Analysis of soccer player's activity profiles using deep learning technique

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1. Introduction

Recently, with the development of technology, the measurement of physical data using wearable devices has become a common in the field of team sport coaching. Wearable devices are now widely used to understand the physical demands of soccer matches (Krustrup, Mohr, Ellingsgaard, & Bangsbo, 2005). The devices contain Global Positioning System (GPS) and inertial measurement units (IMU) with accelerometers, gyroscopes, and magnetometers which can quantify the movements of non-running-based work such as acceleration, deceleration and change of direction.

Activity profile (Suarez-Arrones et al., 2015; Varley, Fairweather & Aughey, 2012) and time-motion analysis (Castellano, Blanco-Villasenor & Alvarez, 2011) are the major research tools using wearable devices as they can measure a large number of players simultaneously and analyze them in a short time. Although the data taken with wearable devices has been used to measure the items, not many applications of machine learning methods such as deep learning to analyzing the raw time-series data has been reported so far in terms of soccer. The aim of this study was to classify the activity profiles of soccer players during a game based on the time-series data measured by wearable devices utilizing a Fast Fourier Transform (FFT) method. If detailed analysis using raw data can be conducted through this research, it will be possible to analyze the movement patterns of players from the data alone, which will enable analysis in a shorter time than the conventional method of analysis that requires considerable time and effort and will contribute to the coaching field.

2. Method

2.1 Subject and match data

Eighteen collegiate female soccer players (age: 20.3 ± 1.29 years; height: 161.1 ± 5.65 cm; body mass: 55.6 ± 6.24 kg) from the same college league team participated in this study. Goalkeepers were excluded from this study. Eight matches (weather: sunny or cloudy; temperature: 22.9 ± 4.45 ℃; humidity: 62.7 ±15.1 %) of the 33rd Kanto University Women Football League 2nd Division in 2019 were examined. The match times were a total of 90 minutes with 45-minute halves and a 15-minute interval between the halves.

2.2 Data measurement and analysis

Activity data from IMU were collected using wearable devices (OptimEye S5 and G5, Catapult Sports, Australia) operating at a sampling frequency of 100 Hz. By combining the obtained information, we could detect the inclination and direction. Thus, it was possible to measure not only the acceleration and deceleration frequencies but also the right and left movement frequencies.

The players wore special harnesses that enabled these devices to be fitted to their upper backs. To extract and analyze the data of only those players who competed in the match, the match start time, the first half end time, the second half start time, and the full time were recorded based on the ratio clock. Moreover, the time of a player exiting and coming on as a substitute was regarded as her time of leaving and entering the soccer field, respectively. After recording, the data were uploaded into a PC and analyzed using the software package (Openfield version 2.2.0, Catapult Sports, Australia). After analyzing with the specific software, we extracted 100 Hz raw data and performed a FFT of the data with Python to analyze the movement patterns of each player. The items to be analyzed were the value of acceleration for the x-, y-, and z- axes. After analyzing the data, we compared the video to the data to see what movements were measured. Using the data transformed by FFT, we have been trying to identify event or play according to each part of time series data.

To identify the event or play we apply unsupervised clustering method of deep learning, aiming to group the FFT data into classes entirely without labels. Here, we try to cluster any kind of unlabelled paired data (X, X') by training a network (Φ) to predict cluster identities.

3. Result and discussion

In order to evaluate the analysis of players during matches based on the above models, we needed to divide 100 Hz raw data measured over 90 minutes into 3 seconds intervals. Figure 2 shows an example of the time-series acceleration data and its FFT when the player cleared the ball.

As shown in Figures 2, we can see the pattern of the amplitude of frequency between directions. We can also see the difference of the patterns between plays appeared in the game.

In addition to Figures 2, we were able to analyze more types of the movement. For example, we were able to analyze movements of contact with opposing players, running speed changing to fast speed, driving a cross and throw-in and so on.

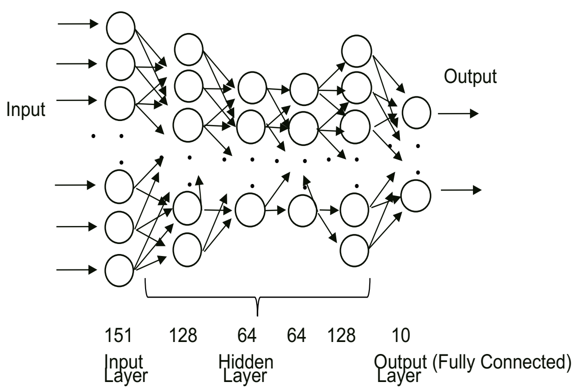

Figure 1. Example of a simple deep network architecture

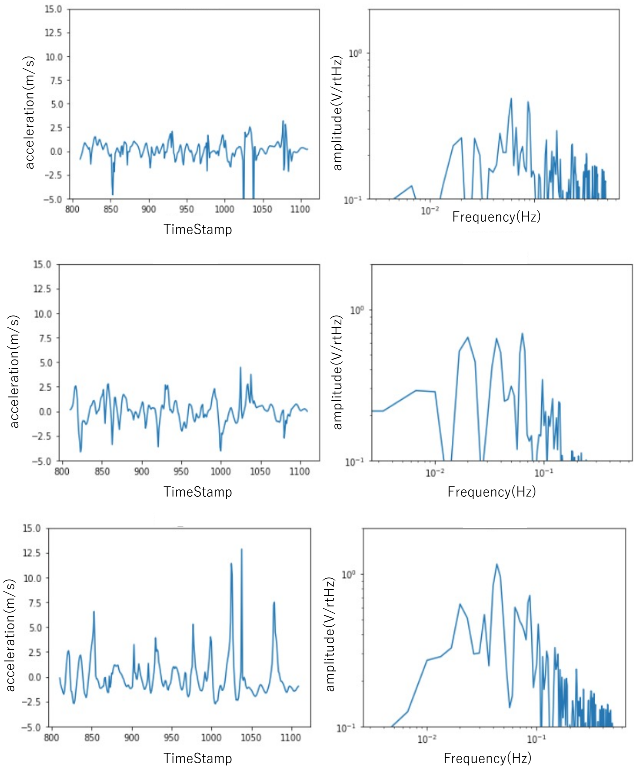

Figure 2. Acceleration of the player cleared the ball (Top: x-axes, Middle: y-axes, Bottom: z-axes)

4. Conclusion and Further study

In this paper, we have used the FFT method to analyze the movement patterns of each player from 100 Hz raw data. As a result of analysis, this procedure could make it possible to identify each movement pattern appeared in the game without watching a video.

In this paper, we have just analyzed the situation of play from 100Hz raw data using FFT. In order to contribute to soccer teams that use wearable devices to measure data, it will be necessary to analyze data about every movement during a soccer game in the future. As this study is still in progress, we plan to present more in the conference.

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