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ANALYSIS OF SOM AND PCA CLASSIFIER FOR FINGER GRASPING ACTIVITIES BY USING *GLOVEMAP*

Nazrul Hamizi Adnan[1,2], Khairunizam Wan[1,3], Shahriman Abu Bakar[1]
Hazry Desa[3], Zuradzman Mohamad Razlan[3] and Muhammad Hazwan Ali[1]

[1]Advanced Intelligent Computing and Sustainability Research Group
School of Mechatronic Engineering
[3]Centre of Excellence for Unmanned Aerial Systems (COEUAS)
Universiti Malaysia Perlis
Kampus Pauh Putra, 02600 Arau, Perlis, Malaysia
nazrulhamizi.adnan@gmail.com; { khairunizam; shahriman; hazry; zuradzman }@unimap.edu.my

[2]Bahagian Sumber Manusia, Tingkat 17 & 18, IbuPejabat MARA
Jalan Raja Laut, 50609 Kuala Lumpur, Malaysia

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Abstract. *This research study presents the comparison of two classifier methods for grasp recognition based on human grasping activities using selected objects (Bottle, Mouse and Glue) without any limit in grasping style. Both classifier PCA and Self-Organizing Maps (SOM) are employed to train the system by recognizing the objects using data glove called as GloveMAP. The main purpose for this research is to differentiate the performance between classifiers whiles the recognition task is done. At the end of the research, the experimental results will show the difference in grasp recognition percentage between PCA and SOM classifier to show the capabilities of classifiers in terms of suitability and recognition performance.*
Keywords: Data glove, Finger grasping, Grasping classification, Grasping recognition

1. **Introduction.** Recently, technological capability in recognizing the human activities such as motion control [1,2], hand grasping [3,4] and robot grasping [5] is more and more developed. They are demonstrated using such popular methods such as EMG [6], Data glove [7-9], *GloveMAP* [10,11] and humanoid hand [12]. Nowadays, many researchers classified the recognition of grasping motion into hand and finger joint motions. Napier [13], Cutkosky [14] and Iberall [15,16] classified grasping into some clusters of categories by considering the opposable thumb, and analyzed human hand motion especially for robot hands based on the human grasping purpose.

Principal Component Analysis (PCA) generally functions as to reduce the dimensionality of dataset in which there are a large number of interrelated variables, while maintaining them as much as possible in dataset changes. According to [17,18], PCA analysis methods are capable to identify and express all dataset in such a way as to differentiate their similarities and differences. Another classifier method such as Self Organizing Map (SOM) motivated a new research area concerned with data interactions and it becomes very popular among researchers. According to Kohonen [19], Self-organizing map (SOM) classifier is an effective approach for high dimensional data analysis and processing. Both classifiers (SOM and PCA) are capable to be the best classifier to finger grasping analysis by using *GloveMAP* data glove (refer to Figure 1) in case to categorize the raw finger movement data and are capable to supply an attractive alternative solution for recognizing data from the selected objects. The objective of this research is to verify the best

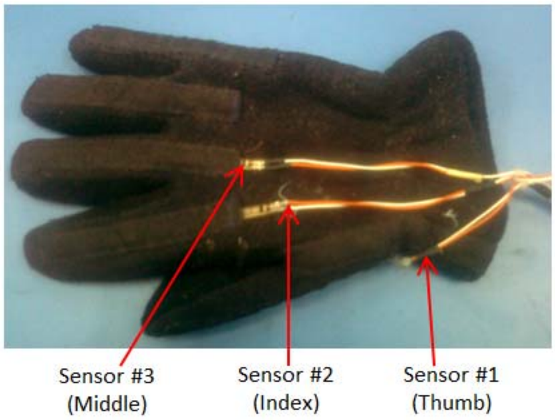

FIGURE 1. Resistive interface glove (*GloveMAP*) [11,12]

recognition method for entire finger bending movement/motion signals using the selected objects (Bottle, PC Mouse and Glue) that is recorded using *GloveMAP*. The improvement to this research study is no limited to any subject grasping style or hand size. At the same time, the result data might have difference between the subjects and also the shape and size of an object grasped by every subject. Finally, the results are depending on the *GloveMAP* data information received from finger object grasping before to be analyzed using the proposed system.

This research paper is structured as follows. Section 2 addresses the literature review including the approaches, applications and some problems regarding to process of recognition task. Section 3 focuses on the methodologies and proposes some classifier study. Meanwhile for the Section 4, it describes the results and discussions. Finally, Section 5 describes the conclusions and proposes some possible future works.

2. **Literature Review.** Manipulation of human fingers grasping makes possible the interaction of human beings with the environment around them. The human finger hand, is a complex and adaptable system, capable of both delicate and precise manipulation and power grasping of any kind of objects [20,21]. According to Ratnasingam and McGinnity [22] humans perform recognition tasks among to any object almost immediately and with unlimited number of times. Human grasping of an object depends on feeling the contour shape of an object by using fingers and the use of hand palm to grasp or move over the object. The shape of an object can be described sufficiently using curvatures, angles and surface contours [22,23].

According to Feix et al. [24], there are three type of grasping clusters compared with the grasp taxonomy of human hand. They are regarded as grasp taxonomy from statistical point of view (refer to Figure 2). One of the researches regarding to finger grasping is about a prototype humanoid grasping developed by Dario et al. [25], which integrates with major methods vision and tactile sensing for object manipulation using two fingers and also a thumb. Meanwhile, according to Cobos et al. [26] the direct kinematics of fingertips is used to grasp the objects and they also proposed the position and orientation as the best methodologies for the study. Meanwhile, for the classifier for finger grasping, Jerde et al. [27] stated PCA is the best classifier especially for the motionless position synergy angle configuration of the physical posture and contour of human hand/fingers whilst grasping the object. The authors also stated the use of PCA is capable to determine postural synergies or kinematic movement of fingertips.

1	Large diameter		6	Index finger extension		11	Tripod	
2	Power sphere		7	Distal type		12	Palmar pinch	
3	Extension type		8	Tripod variation		13	Precision sphere& disk	
4	Medium wrap		9	Writing tripod		14	Prismatic 3 finger	
5	Fixed hook		10	Lateral		15	Parallel extension	

FIGURE 2. Grasp taxonomy proposed in [24]. In this table, all labels correspond to power (labels 1 to 7), intermediate (labels 8 to 10), and precision grasp (labels 11 to 15) respectively.

However, according to [19], Kohonen stated the SOM classifier method is the best among other classifiers in terms of the capability of producing the spatial organization "internal representations" efficiently, and by using the SOM classifier various features of input signals could be determined. SOM is one of the neural network methods that always to be the famous method for computer applications analysis such as data extraction, dimension reduction. SOM is known capable to provide the unsupervised learning network which can map any entry mode to become one or two-dimensional discrete graphics of the grasping features. The SOM is also capable to identify classes of grasping features meaning after automatic clustering by the network, and SOM is necessary to simulate the sample data.

3. **Methodologies.** A lot of work has been done in the field of principal component and self-organizing [28,29]. Since these noticeable patterns should appear in the high-dimensional joint space, a dimension reduction technique such as PCA could be effective. By this research also it shows the SOM and PCA classifier could be as a fundamental means for grasp analysis and synthesis based on the anatomy of human hand as shown in Figure 3 below.

3.1. **Self-Organizing Map (SOM).** The advantage of SOM is to provide the unsupervised learning network which can map any entry mode to become one or two-dimensional discrete graphics of the grasping features. The SOM is capable to identify classes of grasping features meaning after automatic clustering by the network, and SOM is necessary to

FIGURE 3. Anatomy of the hand [30]

simulate the sample data. A SOM does not need a target output to be specified unlike many other types of network. Instead, there is a way how the node weights match the input vector by training the weight vector. The process of SOM training occurs in several steps:

(1) Weight initialization.
(2) Vector is randomly selected from the training data set and presented to the lattice.
(3) Every node is calculated and then to be examined in which one's weights are most similar to the input vector. At this stage the winning node is known as the Best Matching Unit (BMU).
(4) Every single node in the lattice has their own neighbourhood, so at the same time the BMU neighbourhood radius could be calculated. The value always starts large, typically is 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 neighbourhood.
(5) Each neighbouring 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.

The BMU training algorithm is based on competitive learning which is a particularly same as the neural network supervised learning technique. 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:

$$\|x(t) - w_c(t)\| = \min_i \|x(t) - w_i(t)\| \tag{1}$$

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 [19]. Specifically, all such neurons $i \in \Theta(i_q^*)$ are adjusted as follows:

$$W_i(q+1) = W_i(q) + \Theta(i,q)\alpha(q)(p(q) - W_i(q)) \tag{2}$$

where $\alpha(q)$ is a monotonically decreasing learning coefficient and $p(q)$ is the input vector. According to [24], it 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. V is known as the input vector and while W is called as the node's weight vector.

$$Dist = \sqrt{\sum_{i=0}^{i=n} (V_1 - W_1)^2} \tag{3}$$

3.2. **Principal Components Analysis (PCA).** PCA was found useful in many applications such as data analysis, process monitoring and data rectification [29]. PCA is a dimensionality reduction technique in terms of capturing the variance of the data and it accounts for correlation among variables. The new axis coordinates are calculated by converting the coordinate of the ordinary data. It is called as the space of *Eigenfingers* (feature spaces). For example, let the dataset, consisting of p observation variables and q observations for each variable be stacked into a matrix $X \in R^{q\times p}$ and it is expressed in Equation (4):

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ x_{q1} & x_{q2} & \cdots & x_{qp} \end{bmatrix} \tag{4}$$

The principal component transform is defined by:

$$J = A^T F \tag{5}$$

A equals the *Eigenfingers* matrix after normalizing the covariance matrix of F. Then J is called as diagonal covariance matrix of principal component shown in Equation (6):

$$C_j = AC_X A^T = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & \cdots \\ \vdots & \vdots & \cdots & \vdots \\ 0 & \cdots & \cdots & \lambda_n \end{bmatrix}; \text{ where } C_X = \lambda_i t_i;\; A^T A = A^T \tag{6}$$

$\lambda_1 > \lambda_2 > \ldots > \lambda_n$ could be called as the eigenvalues of the covariance (some other researchers call it as the diagonal covariance matrix) of F. The analysis of PCA that could be used by both *Eigenfingers* and Eigenvalues are requisite. Whereas Eigenvalues can be simplified as ***Eigenvalues = Eigenfingers*original data***. According to [31], the analysis of the real numbers is dependent on both concepts (vectors and linear transformations). *Eigenfingers* J of A and Eigenvalues λ can be determined as:

$$A_J = \lambda_J \tag{7}$$

and simplified as:

$$(A - \lambda I)X = 0 \tag{8}$$

The concept of Jacobi method [32] is applied where λ and A are calculated and I is known as the identity matrix. Lastly, it is simple to find the *Eigenfingers* determinant as shown in Equation (9).

$$\det(A - \lambda I) = 0 \tag{9}$$

In particular, the activity of fingers grasping bending could reduce the number of features needed for effective data representation by discarding the bending data. Equations (10) to (12) show only the small variances and keep only those data terms that have a large variances numbers [33]. For example, 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 be written as:

$$\bar{J} = \sum_{X=1}^{I} A_X Q_X \tag{10}$$

$$\bar{x} = \frac{1}{f}\sum_{i=1}^{f} x_i \tag{11}$$

$$\delta^2 = \frac{1}{f}\sum_{i=1}^{f}(x_1 - \bar{x})^2 \tag{12}$$

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 (11). The standard deviation is the square root of the variance and it is presented by Equation (12).

3.3. **Flow chart of works.** Flow chart of works shown in Figure 4 provides overview of the proposed system.

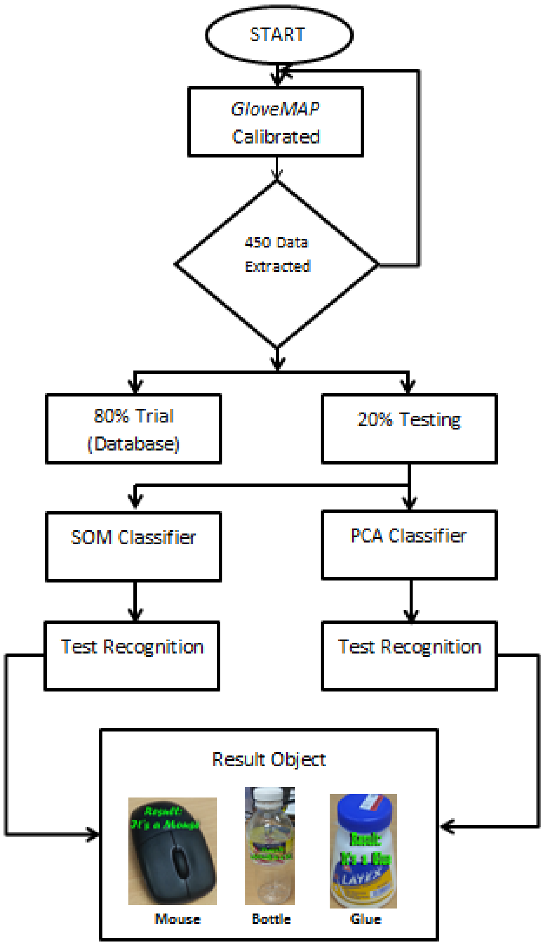

FIGURE 4. Flow chart of overall recognition system

3.4. **Experiments.** Six subjects (right-handed) participated in the experiment. Each subject was fitted with a right-handed *GloveMAP*, which recorded all 3 flexible bend sensors of the hand. Each subject participated in four experimental conditions. Figure 5 shows the activity involved in this research and all the subjects should follow the step to extract the hand grasping data reading as follows:

a. Subjects were instructed to generate a set of hand grasping postures, designed to reach all joint limits. Data from this condition was only used for calibrating the hand grasping.
b. Subjects were asked to hold an object. The object was placed on a table and held within 5-6 seconds and placed back to a table.

4. **Results and Discussions.** The experiment results from the study case analysis based on object grasping by six subjects were presented. In this research study, the experiments performed on three different objects (shown in Figure 6) with different object sizes. All subjects under various grasping objects data were captured by MATLAB®SIMULINK software using *GloveMAP*. Meanwhile the process step of object grasping recognition

FIGURE 5. Object grasping activity

FIGURE 6. Selected objects (Bottle, Mouse and Glue)

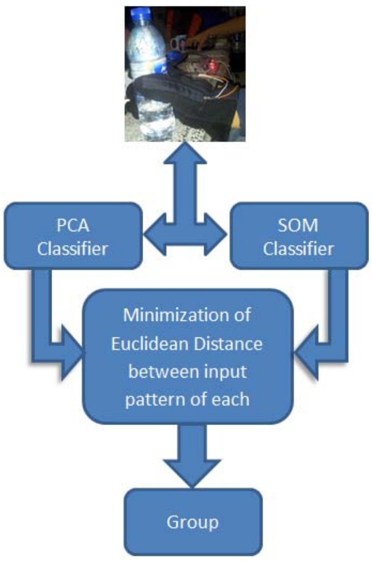

FIGURE 7. The flow chart of the comparative studies between PCA and SOM classifiers

was shown in Figure 7. The comparisons of different recognition algorithms between two classifiers have always been a tough problem no matter what the classifier classified or recognized. In order to comparatively evaluate the recognition performances of the *GloveMAP* grasping activities, the classifiers were tested by using 20% of the total of 450 types of grasping style and another 80% were used to develop the database. The database contains 360 grasping styles of 10 subjects. The confusion matrices for PCA and SOM

Table 1. Confusion matrix for PCA algorithm on finger grasping

Object	Bottle	Mouse	Glue	PCA Recognition Rate (%)
Bottle	9	7	2	**50.0**
Mouse	1	15	2	**83.3**
Glue	6	3	9	**50.0**

Table 2. Confusion matrix for SOM algorithm on finger grasping

Object	Bottle	Mouse	Glue	SOM Recognition Rate (%)
Bottle	10	8	0	**55.6**
Mouse	3	14	1	**77.8**
Glue	5	1	12	**66.7**

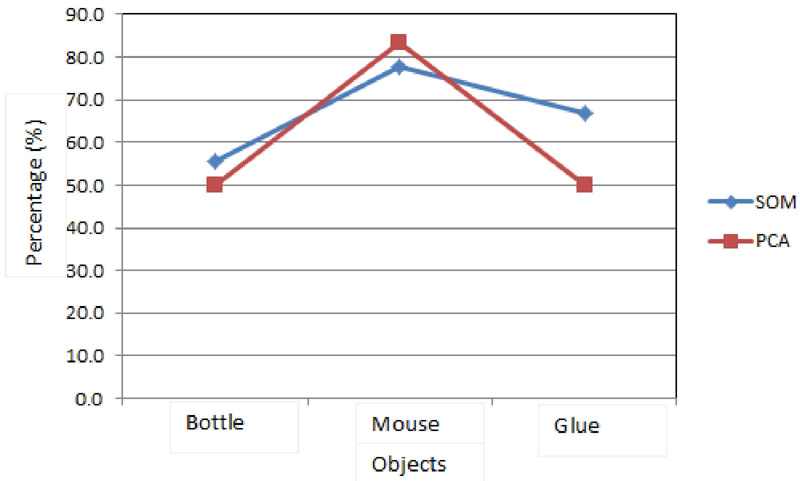

Figure 8. Recognition percentage vs. object grasping

classifiers were shown on Tables 1 and 2. Table 1 shows that PCA recognized "Bottle", "Mouse" and "Glue" with the accuracies 50%, 83.3% and 50%, respectively. Meanwhile Table 2 shows that SOM recognized "Bottle", "Mouse" and "Glue" with the accuracies 55.6%, 77.8% and 66.7%, respectively.

In Figure 8, the X-axis represents the selected objects for this experiment (Bottle, Mouse and Glue) and Y-axis shows the percentage of recognition for all classifiers. As can be expected, the performance of three classifiers degrades with reduced amount of training dataset.

5. **Conclusion.** The research paper proposed the comparative studies to classify finger grasping by using low cost data glove called *GloveMAP*. From the analysis, the result shows PCA and SOM are capable to classify finger grasping activities. Based on the overall observations, it can be concluded that PCA has less recognition performance rate compared with SOM. For the future works, the analysis could be extended to other objects which are not limited to the size and shape of the object.

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