# Change point detection of fatigue using the martingale statistic

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## ABSTRACT

In this paper, we research the change points of fatigue that are computed with the martingale statistic by comparing them to the Rate of Perceived Exertion (RPE) and the change points of lower extremity joints. The data that was used is IMU data collected from 5 participants who performed a fatiguing run, during which they also assessed their RPE. The martingale trajectory is a newly introduced novel method, which is used for testing change in a data stream. The change point is the moment that the data stream has significantly changed. The relation between the change point and the RPE showed deviating results and should be investigated further. Patterns in the timing of the change points were found, and an investigation with a bigger population should be done to test the validity of the results.

## KEYWORDS

running, martingale statistic, fatigue detection, change point detection, IMU, RPE

## 1 INTRODUCTION

Running is one of the most popular exercise activities in the world in terms of participation. The popularity probably comes from a combination of its health-related benefits and low entry-level [1]. Next to that, it can also be rewarding and anti-depressive[2]. The group of people that practice running is diverse, which leads to various runner types, all having their own attitudes, interests and opinions [1].

Although running is popular, the dropout rates of running are also high. This is due to running-related injuries and demotivation [1]. The most seen running-related injuries are injuries in the knee, ankle, lower leg and foot/toes [3]. One of the causes of these injuries can be fatigue [4].

In recent years, the availability and use of running-related technology have also increased exponentially [1]. Not only professional athletes are collecting and analyzing data but also amateur runners are collecting data to see how they did. The use of wearable sensors, which can measure the speed, distance and heart rate, is getting more popular [5]. On Strava alone, more than 7 billion activities are shared [6]. Next to mobile phones and smartwatches, there are various other techniques to collect data about a run. This could e.g. be with IMU sensors or cameras[7]. These sensors could focus more on separate body parts, e.g. the lower extremity joints.

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Data collected from a run could be used to come to new insights, using analytical techniques, e.g. machine learning. One of the applications could be to use the data from the IMU sensors to distinguish between fatigue levels with a machine-learning classification algorithm trained on bio-mechanical features [8].

The martingale test statistic is a recently introduced novel method for detecting change in a data stream. This method was used in previous work for fatigue detection in a fatiguing run, where was concluded that all runners had at least one joint suitable for that task [7]. This paper uses the martingale statistic to investigate how the change points of fatigue and the Rate of Perceived Exertion (RPE) assessed by the participants relate to each other. Secondly, we want to see to what extent there is a pattern in the timing that the change points of different joints occur.

We define the following research questions:

**RQ1** What is the state of the art in fatigue detection while running?
**RQ2** How do the change points of fatigue found in measured data relate to the RPE level as expressed by the participant?
**RQ3** To what extent is there a pattern in the timing that change points of different joints occur between different participants, and between different joints within participants?

This paper will first provide some background in fatigue and data collection, followed by related work, aiming to look at different machine-learning approaches that have been used for fatigue detection. The methodology explains the data source, the preparation of the data and how the martingale statistic was applied. Afterwards, the resulting graphs are shown, together with graphs derived from the change points. These results are then discussed and concluded.

## 2 BACKGROUND AND RELATED WORK

This section provides a background on fatigue and sensors that can be used for collecting data during a run. Related work is shown, where the focus lies on the different machine-learning techniques that have been used for fatigue detection.

### 2.1 Fatigue

Enoka and Duchateau [9] divide fatigue into two attributes, perceived fatigability and performance fatigability. Perceived fatigability describes the changes in the sensation of the performer and can be seen as psychological fatigue. Performance fatigability describes the decline in an objective performance measure over a period and can be seen as physical fatigue.

Research has shown that fatigue leads to higher step variability and lower leg stiffness. There is greater contact with the ground and shorter flying time [10]. Fatigue also increases the risk of injuries. Exercising while fatigued shows an increase in stress, strain, shear and impact in the lower limbs, potentially increasing the risk of injury [4]. Acute fatigue affects the lateral ankle sprain (LAS), patellofemoral pain syndrome (PFPS) and hamstring injury risk profile [11].

## 2.2 Sensors

There is a broad scale of sensors available for collecting data during a run. A smartwatch can record e.g. the heart rate, speed and distance [5]. An inertial measurement unit (IMU) can be attached to the body of an athlete and measures the linear acceleration, orientation and angular velocity. It does so with the use of an accelerometer, gyroscope and magnetometer. An accelerometer is a sensor which measures the inertial acceleration and angular rotation A gyroscope sensor measures angular rotation and angular velocity. The magnetometer measures the bearing magnetic daring, with which it can improve the reading of the gyroscope. The different sensors can be calibrated to get more accurate output data [12].

The data from these IMUs could derive bio-mechanical features which can be used for distinguishing between different fatigue levels using a machine learning classification algorithm trained with those features [8].

Other sensors that have been used to collect data that can be used for machine learning are surface-electromyography (sEMG) sensors [13] and ETHOS devices [14].

## 2.3 Related work

Much research has been conducted regarding fatigue detection. Marotta et al. [15] performed a literature review on accelerometer-based identification of fatigue during physical exercise. The chosen papers either performed fatigue identification or analyses of changes in biomechanical parameters due to fatigue and either used accelerometers or IMUs. They concluded that machine learning could help detect fatigue as fatigue classification had an accuracy between 78% and 96%. Their discussion concludes that there is still work to be done regarding the use of machine learning for fatigue detection.

Not only do machine learning models influence the results of machine learning, but the smoothing of data could also help improve performance. Smoothing filters raw data to decrease the noise and can help increase the accuracy of RF with a single IMU by 15% [16].

*2.3.1 IMU data.* Binary classification of single IMUs data can differentiate between non-fatigued and fatigued running states with a high level of accuracy and shows the potential of the use of IMU data [17]. IMU data have been used further in other research, with different machine learning principles being applied.

Random forest (RF) and support vector machine (SVM) model validation have been applied to the dataset received from IMUs to classify running fatigue and fatigue levels. It was concluded that the classification with RF is better than SVM, with the accuracy of tibial IMU data accomplishing 87.5%. Further, they also conclude that the increase of sensors improves the accuracy, as the highest classification accuracy was found when the data coming from the tibia and thigh IMU are combined [18].

Chang et al. [19] used deep learning to predict running fatigue. With the use of IMU-derived data, several deep learning models were used to classify running fatigue and fatigue levels. They concluded that both CNN and LTSM could complete the classification of fatigue IMU data and that the combination of the two models is superior to the independent models.

Basu and Proksch [7] used a newly introduced novel method for detecting fatigue, namely the martingale statistic. In their paper, a mathematical definition was provided and a case study was performed. The martingale statistic is used to sequentially test for change in a data stream. Two graphs are plotted, the martingale bound and the martingale trajectory. If the distribution of the data changes throughout a run, an upcrossing of the trajectory over the bounds is expected and the crossing is called the change point. The performed case study concluded that all runners have at least one joint suitable for fatigue detection. They also concluded that the behaviour of the martingale trajectory is in line with the assessed RPE level.

This paper will use the same method for detecting fatigue. However, our focus lies on the change points of the joints that occur. As concluded, the martingale trajectory is in line with the assessed RPE level and we want to see whether the change point of the joints relates to the RPE at the time of the change point. Next to that, we want to see how the timing change points of the joints of a participant relate to each other and whether there is a pattern to be found across participants.

*2.3.2 Other sensors.* Surface-electromyography (sEMG) sensors could also be used for fatigue detection. The sensors can be used to predict muscle fatigue while running by estimating lactate concentration in blood. The collected samples were labelled with a class of fatigue level. A random forest model was trained with the labelled samples and could classify fatigue and could classify fatigue with high accuracy [13].

# 3 METHODOLOGY

Figure 1 shows the overview of the methodology, including the source of the data, the data preparation and the computation of the martingale statistic. This section explains the scheme in more depth.

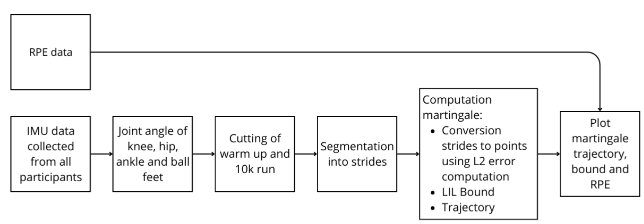


**Figure 1: Block scheme methodology**

## 3.1 Data source

The data I used was earlier collected by other people[1]. For the data collection, 11 athletes performed an indoor run with Xsens IMUs attached to their body. The data collected of the x, y and z values of velocity, acceleration, angular velocity, angular acceleration, position and joint angles.

[1]Benchmarking paper, unpublished

During the indoor run, the athletes were asked to assess their Rate of Perceived Exertion on a scale of 1 to 10 every 90 seconds. The picture in appendix A was shown to the athletes before their run, such that they knew how to assess the RPE.

From the data collected, we used the data and RPE from 5 participants, numbered 1, 4, 6, 7 and 9. We chose to use the z-axis of the joint angle of the lower extremity joints, namely the hips, knees, ankles and the balls of the feet, based on the bio-mechanical point of view.

## 3.2 Pre-processing data

Figure 2 shows the structure of the executed run. Our focus lies on the fatiguing run, and therefore we need to cut off the the warm-up and the 10k part, indicated with the striped line. The 10k part is a part where the athletes were asked to run at the average speed that they would run for a 10-kilometer run. After that, the fatiguing run starts, where the speed is set to 103% of the average speed they did before such that fatigue is induced. The martingale statistic is an increasing process, which means that, on average, it tends to rise over time, eliminating the need to cut off the last part of the run for analysis.

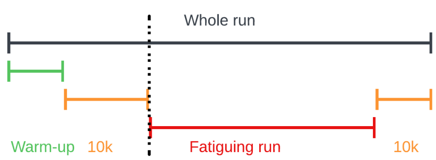


**Figure 2: Structure of executed run**

Figure 3 shows a snippet of the data that is used, where the y-axis shows the angle of the right knee. For the martingale statistic, the data has to be segmented into strides. To segment the stride, the strides are cut at a peak or a through. A stride could contain multiple peaks or throughs, a knee stride e.g. contains 2 peaks. To cut off the stride at the right peak, a minimum height to look for peaks should be determined.

The minimum height is determined by first looking at a snippet of the data similar to Figure 3. From the snippet, we estimate a height, which falls above the lower peak, as that peak is part of the stride. With the estimated minimum height, the data points of the peaks are determined. The data points between two peaks are a stride. If the minimum height is estimated correctly, a plot of all strides would show that all have a similar curve. If there are anomalous lines in the plot, a different minimum height is tested, until all strides have similar curves, as in Figure 4.

## 3.3 Martingale statistic

Next, we want to convert all strides into points, where every point represents a stride. We select the average curve of the first 10% of the data as a benchmark. The remaining curves are compared 1 by 1 to the benchmark using the L2 error function. This function subtracts the curve from the average curve. The outcome is the absolute value

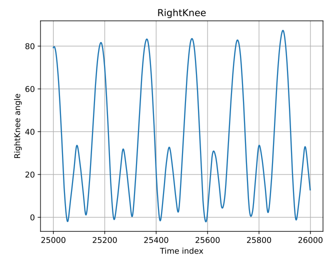


**Figure 3: Snippet data**

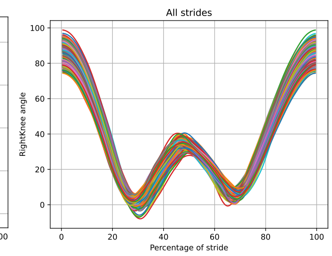


**Figure 4: All strides**

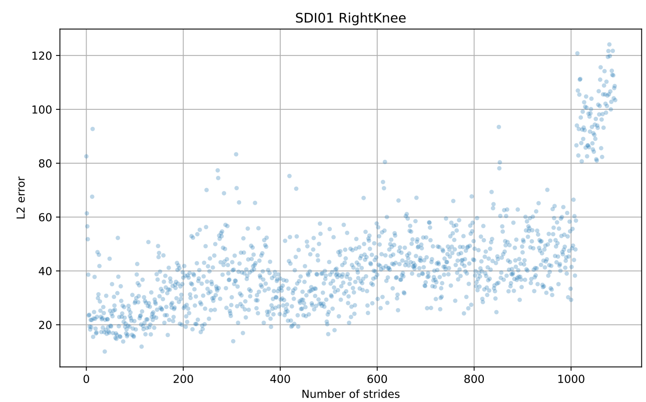


**Figure 5: Plot of point data**

of the subtraction. An example outcome of the comparison of all curves of a joint can be seen in Figure 5.

With the point data, the computation of martingale trajectory and bounds is executed, using the algorithm defined by Basu and Proksch [7]. The martingale statistic is a sequential test statistic that detects changes in stride patterns. The martingale trajectory is the line that shows the change that occurs in the point data that was given. The martingale bound is used to determine the moment that the change in the data is significant. If the trajectory crosses the bound, the change in data is significant and that point is called the change point.

For the computation, the local level $\alpha = 0.22$ was chosen, based on the conclusion of Basu and Proksch [7].

## 3.4 Plotting

The martingale trajectory and LIL bounds are plotted over the number of strides taken. To be able to compare the possible change points with the RPE, the RPE should be plotted within the same graph as the trajectory and bound.

First, the starting points should be set equal to each other, as the start was cut off from the data. By computing the amount of data points there are every 30 seconds, we could determine where to start with the RPE line. After that, the RPE is distributed along the length of the martingale trajectory.

## 3.5 Derivative plots

After the results were studied, there were intuitions about the result. To test these intuitions, derivative plots based on the change points were created.

To assess the order of change points, they are normalized on a scale from 0 to 1. Here, 0 corresponds to the stride number of the first change point, while 1 corresponds to the stride number of the final change point. For every change point of a participant, the stride number of the change point is subtracted by the stride number of the first occurring change point and the result is divided by the difference between the stride number of the initial change point and that of the last change point.

The second plot is created to illustrate the timing of the change points as a percentage of the run.

# 4 RESULTS

In this section, the resulting graphs of the computation of the martingale statistic are shown, together with the derivative plots.

## 4.1 Computation results

Figure 6 shows the outcome of the computation for the right knee of participant 1. The x-axis is the number of strides taken and the y-axis is the outcome of the martingale formula. The martingale trajectory and LIL bound are plotted over these axes. The right y-axis plots the RPE on a scale of 0 to 10 at the given number of strides taken.

The change point of a joint is the moment that the stride curves statistically have changed. In the graph, the change point is the moment the martingale trajectory crosses the martingale LIL bound. In the figure, we observe that the change point occurs after about 600 strides.

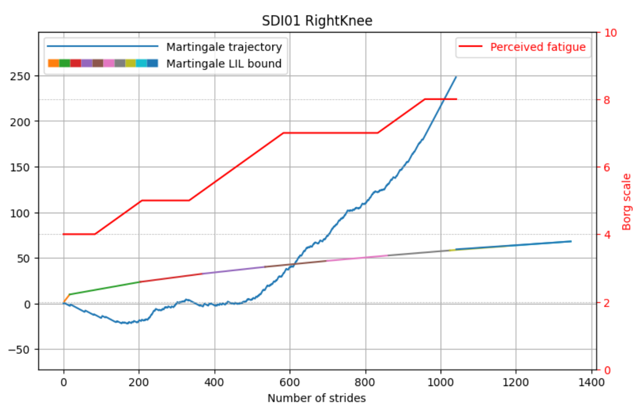


**Figure 6: SDI01 Right knee results**

Figure 7 shows the martingale trajectories from all joints of Participant 1, together with the LIL bound and the RPE. We observe that all joints have a change point, with the first change point occurring after about 400 strides and the last change point occurring after about 1000 strides. The change points of the hip are the only joints where the left and right are within 10 strides of each other, while the right and left ball feet have the biggest interval between them, with almost 500 strides.

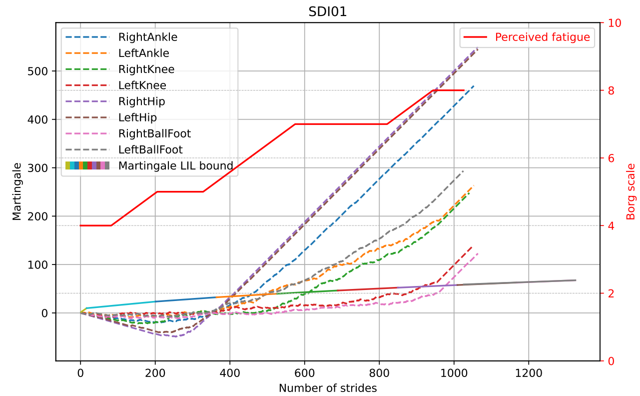


**Figure 7: SDI01 all joints**

In appendix B, the results of the computation of martingale for all athletes that participated can be found.

## 4.2 RPE

The change points and RPE are compared by determining the location of the change point and the corresponding RPE level. The athlete was asked to assess their RPE every 1,5 minutes, and this converts for participant 1 to about 150 strides. When there is a rise in RPE level, it happens somewhere in the interval between the two moments that it was asked.

Observing Figure 7, the participant starts the fatiguing run at RPE level 4 and rises eventually to level 8. Participant 1 shows a rise from RPE level 5 to 7 over 2 intervals, during which the change points of the hips, ankles and left ball foot occur. For Participant 4, the change points of the hips and ankles occur in the 2 intervals that the RPE rises from 6 to 8, and the same change points for Participant 6 occur around the interval where the RPE level goes from 5 to 6. All change points of the joints of participant 7 occur when the RPE level is stable at 7. Participant 9 has the first change points around the rise of RPE level 7 to 8.

## 4.3 Joint patterns

When looking at the graphs of all participants in B, it can seen that all joints have a change point. When eyeballing the results, the change points seem to be distributed widely across the run, with Participant 7 having the smallest interval of change points, namely 150 strides. It seems like the right and left hip often have a similar trajectory and change points around the same stride, with the biggest interval of all participants between them being just under 70 strides. It also seems that the hip joints are always among the first change points. However, these intuitions are from eyeballing the results. To get more quantitative insights into these intuitions, two derivative graphs were made, seen in Figure 8 and 9.

In Figure 8, the change points are distributed in normalized time for all participants, with 0 referring to the first occurring change point, and 1 referring to the last occurring change point. The change points of all participants are plotted per joint, to be able to compare them. The different colours referring to the participants have been

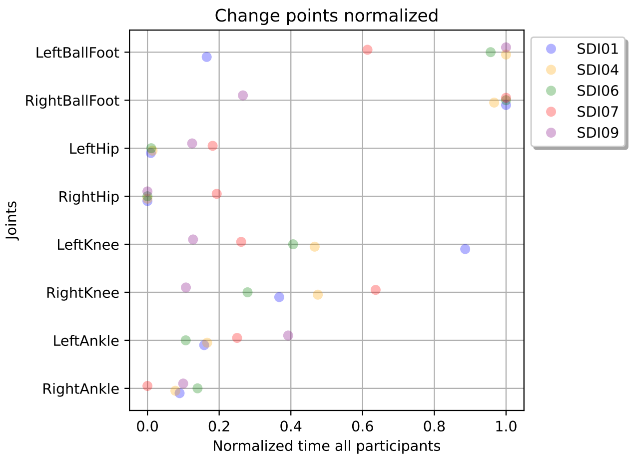


**Figure 8: Change point distribution normalized time**

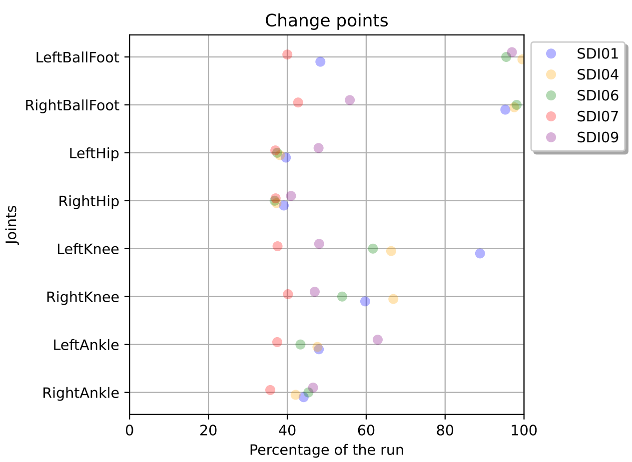


**Figure 9: Change point distribution throughout the run**

plotted with a small offset, such that overlapping points all can be seen.

Figure 9 shows at what percentage of the fatiguing run the change points of the joints occur. There again is a small offset for showing overlapping points. The first change point for every participant occurs after about 35-40% of the run. All change points of participant 7 occur between 35 and 45% of the run. It can be determined that the change points of the hips and right ankle occur between 35 and 50% of the fatiguing run. The occurrence of the other change points varies between 35 and 100% of the run.

## 4.4 Changing starting points

To test the robustness of the martingale statistic, different starting points can be compared. If the martingale statistic were to be robust, the change points would occur around the same stride as the first results, minus the number of strides that have been cut off at the start.

In the results in appendix B, the first 2 minutes were cut off. Appendix C shows the results where the first 2.5 minutes were cut off. The difference between these two results is about 50 strides, and the expectation therefore is that the change points would be 50 earlier.

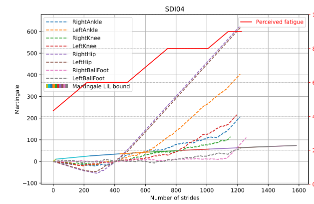


**Figure 10: Results Participant 4 where the first 2 minutes were cut off.**

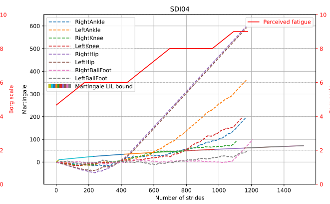


**Figure 11: Results Participant 4 where the first 2.5 minutes were cut off.**

When comparing the results from Participant 4 in Figure 10 and 11 to each other, we can see that not all joints have a change point in Figure 11, while they do in Figure 10. Next to that, it can be observed that the order of the change points is not the same in the two figures.

## 4.5 Observations

When eyeballing the graphs in Appendix B, we see that in all graphs the martingale trajectories of the different joints of one participant cross each other around the same time. When looking at the trajectories of the joints, it seems that when a trajectory dives deeper before the change point, it rises higher after that point.

# 5 DISCUSSION AND FURTHER WORK

In this section, the results from Section 4 are discussed and further steps are discussed.

## 5.1 Relation change points and RPE

Using the results described in Section 4.2, it seems that on average the first change points occur around a rise in RPE level and that the change points of the hips often happen around a rise in RPE level. The RPE level around these first change points lies between 5 and 8. Change points that occur after the first change point differ in whether they occur around a rise or when the RPE level is stable.

It should be considered that the distribution of the RPE across the strides taken is an estimation. It was computed based on the amount of data points that were collected, but it is uncertain to what extent this is correct.

Next to that, although the guidance in appendix A was shown to the participants, the assessment of RPE done by the participants might have some bias. To get to a better basis for the assessment per participant, the participants could do more runs where they assess their RPE and the results of the same participant can be compared. A smaller interval of assessing the RPE could help here, to come to even better results.

## 5.2 Joint patterns

As described in Section 4.3, the distribution of the joints for most participants seems to have a wide distribution and Figure 8 and 9 increase these suspicions.

When eyeballing the results in Figure 8, some interesting patterns can be found. We see that change points for the hips either occur as first or occur before 0.2 of the normalized time once that first change point has occurred. The knees and left ankle have a wide distribution of change points. One of the ball feet is always the last, and on average they occur late in the run.

When comparing the left and right sides of a joint with each other, the hips seem to be the only ones where the right and left sides of the same participant have a change point around a similar moment. The other joints also seem to have a similar distribution, except for the ankles. The left and right ankles seem to have a deviation in their distribution.

From eyeballing the results, the hips have on average their change point earlier than the knees. To prove this, a statistical test could be executed.

The results in Figure 9 mostly back up the conclusions we got from Figure 8. We again see that the left and right hips are always close to each other and that the knees and ball feet have a wide distribution. It does not back up the suspicion of the left and right ankle having a deviation in their distribution, as they on average occur around the same time in the run. A statistical test on the mean difference of the change points location of the left and right sides of a joint could be executed.

Figure 9 also shows that Participant 7 is an outlier where all change points lie within 10% of the run once the first one occurs. It also shows the wide distribution of the joints of the other participants, with the change points occurring between 35 and 100% of the run.

Although some patterns were found in the results of the 5 participants, it is hard to make definitive conclusions out of these. This firstly is because it is unknown whether a single participant shows the same results over multiple runs. An investigation into this would result in more reliable conclusions for that individual participant. The small population that was tested already showed deviations and therefore research with a bigger population could generalise the conclusions.

### 5.3 Robustness martingale statistic

In section 4.4, different starting points were compared. As it is not known what the exact moment that the fatiguing run started, the moment where to cut off the data is hard to determine. Different results can be seen when the graphs with different starting points. In Figure **??**, we can see that not all joints have a change point with a different starting point and that the order of occurrence of change points is also different. The other figures also show that the change points on average do not 50 strides earlier as we expected.

Further investigation should be conducted into the reliability of the martingale statistic. In such an investigation, the start of the fatiguing run should be more clear, such that the correct cut-off point can be chosen.

### 5.4 Observations

As described in Section 4.5, we observed that the trajectories of the joints seem to cross each other and that a trajectory that dives deeper rises higher after the change point. This observation should be tested mathematically in further work to see what happens at that point and why this happens.

### 5.5 Limitations and further work

It should be considered that all results shown and analysed, are limited to a small population. The conclusions that are made, are based on the data collected from 5 participants, 1 run per participant. A bigger population and more runs per participant should be used to test the validity of the results.

The martingale statistic checks whether there occurs a statistical change in the strides throughout the run, we do however not know what changes to the stride curves. Therefore, it should be investigated bio-mechanically what changes in the stride curves when the change point is detected. It is also unknown what the change in the stride curve does to the joints and whether it increases the chance of injury risk or not. This could also be investigated bio-mechanically.

## 6 CONCLUSION

This paper has provided a background into fatigue and sensors that can be used for collecting data during a run. The state of the art in fatigue detection has been provided by demonstrating several machine-learning techniques that have been used for fatigue detection.

The martingale statistic has been used to compute change points of fatigue. This work compared the computed change points to the RPE assessed by the participants, but a definitive conclusion could not be made from the comparison.

Next to that, this work researched whether there was a pattern to be found in the timing of change points. For this purpose, the timing change points of the joints of a single participant were compared to each other as well as the timing of the change points of the joints across participants. We have shown that there were patterns found in the data collected from 5 participants.

In conclusion, this paper has shown that the martingale statistic can detect change points, it should however be tested on a bigger population to conclude how the occurring change points from different joints relate to the RPE and each other.

## 7 ACKNOWLEDGEMENTS

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## GLOSSARY

**ETHOS** ETH orientation sensor: customized IMU for unconstrained monitoring of human movement. 2

## ACRONYMS

**CNN** Convolutional Neural Network. 2

**IMU** inertial measurement unit. 1, 2, 6

**LTSM** Long short-term memory. 2

**RF** random forest. 2

**RPE** Rate of Perceived Exertion. 1, 2, 3, 4, 5, 6

**sEMG** surface-electromyography. 2

**SVM** support vector machine. 2

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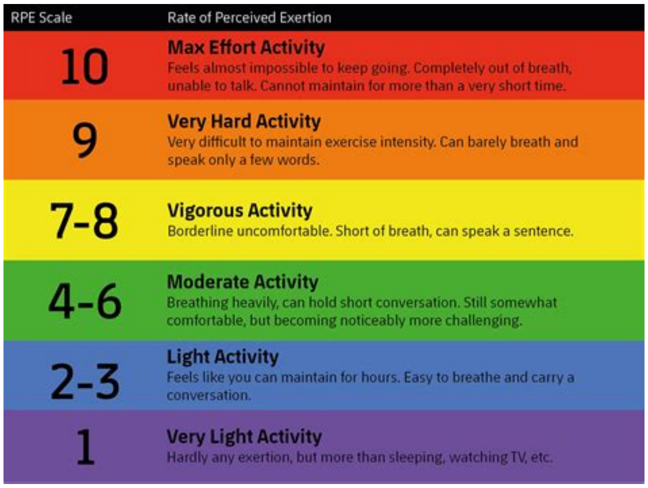
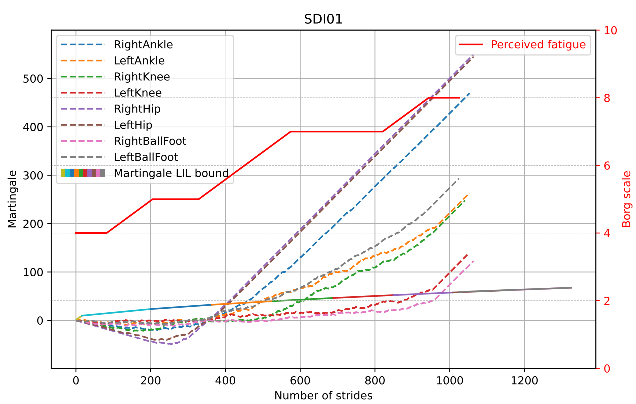
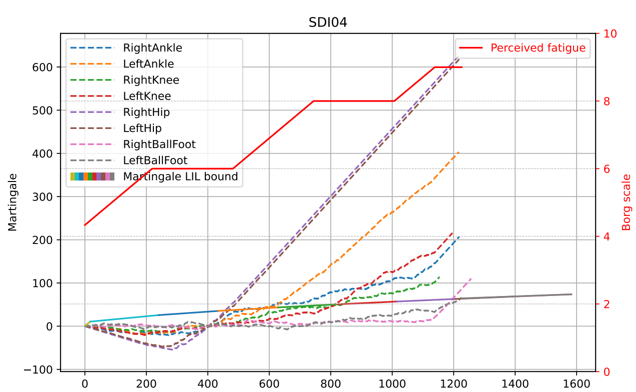
## A RPE

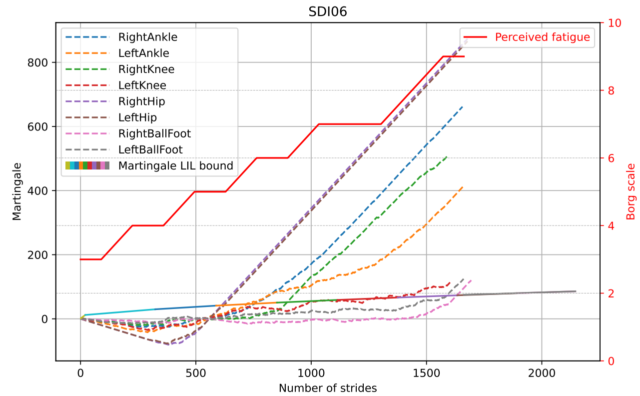


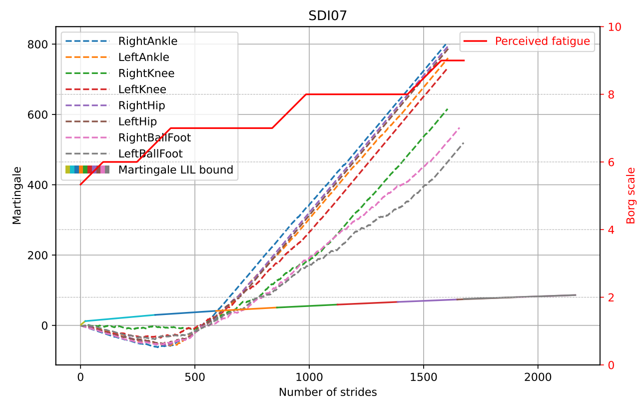
| RPE Scale | Rate of Perceived Exertion |
|---|---|
| 10 | **Max Effort Activity** Feels almost impossible to keep going. Completely out of breath, unable to talk. Cannot maintain for more than a very short time. |
| 9 | **Very Hard Activity** Very difficult to maintain exercise intensity. Can barely breath and speak only a few words. |
| 7-8 | **Vigorous Activity** Borderline uncomfortable. Short of breath, can speak a sentence. |
| 4-6 | **Moderate Activity** Breathing heavily, can hold short conversation. Still somewhat comfortable, but becoming noticeably more challenging. |
| 2-3 | **Light Activity** Feels like you can maintain for hours. Easy to breathe and carry a conversation. |
| 1 | **Very Light Activity** Hardly any exertion, but more than sleeping, watching TV, etc. |

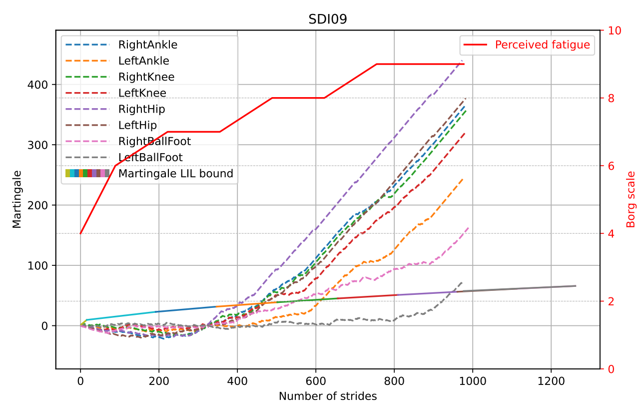
## B PARTICIPANT GRAPHS 2 MINUTES



# C PARTICIPANT GRAPHS 2.5 MINUTES