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Dance Gesture Recognition Using Laban Movement Analysis with J48 Classification

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ABSTRACT

This study describes the introduction of classical dance movements using the Laban Movement Analysis (LMA) method, which consists of 3 main components: Body, Space, and Shape. How to carry out the classical motion recognition process using Kinect, which is then read by the screen using the Brekel Kinect and produces dance motion pictures in different formats (. * BVH). After that, it is calculated using the LMA method by obtaining the results obtained in the form of numerical data from each joint from the direction of the axis (xyz), then classification is carried out using the J48 classification method provided at WEKA tools after 50 training data is carried out. 96% truth is recognized because it guarantees those who meet the requirements. Twelve (12) data tests are carried out apart from training data, which can be 92% accurate on average, so it is possible that this method can be used in dance preparation, especially in classical dance.

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1. INTRODUCTION

Recognition of dance movements requires the ability to read the image frame formed by the capture sensor, but when the dancer moves and moves, it causes image distortion and causes problems with changing time and location[1]. [1]. In addition, motion detection also becomes complex when dancers make movements that are not standard with the basic pattern of the dance [2],[3]. Based on research [4], There are weaknesses in the detection of dance movements due to the problem of movement flexibility, while research shows that to detect motion features, special parameters and algorithms are needed that can read the dancers' poses when performing dance movements. Thus the parameters and algorithms used must be accurate enough to help the computer perform comprehensive classification on full body recognition [5],[6],[7]. Use of machine learning for automatic detection using Kinect sensors in whole-body recognition. In one of the classical dance movements, there is a dancer's movement kinematics problem that can hinder the recognition process by machine learning [8]. In research [9], only 3D data can be used to produce a high level of reliability, but processing 3D data accurately requires a learning machine capable of detecting the form of clothing and accessories worn by dancers.

Based on the problems of previous researchers, trying to make an idea related to the introduction of dance movements, where the dance movements used in this study are classical dance movements using the Laban Movement Analysis (LMA) method which consists of the main components, namely, Body, Space, shape and effort. In this research, the LMA method was developed by using only 3 components, namely body, space and shape to extract the motion data feature.. After that, the classification was carried out using the J48 classification method provided by the WEKA tool. The LMA method developed by Rudolf Laban was used because the introduction of dance movements carried out included quantitative analysis and discussed qualitative changes in movements that occurred in time and space, then to provide a classification based on motion dances that are trained and tested using the J48 classification. Classification can be done after the tested and trained dance movement data has been calculated using the LMA method, with the results obtained in the form of numerical data from each joint from the direction of the axis (xyz).

2. RESEARCH METHOD

Broadly speaking, this research method is described as shown in Figure 1.

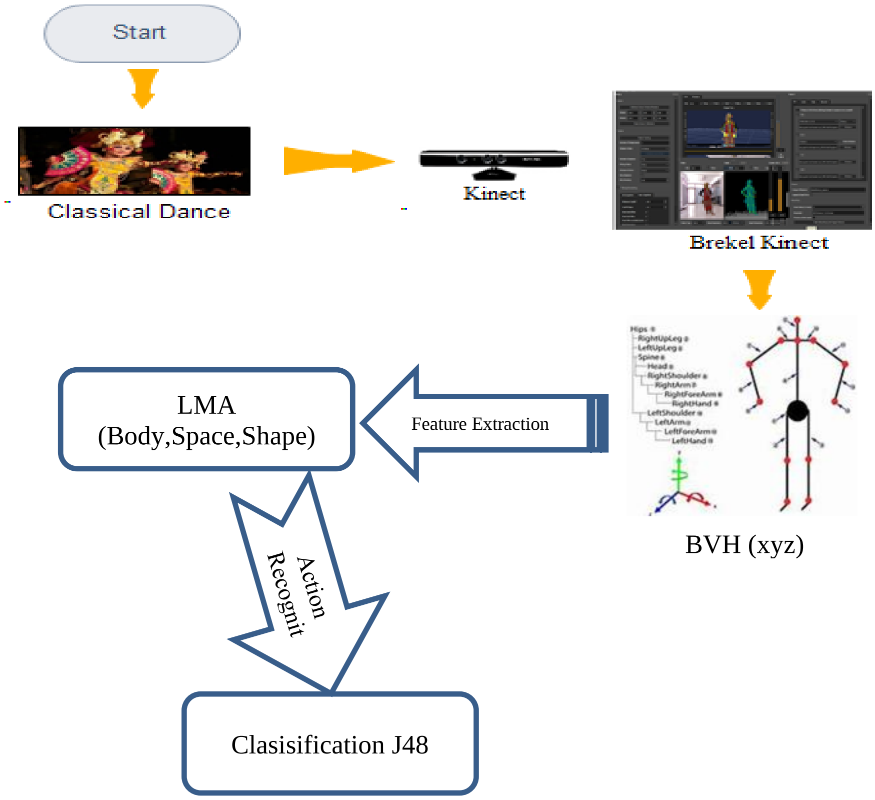


Figure 1. Research flow dance gesture recognition

Figure 1 is a research flow in recognizing classical dance movements. In the research, the data used is dance motion from the results of motion capture using the Kinect sensor with the Kinect Brekel software so that BVH motion data is obtained which consists of xyz coordinate motion data. Furthermore, the data is extracted using the Laban Movement Analysis (LMA) method with body, space and shape components. From the results of the feature extract, an identification process is carried out using data mining in the form of classification using the J48 method.

2.1. Preprocessing data

Data preprocessing carried out in this study was to collect various classical dance movements in Indonesia in the form of capture or images, after which the dance movements were captured by the Kinect, which was then read on the screen using the Kinect brackets and produced a dance motion image in different formats (. * BVH). Brekel Kinect software is useful for converting raw data in the form of depth image data into a Biovision Hierarchy (BVH) file containing the coordinates of the virtual joints [10],[11]. If these virtual joints are connected to form a skeleton structure with coordinates (x, y, z) [12],[13]. The BVH file is a file that stores the entire dance movement in the form of an array, a motion consisting of frames, nodes, and a collection of all nodes from the frame [14],[15]. The structure of the object and the BVH file from the dance movement can be seen in Figure 2.

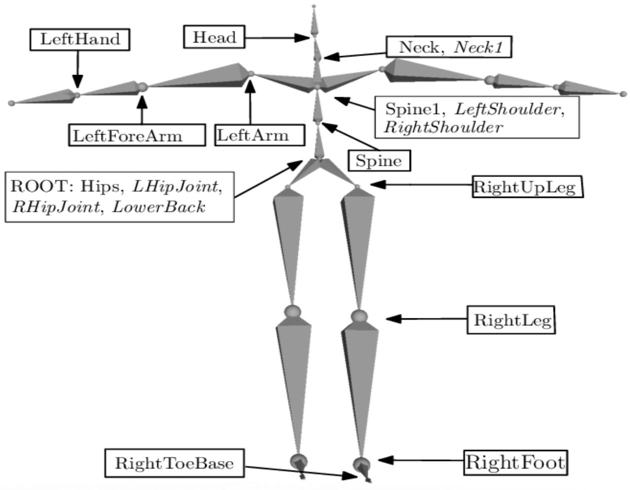


Figure 2. Dance Movement Object Structure

In Figure 2, the dancer acts in the centre with all the bones, among others (head, neck, chest, hips, left hip, left knee, left knee, left joint, right hand, right knee, right ankle, left shoulder, left). neck, left hand, left finger, right shoulder, right neck, right knee, right wrist and right thumb) [16],[17]. All of the bones are bones to create the character of a moving dance where the movements are coordinated with Kinect in 20 joints, as shown in Figure 2.

2.2. Feature extraction

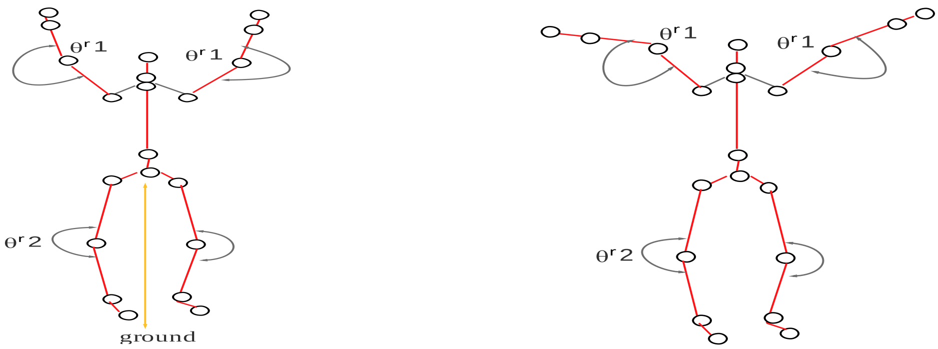
One of the keys to the success of pattern recognition techniques, in this case, dance recognition techniques, is the use of accurate features that can recognize ancient dance movements [18], [19]. Therefore, it is important to study the use of algorithms that can be used to select and analyze the appropriate features of the feature. In general, this study performs feature extraction on images of classical and contemporary dance movements using the Laban Movement Analysis (LMA) method, which consists of 3 main components, namely, Body, Space, and Shape.

2.2.1. Body component

In the body component, the things that are assessed in determining dance gesture recognition are the relationship between the joints of the lower components (hands and feet) and the joints of the upper components (each shoulder and hip) [20]. Based on this, the researcher calculated the angle between the hand and shoulder joints, which is seen in equation (1) and the angle between the leg and hip joints on the right and left, as shown in Figure 3 [9].

$$\boldsymbol{\theta_1^{l/r} = h^{l/r}\widehat{el^{l/r}}sh^{l/r}\ ;\ \theta_2^{l/r} = f^{l/r}\widehat{kn^{l/r}}h_i^{l/r}} \quad (1)$$

In equation (1) $h^{l/r}$ and $f^{l/r}$ are the joints of the left/right hand and foot, $sh^{l/r}$ and $h_i^{l/r}$ Are the left/right shoulder and hip joints, $el^{l/r}$ and $kn^{l/r}$ Is the elbow and knee joints left / right [21].



a.Distancing variation 1 b. Distancing variation 2

Figure 3. Distancing variation

2.2.2. Space component

In the space component, the things that are analyzed to determine dance gesture recognition are the relationship between the human body and the three-dimensional space that surrounds the body with spatial patterns, directions and paths [22]. In the category of the space component, researchers consider the hand to be the most active part of the human body. Based on this, the researcher calculated the length (L), which is seen in equation (2) and the angular position between the hands on the right and left, as shown in Figure 4.

$$\mathbf{L}^{\mathbf{l/r}} = \sum_{\mathbf{t=1}}^{\mathbf{T-1}} \left\| \mathbf{P}_{\mathbf{t+1}}^{\mathbf{l/r}} - \mathbf{P}_{\mathbf{t}}^{\mathbf{l/r}} \right\| \tag{2}$$

In equation (2), T is the number of frames, $P_t^{l/r}$ and $P_{t+1}^{l/r}$ Is the position of the right/left hand in 3D space, t and $t+1$ is the joint of the hands from the position thereafter [23].

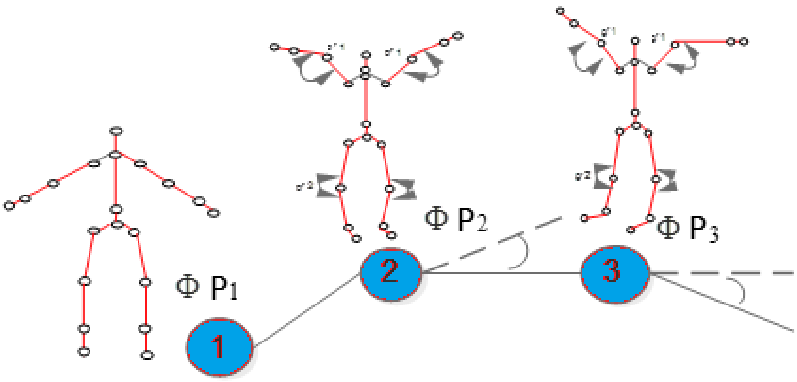


Figure 4. Position of dance movements until there is a change in motion

2.2.3. Shape component

In shape components, the things that are assessed in determining dance gesture recognition consist of three parts, namely Shape Flow, Directional Movement and Carving.

The Shape flow section analyzes the shape changes that occur from body movements during movement [9]. Based on this, the researchers calculated by performing the smoothing index (f) as a measure of the extension of the hand in 3D space, which is seen in equation (3).

$$\boldsymbol{f} = \frac{\boldsymbol{max}\left(\boldsymbol{d_{hands}}, \boldsymbol{d_{neck\_Shc}}\right) - \boldsymbol{min}\left(\boldsymbol{d_{hands}}, \boldsymbol{d_{neck\_Shc}}\right)}{\boldsymbol{max}\left(\boldsymbol{d_{hands}}, \boldsymbol{d_{neck\_Shc}}\right)} \tag{3}$$

In equation (3), the centre point is the maximum value between two distances, where the first distance is the distance between the hand joints $\mathrm{d_{hands}}$, and the second is the distance of the connection between the head and shoulders, which is symbolized $\mathrm{d_{neck\_Shc}}$.

In the Directional Movement section, doing directed movements represents a relationship where the body is directed to several parts from various positions so that it looks Spoke and Arc-like. The researcher defines the hand path by calculating the curvature shown in Figure 5 and Figure 6. Based on this, the researcher calculates the gradual angle change that occurs between changes in position using equation (4).

$$\boldsymbol{\phi P_t} = \boldsymbol{arccos}\left(\frac{\overrightarrow{\boldsymbol{P_{t-1}P_t}}}{\left\|\overrightarrow{\boldsymbol{P_{t-1}P_t}}\right\|} \cdot \frac{\overrightarrow{\boldsymbol{P_tP_{t+1}}}}{\left\|\overrightarrow{\boldsymbol{P_tP_{t+1}}}\right\|}\right) \tag{4}$$

In equation (4), Pt is the position of the hand joint on the t frame, and Pt + 1 is the position of the hand joint on the next frame, t + 1. This equation describes the curvature of the hand path.

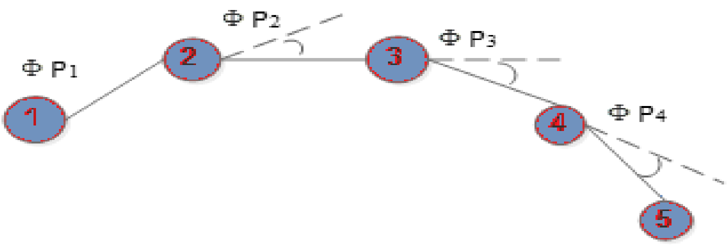


Figure 5. Gradual angles between successive samples

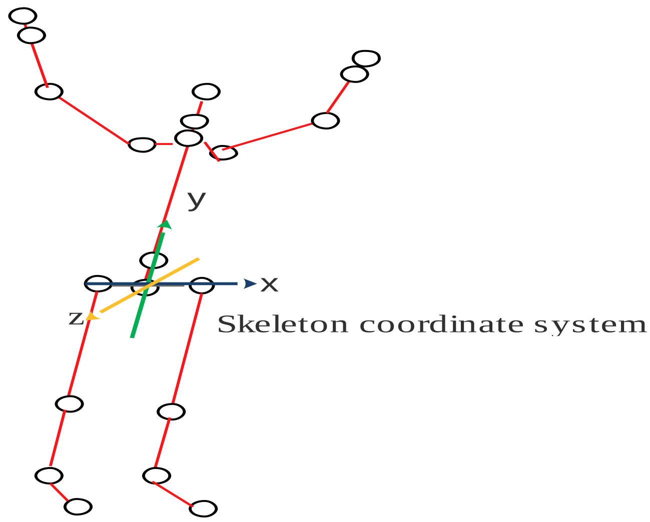


Figure 6. Skeleton coordinate system

Based on equation (4), it produces the curvature feature (C) as seen in equation (5).

$$\boldsymbol{C = \Sigma_{t=2}^{T-1} \phi P_1} \tag{5}$$

Where T is the number of frames, when the linear curvature index approaches the value 0, but in the curved path, the value changes to a very high value.

The Carving section deals with the formation when the body interacts. Researchers describe this section by projecting the displacement of the head and joints of the upper and lower limbs in three planes, namely horizontal (spreading/closing movements), frontal (rising/falling movements) and sagittal plans (forward / backward movements), which are related to the spine.

2.3. Action Classification

The method used in handling the classification is J48 using WEKA tools. The J48 algorithm is a C4.5 algorithm (based on Java) on WEKA [24]. In general, the J48 algorithm in carrying out the classification process, namely, selecting the criteria as the root, creating a value branch, dividing the three branches in each case, and repeating so that the cases on the branches have the same class [19]. The determination of the criteria as the root is based on the maximum gain value of the existing criteria. Here is calculating the gain value using equation (6).

$$Gain(S, A) = Entropy(S) - \sum_{i=1}^{n} * \; Entropy(Si) \tag{6}$$

S is the set of cases, while A is the criterion, n is the number of partitions of criterion A, and the equation for finding the entropy value uses equation (7).

$$Entropy\ (S) = \sum_{i=1}^{n} - pi * \log 2\, pi \tag{7}$$

Where n is the number of partitions S, and pi is the proportion of S. After doing training data, the data used is 50 dance data that has been extracted by paying attention to the main components, namely, Body, Space, and Shape, the classification results are 96%, the detailed results of the training data classification can be seen in Figure 7.

```
Classifier output

Correctly Classified Instances          48               96      %
Incorrectly Classified Instances         2                4      %
Kappa statistic                          0.8344
Mean absolute error                      0.0764
Root mean squared error                  0.1954
Relative absolute error                 27.4994 %
Root relative squared error             53.2663 %
Total Number of Instances               50

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall   F-Measure   ROC Area   Class
                 1         0.25      0.955      1         0.977       0.875     TRUE
                 0.75      0         1          0.75      0.857       0.875     FALSE
Weighted Avg.    0.96      0.21      0.962      0.96      0.958       0.875

=== Confusion Matrix ===

  a  b   <-- classified as
 42  0 |  a = TRUE
  2  6 |  b = FALSE
```

Figure 7. Training data classification accuracy

3. RESULTS AND DISCUSSION

The dance movements tested in this study are classical. As many as 12 data from classical dance movements are shown in Table 1.

Table 1. Test data

No	Classic Dance	Symbol	Classic Dance	Symbol
1	Atrajamang	A	Sabetan	G
2	Jeblos	B	Pencak Silat	H
3	Lampah Sekar	C	Sembahan	I
4	Ngingset Udet	D	Tancep	J
5	Nyimpet Maju	E	Tangkepasta	K
6	Pencak	F	Ulap	L

After being tested, the results produced a classification accuracy of 91.67%. The following are the details of the classification of classical dance movements, shown in Figure 8.

```
Classifier output

Correctly Classified Instances          11               91.6667 %
Incorrectly Classified Instances         1                8.3333 %
Kappa statistic                          0
Mean absolute error                      0.1528
Root mean squared error                  0.2764
Relative absolute error                 75.4902 %
Root relative squared error             97.7586 %
Total Number of Instances               12

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall   F-Measure   ROC Area   Class
                 1         1         0.917      1         0.957       0.5       TRUE
                 0         0         0          0         0           0.5       FALSE
Weighted Avg.    0.917     0.917     0.84       0.917     0.877       0.5

=== Confusion Matrix ===

  a  b   <-- classified as
 11  0 |  a = TRUE
  1  0 |  b = FALSE
```

Figure 8. Test data classification accuracy

Based on Figure 8, a detailed classification for each dance movement tested is shown in Table 2.

Table 2. The results of the tested dance movement classification

Dance	A	B	C	D	E	F	G	H	I	J	K	L
A	0.91	0.09	0	0	0	0	0	0	0	0	0	0
B	0	0.92	0	0	0.08	0	0	0	0	0	0	0
C	0	0	0.93	0	0	0	0	0.07	0	0	0	0
D	0	0	0	0.92	0	0	0.08	0	0	0	0	0
E	0	0	0.1	0	0.90	0	0	0	0	0	0	0
F	0	0	0	0.08	0	0.92	0	0	0.08	0	0	0
G	0	0	0	0	0	0	0.91	0	0	0	0	0.09
H	0	0	0	0	0	0.07	0	0.93	0	0	0	0
I	0.08	0	0	0	0	0	0		0.92	0	0	0
J	0	0	0.08	0	0	0	0	0	0	0.92	0	0
K	0	0	0	0	0	0	0	0	0	0.07	0.93	0
L	0	0	0	0	0	0	0	0	0	0	0.07	0.93

Based on the results of the average sum of the diagonal values from the matrix in table 2 above, the average recognition rate of motion classification using the J48 method from the feature extract results using data from the LMA study with the 3 main components body, space and shape is 91.6667% .

4. CONCLUSION

Based on the results and discussion, the accuracy obtained reaches 91.67%, which the author rounds to 92% based on the results obtained using the J48 classification with 12 classical dance objects, so it is possible that this method can be used in recognizing dance movements, especially dance movements classic.

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