N., Pers, J., Ramón-Llin, J., & Vuckovic, G. (2013). Movement characteristics of elite tennis players on hard courts with respect to the direction of ground strokes. *Journal of Sports Science and Medicine*, *12*(2), 275–281.

Mendes, J. J. A., Vieira, M. E. M., Pires, M. B., & Stevan, S. L. (2016). Sensor fusion and smart sensor in sports and biomedical applications. *Sensors (Switzerland)*, *16*(10). https://doi.org/10.3390/s16101569

Meylan, C., Cronin, J., Oliver, J., & Hughes, M. (2010). Talent Identification in Soccer: The Role of Maturity Status on Physical, Physiological and Technical Characteristics. *International Journal of Sports Science & Coaching*, *5*(4), 571–592. https://doi.org/10.1260/1747-9541.5.4.571

Mulazimoglu, O., Yanar, S., Celikbilek, S., Kizilkaya, F., & Cetin, B. (2015). EXAMINATION OF THE EFFECT OF FATIGUE ON TENNIS PLAYERS â€™ FOREHAND AND BACKHAND SHOT ACCURACY : A RESEARCH ON TENNIS STUDENTS * EXAMINATION OF THE EFFECT OF FATIGUE ON TENNIS PLAYERS ’ FOREHAND AND BACKHAND SHOT ACCURACY : A RESEARCH ON TENNIS STUDENTS *, (January), 1–6. https://doi.org/10.7813/jhst.2015/6-1/10

O’Donoghue, P., & Ingram, B. (2001). A notational analysis of elite tennis strategy. *Journal of Sports Sciences*, *19*(2), 107–115. https://doi.org/10.1080/026404101300036299

Rhodes, J. M., Mason, B. S., Malone, L. A., & Goosey-Tolfrey, V. L. (2015). Effect of team rank and player classification on activity profiles of elite wheelchair rugby players. *Journal of Sports Sciences*, *33*(19), 2070–2078. https://doi.org/10.1080/02640414.2015.1028087

Sarro, K. J., Misuta, M. S., Malone, L., Burkett, B., M, R., Barros, L., & Foundation, L. (2008). Correlation Between Functional Classification and Kinematical Variables in Elite Wheelchair Rugby Players. *Science*, (July), 5–6.

Shimmer. (2017). IMU Sensor Development Kit | Wireless IMU Sensor | 9DOF Motion Sensor | IMU Development Kit. Retrieved from http://www.shimmersensing.com/products/shimmer3-development-kit

Smekal, G., von Duvillard SP FAU - Rihacek, C., Rihacek C FAU - Pokan, R., Pokan R FAU - Hofmann, P., Hofmann P FAU - Baron, R., Baron R FAU - Tschan, H., … Costill, D. L. (2004). A physiological profile of tennis match play. PG - 999-1005, (0195–9131 (Print)), 999–1005. Retrieved from https://books.google.es/books?id=QOM901Sb8G0C

Usma-Alvarez, C. C., Chua, J. J. C., Fuss, F. K., Subic, A., & Burton, M. (2010). Advanced performance analysis of the illinois agility test based on the tangential velocity and turning radius in wheelchair rugby athletes. *Sports Technology*, *3*(3), 204–214. https://doi.org/10.1080/19346182.2011.564284

van der Slikke, R. (2016). Development of a Field-Based Mobility Test in Wheelchair Basketball Development of a Field-Based Mobility Test in Wheelchair Basketball, (April), 5.

van der Slikke, R., Berger, M. A. M., Bregman, D. J. J., & Veeger, H. E. J. (2016). From big data to rich data: The key features of athlete wheelchair mobility performance. *Journal of Biomechanics*, *49*(14), 3340–3346. https://doi.org/10.1016/j.jbiomech.2016.08.022

van der Slikke, R., Mason, B. S., Berger, M. A. M., & Goosey-Tolfrey, V. L. (2017). Speed profiles in wheelchair court sports; comparison of two methods for measuring wheelchair mobility performance. *Journal of Biomechanics*, *65*, 221–225. https://doi.org/10.1016/j.jbiomech.2017.10.040

Warner, M. B., Wilson, D., Heller, M. O., Wood, D., Worsley, P., Mottram, S., … Batt, M. (2018). Scapular kinematics in professional wheelchair tennis players. *Clinical Biomechanics*, *53*(January), 7–13. https://doi.org/10.1016/j.clinbiomech.2018.01.022