Quantitative Method for Evaluating the Coordination between Sprinting Motions using Joint Coordinates Obtained from the Videos and Cross-correlations

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Abstract: This paper proposes a method for quantitatively evaluating sprinting motions using the videos of runners. Specifically, this paper explores the coordination between physical motions, which has been recognized as very important in sprinting. After detecting and normalizing the joint coordinates from sprinting videos, the cross-correlations of two windowed time-series data are calculated using the windowing cross-correlation function, and the coordination between the motions of the two joints is quantified. Experiments that use 20 subjects are conducted. As a result of classifying the cross-correlation obtained from the subjects' data into two clusters using k-means clustering, conditions in which the obtained cluster includes a high percentage of inexperienced sprinters are found. To verify whether the motions corresponding to these conditions are valid as the evaluation criterion of sprinting, Spearman's rank correlation coefficients between cross-correlations and 30-m time records are calculated. The results show a weak correlation with respect to the coordination between the elbow and knee motions. Therefore, it can be said that the cross-correlation corresponding to the coordination can be used as a quantitative criterion in sprinting.

1 INTRODUCTION

Improving the quality of runners' sprinting motions in physical education or athletics requires objective and appropriate evaluation of motion quality. Suzuki *et al*. (2016) and Kaji *et al*. (2017) proposed methods for evaluating the quality of sprinting motions using qualitative criteria. Using such qualitative criteria, evaluators can assess a runner's motion by directly observing it or by reviewing the recorded video. However, the evaluation of motions based on qualitative criteria does not allow for consistent evaluations because of variations in interpreting such criteria by different evaluators, such as the runner himself and the coach. Therefore, if details of the motion can be evaluated using quantitative criteria, rather than the qualitative criteria, the runner's motion can be evaluated more consistently.

However, it is difficult for humans to quantitatively evaluate the details of the motion through visual observation. In recent years, many technologies have been developed to acquire athletes' motion data using video processing or sensor information processing and evaluating their motions quantitatively by computer (Pirsiavash *et al*., 2014, Parmar *et al*., 2019). However, these studies aimed to automate experts' traditional evaluation or scoring of the sports motion using computers, and none of them proposed new evaluation criteria that determine athletes' body portions and the timing to be focused for improving the athletes' motions, while only qualitative approaches by Suzuki *et al*. (2016) and Kaji *et al*. (2017) can be seen.

In addition, although many studies have analyzed sprinting motions from the perspective of biomechanics (Maeda *et al*., 2010, Fukuda *et al*., 2010), few studies have aimed at proposing new evaluation criteria. For sprinting motion, this paper proposes a quantitative evaluation criterion obtained by computer-based analysis of the time-series information of joint coordinates obtained from the video. One of the items, whose quantitative evaluation criterion can be clarified only when assuming computer evaluation, is the coordination between physical motions in sprinting. With regard to the coordination between physical motions, Tellez

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emphasized its importance in the 1980s (Muraki et al., 2015), and in recent years, Nobuoka (2010) and Takano (2008) incorporated the awareness of it into their sprinting training methods. However, few studies have quantitatively evaluated the coordination between physical motions in sprinting, and whether physical motions are well-coordinated has not been clarified.

Therefore, in this paper, we clarify the sprinting motion features that indicate whether physical motions are well-coordinated, and based on the results, we propose a quantitative sprinting evaluation method.

The rest of this paper is organized as follows. Related studies are described in Section 2. In Section 3, our proposed methods are explained. Section 4 shows experiments to quantify the coordination of physical motions and to determine the characteristics of the motions of experienced and inexperienced runners. In Section 5, the details and validity of the evaluation criteria are discussed and our proposed methods are validated. Finally, this paper is concluded in Section 6.

2 RELATED WORK

Most studies that proposed methods for evaluating sprinting motions assumed that the motions were evaluated by visual observation, and the criteria only described the sprinting motions qualitatively. Suzuki *et al*. (2016) and Kaji *et al*. (2017) proposed some evaluation methods for sprinting in elementary-school education. These evaluation methods were based on biomechanical findings on sprinting, and the effectiveness of the proposed criteria was demonstrated by correlating their candidate criteria with sprinting speed. These studies evaluated the sprinting motions on a scale of A to C (where A is the best) by seeing a runner's motion using qualitative criteria, such as "putting the elbow forward or not." However, such qualitative evaluation criteria include unclear phrases that can be interpreted differently by each evaluator. This situation makes it difficult to consistently evaluate the sprinting motions. The reason why sprinting evaluations are limited to qualitative criteria is that sprinting motions have generally been evaluated visually by humans.

However, in other areas than sprinting, many methods for evaluating sports motions using computational methods have been developed in recent years. Pirsiavash *et al*. (2014) proposed a machine-learning method to predict the performance scores given by experts to skaters and divers using videos of their performance. In addition, Parmar *et al*. (2019) predicted not only experts' scoring but also their evaluation of athletes' motion skills from the video of diving. However, these proposed methods only predict the evaluation of sports motions by experts and do not propose new evaluation criteria that determine athletes' body portions to be focused for improving the athletes' motions.

Several studies have analyzed the motions of sprinters from the perspective of biomechanics. Maeda *et al*. (2010) analyzed the role of arm swinging in sprinting by comparing the angular momentum of each body part, sprint speed, pitch (number of steps per unit time), and stride width with and without fixed arm swinging. In addition, Fukuda *et al*. (2010) analyzed the characteristics of the motions of top sprinters in terms of sprint speed, pitch, stride width, and angle and angular velocity of each body part with respect to the motions of the swinging and kicking legs. However, these studies did not propose new quantitative criteria for evaluating motions.

Our previous study (Sabanai *et al*., 2019) focused on the coordination between physical motions, as in this paper, and proposed quantitative evaluation methods for sprinting using joint coordinates detected from videos. However, it is unclear what kind of relationship exists between the coordinating parts of the body because the joint coordinate data are converted into frequency components. Therefore, it is difficult to interpret the evaluation criteria.

In this paper, we propose a method that can interpret the relationship between coordinating body parts using the windowing cross-correlation function (WCCF).

3 PROPOSED METHOD

3.1 Overview of the Proposed Method

An overview of the proposed method is shown in Fig. 1. First, the time-series information of the joint coordinates is obtained from the video data of sprinting motions. For that, person detection algorithms for videos and the method of Yang *et al*. (2017) are used. Second, an athlete's motion data used for exploring the coordination are obtained. Specifically, information of two motion items (e.g., elbow motion and knee motion) that are expected to coordinate with each other is extracted from the time-series of joint coordinates and normalized so as to be used in the subsequent analysis. Third, the coordination between the two motion items is quantified. For that, the WCCF is applied to the

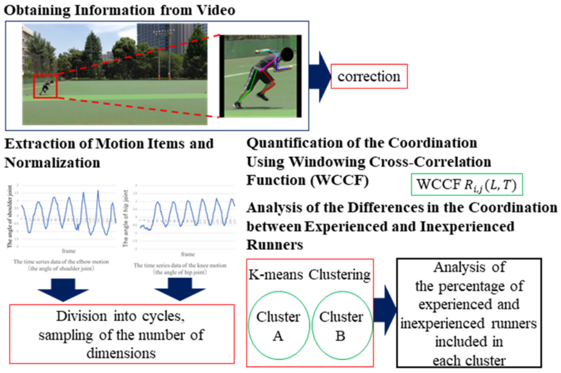

Figure 1: Overview of the proposed method.

information obtained in the above-mentioned processes. Finally, differences in the features of the coordination between the physical motions of experienced and inexperienced runners are identified. For that, k-means clustering is used for the calculated cross-correlations to classify the dataset into two clusters, and the percentage of experienced and inexperienced runners in each cluster is explored.

3.2 Obtaining Information from Video

First, the video data of sprinting captured from the side are divided into frame-by-frame images. The person is detected from each of the images, and the joint coordinates are obtained from the detected person area. Methods such as YOLOv3 (Redmon *et al.*, 2018) and Faster R-CNN (Ren *et al.*, 2015) can be used for the person detection. Next, in the person area in each image, the method of Yang *et al.* (2017) is performed to extract 16 joint coordinates.

In this case, some of the joint coordinates might be falsely detected. The false detection can affect the analysis proposed in this paper. Therefore, the method used in our previous study (Sabanai *et al.*, 2019) is used to correct the false detection.

Furthermore, if the video is captured with a general camera from the side, the coordinates away from the center of the image are affected by the perspective projection of the camera: e.g. if the horizontal coordinates of two points with different depths in the real world are same, the horizontal coordinates of the two points projected to the image are different. To correct the effect of the perspective projection, Eq. (1), which transforms the real-world coordinate system (X, Y, Z) to the image coordinate system (u, v) is used. In Eq. (1), f is the focal length, c is the image center, r is the rotational parameter, and t is the translation parameter, where x and y denote the horizontal and vertical directions in the image coordinate system before the correction respectively, and 1, 2, 3 are suffixes.

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \quad (1)$$

Expanding Eq. (1) yields

$$u = c_{11}X + c_{12}Y + c_{13}Z + c_{14} \quad (2)$$

where c denotes the coefficient.

When videos of sprinting motions are captured, the origin of the real-world is set, and four real-world coordinates are measured at each of the right and left halves of the videos. By substituting the four points' coordinates into the (X, Y, Z) of Eq. (2) and solving the simultaneous equations, c_{11}, c_{12}, c_{13}, and c_{14} can be determined. Since c_{12} is smaller than the other coefficients, the term including c_{12} is ignored.

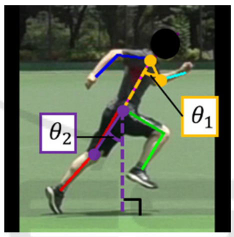

Figure 2: Examples of angles used for motion items.

In this study, the horizontal coordinates of the joints on the right side are assumed to be correct, and that of left side are corrected. The linear equation is solved by substituting the horizontal coordinate of the joint to be corrected into u and the distance between the joint to be corrected and its counterpart joint into Z in Eq. (2). The real-world coordinate X of the joint to be corrected is determined by solving the linear equation. Finally, the corrected horizontal coordinate is obtained by substituting X and $Z = 0$ into Eq. (2).

3.3 Extraction of Motion Items and Normalization

From the information of the obtained joint coordinates, two motion items that are expected to coordinate are extracted. Specifically, as shown in Fig. 2, the two motion items include the time-series information of values such as θ_1, which represents the angle between the line segment passing the thorax and elbow and the trunk line passing the thorax and pelvis, and θ_2, which represents the angle between the line segment passing the pelvis and knee and the vertical line passing the pelvis.

After the time-series data of the two motion items are obtained, the acquired data are divided into cycles. The moment at which one foot is grounded is defined as the beginning of a cycle, and the moment at which the same foot is grounded again defined as the end of the cycle (Sabanai *et al*., 2019), so that the motions of the right and left feet are included in one cycle. In addition, the time-series data are automatically divided into cycles by detecting the grounding using our method (Sabanai *et al*., 2019).

Since the number of frames per cycle depends on the time-series data, linear interpolation is used to unify the number of the sampled data to N, which is the number of dimensions of the data inputted to the analysis using the WCCF described in Section 3.4.

3.4 Quantification of Coordination using the Windowing Cross-correlation Function

A cross-correlation function is applied to each cycle having N data to quantify the coordination between the two motion items. The cross-correlation function can calculate the agreement of two time-series data. For example, the coordination between arm and leg motions can be expressed by applying changes in arm and leg positions per unit time to the cross-correlation function. The cross-correlation function is applied to each cycle because the characteristics of sprinting motions change from the first to later cycles, and the same cycles, which have similar characteristics, should be compared. Furthermore, since variations in sprinting motions are large immediately after the start of the running, the second or later cycles in which the motion is more stable and the motion variation is smaller are analyzed.

In this paper, when the coordination between two motion items is calculated using the cross-correlation function, we compare the coordination of two items not only at the same time point, but also at two different time points such as the leg motion after the arm motion. Let L be the time difference between the two time points. Regarding the coordination at the same point: i.e., $L = 0$, the data of the two motion items of the first to Nth values of nth cycle are compared. In contrast, regarding the coordination at two time points: i.e. $L \neq 0$, the cross-correlation function is applied to the first to Nth values of the nth cycle of one motion item i, while for the other motion item j, in case of $L > 0$, the function is applied to the $(L + 1)$ to Nth values of the nth cycle and the first to Lth values of the $(n + 1)$ cycle, and in case of $L < 0$, the function is applied to the first to $(N + L)$ values of the nth cycle and the $(N + L + 1)$ to Nth values of the $(n - 1)$ cycle.

Furthermore, in this paper, the coordination of one cycle's entire length (N) is not quantified; instead, portions of one cycle are focused on and compared to quantify the instantaneous coordination. Therefore, the window function $W(t)$ in Eq. (3) is introduced into the cross-correlation function, assuming that the Tth to $(T + N')$ values of one motion item i are focused on. In this paper, the cross-correlation function in which the window function is introduced is called the WCCF (Windowing Cross-Correlation Function).

$$W(t, T) = \begin{cases} 1 \ (T \leq t \leq T + N') \\ 0 \ (otherwise) \end{cases} \tag{3}$$

Let $F_i(t)$ and $F_j(t + L)$ be time-series functions of the two motion items; then, the WCCF $R_{i,j}(L, T)$ of the items i and j is defined as

$$R_{i,j}(L,T) = \frac{\sum_{t=(n-1)*N+1}^{n*N} \left(F_i(t) * F_j(t+L) * W(t,T) \right)}{\sqrt{\sum_{t=(n-1)*N+1}^{n*N} \left(F_i(t) * W(t,T) \right)^2} \sqrt{\sum_{t=(n-1)*N+1}^{n*N} \left(F_j(t+L) * W(t,T) \right)^2}} \tag{4}$$

This function contains three parameters n, N, and N', whose values are set based on our preliminary studies. In addition, values of the cross-correlation are analyzed by changing the two variables L and T. The time range to which the WCCF is applied (in case of $L > 0$) is shown in red in Fig. 3. In Eq. 3 and Fig. 3, t is the time when each cycle is divided, and in Eq. 4, t is the time when all cycles are connected.

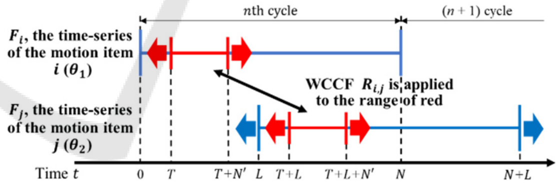

Figure 3: Range of time-series to which the WCCF is applied.

3.5 Analysis of the Differences in Coordination between Experienced and Inexperienced Runners

To find out what sprinting motions coordinate well or not well, differences in motion coordination between experienced and inexperienced runners are analyzed. In this paper, subjects with two years or longer experiences in athletics are defined as the experienced, otherwise, as the inexperienced.

By calculating the cross-correlation for a data set in Section 3.4, a set of numbers between −1 to 1 is obtained. By performing k-means clustering to the set of numbers, the data set is classified into two clusters. In the classification result, by calculating the percentage of the experienced and inexperienced subjects in each cluster, we clarify the two body parts and the timings that show difference characteristics of physical motions between experienced and inexperienced runners. For example, as a result of performing the clustering for the coordination for the leg swing soon after the arm swing, if clusters for the experienced and inexperienced subjects are separate from each other, the coordination for the experienced and inexperienced subjects are different.

4 EXPERIMENTS AND RESULTS

4.1 Capturing Video of Sprinting Motions

Videos of sprinting motions of 20 male subjects (7 experienced and 13 inexperienced, 20-25 years old) were taken under the conditions shown in Fig. 4. Each subject ran 30 meters (along a straight line) as soon as he heard the start signal. We instructed that the subjects should not slow down till they reach the finish line. Each subject ran five to six times in average. The subjects were provided adequate warm-up time before the initial run, and sufficient time was given between successive runs so that fatigue caused by one run does not affect the next run. A total of 115 runs (45 experienced and 70 inexperienced subjects) were video-recorded. The first 15 meters of each 30 meters run was video-recorded and used for the analysis. The time for the 30 meters run was recorded. The camera used was a Handycam HDR-CX680 (Sony Inc., Japan). The frame rate is set to 60 fps, and the video resolution is set to 1920 × 1080 pixels.

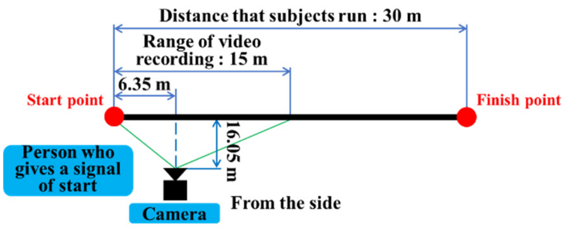

Figure 4: Video capture conditions in this study.

4.2 Obtaining Information from Videos

The obtained video data are split into frame-by-frame images, and the runner was detected from each image using YOLOv3 (Redmon *et al*., 2018). The length of the larger side (width or height) of the detected bounding box of the runner is scaled to 256 pixels, so that the size of all the images is 256 × 256 pixels by multiplying the same magnification as the longer side to the shorter length and by filling black to the void areas caused by the multiplication as shown in Fig. 2.

Next, the joint coordinates are detected from the obtained images using the method of Yang *et al.* (2017). Then, as explained in Section 3.2, false detections and replacements of the coordinates are automatically corrected.

In addition, the influence of the perspective projection on the horizontal coordinates of the runners' right and left joints is corrected using Eq. (2). To obtain c_{11}, c_{12}, c_{13}, and c_{14} in Eq. (2), the real-world coordinates (X, Y, Z) and the corresponding image coordinates u of four points in each of the right and left halves of the videos are needed. In this study, c_{11}, c_{12}, c_{13}, and c_{14} are calculated using the real-world coordinates and corresponding image coordinates of the six points: the start point, the 15-m point, two points in front of the camera, and two arbitrary landmarks, as shown in Table 1. Since the videos were taken over four days in the experiment, the image coordinates u changes depending on the day (only on the fourth day, the arbitrary landmark was used instead of the 15-m point). Since X = 6.35 [m] is in front of the camera and located at the center of the field of view of the image, the corresponding two points in Table 1 were used to correct both the right and left halves of the images.

Table 1: Image coordinates and real-world coordinates used to correct the effect of perspective projection (image coordinates u are represented in the order of the first to the fourth day of data collection).

Part of video	Position	Image coordinates u	Real-world coordinates (X, Y, Z)
Left half	Start	65, 37, 410, 453	(0, 0, 0)
	Arbitrary landmark (1)	565, 539, 839, 892	(0, 0, 67.00)
Common	In front of camera (1)	On all four days, 960	(6.35, 0, 0)
	In front of camera (2)	On all four days, 960	X = 6.35, Y and Z are arbitrarily small positive values
Right half	Arbitrary landmark (2)	1418, 1453, 1476, 1575	(31.20, 0, 52.50)
	15-m point (on fourth day, arbitrary landmark (3))	1902, 1908, 1741, (1467)	(15.00, 0, 0) (on fourth day, (12.70, 0, 0))

To calculate the real-world coordinates X of the (left) joints of the runner's left side (left ankle, knee, hip, wrist, elbow, and shoulder), the values of u and Z are inserted into Eq. (2) (Y values need not be inserted, because c_{12} is small enough to be ignored compared with the other coefficients, as described in Section 3.2). The horizontal coordinates of each joint in the image are inserted into u. Regarding Z, all the Z-coordinates of the right joints are set to 0, and the Z -coordinates of the corresponding left joints are replaced by the difference in Z between each two joints. Specifically, for the joints of the upper body (wrist, elbow, and shoulder), $Z = 0.4562$ [m], the mean shoulder width of men (Kouchi, 2005), is inserted. For the joints of the lower body (ankle, knee, and hip), $Z = 0.3067$ [m], the mean great trochanter width of men (Kouchi, 2005) is inserted. From these values, X is calculated, and the corrected horizontal coordinates are derived using this value as explained in Section 3.2.

4.3 Extraction of Motion Items and Normalization

To analyze the coordination between physical motions in sprinting using the time-series data of joint coordinates acquired and corrected as described in Section 4.2, in this study, the amounts of changes per unit frame in the angle θ_1 formed by the thorax, pelvis, and elbow (the angle of the shoulder joint) and the angle θ_2 formed by the perpendicular line in the y-axis direction, the pelvis and knee (the angle of the hip joint), are used as the two motion items to be extracted. This approach enables the quantitative expression of the coordination between the upper and lower body; for example, when the elbow is moving forward and the knee is also moving forward, the cross-correlation is high. The (right or left) joints on the same side as the arm that is put forward when starting are defined as the joint-A, and joints on the other side are defined as the joint-B (e.g., elbow-A, knee-B). In Chapter 5 and later, the same definition is used for foot. The coordination between the elbow-A and knee-A motions and the coordination between the elbow-A and knee-B motions are analyzed as follows.

After the two motion items were extracted, the time-series information was divided into cycles and sampled to unify the number of dimensions per cycle as explained in Section 3.3. The number of frames per cycle is approximately 30 in most of the collected data of sprinting motions. Therefore, the number of dimensions of sampling is set to $N = 30$ to minimize the effect of sampling.

4.4 Quantification of Coordination using Cross-correlation and Analysis of Differences between Experienced and Inexperienced Sprinters

By applying the WCCF in Eq. (4) to the data obtained as described in Section 4.3, the coordination between the elbow and knee motions was quantified. This paper analyzes the $n = 4$ cycle, which is relatively accelerated cycle in the sprinting motions in our experiment and for which sufficient data were obtained. The coordination between instantaneous motions of the elbow and knee is analyzed, with $N' = 1$. Here, L is varied from -29 to 29; T is varied from 1 to 29; thereby, a total of 59 × 30 cross-correlations are calculated for each data of the sprinting motions.

Moreover, the set of the cross-correlations obtained for each L and T is classified into two clusters using k-means clustering, and the percentages of experienced and inexperienced subjects in each cluster are obtained.

4.5 Results of the Application of WCCF and k-Means Clustering

An example of the distribution of the obtained cross-correlations (L = 15), for the coordination between the elbow-A and knee-A motions, is shown in Fig. 5. Regarding each T and cross-correlation, the intensity of the red color indicates the number of experienced subjects, and that of the blue color indicates the number of inexperienced subjects. In Fig. 5, for example, it can be seen that around T = 25, the number of inexperienced subjects is large if the cross-correlation is close to -1, and the number of experienced subjects is relatively large if the cross-correlation is close to 1. Thus, for some L and T values, characteristic distributions of experienced and inexperienced subjects can be seen, depending on values of the cross-correlation.

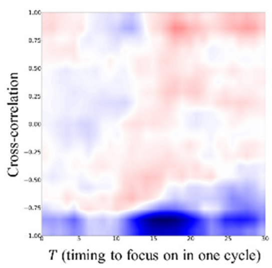

Figure 5: Distribution of experienced and inexperienced subjects regarding the size of T and the cross-correlation between the elbow-A and knee-A ($L = 15$).

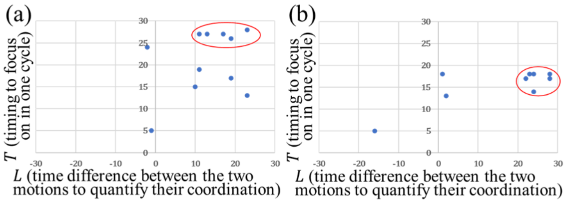

Figure 6: L and T values for which the percentage of inexperienced subjects in the cluster with small cross-correlations was more than 75% when the set of cross-correlations was divided into two clusters, where (a) the coordination between the elbow-A and knee-A motions, and (b) the coordination between the elbow-A and the knee-B motions.

As a result of the classification of the obtained set of the cross-correlations into two clusters using k-means clustering for each L and T, clusters with small and large cross-correlations are obtained. The plot of L and T is shown in Fig. 6, where the percentage of inexperienced subjects included in the cluster with small cross-correlations is more than 75%. Figure 6 (a) shows the result of the coordination between the elbow-A and knee-A motions, and Fig. 6 (b) shows the coordination between the elbow-A and knee-B motions. The points are relatively more concentrated around (L, T)= (13,27) in Fig. 6(a), and near (24,18) in Fig. 6(b).

5 DISCUSSION

As described in Section 4.5, the coordination between the elbow-A and knee-A motions and the coordination between the elbow-A and knee-B motions are quantified using cross-correlation, and the quantified values are used to classify the sprinting dataset into two clusters. As a result of the classification, we found the conditions (variables L and T) in which a large percentage of inexperienced subjects are included in the cluster with the smaller cross-correlations, as shown in Fig. 6; specifically, $L = 13$, $T = 27$ for the coordination between the elbow-A and knee-A motions, and $L = 24$, $T = 18$ for the coordination between the elbow-A and knee-B motions are such conditions.

To visualize what sprinting motions these conditions correspond to, examples of the image data are shown in Fig. 7. In Fig. 7, in case of $L = 13$, $T = 27$ for the coordination between the elbow-A and knee-A motions, the specific motions are the elbow-A motion at the moment the foot-B is grounded and then the knee-A motion just before the foot-A is grounded. In case of $L = 24$, $T = 18$ for the coordination between the elbow-A and knee-B motions, the specific motions are the elbow-A motion at the moment the foot-A leaves the ground and then the knee-B motion at the moment the foot-A is grounded. Under these conditions, motions with small cross-correlation values tend to correspond to inexperienced runners' motions; therefore, it can be considered that if inexperienced runners improve their motions so that the cross-correlation values get larger, quality of their motions can be better. Based on these, it might be possible to evaluate the coordination quantitatively using the cross-correlation.

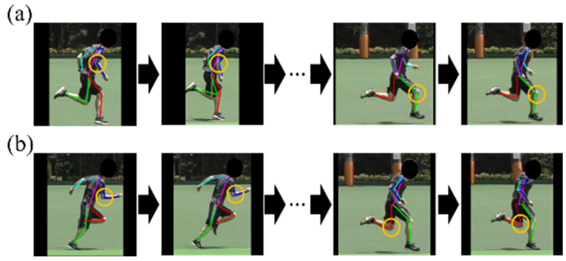

Figure 7: Specific motions corresponding to the variables L and T for which the cluster of the smaller cross-correlation includes the higher percentage of inexperienced runners: (a) The case of the coordination between elbow-A and knee-A motions, where $L = 13, T = 27$; (b) the case of the coordination between elbow-A and knee-B motions, where $L = 24$, $T = 18$.

Meanwhile, to validate evaluation methods for sprinting motions, Suzuki *et al.* (2016) and Kaji *et al.* (2017) investigated correlation between sprinting speed and their proposed evaluation criteria. In this paper, the validity of our evaluation criteria is investigated by calculating the correlation between the cross-correlations and the subjects' 30-m sprinting time records. The cross-correlations are not normally distributed, while the 30-m time records are normally distributed in the data collected in our experiment. Therefore, Spearman's rank correlation coefficient is used to derive the correlation. After obtaining the rank correlation coefficients r out of all L and T values, the L and T values are plotted for r larger than 0.300 (the relatively large values), as shown in Fig. 8. Figure 8(a) illustrates the case of the coordination between the elbow-A and knee-A motions, and (b) shows the case of the coordination between the elbow-A and knee-B motions.

Points relatively densely exist near (L , T) = (14, 27) in Fig. 8(a); r = 0.306 for (14,27) in (a). The motions corresponding to (14, 27) mostly coincide with the motions shown in Fig. 7 (a). Thus, under the condition in which the percentage of the inexperienced subjects included in the cluster with

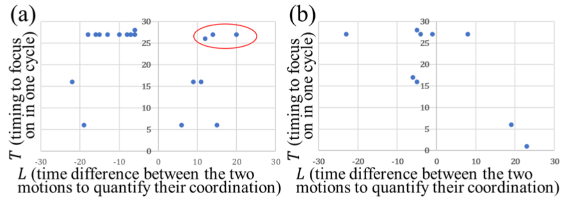

Figure 8: L and T values for which Spearman's rank correlation coefficient between cross-correlations and 30-m time records was larger than 0.300: (a) The case of the coordination between the elbow-A and knee-A motions, and (b) the case of the coordination between the elbow-A and knee-B motions.

small cross-correlations is large, a weak correlation between the cross-correlations and 30-m time records can be seen. Therefore, the case of $L = 14$ and $T = 27$ in Fig. 8 (a), which corresponds to the coordination between the elbow-A motion at the moment the foot-B is grounded and then the knee-A motion just before the foot-A is grounded, is related to the sprinting velocity and is considered to be valid as a criterion to evaluate the sprinting motions. Therefore, it could be possible to evaluate sprinting motions by the quantitative and consistent criterion unlike the qualitative criteria proposed by related studies. However, to achieve a more valid criterion, it is necessary to verify the reproducibility of the evaluation with different datasets, increase the number of data, and verify the criterion based on mechanical analyses.

6 CONCLUSIONS

This paper has developed a quantitative method for evaluating the coordination between sprinting motions, which has been considered to be important in sprinting. The joint coordinates of the runner are detected from the videos of runners and are normalized, and the WCCF is applied to the two time-series data of the elbow and knee motions obtained from the normalized joint coordinates; then, the coordination between their motions is quantified.

In our experiments that use 20 subjects as runners, as a result of classifying the cross-correlation obtained from the subjects' data into two clusters using k-means clustering, we found conditions for L and T in which the obtained cluster includes a high percentage of inexperienced sprinters. To verify whether the motions corresponding to these conditions are valid as the evaluation criterion of sprinting, Spearman's rank correlation coefficients between cross-correlations and 30-m time records are calculated. The results show a weak correlation near $L = 14$, $T = 27$ ($r = 0.306$) with respect to the coordination between the elbow-A and knee-A motions. Therefore, it can be said that the cross-correlation corresponding to the coordination between the elbow-A motion at the moment the foot-B is grounded and then the knee-A motion just before the foot-A is grounded can be used as a quantitative criterion to evaluate the coordination between physical motions in sprinting. This criterion may be applicable in evaluating sprinting motions in physical education or athletics.

In the future, it is necessary to validate the reproducibility using different datasets. We need to increase the data size to ensure more validity, verify based on mechanical analyses, extend the running distance, obtain three-dimensional motion information, and verify the motion items other than the angles θ_1 and θ_2 in Fig. 2. In addition, this study involves only a proposal of an evaluation criterion of motions, not a proposal of how to improve the motions based on the criterion. Therefore, we need to develop training methods to improve the motions based on the proposed criterion.

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