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Detecting fatigue in professional football

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The work contained in this thesis is my own work unless otherwise stated.

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Abstract

In football, data analysis is now ubiquitous among all professional teams. The analysis is divided in different areas, the two mains one are performance and player health that are intrinsically linked although the aim is different. This project falls into the second category. Even if professional players are in perfect health and in great physical condition they do not escape injuries. Some of these injuries are inevitable due to unfortunate game events but the rest is due to high fatigue among players. These injuries could be avoided if fatigue were better detected. At first sight, fatigue appears easy to apprehend. However, it's a complex phenomenon difficult to define and above all to quantify. The aim of this project is to detect fatigue among players.

In this report, several tools are proposed and applied to a specific Premier league team. The main of this work is based on players coordinates on the pitch. First, focus is made on fatigue definition. Followed by an initial analysis on the studied data illustrating fatigue presence throughout the game. Then, change point algorithm is tested as a fatigue detection tools along with new tools. Interesting results were obtained, however the unlabelled nature of the data (no information if indeed a given player is fatigued) doesn't allow to validate models proposed as we can not check whether it successfully detects fatigue.

Acknowledgements

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Contents

1 Introduction

Football is widely known to be the most popular sport in world. For instance, more than half of the world's population (3.572 billion) watched the 2018 world cup (FIFA, 2018). This popularity comes with huge cash flows especially at clubs level, the total revenue for the top 20 revenue generating clubs in 2021/22 stood at €9.2 billion (Bridge *et al.*, 2023). Furthermore, like in all money attracting areas nowadays, cutting edge technologies are used to support its development. From video analysis in the nineties to hyper accurate tracking system today, data has been used for different purposes, such as tactics (Low *et al.*, 2020), betting (Tax et Joustra, 2015) or player health and performance. Recently, thanks to cheaper and more accessible software it's no longer a privilege for best teams, smaller professional clubs are jumping on the bandwagon. It became mandatory to have a data analyst team in the club to perform (Harper, 2021), coaching staffs rely on their work and have high expectation on the benefits.

During a football season, professional football players are subject to a high physical load. Indeed, there are up to two high intensity games a week joined with daily training sessions. This causes necessary appearance of fatigue at several levels. Even for professional this can lead to poor in-game performance or in worst case, to injuries. Therefore, fatigue management is a substantial aspect to consider for the coaching staff. This project will be focusing on fatigue detection among players. This detection will be based on player spatial position and movement. The studied dataset is made of 31 games of a specific Premier league team. The first thing done is to define what exactly is Fatigue in the second chapter. Then, in the following chapter the dataset is presented in details alongside some basics of footballs. Chapter 4 is an illustration of fatigue presence by reproducing results obtained in previous studies. Then, novel methods and metrics are introduced to detect fatigue. First, change point is applied to individual player metric. Then, a global team metric is introduced and the change point is performed as well. Finally, a local relative metric is introduced. Methods and results are respectively detailed in Chapter 5 and 6.

2 Fatigue

2.1 Definition

Fatigue is a polysemous word, it has numerous meaning depending of the context. Therefore, broad definitions are used such as the decrease or failure in the muscle ability to provide a full performance during a physical activity (Edwards, 1983). In a football game, this results in a drop of distance ran and less high intensity sprints towards the end of the game (Rampinini *et al.*, 2009; Mohr *et al.*, 2005). Although it is the most obvious illustration of fatigue it is not the only one. Other features can be used to show presence of fatigue. This is what makes this problem complex, there is no universal measure of fatigue. Several indicators are used and put together according to a given situation.

One way of making fatigue detection more intelligible is to be specific and consider various kind of fatigues. Two different kinds of fatigue are introduced below.

2.1.1 Transient Fatigue

A football game is characterized by a lot of rhythm fluctuations. There are periods when most players are jogging at a slow pace in contrast with periods when player are running at high pace with numerous of change of directions (turns). These high intensity periods (Peak periods) can be exhausting for player metabolisms. Transient fatigue is defined as the fatigue caused by a Peak period. Studies have shown it presences in football with a significant drop of player performance on the period following the Peak (Akenhead *et al.*, 2013; Mohr *et al.*, 2003; Alghannam, 2012). However, this is considered as temporary fatigue since professional players are partially able to recover from it during the course of the game.

2.1.2 Relative Fatigue

The final goal of fatigue studies in sport science is to provide the best expertise to sport player on how to manage a physical effort. When it comes to professional player, injuries can be important obstacles to a successful career. A study showed that on average a player can expect to have 0.6 muscle injuries by season (Ekstrand *et al.*, 2011) (Players are also exposed to knee, ankle ligament injuries or bone fractures) . Furthermore, a healed player who was injured in the past is more likely to get injured again. Therefore injury prevention is a crucial aspect to consider for players and coaching staff. For muscle injuries, they often happen when the peak action load[1] of the game is greater than the peak action load than a player can perform (Ekstrand *et al.*, 2023). That's what we will call relative fatigue for the rest of this thesis. In other words, the capacity for a player to perform in comparison of the other players on the pitch.

In this thesis, we will use this two notions of fatigue at some points. However, firstly we will refer to fatigue as the broad definition in a drop of physical performance. It will allow to have a better understanding of all aspects involved in fatigue.

2.2 Acceleration as a fatigue indicator

As mentioned previously there are several metrics used in sport science to evaluate fatigue. For a while, studies have focused on total distance ran and high speed distance ran above given speed threshold. But acceleration was somehow neglected (Akenhead *et al.*, 2016). This is likely the consequence of the lack of precision in older tracking devices, we will discuss details of data accuracy later in the Data presentation chapter. A study suggest that omitting acceleration is likely to underestimate high-intensity activity of a player (Varley et Aughey, 2012). This is due to acceleration on short period that do not breach a given sprint speed threshold whereas this kind of action when they are repeated can cause fatigue. Acceleration can be derived to Player Load (PL) as a load indicator . It can also be derived to energy cost of the activity (EC). Which is used to compute the Metabolic Power (MP) by taking the product between EC and the speed. As we could expect, it has been shown that MP and PL are highly correlated because of their high dependence on acceleration (Reche-Soto *et al.*, 2019a).

[1] Load in sport science has a broad definition and is sometimes misused, here is a definition from a consensus statement (Herring *et al.*, 2019):
"Load in activity may be defined as a stimulus experienced and responded to by an individual prior to, during or after participation. Load creates a demand or stress (both physiological and psychological) and has internal and external components. Load that is safely managed may result in improved athletic capacity and performance, and injury and illness risk reduction."

3 Football spatial Data

Player tracking systems evolved significantly these last years. First, games were recorded with VHS-format cameras and then were later replayed on a monitor for computerized coding of the activity pattern (Mohr *et al.*, 2003). But this method was not accurate enough to derive the acceleration resulting in a lot of studies constrained in speed. Then came classic GPS technologies fixed directly to players (Di Prampero *et al.*, 2015) . But still, acceleration derived from GPS technologies has shown serious limit (Akenhead *et al.*, 2014). As a result, manufacturers have added accelerometers to the GPS to make the tracking devices the most complete possible (Barrett *et al.*, 2014; Reche-Soto *et al.*, 2019b). However, recently a new cutting-edge have emerged. LiDAR (Light Detection And Ranging) is a laser detection method to determine range between a target and a sensor. LiDAR has been used in numerous fields such as ecological sciences (Eitel *et al.*, 2016), object recognition (Che *et al.*, 2019) or motion tracking (Dewan *et al.*, 2016). In football, it has been implemented by Sportlight Technology Ltd (https://www.sportlight.ai), a UK-based start-up. LiDAR is described as a hyper-accurate tracking system by Sportlight which now work in collaboration with most of English Premier League teams. Furthermore, despite the novelty of this technology, already one paper suggests that it provides valid and accurate metrics including acceleration (Bampouras et Thomas, 2022).

3.1 Data presentation

The data used in this paper are kindly provided by Sportlight and a specific Premier League team. It consists of 31 games of the studied team during the 2022/2023 season. For a given game, opponent data are also provided (except for one game). For privacy reasons, the teams as well as the players names are not disclosed. For a given game, the main dataset is a file containing one csv file by player. The structure is illustrated in the diagram below 3.1 .

```
.
└── Main_dataset/
    ├── Game_id1/
    │   ├── Team_studied/
    │   │   ├── player_id1
    │   │   ├── ...
    │   │   ├── player_id11
    │   │   ├── substitute_id1
    │   │   ├── ...
    │   │   └── substitute_idn
    │   └── Opponent
    ├── ...
    └── Game_id31
```

Figure 3.1: Structure diagram of the main dataset

Note: While the number of starting player is fixed to 11 by team, the number of substitute per game is variable. For a while, the maximum number of substitute was fixed to three. However, a very new Premier League rule raised this number to five for the 2022/2023 season on the condition of splitting them on a maximum of three distinct moment (i.e operating more than one substitution at the same time).

Each of these personal dataset are positional and movement information of the player every 0.1 seconds (10Hz). It is made of the following variable :

Stamp : Timestamp of the measure (nanoseconds epoch since 1-1-1970)

X,Y : Two dimensional coordinates of the player (meters). X and Y axis are not aligned with the football field. The raw coordinates are given with respect to the LiDAR sensor.

Smoothed_speed : Speed value derived from the position and smoothed through an unspecified low pass filter (meter per second)

Smoothed_acceleration : Acceleration value derived from the position and smoothed through an unspecified low pass filter(meter per second squared)

Angle : Player orientation relative to the sensor(degrees)

We observe negligible missing data, it often happens when players are in corners of the pitch and escape the sensor range. However, in most cases this corresponds to game pause (corner kick, end of action, ...). And it never exceeds few seconds. Most of the work presented in this thesis is directly derived from this main dataset. Nevertheless, Sportlight provided additional datasets which correspond to different players key performance indicators (KPI) such as count of sprints for a given speed threshold or distance ran for a given window of time among others. For flexibility reasons on the parameters the KPI used further are derived from the main dataset and the additional datasets are not used except for significant turn. A significant turn is characterised by a high deceleration, a change of direction and then a high acceleration. Turn metrics are mainly used in rackets sport where turns are ubiquitous, for instance in tennis turns are used to evaluate a player performance (Ferrauti *et al.*, 2011). However, in football turn are less studied but Sportlight believes that it could be a interesting indicator to investigate for fatigue purpose. Indeed, sprint is stressful for muscles whereas lower body joints are quite spared. Unlike sprint, turn are also stressful for body joints and the repetition of it could lead to ligament failure and injuries (Zago *et al.*, 2019). The turn dataset has several variables, here are those that we use:

Stamp : Timestamp of the turn (nanoseconds epoch since 1-1-1970)

Session_id : Corresponding game id

Player_id : Corresponding player id

Finally, there is a dataset which is rather oriented on games outcome than directly related to players physical performance. It is the shot table structured as follow :

Session_id : Corresponding game id

Player : Corresponding player name

Minute : Game time the shot was made

Outcome : Whether the shot is a goal or not

Data limitation

The data provided offer a rewarding insight of a football game. Nevertheless, there are some limitation to the data that are worth noticing . There is no access on ball position throughout the game which reduces the analysis spectrum , attacking and defensive phase are not taken into consideration as well as passes. Player coordinates are restricted in the horizontal plan. As a result, speed and acceleration values do not consider the vertical movements which can be not negligible while jumping or tackling. Therefore, we won't use PL and PC defined in the previous chapter as their are defined with respect of the three axis. Instead, we will focus our analysis on horizontal acceleration value. Another point that is very important to mention and worth keeping in mind for the rest of this work is that we are working with 'unlabeled' data. Indeed, we actually have no idea whether a given player is fatigued. To be more precise, we do know that toward the end of the game all players are both physically and mentally fatigued (Coutts, 2016) but we have no idea on the scale. As said in the relative fatigue section before if fatigue is equal among all players the risk of injuries is low. However, this risk raises if one or few players are over-fatigued in comparison of the others. The aim of this thesis is to provide tools that could likely help detecting these players but with the given data we won't be able to check accuracy. Although the final aim is based on the specific concept of relative fatigue, it is necessary to have first a clear comprehension of fatigue as an individual general drop of performance. This is

3.2 Basics of football

Now that data are introduced, it is necessary to remind some football rules and notions.

3.2.1 Game rule

Firstly, a football game is made of two halves of 45 minutes split by a 15 minutes half-time. During the playing time the game could be stopped due to an injury or substitution. However, the clock is not stopped and there is a loss in playing time. This is compensated by adding extra time at the end of both halves. Each team start with 11 players and are able to make up to 5 substitution as specified in the 3.1 *Note*. The number of playing player can be lower if a red card is given by the referee, in the studied games only one include a red card.

3.2.2 Team formation

Each team has a specific tactical formation on the pitch. The following table 3.1 from Clarke (2023) summarizes the season formation frequencies in the the Premier League :

Formation	4-2-3-1	4-3-3	3-4-2-1	4-4-2	3-5-2
Frequencies	261	221	64	62	23
Compared with 21/22	+61.1%	+20%	-5.9%	-31.1%	-59.6%

Table 3.1: Formations summary for all 2022/2023 Premier League games

Note that for a given team there is no fixed formation, it can change (mostly not) from one game to the other. It also sometimes can change during the game. The studied team plays all of its 31 games in a 4-3-3 formation. Also, the sum of the figures in a formation is 10 because the goalkeeper is omitted.

3.2.3 Player position

It is widely recognized that there are significant disparities in game load for different player positions Ade *et al.* (2016); Reche-Soto *et al.* (2019b). Thus, it is necessary to differentiate them in metric analysis to catch trend subtleties and provide a more specific fatigue overview with respect to the position. As said in the previous subsection, the studied team plays in 4-3-3. Each figure corresponds to a position, respectively :

- Defenders, 2 centre-backs (CB) and 2 full-backs (FB)
- Midfielders (M)
- Forwards, 2 wingers (W) and 1 centre forward (CF)

The focus will be on these 10 outfield players, the goalkeeper is omitted due to the very specificity of the position and the low physical load. These positions are illustrated in the following plot 3.2 :

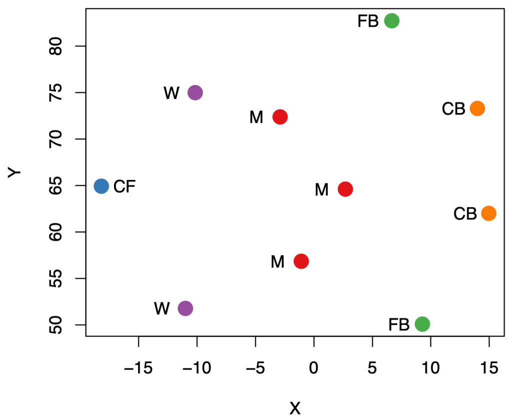

Figure 3.2: Mean position of players during one half (Coordinates have been rotated to be aligned axis with the pitch)

It is important to keep in mind that this position distribution is specific to 4-3-3 composition, another team composition results in a different position distribution. Then, to give a more precise idea of position role in a game a heatmap is shown 3.3 representing each position activity during one half of a game. This has been made using *soccerHeatmap* function from the *soccermatics* package.

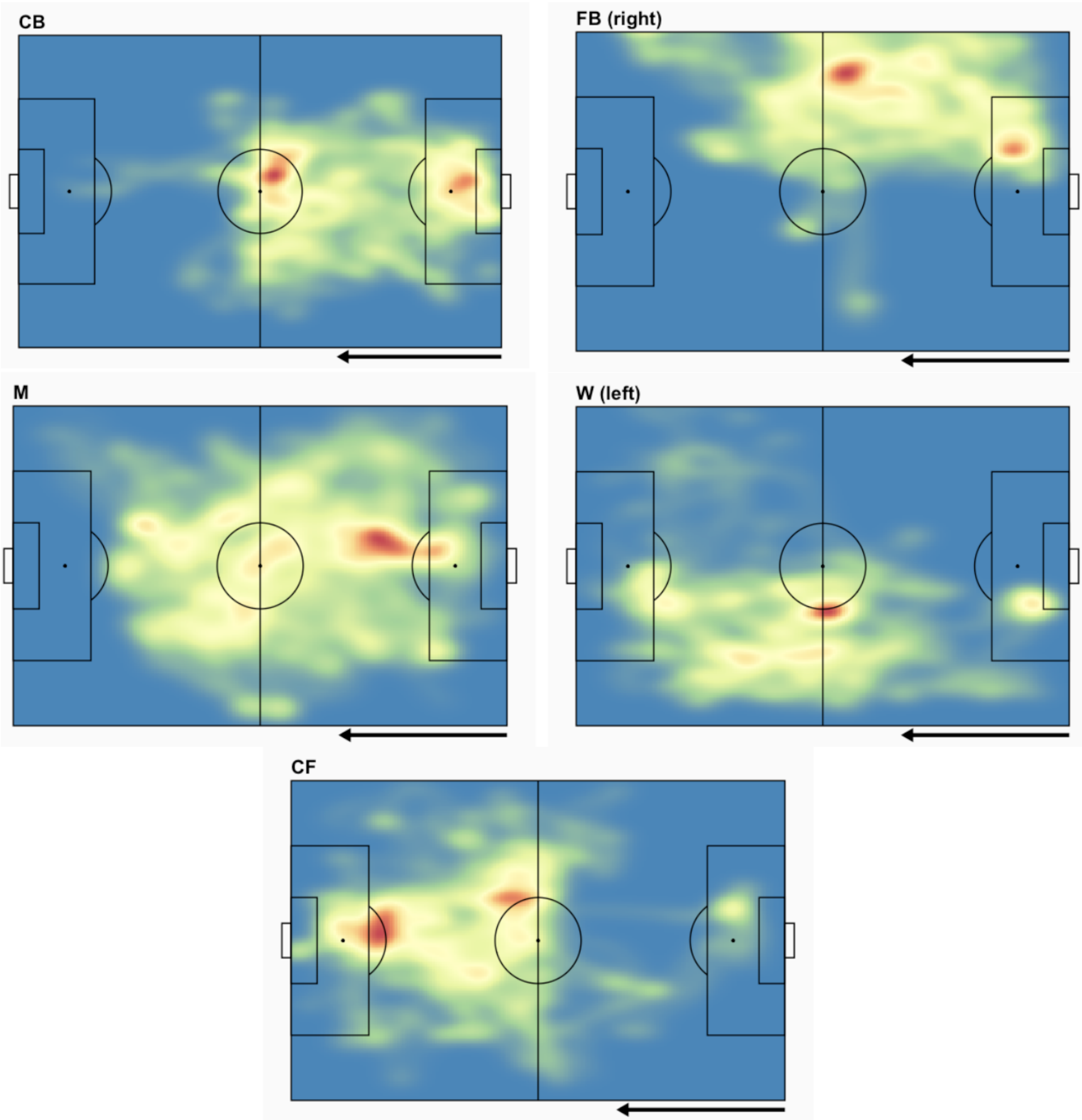

Figure 3.3: Heatmap by position. The arrow represents the direction of play

4 Fatigue metrics

In this chapter we will initially investigate and reproduce tests on metrics that have been used before to highlight fatigue presence. Nevertheless, it is worth keeping in mind that the studied team might have specificities in term of play style that could differentiate these metrics outcome from other studies which in general considers different teams. We will introduce the same threshold values for acceleration as used in previous literature Suibkitwanchai (2022); Mohr *et al.* (2005).

- Low acceleration ($\mathrm{L_{ACC}}$: between 1 and $2\ \mathrm{m/s^2}$)
- Moderate acceleration ($\mathrm{M_{ACC}}$: between 2 and $3\ \mathrm{m/s^2}$)
- High acceleration $\left(\mathrm{H_{ACC}} :> 3\ \mathrm{m/s^2}\right)$
- Low deceleration ($\mathrm{L_{DEC}}$: between -2 and $-1\ \mathrm{m/s^2}$)
- Moderate deceleration ($\mathrm{M_{DEC}}$: between -3 and $-2\ \mathrm{m/s^2}$)
- High deceleration $\left(\mathrm{H_{DEC}} :< -3\ \mathrm{m/s^2}\right)$

4.1 Halves analysis

The most straightforward way to illustrate fatigue is to look for significant change between both halves. For a given half, we will also look at the potential differences between group of players. Let's first introduce the metrics considered as well as the methodology.

First, we calculated the distance distance ran for both halves as well as the distance ran at $\mathrm{H_{ACC}}$ and $\mathrm{H_{DEC}}$ (high acceleration in magnitude). Distance is calculated by summing Euclidean distance computed at each 0.1 seconds interval. Only player who played the whole game are considered. Then, a comparison between both half is made using a a paired t-test with a significance level of 0.05 . The normality assumption on the data has been verified by running a Shapiro-Wilk test resulting with a p-value greater than 0.05. The same analysis is performed on the count of significant turn. Finally, we investigate whether different positions presents significant differences on these metrics within one half. This is made by a pairwise comparison using the one-way ANOVA with the Tukey-Kramer post-hoc test. The Tukey-Kramer post-hoc test has been chosen because it's better suited for situations where groups have unequal sample sizes which is the case here.

4.2 15 minutes periods analysis

Although halves analysis provide a good first perspective of fatigue, it could be interesting to reduce the length of the time window. Numerous studies did so by considering 6 periods of 15 minutes (3 by half) (Barrett *et al.*, 2016; Suibkitwanchai, 2022; Mohr *et al.*, 2005). It allows to have a better insight of performance inside halves. Over-time is not considered so each period have identical time length. And for a given period, we consider every player who player it in full regardless of whether they played the whole game. The focus will be made on both total covered distance and distance ran at high acceleration in magnitude. The normality assumption is verified by a Shapiro-Wilk test with a p-value greater than 0.05. Tests are performed only between consecutive periods and on all players without distinctions on the position. However, Fisher tests are made among periods and for some of them there are significant variance differences. Therefore, unpaired t-test can not be performed on these period. Thus, we will compare periods using Welch's t-test. And unpaired t-test will be performed otherwise.

4.3 Area analysis

So far common metrics of sport science have been used to monitor fatigue. All of them are individuals performance measurement and in someways it omits the collective aspect of the football game. A novel idea is to consider a football game as a dynamic system. Frencken et Lemmink (2008) summarize this situation in a insightful introduction paragraph :

> "In recent years, the growing need and interest in performance analysis has led to new forms of match analysis techniques. Modern day techniques include video-based statistical analysis systems, video-based tracking systems and electronic tracking systems.[...] This kind of analysis mainly focuses on activities of the player holding the ball. However, another important characteristic that can make the difference in competitive playing is tactics. Analyses from a tactical perspective are scarce but would be beneficial to performance analysis. Often, analyses of team performance are the sum of individual player performances. However, we argue that studying the team as a whole has greater and added value. Thus, what is lacking in performance analysis is an analysis of the team as a whole. This means that the team is more than

> the sum of all players. However, in order to study tactics, an adequate tool must be used. ”

The tools in question to describe a team as a dynamic system are the centroid position and the surface area of a team. It has been since studied few times in tactic analysis of teams (Frencken et Lemmink, 2008; Moura *et al.*, 2013). However, nothing has been yet in the fatigue area. The idea here is to use team surface area of team as an extra indicator to the team performance allowing to catch trend and insight that individual metrics do not reflects. This approach falls into the case of relative fatigue, by comparing the behavior surface area of the studied team to the surface area of the opponent. The area itself isn't really meaningful. Indeed, area values can varies from one team formation to another and thus make the comparison irrelevant. In other words, evaluate the overall fatigue of the team relatively to the opponent. The surface area of a team is defined as the area of the convex hull of players (i.e the smallest convex set that contains every player). However, looking at the standard deviation (SD) of this area seems to be more suitable for the comparison between team. It can be seen as how much a team 'streches' and thus give an indication on the team physical performance. The goalkeeper is omitted from the process. The plot 4.1 below illustrates it :

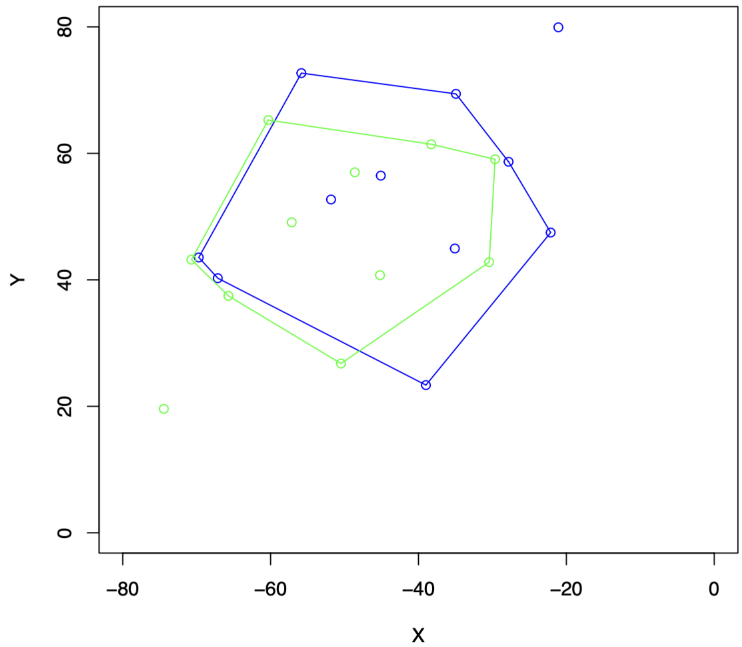

Figure 4.1: Convex hull of the two teams at a random moment during a game. In blue the studied team, in green the opponent. (Coordinates are not rotated)

Another point that we will introduce here is to evaluate team and player performance by looking at games outcomes and goals. Indeed, as said in the Data limitation section, it's an unlabeled problem. However, these game event could be considered as alternative label. It does not reflect directly fatigue but for instance at a same technical and tactical level fatigued player are more likely to concede a goal. It partly explains why there are more goals conceded towards the end of both the first and second halves (Alberti *et al.*, 2013; Armatas *et al.*, 2007) .Note that in this case relative fatigue is more relevant as we compare both team performance. However, this is to be considered with great care. For instance, not all goal are due to fatigue it could be just a technical gap between a defender and a winger. Paradoxically, the cause/consequence link between performance and player fatigue is at the same time obvious but hard to define precisely. It has been shown that less successful team run more at high intensity than successful team (Rampinini *et al.*, 2009). Loosing is likely correlated with fatigue but we can not say if it is a consequence or a cause of fatigue or both. It probably depends of the game considered. Winning could also be correlated to fatigue in some game because of physical attacking phase. In this work we will associate conceded goal and game results with relative fatigue. With winning resulting in a less likely relative fatigue presence whereas losing is the making fatigue presence more likely. We will consider draw as an intermediate. It's worth keeping in mind that these are strong assumption and may not be always be true. Indeed, for instance, games result does not always reflect the game scenario and player performance. A team can physically and technically outperform a team but still losing the game. To counter this issue a new metric emerged : expected goal (Spearman, 2018). It allows to give a more accurate representation of the game. However, we won't use this in this analysis but it could be useful for further work. Furthermore, we will also use halves outcomes to have a more precise idea of the half scenario. In other words, first half outcome is the result of the game when the first half ends, the second half outcome is the result of the second half where only goal scored in the second half are considered.

Let's introduce the method used to compute the SD of the area as a time-series. First, for a given player positions we use the *chull* R function which determine the convex hull of the coordinates. Then *areapl* function from the R package *splancs* is used, it computes the area of a polygon. Although we have data at a 0.1 rate, we repeat this process every second to reduce the computational cost. Finally, for every minute (60 area values) the SD is computed. Overtime is considered, thus the ith element of the final time series represent the SD of the team area within the ith minute of the game. This is made for both the studied team and its opponent. Furthermore, the 10 playing players are considered at any time. Thus, the substitutes are taken into consideration when they go in.

At first in this chapter, we will make an exploratory analysis of this new metric and consider these SD values the same way we have looked to previous metrics,by 15 minutes period. We will consider the mean of all SDs within the given window of time. And then look at the values obtained with respect to halves outcome and goal conceded throughout the game . Then, we will compute the mean of the SDs difference by halves with the opponent to have a better overview of the relative behaviour with respect to the half outcome. No test will be performed, this first approach has the goal to provide an introductory overview of area behavior with respect to game event. One game is considered as an outlier due to a red card the area behaviour of the team is significantly different, thus this game is omitted and the analysis is made on 30 games.

4.4 Result

4.4.1 Halves analysis

Total distance covered

A drop of distance ran between halves has been well documented Rampinini *et al.* (2009); Mohr *et al.* (2005); Suibkitwanchai (2022). It is the most obvious and straightforward way to illustrate fatigue presence. Distance ran for the studied team is summarize in 4.1. Overall, there is a significant drop in distance covered between the two halves (p-value < 0.01). We can see that the drop also occurs for every position except W. Position wise, the results are illustrated within each half in 4.2. First, for both halves M are significantly performing more than any other positions. This result is in accordance with other paper where M is the position covering the more distance Modric *et al.* (2020). Then, we can see that pairwise the trend doesn't change between each half except for the W/CB pair. Also, we could have expected position to behave similarly regarding to proximity on the pitch. However, FB and CB, both defensive position present significant differences whereas CF and CB are pretty similar despite their very different role.

Position	First half	Second half	Full match
All ($n = 183$)	5541.68 ± 524.78	5396.22 ± 477.37	10937.9 ± 928.343
CB ($n = 53$)	5078.90 ± 343.16	4902.95 ± 265.68	9981.85 ± 498.10
FB ($n = 51$)	5456.87 ± 389.76	5293.05 ± 309.88	10749.93 ± 522.60
M ($n = 58$)	6000.29 ± 392.91	5703.89 ± 400.52	11704.19 ± 707.61
W ($n = 16$)	5301.29 ± 399.53	5322.54 ± 438.19	10623.83 ± 686.31
CF ($n = 5$)	5186.23 ± 340.14	4971.81 ± 308.82	10158.05 ± 601.65

Table 4.1: The mean and standard deviation of the total distance covered in metres for 183 players (All and by group) who played the whole game.

	CB	FB	M	W	CF
CB	_	*	*	/	/
FB	*	_	*	/	/
M	*	*	_	*	*
W	*	/	*	_	/
CF	/	/	*	/	_

Table 4.2: The significant difference test of the means of the total distance covered within each half between each pair of position. '*' for significant difference (p-value < 0.5) and '/' for no significant difference. Upper triangle corresponds to first half while lower triangle correspond to second half.

Distance covered at high acceleration in magnitude

Distance at high acceleration magnitude are presented in 4.3. As well as for the total distance covered we observe a overall significant drop between both halves (p-value < 0.01). W is the position with higher distance covered at high acceleration whereas CB has the lowest. Ade *et al.* (2016) have studied high intensities distance by position. However, since the studied team plays in 4-2-2 they do not consider W but Wide Midfielder. Despite the difference of position name a lot of common point exists between this position especially in attacking phase. This being said, Wide midfielder are those having the greatest high intensity distance covered whereas CB have the lowest. The results of pairwise significant difference within a half are shown in table 4.4. Only two pairs present a significant difference in both halves, CB/M and CB/W.

Position	First half	Second half	Full match
All ($n = 183$)	139.00 ± 25.35	125.02 ± 25.91	264.02 ± 41.90
CB ($n = 53$)	127.66 ± 20.82	112.72 ± 20.87	240.38 ± 35.23
FB ($n = 51$)	140.44 ± 30.65	123.34 ± 27.81	263.79 ± 46.75
M ($n = 58$)	142.19 ± 21.81	128.63 ± 23.31	270.83 ± 33.75
W ($n = 16$)	150.13 ± 20.54	137.90 ± 33.14	288.03 ± 44.88
CF ($n = 5$)	143.36 ± 16.05	127.51 ± 16.77	270.88 ± 25.14

Table 4.3: The mean and standard deviation of the distance at high acceleration magnitude covered in metres for 183 players (All and by group) who played the whole game.

	CB	FB	M	W	CF
CB	_	/	*	*	/
FB	/	_	/	/	/
M	*	/	_	/	/
W	*	/	/	_	/
CF	/	/	/	/	_

Table 4.4: The significant difference test of the means of the distance covered at high acceleration magnitude within each half between each pair of position. '*' for significant difference (p-value < 0.5) and '/' for no significant difference. Upper triangle corresponds to first half while lower triangle correspond to second half.

Significant turns

First of all, as the two previous metrics. Paired t-test resulted in a significant difference of mean (p-value < 0.01). Detailed count is represented in table 4.6. As for the total covered distance, M represent the higher output for this metric. However unlike before we have CF considerably below others, almost two time less than M. One-way ANOVA test significance results are reported in table 4.5. Within the first half only M/CF pair presents a significant mean difference, whereas in the second half, M/CB and M/FB are added to the previous pair.

	CB	FB	M	W	CF
CB	_	/	/	/	/
FB	/	_	/	/	/
M	*	*	_	/	*
W	/	/	/	_	/
CF	/	/	*	/	_

Table 4.5: The significant difference test of the means of significant turns within each half between each pair of position. '*' for significant difference (p-value < 0.5) and '/' for no significant difference. Upper triangle corresponds to first half while lower triangle correspond to second half.

Position	First half	Second half	Full match
All ($n = 183$)	13.56 ± 4.97	11.69 ± 4.71	25.25 ± 8.09
CB ($n = 53$)	13.01 ± 4.3	10.73 ± 3.39	23.75 ± 6.18
FB ($n = 51$)	13.03 ± 4.79	10.41 ± 4.10	23.45 ± 7.08
M ($n = 58$)	15.17 ± 5.43	13.72 ± 5.60	28.89 ± 9.28
W ($n = 16$)	11.87 ± 5.00	10.93 ± 4.04	22.81 ± 7.10
CF ($n = 5$)	8.60 ± 0.89	7.20 ± 1.30	15.80 ± 1.30

Table 4.6: The mean and standard deviation of the count of significant turns for 183 players (All and by group) who played the whole game.

4.4.2 15 minutes period analysis

Total distance covered

The total distance covered by all players by period is illustrated in the first boxplot in the 4.2 figure. To be more specific means and standards deviation are indicated in the 4.7 table. We can see that except between the second and third period every consecutive periods have significant difference in means. Note that between the third and fourth period the difference is smaller than for others, this is due to half time recovery. A more surprising result raises, there is a significant rise in the last period. This result contrasts with those obtain by Akenhead *et al.* (2013) where drops are happening between each periods. This results is likely due to a specific play style of the studied game. Furthermore, this could be an illustration of transient fatigue. Indeed, players start the second half intensively in the fourth period illustrated by in a relatively small drop between third and fourth period. This results to a high fatigue in the fifth period but players are able to partially recover from it and provide a better performance in term of distance covered. Position-wise, the boxplots in 4.2 figure show a that the trend are similar for every positions. Only CF are not rising their performance between the two last periods.

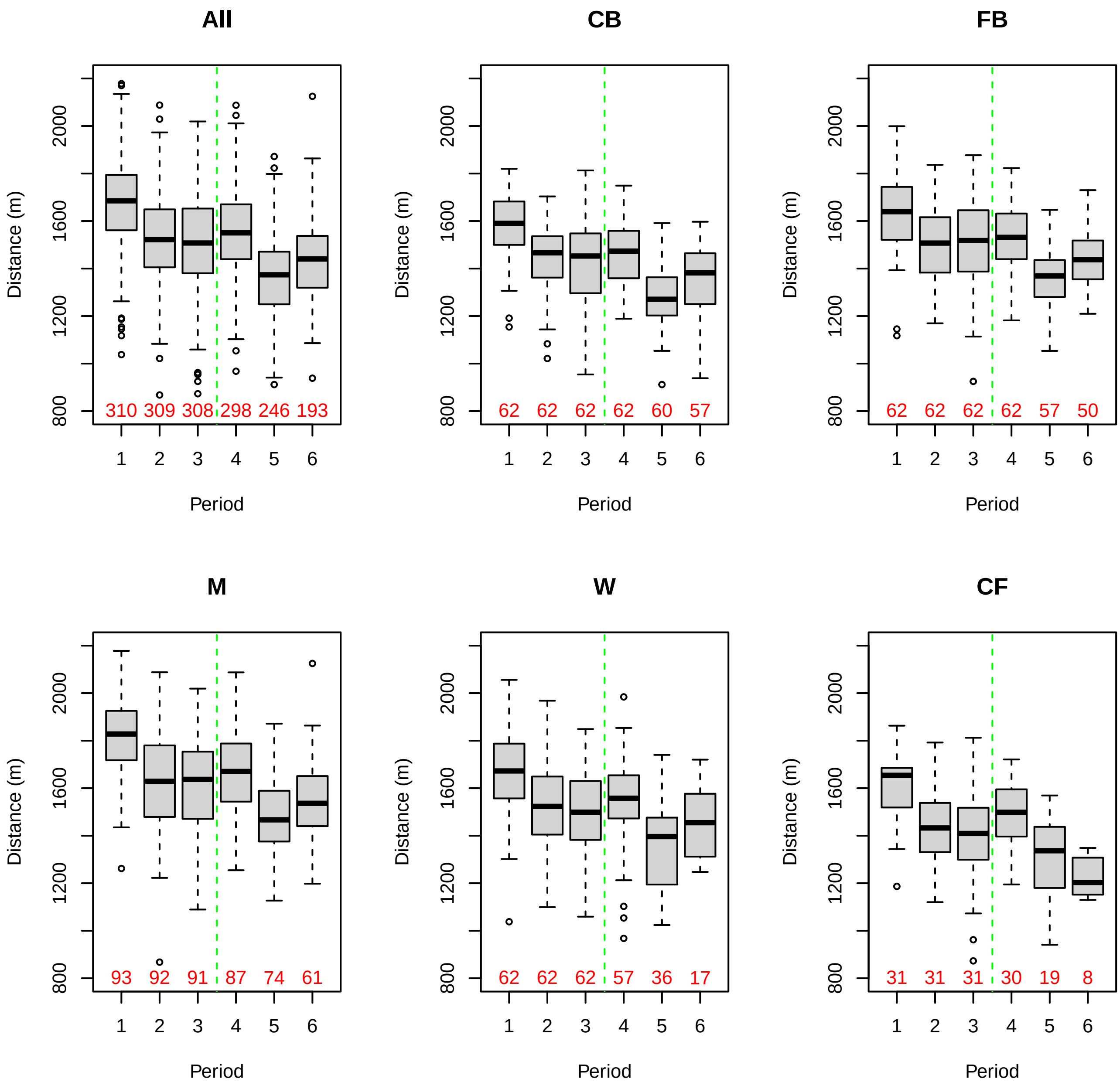

Figure 4.2: Boxplots of the total distance covered by player positions in six 15-minute periods. Red numbers above the periods are the sample size for each period and the green dotted line represents the half time

	P1	P2	P3
Mean±SD	1663 ± 188	1513 ± 187	1495 ± 208
Significance result	-	*	/
	P4	P5	P6
Mean±SD	1538 ± 178	1352 ± 165	1426 ± 168
Significance result	*	*	*

Table 4.7: Period mean and standard deviation by period for all players. Significance result of mean comparison test for a period with the period before, '*' significant difference ($p < 0.05$) and '/' no significant difference.

Distance covered at high acceleration in magnitude

The total distance covered at high acceleration in magnitude by all players by period is illustrated in the first boxplot in the 4.3 figure. Here we can see a constant decreasing behavior confirmed by mean values in the 4.8 table. This global decrease at high acceleration is in accordance with both Akenhead *et al.* (2013) and Suibkitwanchai (2022) findings. However, significant test on the means only resulted in significant drop between the two first period of each half (i.e P1/P2 and P4/P5). This is likely due to high intensity in the first period of both halves followed by a notable fatigue. Position-wise, the trends are the same. CF and W have greater drop than others respectively in the second and fifth period.

	P1	P2	P3
Mean±SD	51 ± 15	42 ± 12	42 ± 13
Significance result	-	*	/
	P4	P5	P6
Mean±SD	44 ± 13	36 ± 10	35 ± 11
Significance result	/	*	/

Table 4.8: Period mean and standard deviation by period for all players. Significance result of mean comparison test for a period with the period before, '*' significant difference ($p < 0.05$) and '/' no significant difference.

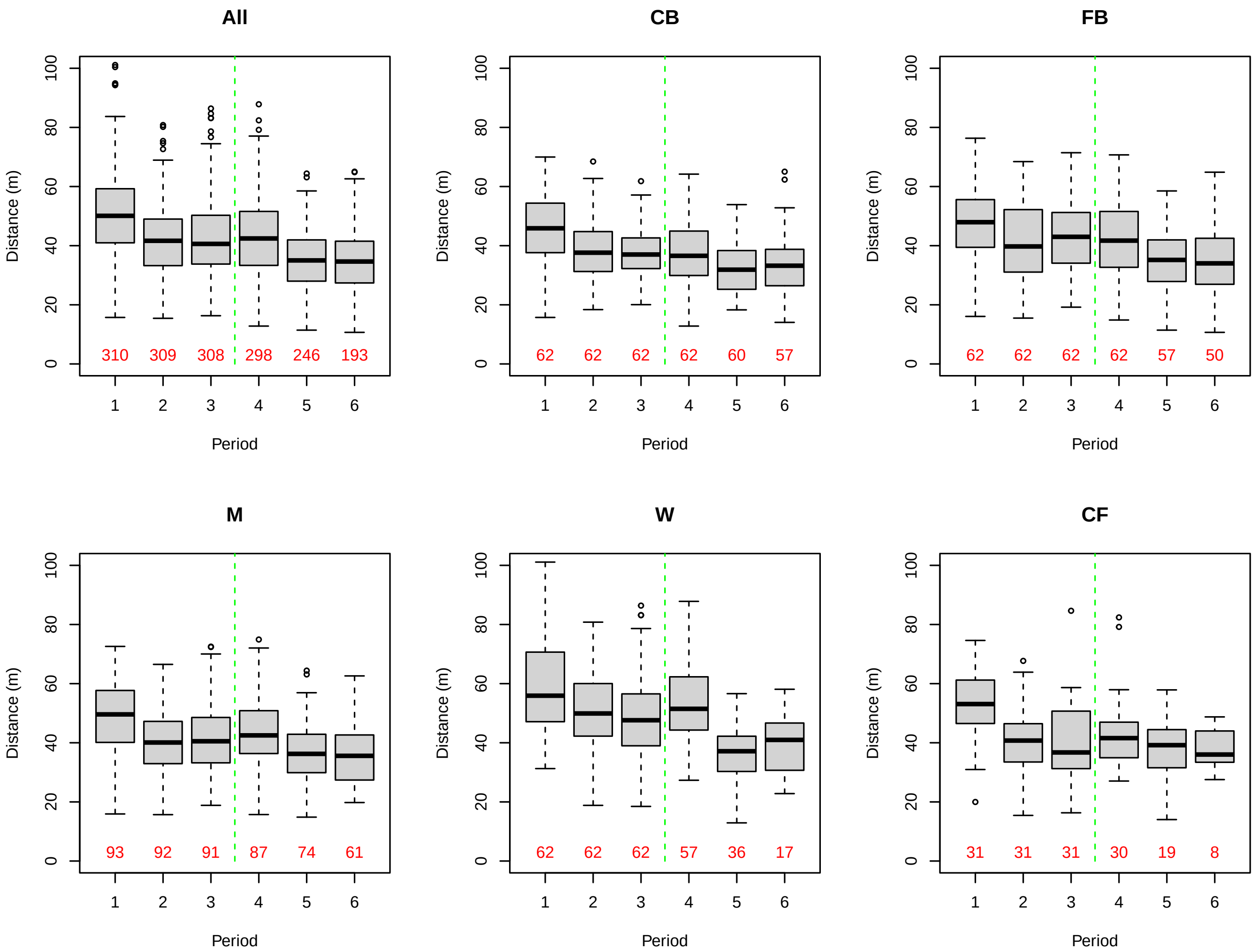

Figure 4.3: Boxplots of the total distance covered by player positions at high acceleration in magnitude in six 15-minute periods. Red numbers above the periods are the sample size for each period and the green dotted line represents the half time

Area analysis

The four plots in the 4.8 figure correspond to the mean of SDs by period with respect to goal conceded and halves outcome. The first noticeable pattern is that for 3 out of 4 plots the lines variations are the same among the different categories within a plot. Only the second half conceded goal plot shows a change in behavior among the lines. For plots with respect to the outcome, it is interesting to see how outcome has a translating behavior on the values. Furthermore, this translation changes of sign with half-time. Indeed, in the first half outcome is negatively correlated with the mean of SDs whereas in the second half it is positively correlated. The change of correlation sign is also noticeable in the relative SDs analysis with the opponent. Table 4.9 also reflects this change of sign between the two halves. When losing the first half the difference is positive, which means that in average the team area SD is above its opponent, whereas winning results in being below the opponent. The opposite happens in second half. This change will be discussed further in next chapters. Moreover, we see that draws give a difference near zero in both halves. This result consolidates the idea of using area SDs as a performance/fatigue indicator as draw are likely close game where both teams are not able to take the lead. For goal conceded, patterns are less obvious than before. A most significant change appears in second half where in second period a raise happens in game with no conceded goal whereas in games with conceded goal(s) a drop happens. This resonates with the fact that the fourth period of the game is when the studied team conceded the most goals by far among all 15-minutes periods. However, it's hard to say if this drop is whether a cause or a consequence of goal conceded.

	L	D	W
First Half	11.42	0.51	9.35
Second Half	-12.15	1.11	-17.35

Table 4.9: Mean by halves of SD differences between the team studied and its opponent ($SD_{team} - SD_{opp}$, thus positive value means greater mean for the studied team). As in 4.4 figure L,D,W in the first row correspond to the first half result and to second half result in the second row.

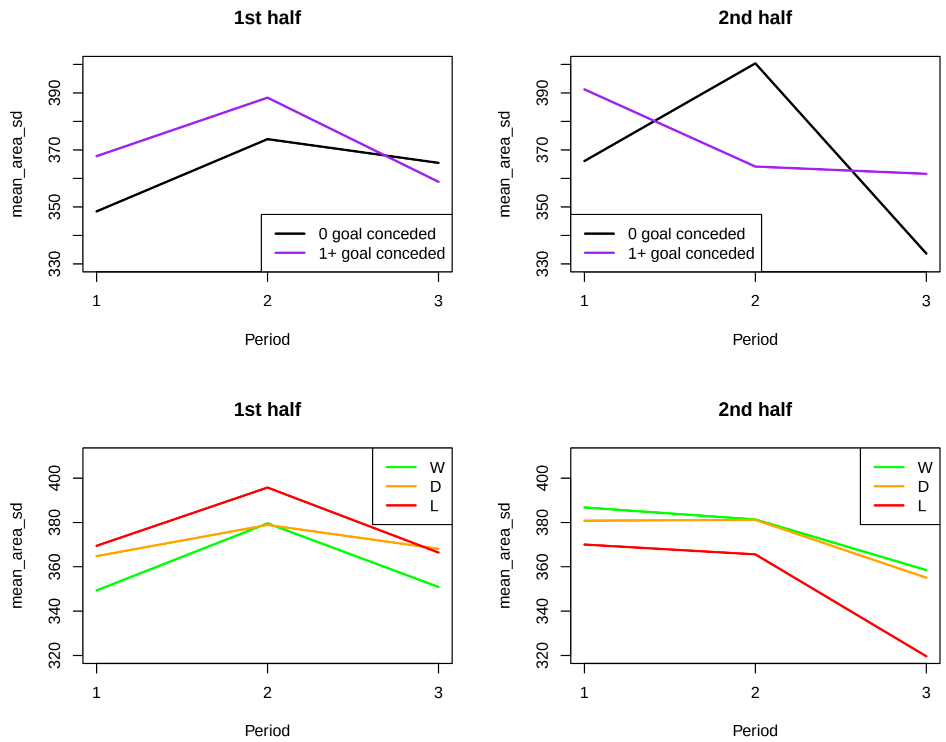

Figure 4.4: Mean of SDs by period with respect to halves outcomes and goal conceded (1+ means at least one goal conceded). Note that for goal conceded, goals from all the game are considered whereas for the outcome it's the outcome of the half considered that is displayed.

5 Analysis

So far, different fatigue metrics have been introduced as well as their evolution throughout the game as an illustration of fatigue. This being said, the aim of this thesis is to introduce tools that could maybe useful to detect fatigue at different levels. A first point worth raising is getting rid of fixed time window. Indeed, using fix window can obscures important insight of player performance by missing local pattern which nevertheless could be worth studying. Analysis made on predefined fixed window of time are way less accurate to catch peak intensity period than rolling window (Varley *et al.*, 2012). However, the goal here isn't to find peak period but to try to catch trends illustrating fatigue without the constraint of fixed window. To this extent change point detection is used. Although using change point is not very frequent yet in sport some studies have introduce it. Corbett *et al.* (2019) used change point in Australian football in a goal of having a better understanding in how physical and skilled output fluctuate during a match. In football, Kim *et al.* (2022) used change point in a spatial way to detect spatial team formation. Performance-wise, van Engelen (2022) used change point detection on Metabolic Power which is highly correlated with acceleration as explained before in the Fatigue chapter. In this chapter change point will be performed on two different metrics : acceleration variance and the area standard deviation introduced in the previous chapter. Also a local performance metrics will be introduced.

5.1 Change point

Change points, in the context of time series data, refer to sudden and noticeable shifts or alterations in the data's pattern. These abrupt variations often signify significant transitions between different states or conditions. Identifying these change points is a valuable task with wide-ranging applications, including time series modeling and forecasting. It finds practical use in various domains, such as monitoring medical conditions, detecting climate change trends, analyzing speech and images, and understanding human activity patterns (Aminikhanghahi et Cook, 2017). Furthermore, there are numerous methods of implementing change point algorithm and a lot of parameters to tune. One of the main parameter to tune is the number of change point to consider. For single change point, Binary Segmentation is mostly used. It operates through a repetitive process of applying a single change point to every possible point on the entire sequence. Then, for the two resulting segments the residuals are computed with respect to the segment mean. Then, the point with the lower residuals is picked. For multiple change points, Binary Segmentation can be used iteratively for a given number of change points. But another method, Pruned Exact Linear Time (PELT) provide a lower computational cost. However, the number of change points can not be fixed. Instead, several penalty functions (proportional to the number of segment) are used to avoid over-fitting by returning too many change points. This method have been used by van Engelen (2022) and it results still in over-fitting. Indeed, every pause in the game such as substitution, VAR (Video Assistance Referee) or faults were spotted by the PELT method. Therefore, the interpretation of these results are ambiguous especially since there is no information on these game events. Thus, in this work the number of change points will rather be underestimated by using only single change points with Binary Segmentation than overestimated by using PELT method. Although we might underestimated the number of point the most significant will be returned and they will be more likely due to player performance than game events.

5.1.1 Change point on acceleration variance

First of all, as justified before acceleration is recognize as the best fatigue indicator. Therefore, further studies in this thesis on individual metric will be focused on acceleration. Thus, let's investigate further on it. Figure 5.1 reports some properties of the acceleration distribution. For all players, both median and means are close to zero, thus we will assume for the rest of this work acceleration distribution as symmetric. Fitting models have been tried without significant results. The closest distribution found was the Cauchy distribution. But it fits only locally near zero as Cauchy distribution is Heavy-tailed unlike acceleration which is bounded. Further work on fitting acceleration distribution could be interesting to consider. This being said, using raw acceleration values for the change point is an option. But as a fatigue detection problem, emphasizing high-acceleration in magnitude is chosen. To this extent, we will use variance. Indeed, variance is defined as the squared deviation from the mean. First, by squaring the sign is omitted and only the magnitude is taken into consideration. This omission has no consequence because of the symmetric behavior of acceleration. Then, squaring highlights the high acceleration values for the study.

The acceleration variance time-series will be constructed with the same structure as the surface area. For a given player in a given match, the variance of its acceleration is computed for each minute. Overtime is considered, so each game provides times-series with different lengths. Furthermore, all starting player are considered even though he is substituted resulting in shorter times-series for those.

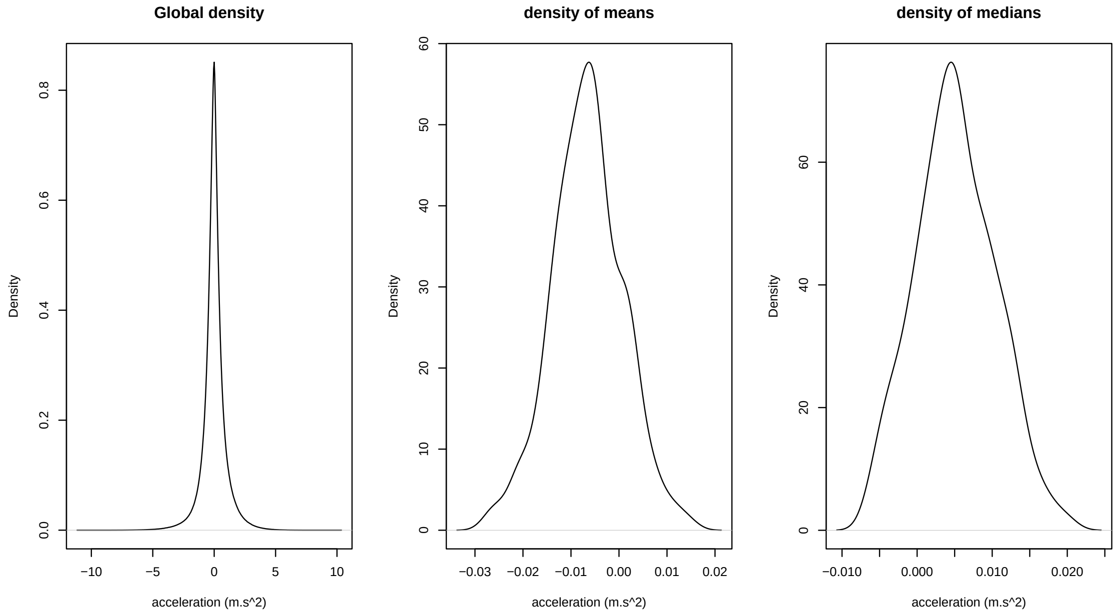

Figure 5.1: Global,means and medians acceleration distribution among all players

Then, the time series is split in two sub time series for the two halves. Then, single mean change point is made separately on both of the halves for two reasons. First, findings in the previous chapter suggested a potential difference of behavior beyond fatigue and drop of performance. Secondly, the half time discontinuity will likely biased the change point. Last but not least, the minimal segment size has to be set. For single change point, if this number is too small, change point will spot high/low intensity starting or ending period and omit the rest in the other segment. Delaney *et al.* (2015) studied different window size for rolling-average method on velocity. For each game the highest value corresponding to the peak period was observed and compared. For a same game, smaller window of time gave higher value on the peak value. Indeed, increasing the window size tends to smooth the peak by considering more value around the peak. Window sizes were tested from 1 min to 10 min with an 1 min interval. Peak value was significantly decreasing as window size was increasing until 9 min. Only the 9 min and 10 min difference of peak was not significant. Larger periods are not considered as it will over-smooth the values and lose peak period meaning. Therefore, the minimal period chosen for the change point analysis is 10 min (i.e 10 points). This value appears as an acceptable trade-off between local and global analysis. When a player is substituted during one of the halves,the minimal segment size is set to the minimum between 10 and its playing time. If he is substituted in the 63^{th} minute, corresponding to 63-45=18 minutes played in the second half the size is set to 18/3=6.

First, an overall analysis will be made on how the change point is happening among players. Also, the time and the potential link for player between first half and second half is studied. Then, the change point will be also considered under the perspective of halves outcome and global outcome.

5.1.2 Change point on surface area Standard Deviation

Mean change point is also applied to the times-series of area SDs. Like the acceleration variance, this time-series will be split by halves. A single change point will be performed on each half. Results will be considered with respect to game outcome.

5.2 Radius analysis

Although the surface area analysis looks promising in term of relative fatigue, it is still something global as it includes all player within a team. The idea here is to push the relative fatigue analysis to a more local perspective.We will introduce here the radius analysis. For a given time window, every player mean position is computed. Then for each player a circle is drawn around him with a given radius. All players within this circle, opponent and team mate, are considered for a comparison analysis. The metric used further is acceleration variance but other could be used. The mean of all players inside the circle is computed and then the relative difference between the center player and the mean is the final output. The time window used here is one minute allowing to use previous time series.

First of all, the radius has to be determined. For this matter, we will look to the average number of neighbors with respect to the radius size and then choose an adequate value. Then overtime is considered as well, for the seek of comparison periods has to be determined as each game time differs. The number of period will be increased to 5 by halves. For each half , the period size is set to the length of the half divided by 5 so it varies from one game to another. Then within a period, the mean of relative difference for all minutes within the period is computed. Results are first displayed with respect to position. For comparison, the relative difference in high acceleration distance covered within the studied team is computed as well in the same periods. Then, results are also analysed with under the spectrum of final outcome.

6 Result and discussion

In this chapter, results are presented and interpreted. An effort is made of giving some concrete cases on interpretation to make the results more tangible. However, these interpretation are based on strong hypothesis such as correlation between fatigue and outcome/goals. Therefore, some the given interpretation below are potentially wrong.

6.1 Change point on Acceleration variance

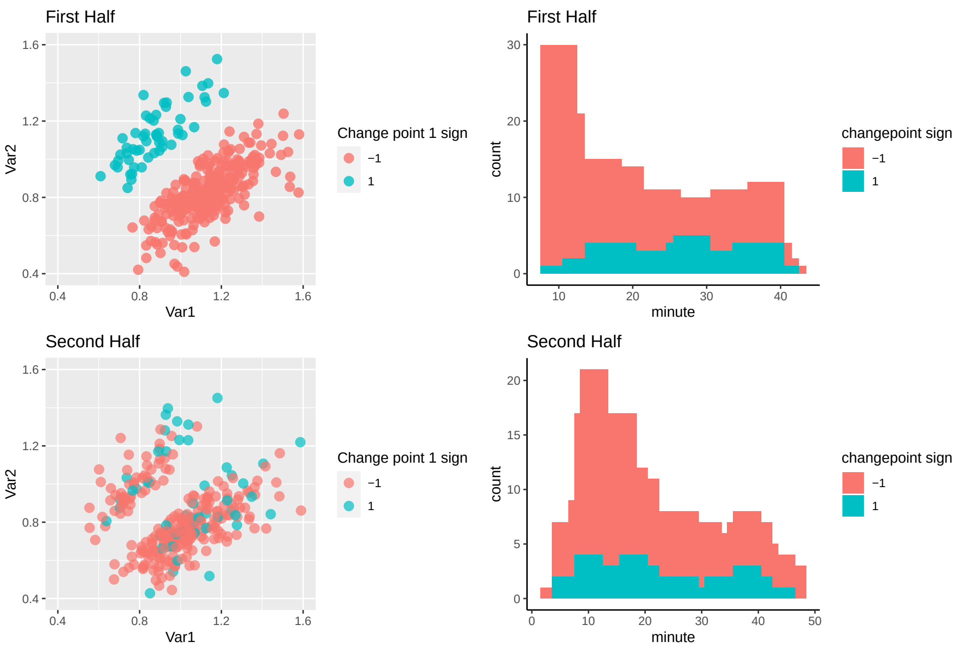

Figure 6.1: Mean change point on acceleration variance. X and Y axis correspond to the mean of the acceleration variance segment respectively before and after the change point. Points are plotted with respect to the first change point sign. Histograms corresponds to the time distribution of these change points

The 6.1 figure represents change point applied on all players on both halves. Positive change point (PC) is a change point where the mean after the change point is greater than the mean before . Contrary to negative change point (NC). An overall summary is shown in 6.1 table. First of all, NC are majority in both halves. This could be due to fatigue and therefore making change point relevant to detect fatigue. However, this result must be contrasted with time distribution of change points. Indeed, a significant amount of NC happen around the 10^{th} minute (i.e the minimal segment size) meaning that represents a high intensity start and a calmer rest of the half. This is rather a game pattern than an individual sign of fatigue. Magnitude-wise fatigue presence is highlighted by averages NC and PC points. Both decrease in magnitude in the two coordinates in the second half. Furthermore, among player who had a PC in first half (red), 21% had a PC in second half. Whereas players who had a NC in first half (blue), 33% had a PC in second half. Having a PC in first half doesn't reduce odds of having PC again in second half. These results have to be considered with great care as the sample size of NC is significantly lower than PC.

	1st H	2nd H	Average 1st H	Average 2nd H
NC	82%	77%	(1.14, 0.82)	(1.05, 0.76)
PC	18%	23%	(0.88, 1.13)	(0.80, 1.04)

Table 6.1: Change point summary

		PC	NC
1st H	1st H outcome	L: 19% D: 33% W: 48%	L: 18% D: 48% W: 34%
	2nd H outcome	L: 23% D: 60% W: 17%	L: 15% D: 44% W: 40%
	Final outcome	L: 28% D: 15% W: 57%	L: 10% D: 40% W: 50%
2nd H	1st H outcome	L: 23% D: 44% W: 33%	L: 17% D: 46% W: 37%
	2nd H outcome	L: 4% D: 52% W: 44%	L: 20% D: 44% W: 36%
	Final outcome	L: 7% D: 34% W: 59%	L: 15% D: 37% W: 48%

Table 6.2: Change point for each half with respect to outcomes and goals conceded. Overall games outcomes for the 31 studied games : L: 13% D: 35% W: 52%

Table 6.2 displays change point sign with respect to games events. We will compare outcome and goal of each case Let's discuss each case :

PC in first half

Having a PC in first half leads to a neutral first half in comparison of the overall studied result. However, the second half is under performed with a majority of draw (60%) and only 17% of win. Surprisingly, the final outcome has a low draw rate with only 15 %. The low win rate in second half could be a cause of fatigue due to the PC in first half. To go further, both lose and win have a higher rate in the final outcome than in average. A way to interpret that is having a great start (i.e PC in first half) is a risky 'gamble' for the team. If they win the first half, they play in a tactical close play style to avoid conceding goals way and therefore the draw in the second half is acceptable. On the other hand, if they lose the first half despite PC, they are not able to make the difference in second half because of fatigue and it leads to a 29% lose rate whereas the average lose rate is 13%.

PC in second half

In this case, the lose rate in first half is the highest (23%) and this could be the cause of the PC in the second half as a need of increasing performance. Performance are indeed increased with only a 4% lose rate in the second half and a 7% lose rate in the final outcome. One possible interpretation is that the first half was played in a energy saving way, allowing to push to a PC in the second half which has a great impact against fatigued opponent.

NC in first and second half

NC in both halves resulted in a slightly under performance in the half it occurs in comparison to the other one. A more interesting result is that for both cases the final outcome is better than individual half result (1st half NC leads to 18% lose in first half, 15% lose in the second but only 10% lose at the end, same trend for NC in second half). It means than when the studied team lose one half to a certain scale it wins the other half in a greater scale goal-wise (i.e losing first half 0-1 but winning the second half 2-0 resulting in a final 2-1 win).

6.2 Change point on surface area Standard deviation

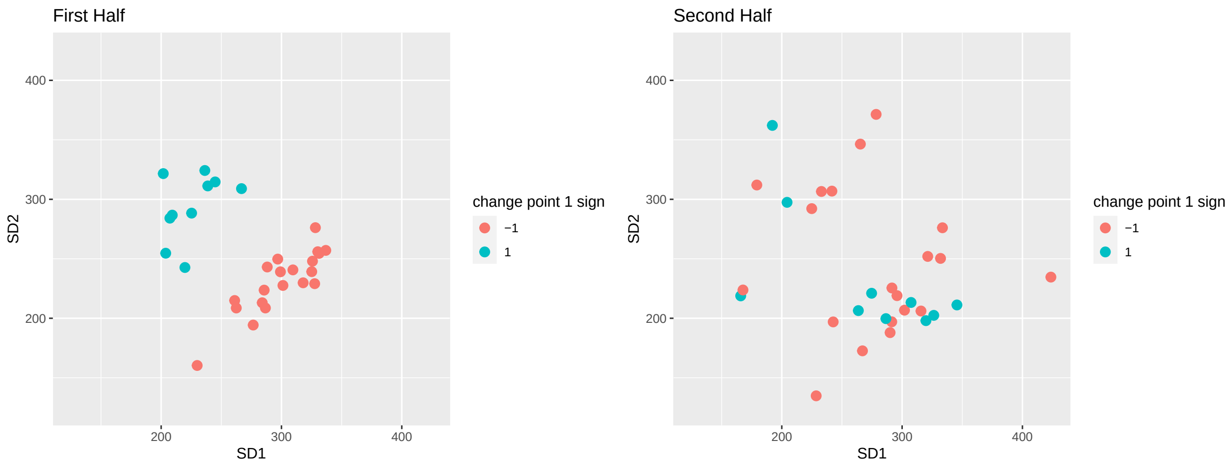

Figure 6.2: Mean change point on surface area SD. X and Y axis correspond to the mean of the SD segment respectively before and after the change point. Points are plotted with respect to the first change point sign.

	1st H count	2nd H count	Average 1st H	Average 2nd H
NC	20	20	(300, 231)	(304, 215)
PC	10	10	(225, 295)	(211, 303)

Table 6.3: Change point summary

As for player variance acceleration, NC are majority but PC are represented in a higher proportion with a third of game in both halves. A more interesting thing is looking at SDs in both halves. First of all, visually points are more compact in first half than in second half. Second halves surface area variation vary more among different games than first halves. Unlike the previous section, average NC and PC doesn't decrease in both coordinates in second halves. However, we do know that there is fatigue among players in second halves and they run less. In contrast to individual metrics that are unanimously dropping with fatigue, this metric seems to spread more with fatigue. Therefore, it could be interpreted as a the measure of chaos among players within a same team. The fact that substitute are considered could also be one reason of this spread as they are creating a fatigue gap between them and the rest of players.

		PC	NC
1st H	1st H outcome	L: 2 D: 4 W: 4	L: 4 D: 9 W: 7
	2nd H outcome	L: 5 D: 3 W: 2	L: 2 D: 9 W: 9
	Final outcome	L: 2 D: 2 W: 6	L: 2 D: 9 W: 9
2nd H	1st H outcome	L: 2 D: 4 W: 4	L: 4 D: 9 W: 7
	2nd H outcome	L: 1 D: 5 W: 4	L: 4 D: 9 W: 7
	Final outcome	L: 1 D: 5 W: 4	L: 3 D: 6 W: 11

Table 6.4: Change point for each half with respect to outcomes and goals conceded. Overall games outcomes count for the 31 studied games : L: 4 D: 11 W: 15

PC in first half

PC in first half to a neutral first half in comparison of team average outcomes. The second half is poor with 5 loses and only 2 win. However, the final outcome stays positive. As before this means that in term of scale they win 'more' in first half relatively to what they loose in second half. Therefore it's difficult to say whether this bad second half is due to fatigue or to a specific strategy of not losing 'too much'.

PC in second half

This case has the same outcome distribution on the first half than the case before. However, it shows a more successful second half outcome. Despite the chaos aspect mentioned above, a high value of SD surface area isn't necessarily negative performance-wise. Indeed, it could be a way to out perform the opponent by having a more open and offensive play style. Unlike player acceleration variance, the PC in second half doesn't improve the the final outcome in comparison of PC in first half.

NC in first and second half

NC in first half leads to a more dominant final outcome. There are 2 game lose as in PC although there sample size is twice bigger. The end of halves corresponds to fatigue presence among players and there are the most likely periods to score for both teams and thus modify the outcome. Nevertheless, NC leads to low variation among outcomes between halves or for the final outcome. In other words, NC represents close games because players are not able to make the difference at the end of each half because of low SDs surface area values symbolizing a neutral game style.

6.3 Radius analysis

The analysis is centred only on starting player. However, when it come to consider player inside their circle, substitute are also considered so that substitution doesn't biases the number of neighbors. Results are plotted in 6.3, visually there is a strong linear relation between the two variable. The positive correlation between these two variable is obvious, though the almost perfect line obtained (Pearson correlation coefficient of 0.99) is not that obvious. The neighbourhood relationship could be an rewarding line of research for further work. This being said, the radius chosen for the rest of the analysis is set to 12 m. With this radius value there are in average 4.7 neighbors for a studied player.

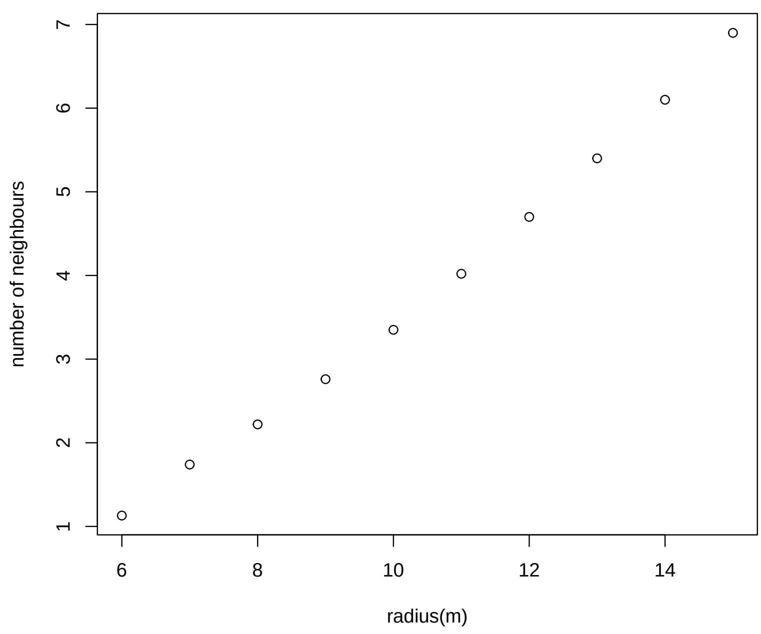

Figure 6.3: Average number of neighbors with respect to circle radius among all players

The results of the radius analysis is displayed in the left plot in 6.4 figure. The main result is the gap between FB and others. This may be very specific to the studied team but we can see that FB out perform their neighbours acceleration-wise. To make this result more significant further analysis is needed to analyse in details the average neighbors profile of FB such as their total number and their position. However, this study of neighbors position is limited by the fact that each different opponent position has to be known. Another result is that the metric is below 0 among all of other positions . However, the fact of being under the radius mean doesn't have to a sign of fatigue. On the contrary, in the beginning of the game this could be a signal of tactical superiority needing less high intensity running than the opponent to play the game resulting in a less likely development of fatigue for the rest of the game. The metric is globally decreasing throughout the game but this is likely due to the fact that substitute are considered as neighbours which is somehow biasing the comparison with starting player. To make a comparison, the high acceleration magnitude dis- tance covered studied in the Fatigue metrics chapter is computed for each period and then the relative mean relative difference within the studied team is displayed in the right plot. The comparison has to be made with great care as the first consider a local difference including opponent whereas the other consider a difference within the same team. The purpose is more on showing that to measure fatigue and thus helping detecting it can highly vary from the perspective taken. In this second plot, we see than relative result are not the same the in the first. Result are more 'usual' with W above others, CB under others and M/FB/CF in the average.

The 6.5 figure represent the same radius result but split by global outcome. This results highlight the FB role in the studied team result. The gap between FB and others is positevly correlated to the team outcome. This is probably very specific to the studied team, however by having a general profile of local relative acceleration variance difference for every position it could help to see whether a player is under/over performing in comparison to the reference profile. As we could expect in draw and lose CF/FB are above W/CF/M because of most frequent defensive tasks.

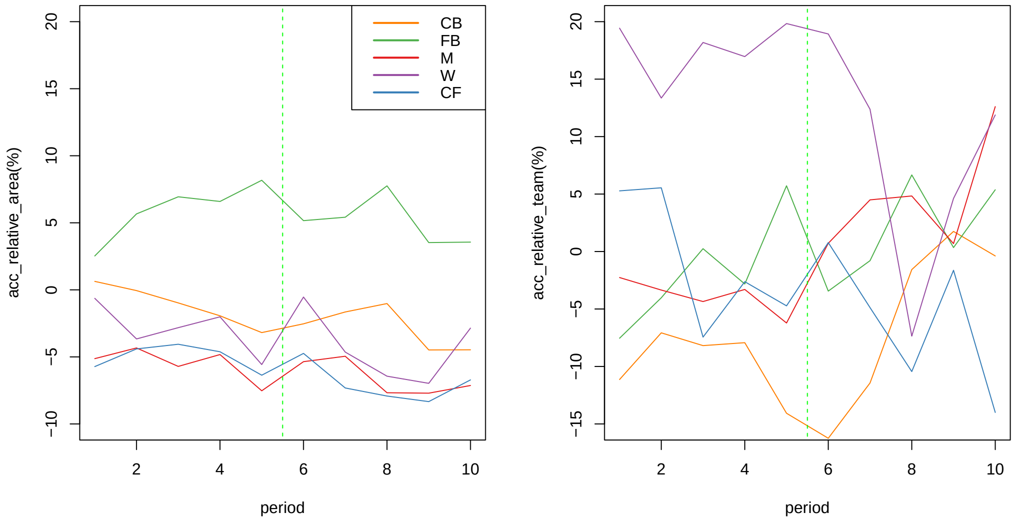

Figure 6.4: Mean relative acceleration variance difference within player radius with respect to position. Mean relative high acceleration magnitude distance covered distance difference within the studied team with respect to position. Green dotted line represents half-time.

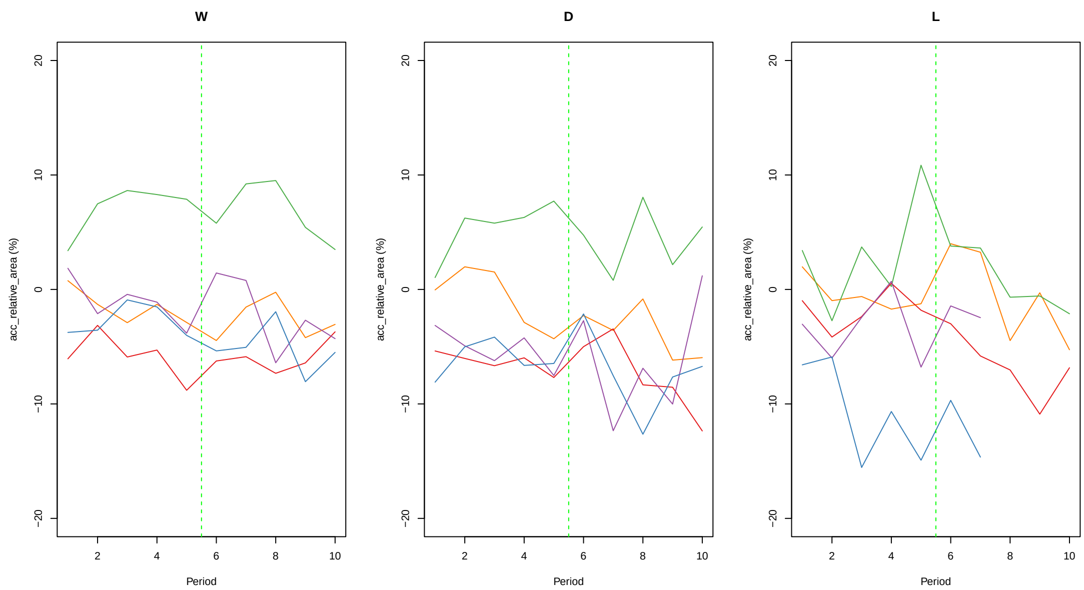

Figure 6.5: Mean relative acceleration variance difference within player radius with respect to position and game final outcome. In the L case W and CF are truncated because of a too low sample size at the end due to substitutions

6.4 Change point on a known player injury

In late august 2023, Sportlight provided a player data who was slightly injured during an opening game of the studied team for the season 2023/2024. A change point is performed on the player acceleration variance as for the rest of the dataset. Results are illustrated in 6.6 figure. First of all, the first half is average as we can visually see in first plot. However, the second half starts with a relatively high acceleration variance in comparison to the rest of the dataset (X axis in second plot).Which is potentially causing the injury. The change point details are shown below. Indeed, the second half is marked by a negative change point with a huge drop arround the 20th minutes. This is likely when the injury happened. However, we see that the player still continues to play potentially worsening his injury.

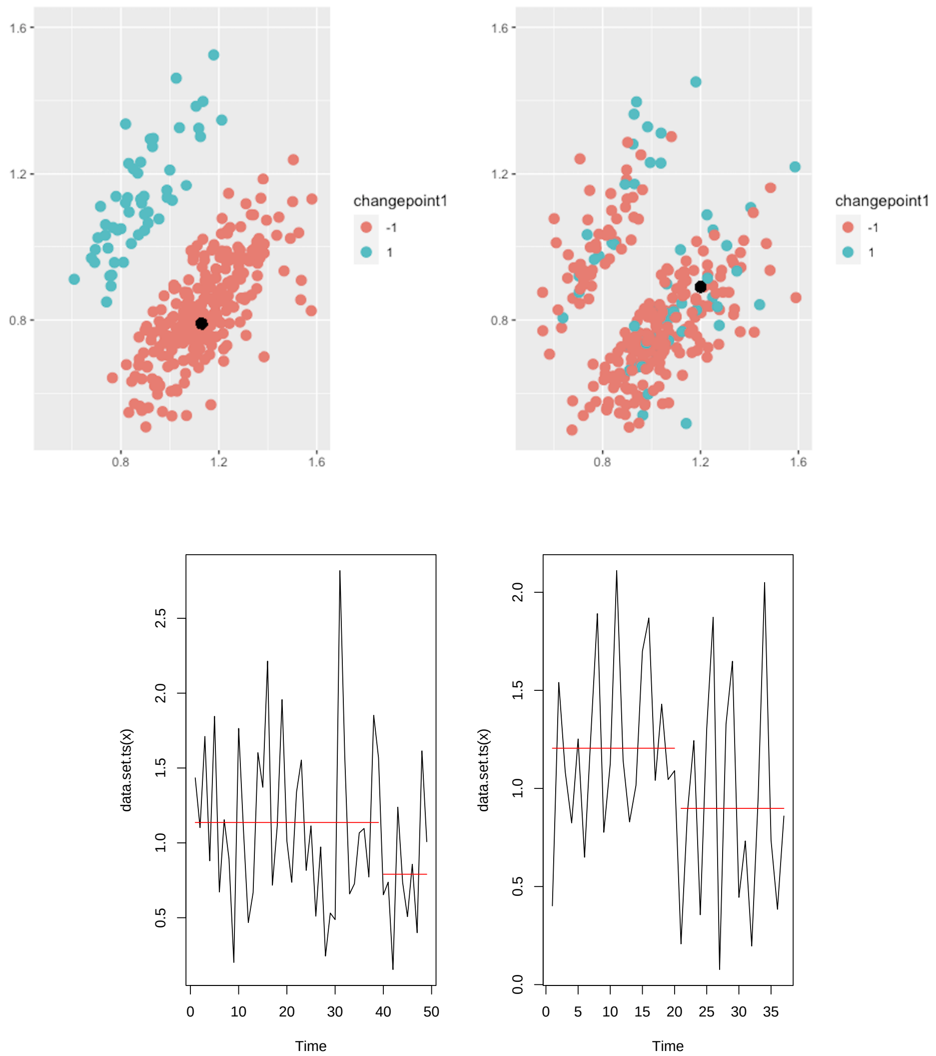

Figure 6.6: 1. Change point of the injured player (black dot) in comparison of the studied dataset.
2. Change point on variance acceleration

6.5 Discussion

In this work, we have seen different tools that could help to detect fatigue at different levels. First of all, different results showed significant difference between both halves. Obviously, there is a global metrics drop among player individual performance. Some might say that the second half is like the first half with lower intensity. But maybe it's more than that and both halves have to be considered in a different way. For instance, signs of change point obtained above do not have the same interpretation/impact on the game outcome depending on the half it occurred. Both in variance acceleration and surface area variation. To briefly summarise findings, dominating the first half is more about strategy and team play where a positive change point (i.e finishing the first half in higher standard) does not improve outcome. However, in second half the physical aspect is more important, a positive change point , who are performed by player less fatigued than those with negative change point are able to make a significant outcome difference. Thus, for future work it could be interesting to adapt fatigue quantification and detection with respect to the half considered.

The main point of detecting fatigue is to avoid injuries. Therefore, to be helpful to coaching staff these tools have to aim to measure and detect fatigue to make a substitution before the potential injury occurs. However, here we performed only offline analysis with considering data of the whole game. Regarding change point, there are method to perform online change point and thus could be a further research line to consider.

Global/local metrics such as surface area variation and radius analysis could help to catch fatigue trends that individual metric do not reflect. Those introduced in this work are just some examples and probably other more relevant metrics can be use instead.

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