Archery shots visualization by clustering and comparing from angular velocities of bows

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ABSTRACT

In individual competitions consisting of repetitive movement sports, it is necessary to increase the reproducibility of movements by recognizing and correcting movement changes per second. Since it is difficult to obtain sufficient awareness only by subjectivity, a mechanism that can objectively confirm the movement is required. In this paper, we propose a system that can easily search for differences in multiple trial motions by the same person for archery movements. The proposed system uses Dynamic Time Warping to determine the similarity of multiple shots of one competitor from the time-series data from the angular velocity sensor attached to the competitor's bow. Based on the similarity distance, K-means Clustering is performed. In addition, the video corresponding to the time at which there is a difference is cut out from the video recorded simultaneously to the sensor data, and the two images are superimposed and presented to visualize the difference. When the proposed system was tested with five intermediate- and advanced-level archers, it was possible to detect differences such as minor shaking, the posture, and the motion speed for approximately 0.5 seconds. These differences can be found by advanced-level archers by carefully comparing the videos for many times, but are difficult to identify by intermediate-level archers.Feedback from interviews with the instructor suggested that the differences detected were meaningful to find out the points for improve archery skill.

CCS CONCEPTS

• **Human-centered computing** → *Information visualization*;

KEYWORDS

Archery, DBA, k-means, Clustering, Difference Extraction

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1 INTRODUCTION

It is important to realize how one's body has moved during playing sports [14]. In particular, sports, such as golf, archery and shooting that consist of repetitive actions, was involved in many studies for its importance [18]. Athletes perceive changes of their movements and the postures sensuously during their performance, but there may be a discrepancy between the movement perceived subjectively and the actual movement. It is important to identify the problems of one's movements early, as the body would remember the wrong movements if the competitor did not realize and repeated the incorrect ones [16].

To help sports players be aware of their own sports movements, there are researches [5] overlaying the experts' and players' movements. It was pointed out that it helped to find the differences between the movements of the experts and the players, although there is a limitation that the best form of sports movements depends on individual physical characteristics [11]. There are also differences in relationship between movement patterns and scores in archery for each individual [22].

According to an interview with expert archers (Olympian), when they reach intermediate level or higher, they establish successful forms of movements (later mentioned as forms) based on their experience of good results. Therefore, in the actual field, they use videos to check their forms, and improve upon the videos. Thus, a system that makes comparisons of the forms from one athlete easy would be useful.

In this paper, we propose a system for archers and coaches that can detect differences in shots of the same person. The system helps to compare shots by clustering shots based on the similarity and visualizing differences of a pair of shots. For example, all shots might be clustered into good-form groups and bad-form groups. We chose archery as the target sport, since archery movements have high reproducibility. Shot forms are different between individuals and there is necessity to compare for the same archer.

In this paper, advanced, intermediate, and beginners refer to those defined as follows:

- Advanced: the personal best score in double score (70m, 50m) is more than 650 points.
- Intermediate: the personal best score in double score (70m, 50m) is around 600 points.
- Beginner: the personal best score in 30m is less than 330 points.

2 PREVIOUS STUDIES

As a method of analyzing exercise states, videos that capture movement during exercise are widely used because they are intuitive and easy to understand. There are dirt fish [7] and siliconcoach [4] as motion analysis systems using movies. This is a system that supports the analysis of the motion by marking on videos. It can visualize any changes in the waist position or the angle of rotation of the foot. However, three points need to be specified on the image once for the foot angle, if the changes of the foot angle need to be obtained. In this system, operations on the PC take much time.

Motion capture is one of the methods that can analyze motion in three dimensions. It is suitable for analyzing the player's movement in details, but it takes time to set up cameras and markers [21].

Kinect has been used for the purpose of simple 3D motion analysis. However, since it has errors on a scale of of several centimeters, it is not suitable for motion analysis that requires high accuracy but more suitable for the analysis of large movements such as dancing and walking [10][9].

There are studies that use sensors and visualize movement. Y. Loke [13] made a realtime monitoring system for archery by using ultrasound sensors. In shooting, SCATT trainig system [1] that measures the vertical and horizontal trajectories of a gun using an optical sensor has been widespread. Sasayama [23] made a system that provides feedbacks of azimuth and elevation information by the sound in realtime. It is possible to visualize muscle activities during archery shooting and help with anyalysis using electromygraphy (EMG) [3].

These methods are effective for players to check their own movements. It is basically a one-to-one comparison, with the ability to go into details of the differences. However, to compare all trials, it is required to go through all possible combinations, which is likely to be very time-consuming.

3 METHODS

In this section, we describe the method used to cluster individual and visualize comparisons, and that of data acquisition. The proposed method classifies the angular velocity sensor values of many (100 or more) shots of the same archer by k-means method [12] based on the distances of Dynamic Time Warping. In the comparison between two different shots, it is easy to search for the differences by finding and highlighting the time at which the distance increases. The average value (Centroid) required for the clustering of the shots is calculated using Dynamic Time Warping Barycenter Averaging.

3.1 Measurement of angular velocity

A small 9-axes motion sensor manufactured by Sports Sensing was used as an angular velocity sensor for measuring and recording movements. The reasons for selecting this sensor are as follows:

- Wireless operation is possible
- Measurement of minute movement suitable for archery is possible (measurement range of angular velocity sensor is ± 300 degrees per second, sampling frequency is up to 1000Hz)
- Light weight (30g)

Among all sensor data, only the angular velocities were used. Details of the measurements are described in Section 4.1.

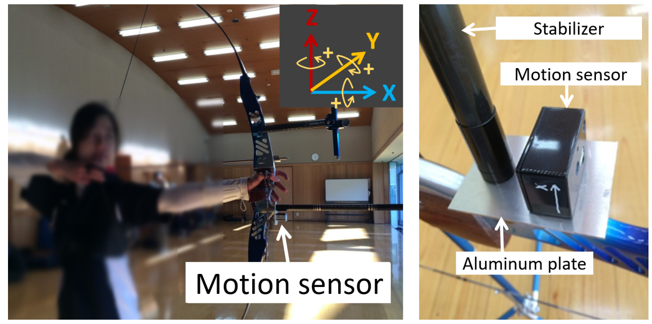

Figure 1: An angular velocity sensor on the bow.

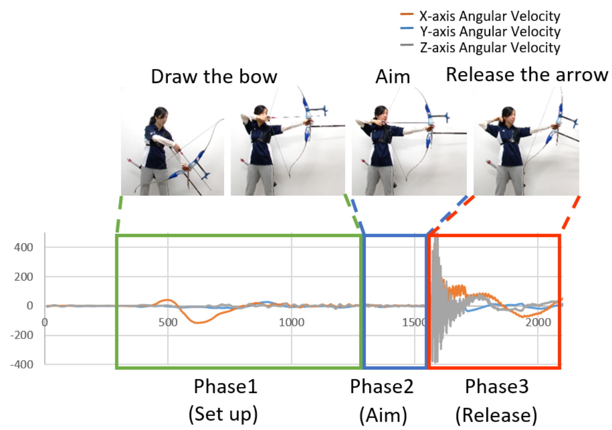

Figure 2: Angular velocity change in archery shot.

3.2 Preprocessing

Preprocessing is performed before performing classification on the acquired angular velocity data.

3.2.1 Segmentation. When measuring the motion of archery with the angular velocity sensor, there are places where the change is large or more intensive, e.g. firing an arrow, and the change is small or less noticeable, e.g. aiming at the target. When clustering is performed on the series of angular velocity data, small differences may be overlooked in motions with small time-series changes. Therefore, a series of angular velocity data is automatically segmented to three phases, "bow drawing (phase 1)", "target aiming (phase 2)", and "arrow releasing (phase 3)" as shown in Figure 2 using the following features. At phase 2, the change in angular velocities is small (-2 to 4 degree per second around the Y-axis), immediately after which there is a big pulse as an arrow is released. At phase 3, the 1.2-second period within which the angular velocity change instantaneously reaches its maximum is cut out. At phase 1 corresponds to the period immediately after the start of sensor measurements and before entering phase 2. Classifications and comparisons described in the upcoming sections are conducted for each phase.

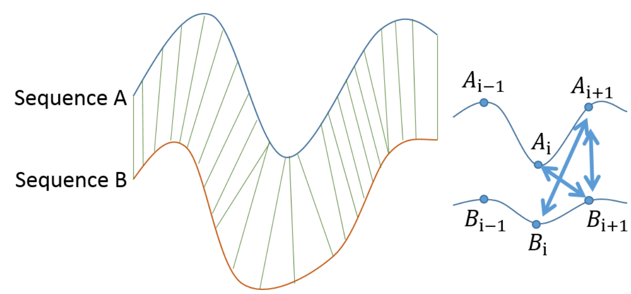

Figure 3: Dynamic Time Warping.

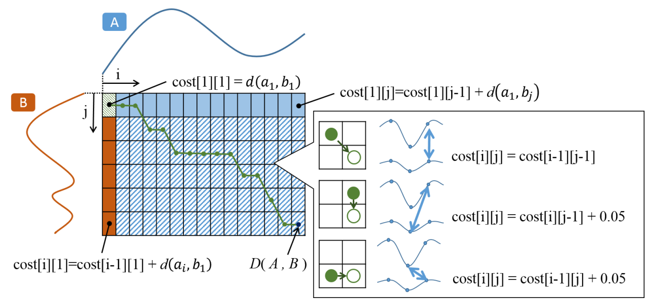

Figure 4: How to calculate DTW.

3.2.2 Cut off natural vibration. In order to eliminate the effect of the natural vibration of the bow, the time-series data divided into phases were subjected to an FIR filter to remove high frequencies that are above 5Hz. Tfilter [8] was used for filter design. The filter was designed by the Parks McLaren filter design algorithm [15]. The cut-off frequency of the pass-band was 5Hz, and the cut-off frequency of the stop-band was 10Hz. The sampling frequency was 200 Hz. The pass-band ripple was 20dB. The stop-band ripple was -20dB.

3.3 Comparison and classification methods

3.3.1 DTW. Dynamic Time Warping (abbreviated as DTW in all later sections) is a method to evaluate the similarity between two different time-series data [19]. It is especially used to evaluate the similarity of patterns of time-series data, more intuitive results could be obtained. This method was used due to the use of time-series data. Cheng-Hao [17] has suggested that DTW should be used as an evaluation axis. If multiple shots of the same person have low DTW value, that person is considered to be highly reproducible and is an advanced player.

It is able to calculate the cost stretch and mismatch in different weights and compare data of which the lengths are different with DTW. The Euclidean distance of three-dimension vectors was used when calculating the distance between the data because the time-series data involve data corresponding to three axes. When there are wave-A and wave-B as shown in Figure 3, the distance between a pair of wave-A and wave-B head data is calculated at first. Secondly, the shortest distance that corresponds to the lowest similarity in three directions (vertical, horizontal and diagonal) is searched, and upon finding the shortest distance, the time-series index is incremented and the searching process is repeated. The similarity at the end is D (A, B), which is the overall similarity between wave-A and wave-B. If the combination of data is vertical and horizontal, 0.5 (degree per second) is added as the cost of deviation. It is also possible to compare data with different data lengths. In this paper, this method is used for comparing different shots and comparing average (centroid) wave forms of clustering.

3.3.2 DBA. Dynamic Time Warping Barycenter Averaging (abbreviated as DBA in later sections) is a method to calculate the average values of data groups compared in DTW [20]. This method was applied because k-means method uses the average of the data group for updating the clustering result. When generating the average data of time series (centroid) of a group, the first-time series data as a temporary centroid is input firstly. Secondly, matching pairs of data between centroid data points and each data point group of time series data are set in the same way as DTW. In addition, the centroid is made smooth by updating the data points for multiple times (four times in this paper), as shown in Figure 5.

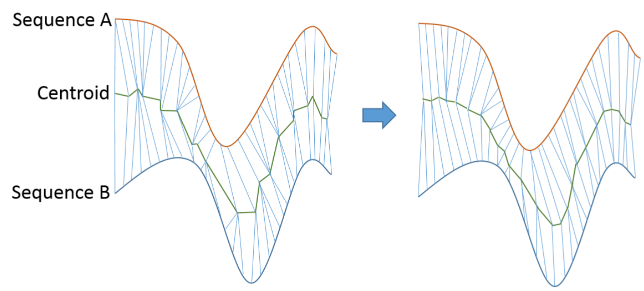

Figure 5: Dynamic Time Warping Barycenter Averaging.

Table 1: k number on each data.

	A	B	C	D	E
Data number	108	119	145	104	177
Phase1 K	16	11	15	12	16
Phase2 K	11	11	15	12	16
Phase3 K	14	14	15	12	15

3.3.3 Determining the number of clusters. Clustering on the time series data of each phase was conducted using the k-means method. The number of clusters K was estimated by the elbow method [24] (Table 1). Each test participant performed 110 to 180 shots unequally and some data were not successfully recorded due to sensor malfunction and thus omitted.

4 EXPERIMENT

In this section, the methods to measure the angular velocity data as input data and to design the application that presents experiment results are explained.

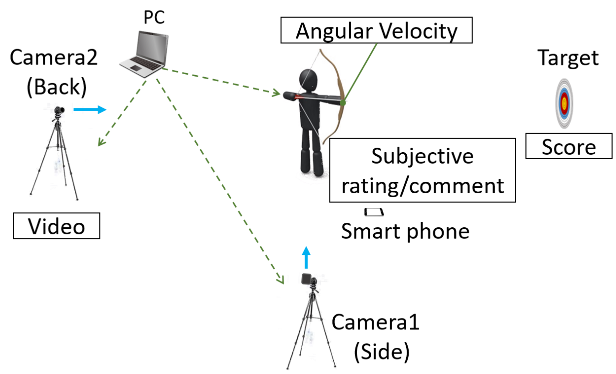

Figure 6: Measurement setup for the experiment.

4.1 Angular velocity and video acquisition

The motion data of five intermediate and advanced archer (three male and two female) were obtained with the following method. The angular velocity sensor data were sampled with a frequency of 1000Hz. Arrows were shot on the target that was square with 82cm of side length and 50m away from the archer. All of participating archers used recurve bow (RC). In this experiment, data were obtained at each shot according to the following four rules.

- Angular velocity was measured with angular velocity sensors every shot.
- Videos were captured at 300 fps in synchronization with the angular velocity sensor from two directions, one side and the back of the test participant.
- At the end of each shot, seven levels of subjectivity (very bad/bad/mildly bad/normal/mildly good/good/very good) and comments of the shot were given. Audio comments were recorded by a smartphone when the test participant finished the shot.
- Target score was recorded. In addition, the position of the arrow on the target was recorded as well.

Figure 6 shows the schematics of the measurement system.

4.2 Windows application

The application for archers was developed as a Windows application. The Windows application of Visual C# 2019 was used as the development environment. When the identification symbols (A to E) for test participants were allocated and input data were selected, comparisons and classifications were performed automatically, the results could be displayed as follows. In order to make it easier for test participants to understand, the angular velocity axes X, Y, and Z were shown as bow roll, bow pitch, and bow yaw, respectively. The information obtained from the Windows application is explained below.

Centroid comparison. Each classified group as result of k-means method is called a "cluster". The average waveform of shots belonging to the cluster is called its "centroid". As shown in Figure 7, centroids can be compared by selecting two clusters. It is possible to search for the part of difference between two shots easily,

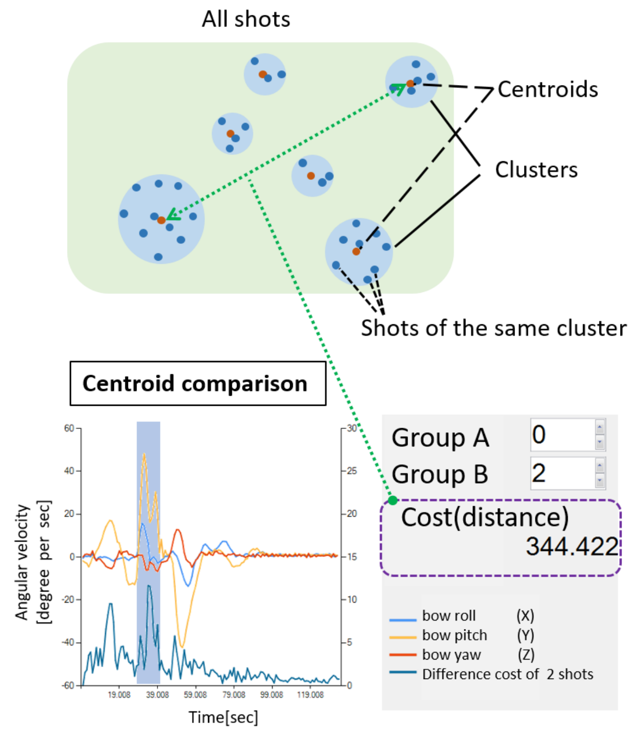

Figure 7: Centroid comparisons on the Windows application.

just look at the part where the value of cost waveform is high on the graph. The degree of similarity between the two clusters is determined based on the calculated distance. The graph shows the similarity between the centroid waveform of cluster A and that of cluster B. As shown in the Figure 7 cluster comparison, there is a section where the cost waveform significantly increases. It is to be noted that the part where the cost value is highest is indicated by the filled part. Since the centroid is the average of all the shots belonging to that cluster, the features of each cluster could be estimated from the features of the centroid waveform. The cluster numbers are given in ascending order from the one with the largest number of shots belonging to the cluster.

Two shots comparison. As shown in Figure 8, any two shots could be compared. The time when the difference between shots appears can be confirmed from the value of the cost in the graph. When comparing the angular velocity data of two shots, it is possible to associate similar data points using DTW. The similarity of the corresponding points is calculated from the Euclidean distance of the three-dimensional angular velocity vector and is drawn in the angular velocity graph, so that it is possible to roughly identify the movement that is different.The video of each shot could be checked from the "movie of shot" button, but if the viewpoints of the cameras are almost the same, it is easier to understand the video by an overlaid video with the two shots using the "overlaid video" button. In addition, ffmpeg [2] was used for make an overlaid video

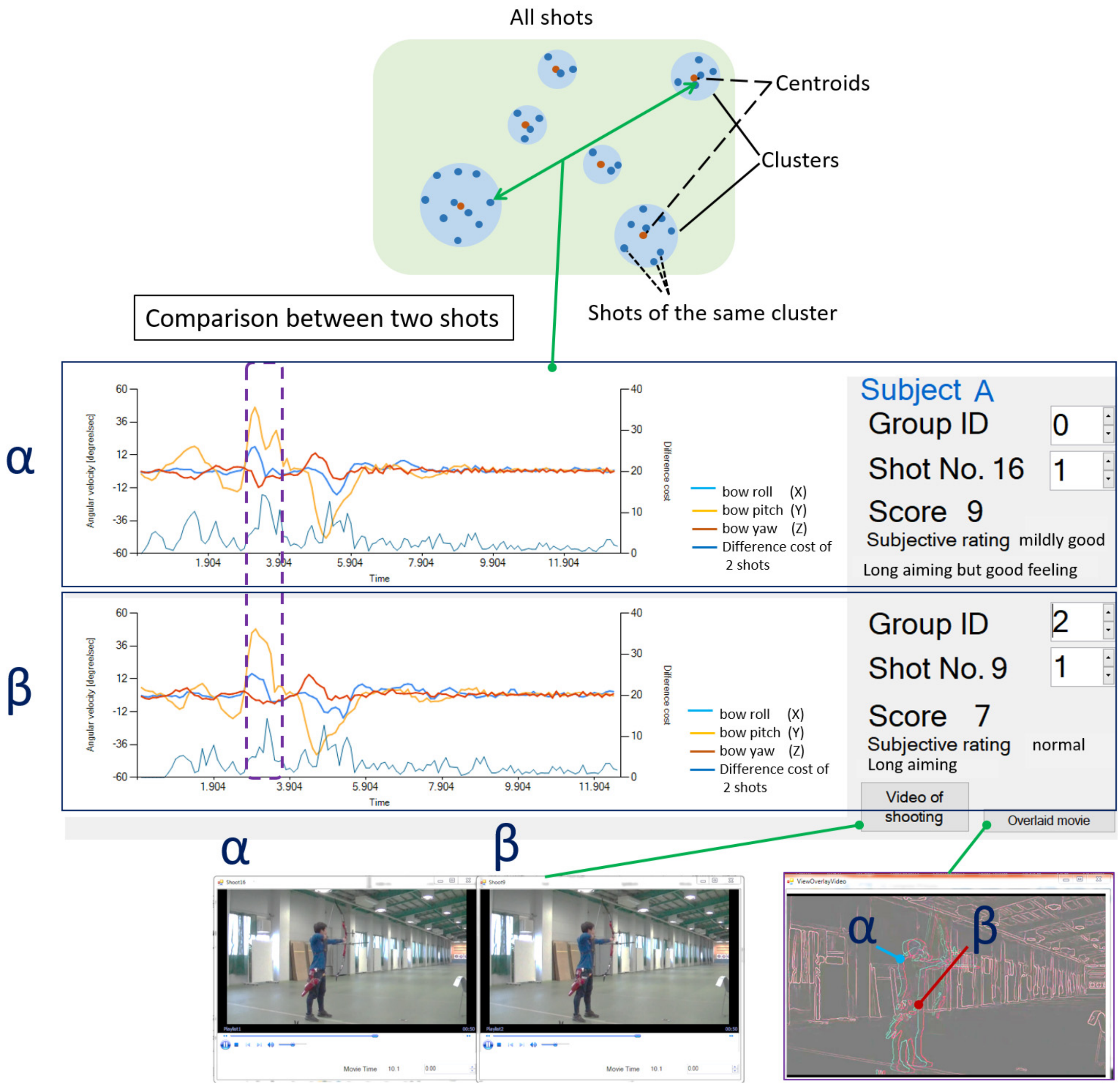

Figure 8: Comparison between two shots on the Windows application.

in which the section with noticeable difference was cut out. Moreover, in the overlaid video, the shot corresponding to α is shown in blue, and the shot corresponding to β is shown in red. The target score and subjectivity are presented as reference indices for archers to remember the shot and match it with their feeling.

Visualization of clustering results. As shown in Figure 9 the clustering result of the input data can be visualized. The numbers are cluster indices, and are organized in descending order according to the number of shots included. The diameter of the circle is proportional to the shot number included in the cluster. The solid line between the clusters connects the clusters with a short distance (distance less than 300). In addition, since the high dimension is reduced to two dimensions by the automatic drawing of graphviz[6], the positional relationship of the cluster may not be correlated with the similarity.

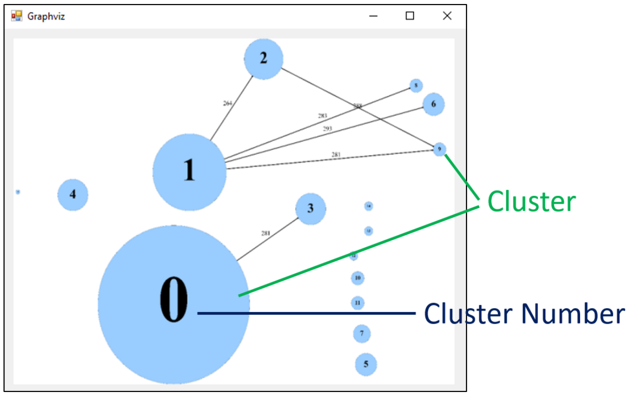

Figure 9: An output result that visualizes the clustering results by the Windows application

This graphic (Figure 9) was added to present additional information to the user to visualize cluster results. By using this function, the number of shots included in each cluster and the distance between each cluster can be checked visually.

5 RESULTS OF COMPARISONS AND CLASSIFICATIONS

The results of comparisons and classifications were obtained with the Windows application developed by the author.

5.1 Description of visualization contents

Figure 10 shows some of the differences between the different patterns that could be found from the clustering results. The content of each item is explained below.

Cluster. The cluster diagram shows the clustering result of the specified subject and phase. The closest shot to the centroid in the cluster was selected. Hereinafter, every two shots to be compared are called α and β respectively. The number of clusters is available in Table 1.

Angular velocity waveform. A frame that cut from the video of each shot before overlay is shown. There is a dashed line on the angular velocity waveform indicating the time when the frame image was taken. In addition, the cut-out time of a frame from overlaid video can be adjusted automatically by using the method of DBA. The difference is indicated by a white line. The positions of the α posture and the bow were marked with a white line by hand, and the same was done for β.

Video. A frame that cut from the video of each shot before overlay is shown. There is a dashed line on the angular velocity waveform indicating the time when the frame image was taken. In addition, the cut-out time of a frame from overlaid video can be adjusted automatically by using the method of DBA. The difference is indicated by a white line. The positions of the α posture and the bow were marked with a white line by hand, and the same was done for β.

Description. Differences were found via checking the overlaid videos and the angular velocity waveform by the first author.

5.2 Differences seem by visualization

In phase 1 of archer A, a difference of "whether archer A stretched his arm or not" before he set up his bow could be detected. The angular velocity waveform of α around Y-axis has two hills similar to the shape of "M", which means that his arm stretched on two steps. The same part of β around Y-axis shows one hill like the shape of a bell, meaning that his arm stretched on a step.

In phase 1 of archer B, a difference of "whether the string was drawn continuously or in 2 steps" when archer A raised up her bow and lowered it could be detected. The angular velocity waveform of α around Y-axis has two hills in the shape of "W", and X- and Z-axes also have two steps wave, it means that the archer drew the bow in two steps. When the movie was checked, the bow was raised higher in shot α than shot β. It is thought that the archer drew the bow in two steps because the archer raised the bow higher than usual and it is hard to draw the bow continuously.

In phase 2 of archer C, we can see the cost is high when he release an arrow. We can check a difference that "when he release the arrow finger hooked the string of the bow or not". The shot β which is hooked the string, had more shake than shot α during aiming the target.

In phase 3 of archer C, a difference in the posture of the bow when the archer released an arrow could be seen. From the angular velocity waveform, β had spinning speed of approximately twice of that of cluster 0 even though α did not have significant spin around X- and Z-axes.

In phase 2 of archer E, the aiming time is significantly different between shots α and β. The aiming times in average are about 4 seconds for α and 2.5 seconds for β. Shots in cluster β involve more shaking than that in cluster α. α had periodic rolling shake that β did not have. It is difficult to find a corresponding image but it is possible to check small shaking as a difference in the overlaid movies.

These detected differences were significant according to the archery coach. In addition, the differences were hard to notice by the archers themselves. From above, it could be said that the proposed method could automatically extract differences between shots that could indicate where improvement could be made.

5.3 Check similarity of shots within clusters

Similar shots were checked to make sure that they were categorized into the same cluster. Figure 11 shows comparison of a few shots in cluster 0 (α) and the shot closest to the centroid of cluster 2 (β) in phase 1 of archer A is shown in Figure 10. Figure 11 uses an output figure of phase 1 of archer A and was added some points in a cluster.

The top graph is a centroid waveform of cluster 0. The waveform is an average of all of angular velocity forms in that cluster. The graph below is the angular velocity waveform of shots corresponding to the closest, the second closest and the farthest shot to the centroid. By comparing these shots and the closest shot to the centroid in cluster 2, the part that the cost of difference raised could be seen. The common point of cluster 0 is that "he stretched his arm in two steps before raising his bow", which is the same as explained in Figure 10.

The right part of the figure shows a dashed line on the angular velocity waveform which indicates the time when the frame image was taken. The difference between cluster 0 and cluster 2 is indicated by a white line when the archer did not expend his arm.

In the farthest shot, the 88th shot, from the centroid, there is a big moving wave before holding up the bow. This part raises the cost of differences and the distance from Centroid is thought to be large. In the movie of the shot, this big moving wave corresponds to the movement of holding up the bow. It wasarcher included in the data unintentionally because the timing of the start of the measurement was early.

As described above, even if it contains a difference for a short period, it can be seen that the shot operation is similar in many parts and could be classified into one cluster.

6 USER STUDY

In this section, the classification results to archery coach and archers are shown, and the usefulness of this system is evaluated. Not only technical evaluations were conducted, but comments from the test participants were gathered as well.

6.1 Evaluation from an instructor

The test instructor is an archery coach at Nippon Sports Science University. The level of the archery club activities is high, with students aiming to become Olympic archers. The comments are as presented with summaries being • and archer comments from the interview quoted directly.

- The overlaid videos are visually easy to understand.

"It was easy to understand the differences such as the expansions and contractions of the arms with this system. It might have been hard without it. Overlaid videos make it easy for anyone to see the differences. If I could use this system right after each shot, it would be helpful to understand my own archery form."

- It is worthy even if only knowing the time of the difference.

"Even if this system only pointed out the point where there are differences, it still makes it much easier for us to see how to improve (my archery form), which makes the system very valuable. After we obtained information from this system, we should try it by ourselves and decide whether the obtained information is useful. It is hard to find the fundamental reasons resulting in the differences between forms, so it is obvious that trial and error is a must. Whether the archers are aware of the differences detected by this system depends on their individual abilities (more noticeable for advanced archers and less for beginners). I think it would give us more effective feedback if there is someone who can analyze (the results) professionally. It would be fascinating if the system could be used only by an archer (without the help from a professional)."

"The visualization of clustering results is interesting and would help us understand shots."

According to the coach, it is important to maintain consistent shooting movements and timings for each shot. It is worthwhile even if only a small difference is detected. If there was an unintended difference, it would helpful to find out where improvements in consistency could be made. In addition, regarding the analysis of a series of archery movements divided into three phases, the coach said that it would be easier to understand if the video could be limited to the phase where the difference appeared.

6.2 Evaluation from archers

Five test participants in the data acquisition experiment were notified when differences in individual shots appeared, and were also presented with the results displayed in the software application. The comments obtained are shown below. Some comments were repetitive and thus omitted.

- Easy to compare different shots and useful for practice

"As for the current state, there is a system that plays the video of the shot with a delay of several seconds, immediately before which the shot was made, and uses it to check the shot shape. It is useful but it is not possible to check or compare past shot. In the past, motions were analyzed using motion capture, but it took a long time to take measurements and feedback was not obtained yet. Being able to perform comparisons and confirmations with ease would be preferable for daily practice. Since the feeling of shooting tends to fade as times goes on, it would be very useful if the system could be checked immediately after each shot."

- There is a discovery that has not been noticed because the archer's own shot could be analyzed objectively.

"Scores, subjectivity, and shot forms are sometimes not correlated. I am sure that subjectivity is unreliable. I could find the differences without being aware of it. I would like to be clearly aware (of such differences) from the next time (and onwards). I'm interested in how the differences in the archery form affect the score. I would like to make use of the correlation between my shot form and the hit rate."

Feedback from all test participants(archers), showed that this system was generally considered helpful and there is a demand on availability of such a system. On the other hand, the following comment were collected as suggestions for further improvements.

- "I would like to check the movement of the shoulder position, the pulling hand, and the looseness of the strings (the degree of string pulling)."
- "It would be better if one shot could be compared in a single time series (no phase cut)."
- "It would be easy to understand if the bow displacement could be related to the body displacement."

The levels of the five archers above varied from intermediate to all-Japan championship entry level, while the advanced archers could understand the movement of the body only by correlating their feeling of movements and the graph of the bow movement, and might ask for a more detailed analysis. On the other hand, there were archers who could not imagine the movement even if they looked at the graph. It is important to determine which kinds of archers are targeted for future improvement on the user interface of the system.

7 CONSIDERATION

In this paper, the proposed method was able to perform clustering and comparisons based on the similarity of waveform features using angular velocity data. The following differences could be found.

- Differences between continuous and discontinuous movements
- Differences in the length of time of movement
- Differences in the speed of movement

To some extent, the proposed method would be considered effective even if it is thought that there was a limit to the comparison and classification of archery movements, since the angular velocity data simply represent the behavior of the bow. The difference in the body position, such as the differences in height at which the bow is lifted, appears as a difference in the angular velocity sensor. It could be seen that different body movements also affected the behavior of the bow.

8 CONCLUSION

In this paper, we proposed a method to compare archery shots easily by clustering archery shots using an angular velocity sensor. Interviews with experts suggested that the ability to detect small differences between different shots would be helpful in order for efficient practice. As of future work, it is needed to further improve the system so that it could be used on site when archers were practicing.

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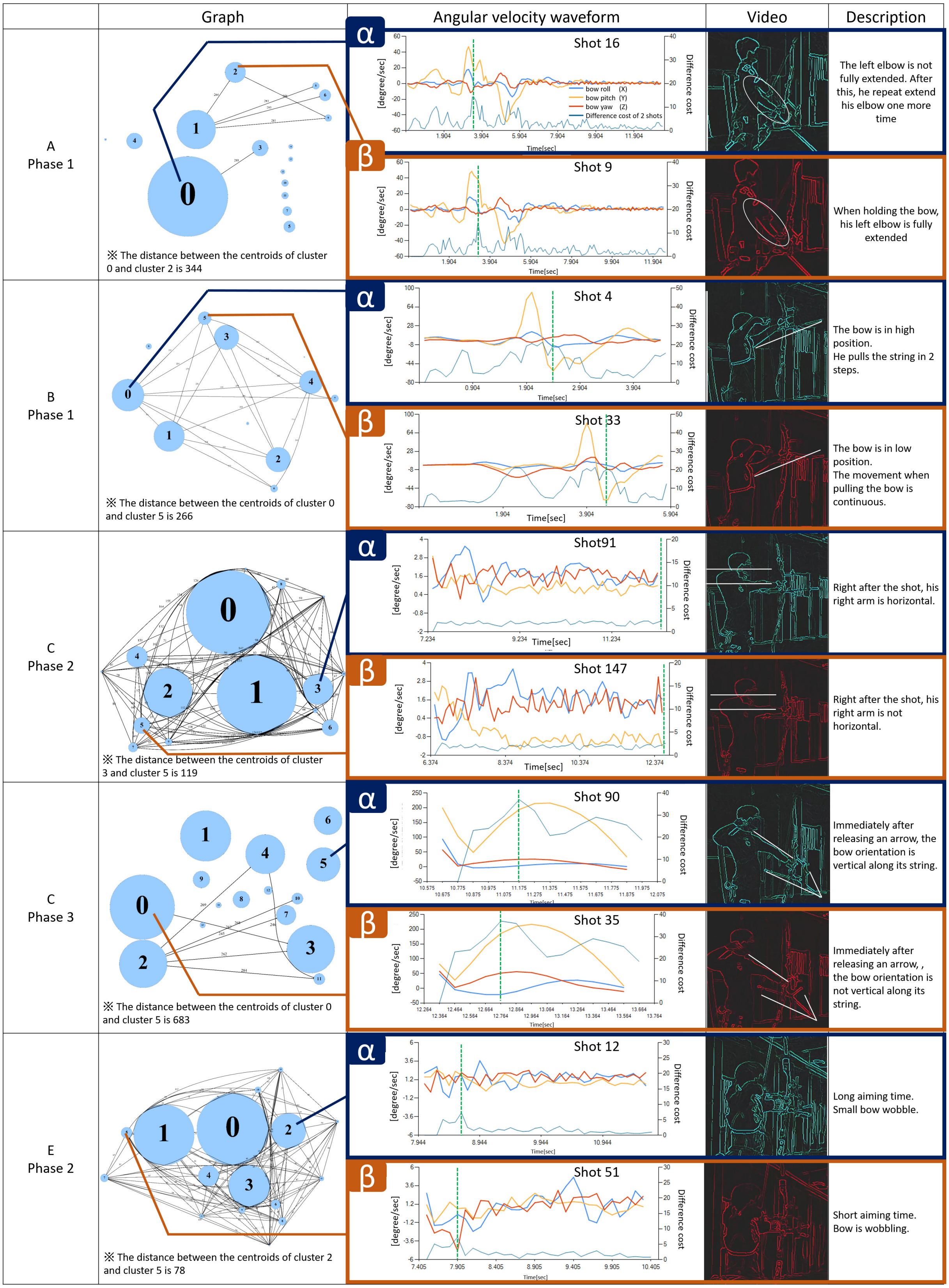

Figure 10: Clustering results and obtained differences.

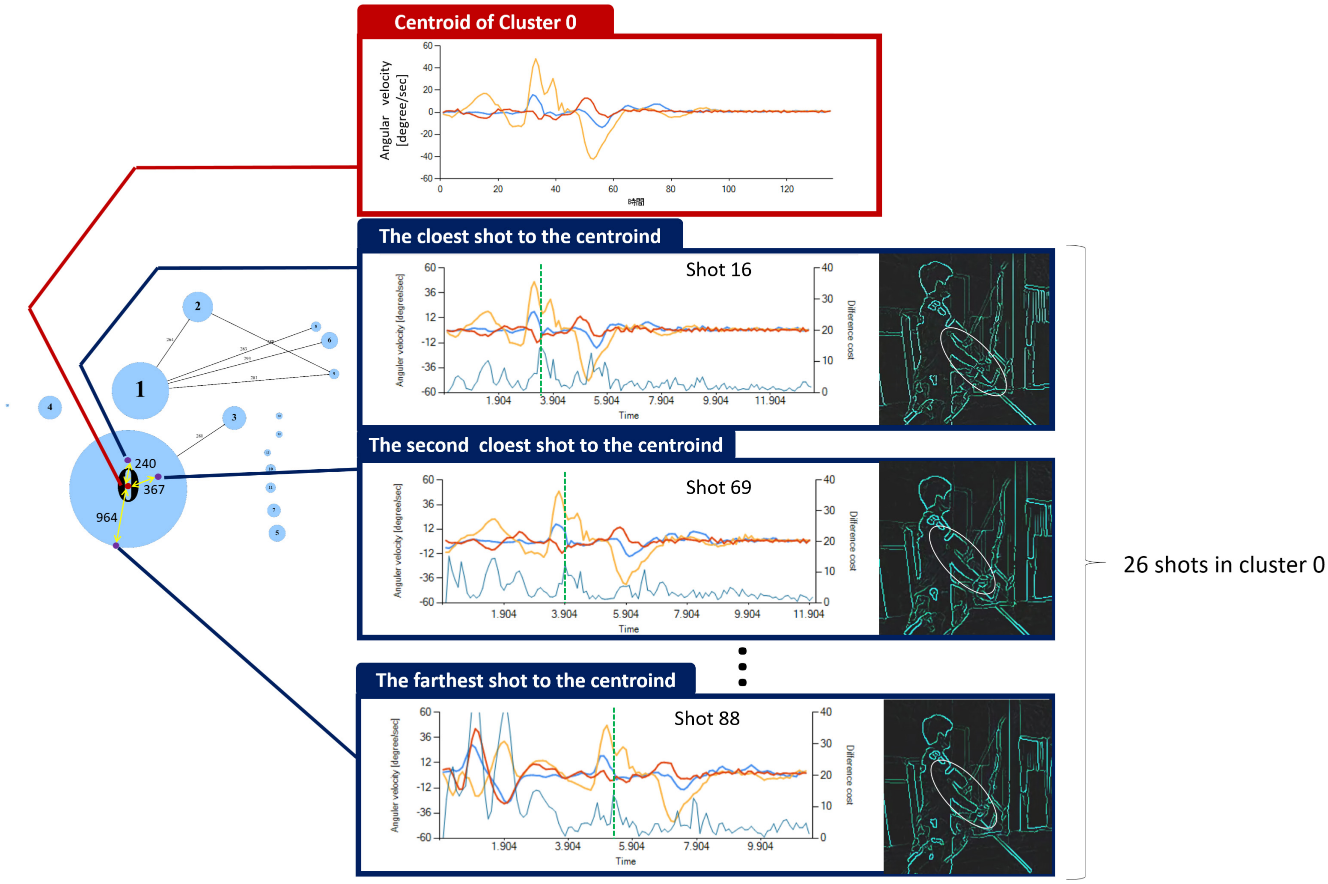

Figure 11: Shots in the same cluster.