Visualizing the Difference between Two Motions Using a Color Matrix

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***Abstract*—This study proposes a visualization method using a color matrix to intuitively highlight differences between two motions. Traditional tools like stick figures or graphs often fail to clearly convey where and how motions differ, especially across multiple body segments and time frames. By combining stick figure visualization with a color matrix representing motion differences over time, the proposed system allows users to identify which body parts differ, when those differences occur, and how they propagate. An experiment using golf swing data demonstrated that the method effectively reveals subtle discrepancies in motion, such as asymmetries and shifts in posture, aiding in more precise motion analysis.**

Keywords— Sports Training, Motion Visualization, Color Matrix, Visual Feedback

I. INTRODUCTION

During sports training, repeating the same motion does not always lead to the same result. In many cases, even when the motion appears similar, the positions of certain body segments or the movements of surrounding areas may differ. However, it is often difficult to identify which specific parts of the motion differ. One common method for visualizing differences in motion is to use skeletal models displayed as stick figures. However, such methods struggle to clearly visualize the magnitude of the differences. Another approach involves using bar or line graphs to display motion differences, but these methods become less visually effective when attempting to show temporal differences across multiple body segments simultaneously.

Therefore, this study aims to visualize the continuous changes in the magnitude of errors between two motions across all body segments using a color matrix. A color matrix is a heatmap where the vertical axis represents each body's segment, the horizontal axis represents time, and the hue indicates the feature error. This method is well-suited for visually comparing multidimensional information, namely the temporal variation of feature errors in each body segment. Unlike other types of graphs, the color matrix minimizes information overlaps that could reduce readability and leverages color to facilitate intuitive understanding of error magnitude. Moreover, because it displays the transitions of errors in specific segment groups, it can help identify which body segments initiate the differences in the overall motion and influence the outcome.

In this study, three-dimensional positions of segments and joints are calculated from two sets of motion data. A segment refers to the central position of each body part, while a *joint* refers to the position at the connecting points between segments. Using this information, the positional and orientational differences of each body segment are computed. Then, Dynamic Time Warping (DTW) [1] is applied to generate a path that aligns similar postures across frames. Based on this path and the computed feature differences, a color matrix is generated.

The results of this study confirm that the color matrix allows visual identification of motion discrepancies. It enables observation not only of changes in error for a single segment but also of error transitions across multiple adjacent segments.

II. RELATED WORK

Oshita [2] visualized the characteristics of multiple movements by making the trajectories of the movement parts visible. However, this is not very visible for many body sections. In addition, the user is not guided as to where the major misalignment occurs, so it is difficult to know where to correct the misalignment, and it is impossible to compare the misalignment of two movements over time. In addition, in this study, it is not necessary to find characteristics from multiple movements, but to visualize the differences between two movements, so we believe that visualization using regions is not appropriate. Inaba et al. [3] proposed a method for visualizing human sensing information by changing the color of body parts using hue. This method is considered unlikely to reduce visibility, even when visualizing posture information from two sets of motion data. However, this method alone offers limited means for observing continuous changes. This study solves these problems by using a color matrix to show changes in errors with time, while incorporating a method of expressing errors by changing the color of body sections. The color matrix is like a heatmap, where the intensity of the color represents the magnitude of the value. It is effective for visualizing patterns in multidimensional data [4]. Kobayashi et al. [5] proposed a method for visualizing high-dimensional categorical data by representing data characteristics using colors. By expressing quantitative data in terms of categories, their approach enables the visualization of high-dimensional data.

III. DEVELOPMENT SYSTEM

A. Input and Output of Data

In the proposed system, two sets of motion data are used as input to extract the positional information of 21 body segments and 20 joints, and the system outputs both stick figures and a

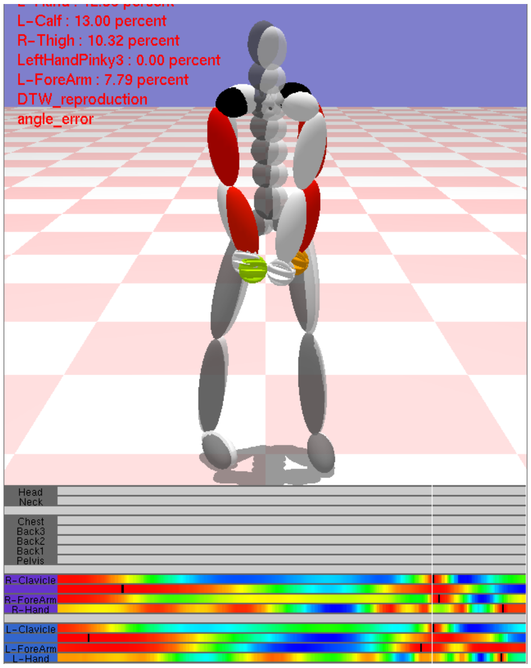

Fig. 1. Overall view of the screen. Two stick figures are shown near the center of the screen. The color matrix is shown at the bottom of the screen.

color matrix on the screen. Motion data is captured using a motion capture system, and positional information is obtained by calculating the posture data for each frame. Fig. 1 shows the system's output interface. The visualization of postural motion data is presented at the center of the screen using two stick figures. Since the magnitude of three-dimensional displacement cannot be represented directly by the color matrix, the stick figures provide a spatial visualization of the motion differences. One of the stick figures is color-coded based on the feature error, as in [3], allowing users to selectively display only the body segments of interest. The color matrix is displayed in the lower part of the screen.

B. System Processing

The processing pipeline of the proposed system is described as follows. This system processes two motion data inputs to calculate posture data $\boldsymbol{p}$ for each frame using forward kinematics. Then, it computes feature differences using the transformation matrix $\boldsymbol{M}_i$ for each segment i. In this study, two types of feature differences are used: First, the segment position difference S, which is the difference in three-dimensional positions $\boldsymbol{s}$ of the segment centers. Second, the joint position difference J, which is the angular difference calculated from the three-dimensional positions $\boldsymbol{j}$ of each joint k. The joint position difference is obtained by calculating the angle between direction vectors $\boldsymbol{a}$, derived from the positions of joints adjacent to each segment. As input, the system takes an array of posture data $\boldsymbol{p}$ extracted from all frames of two motion data sets. Each posture $\boldsymbol{p}$ is represented by the root position $\boldsymbol{v}_r$, root orientation $\boldsymbol{o}_r$, and the rotations $\boldsymbol{r}$ of all n joints. Based on this information, a transformation matrix $\boldsymbol{M}_i$ is computed for each body segment i, which is then used to calculate the feature errors.

DTW is used to compare similar postures across the two motion sequences. Using DTW, a path p is computed to align frames f_1 and f_2 from the two motions such that the sum of their feature errors c is minimized, allowing meaningful comparisons between similar postures regardless of temporal misalignment.

Finally, either of the two feature errors is visualized in a color matrix. An example of a color matrix is shown in Fig. 2. The left side lists the names of the body segments, while the right side displays a matrix where the vertical axis represents body segments, and the horizontal axis represents time-based feature errors. The hue is determined for each segment based on the maximum error values S^{max}, J^{max} (shown in black) and the minimum error values S^{min}, J^{min}. The hue H at the l-th frame path p_l is calculated from the ratio C. H is represented using RGB values. Colors close to the maximum error appear red, while those near the minimum appear blue.

IV. Proposed Method

As for data input and output, the system takes posture data $\boldsymbol{p}$ from motion data as input and outputs hue values H in the color matrix. In the overall processing flow, the system first uses forward kinematics to obtain the transformation matrix $\boldsymbol{M}_i$, which represents the position and orientation of each segment i, from the posture data $\boldsymbol{p}$ at each frame. Then, it calculates the three-dimensional positions $\boldsymbol{s}_i$ of each segment and $\boldsymbol{j}_k$ of each joint. Using $\boldsymbol{s}_i$, the system computes the segment position difference S, and using $\boldsymbol{j}_k$, it calculates the joint position difference J based on a vector $\boldsymbol{a}_i$ representing the segment orientation. Next, to enable comparison of similar postures based on feature differences, DTW is used to find similar posture pairs with small error values, generating a warping path p. Finally, the error values are visualized in a color matrix using the hue values H.

A. Forward Kinematics Calculation

The feature values of the input data are obtained using forward kinematics. From motion data, posture data $\boldsymbol{p}$ is calculated for all frames, and based on this, the transformation matrix $\boldsymbol{M}_i$, representing the position and orientation of each segment i, is computed. These matrices are represented as shown in (1).

$$\boldsymbol{M}_i = \boldsymbol{M}_{i-1}\boldsymbol{T}_{(i-1)\to k}\boldsymbol{R}_k\boldsymbol{T}_{k\to i} \tag{1}$$

Here, $\boldsymbol{T}_{(i-1)\to k}$ is the translation matrix to the next joint k, $\boldsymbol{R}_k$ is the rotation matrix at joint k, and $\boldsymbol{T}_{k\to i}$ is the translation matrix to the next body segment. From the translation component of $\boldsymbol{M}_i$, the three-dimensional positions $\boldsymbol{s}_i$ of each body segment are obtained. The joint positions $\boldsymbol{j}_k$ are extracted from the intermediate steps used in calculating $\boldsymbol{M}_i$, as shown in (2) and (3).

$$\boldsymbol{s}_i = (\boldsymbol{M}_{i_{m03}}, \boldsymbol{M}_{i_{m13}}, \boldsymbol{M}_{i_{m23}}) \tag{2}$$

$$\boldsymbol{j}_k = (\boldsymbol{M}_i\boldsymbol{T}_{i\to k_{m03}}, \boldsymbol{M}_i\boldsymbol{T}_{i\to k_{m13}}, \boldsymbol{M}_i\boldsymbol{T}_{i\to k_{m23}}) \tag{3}$$

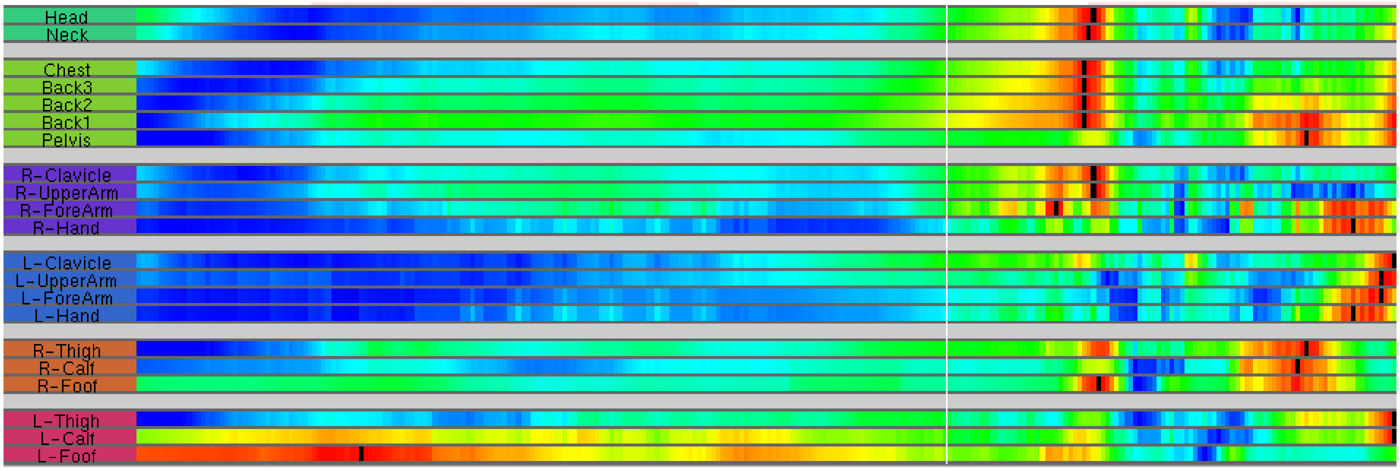

Fig. 2. An example of the color matrixThe body parts are displayed from top to bottom in order of their height: head, torso, right arm, left arm, right leg, and left leg.

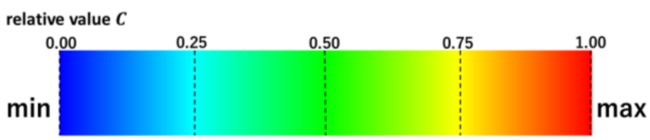

Fig. 3. Hue change. As the error ratio increases, the colors are displayed in the order of blue, light blue, green, yellow, and red.

B. *Calculating feature error*

The segment position error S is calculated as the Euclidean distance between the positions $\boldsymbol{s}$ of corresponding body segments. In this study, the goal is to highlight where differences occur, so instead of using joint positions or rotation angles as feature values, segment position differences—more intuitive and easier to understand—are used. The joint position difference J is calculated using the three-dimensional positions $\boldsymbol{j}$ of two joints adjacent to a segment. It evaluates the angle $\cos\theta$ between the direction vectors $\boldsymbol{a}$, defined from the joint closer to the waist toward the farther joint. Since this value is not directly suitable as an error metric, it is converted so that 0° corresponds to 0.0 and 180° to 1.0. This metric is important because if a user only receives information about positional differences between adjacent segments, they might mistakenly adjust only the neighboring segment's position, even when the actual cause lies in the segment's orientation. To prevent such miscorrections, joint position difference is used as a feature.

C. *Dynamic Time Warping*

The warping path p for each frame, as computed by DTW[1], is obtained by connecting the frames of the two motion datasets in such a way that the sum of the feature errors, denoted as cost c, is minimized. The calculation of ccc is shown in (4). The same calculation method is applied for the joint position error J. First, the cost matrix for dynamic programming is computed. After constructing the cost matrix, the optimal path p is determined such that the cost is minimized. The path p serves to link the frames f_1 of the first motion and f_2 of the second motion, and this linkage is used to display the color matrix.

$$c(f_1, f_2) = \sum_i S_i(\boldsymbol{s}_{i,}^{f_1}, \boldsymbol{s}_i^{f_2}) \tag{4}$$

D. *Calculation of color hue in color matrix*

Regarding the hue representation of feature errors, the minimum error for each body segment is mapped to blue, and the maximum error is mapped to black. The hue transitions progressively through light blue, green, yellow, orange, red, and finally to black. The color black is applied only to the maximum value, while the next highest error values are represented in red. The hue is determined based on the relative magnitude of feature errors for each segment i along the path p, across all frame correspondences l. The ratio $C(i, p_l)$, shown in (5), is calculated by subtracting the minimum error value S_i^{min} from the segment position error $S_i^{p_l}$, and dividing the result by the difference between the maximum S_i^{max} and minimum error values for that segment. The same calculation method is applied for both the segment position error S and the joint position error J. An example of this hue transition is shown in Fig. 3. The resulting value C becomes the hue H for the color matrix at vertical axis i and horizontal axis p. The calculation of $H(i, l)$ is based on RGB values and determined according to the ratio C, allowing the hue to be expressed as shown in Fig. 3.

$$C(i, p_n) = \frac{S_i^{p_l} - S_i^{min}}{S_i^{max} - S_i^{min}} \tag{5}$$

V. Experiment

A. *Experimental Content*

In this experiment, we compared a conventional system that changes the color of motion body parts with a proposed system that adds a color matrix to determine whether differences between two motions are more easily interpretable.

For the experiment, similar motions were recorded using the Perception Neuron Pro motion capture system, capturing golf swing actions performed by the same individual. During the recording, participants were instructed to repeat the same motion several times without any specific guidance on how to perform it. According to the participants, they did not perceive any clear differences among the recorded motion data.

TABLE I. Experimental Result

	Time[s]		Accuracy [%]	
	Average	SD	Average	SD
Conventional system	341.0	95.5	79.6	2.89
Our proposed system	307.3	60.5	98.1	2.61

The experiment involved six participants, who were divided evenly to use either the conventional system or the proposed system. Each participant was presented with a list of all body segments and asked to identify, for each defined time segment, which body segment exhibited the greatest error. The evaluation metrics were the time taken to complete all selections and the accuracy of correctly identifying the time ranges in which each segment showed the maximum error. Both the average and standard deviation of these metrics were used for evaluation. Additionally, we assessed what kind of information could be interpreted from the visualization results produced by the proposed method.

B. *Experimental Result*

We first describe the insights gained from the visualization results using the proposed method. As an example, Fig. 4 shows the visualization of errors from the head to the torso. Participants were instructed to identify the moments of maximum error, such as the one shown in Fig. 4(4). By referring to the color matrix, it becomes evident that multiple body segments reached their maximum error nearly simultaneously. Although not explicitly mentioned in this experiment, as shown in Fig. 4(1)–(3), it was also possible to observe the propagation of errors from the waist to the head. There is no significant difference in the initial ready position; however, as the motion begins, it becomes apparent that segments gradually deviate outward from the waist. This allows not only the detection of instantaneous errors in specific segments, but also the discovery of relational information across multiple segments. Such information is useful for motion correction, as it helps infer how to adjust a posture by tracing back from the detected error.

Next, Table 1 summarizes the results of the user study. Compared to the conventional system, the proposed system enabled participants to identify the maximum error in each body segment in a shorter average time. In terms of accuracy, the proposed system also showed better results. Additionally, the standard deviation was smaller in the proposed system, suggesting more consistent outcomes across different users. In contrast, the conventional system exhibited relatively larger variance, indicating greater variability depending on the individual.

VI. Discussion

Based on the results of this experiment, the proposed method using a color matrix for motion visualization proved to be more effective than the conventional method [3] in identifying motion differences. Both the higher accuracy and shorter measurement time suggest that the color matrix makes it easier to interpret visualized error information. The conventional method relied solely on stick figures, requiring users to identify the moment of maximum error for each body segment through visual inspection alone, which may have led to oversight and lower accuracy. In contrast, the proposed system allowed users to identify approximate moments of maximum error by referring to the color matrix, thereby reducing the measurement time.

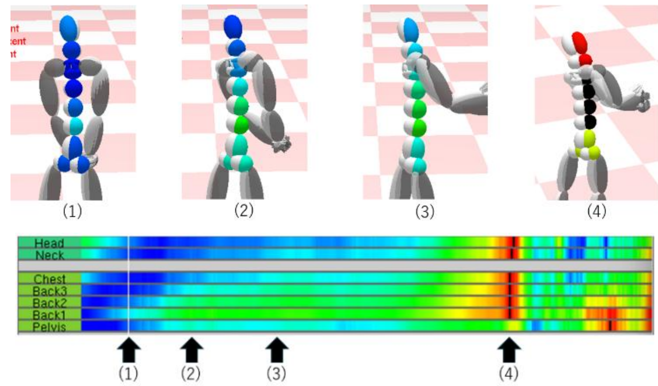

Fig. 4. Figures comparing the movement of the tennis backswing from (1) to (3). The top three figures display the stick figures with color coding. The lower figure is an enlarged view of the color matrix, where the position of the arrows indicates the display time in the color matrix for each stick figure's posture.

In this experiment, we did not compare the color matrix with other visualization methods such as bar or line graphs. Future work includes conducting such comparisons to identify further areas for improvement. Additionally, this experiment focused only on a specific type of motion, so verifying the effectiveness of the proposed method on other types of motion remains a task for future study. While the method is expected to be effective for stationary movements, it may be difficult to visualize motions that involve significant movement. For actions involving large movements such as running—where the start and end positions of the body differ—or for comparing motion data from different individuals, the proposed method is likely to face difficulties in providing appropriate visualization.

Acknowledgments

This work was supported in part by a Grant-in-Aid for Scientific Research (No. 25K15404) from the Japan Society for the Promotion of Science (JSPS)

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