The Development of Automatic Training Analysis Using 3D Accelerometer in Male Young Elite Soccer Team

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Abstract: In recent years, there has been a growing need to introduce IT technology to improve performance in professional sports and athlete training. However, while technological innovation is taking place, the amount of data that can actually be acquired is becoming enormous, and unless there are people who can provide expert advice, the compatibility with training is not high. In this study, we aimed to build a system that uses a three-dimensional accelerometer to appropriately evaluate the performance of athletes during training. We developed a classification function that detects and separates intervals from the measured time series data and automatically divides the separated sections by type of training. As a result of evaluation using data from 16 days of training for a U-18 soccer team (n=33), intervals were detected with 100% accuracy, and five types of training were detected with 80% accuracy. We confirmed that a system equipped with the developed function could speed up feedback to athletes.

1 INTRODUCTION

1.1 Background

In the field of professional sports and athlete training, there is a growing need for the introduction of IT technology for the purpose of performance improvement and injury prevention. In the past, evaluation of individual athletes' performance and team tactics and strategies in each sport was done subjectively by visual observation and video analysis by the coaches and instructors involved in the respective sports. Currently, with the development of highly accurate and compact wearable sensors and video analysis (Vickery *et al*.,2014). it is becoming possible to collect objective and quantitative data at all times during daily training.

Dhruv et al. (Dhruv *et al*.,2019) have shown that comparing the intensity of exercise during the week in question with the intensity of exercise in the past can lead to an estimation of the risk of injury to the athlete. The objective evaluation of the conditioning of athletes without relying on subjectivity is very useful not only for the individual but also for the team.

In addition to measurement technology, it is also expected to prevent injuries caused by overtraining by constantly monitoring the condition of players in various sports during games and practices and providing real-time feedback to the staff and players on site. Among IT technologies, wearable sensors are particularly suited to grasp actual numerical behaviours in various competitions because they can measure physical activity and vital conditions by simply being worn.

However, the burden of analysis is heavy on the field staff and others, and time is required for analysis after games and practices. For example, time is required to organize and manage the obtained data by linking them to the practice contents, and to adjust the analysis methods to the team characteristics. Although it is important to analyse the relationship between the level of physical activity and the occurrence of traumatic injuries and disabilities in sports and to use this information for prevention, it is still difficult to immediately predict the risk in the field.

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In addition, in the case of exercise data, for example, a decrease in running distance can be considered as a decrease in the condition of the athlete. However, it is not easy to distinguish which factor is responsible for the decrease in running distance, because the values change depending on the conditions and types of training menus that athletes are required to follow, regardless of their own conditions.

To achieve this, it is necessary to view the obtained data instantly and in an easy-to-understand manner. It is also necessary to provide numerical values that can be easily conveyed to athletes even by staff who do not have much specialized knowledge. Therefore, this research focused on developing equipment and measurement systems that meet the needs of the field.

Therefore, in this research, the time required for data analysis is greatly reduced by automating the organization of acquired data by dividing the time according to the content of practice by introducing AI analysis technology for sensor and video data and past injury history, etc., which has been difficult in the past, and by detecting signs of injury in real time and adjusting the amount of practice, which have been difficult in the past. The system aims to detect signs of injury in real time and to provide feedback such as adjusting the amount of practice, which was difficult in the past.

1.2 Purpose of Research

This study aims to reduce the burden of on-site data analysis, we aimed to develop technology that automatically classifies practice types from data collected using wearable acceleration sensors and to verify its accuracy.

2 MATERIALS AND METHODS

2.1 Performance Analysis Using IT Technology

This study clarifies the elements necessary for young players to make their professional debut and play soccer as a professional contract player not only in Japan but also in other countries. By analyzing in detail what kind of training is being done on a daily basis, we hope to give the players an opportunity to think about it. We will clearly and visually appeal to them what kind of training will produce what level of exercise intensity. In addition, teams with abundant financial resources can purchase and wear famous IT equipment, but if they are not economically well-off, there are fewer opportunities to wear cutting-edge equipment. In response to these, using our own developed sensors will also help eliminate economic disparities in sports. To achieve this, data from games and practices must be analyzed quickly. It is important to acquire data in real time and use it to protect players. Therefore, we devised a system that not only measures data but also provides real-time feedback as shown in Fig 1.

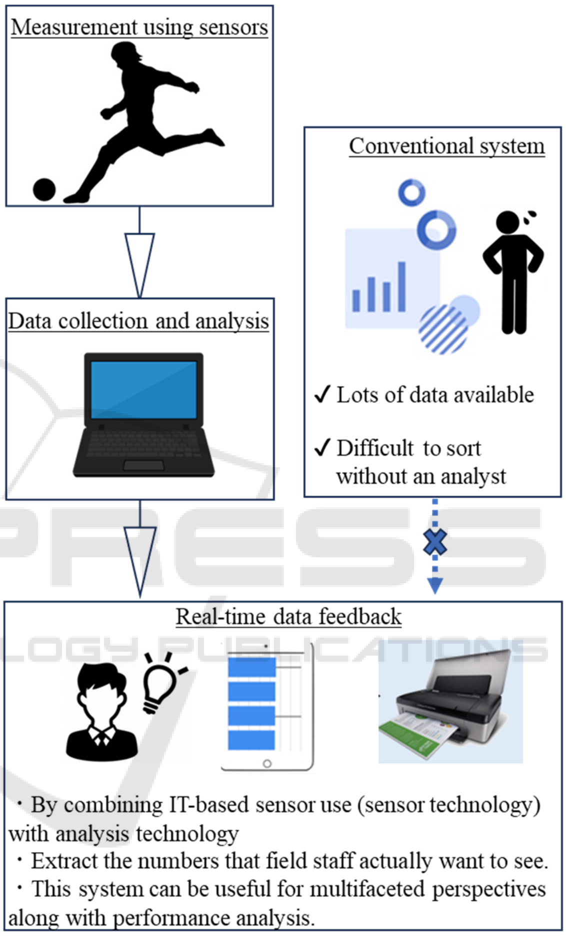

Figure 1: Packaged data feedback system.

2.2 Male Young Elite Soccer Player

The subjects were 33 youth soccer team players from the Japan Professional Football League (J-League) (teams with experience in the top ranks of international youth soccer tournaments), aged 15-18 years old. The period of the study was 16 days, excluding days when practice was suspended and days of international matches. The average practice time was 100 minutes/day, with a maximum of 2 hours/day and a minimum of 1.5 hours/day. Since some of these youth players will be promoted to the top team and become candidates for the national team, the data from their youth period is very important.

2.3 Measured Training

The content of the exercises was confirmed with the team coaches and consisted of five types of training: warming up and basic training (including stretching), group training (in which the amount of exercise varied greatly from player to player), low (Tactics training), medium, and high (Game training) intensity training in which all the players had the same amount of exercise. The training consisted of five types of training, which could be classified into low (Tactics training), medium and high intensity (Game training). The composition of the training sessions (Day 11 and Day 15) and the start and end times of each session were recorded visually and on video.

2.4 Wearable Acceleration Sensors

As shown in table1, a wristwatch accelerometer UW-301BT manufactured by A&D was used to measure athletes' exercise intensity. Figure 2 shows that the sensor was worn on the opposite wrist of the dominant hand, the measured data was triaxial acceleration, the sampling rate was 20 Hz, the measurement range was -4~+4 G, and the oxygen uptake at rest of 3.5 (mL/kg/min) was set as 1 G. It was also confirmed that the device could be used without any load or discomfort to the athlete and without interfering with the athlete's movement or training.As an index to evaluate the athlete's exercise, we scalarized the 3-axis acceleration vectors and calculated the averaged value in seconds as the exercise intensity (unit:G). By averaging over seconds, changes in acceleration due to minute arm movements can be smoothed out and converted into values that reflect whole-body movements, thus reducing the amount of information handled to the minimum necessary and facilitating analysis.

Table 1: Specification of wearable device.

Size	20 mm（W）×39 mm（L）×14 mm（H）
Weight	20 g
Measurement data	3-D acceleration(±4G)
Sampling rate	20 Hz
Communication	Bluetooth, USB
Battery	160mAh(Lifetime:10 days)

Figure 2: Appearance of wearable device.

2.5 Methods

In order to reduce the burden of data analysis in the field, which is the purpose of this study, we first aimed to detect intervals during practice by automatically dividing the data into practice types. Using the characteristic that the waveform of the exercise intensity of all the athletes decreases during intervals, we extracted the time period when the average value of the exercise intensity of the athletes performing the same practice for a certain period of time was less than a predetermined threshold value. The threshold value and the length of time for calculating the average value were determined by searching for the value that would increase the accuracy of interval detection the most (see table2).

The classification of practice content was then calculated from the athlete's exercise intensity data for each interval separated by intervals. Using multiple features corresponding to each interval, we used the K-means clustering method (Andri, 2022; Luiz et al, 2017), one of the popular unsupervised clustering methods, to mechanically classify the data into a pre-defined number of clusters. In general classification algorithms such as K-means clustering methods, it is necessary to select features that clearly differ by practice content in order to obtain the desired classification accuracy. Based on the observation of the practice contents and the investigation of the practice contents of general group sports, we hypothesized that the magnitude of players' movements (maximum/average), the similarity of movements among players (small variation), and the uniformity of exercise intensity within a segment (small variation) would be useful features, and designed a set of features shown in (see table3).

The proposed method was applied to the collected data for 14 days to detect intervals and classify each interval. For the classification, the number of classifications (see table3), which indicates the type of practice, is set to 4, since the team has roughly four types of training. The detected intervals and the

Table 2: Interval detection (study by exercise intensity and time).

Met's		Day1			Day2			Total(Day1+Day2)		
	(sec)	Positive	PPV	FP	Positive	PPV	FP	PPV	FP	FPR
1.5	20	0	0	0	3	32	0	23.1	0	0.0
	40	0	0	0	2	20	0	15.4	0	0.0
	60	0	0	0	0	0	0	0.0	0	0.0
	80	0	0	0	0	0	0	0.0	0	0.0
2	20	3	100	2	8	80	1	84.6	3	21.4
	40	1	33	0	7	70	0	61.5	0	0.0
	60	1	33	0	6	60	0	53.8	0	0.0
	80	0	0	0	6	60	0	46.2	0	0.0
2.5	20	3	100	5	10	100	8	100.0	13	50.0
	40	3	100	4	10	100	3	100.0	7	35.0
	60	3	100	0	10	100	0	100.0	0	0.0
	80	2	67	0	8	80	0	76.9	0	0.0
3	20	3	100	7	10	100	7	100.0	14	51.9
	40	3	100	4	10	100	4	100.0	8	38.1
	60	3	100	4	10	100	2	100.0	6	31.6
	80	3	100	1	9	90	1	92.3	2	14.3

PPV-positive predictive value,FP-false positive, FPR-false positive rate

Table 3: Practice menu detection by K-means clustering method.

Practice	PA/TA	PA/TSD	PSD/TA	MAX/TA
Training A	0.19	0.2	0.07	0.38
Training B	0.35	0.19	0.17	0.78
Training C	0.24	0.17	0.14	0.6
Training D	0.28	0.23	0.11	0.57
Training E	0.12	0.13	0.04	0.28

PA-player average,TA-time average, TSD-time standard deviation,
PSD-Practice intensity standard deviation,MAX-Maximum exercise intensity

classification results were compared with the records of the two days, and the accuracy was evaluated by the rate of agreement.

3 RESULTS

In the detection of practice intervals, the interval duration and threshold values were defined by observation and investigation of actual training and analysis of exercise intensity data. The specific values for the threshold values were set by using the values of Day 11 and Day 15, which were the teacher data within the measurement period, and by comparing the exercise intensity with the records of the content of the training for the two days by combining the time of 20, 40, 60, and 80 seconds for the four types of exercise intensity of 1.5, 2, 2.5, and 3 METs. We searched for the values that resulted in a 100% positive predictive value and a 0% false positive rate (see table 2). As a result, the categories of 2.5 METs and 1 minute were found to be the most consistent with the actual intervals.

In general, during intervals, athletes often listen to instructions from their instructors, in addition to rehydrating and preparing for the next training session. These criteria are also considered to be appropriate in that, based on the same observations, the threshold values are considered to be appropriate for exercise intensities that indicate walking or standing still. Fig 3 shows, with reference to these results, the exercise intensity data of Team A, which consists of 16 members, the team with the highest level among 33 members, for one day of practice. The waveforms representing the exercise intensity are also consistent, and as mentioned above, it is suggested that the interval is also the place where the intensity drops all at once.

Next, the classification of practice content was calculated from the athlete's exercise intensity data for each interval (see table 3). The results of the detection of intervals and the classification of practice are shown in Fig 4. Especially for the two days with visual recordings (Day11 and Day15), we compared the classification results with the results of visual and video recordings. The validity of the results of the classification of the training menus was also examined by interviewing the coaches and by visual recording. The results of applying the classification of the automatically clustered training menus to the classification of actual training sessions are also shown, based on the comparison with the values of the feature values and the observation recordings.

The training menus automatically clustered by the developed process were classified into 5 levels from Training A to E based on the values of the feature values (see table3). In comparison with the observation records, we found that the classification of Training A (Warming up), Training B (Group training), Training C (Game training), Training D (Tactics training), Training E, and the actual training menus are one-to-one. Training A (Warming up), Training B (Group training), Training C (Game training), Training D (Tactics training), Training E, and the classification of actual training menu. On the other hand, the classification E was found to indicate a rest interval that was not detected as an interval or a training session with particularly low exercise intensity. This may be due to the fact that physical training was not conducted during the measurement period, resulting in a different classification from the actual one.

Next, the results of the classification of training menus were compared in detail with the observation records to evaluate the accuracy of the classification. We found that all of the training breakpoints were consistent with those in the observation records. Furthermore, the classification of the training menus was found to be consistent with the observed data with a precision of 9/11. In particular, group training, including 4-on-2 ball keeping, which is the most frequently practiced exercise by the subject teams and is performed almost every day, was consistent without error. On the other hand, warming up and basic training, which are generally less intense, were difficult to distinguish from the other categories, especially when a more intense element was added.

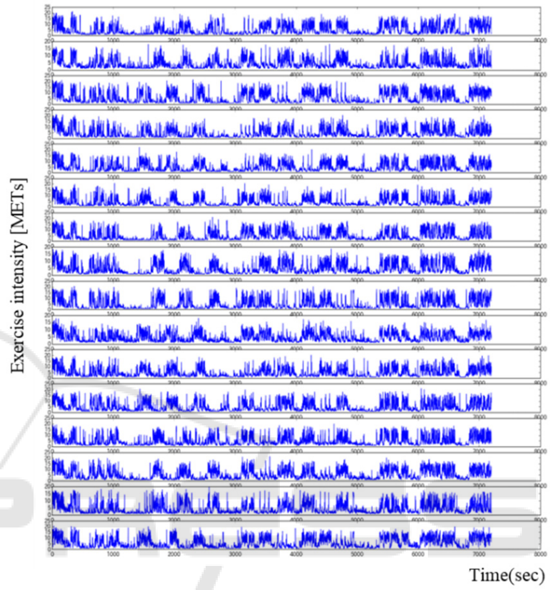

Figure 3: Exercise Intensity per Day.

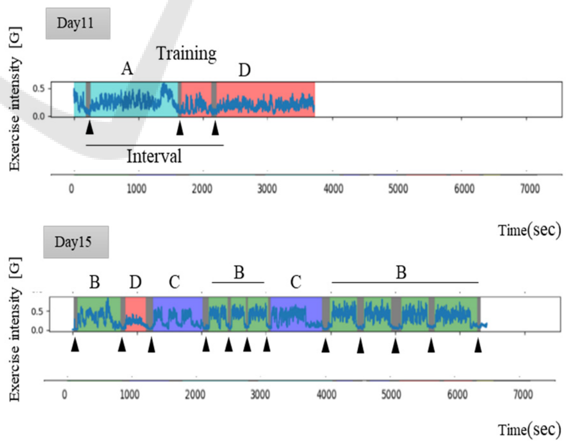

Figure 4: Interval detection and practice classification.

4 DISCUSSION

In this study, based on the data obtained from the results of practice and games with the wristband-type wearable accelerometer, a feedback report was prepared on the exercise intensity of each player regarding the evaluation items, and a report was made to the team. However, since each player and coach interpreted the measured data, there were cases in which it was difficult to understand the numerical values obtained and the implications derived from them unless a researcher was present. Even if an existing measurement system is introduced, it is not uncommon in the field of sports such as soccer that the data are not actually utilized in training, and the difficulty of how to process the huge amount of data obtained and how to make sense of them and how to understand the numerical values and utilize them in the field is also a problem that needs to be addressed. The challenges are not limited to the field of sports, but include the difficulty of how to make sense of the huge amount of data obtained and how to understand and utilize the numerical values. We have to give due consideration to this issue because it is related to our own health care (Mowafa & Bakheet,2017). Therefore, we referred to specific advice from team doctors, trainers, and coaches, as well as surveyed the opinions of athletes who actually took the measurements, and extracted usefulness and issues related to the report content and evaluation items. In addition, in the description of exercise intensity, the measured acceleration values (unit:G) are not directly described, but are converted into METs -Metabolic equivalents, (Jette *et al.,*1990) which is a standard to indicate the amount of physical activity. METs are based on energy expenditure, and the correspondence table between specific physical activities and METs conversion is also available, making it easy to intuitively understand the intensity of exercise. To convert acceleration into METs, three subjects (age 39.7±1.5 years; height 180.0±7.9 cm; weight 79.6±12.6 kg) were asked to wear a prototype with the same performance as the UW-301BT and Suzuken's Lifecoder EX at all times except when taking a bath for one month. The absolute values of the 3-axis acceleration measured by the UW-301BT were summed up in correspondence with the 9 levels of METs (Kumahara *et al.,*2004) that can be calculated from the LifecoderEX data, and the average value per unit time (minutes) was calculated. Regression analysis using these nine data points yielded a coefficient of determination of R^2=0.928 ($p<0.001$). As a result, the results can be confirmed at a glance with easy-to-understand indicators, as in the feedback report reported in the previous issue. Since the analysis with utility is also possible, G notation is also available upon request, as shown in Fig 4, in response to the needs from the field. In order to realize the quantitative condition evaluation by the wearable sensor, the policy of the team conducting the actual measurement and the numerical values and items to be examined are likely to change, so it is necessary to continue to give sufficient consideration to how to feed back the results to the field. As shown in fig.3, the waveforms of the exercise intensity of all the athletes show that the exercise intensity increases during the training and decreases during the interval when the athletes move to the next training. In other words, it is necessary to detect the interval time when the exercise intensity decreases in order to delimit the time of the training menu itself. However, even when the same training menu is performed by a team, it is possible that there are variations in the exercise intensity of each individual, and this becomes more pronounced in the case of injury (Gabbett,2016,2018).

Depending on the menu, it is possible that not all the participants necessarily participate in the training, but only some of them do, or that they take a break. Therefore, we averaged the waveforms of the exercise intensity of all the athletes who were performing the same pattern of training menu, and then we set up a break in the training menu. This approach is considered to have reduced the influence of individual variations and enabled more accurate automatic detection of training intervals. There are a wide variety of patterns in the automatic detection of intervals, depending on each athletic organization. There are differences between individual and team competitions, and between ball games and other sports. Therefore, we defined the characteristics of intervals in this study by analyzing visual observations, surveys, and video analysis of actual training sessions. As shown in table 2, we found the optimal interval value of 2.5 METs or less to be detected from the exercise intensity data, and we also examined the time during the interval as a condition. Specifically, when the interval is shorter than 1 minute, it is often not accompanied by a change of the training menu, such as the switching of roles of the athletes depending on the menu, including hydration, assuming the movement of the athletes themselves. Considering a complete changeover, the interval should be at least 1 minute at the shortest. Therefore, we considered not only the intensity of the exercise but also the duration of the exercise. Therefore, it is necessary to consider not only the exercise intensity but also the time in future efforts to detect intervals, as this will increase the accuracy. In addition, the waveform data of the exercise intensity of each athlete obtained from each training menu was used to classify the exercise intensity patterns of each training segment by the feature values, and the K-means clustering method was used to classify the data. In this study, the classification was performed comprehensively based on variables such as the waveform of exercise intensity, length of time, and order of exercise intensity. However, it is necessary to develop an original algorithm depending on the competitions actually performed within a narrow range. Regarding the classification of training menus (see table 3), the overall accuracy was 80%. However, there was no error in the group training. On the other hand, it was found to be difficult to distinguish between warm-up and basic training, where the intensity of exercise was generally low, and other training sessions where a transient element of high intensity was added, which is a subject for future study. In this study, there was a strong need for quantitative measurement to detect signs of injury and prevent injury, since it is not possible for athletes to detect signs of injury by their own judgment or that of their coaches. The findings of this study suggest the possibility of not only comparing the daily exercise intensity and other conditioning data of the same athlete, but also comparing the physical activity level of other athletes, not on a weekly basis, but by extracting only specific practices. This finding is not only highly useful for conditioning the team and each player, but also leads to the possibility of utilizing the physical activity assessment for prevention of trauma and injury. It is also possible to analyze effective values for passing and ball possession practice in a limited and confined space, and to analyze the performance in detail. This new approach is useful not only for training and games, but also for recovery. It is suggested that the understanding of exercise intensity for each training session and the management of conditioning of each athlete, as well as the implementation of practice, are highly likely to lead to injury prevention.

5 CONCLUSIONS

In this study, we calculated the exercise intensity of each individual in one second from the acceleration data of all athletes during training. In addition, the detection process was examined by finding the characteristics of the breaks in the training menu. As a result, it was possible to extract and compare the measurement results that matched the target training conditions, and to calculate indices such as exercise intensity and running distance by analyzing the measured acceleration data. Our original analysis made it possible to automatically detect intervals in group training, and furthermore, to automatically classify them by training intensity. The results suggest the possibility of utilizing the physical activity evaluation for the prevention of trauma and injury and for conditioning by comparing the exercise intensity of athletes by training intensity on a daily basis.

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