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Tensor Decomposition and Algorithm a Genetic-Learning Vector Quantification in Golek Menak Dance Motion

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Abstract: Golek Menak dance is a transformational form of Golek Menak puppet show. This dance has a lot of different motion attitudes and has meaning of each motion physically and mathematically (aspect of tensor, flexibility, geometry). Considering that, now there are still many people who have not understood types of dance motions both classical and traditional dances and meaning of each dance motion so that this study presents introduction of motion attitude types in Golek Menak dance. This study used Kinect sensor to obtain skeleton data of dancer. The introduction of motion attitude types in the Golek Menak dance through 4 stages, namely data collection, feature extract with tensor decomposition, classification of motion attitude introduction using Learning Vector Quantification (LVQ) method with Genetic Algorithm (AG) optimization. This study aims at helping people recognize motion of Golek Menak dance. Modernity of this study is combination of tensor decomposition, LVQ and AG to identify motion attitude types of Golek Menak dance. This study took samples of jogetan and sabetan motions as a part of Golek Menak dance motion. Based on the results of study, test for suitability of motion attitude recognition (Jogetan and Sabetan) found percentage of 90%.

Key words: Decomposisi tensor, LVQ, AG, Tari Golek Menak, dancer, recognition

INTRODUCTION

Dance is motion class with very wide coverage having many different styles and special characteristics. Considering that now there are many people still who haven't understood classical and traditional dance motion types and meaning of each dance motion as to need research on recognition of dance motion attitude types useful for this study in other field, learning and evaluation (Heryadi *et al.*, 2012, 2013) and maintain Indonesian cultural art assets (Hariharan *et al.*, 2011). Research on recognition of dance motion attitude gains more attentions in the world and has great impact on our daily life (Nussipbekov *et al.*, 2014). However, the total researches on recognition of dance motion attitude are still limited. Easy recognitions of dance types in various previous studies are: Indian classical dance (Saha *et al.*, 2013a-c), Kazakh traditional dance (Nussipbekov *et al.*, 2014), Greek traditional dance (Kapsouras *et al.*, 2013), Bharatanatyam dance (Saha *et al.*, 2013a-c), Odyssey dance (Saha *et al.*, 2013a-c) and Balinese dance (Heryadi *et al.*, 2012, 2013).

Recognition of dance motion is recognition of expressive meaning of dancer in different dance motion attitudes. Each type of dance motion has most distinctive characteristic or emphasizing on motion of body parts as shown in hand motion, facial expression, body and head movements (Nussipbekov *et al.*, 2014; Saha *et al.*, 2013a-c). Golek Menak dance is transformation form of Golek Menak puppet show. Where Golek Menak puppet is performance using Serat Menak as story source (Sukistono and Haryono, 2013). Previously, Golek puppet art was form of cultural art activities of Indonesian people reflecting aspects of social, political, economic, religious, linguistic and relational life of society. Then, Sultan Hamengku Buwono IX combined Golek puppet show and Javanese classical dance called Beksa Golek Menak or Golek Menak dance.

This study aims at detecting and recognizing dance motion types of Golek Menak dance. Where Golek Menak dance is generally classified into 3 parts as follows: maju gending (opening), Enjer (middle with conversation between dancers) and Panutup (closing). Each part has different motion attitude types. Motion attitude types of

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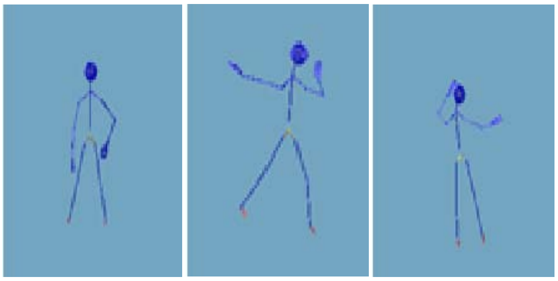

Fig. 1: Attitude motion of Jogetan

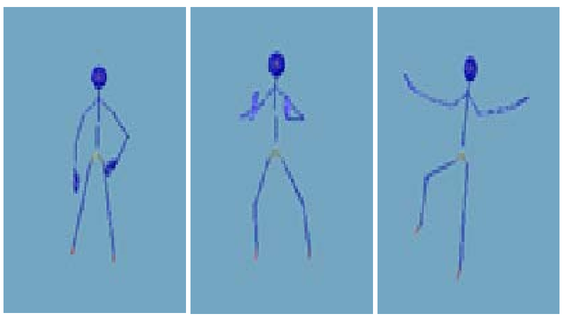

Fig. 2: Attitude motion of Sabetan

Golek Menak dance consist of: sabetan, joget, sambahan sila, ulap-ulap, muryani busana, lampah sekar, nyingset udet, pencak silat and peperangan. About 2 following motion attitude types are taken from the motion attitude types, namely sabetan dan jogetan as motion types recognized in this study (Fig. 1 and 2).

This study was begun by arresting dance attitude existing at Golek Menak dance using Kinect camera. Results of the form of motion capture data are skeleton and the position of the motion of the dancers. Kinect camera is often used to capture human motion (Patsadu *et al*., 2012) and dance movement (Kapsouras *et al*., 2013; Nussipbekov *et al*., 2014; Saha *et al*., 2013a-c). Introduction and classification of the type of attitude dance of Golek Menak are made through 3 stages: retrieval of data from the motion capture dancer with Kinect obtained from motion data as a data tensor (matrix high-order) (Barmpoutis, 2013; Barmpoutis *et al*., 2007; Chen *et al*., 2013); decomposition of feature extraction algorithm using tensor (Hasan and Kareem, 2014) and the classification of dance using Learning Vector Quantization (LVQ) with AG optimization (Gen and Cheng, 1997; Gen and Runwei, 2000).

Research on the dance gesture recognition is a special case of the introduction of human movement in general. Therefore, many researchers are using various methods and techniques. One of the input tool catcher is Kinect motion (Kairat and Gaber, 2012). Kinect is an input device for detecting the movement produced by Microsoft (Obdrzalek *et al*., 2012). Kinect has a RGB camera facility (Saha *et al*., 2013a-c) and a depth sensor. Kinect is more excessive compared to other devices that is able to capture and track the motion or action of 3D objects accurately (Saha *et al*., 2013a-c), the price of Kinect is quite affordable (low cost) (Patsadu *et al*., 2012), jamproof (non-intrusive) and can work even if lighting is less (Saha *et al*., 2013a-c). But the Kinect motion capture systems require calibration distance fishing right object (Gabel *et al*., 2012). This study used the Kinect camera calibration with a distance of about 1.5-2 m without markers. Kinect typically generates data skeleton consisting of 20 joints (Nussipbekov *et al*., 2014; Saha *et al*., 2013a-c). This study used data skeleton consisting of 18 joints. Kinect provides detailed information on the parts of the body, particularly the hands and feet (Nussipbekov *et al*., 2014).

In the classification stage in general, researchers can use a variety of LVQ methods, K-Means (Nussipbekov *et al*., 2014), Neural Network (Hasan and Kareem, 2014; Ibraheem and Khan, 2012; Patsadu *et al*., 2012), Bayes Network (Patsadu *et al*., 2012), Hidden Markov Model (Nussipbekov *et al*., 2014), Support Vector Machine atau (SVM) (Patsadu *et al*., 2012; Saha *et al*., 2013a-c), fuzzy (Saha *et al*., 2013a-c), KNN (Heryadi *et al*., 2012, 2013) and other approaches. This research used LVQ and AG to make the process of classification and recognition of Menak puppet dance. Some previous researchers using Hidden Markov (Nussipbekov *et al*., 2014). Nussipbekov *et al*. (2014) used the HMM method for gesture recognition of Kazakh dance movement, based on the research results, recognition rate is 90.82%. Researcher used K-means and HMM to classify and identify the kind of attitude of the dance movement with motion skeleton reasons of data in the form of time series so that special methods are needed to identify these movements with seek median value of the object similarity distance.

Wuryandari conducted a study on comparison of methods of Artificial Neural Networks back propagation and learning vector quantization in face recognition (Wuryandari *et al*., 2012). Results from these studies are 252 pictures (37.33%) of suitable recognition results using back propagation and 254 images (37.63%) match the recognition results using the method of learning vector quantization of total recognition as much as 675 times to 25 facial images using 27 types of learning parameter combination; the average time of introduction is 130 msec using back propagation and 32 msec using learning vector quantization. From the test results, it can be recommended in terms of accuracy and time, learning vector quantization method is better than backpropagation. This level of recognition accuracy is 37.63% and an average time is 32 msec introduction. In this study, the need for feature extraction features to make the process better recognition. The contribution of this research is the application of Learning Vector Quantization (LVQ) method is better for facial recognition.

Original LVQ has been introduced based on heuristics. This model has undergone many modifications in achieving better convergence and stability. It also motivates modifications showing better stability. LVQ has so far not been thoroughly investigated (Qiu *et al*., 2015).

MATERIALS AND METHODS

This study consists of 3 phases can be shown on Fig. 3. These stages include: preprocessing, feature reduction, feature extraction and classification.

Pre-processing stage: Pre-processing stage is to visualize the Golek dance movements performed by Menak dancers which were later arrested (motion capture) by the sensor Kinect X-Box 360 (Fig. 4). The results of the Kinect dance motion capture are forms of skeleton data consisting of 61 joints (points of the body), each having a 3-Dimensional or 3D coordinates (X, Y, Z). So, that each type of skeleton motion has a number of frame sizes (time) x number of joint (variable). Kind of flick attitude motion and captured jogetan motion of each has duration of 4-6 sec.

Skeleton Data consist of 61 joints (points of the body), each having a 3-dimensional or 3D coordinates (X, Y, Z). The names of joint are: hips, left up leg, left leg, left foot, right up leg, right leg, left arm, left fore arm, left hand, right foot, spine, left shoulder, right arm, right fore arm, right hand, right shoulder, neck and head.

This study used data for the number of blows as much as 5 types of motion and jogetan motion as much as 5 data. Of the ten data, each kind of attitude motion used 5 data as training data and 5 data as the test data. The sizes of the training data and test data for each of jogetan and sabetan data are different. Furthermore, each of dance motion take 60 jont with 50 frame per movement (jogetan and sabetan) Tensor is a data matrix with higher order expressed in the equation:

$$A \in \mathbb{R}^{I_1 \times I_2 \times \ldots \times I_N} \quad (1)$$

Dance motion data is the tensor data, arranged as a matrix with the combination (joint, frame and

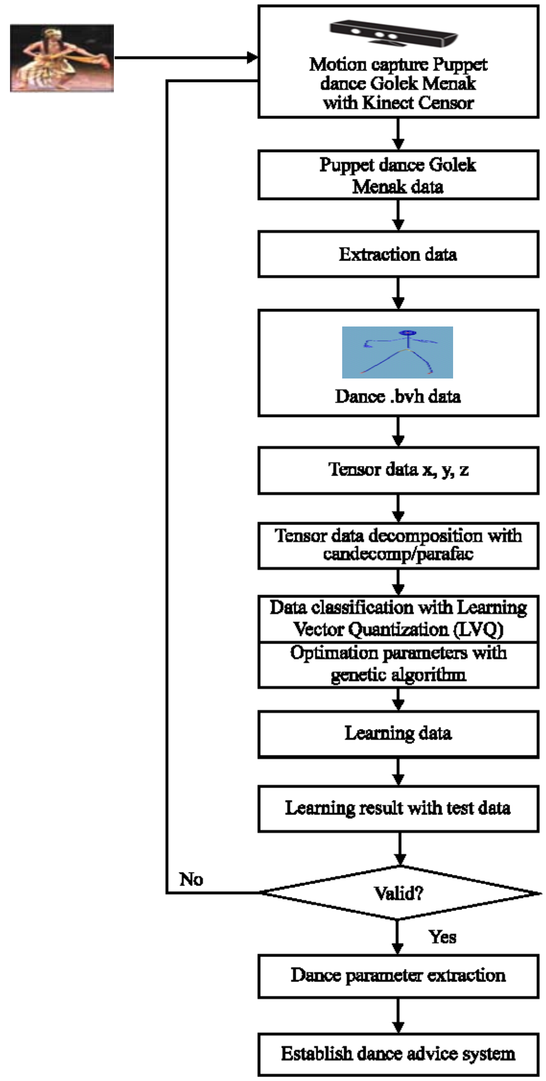

Fig. 3: Flow research

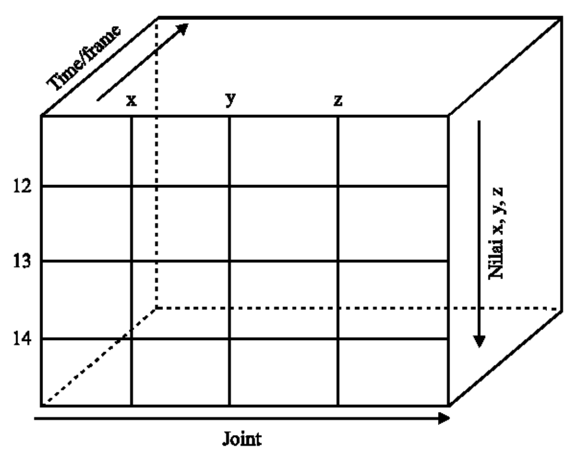

Fig. 4: Matrix for motion (x (motion), y (joint), z (frame))

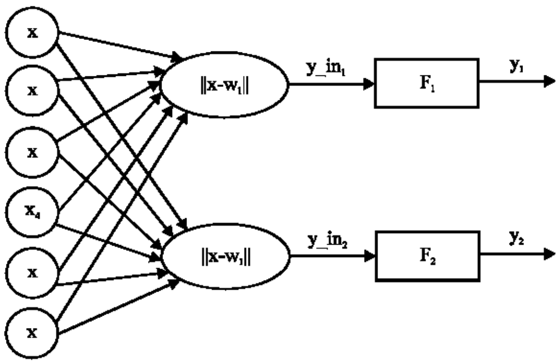

Fig. 5: The LVQ architectural model

coordination of motion of each joint) or 3-dimensional (xyz). The matrix represents (point joint, frame/time and position xyz).

Phase classification: Classification phase is the last stage in the recognition and classification of Menak Golek dance movements using LVQ. LVQ architecture model recognition and classification comprises the types of blows and jogetan motion (Fig. 5).

RESULTS AND DISCUSSION

Golek Menak dance has a lot of kind of attitude motions and the movement of the hand is more prevalent contained in the thug attitude and jogetan motion. Therefore, this study performed recognition and classification of motion gesture that are only slashes and jogetan. This experiment used the 2 dancers each performing 2 types of dance attitude is Thug and Jogetan 5 times. Dataset is labeled manually. Total motion data is about 10 dance movements. After the process carried reduction features, the training data attitude of dance (2 dance flick and 2 dance jogetan) carried out the process of feature extraction algorithms using tensor decomposition results for dance movements of golek Menak puppet obtained from the motion capture using Kinect sensor form of the skeleton motion data is the data tensor x, y, z. Types of dance movements of Menak puppet show that would be classified are jogetan slashes and movements.

The amount of movement used is 5 Sabetan movements and 5 Jogetan movements. Each movement has a joint 61 by points on the skeleton. Of the joint 61, a swab of 3 joint (right hand) on each movement to the classification process, namely in 7-9th joints. In addition, in order to limit the computation, the number of frames captured at each movement is 60 frames. The results of the pre-treatment continued decomposition process.

Table 1: Results of dance movement decomposition

	Features				
Motion	Class	1	2	...	114
1	1	3183,474	3610,85	...	3398,694
2	1	2529,755	3251,894	...	3417,85
3	1	2212,85	2407,155	...	3404,703
4	1	2202,513	2970,806	...	3420,897
5	1	2289,12	2620,507	...	3398,34
6	2	2463,493	3287,49	...	3364,497
7	2	2254,147	3605,494	...	3367,222
8	2	2452,839	3280,97	...	3374,54
9	2	2334,079	3285,085	...	3366,9
10	2	2439,368	3442,75	...	3381,888

The decomposition process used candecomp (canonic decomposition)/parafac (parallel factor analysis) with tensor function matlab tool box developed by Sandia labs as follows.

ALS algorithm:

procedure CP-ALS (T, R, M)
give initial guess $A^{\circ} \in R^{IxR}$, $B^{\circ} \in R^{jxR}$, $C^{\circ} \in R^{KxR}$
for n = 1, ..., M do
$A^{n+1} \leftarrow T_{(1)}/(C^{n} \odot B^{n})^{T}$-% solving least squares to update A
$B^{n+1} \leftarrow T_{(2)}/(C^{n} \odot B^{n+3})^{T}$-% solving least squares to update B
$A^{n+1} \leftarrow T_{(2)}/(3^{n+2} \odot A^{n+2})^{T}$-% solving least squares to update C
end for
return A^{M}, B^{M}, C^{M}
end procedure

The results from the decomposition/extract feature data indicate numbering features of 114 numbers on each movement and the class of the 2 types of dance movements where the class 1 serves as jogetan movement (the 1-5 movement) and class 2 serve as a sabetan movement (the 6-10 movement) (Table 1).

Training: Training dance movements that have been processed in the pre-processing and decomposition/ extract features, furthermore conducted training process using Learning Vector Quantization (LVQ) based genetic algorithm to classify Menak dance movements (Sabetan and Jogetan).

All data of decomposition do LVQ based training using genetic algorithms The parameter are used to find the value of fitness. Exercises are performed repeatedly to obtain the best fitness value.

Table 2 indicates the process of finding the best fitness value by conducting 30 trainings using the parameter number of chromosomes, crossover and mutation, the result is the highest fitness, 770, 876, 110.81 on population size parameter 300, crossover probability mutation probability of 0.8 and 0.05. Each training for up to 10 generations later obtained the maximum value at the maximum value of the parameter used as a parameter to the next training.

Table 2: Sample of fitness training results for finding the best

Generation	Chromosome	Crossover	Mutation	Best fitness
Training 1				
1	300	0.8	0.05	770876110.8052
2	350	0.8	0.05	750322326.3647
3	400	0.8	0.05	770876110.8052
4	450	0.8	0.05	770876110.8052
5	500	0.8	0.05	732011850.4323
6	550	0.8	0.05	770876110.8052
7	600	0.8	0.05	750322326.3647
8	650	0.8	0.05	737589432.2843
9	700	0.8	0.05	750322326.3647
10	750	0.8	0.05	770876110.8052
Maximal value				770876110.8052

Table 3: Code Vector (CV)

		Features			
Code vector	Class	1	2	3	4
2268,105	1		1		3183,474
2707,3	1		2		3610,85
-25113	1		3		-24632,5
2395,046		2		1	2463,493
3380,177		2		2	3287,49
-24566,4		2		3	-24498,2
⋮	⋮	⋮	⋮	⋮	⋮
3402,068	1		112		3394,639
3406,237	1		113		3398,678
3406,254	1		114		3398,694
3380,357		2		112	3373,122
3374,957		2		113	3364,532
3374,935		2		114	3364,497

LVQ has a weight parameter and the initial learning rate, the initial weight is determined randomly if not right that cannot be convergent for it is assisted by a genetic algorithm to optimize the selection of random and learning rate on LVQ training process. After the optimization process that uses AG then generates code vector as in Table 3.

The results obtained initial weight training code vectors of the captured motion to third from first grade (Jogetan) and the movement to 7 from grade 2 (sabetan) of 10 movements and learning rate = 0.01 but the value of the initial code vector and the code can be changed when any data were trainings. The results of the training process will be used to process the test data.

Examination: The test data used the data of dance in the training process. the testing of Motion 1 obtained distance to the code book 1 of 0.0100414 and the distance to the code book 2 of 0.0111496 because the distance between the calculation results of the test data with the code vector is smaller than the distance code vector obtained from results with two classes 1 (Jogetan), meaning that the first motion is made for suitable or valid test with data that have been trained, the motion of Jogetan.

Table 4: Results of testing data of movement dance

Test motion	Distance to code book 1	Distance to code book 2	Class	Results of test
1	0.01004140	0.01114960	1	Suitable
2	0.01237560	0.01302080	1	Suitable
3	0.00584275	0.01266260	1	Suitable
4	0.01353870	0.01107510	2	Unsuitable
5	0.00693770	0.01136670	1	Suitable
6	0.01177110	0.00317677	2	Suitable
7	0.01185060	0.00109051	2	Suitable
8	0.01179720	0.00505872	2	Suitable
9	0.01104580	0.00467893	2	Suitable
10	0.01097630	0.00422352	2	Suitable

Results of testing 10 data dance movements are dance movement data that have been trained in Table 4. The fit of the data is obtained by 90% of the 10-tested data.

CONCLUSION

Based on the experimental results, the classification of types of Golek Menak dance used LVQ algorithm and GA: 9 out of 10 dance motion data of test data successfully identified with the level of recognition accuracy dance attitude kind by 90%. In the future, we will consider joints which are the most prominent (have many differences) to be taken as research. The most prominent joint is a joint that has an emphasis as a differentiator between motion with each other.

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