Design and Development of Human Skill Transfer System with Augmented Reality

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***Abstract*—This paper presents the design and development of a skill transferring system of a human's hand trajectory. Aims of this system are capturing, encoding, and playing back of the demonstrator's hand trajectory in both spatial and temporal data. To capture a human's hand movement, the Microsoft's Kinect sensor is selected to track the human skeleton and send it to the trajectory modeler to encode the demonstrator's movement. The Gaussian mixture model with its modification of initial parameter estimation is applied in the encoding process. In the playback phase, augmented reality is implemented to provide the learner with some guided positions and times in the form of 2D and 3D computer graphics. The result of applying the proposed algorithm in Gaussian mixture model with initial parameter estimation which is compared with the traditional k-means and incremental k-means approaches takes the least training time. In the playback process, the averaged errors of the playback graphics information for the hand movement skill transfer system are about 2.7 cm. in x axis and 6.25 cm. in y axis. The implementation results demonstrate that the proposed system can capture, encode, and play back the demonstrator's hand trajectory along with augmented reality effectively.**

***Index Terms*—human skill transfer, motor learning, augmented reality**

I. Introduction

Based on literature surveys, there are three aspects of human motor skill [1], [2], and [3]. First, the motor skills should have purposes or goal to be achieved. Next, those skills need to be performed intentionally. Last, the motor skills need some movement of body to reach the goal of task. Many human motor skills such as playing musical instrument, sport, or hand writing needs time and trainer. For the learners who are far from the teacher or trainer, they will face the difficulty in practicing his or her interested skill. In the recent, there are many technologies such as haptic technology virtual reality and augmented reality to improve the learner in practicing their motor skill. Some research works applied neural network in the learning process to transfer human control strategy in a simulated inverted pendulum system from an expert to a mouse. K. Henmi and team [5] utilize a haptic device in a calligraphy skill transferring system. This system presents the proper force to help user to perform tasks appropriately. While T. Tonggoed and S. Charoenseang [6] contributed on a skill transferring system of human hand movement through the Novint Falcon which is a 3 DOF haptic device. The techniques of virtual reality and augmented reality have been utilized to enhance the practice of motor skill. Just Follow Me [7] has a success in applying virtual reality technique with the first person view in the training system. In Your Shape [8], Virtual Sensei [9], and Transfer of Juggling Skills [10] apply virtual reality technique with tracking technology i.e., the Microsoft's Kinect to provide the training system to the learner. Their systems give a specific training such as body exercise and sport. In Your Shape and Transfer of Juggling Skills consist of pre-program sequences of motion while Virtual Sensei is a training system with captured body motion. For using augmented reality technique in training system, YouMove [11] applied this technique in a generalized full-body movement training system. This system will record a trainer's full-body movement and provide guideline to the trainee. However, all these systems provide the skill training system with pre-defined and recorded movement.

Besides the concept of virtual reality and augmented reality training with pre-defined and recorded skill system, this paper presents the system with ability in capturing and encoding skill related to motion trajectory using probabilistic model. An advantage of the probabilistic modeling is the ability in taking care of any uncertainty of the demonstrator's movement. The proposed system will play back the reproduced trajectory of the demonstrator to the learner using augmented reality technology.

II. System Design

A. System Overview

The system consists of human demonstrator, Kinect, and a computer as shown in Fig. 1. In this system, the demonstrator plays the role of a teacher who transfers motion skill by a demonstration of two-hand movement via the Kinect. The Kinect is a motion sensing device that will capture and send the hand's trajectories of the demonstrator to the system. The computer will record both spatial and temporal data during training of captured

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skill. The computer will build the hand's trajectory model from the recorded data and reproduce the trajectories from the models.

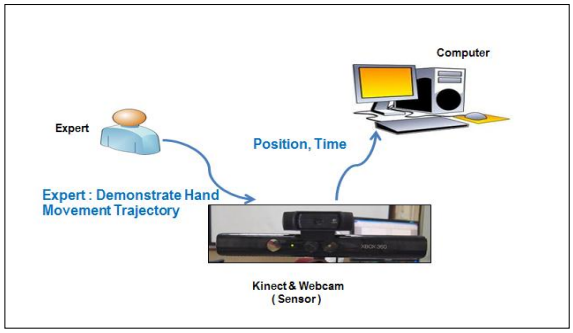

Figure 1. System overview

After the reproduction process, the reproduced trajectory will be played back. In this playback process, an augmented reality technique is applied to present the reproduced trajectory in the form of 3D computer graphics. The implemented system configuration is shown in Fig. 2.

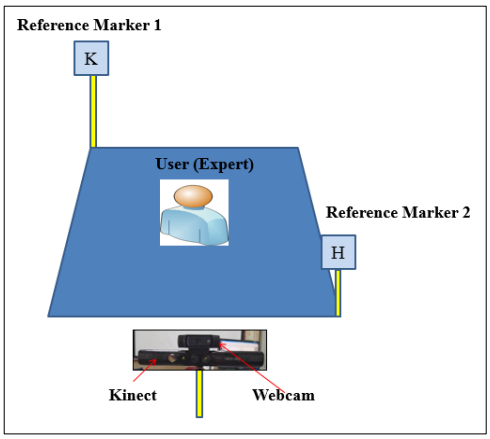

Figure 2. System configuration

B. System Data Flow

In system training, the demonstrator will stand in front of the Kinect and demonstrate the hand movement. Then, the data gathering module records that trajectory in the form of position (x, y, and z) and time (t). The recorded data will be sent to the GMM initial parameter calculation module. This module will process the recorded data using moving average method to obtain more clean data with less noise. To get GMM initial parameters, an algorithm for calculation those parameters will be described later. The clean data will be sent to the trajectory modeling module which builds the captured trajectory's model using the Gaussian mixture model algorithm. Next, the system will reproduce the captured trajectory from the model by the reproduction module. Time steps and Cartesian positions are the outputs of this module. After this process, the reproduced trajectory will be clustered at the trajectory clustering module. The outputs of clustering are the positions of important points in the reproduced trajectory and period of time that will present at each significant point. Then, augmented reality playback module will present virtual objects in the form of 3D computer graphics. These virtual objects will present via points of trajectory according to corresponding time on the screen display. The system data flow is shown in Fig. 3.

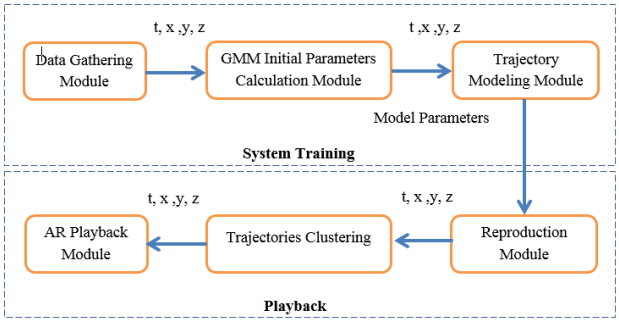

Figure 3. System data flow

III. Learning Algorithm

A parametric model of a probability density distribution which is applied in modeling module is Gaussian Mixture Model (GMM). To retrieve smooth and generalize trajectory from the model, Gaussian mixture regression (GMR) is applied in reproduction process.

A. Gaussian Number and Initial Parameter Estimation Algorithm

Gaussian mixture model which is applied to encode the recorded trajectory follows the main equation, as in (1) [12].

$$p(\alpha_j) = \sum_{k=1}^{K} p(k)p(\alpha_j|k) \qquad (1)$$

In eq.1, p (k) are priors of each K Gaussian and p (α_j |k) is a conditional probability density function. The important parameter of GMM are Gaussian number and initial parameters (prior probability, cluster center, and cluster covariance) of EM-Algorithm.K-Means algorithm with fixed Gaussian number is applied in some part of [12] to initiate the initial parameters. Gaussian number is one of parameters which is obtained from initial process with k-means. Choosing a suitable number of the k in k-means is usually not obvious [13]. A big k in k-means leads a big Gaussian number and it will cause a large training time with over fit model. In the other hand, it takes less time when a tiny number of Gaussian is applied but may obtain less accuracy. In this paper, Gaussian number is unknown because the system allows the demonstrator to demonstrate various trajectories. Therefore, the Gaussian number could not be set before consider the whole trajectory. From this problem, Tarinee and Siam [6] discussed the algorithm of Gaussian component number estimation for gesture trajectory based on direction changing in 2D space. After Gaussian component number is obtained from that algorithm, it is applied in k-means to calculate the initial parameters of EM-Algorithm. To modify the estimation algorithm appeared in [6], the modified Gaussian number estimation algorithm is described as follows.

In the first step of this algorithm, the gathered trajectory will be pre-processed by moving average method. Principal component analysis (PCA) then is

applied to reduce its dimensions into one dimension for more simpler. After dimensional reduction process, the reduced trajectory will be calculated for difference between data at time step t and t+1.Then, it is labelled into groups depend on the distance criteria. The Gaussian number will be determined from the label changing. After the estimation of Gaussian number, the results are Gaussian component number and the trajectory with cluster label. After this process, the initial parameters of EM-Algorithm which is used for GMM parameters updating need to be initiated. These parameters are Gaussian's center (Mu), covariance (Sigma) and prior probability (Priors). The parameter estimation algorithms are shown as follow.

```
Algorithm: Initial Parameter Estimation

Input: Cluster Number, Clustered Trajectory,
Feature Trajectory Data
Begin PROCESS
        1: For i ==1: Cluster Number
        2: Find Feature Trajectory Data index
        with label i.
        3: Count cluster i member number.
        4: Calculate the average center of data
        with same label.
        5: Calculate Covariance (Sigma) of data
        in cluster i.
        6: Calculate Priors of data in cluster i.
        7: End For
        8: Output of This Section: Initial
        parameters of EM-Algorithm (Mu, Sigma,
        Priors)
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B. Trajectory Clustering Algorithm

Because of the advantage in taking care of the arbitrary shape [14] [15], the density based spatial clustering of applications with Noise (DBSCAN) is selected to cluster the reproduced trajectories in the playback process.

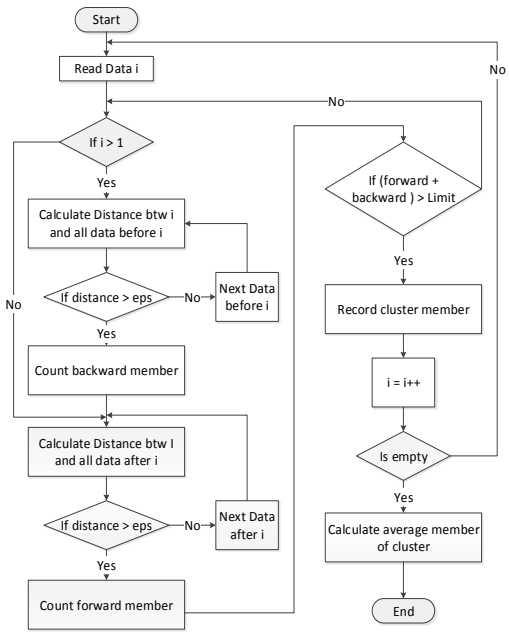


Figure 4. The flowchart of trajectory clustering algorithm

The main parameters of Density based clustering algorithm are minimum number of points (minPts) in each cluster and a distance between center of each cluster to considered point (dist). For this system, a distance between centers of each cluster to the considered point can be estimated from the accuracy of the Kinect. In the other hand, the difficulty is to determine minPts. Then, algorithm of minimum number of point (minPts) in each cluster is proposed as in flowchart in Fig. 4.

C. Mapping Algorithm in Playback Process

In the trajectory playback process, NyARToolKit [16] which is a marker based augmented reality SDK is applied in the system. The technique of augmented reality will superimpose a computer graphics which is in the form of 2D and 3D graphics on a real time video streaming. The idea of playing back the reproduced trajectory to the user is to provide some important positions of reproduced trajectory in the form of virtual object. These virtual objects will be overlaid on the video streaming with user's video in the frame. In this paper, there are two main coordinate systems which are augmented reality (AR) and Kinect spaces. To render the reproduced trajectory which is modeled from Kinect space on AR space, it needs to map the data extracted from model to the rendering space. Fig. 2 presents the system configuration, there are two referenced markers in the workspace. Then, the mapping scale will be calculated from the marker position and the human's hand position.

IV. Experimental Setup and Results

Figure 5. Experimental setup

The experimental setup is shown in Fig. 5 which illustrates the demonstrator, a screen display, a computer and a Kinect. In the experiments, the demonstrator is asked to perform two-hand movement. There are 3

experimental sets to evaluate the system performance. The first set is to evaluate the performance of the proposed algorithm in Gaussian number and initial parameter estimation. The second set is to test the performance of trajectory clustering algorithm. The last experimental set is to evaluate the system performance in playback process.

A. *The Experimental Results of Gaussian Number and Initial Parameter Estimation Algorithm*

The results of Gaussian number and initial parameter estimation algorithm which are presented in this paper will be compared with K-Means and incremental K-Means algorithms. Comparing with K-Means algorithm will be occurred after the Gaussian number and Bayesian information criterion (BIC) value are obtained from the proposed algorithm. To compare with incremental k-means algorithm, BIC value is selected to be the stopping condition of the incremental k-means algorithm. In this experiment, the demonstrator shows two - hand movement along virtual object's positions guided as in Fig. 5. During this demonstration, positions of the user's upper limb skeleton are captured. In this section, two trajectories of the right hand will be considered. The first3D trajectory has 415 time steps and the second 3D trajectory covers 712 time steps. After the reduction of trajectory dimension, the proposed algorithm is applied in reduced trajectory to segment it into each cluster. Fig. 6 presents both trajectory after dimension reduction process and separated into each section.

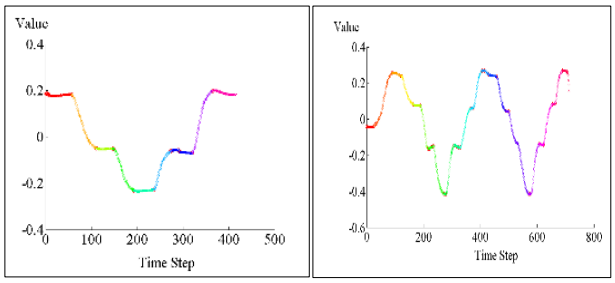
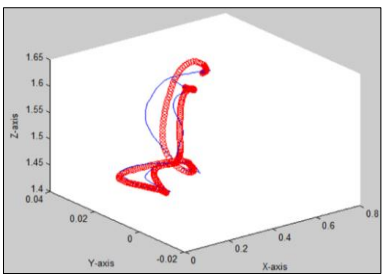


Figure 6. Both trajectory after dimension reduction process and separated into section. The left graph shows the first trajectory with 9 clusters and the right graph is the second trajectory with 19 clusters.



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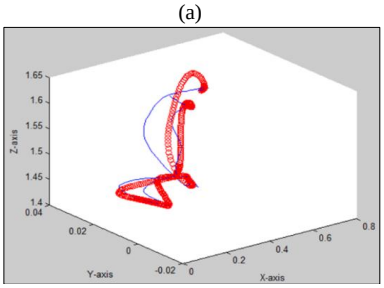

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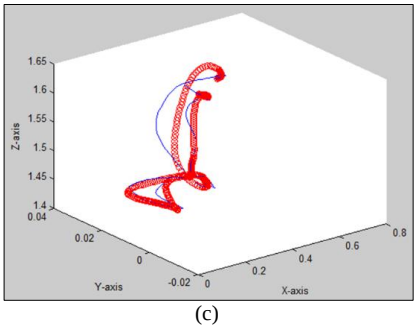
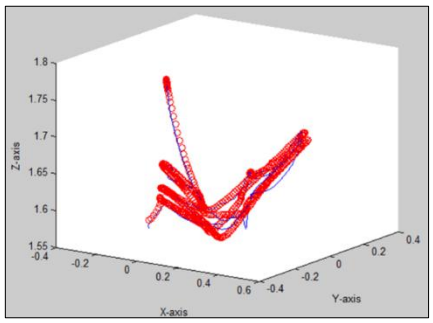


(c)

Figure 7. The reproduction trajectory of the first trajectory under 3 different methods in parameter estimation phrase.

The results shown in Fig. 7 and Fig. 8 present the reproduced trajectory of the first trajectory and the second trajectory, respectively. Blue lines in Fig. 7 and Fig. 8 represent the reference trajectories and red lines are the reproduced trajectories. Fig. 7 (a) and Fig. 8 (a) are the reproduced trajectories which the proposed algorithm is applied in parameter estimation phrase. The results of using K-Means in parameter estimation are shown in Fig. 7 (b) and Fig. 8 (b). Fig. 7 (c) and Fig. 8 (c) present the reproduction trajectories after applying incremental K-Means to estimate the initial parameters.



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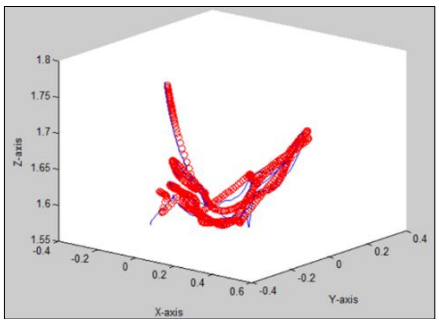

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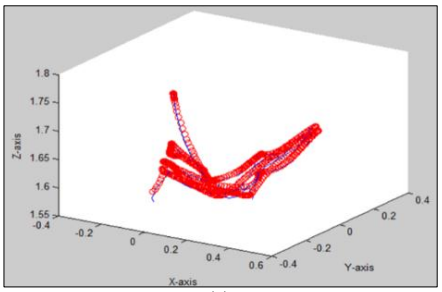


(c)

Figure 8. The reproduction trajectory of the second trajectory under 3 different methods in parameter estimation phrase.

After the demonstration, the recorded trajectory with undefined time period will be modelled under 3 methods of parameter estimation as described above. The average value of Euclidean distance between the reference trajectory and the reproduced trajectory is applied to evaluate the proposed algorithm. Furthermore, training time and reproduction time are important values to be considered. The results of demonstrated trajectories are presented in Table I.

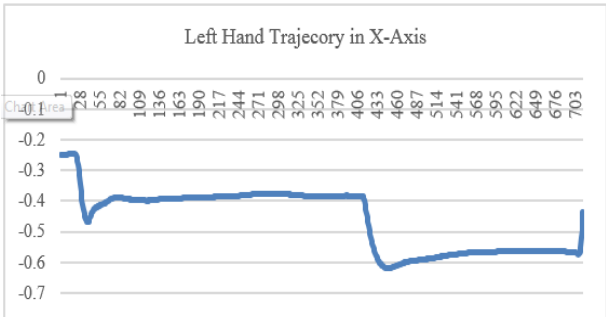
TABLE I. THE RESULT OF GAUSSIAN NUMBER AND PARAMETER ESTIMATION ALGORITHM

Trajectory and Algorithm	Gaussian Number	Training Time(s)	Error (cm)
1'st Trajectory			
Proposed Algorithm	9	0.4712	0.6
K-Means with fixed K number	9	0.3513	0.98
Incremental K-Means	9	1.9898	0.56
2'nd Trajectory			
Proposed Algorithm	19	10.9657	1.7
K-Means with fixed K number	19	2.5881	2.7
Incremental K-Means	20	19.878	1.49

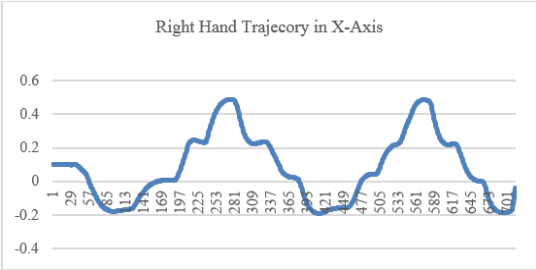
From the results, it shows that the proposed algorithm takes the least time in modeling process with an acceptable error if the K number is unknown.

B. *The Results of Minimum Point Estimation Algorithm for Density Based Clustering*

To evaluate the accuracy of the minimum point (minPts) estimation method for the density based clustering algorithm, the trajectory of the left and right hands with 712 time steps are considered. The obvious trajectories changing in x axis of the left and right hands are shown in Fig. 9. They are not complicated trajectories so they can be clustered manually. From the Fig. 9(a), the trajectory should be clustered into two groups and the main positions in x-axis may present at -0.4 and – 0.6. In Fig. 9(b), it should be separated into 14 groups with the centers in x-axis at-0.2,0,0.23,0.5,0.23,0,-0.2,0,0.23,0.5,0.23,0,-0.2.



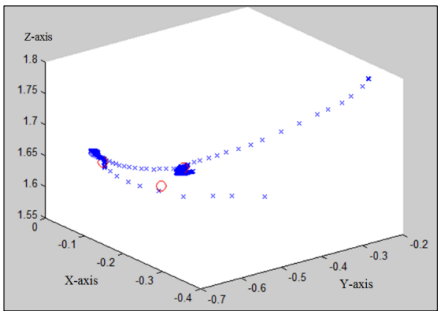
(a) Left hand trajectory changing in X-Axis



(b) Right hand trajectory changing in X-Axis

Figure 9. The obvious trajectory changing in x axis of left and right hands.

When DBSCAN is applied on the reproduced trajectory with fixed minPts at 50 and 15 and eps equals 0.05, the results of setting minPts at 50 are demonstrated in Fig. 10(a) and Fig. 10(b). Fig. 10 (a) presents the cluster i.e., red circle of the left hand trajectory. Fig. 10 (b) shows the cluster of the right hand trajectory. The result in Fig. 10(a) and Fig. 10 (b) illustrate that minPts with valut of 50 seems to be suitable for the left hand movement because it can cluster the left hand trajectory into 3 clusters. On the other hand, if minPts is set to 50 for the right hand motion, this algorithm could not provide the correct clustering. For setting minPts with 15, the right hand trajectory can be clustered into 14 groups. While the cluster number of the left hand movement is 4 as shown in Fig.10 (c) and (d).



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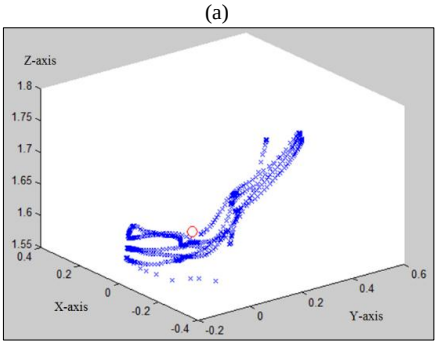

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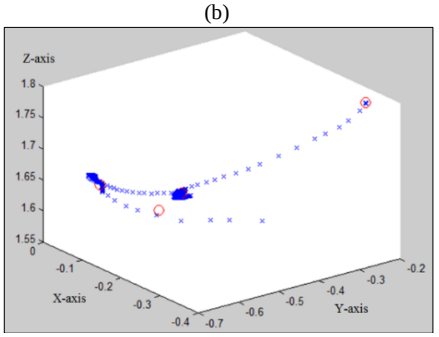

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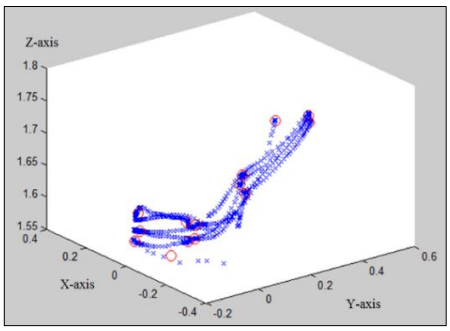
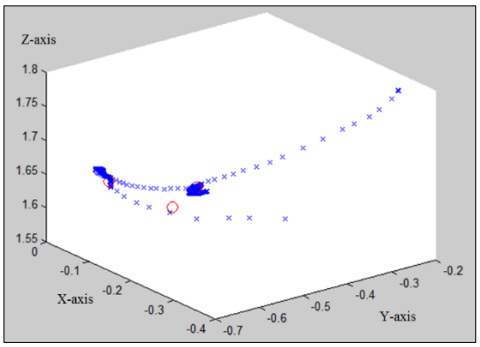


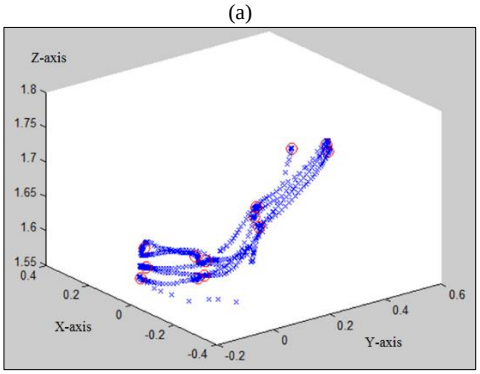
(d)

Figure 10. The results of DBSCAN with fixed minPts.In Figure 10(a),there are 4 clusters of the left hand trajectory. In Figure (b), only 1 cluster is the result from DBSCAN with minPts equals 50.In Figure (c),there are 4 clusters of the left hand trajectory. In Figure (d), 14 clusters are the result from DBSCAN with minPts equals 15.

From the results above, it can conclude that mintPts is a significant parameter of DBSCAN which effects the accuracy of clustering. Then, the estimation algorithm for density based clustering is proposed. The results of applying this algorithm on the trajectory are presented in Fig. 11.



(a)



(b)

Figure 11. (a)3 clusters of the left hand trajectory with minPts = 42. (b) 14 clusters with minPts = 12.

The result in Fig. 11 presents that using this proposed estimation algorithm of minPts provides more accuracy than manual adjustment.

C. *The Results of Trajectory Information in 3D Object Using Augmented Reality*

In this experiment, 11 reference positions are generated. These positions will be rendered as red box on the screen display as Fig. 12. The demonstrator will show his or her two hand movement along these virtual reference positions while computer will record the demonstrator's trajectory. After trajectory modeling and reproduction process, the reproduced trajectory is obtained. This section presents the result of playing back the reproduced trajectory to the user. As discussed in the previous section, this system will present the main important positions which appear in the whole movement trajectory. This important positions will be presented to the user accordingly to the demonstrator's demonstration. Then, DBSCAN is applied to find the important positions in the reproduced trajectory and calculate the appearing period of these positions.

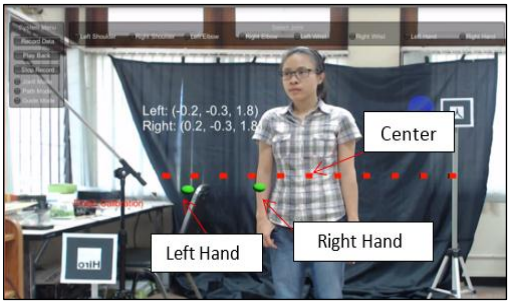


Figure 12. The information which is presented to the user using augmented reality

The important positions which presented in the reproduction trajectory are shown in Table II and Table III.

TABLE II. THE MAIN POSITIONS OF THE LEFT HAND MOVEMENT AFTER APPLYING DBSCAN

No	After Mapping (mm)		Error (mm)		Ref. Point
	x	y	x	y	
1	-372	-92	12	61	10
2	-552	-71	107	40	11
3	-531	-265	86	235	11

TABLE III. THE MAIN POSITIONS OF THE RIGHT HAND MOVEMENT AFTER APPLYING DBSCAN

No	After Mapping (mm)		Error (mm)		Ref. Point
	x	y	x	y	
1	-165.6	-84.6	24.0	53.8	8
2	-1.32	-110.0	18.2	79.4	6
3	230.9	-86.4	4.9	55.6	3
4	467.6	-91.2	61.5	60.3	1
5	222.2	-85.9	13.7	55.0	3
6	23.87	-135.0	43.4	104.4	6
7	-163.0	-91.9	26.3	61.1	8
8	31.05	-110.7	34.7	79.8	5
9	463.7	-86.2	57.6	55.3	1
10	216.3	-80.9	19.6	49.9	3
11	14.2	-97.9	33.7	66.9	6
12	-176.8	-81.8	12.9	50.9	8

The results shown in Table II and Table III can be concluded that the averaged errors in x and y axis are about 2.7 cm. and 6.25cm., respectively. This error is an acceptable for using in this hand motion skill transfer system.

V. Conclusions

The system of human hand motion skill transfer from the demonstrator to the learner was proposed. This system consist of three main components which are the demonstrator's trajectory encoding, trajectory reproduction, and playback process. The proposed system applied a parametric model of a probability density distribution which is Gaussian Mixture Model in trajectory encoding process. The estimation algorithm of EM initial parameters and Gaussian component number is presented. K-means and Incremental k-means were compared with the proposed estimation algorithm. Reproduced trajectory retrieved from the model by Gaussian Mixture Regression was played back to the learner with the idea of main position playback. For the playback process with the main positions of each reproduced trail, DBSCAN is the algorithm for finding the significant points in the trajectory with the proposed algorithm. A marker based augmented reality is the technique of information presenting to the user in the form of computer graphics. The experimental results demonstrate that the system has ability in capturing, reproducing, and playing back the demonstrator's hand movement. The proposed algorithms discussed in this paper covering the EM initial parameter, Gaussian component number, and DBSCAN parameter estimation show the sufficient in both modeling and playback processes.

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