Visualization of the repetitive practice of dance motion: Case study with multiple genres of dance

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***Abstract*—With the enhancement of relatively inexpensive human motion capture technology using cameras and infrared sensors, the measurement of human body motion has been easier and its applications have expanded dramatically. We are using this technology to develop a visualization system for the assistance of dance skill improvement by visualizing differences and changes in the motions of novice dancers while theur repetitive practice of the same dance. This system applies a body size correction between the dancer and the instructor, a time correction that aligns the timing of the motions, and a spatial correction that aligns the dancer's position and body orientation. The system then applies a clustering process is to the body parts, and visualizes the clustering results. Users can then select multiple arbitrary motions and animate them to check the differences and changes in the dancer's motions. This paper firstly presents the processing flow and functions of the visualization system, and then introduces the results of the motion data of three novice dancers in three different dance genres to verify the effectiveness of this method.**

***Index Terms*—Visualization, Dance, Motion capture.**

I. Introduction

Repeatation of the same motion is one of the most common and effective practices for novice dancers. Here, there are two main problems for beginners. Firstky, it is often difficult to feel the long-term progress. Also, it sometimes happen that dancers feel the practices as boring routines. But still, dancers need to find changes and modifications in their own motions during the practice. In other words, identifying one's own changes and modifications will improve one's dancing. A deeper understanding of their own motions will lead to more efficient repetitive practice.

We are developing a visualization system to support dancers in finding modifications in their unconscious motions. Specifically, the system improves the efficiency of repetitive dance practice by visualizing the following points: when the dancer shows improvement in dance, which parts of the body are prone to motion deviation, how often the dancer achieves the correct motion, and where the dancer's habits tend to occur.

The procedure of this system is as follows. First, the same dance by the same dancer is measured multiple times using a motion capture system. Then, scale, time, and position corrections are applied to the motion data. After completing the above processing, the system applies a clustering process to the motion data, and visualizes the clustering results. Users can play the animation of user-specifed multiple motions to allow comparison and observation of the dancers' motions.

This paper also presents the case study of motion data measured for four different dance genres. In addition, the effectiveness of the system is discussed by visualizing the motions of three beginner dancers for three genres of dances.

The reminder of this paper is as follows: Section 2 describes related work, Section 3 describes the proposed method, Section 4 shows the case study results, and Section 5 summarizes the paper.

II. Related Work

Developments of computer-powered assistance systems for dance lesson has been a well-discussed research topic [4]. This section introduces related studies on dance lesson systems and visualization for dance lessons.

Some studies on dance support focused on the development of specialized hardware systems. Groβhauser et al. [5] presented a sonification system as feedback of motion and foot pressure of a dancer. Nakamura et al. [9] presented a robot that displays a reference dance motion and moves along with the motion of a real dancer. Silveira et al. [11] applied soft-robotics for the support of dance lessons.

Virtual reality (VR) and augmented reality (AR) technologies are also very helpful for the development of dance lesson systems. Anderson et al. [1] developed "YouMove" that assists the self-check of dancers' own motions by the metaphor of an augmented mirror. Chan et al. [3] presented a VR system that projects the motions of an instructor and captures the movements of students. Senecal et al. [10] presented a VR-based practice system for salsa dance by displaying the dance of a virtual partner.

One of the authors also has a series of studies on dance lesson systems, including a system for practicing formations applying a self-propelled screen [12], a practice system for self-dance modeling [13], an online support system for flipped classroom [14], and experiments on effects on separated learning of acquiring movement skills [15].

Visualization techniques are very helpful tools for the analysis of human motion data and have been actually applied to a variety of motion capture data. Liu et al. [8] proposed a new visualization method that represents gestures as vectors and plots them on a sphere. Keefe et al. [7] propose a method

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DOI 10.1109/IV60283.2023.00068

for interactive visualization of multiple motion data in the biomechanical field by applying pig chewing motion data.

A small number of studies have been focusing on visualization and visual analytics of dance motions. DanceMoves by Arpatzoglou et al. [2] realizes the visual analytics to compare the dance motions and visually search dance features.

As described above, there are many studies for teaching, analyzing, and comparing dance and visualization methods for motion data. However, most of the conventional studies compare and analyze experienced dancers and novice dancers, and there are few studies that deeply analyze the repetitive practice of a single dancer. Therefore, the purpose of this study was to measure repetitive practice by a single dancer and to compare and analyze them as time series data.

III. Processing Flow

This section presents the processing flow of the proposed system consisting of the following four steps: motion measurement, motion data correction, clustering, and visualization.

A. Motion measurement

1) Azure Kinect DK: Our current implementation uses Azure Kinect DK to measure the dancers' motion. It has a built-in distance image sensor using near-infrared light and a video sensor (video camera), which can measure the positions of 24 joints of human bodies. Users can archive motion captures using Azure Kinect DK relatively easily without wearing special devices or markers.

We measured the repetition of the same dance by the same dancer over several repetitions (typically 10 to 20 repetitions) in this study. In addition, we measured the dance of an instructor who has mastered exemplary movements once or twice to visualize the difference from other dancers.

B. Motion data correction

Temporal and spatial correction for the motion data should be applied prior to the clustering process. If dancers want to compare their own motion data with the motion of the instructor, body size correction between the dancer and the instructor should also be applied prior to temporal and spatial correction.

1) Body size correction: The difference in body size between the dancer and the instructor is compensated for. Our current implementation simply applies an affine transformation.

2) Time correction: The acquired time series data may not have the same relative time of the motion start to the recording start time. Dynamic Time Warping (DTW) is a method for calculating the similarity between time series data. It calculates the similarity by finding the shortest path after calculating the distance between points. Since each joint has position data in the XYZ coordinates, Multi-Dimensional Dynamic Time Warping (MD-DTW) [6], which is an extension of DTW to multiple dimensions, is used instead of ordinary DTW.

3) Spatial correction: The acquired time-series data are corrected for differences in standing position and body orientation. A simple affine transformation (scaling and translation) is currently applied.

C. Clustering

Clustering is applied to the corrected motion data. Here, our implementation applies the clustering independently to the left hand, right hand, left leg, right leg, and head. Each part is composed of the following joints in Figure 1.

- **Left arm:** CLAVICLE_LEFT, SHOULDER_LEFT, ELBOW_LEFT, WRIST_LEFT
- **Right arm:** CLAVICLE_RIGHT, SHOULDER_RIGHT, ELBOW_RIGHT, WRIST_RIGHT
- **Left leg:** HIP_LEFT, KNEE_LEFT, ANKLE_LEFT, FOOT_LEFT
- **Right leg:** HIP_RIGHT, KNEE_RIGHT, ANKLE_RIGHT, FOOT_RIGHT
- **Head:** HEAD, NOSE, EYE_LEFT, EAR_LEFT, EYE_RIGHT, EAR_RIGHT

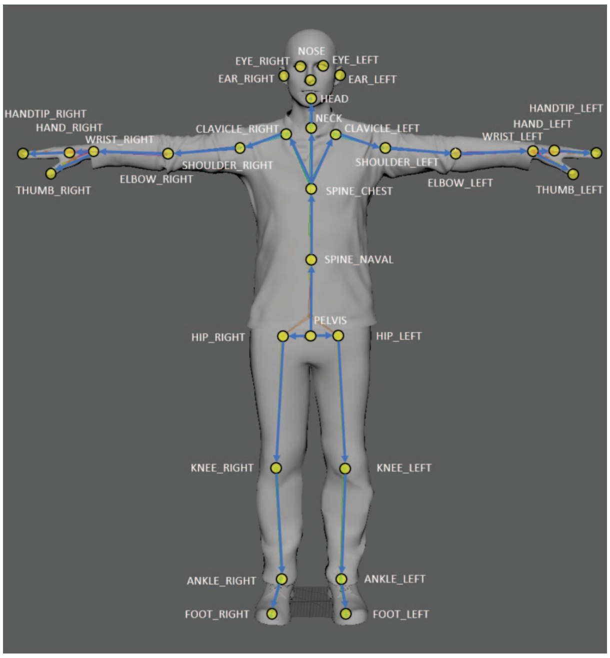

Fig. 1. Joints measured by Azure Kinect DK. [1]

We experimented with the following three types of inputs for the clustering process/

- The positions of the joints as vectors.
- The movements between adjacent frames of the joints as vectors.
- The angle of the joints as vectors.

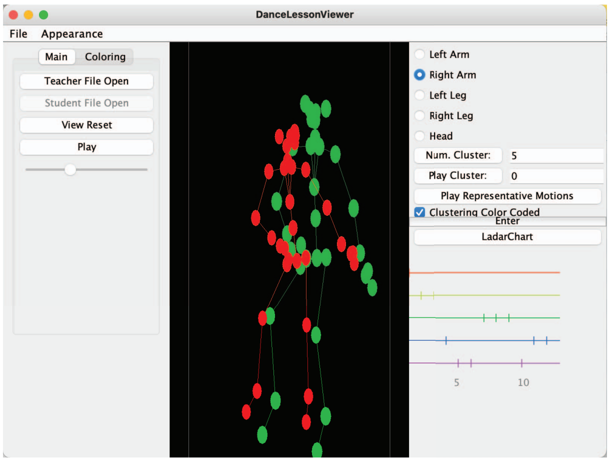

Fig. 2. A snapshot of the developed visualization system.

D. Visualization System

This system then visualizes the clustering results of the motion data. Figure 2 shows a capture of the visualization system. Users can specify multiple dance motions by manipulating this system to observe and compare the multiple motions. The "coloring" tab next to the "main" tab on the left side of the window displays a list of the motion data.

This system also displays the clustering results described in Section III-C on the right side of the window. The clustering results of the left arm, right arm, left leg, right leg, and head are displayed from the top. Users can specify the number of clusters interactively on this panel. The "play cluster" button allows specifying which clusters of the motion data are played. Or, the system can play representative dance motions of each cluster simultaneously by pressing the "Play Representative Motions" button. Here, the representative dance motion is selected based on the distance from the median of each cluster.

In the drawing areas for clustering results, the horizontal axis represents a time series, with the leftmost cluster representing the first dance and the rightmost cluster representing the last dance. The horizontal lines represent the clusters, arranged in order of similarity to the instructor's motion data from the top. The vertical lines in the display visualize the number of times the motion data is stored in each cluster. Users can analyze their own dance in chronological order by observing the clustering results. For example, users can observe which habits are common in the early stages of practice, which habits appear suddenly and occasionally, and how their motions change as practice progresses.

IV. Examples

A. Verification with four genres of dances

1) Measurement and visualization: The measured motion data were visualized using the proposed system. In the first experiment, we measured dance motions of four genres, "Jazz," "Waack," "Lock," and "Girls," to verify the effectiveness of the proposed method for each genre of dance.

In this experiment, one of the authors choreographed all dances and danced for approximately 10 seconds (2 x 8 minutes in length) to a metronome sound with a BPM of 110. The dancers danced in a way that they themselves considered correct from the first to the third time, relaxed from the fourth to the sixth time, considered only the arms correctly from the seventh to the ninth time, and considered only the legs correctly from the tenth to the twelfth time.

In order to demonstrate the validity of the system, we compared the data of the same dancer without the need for body size correction. Therefore, in this experiment, the instructor's dance was not measured, but one of the dances by the same dancer was selected and visualized as the dance motions of a fictitious instructor. In addition, we performed visualizations using each of the three types of inputs for clustering described in Section III-C.

2) Visualization results: The clustering results for each genre of dance are described below. The number of clusters was set to 5 in each case.

We assumed that for the left and right arms, the 1st to 3rd and 7th to 9th times are stored in the upper cluster, and the 4th to 6th and 10th to 12th times are stored in the lower cluster. The left and right legs are assumed to be stored in the upper cluster for the 1st to 3rd times and the 10th to 12th times, and in the lower cluster for the 4th to 9th times. We compared these assumptions with the actual results.

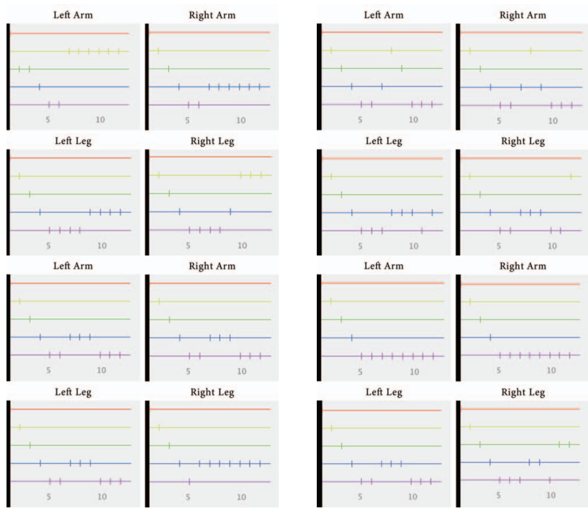

Fig. 3. Clustering (1). (Upper-left)Jazz. (Upper-right)Waack. (Lower-left)Lock. (Lower-right)Girls.

Figure 3 shows the results of the visualization using the input (1) for clustering described in Section III-C.

For Jazz, only the right leg showed the visualization results as expected by the authors. For the 7th to 12th motion, all motions after the 7th motion were stored in the second cluster for the left arm, whereas all motions for the right arm were stored in the fourth cluster, suggesting a large difference

[2]https://docs.microsoft.com/ja-jp/azure/kinect-dk/body-joints

between the left and right arms. Waack's results were as expected for the left and right arms, as the seventh to ninth motions were stored in the second to fourth clusters, and the tenth to twelfth motions were stored in the fifth cluster. The similarity was high for the left and right arms and the left and right legs, respectively. Lock did not show the expected results, as the 7th to 12th motions were classified into the 4th to 5th clusters for all sites. The results of the 7th to 12th motions were highly similar for the left and right arms, and the left and right legs, respectively. The Girls' results were as expected for the right leg, as the left leg was classified in the 4th to 5th cluster for the 7th to 12th motion, while the right leg was classified in the 3rd cluster for the 11th to 12th motion.

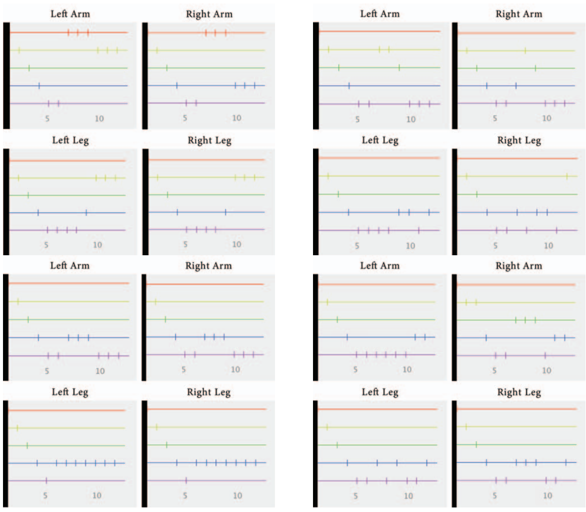

Fig. 4. Clustering (2). (Upper-left)Jazz. (Upper-right)Waack. (Lower-left)Lock. (Lower-right)Girls.

Figure 4 shows the results of the visualization using the input (2) for clustering described in Section III-C.

The visualization results of Jazz appeared as expected for the right arm, left leg, and right leg. The left and right legs showed the same results, while the left and right arms showed different results, suggesting a large difference between the arms as applying the input (1). The results of Waack were also as expected for the left and right arms as applying the input (1). The results for Lock are exactly the same as applying the input (1). For Girls, only the right arm was close to the expected result. In addition, the difference between the arms is larger than that of applying the input (1).

Figure 5 shows the results of the visualization using the input (3) for clustering described in Section III-C.

Jazz's results were somewhat close to the expected results only for the left and right legs. In addition, the similarity between the left and right arms was higher than applying inputs (1) and (2). Waack did not produce the expected results for all the regions. The similarity between the left and right arms and between the left and right legs was high as applying inputs (1) and (2), but the similarity was lower than

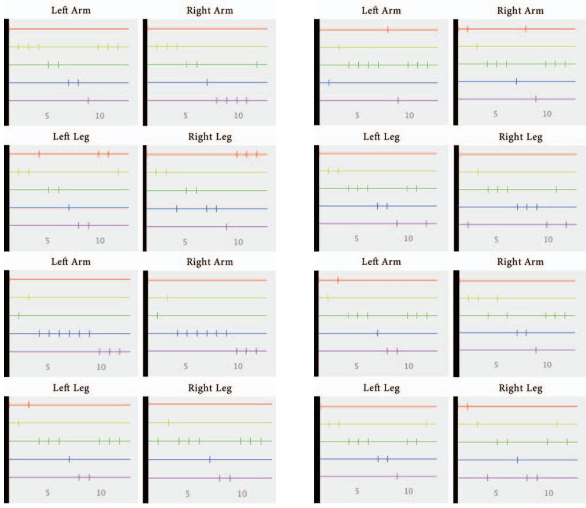

Fig. 5. Clustering (3). (Upper-left)Jazz. (Upper-right)Waack. (Lower-left)Lock. (Lower-right)Girls.

applying inputs (1) and (2). The results for Lock were different from those while applying the inputs (1) and (2), but not as expected for all regions. For Girls, the results for the legs were somewhat similar to the expected results.

As a result, we determined that input (2) was the most effective in all three inputs. In addition, four of the six sites while applying input (2) were arms, while all of the six sites while applying input (3) were legs, indicating that input (3) is more effective for legs than arms. In both inputs, Lock did not produce the expected results for all sites.

B. *Visualization of practice process of beginners*

1) Measurement: As the second experiment, we measured the dances of novice dancers and visualized them using the presented system. The choreographies used in the measurement were Jazz, Waack, and Girls, except Lock, for which no sufficient validity was observed in the previous experiment. Three beginners with one to two years of dance experience danced 12 times each for approximately 10 seconds (2 x 8 minutes in length) to a metronome at 110 BPM. In addition, the author also measured one dance of each genre as the instructor's data.

2) Visualization results: The clustering results for each dancer are introduced below. The number of clusters was set to 5 for each dancer, and the input (2), which was validated in Section IV-A, was used.

Figure 6 shows the visualization results for dancer 1.

All body parts had different clustering results for Jazz. In particular, the left arm, right arm, and right leg had four to five motions stored in the second cluster, whereas the left leg had only one motion stored. The fact that the fifth and later motions were stored in the second to fourth clusters in all regions suggests that the dance improved from the fifth motion.

Waack showed that most of the motions were stored in the second cluster after the sixth time for the left arm, after the

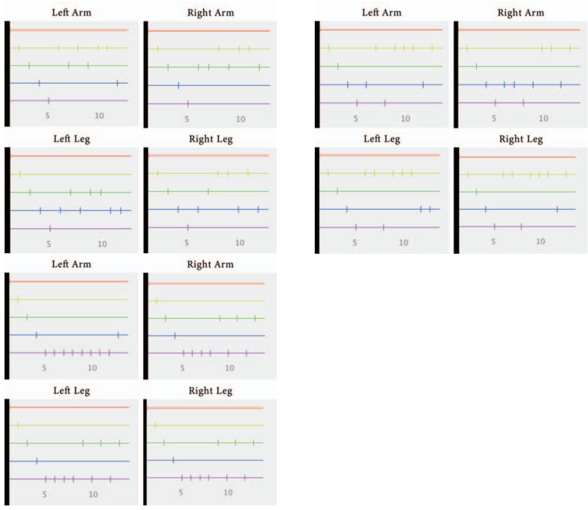

Fig. 6. Result of dancer 1. (Upper-left)Jazz. (Upper-right)Waack. (Lower)Girls.

fifth time for the left and right legs, and after the ninth time for the right arm. The results for the left and right arms were different for the sixth to eighth trials, but the results for the first to fifth trials and the ninth and later trials were exactly the same.

The results of Girls for the left and right arms were different, but the results for the first, fifth, and ninth results were exactly the same. In particular, the results for the right arm, left leg, and right leg were identical.

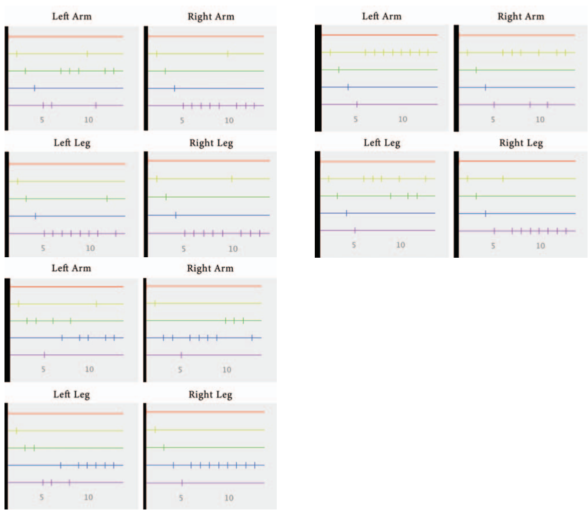

Fig. 7. Result of dancer 2. (Upper-left)Jazz. (Upper-right)Waack. (Lower)Girls.

Figure 7 shows the visualization results for dancer 2.

In the Jazz data, the left arm was stored frequently in the third cluster, while the right arm, left leg, and right leg motions were stored most frequently in the fifth cluster. This indicates that the progress of the right arm, left leg, and right leg are highly similar. In addition, motions of the left arm were stored in the third cluster after the sixth motion, suggesting that the dance improved from the sixth motion.

Waack showed that the left and right arms had the most motions stored in the second cluster after the fifth motion, the left leg had the most motions stored in the second and third clusters after the fifth motion, and the right leg had the most motions stored in the fifth cluster. This result suggests a high degree of similarity between the left and right arms. Also, the result suggests that the left arm, right arm, and left leg showed improvement in dance from the fifth motion.

Girls showed the highest number of motions stored in the fourth cluster for all regions. In particular, the left and right legs are highly similar to each other since all motions after the fifth motion are stored in the fourth and fifth clusters.

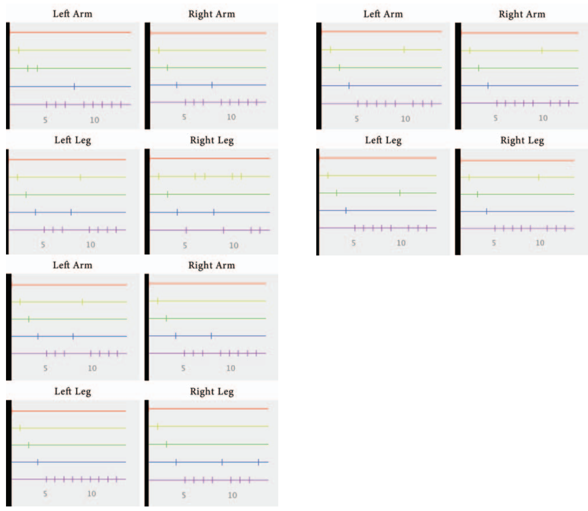

Fig. 8. Result of dancer 3. (Upper-left)Jazz. (Upper-right)Waack. (Lower)Girls.

Figure 8 shows the visualization results for dancer 3.

Jazz showed that the left arm, right arm, and left leg had the most motions stored in the fifth cluster, while only the right leg had the most motions stored in the second cluster. In particular, the results for the left and right arms were exactly the same. This means that the progress of the left arm, right Arm, and left leg are highly similar.

Waack showed the highest number of motions stored in the fifth cluster for all parts of the body, resulting in a high degree of similarity.

Similar to Waack, Girls showed the highest number of motions stored in the fifth cluster for all the regions, resulting in a high degree of similarity.

3) Discussion: This section discusses each subject and each genre based on the above visualization results.

For Jazz, dancer 1 showed improvement in dance from the fifth time, while dancers 2 and 3 stored more motions in the fifth cluster, which was significantly different between dancer 1 and dancers 2 and 3. On the other hand, the left arm of dancer 2 showed improvement in dancing from the sixth time, and this timing is close to the timing of the improvement of dancer 1. This result suggests that Jazz tends to show improvement from the fifth to the sixth time. In addition, the results showed that the left-right difference in arms was large for Jazz, but this result was contradicted only for dancer 3.

Waack showed improvement from the fifth to the sixth session for dancer 1 and from the fifth session for dancer 2, suggesting that Waack, like Jazz, tends to show improvement from the fifth to sixth session. In addition, the results in Section IV-A showed that Waack had a high similarity between the two arms and between the two legs, but the right arm and right leg of dancers 1 and 2 contradicted this result. This suggests that the dancer 1 had more difficulty with the right arm and the dancer 2 with the right leg than with the other parts.

The results for the Girls were more similar between the dancers than for the other genres, with more motions stored in the fourth and fifth clusters for all subjects. This suggests that the clustering accuracy is lower for Girls than for the other genres, since the input (2) in Section IV-A produced the expected results only for the right arm. But even, the motions of the dancers 1 and 3 were clustered in the fifth cluster more frequently, while those of the dancer 2 were clustered in the fourth cluster more frequently, indicating slight individual differences.

While comparing the results between dancers without fixing the genre, the dancers 1 and 2 showed variations in the visualization results for each genre, while the dancer 3 showed high similarity in all genres. This result may suggest that clustering is not working correctly for the dancer 3. Possible reasons for this include inaccurate body size correction and spatial correction.

V. Conclusion

This paper introduced the visualization system developed for the dance practice process and discussed its effectiveness by showing the results of visualization of dance motions in four different genres and the results of visualization of dance motions by three beginning dancers. This visualization system applies clustering to multiple dances by the same dancer measured with a motion capture system after applying correction as a pre-processing step, and visualizes the classification results regarding the differences between motions. This system makes it possible to simultaneously play back the skeletons of different time series of dances for comparison and observation. It is also possible to examine the effects of repetitive practice and the differences in clustering results by region.

The visualization results of dance motions of four different genres indicate that clustering is effective when the movements of joints between adjacent frames are used as the input of clustering. The results were as expected for the right arm, left leg, and right arm of Jazz, the left arm and right arm of Waack, and the right arm of Girls.

The visualization of dance motions by the novice dancers revealed the timing of dance improvement in each genre, as well as the parts of the body that each subject had difficulty with. In addition, the clustering accuracy was low for Girls, and the clustering did not work correctly. This could be due to the characteristics of each genre, or to insufficient correction for body size and space. We would like to further verify these issues and improve the system as future work.

Another issue is that it is not easy to understand the differences in motion data and the characteristics of each cluster from the visualization results. We would like to add functions such as displaying joints that differ significantly from the instructor's model motion in different colors as important joints, and making it possible to play back the choreography for each movement.

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