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Dense Trajectory Length and Direction Feature Based Player Receive Reaction Time Detection in Volleyball Game

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***Abstract*—The player reaction time plays an important role in volleyball game analysis which has been widely applied in volleyball strategy analysis and coach assistance. In order to achieve the purpose of detecting the reaction time, the difficulties including 1) distinction of feet motion change, 2) small motion of moving arms, 3) various motions of moving arms. Aiming to overcome these difficulties, this paper proposes the feet trajectory length change feature and the arms trajectory direction change feature based on dense trajectory method. Instead of using the whole body trajectory feature, the first proposal analyzes feet trajectory length curve to detect the Standby motion and the reaction motion to distinguish the feet motion effectively. The second proposal uses the vector angle difference between the head vector and the tail vector of arms trajectory to describe the arms motion, which is robust to detect small motion and various motions of arms. The dataset is 2014 Inter High School Mens Volleyball Games held in the Tokyo Metropolitan Gymnasium in Aug. 2014. The proposed reaction time detection system can achieve 50.6%, 79.5% and 94.0% within 17ms, 33ms and 50ms tolerant error respectively.**

I. Introduction

Nowadays the computer vision based volleyball analysis plays a very important role in the volleyball field, because it is widely applicated in coach assistance or player evaluation system. Above these applications, data acquisition is the most fundamental part, because volleyball experts and analysts can use these data to analyze the game. Current existing volleyball analysis systems such as Data Volley not only require manually labor which will cause the heavy cost, but also is limited to some data which are difficult to observe by human eyes such as player spike height or reaction time. Therefore, automatic volleyball game data acquisition is very necessary. Among several data of volleyball game, the Receive reaction time is one of the most important data, cause when the blockers cannot block the ball, receiving the opponent's spiking is the last defense line of the whole team. Analyzing the Receive reaction time during the Receive event is the key information not only for player evaluation in the player level, but also for defensive formation and player arrangement in the team level. Therefore, this paper mainly focusses on player reaction time detection in Receive event of volleyball game.

The definition of the Receive reaction time is the time it takes between when the opponent *spikes* and when the Receiver (the player who receive the ball) *start to move feet or arms* for receiving the ball. The moment of opponent spiking can be obtained by previous work [1], but the key of reaction motion is to detect the moment when the Receiver react to receive the ball, which is called *reaction frame*. This research aims to find out the reaction frame of the Receive process and need to analyze the motion of the Receiver. Based on the difference motion of Receiving the ball, the Receive reaction motion is divided to two patterns: From Standby to *moving feet* and from Standby to *moving arms*. For feet motion pattern, as the Fig. 1 shows, the reaction motion is starting to move feet. For arms motion pattern, as the Fig. 2 shows, the reaction motion is starting to move arms.

To analyze the two motion patterns of the Receiver, there are three problems: difficult distinction of feet motion change, small motion of moving arms and various motions of moving arms. For detecting feet motion pattern, the analysis of the Receiver's feet motion is needed, which is difficult to describe and distinguish. For detecting arms motion pattern, because of the small motion of moving arms, the Receivers arms motion is too similar to be distinguishable in several continuous frames around reaction frame. And the various motion of moving arms, which means the Receiver will move to various directions to receive the ball. It is also a difficult point to detect these motions.

For detecting the reaction frame, the Receiver's reaction motion is needed to be detected. There are several previous works for analyzing the Receiver's motion: Kubota's work [2] has proposed a clustering trajectories feature and SVM classification based volleyball player action recognition method. Because of the various motions of reacting, there are different feature of whole player body when the Receiver reacts. It is hard to use the player's whole body trajectory feature to find the reaction frame. Therefore, this method is not suitable for detecting the Receivers reaction. Liu [3] has proposed a descriptor using convex hull geometric difference between the Receiver motion of Standby and Receive to describe the motion change. But this method has two limitations: Lack of body part motion and temporal information, so it can not detect feet and arms motion and distinguish the small motion change. To detect reaction frame with solving these three problems, this paper proposes a feet trajectory length change feature and arms trajectory direction change feature combined method. The feet trajectory length change feature means to generate a scalar to describe the feet motion directly, and it can detect

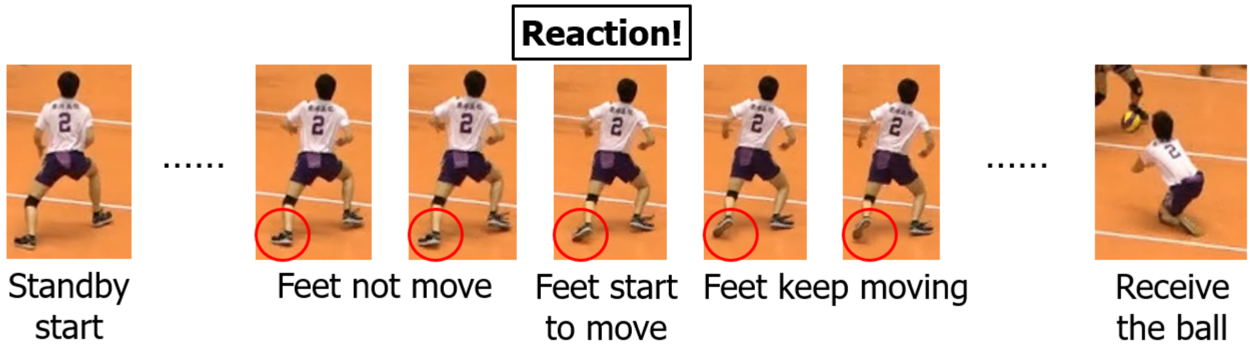

Fig. 1. Feet Motion Pattern During the Receive Event

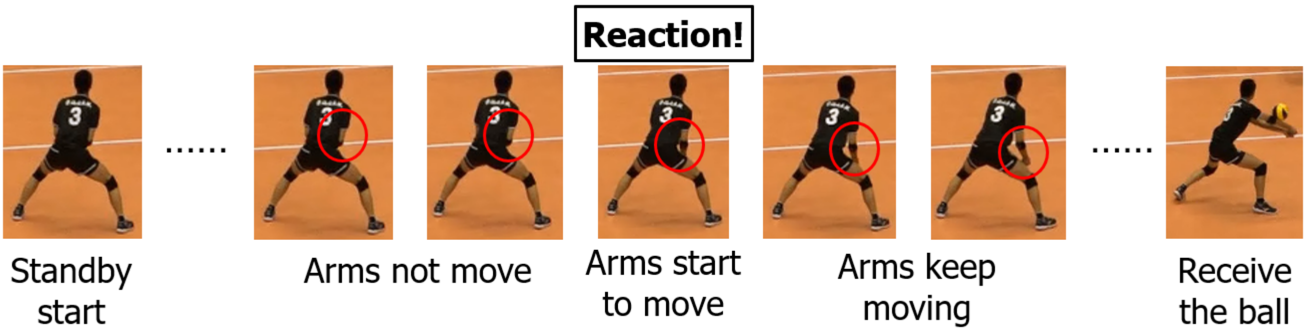

Fig. 2. Arms Motion Pattern During the Receive Event

the Standby and *start to move feet* posture of the Receiver. The arms trajectory direction change feature means to generate a scalar to describe the direction change of arms trajectory, which detects the small motion change of arms motion and are robust to various receive directions. Through these two features, the reaction motion can be detected, and the reaction frame can be found.

The rest part of this paper is organized as follows: Section 2 shows the detail of the proposals; Section 3 shows the experiment results with each tolerant error; Section 4 which is final part shows the conclusion of whole research and the outlook of future work.

II. Proposals

The framework of the whole reaction frame detection system is shown in Fig. 3. There are five processes in this framework. The input of this system is Receive action video which can be obtained by previous work [3]. The input video has four camera views, and the two back views have less occlusion or overlap and less interference of net and ball. As shown in Fig. 4, for these two back view, because the side-back view clearly shows the Receiver's arms, and it is can distinguish the arms and torso trajectory. And this side-back view can be selected according to the Receivers position [4].

The feature extraction step uses dense trajectory method [5] to get the dense trajectory feature of the Receiver, and use K-means method [6] to cluster [2] all the trajectory to 10 clusters by coordinate. The each trajectory consists of 16

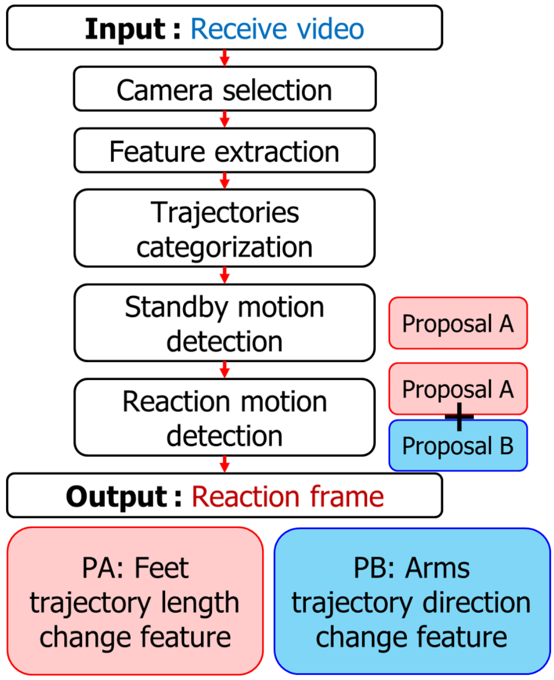

Fig. 3. Framework of Reaction Frame Detection System

points connected on the graph and is represented by a vector of point coordinates. The vector is as follows:

$$Trajectory = \{x_0,\ y_0,\ \dots\ x_{15},\ y_{15}\} \tag{1}$$

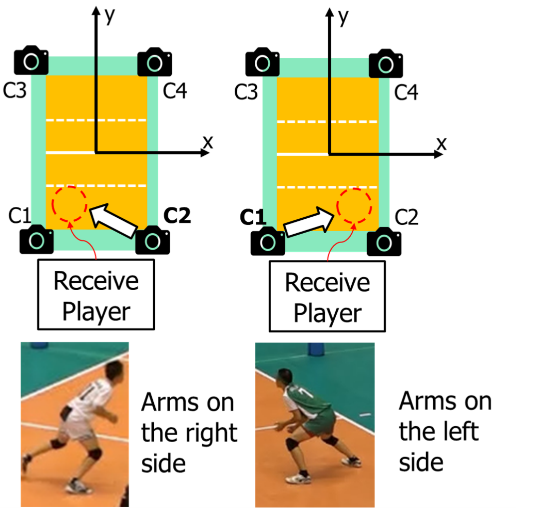

Fig. 4. Camera View Auto Select

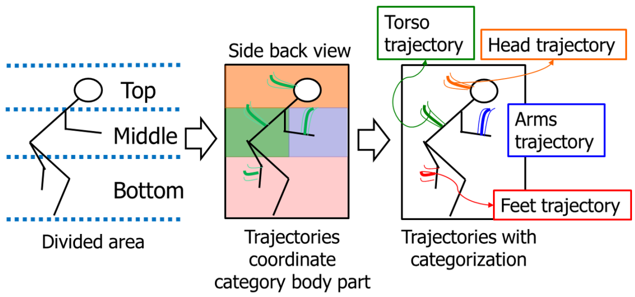

Fig. 5. Body Parts Trajectory Categorization by Cluster Position

As shown Fig. 5, the trajectory categorization step uses fixed relative position of the Receiver's head, torso or arms and feet during the Receive event to distinguish each trajectory. Therefore, by using the a priori information of the relative position of the human body in the Receive event, and the merit is that the trajectory of each body part is categorized and labeled without knowing the exact position of each body part.

The Standby motion detection step means to find the start point of the activation detection reaction frame, because reaction motion is happened after standby motion, so the reaction motion detection should start from standby motion. The Receiver will not move feet during the Standby posture, so the feet trajectory length change feature can describe and find this feet motion to detect the Standby posture.

The final step is reaction motion detection, which contains two motion patterns detection: From Standby to *start to move feet* and from Standby to *start to move arms*. Because of various situations of volleyball game, these two motion pattern will happen in different sequences, and in some situations, the Receiver will run to receive the ball, so starting to move feet is regard as reaction, and in other situations, the Receiver will reach out arms to receive the ball, so starting to move arms is regard as reaction. The reaction time of these two kinds of situations will be detected by using proposal A and B respectively. The two proposals can generate a scalar to describe the feet and arms motion and detect the frame when the feet or arms motion changes.

A. Feet Trajectory Length Change Feature

As shown in Fig. 6, this is the concept difference of trajectory feature. For the conventional method, it focuses on all body trajectory, and it has no regular feature change for Receive process. Therefore, in the feet motion pattern of Receive process, the conventional method is difficult to distinguish the Receiver motion change, but our feet trajectory length change feature only focuses on the feet area of the Receiver and uses length change to describe feet motion of the Receiver. The merit of this feature is not only can distinguish feet motion change clearly, but also can quantify the feet motion change. The length of the trajectory is defined as follow:

$$Length = \sum_{i=0}^{14}[(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2] \qquad (2)$$

As shown in Fig. 7, this is the feet motion pattern of the Receive process, the Receiver moves to Standby posture before Standby stage, and the feet trajectory length will change randomly, but this is not what we care about. When the Receiver enters into the Standby stage, the Receiver's feet do not move, so the trajectory length of feet will decrease continuously. The start to decrease point is not only the starting point of the Standby stage, but is also the starting point of the activation detection reaction frame. And then, in

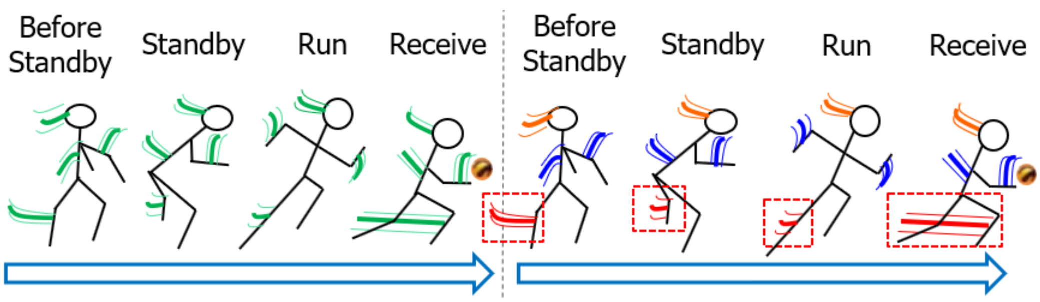

Fig. 6. Concept Difference of Trajectory Feature

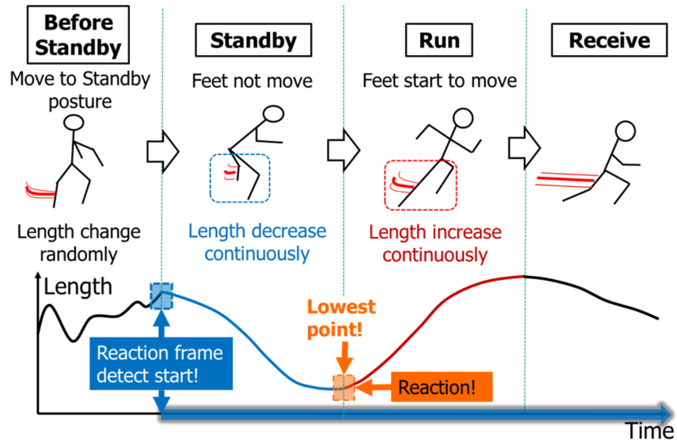

Fig. 7. Feet Trajectory Length Change Feature

Run to Receive stage, the Receiver starts to move feet, so the trajectory length of feet will increase continuously. The reaction point which means the Receiver start to run is at the lowest point of the feet trajectory length curve.

B. Arms Trajectory Direction Change Feature

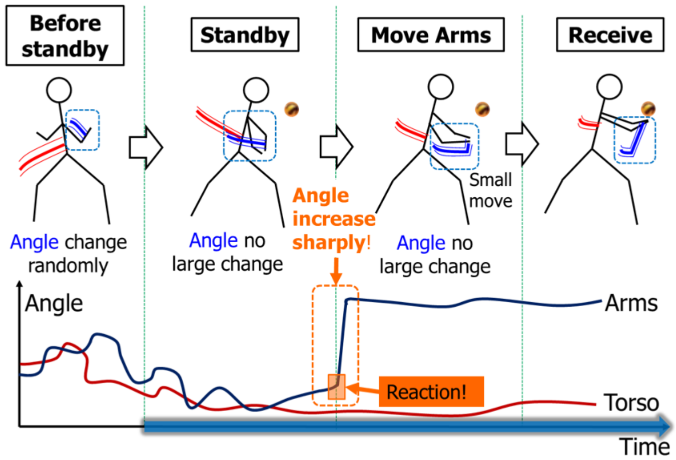

Fig. 8. Arms Trajectory Direction Change Feature

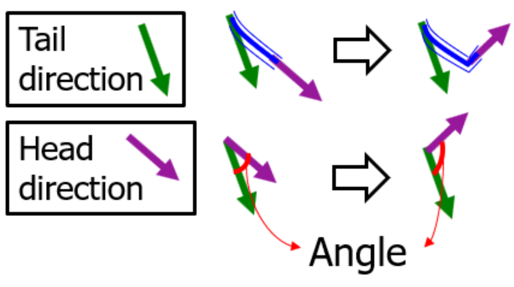

Fig. 9. Angle Describe Direction Change

As shown in Fig. 8, this is the arms motion pattern of the Receive process. Because the Receiver will move arm to receive the ball during this process, the direction of the Receivers arms trajectory will change, but it can use direction change to distinguish the arms and torso trajectory. The descriptor of the direction change of trajectory is the angle which means the difference between the tail direction and head direction of the trajectory. The meaning of each parameter is shown as follows:

$$\overrightarrow{Tail\ vector} = (x_{15} - x_{14},\ y_{15} - y_{14}) \tag{3}$$

$$\overrightarrow{Head\ vector} = (x_1 - x_0,\ y_1 - y_0) \tag{4}$$

$$Angle = acos(\frac{Tail\ vector \cdot\ Head\ vector}{||Tail\ vector|\,|Head\ vector||}) \tag{5}$$

$$Angle \in [0^\circ,\ 180^\circ) \tag{6}$$

For the reaction frame detection, based on the arms motion pattern of the Receive process, in the stage before Standby, the angle will change randomly, because the detection method is not activated, it will not influence the detection result. When the Receiver is detected entering into the Standby stage by using proposal A, the reaction detection method using arms trajectory direction change feature will be activated. The reaction frame which is the moment when the Receiver start to move arms, so it can be found at the point which increasing sharply in the angle curve by using proposal B.

III. Experiment Result

A. Experimental Datasets and Environment Setting

The performance of the proposed reaction frame detection method is evaluated by implementing in multi-view videos of an official volleyball match, which is 2014 Inter High School Mens Volleyball Games held in the Tokyo Metropolitan Gymnasium in Aug. 2014. The four cameras which captured this volleyball game video were located at each corner of the court. The video resolution is 1920*1080, and the frame rate is 60 frames per second (FPS), and the shutter speed is 1000 frames per second. C++ language and OpenCV 2.4.10 are implemented for the proposed algorithms, and the test machine has 3.40GHz CPU and 8 GB RAM.

B. Evaluation Method

In this research, the successful rate and accuracy are used to evaluate the result. The successful rate is defined as

$$\text{Successful rate} = \frac{\#\ \text{Detected sequences}}{\#\ \text{Total sequences}} \tag{7}$$

The detected sequences within each accuracy means that the difference between the detected reaction frame and ground truth frame is equal or lower to each accuracy.

$$|Detected\ frame - ground\ truth\ frame| <= \frac{Accuracy}{FPS} \tag{8}$$

As shown in Fig 10, the accuracy is defined as the difference between the tolerant reaction frame and ground truth frame.

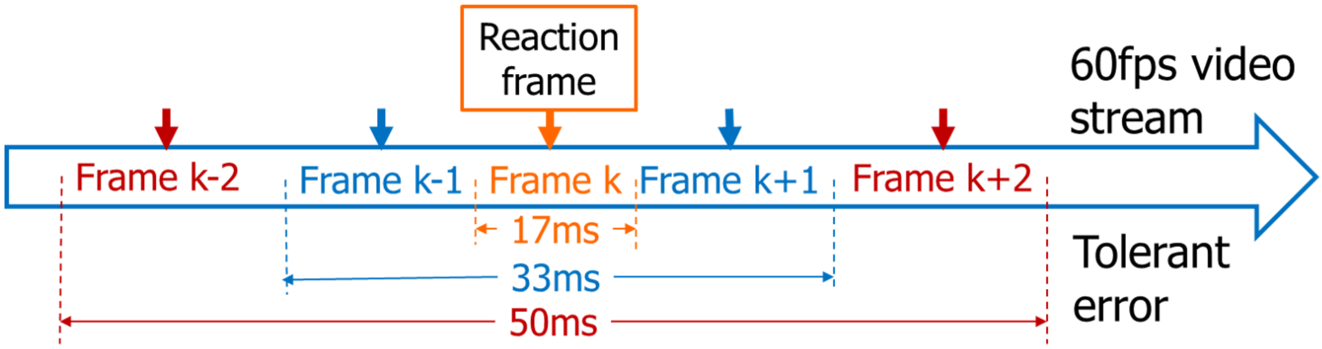

Fig. 10. Different Accuracy

TABLE I
EXPERIMENTAL RESULTS

Sequence	Total	17ms error	33ms error	50ms error
Type A	13	84.6%	100%	100%
Type B	70	44.3%	75.7%	92.8%
Total	83	50.6%	79.5%	94.0%

And there are three different accuracy to evaluate the results, which are 16 milliseconds (difference = 0 frame), 33 milliseconds (difference = ± 1 frame) and 50 milliseconds (difference = ± 2 frames).

C. Experimental Result and Discussions

The experiment results of total sequences are shown in Table I. The Type A sequences means the sequence with feet motion pattern; The Type B sequences means the sequence with arms motion pattern. For the proposals, the proposal A mainly solves the type A sequence with feet motion pattern, and can achieve 84.6%, 100% and 100% within tolerant error 17ms, 33ms and 50ms respectively. And the proposal B mainly solves the type B sequence with arms motion pattern, and can achieve 44.3%, 75.7% and 92.8% within tolerant error 17ms, 33ms and 50ms respectively. By combining proposal A and B to the total sequences, it can achieve 50.6%, 79.5% and 94.0% within tolerant error 17ms, 33ms and 50ms respectively.

The current experimental results still have space for improvement, the main problem that causes failure is overlap and occlusion including the Receiver himself and other players influence. Because the dense trajectory feature extraction method is based on 2D video, which is easy to introduce the noise by overlap and occlusion. As for other problems, because sometime the Receiver must do the forced reaction to receive the ball, so the Receivers motion is too strange to be detected.

IV. CONCLUSION

This paper proposes feet trajectory length change feature and arms trajectory direction change feature proposals. The feet trajectory length change feature aims to generate a scalar to describe the feet motion directly, and it can detect the Standby and Start to move feet posture of the Receiver. The arms trajectory direction change feature aims to generate a scalar to describe the direction change of arms trajectory, which can detect the small motion change of arms motion and is robust to various receive directions. The experimental results show the successful rate of all the sequence within the difference tolerant error. The two proposals achieve 50.6%, 79.5% and 94.0% within 17ms, 33ms and 50ms tolerant error.

As for the future work, we expert to generalize our method to other volleyball event and other sports. And we hope to look forward to a more robust, anti-occlusion and anti-overlap reaction time detection method to be implemented to achieve this expectation.

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REFERENCES

[1] X. Cheng, N. Ikoma, M. Honda and T. Ikenaga, Event State Based Particle Filter for Ball Event Detection in Volleyball Game Analysis, *20th International Conference on Information Fusion (Fusion 2017),* July 2017.

[2] S. Huang, X. Zhuang, X. Cheng, N. Ikoma, M. Honda and T. Ikenaga, Player Feature Based Multi-Likelihood and Spatial Relationship Based Multi-View Elimination with Least Square Fitting Prediction for Volleyball Players Tracking in 3D Space, *IEEJ Trans. on Image Electronics and Visual Computing,* Vol. 4, No. 2, pp. 145-155, Dec. 2016.

[3] Y. Liu, S. Huang, X. Cheng, T. Ikenaga, 3D Global Trajectory and Multi-view Local Motion Combined Player Action Recognition in Volleyball Analysis, *Pacific-Rim Conference on Multimedia (PCM2018),* Sep. 2018.

[4] E. Kubota, M. Honda, T. Ikenaga, Action detection of volleyball using features based on clustering of body trajectories, *Technical report of IIEEJ,* vol. 272, Feburary 2015. (in Japanese)

[5] W. Heng, K. Alexander, S. Cordelia and C. Liu, Action recognition by dense trajectories, *CVPR 2011-IEEE Conference on Computer Vision & Pattern Recognition,* pp. 3169-3176, 2011.

[6] J. A. Hartigan, M. A. Wong, Algorithm AS 136: A k-means clustering algorithm, *Journal of the Royal Statistical Society. Series C (Applied Statistics),* pp. 100-108, 1979.