Journal of Engineering and Applied Sciences 13 (Special Issue 6): 5408-5414, 2018
ISSN: 1816-949X


# A Classification of Golek Menak Dancer Poses Based on Learning Vector Quantization (LVQ) and Genetic Algorithm

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**Abstract:** There are still rarely discussed the Golek Menak dance from technology perspective, especially in motion capture detection. Our study proposed a classification model using Learning Vector Quantization (LVQ) which combined with Genetic Algorithm (GA). This is a novelty that the author considered important to improve the accuracy in detecting Golek Menak dancer and resolve their complexity through tensor rule of Canonical Parafac-Alternating Least Square (CP-ALS) method. We also have taken eight poses representing Golek Menak dancer poses and estimating their moves in geometric shapes that cause translational, rotational, dilatational, reflection and geometric slope (shear) translations. The tensor rule is important in our study to estimate the geometrical transformation model of the dancer (e.g., body, hand, head, leg and time duration). After LVQ is implemented, we can finally, deleting repeated poses into single pose as standardized poses. The tensor rule also can reduce the impact on kinematic transformation. Whereas genetic algorithm will find the value of fitness, the higher value of the joints, the more likely the joints to represent the dancer poses. Finally, we presented the result of the body transformation of the dancer motion with complete combination of CP, LVQ and GA to provide a model with higher accuracy. Our study brings contribution to expand the theory of CP, LVQ and GA in the dance motion recognition.

**Key words:** Learning Vector Quantization (LVQ), Canonical Parafac-Alternating Least Square (CP-ALS), Golek Menak dancer, complete combination, dance motion recognition, kinematic transformation

## INTRODUCTION

**Background:** Golek Menak dance is a traditional dance staged in Yogyakarta Palace. It has been widely studied by several researchers in Indonesia (Wu and Ji, 2015; Ramalingam *et al*., 2014; Chai *et al*., 2016; Buys *et al*., 2014). However, these studies only discuss about the development of the dance from artistic knowledge (Ramalingam *et al*., 2014; Buys *et al*., 2014; Wang *et al*., 2014a, b). The previous studies are still rarely discussed the Golek Menak dance from technology perspective especially in motion capture detection. Therefore, this study presented a design of incorporating elements of computer technology in motion capture to detect the dancer gesture (Ramalingam *et al*., 2014; Buys *et al*., 2014). At this time it has been discovered the motion capture technology in markerless mode that can automatically capture 3-D images that can be recognized by machine learning. The technology also can be combined with Kinect sensor which research by capturing dancer gesture into motion features and coordinate position. However, detecting dancer gesture needs some complex estimation and configurations to recognize the dancer's joints to extract into three motion features (position orientation and height) with certain ordered parameter (Buys *et al*., 2014; Wang *et al*., 2014).

Previous studies have proposed several approach to extract dancer features, e.g., methods of Hidden Markov Model (HMM) (Wang *et al*., 2014; Farfade *et al*., 2015), Knowledge Based Hybrid (KBH) (Wang *et al*., 2014; Farfade *et al*., 2015) and machine learning for automated detection (Farfade *et al*., 2015). Their model can be used to explain the dancer motion and extracting the gesture features. However, their approach seems limited from slow process and hierarchical motion classification due to feature extraction will result high complex data. In

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addition, the gesture detection with kinect sensor to extract whole body of the dancer will result in kinematics issue that can inhibit the recognition process by machine learning.

At the stroke of motion, there is the problem of kinematics dancer's movement that can inhibit the process of recognition by machine learning. Several scholars (Buys *et al*., 2014; Wang *et al*., 2014a, b) have proposed extraction approach to estimate dancer gesture in 3D data to generate a high level of reliability, however, processing 3D data needed learning machine that capable of detecting the dancer motion appearance. Even though there are many methods used to identify the dancer movement, however, the result is still not effective. In the Hidden Markov Model (HMM) (Farfade *et al*., 2015) they tried to increase the likelihood of modeling and feature extraction. However, their method are still lack of accuracy and needs other modified algorithms (e.g., LVQ, Genetic algorithm, etc.). Whereas to manage the extracted features into more simplified data we used tensor rule. Based on the above preliminary study, there is still no research to identify the dance movement Golek Menak using LVQ classifications and genetic algorithm.

Our study proposed a classification model using Learning Vector Quantization (LVQ) which combined with Genetic Algorithm. For LVQ, this method research based on nearest prototype adaptive classification. Originally, LVQ has been introduced based on heuristics estimation. This model is also flexible to be modified to achieve better convergence and stable result. The use of Learning Vector Quantization (LVQ) which combined with genetic algorithm is a new thing which proposed in this study to produce the original findings. This is a novelty that the researcher considered important to improve the accuracy in detecting Golek Menak dancer and resolve their complexity through tensor rule.


Fig. 1: Poses of Golek Menak dancer which will be estimated and detected in this study

**Literature review:** Dance is a sequence of several different motion and positional change to express emotional meaning. In Golek Menak dance, it contains two types of poses, e.g., Jogetan and Sabetan. For simplification, this study only taken two it is represented by the names of the dance basics such as Ulap-Ulap poses (pose 1-3, Usap Raw is (pose 4-5) and Peperangan poses (pose 6-8). Farfade *et al*. (2015) and Rogez *et al*. (2014). Basically, all the dancer poses have a variety of motion include silent motion, forward, backward, move the right leg, left leg moved (Farfade *et al*., 2015; Rogez *et al*., 2014). The sequence of the dancer poses are presented in Fig. 1. On poses 1-3, the dancer perform the transformation of motion in both hands with both feet tend to be relatively silent (Buys *et al*., 2014; Rogez *et al*., 2014). Both hands are staged in moving straight to the side and waved to the front. While the up-down is not performed. When a hand in moving straight to the side, hands were regarded as a tube and extension tube transformation occurred on the x-axis (horizontal axis). In a hand waving in moving forward, the dancer does the motion transformation into the frontal axis (z-axis). The position of the feet is considered quiet and not transformed anyway.

On pose 4-5, the dancer perform the transformation of motion in both arms both legs (Wang *et al*., 2014; Rogez *et al*., 2014). Motion transformation occurred in both hands and both feet were up and down the vertical axis (y-axis) with an open hand to the left side move (the negative x axis) and frontal move (positive z-axis).

On pose 6-8, the dancer perform body rotation and sideways against kinect sensor location. Rotational transformation occurred in the body clockwise. Furthermore, the dancer also did not turn rotation clockwise. The dancer also moves going up and down transformation alternately. The dancer second legs also transformed going up and down alternately to kick towards the front (z-axis transformation).

## MATERIALS AND METHODS

**Detection procedures of dancer poses:** Previous study (McCormick *et al*., 2014) proposed a moving object tracking procedures to perform data conversion depth to the field of 3D models of human anatomy and perform certain combinations that machine learning algorithms can identify the object motion (McCormick *et al*., 2014; Yovel and O'Toole, 2016). Other research shows that there are advantages and disadvantages of the 3D Model. Therefore, we propose to add tensor rule to estimate the transformation geometry by measuring and finding the coordinates of joint motion after the dancer location are changing (Pfister *et al*., 2014). The transformation is represented by a matrix that contains aspects of change layout, shape and presented in geometry form (Kitsikidis *et al*., 2014). On the Golek Menak dance, the dancer moves in geometric shapes that cause translational, rotational, dilatational, reflection and geometric slope (shear) translations. The dancer performs transformations on the head, body, arms and legs. The geometrical transformation model of the dancer is given in Fig. 2.

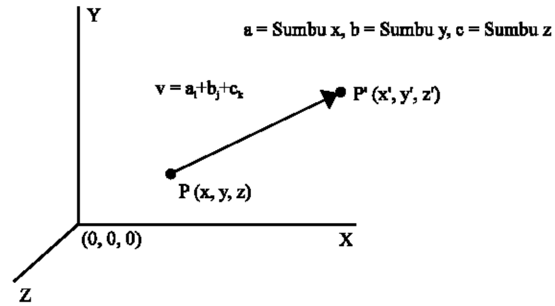


Fig. 2: Geometrical transformation model of the dancer

**Body detection:** To estimate the geometric body transformation of the dancer, it used geometric tensor rule as in Eq. 1:

$$\text{Tx}(\alpha)_r = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha & 0 \\ 0 & \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (1)$$

**Hand detection:** As hands are the most active part of the dancer body, it always do displacement, then the reflection translational tensor rule can be applied to estimate the hand position coordinate (x, y, z) to the plane is (only the z component is changed) is plane or zx plane which is expressed in a matrix equation of reflection as in Eq. 2:

$$\text{T (r) yz} = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

**Stepping to forward and backward:** When the dancer steps over both forward and backward, it can generate shear transformation issues where the dancer poses will be inclined to specific locations to form unique dance poses. The transformation is widely used in the manipulation of graphs on the computer, so that, the object has a different point of view which can be estimated with Eq. 3:

$$S_h(H_x, H_y) = \begin{bmatrix} 1 & 0 & H_x & 0 \\ 0 & 1 & H_y & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

**Head detection:** For the head detection, it used (Vries *et al*., 2016) to reconstruct the human body model especially the head coordinate position by using tensor decomposition. Tensor decomposition is defined as method of dividing the body movement horizontally and vertically. The head is detection in their motion, e.g., translation, rotation and position changes toward geometrical direction. When the head nods to the front and rear, it is applied Eq. 4 and when the head clockwise rotation then it is applied in Eq. 5:

$$\underline{v}+\underline{w} = (v_1+w_1)\,\underline{\delta}_1+(v_2+w_2)\,\underline{\delta}_2+(v_3+w_3)\,\underline{\delta}_3 = \sum\nolimits_{i=1}^{3}(v_i+w_i)\,\underline{\delta}_i \quad (4)$$

$$\underline{vw} = v_1w_1+v_2w_2+v_3w_3 = \sum_{i=1}^{3} v_iw_i \quad (5)$$

**Deleting repeated poses into single pose:** Tensor elements consist of the first translational and rotational states which then can be repeated over certain duration in respect to certain time. When the dancer conducted repeated poses, the system will detect and convert the dancer position into (x, y, z) as in Eq. 6.

$$\delta = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{6}$$

Equation 6 represented the total change of repeated poses in (x, y, z) space which simplified and only taken one pose that symbolized with $\delta$.

**Leg detection:** Legs detection is also captured. When the legs jump, then it can be applied tensor multiplication rule (Eq. 7) and when the legs are dragged (dragging), then Eq. 8 is used.

$$s\,\underline{\underline{T}} = \begin{bmatrix} sT_{11} & sT_{12} & sT_{13} \\ sT_{21} & sT_{22} & sT_{23} \\ sT_{31} & sT_{23} & sT_{33} \end{bmatrix} = s\sum_{i=1}^{3}\sum_{j=1}^{3} T_{ij}\,\underline{\delta_i}\,\underline{\delta_j} \tag{7}$$

$$\begin{aligned} & \underline{\delta_1}\ (v_1T_{11}+v_2T_{21}+v_3T_{31})+ \\ \underline{v}.\underline{\underline{T}} = & \underline{\delta_2}\ (v_1T_{12}+v_2T_{22}+v_3T_{32})+ = \sum_{i=1}^{3}\underline{\delta_i}\left(\sum_{i=1}^{3} v_j\ T_{ji}\right) \\ & \underline{\delta_3}\ (v_1T_{13}+v_2T_{23}+v_3T_{33}) \end{aligned} \tag{8}$$

**Time transformation (kinematic estimation):** The dancer move to change the speed of a moving slowly becoming faster which so-called kinematic transformation is occurred, the dancer is assumed as a kinematic model. Then, it applied the concept of hierarchy tree which composed of chain and node (intersection) which interact to form tensor body model. It is represented in tensor matrix (Eq. 9):

$$R\ (\phi, \theta, \psi) = R_x\ (\phi)\times R_y\ (\theta)\times R_z\ (\psi)$$

$$\begin{bmatrix} \cos\phi & -\sin\phi & 0 \\ -\sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta 1 \end{bmatrix} \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} =$$

$$\begin{bmatrix} -\sin\phi\sin\psi+\cos\phi\cos\theta\cos\psi & -\sin\phi\cos\psi-\cos\phi\cos\theta\sin\psi & \cos\phi\sin\theta \\ \cos\phi\sin\psi+\sin\phi\cos\theta\cos\psi & \cos\phi\cos\psi-\sin\phi\cos\theta\sin\psi & \sin\phi\sin\theta \\ -\sin\phi\cos\psi & \sin\phi\sin\psi & \cos\theta \end{bmatrix}$$

Application of tensor decomposition technique is very essential in extracting tensor dance. That Candecomp/Parafac (CP) can be used to group the tensor coordinate into tensor data to represent total model to estimate each segment of the dancer body. The process to combine all the coordinates of the joints are so called factorization as described in other studies (Wang *et al*., 2014; Rogez *et al*., 2014; McCormick *et al*., 2014) and so called Alternating Least Squares (ALS), since, it used a factor matrix which sequentially estimated as many factors to represent ranked tensor (Ramalingam *et al*., 2014; McCormick *et al*., 2014; Kitsikidis *et al*., 2014; Cho and Lee, 2014).

The factorization needs an equation to change the r-th column of the joint into matrix factor A (n) in geometrical space. In the parafac model developed in 1970 by Carroll and Chang, the CP also so-called Parafac (parallel factor analysis). The factorization used high-level array which simplified into one single matrix as the representative geometrical array (Eq. 10).

$$\begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} \leftarrow A_3 \left(\begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix} \square \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix}\right)\left(\begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix}^t \begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix} * \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix}^t \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix}\right)^{-1} \tag{10}$$

Equation 1-10 is the decompositioned result of BVH data by using tensor rule (Ramalingam *et al*., 2014; Chai *et al*., 2016; Wang *et al*., 2014a, b; McCormick *et al*., 2014; Cho and Lee, 2014).

**Learning Vector Quantization (LVQ):** After the Biovision Hierarchy (BVH) data are converted into tensor data, it then processed into learning machine by implementing another algorithm which so-called Learning vector quantization (LVQ). The LVQ is used to help the system to improve their decision-making process by learning the data provided to the machine learning.

Learning Vector Quantization (LVQ) will conduct the mapping process by looking for the closest distance to the Eclaudian calculation (the shortest distance). The process of determining the distance, i.e. by simulating input block is converted into the cluster which suitable with the data already stored from previous learning. This means that algorithm for Learning Vector Quantization (LVQ) is to find the nearest output with the input vector with the requirement as below.

When almost over, if x and $w_c$ included for the same class then move the final weight to a new input vector, if x and $w_c$ included the different classes then move the weight away from the input vector. The determination rule which used here are:

x = Learning vector
T = Category or class appropriate for the learning vector
$w_j$ = Weights vector to output j ($W_{1j}$, ..., $W_{ij}$, ..., $W_{nj}$)
$C_j$ = Category or class shown by output j

Establishing the reference vector and the learning rate, α (0), weight (w), the maximum epoch, the minimum expected error into two proportional condition (Eq. 11 and 12):

$$\text{If } T = C_j \text{ then: } w_j\,(\text{new}) = w_j\,(\text{old}) + \alpha\left[x - w_j\,(\text{old})\right] \text{ else} \tag{11}$$

$$\text{If } T \neq C_j \text{ then: } w_j\,(\text{new}) = w_j\,(\text{old}) - \alpha\left[x - w_j\,(\text{old})\right] \tag{12}$$

The result of the algorithm will reduce the level of complexity of the process of learning rate, so that, the system can continue the learning to regulate the existing data into category or class that can be recognized, so that, more coordinates of joints can be recognized. Thus, learning the system can recognize the learning vector, category or class which more appropriate to classify the learning vector and determine the category or class of output and selecting suitable weighting while minimizing error rate to get end result, e.g., the quality of the learning rate can be improved.

**Genetic algorithm:** In the Genetic algorithm, the population of candidate solutions to obtain a skeleton needs optimization strategy such as genetic crossover for optimization the joints. It starts with determining code search space followed by combined criteria searching and constraint handling to modify the data in order to find the optimum population consisting of several individuals. It begins by classifying the population in the form of chromosomes as population of coordinate matrix, then the selection is done by computation of iteration process of the DNA in each generated chromosome. The chromosomes represent the poses whereas the DNA represents the joints. The DNA in the home position initialization is done randomly to generate simulated populations to find the probability of the joints as the strong joints which based on the value of fitness, the higher value of the joints, the more likely the joints to represent the dancer poses.

The selection of the main joints is done at random from a population of joints in comparisons to the standardized coordinates from the tensor rules (Eq. 1-10). This will automatically to change the fitness scale through simulation of randomized crossover functions to shape the accurate and stable coordinates till the crossover probability are stopped automatically to produce final optimized model. It also means that the simulation has reached ideal weight through simulated stochastic displacement mechanism which allows the system to find optimum conditions. Thus, Genetic Algorithms (GA) is algorithm to find both higher probability and lowes t value of the minimum data and re-location the maximum value to find optimal values of coordinates to represent grouped matrix which representing the optimal joints. The function is defined in Eq. 1 and 2:

$$\min Z = \sum_{k=1}^{K}\sum_{d=1}^{D}\sqrt[2]{\sum_{\alpha=1}^{A}(x_{da}-p_{da})^2} \tag{13}$$

Where:
Z = Total distance data against class center
k = Index cluster
K = Count clusters
d = Data index
D = Count of data
a = Index data attributes
A = Count data attributes
x = The value of the data of each attribute
p = Weight of the final which is the center of class

## RESULTS AND DISCUSSION

The synchronization of Menak dancer are illustrated in the animated Golek Menak and accompanied with their movements as in Fig. 3.

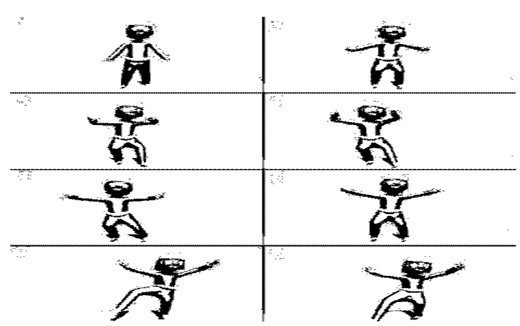

Fig. 3: Result of detected joints in animated version

Table 1: Result of dancer detection with CP, LVQ and GA

| Right hand | Left hand | Right leg | Left leg | Right shoulder | Left shoulder | Right knee | Left knee | Head | Neck |
|---|---|---|---|---|---|---|---|---|---|
| -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1303 |
| -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1303 | -0.1302 | -0.1302 | -0.1302 |
| -0.1293 | -0.1293 | -0.1293 | -0.1293 | -0.1293 | -0.1283 | -0.1283 | -0.1283 | -0.1276 | -0.1277 |
| -0.1277 | -0.1279 | -0.1279 | -0.1279 | -0.1281 | -0.1281 | -0.1280 | -0.1282 | -0.1282 | -0.1282 |
| -0.1280 | -0.1279 | -0.1279 | -0.1280 | -0.1280 | -0.1278 | -0.1278 | -0.1281 | -0.1281 | -0.1285 |
| -0.1285 | -0.1289 | -0.1290 | -0.1290 | -0.1290 | -0.1297 | -0.1297 | -0.1297 | -0.1297 | -0.1298 |
| 0.1291 | -0.1292 | -0.1292 | -0.1294 | -0.1297 | -0.1297 | -0.1297 | -0.1299 | -0.1301 | 0.5828 |
| 0.1301 | -0.1302 | -0.1304 | -0.1304 | -0.1308 | -0.1309 | -0.0702 | 0.0412 | 0.9967 | 0.5769 |

Iter 1: fit = 9.656474e-01, fitdelta = 9.7e-01; Iter 2: fit = 9.666737e-01, fitdelta = 1.0e-03; Iter 3: fit = 9.666738e-01, fitdelta = 1.1e-08; Final fit = 9.666738e-01; P. lambda = (6297.0662)

Result of the body transformation of the dancer motion is given in Table 1 with complete combination of CP, LVQ and GA.

The study resulted that the fitness value as the feasibility of the image to be used as raw data. The value of 0 indicates not found any joint at that location for example at the neck to the chest. The right hand left hand left foot right foot right shoulder left shoulder right knee left knee head neck. GA worked with started creating random initial population that frame (frame) of the BVH data is converted into the frame. In one second, this data has a frame between 60-180 fps. Furthermore, this algorithm will search images and grouped by sequence changes (mutations) in the nearest order for the image to be more in sync. Usually the mutation begins by making very small changes at random to form a data frame sequence and Met heuristic to generate a new sequence so-called crossover process. Thus, genetic algorithms to solve optimization problems by creating a new sequence of frames into motion a dancer. Changes in micro second frame is one of the best ways to solve the problem, so that, more accurate motion detection.

## CONCLUSION

In the Golek Menak dance, there are two types of poses which considered most complex, e.g., Jogetan and Sabetan poses. Their gesture will be recognized by newest tensor rule version which so-called Canonical Parafac-Alternating Least Square (CP-ALS) method. CP-ALS will be used to decompose the complex movement into coordinate position of motion and then optimized with Genetic Algorithms (GA) to improve the computing process in motion classification.

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