Human Classification Based on Gestural Motions by Using Components of PCA

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Abstract. Lately, a study of human capabilities with the aim to be integrated into machine is the famous topic to be discussed. Moreover, human are bless with special abilities that they can hear, see, sense, speak, think and understand each other. Giving such abilities to machine for improvement of human life is researcher’s aim for better quality of life in the future. This research was concentrating on human gesture, specifically arm motions for differencing the individuality which lead to the development of the hand gesture database. We try to differentiate the human physical characteristic based on hand gesture represented by arm trajectories. Subjects are selected from different type of the body sizes, and then acquired data undergo resampling process. The results discuss the classification of human based on arm trajectories by using Principle Component Analysis (PCA).

1. Introduction
The understanding of human physical characteristic specifically to the hand gesture, which can be used as a replacement existing tool to interact with a machine mechanism such as computer, is an interactive alternative in communication area [1, 2]. Recently, human can interact with computer without physical interaction such in computer game application like kinect [3] and changing television program using gesture product by Samsung Smart Interaction TV. All of the non-physical contact interaction can be done through gesture implementations. Human gesture is one of the non-verbal communications for transmitting and receiving information. It is such a way that technology been introduce inside the modern device.

Human gestures are influence by their individuality factors, which are physical body characteristic and emotional state. During the situation of angry or sad, human feeling are revealing by their actions. This action can produce the difference in the gesture performance. Moreover, the result of gesture will vary although the same gesture performs by the same person. The factor of the body size contributes to

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the differences in the performance of gestures. Then, in the research the body size of the performer will be considered in the development of the gesture database.

In this paper, motion of arm trajectories are achieved by using an optical motion captures system (MoCap). Hence, the motion features are extracted from three-dimensional (3D) movement of hand. In classification of the motion features, the distribution of motion data once undergoes resampling process. Principle Component-Analysis (PCA) approach is used to classify motion data.

This paper is structured as follows: Section 2 addresses the related researches to the research approaches, applications and problems of recognizing the human gesture. Section 3 describes the methodologies and describes the proposed PCA algorithm for the classification of human gesture based on motion patterns. Section 4 presents the experiment setup and results of the classification and the article is concluded with the summary in section 5.

2. Related Research

Many researchers relate the human motion to generate and integrate the movement in the robot. Researcher from Hanyang University of Soul, Korea developed humanoid robot that have such ability of human arm motion [4]. Furthermore, the development of dataglove also related to the gesture understanding of hand and figure in controlling machine [5]. Additionally, Okumoto et al. uses the implementation of augmented reality to presenting tactile sensation for tactoglove which can bring the fill on sense although just wearing a glove [6].

K. Wan et al. prove that the use of human gesture especially human upper body motion for recognizing the dynamic human gesture and give good performance in classify the various gesture pattern [7]. In addition, hand gesture recognition suit for discover human gesture because the representation of gesture mostly concentrate on human upper body [8-10]. As such, sign language communication also involves mostly the movement of hand as well as arm movement. In real application of machine vision toward gesture, the most suitable gesture is using hand trajectories.

Many approaches in attaining hand motion data, which are vision system, accelerometer sensor [12] and dataglove [2]. The suitability and user-friendly factors are the main rules for researchers to determine the most favorable way in their experiment approaches. The differences will create the better results and by comparing between one to another is importance in the process for improvement in the future.

3. Methodologies

The Human arm is the most significant body part in performing gesture while support by others like head movements, facial expressions and arm movements. Figure 1 illustrates the flow of the methodologies in processing the arm motion data. In overall, system has three stages and the first is acquisition of raw data, then resampling of motion data and, follows by the classification of motion data by using PCA. In the series of experiment, there are several geometrical gesture involved. Figures 2 shows 10 geometrical gestures used in the experiments. For the acquisition of motion data, motion capture system (MoCap) consist of five high-speed cameras are placed around the subject to record the gestures. Every gesture are captured and stored in term of .csv format for all three dimension x, y and z. These data represent the motion coordinate in time frame format. Figure 3 shows the rectangle gesture performs by the subject.

Huge amount of tabulated raw data are collected and store in excel format. Furthermore, raw data undergo preprocessing stage to eliminate the noise and extract the features of the movement. The preprocessing process are called ‘resampling process’ [7][11] that generate 30 resample points and also known as 30 features point of the gesture movements. Resampling process eliminate the error in time base data then allow it be represented in term of distance based. Every features point represents the gesture characteristic at that certain resample point. Each and every resample point goes through classification process by using (PCA). PCA allows the tabulated data to be grouped according to characteristic of the features point.
Figure 1. Flow of the proposed methods

Figure 2. Geometrical gesture used in experiment.

Figure 3. Subject performs the rectangle gesture.
3.1. Principle Component Analysis (PCA)

PCA is one of the methods in reduce dimensionality of the numerous data and eliminate the factor of redundancy of the identical data value [12]. It has been found in various applications such as data analysis, monitoring process and rectification of data [14]. The coordinate representation of the new data is calculated by changing the coordinate of the initial coordinate. It is the matter of computing the meaningful basis to filter out the noise and reveal the vital data. Moreover, it is also the revolutions of linear multispectral space (measurement space) into a space of Eigengesture (features space) [5]. The initial data \( Y \) are adjusted to be \( Y_n \) by subtracting the mean.

\[
Y_n = Y - \bar{y}
\]  

(1)

Then, series of result yield from equation (1) are arranged in calculating the covariant of the data set. There are more than single covariance measurement can be calculated and the calculation is depending on the dimension of the data.

\[
Cov(Y, U) = \sum_{a=1}^{m} (y_a - \bar{y})(U_a - \bar{u})
\]  

(2)

\[
(m - 1)
\]

Equation (2) shows the covariant formula in determining the two dimensional data. \( \bar{y} \) is the average value of \( Y \). For data that arrange in \( m \times n \) matrix, the possible covariance value between all the different dimensions is,

\[
K^{m \times n} = \left( d_{i,j}, d_{i,j} = cov(Eim_i, Eim_j) \right)
\]  

(3)

where \( K^{m \times n} \) is a matrix with \( m \) rows and \( n \) columns then \( Eim_X \) is the \( x \)th dimension.

Then, to come through PCA process, the determination of eigenvalue and eigenvector called Eigengesture is required. Eigengesture refers to the vector analysis of the eigenvector and it also known as feature vector. Both Eigengesture and Eigenvalue can be determined as:

\[
Ag = \lambda g
\]  

(4)

Can be simplified as:

\[
(A - \lambda I)g = 0
\]  

(5)

\( g \) represent an Eigengesture of data \( A \) and \( \lambda \) is the eigenvalue of the equation which both are calculated using Jacobian method [13]. The number \( \lambda \) is an eigenvalue of \( A \) if and only if \( A - \lambda I \) is singular, so the determinant of the Eigengesture is:

\[
det(A - \lambda I) = 0
\]  

(6)

Deriving the new data set from the PCA analysis as new representation of data is calculated. In other hand, this new data set can be plot in 2 dimensional (2D) and three dimensional (3D) plotting considering the first, second and third principle component.

\[
FinalDataPCA = Eigengesture^T \times OriginData
\]  

(7)

where Eigengesture is the matrix yield from the eigenvector calculation.
4. Experiments

4.1. Experiment Setup
The system consist of five high-speed cameras with an image resolution 640 x 480 pixels and were able to capture 200 frames per second. Optical motion capture system has an ability to capture motion in real time trajectories [15] then image captured were in term of frame per second. The marker was placed in the features point of the body of a performer which the finger. Markers were made of reflective material that can allow the cameras to track the movement.

The environment parameters must be controlled such as less of light intensity around the system to allow the system to work. Figure 4 shows the flow of the system configuration of motion detection and development of gesture data. 12 subjects will perform the experiment and they had been given briefing and watch some example video in performing the gesture experiment. They also fill the form that consist data of weight, height and their arm’s distance. Then, for every gesture, they need to repeat 10 times. The purpose of repetition is to reduce error and enhance the result. Furthermore, the collected data will ultimately be classified. Classification process will determine data substantial enough of classify group of people according to be body size effect. The space of experimental data collection shows in Figure 5.

Figure 4. Experimental setup

Figure 5. An optical motion capture system.
4.2. Experiment Result and Discussion
The subjects need to perform gesture 10 times repetitively to obtain precise data value. The results of 10 trials were shown in Figure 6. Every three dimension (x, y, and z) data for each subject was resampled [11] then revealed 30 resample points. This resample data signify by Figure 7 which only data from one subject.

Figure 6. Raw data for gesture rectangle performed 10 trials continuously.

Figure 7. Single trial for the gesture rectangle.

Figure 8. 30 resampled data for the gesture rectangle.
Meanwhile, Figure 8 shows data after resampling process that make the analysis easier compared to the raw data. 30 features of distance-based data from 12 different subjects were analyzed by using PCA and resulting the classification of data into several groups as shown in Figures 9 and 10. There are three dimensional plotting represent by first, second and third principle components. Analysis of each features point explicates the number of group that can be classified on every features point. Table 1 shows the classification group. It explains that, at every resampled point, how many group data could be possibly classified.

![Figure 9](image1.png)  Three classification groups ‘data for resampled point #14

![Figure 10](image2.png) Four classification groups’ data for resampled point #2

**Table 1**: Number of Classified Group

| Resampled point | Number of Classified group | Resampled point | Number of Classified group |
|-----------------|---------------------------|-----------------|---------------------------|
| #1              | 1                         | #16             | 2                         |
| #2              | 4                         | #17             | 3                         |
| #3              | 4                         | #18             | 4                         |
| #4              | 5                         | #19             | 4                         |
| #5              | 4                         | #20             | 4                         |
| #6              | 3                         | #21             | 4                         |
| #7              | 3                         | #22             | 4                         |
| #8              | 4                         | #23             | 4                         |
| #9              | 4                         | #24             | 4                         |
| #10             | 4                         | #25             | 4                         |
| #11             | 2                         | #26             | 4                         |
| #12             | 4                         | #27             | 4                         |
| #13             | 4                         | #28             | 4                         |
| #14             | 3                         | #29             | 4                         |
| #15             | 4                         | #30             | 4                         |
4.3. Discussion.

Based on Table 1, a further analysis was done to determine the most number of classified groups. From the analysis, four classes group of data was the highest appeared in many resampled points. Table 2 shows the calculated percentage of the classification. For four groups of classification, there was 73.33% of classification rate. Then three classes group performed 13.33%.

| Number of Classification group | % of classification rate |
|--------------------------------|--------------------------|
| 1                              | 3.33                     |
| 2                              | 6.66                     |
| 3                              | 13.33                    |
| 4                              | 73.33                    |
| 5                              | 3.33                     |

Table 2: Percentage of Group’s Classification

Gesture rectangle performed by 12 subjects

5. Conclusion

PCA in this research is used to group human based on their gestural motions. The acquired motion data must primarily be preprocessed to eliminate the noises and errors. In clustering motion data produced by 12 subjects, several groups of them possibly be classified and the best number of group is 4 with the group classification rate 73.33%.

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