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# CLASSIFICATION OF FINGER GRASPING BY USING PCA BASED ON BEST MATCHING UNIT (BMU) APPROACH

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## ABSTRACT

In this paper we proposed to analyze in depth the thumb, index and middle fingers on the fingertips bending or grasping movement against an objects. The finger movement data are measured using a low cost DataGlove "*GloveMAP*" which is based on fingers adapted postural movement of the principal component. In supervised classification, we are provided with a collection of grasping feature whereas the features capable to be categorized using the EigenFingers of the fingertips bending or grasping data. The classification of the fingers activities is analyzed using Principal Component Analysis (PCA) for feature extraction or normalization reduction and is used for fingertips movement dataset. Meanwhile for the finger grasping group features, the method of Best Matching Unit (PCA-BMU) was proposed whereas the concept of Euclidean Distance could be justify by the best grouping features according to the best neuron or winning neuron. The use of the first and the second principal components can be shown in the experimental results that allow for distinguishing between three fingers grasping and represent the features for an appropriate manipulation of the object grasping.

**Keywords:** Best Matching Unit (BMU); EigenFingers; finger movement classification; hand grasping; Principle Component Analysis (PCA)

## 1. INTRODUCTION

Principal Component Analysis (PCA) is one of the basic methods based on the appearances for use as classical linear methods in the field of face recognition. The main application of PCA is to reduce the dimensionality of dataset in which there are a large number of interrelated variables, while maintaining as much as possible in dataset changes. According to [1], PCA analysis methods are capable to identify and expressing all dataset in such a way as to differentiate their similarities and differences. Principal Component Analysis (PCA) has been used formerly on hand poses such as [1], [2], and [3]. Many approaches / methods for effective human-machine communication have been proposed such as verbal, human face and gesture / posture recognition systems. One of the approaches involves that the use of special devices like the sensory gloves (eg. DataGlove "*GloveMAP*" [4]) could overcome some of the hand trajectory problems. PCA has been used formerly on hand poses such as [5][6]. According to [7], the first user of PCA Sirovich and Kirby [8], [9] states that any face image can be reinstalled about a total weighted collection of images that define the basic interface (eigenimages), and the mean face image. Meanwhile Pentland [10] presented a famous Eigenfaces method for face recognition in 1991. Since that PCA become a successful and popular method especially to those who investigate the pattern recognition and computer vision [11]-[14].

The aim of this journal paper was to clarified whether the method of best matching neuron capable to be used to develop a tool for the analysis of finger grasping / fingertips movement while grasp some of the selected objects by verify all the signals recorded from the fingers movement using *GloveMAP* and the performance of data gathered to be determined by data analysis method. In this research, the use of PCA will provide groups of classification principle component of the fingers grasping. The advantage of this evaluation is not depend on size of human hand even though data are might difference because of difference grasping style between the user.

This research paper is structured as follows: Section II addresses the literature review of the related researches to the several approaches, applications and problems of recognizing the fingers grasping movement. Section III describes the methodologies of the system. Experiment will be described on section IV. Section V will present the results and discussion. Finally on section VI described the conclusions of the research paper.

## 2. LITERATURE REVIEW

The fingertips grasping data are measured using *GloveMAP* whereas the development of low cost DataGlove was made by three flexi sensors attached above of the fingers. Flexible bend sensor is unique device / component that capable to change the fingers bending resistance when the physical or structure of flex sensor is bent or flexed. There are many researchers used this flexible bend sensor in order to recognize their main application to suit with their function. The flex sensor is formerly known as the potentiometer that consist the coated substrate, the basic function of flexible bend sensor is normally same as the wired resistance which could change the entire amount of movement bending into an electrical resistivity [15].

The kinematic posture / structure of the human hand capable to be clarified using some significant part of the fingers structure to the human hands. Distal, intermediate, and proximal phalanges are the bone structure of the phalanges of the hand. According to S. Cobos et al. [16] direct kinematics is used to obtain the position and orientation at any angle fingertips together. T. E. Jerde et al. [17] stated PCA found as a support for the existence of a motionless position synergy angle configuration. The physical posture and contour of human hand / fingers whilst grasping the object can be determine using a postural synergies or kinematic movement of fingertips.

## 3. METHODOLOGIES

The methodologies of grasping objects by using DataGlove called *GloveMAP* are shown in Figure 1. The main prerequisite is to represent the human hand grasping / fingertips bending as accurate as possible. All fingers are able to perform the fingertips flexion motions. The measure of the thumb, index and middle finger movement are well-defined in a marginally in different way of grasp due to its special kinematical structure of *GloveMAP*.

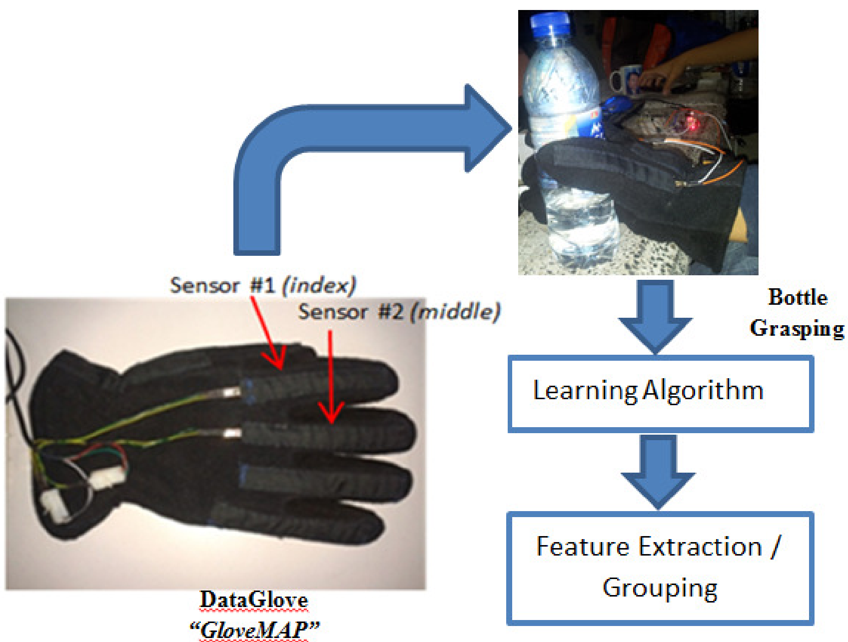


**Fig 1:** The flow of the proposed classification process

### 3.1 Eigenfingers

PCA has been found useful in many applications, such as, data analysis, process monitoring and data rectification [18]. PCA is a dimensionality reduction technique in terms of pick up the variance of the data and it interpretations for correlation among the variable. The coordinates of the new axis is calculated by changing the coordinates of the ordinary data. It is the revolution of linear multispectral space (measurement space) into the space of Eigenfingers (feature spaces). Let the dataset, consisting of $p$ observation variables and $q$ observations for each variable stacked into a matrix $\boldsymbol{X} \epsilon \boldsymbol{R}^{p \times q}$ it is expressed in equation (1)

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1p} \\ X_{21} & X_{22} & \dots & X_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ X_{q1} & X_{q2} & \dots & X_{pq} \end{bmatrix} \tag{1}$$

The principal component transform is defined by:

$$J = A^T F \tag{2}$$

$A$ is an Eigenfingers matrix with a normalized covariance matrix $F$. Then $J$ has a diagonal covariance matrix:

$$C_j = AC_X A^T = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & \dots & \lambda_n \end{bmatrix} \tag{3}$$

Where $C_X = \lambda_i t_i$ ; $A^T A = A^T$

Meanwhile $\lambda_1 > \lambda_2 \ldots > \lambda_n$ are the eigenvalues of the covariance / diagonal covariance matrix of $F$. Then, to meet the terms of the analysis of PCA the use of Eigenfingers and Eigenvalues are required. Whereas Eigenvalues can be simplified as ***Eigenvalues = Eigenfingers*original data***. The analysis can assume to be as a list of real numbers and depending on the concepts of vectors and linear transformations [19]. Eigenfingers$J$ of $A$ and Eigenvalues $\lambda$ can be determined as:-

$$A_J = \lambda_J \tag{4}$$

Can be simplified as:

$$(A - \lambda I)X = 0 \tag{5}$$

Where $\lambda$ and $A$ are calculated using Jacobi method [20], meanwhile $I$ is an identity matrix. By using the equation 5, it is simply find the determinant of the Eigenfingers.

$$\det(A - \lambda I) = 0 \tag{6}$$

In particular, the grasping and fingers bending could be reduced in term of the features number which needed for the effective of data illustration by collecting the bending data. Equation 6 shows only a several number of small variances and preserve only those terms that have only large variances [21]. Let $\lambda_1, \ldots, \lambda_l$ denote the largest $l$ eigenvalues and associated eigenfingers be denoted by $Q_1, Q_2, \ldots, Q_x$ respectively. The equation may write as:-

$$\bar{J} = \sum_{X=1}^{I} A_X Q_X \tag{7}$$

For the calculation of dataset reduction the use of averages and standard deviations are essential for data centering and reduction. $\bar{x}$is the arithmetic mean of each column, it is presented by equation (8). The standard deviation is the square root of the variance; it is presented by equation (9):

$$\bar{x} = \frac{1}{f}\sum_{i=1}^{f} x_i \tag{8}$$

$$\delta^2 = \frac{1}{f}\sum_{i=1}^{f} (x_1 - \bar{x})^2 \tag{9}$$

### 3.2 Classification of the dataset based on Best Matching Unit (BMU)

The Best Matching Unit training algorithm is based on competitive learning which a particularly same as the neural network supervised learning technique. In this study, the BMU approach is employed to the dataset outputted from PCA, and thus the proposed algorithm is called PCA-BMU. To start the BMU features learning, the first step is to initialize all the neurons weights in the dataset features either to make the grouping values or sampled by the two largest principal component eigenvectors of the training samples. In order to utilize the competitive learning training technique, the sample dataset must be functioning as feeder to the features network by calculating the distances between neurons to their positions with a distance function. Euclidean distances between *x* and all the prototype vectors are computed, in order to find the best matching neuron unit. The BMU is selected as the unit that is the nearest to the input vector at an iteration *t*, using equation below:-

$$\|x(t) - w_c(t)\| = min_i\|x(t) - w_i(t)\| \tag{10}$$

Once the new BMU is generated then the winning neuron is identifying $i^*$ then the *"neighborhood"* of the winning neuron could be calculated using the Kohonen rule. Specifically, all such neuron $i \epsilon \Theta\ ({i^*}_q)$ are adjusted as follows:

$$W_i(q+1) = W_i(q) + \Theta(i,q)\alpha(q)(p(q) - W_i(q)) \tag{11}$$

Where *α(q)* is a monotonically decreasing learning coefficient and *p(q)* is the input vector.

According to [24] stated that the other method to simply determine the best matching unit is using the node justification through all the nodes and the winning nodes could be calculated using the Euclidean distance between each node's weight vector and the current input vector. The node with a weight vector closest to the input vector is tagged as the BMU. Where *V* is the current input vector and *W* is the node's weight vector.

$$Dist = \sqrt{\sum_{i=0}^{i=n} (V_1 - W_1)^2} \tag{12}$$

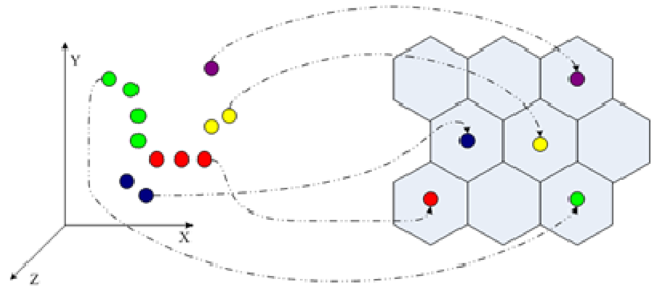


**Fig 2:** The mapping of three-dimensional structure of sample dataset into nine clusters using PCA-BMU [25]

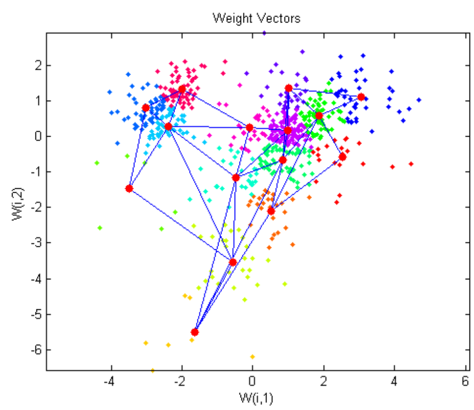


**Fig 3:** Sample of PCA-BMU hierarchical clustering method [26]

Figure 2 shows the clusters of remains dataset with similar input vectors. The left graph denotes a simple representation of sample dataset and the right one denotes the nine clusters using the PCA-BMU Features technique. Circles with the same color denote the member of a remains cluster. In the figure, some clusters don't contain members. Meanwhile for fig. 3 shows sample of best matching dataset unit that capable to perform the group of dataset. According to [24] also stated that training neuron for deciding the BMU and neighborhood using PCA features learning could be occurs in several steps:

[1] Each node's weights are initialized.
[2] A vector is chosen at random from the set of training data and presented to the lattice.
[3] Every node is examined to calculate which one's weights are most like the input vector. The winning node is commonly known as the Best Matching Unit (BMU).
[4] The radius of the neighborhood of the BMU is now calculated. This is a value that starts large, typically set to the 'radius' of the lattice, but diminishes each time-step. Any nodes found within this radius are deemed to be inside the BMU's neighborhood.
[5] Each neighboring node's (the nodes found in step 4) weights are adjusted to make them more like the input vector. The closer a node is to the BMU, the more its weights get altered.
[6] Repeat step 2 for N iterations.

### 3.3 PCA-BMU Normalization Data Reduction

The normalization reduction on the clustering features technique could makes it potential to reduce the neuron number of the dataset while optimizing the features activities that contained in the simplified dataset. This method could be applied to the fingertips grasping dataset in order to ensure a dimension reduction. Once reduced, the new finger grasping groups could be performing after the reduction of neuron scale is formed. Figure 5 shows the sample of data that could be analyzed using PCA-BMU normalization of data reduction and the proposed method can apply to the fingertips grasping dataset.

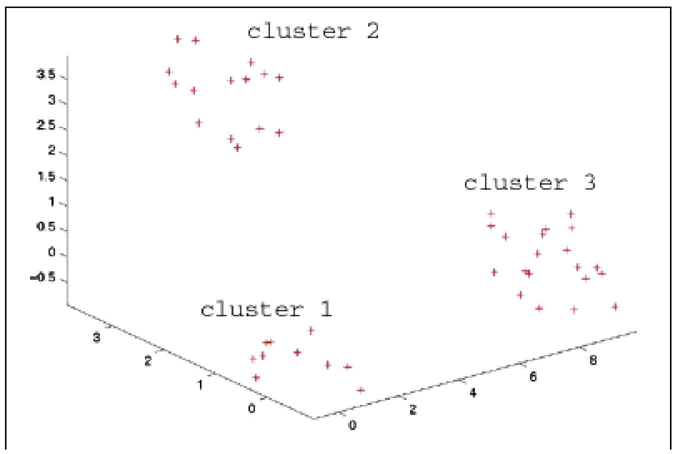


**Fig 5:** Sample of neuron dataset [27]

## 4. EXPERIMENTS

The experiment was carried out using real objects manipulated by a *GloveMAP*. Five people / subjects were selected in doing this experiment for holding objects. Arrangements of *GloveMAP* wearer were required to grasping some objects such as box and cylinder. The chosen of objects depends on the diversity of grasping for every human being was indifferently. According to our previous studied [4][22][23][28], the way of wearing the *GloveMAP* will lead to the correct grip objects and it has already proved by the classification of finger grasping data. Figure 6 shows the fingers movement using *GloveMAP*.

Each experiment was limited to several seconds. The completion task was pretty successful when the subjects grasp the objects such as cylinder and lemon in properly till they're asking to release and the entire measurement end. During the task tested, each of the subjects must wear the *GloveMAP* on the right hand. The entire sensor values of the glove were transformed into data coordinates whilst the number of data configurations was determined accordingly to the grasping duration for each group. It may seem difficult at first trial but after the experiments were done, all data could just be fixing to a maximum number of data and divide it by the number of grasping features groups. For this research, we propose not to justify a maximum number of samples, but some reasonable number of samples per grasping activities.

The definition of the hand grasping for every set of object is explained below. It is really important for human to grasp bottle properly in order to treat bottle handling and measure the signal from DataGlove "*GloveMAP*".

[1] Hold bottle properly.
[2] Carefully grasp the object. Make sure you are comfortable while grasping the bottle and avoid it slip.
[3] Assessment and evaluation will be done with the situation started with before and after holding and grasping an object.
[4] Release the grasp on the object and the evaluation end.

## 5. RESULTS AND DISCUSSIONS

For the experiments result, all data's were analyzed using PCA-BMU methods. All the data's were captured by a MATLAB®SIMULINK using *GloveMAP* and the sample results of the fingers movement data of hand grasping were shown in fig 7 and 8. The Fingers Grasping data were analyzed using PCA-BMU analysis in order to justify the best matching neuron features group. Figure 9 and 10 show EigenFingers for cylinder and lemon grasping. PCA-BMU is a stylish way to minimize the dimensionality of grasping data, while (supposedly) keep most of the information.

Then the use of PCA-BMU clustering could be reducing the impact of a large number of classes on the PCA-based fingertips grasping recognition method. Data's were manipulated using the MATLAB®SIMULINK in order to overcome the correlation between the fingers movement data of principal components and the object grasp by the DataGlove "*GloveMAP*". Research on the sequential learning has ensured that the clustering results in the training dataset can be enhancing the generalization ability in dataset classification.

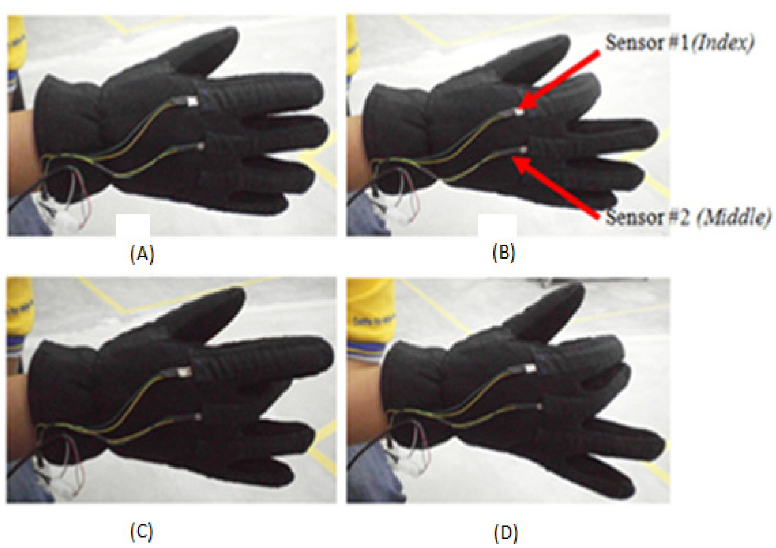


**Fig 6:** *GloveMAP* finger movement activities (**A**) straighten fingers (**B**) bending of index finger (**C**) bending of middle finger (**D**) bending of both fingers [23][24]

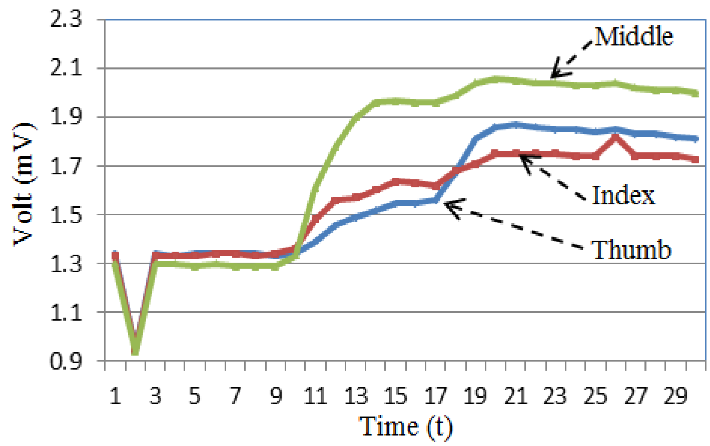


**Fig 7:** Finger movement data for cylinder grasping

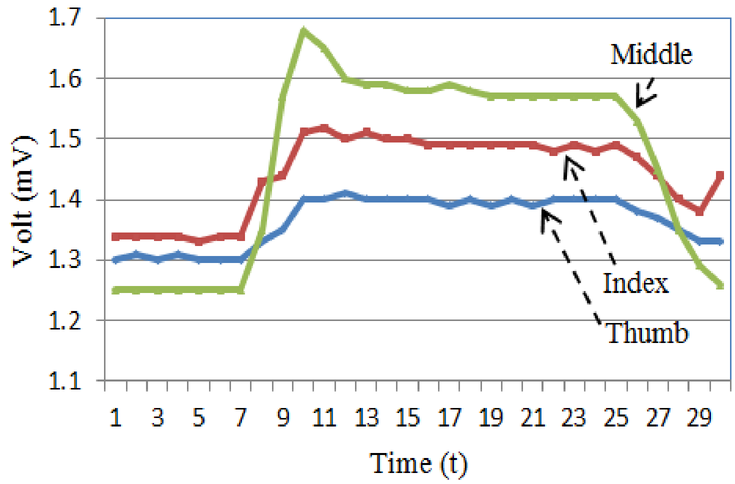


**Fig 8:** Finger movement data for lemon grasping

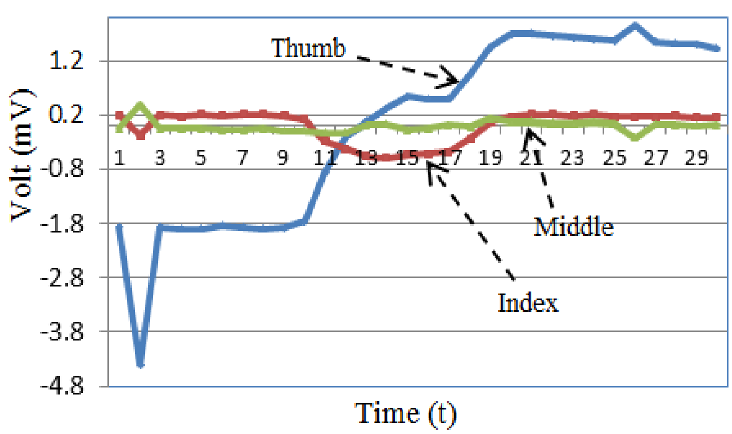


**Fig 9:** EigenFingers data for cylinder grasping

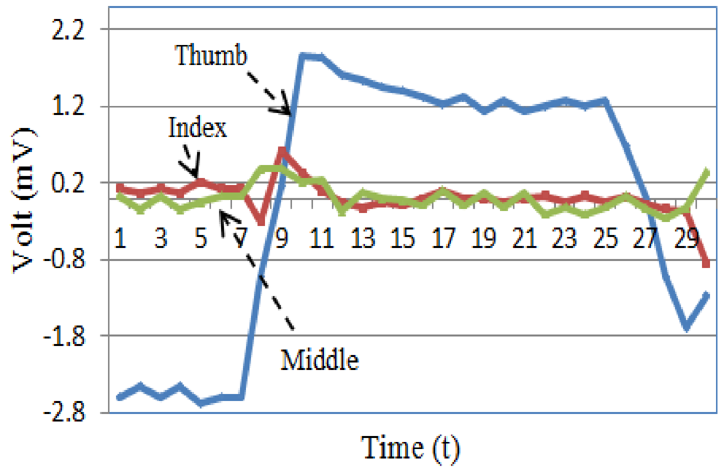


**Fig 10:** EigenFingers data for lemon grasping

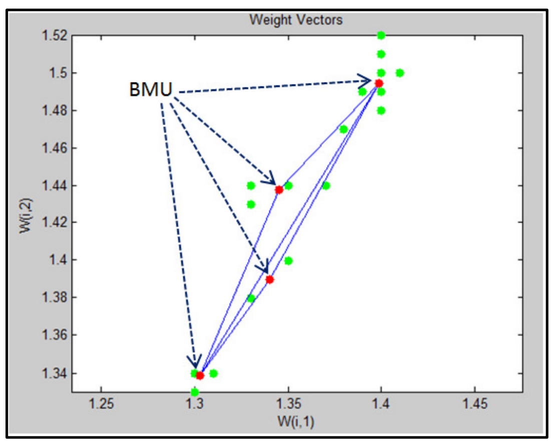


**Fig 11:** The BMU of lemon grasping activity

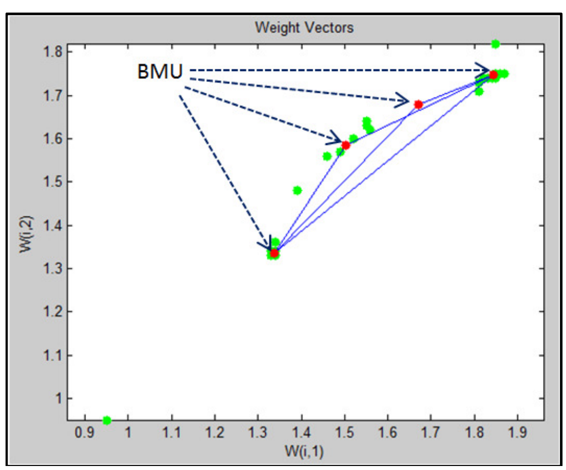


**Fig 12:** The BMU of cylinder grasping activity

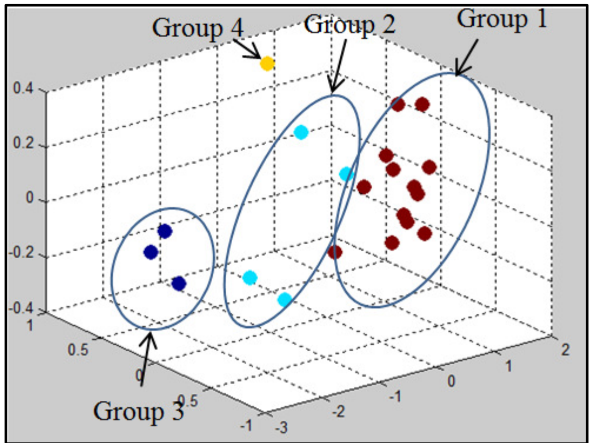


**Fig 13:** PCA-BMU data clustering for lemon grasping activity.

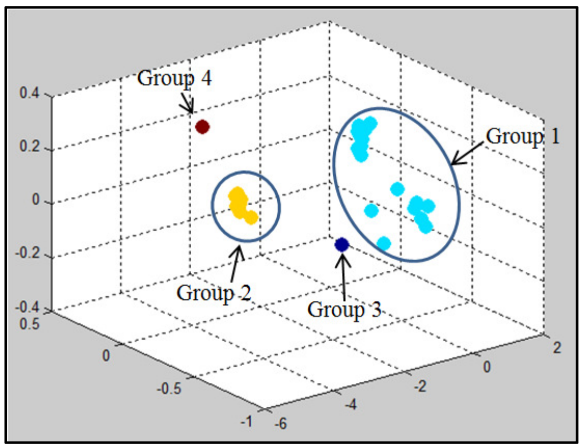


**Fig 14:** PCA-BMU data clustering for cylinder grasping activity.

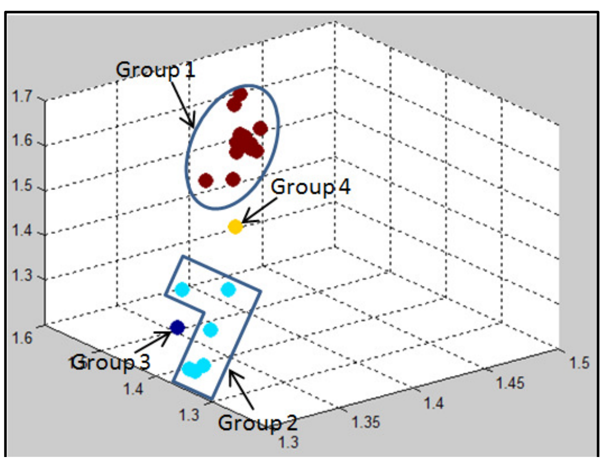


**Fig 15:** PCA-BMU Normalization of clustered data for lemon grasping activity

Figure 11 and 12 show the best distribution neuron number of BMU for finger grasping feature activities. The graphs show that the BMU could be represents as the clustering point or reference point to other neuron of finger grasping features. The other neuron that located nearby the winning neuron could be called as the BMU's neighborhood neuron. After finding the BMU, the original vectors of the BMU and its neighbors are moved or interact closer to the input vector using the mathematical equation 10, 11 and 12. By referring to fig. 13 and 14 the collections of finger movement data from a cylinder and lemon grasping were classified into four groups. Groups 1 shows the finger grasping feature was formed while group 2 show a less data grouping compare to group 1 but data still can be defined as a reference. The other data could be form as a group 3 and group 4 to show as a minimum finger movement grasping and it could be ignore / eliminated in order to simplify the grasping features.

Meanwhile, in order to make the grasping features become more accurate the use of normalization data reduction was presented. Figure 15 shows the result of normalization technique in order to prevent the kind of datasets which the problem of the clustering dataset always emerges. The old-fashioned clustering techniques have been proved their important complexities in determine the grasping feature, so, it is not obviously to be apply them to a large amount of datasets but they're still could be used to facilitate the dataset training and generated the number of grasping features. Both clustering and data normalization could work together to representing the rescale grasping feature especially to reduce the dimension of the grasping dataset. For the forthcoming research, the research study will focus on finger force while grasping the object and the research will no limit only on 3 fingers but the other two ring and little fingers.

## 6. CONCLUSIONS

In this paper, we proposed the method to classify fingertip grasping activities against several objects, which is based on PCA and BMU techniques. A data collection of fingertip movements is done by using *GloveMAP* and the experimental results show that PCA-BMU approach capable to classify and clarified the fingertip grasping features. The results from these experiments could be transforms into various fingers movement for many purposes such as education, medication as well rehabilitation.

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