Clustering Analysis of Human Finger Grasping Based on SOM Neural Network Model

Nazrul H. ADNAN, Khairunizam WAN, Shahriman AB, and Juliana A. AbuBakar

Abstract— **SOM (Self-organizing Maps) model was introduced to cluster and analyse on the human grasping activities of *GloveMAP* based on data reduction of the initial grasping data. By acquiring the data reduction of the initial hand grasping data of the several objects, it will be going to be functioned as the inputs to the SOM model. After the iterative learning of net-trained, all data of the trained network will be simulated and finally self-organized. The output results of models' are farthest approached to the reality in 3-dimensional grasping features. The experimental result of the simulation signal will generate the simulate result of the grasping features from the selected object. The whole experiment of grasping features is derived into three features / groups and the results are satisfactory.**

Index Term— **Cluster Analysis, Data reduction, Fingers grasping, Grasping features, SOM neural networks**

I. INTRODUCTION

Multi-fingers grasping classification become popular to many researchers in order to find the best grasp for many proposed. Generally speaking, many research used grasping force study for robotic grasping force [1][2][3] in order to analyse the force control and grasp stability. Human grasping motion analysis still becomes a challenging task which is often needed in virtual simulation. Napier [4] and Cukosky [5] use the human grasping analysis for classify of grasping classification into more details, and also endeavoured classification considering the best finger motion. Nowadays, many researchers study the classification of hand grasping using many methods such as EMG [6], DataGlove [7][8][9] and humanoid hand [10]. Nazrul *et al.* classified human grasp into

Nazrul H. ADNAN was with the Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis,Kampus Pauh Putra, 02600 Arau, Perlis, MALAYSIA and Bahagian Sumber Manusia, Tingkat 17 & 18, IbuPejabat MARA ,Jalan Raja Laut, 50609 Kuala Lumpur, MALAYSIA (corresponding author to provide phone: +6019-4786589; fax: +6049798334; e-mail: nazrulhamizi.adnan @gmail.com).
Khairunizam WAN., was with the Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis,Kampus Pauh Putra, 02600 Arau, Perlis, MALAYSIA (e-mail: khairunizam@unimap.edu.my).
Shahriman AB was with the Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis,Kampus Pauh Putra, 02600 Arau, Perlis, MALAYSIA (e-mail: shahriman@unimap.edu.my).
Juliana A. AbuBakar was with the Department of Multimedia School of Multimedia Tech & Communication College of Arts and Sciences, Universiti Utara Malaysia 06010 Sintok, Kedah, MALAYSIA (e-mail: liana@uum.edu.my).

several grasping feature using new and low cost development of DataGlove called *"GloveMAP"* [11][12] for classification based on the selected human fingers to grasp the selected object. In addition the *GloveMAP* for classified the human grasping activities is measure using only the thumb, index and middle finger. Figure 1 shows the example of *GloveMAP* and position of the sensor that located at back of the *GloveMAP* fingers. The glove is capable to measures finger flexure or finger bend of the user's hand. The physical customize made for *GloveMAP is* using lycra material and it is one size fits many.

The objective of this research is to verify the entire finger bending movement / motion signals that recorded using *GloveMAP* and the performance of data gathered to be determined by Self Organizing Mapping (SOM) method. The advantage of this evaluation is not depend on size of human hand even though data are might difference because of difference finger bending style between the user. In this research, the use of SOM will provide groups of finger grasping features.

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 bending movement. Section III describes the methodologies of the system. Section IV describes the project experiment. Section V describes results and discussions. Finally on section VI described the conclusions and proposing some possible future work.
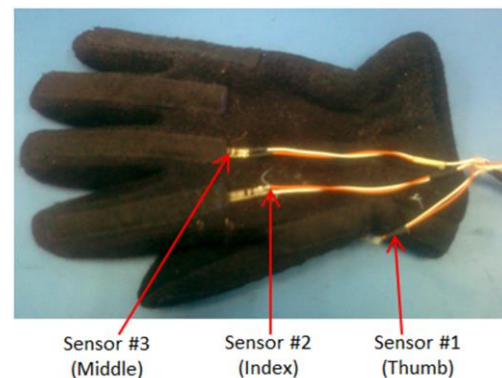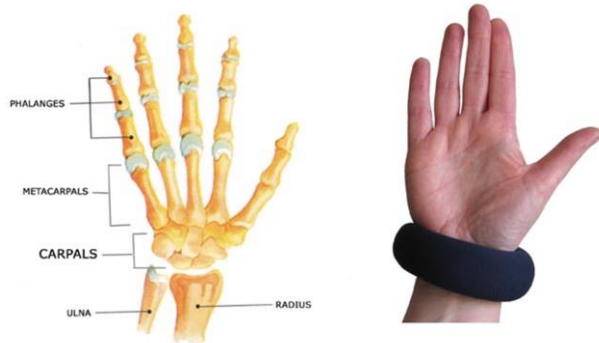
II. LITERATURE REVIEW

Fig. 1. Resistive interface glove (*GloveMAP*)

Fig. 2. Anatomy of the hand [16]

Fig. 3. Diagram of SOM net-structure [17,18].

The physical hand/finger model that applied for this research is based on the actual human hand. Thumb, Index, Middle, Ring and Little fingers act simultaneously in the analysis of fingers grasping. L. Vigouroux et al. [13] stated that the thumb did not compete against the other fingers and there is no secondary moments were functional to the wrist. However, Gregory P. Slota et al. [14] said that to hold an object oriented vertically with your thumb against the four-finger grip prismatic as in holding a bottle of water. The kinematic posture/structure of the human hand is important in order to be clarification 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 as shown in Fig. 2. According to S. Cobos et al. [15] direct kinematics is used to obtain the position and orientation at any angle fingertips together.

III.   METHODOLOGY

The bending of thumb, index and middle human finger for grasping several object are well-defined in a marginally due to its special kinematical structure of *GloveMAP*. As the advantages of SOM 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 capable identify classes' of grasping features meaning after automatic clustering by the network, SOM necessary to simulate the sample data.

A. SOM Net-Structure

Figure 3 shows the SOM net-structure, whereas the structure of SOM is structured by a single-layer network which is consist of the input and competitive layer. The input layer is structured by one-dimensional called as N nodes, and the competitive layer can either one or two-dimensional with M nodes. The neurons in two layers located in the grid nodes, and joint each other with interconnection weights. All the input and output neurons of SOM are linked [19,20].

B. Clustering Function

The principal goal of an SOM is to transform an incoming signal pattern of arbitrary dimension into a one or two dimensional discrete map, and to perform this transformation adaptively in a topologically ordered fashion.

According to [20], the training process of SOM network, the weights (W_{ij}) of output neurons adjusts the direction toward
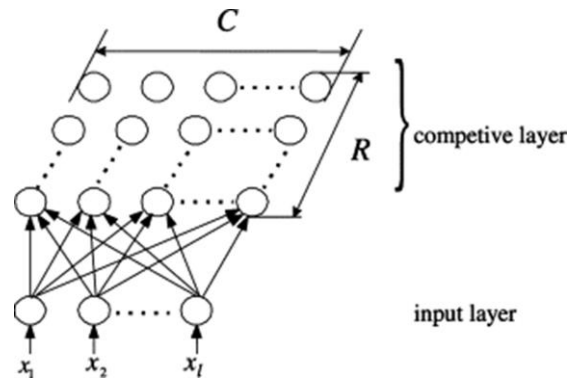
more favour of the winning neuron. After the process of training done, all weights neuron / neurons going to be the process of training for neuron utilizes competitive learning. When a training example is fed to the network, its Euclidean distance to all weight vectors is computed. The neuron whose weight vector is most similar to the input is called the best matching unit (BMU). The weights of the BMU and neurons close to it in the SOM lattice are adjusted towards the input vector. Figure 4 shows the sample of neuron topologies.

C. SOM Algorithm

A SOM does not need a target output to be specified unlike many other types of network. Instead, there is a way how the
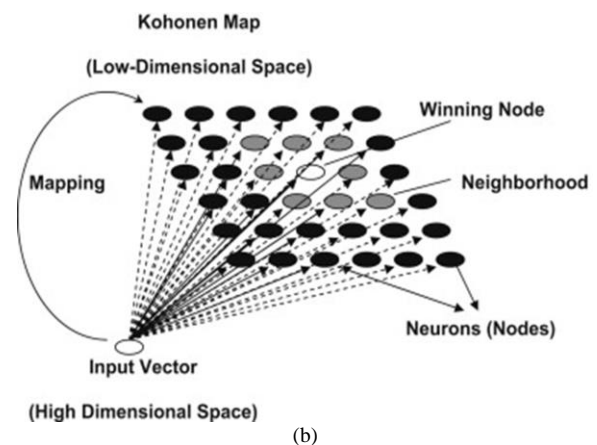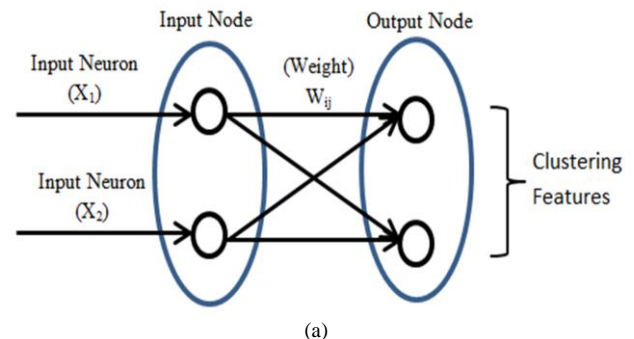

Fig. 4. Neurons mapping topologies (a) neuron clustering (b) Illustration of the winning node and its neighbourhood in the Kohonen Self-organizing Map [17,18].

node weights match the input vector by training the weight vector. Training occurs in several steps and over much iteration:

[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 neighbourhood 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 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 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:-

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

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. Specifically, all such neuron $i \in \Theta (i^*_q)$ 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 [15] 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.

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

IV. EXPERIMENTS

Five right-handed subjects 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. Each subject should follow the step to extract the hand grasping data reading as follow:

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 calibrate the hand grasping.

b) Subjects were asked to hold a bottle. The bottle was placed on a table and held within 5-6 seconds and place back to a table.

Figure 5 shows the activity involved in this research.
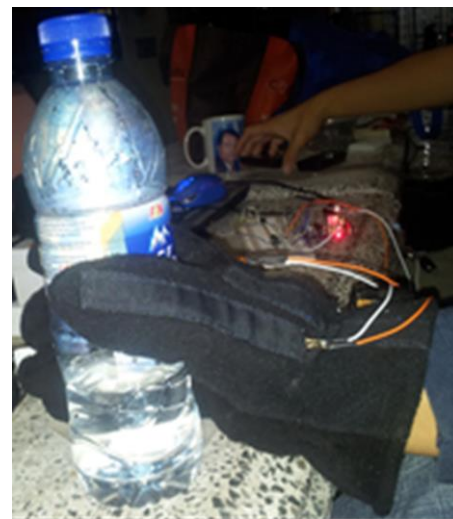

Fig. 5. Bottle Grasping Activity

V.   RESULTS AND DISCUSSION

The SOM algorithm can be used to assign a natural order to objects each characterized only by a large number of attributes. This was done by letting the SOM algorithm create a topological mapping from the high-dimensional attribute space to a one-dimensional output space. As sample data, the usage of a simple / initial dataset of human grasping in order to get this one-dimensional topology, the network has to be trained using a one-dimensional neighbourhood. Figure 6 shows the SOM and neighbourhood of the *GloveMAP* hand grasping. The *GloveMAP* tracks the movements of all three fingers of the hand. Before measuring hand grasping, the *GloveMAP* was calibrated in order to estimate the configuration of the subject's hand. Figure 7 shows the initial / original data of subjects for object grasping using the *GloveMAP*.
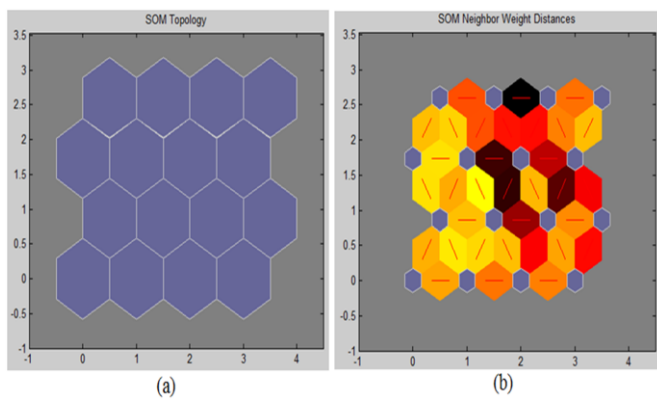

Fig. 8. SOM weight vectors

Fig. 6. *GloveMAP* hand grasping topological map (a) SOM Topology (b) SOM neighbour weight distance

Fig. 9. SOM weight centroid /BMU

Fig. 7. Hand grasping signal (a) original / initial data (b) SOM signal
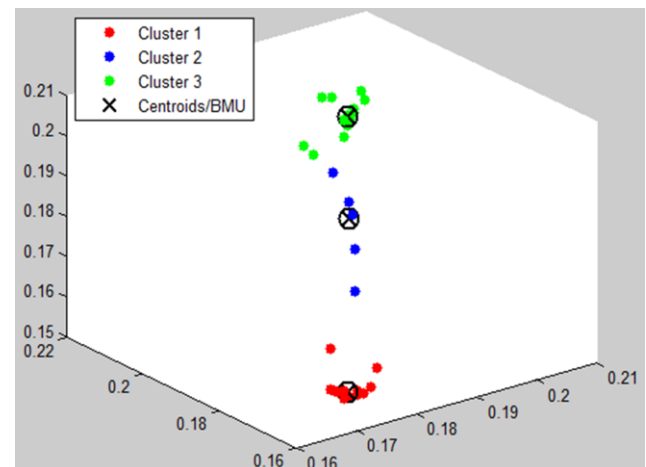
Figure 8 and 9 show the winning neuron or best centroid neuron of *GloveMAP* hand grasping in order to justify the bottle grasping feature. Figure 8 also shows three features / clusters were extracted from the initial bottle grasping whereas each of the clusters consist of centroid called as a best matching unit (BMU). The group of features could be difference between subject and it could be effect of subject hand size and grasping style but the differences will not cause much compare to the fig. 9. However more output space dimensions of the SOM network were the more complex of its topological structure will be needed, thereupon, more neurons will be generated.

VI.   CONCLUSION AND FUTURE WORK

In this paper, we proposed the method to classify the hand grasping feature for bottle grasp using low cost DataGlove called *GloveMAP*. The chosen of Self-Organizing Map (SOM) has proved that the feature of grasping capable to be initialized and identifying the human grasp feature at the same time the determination of one of the main methods of bottle grasp. 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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Nazrul H. ADNAN received his Bachelor Engineering (Hons) in Power Electrical from Universiti Teknologi MARA (UiTM) and Master Engineering in Advanced Manufacturing Technology from Universiti Teknologi Malaysia (UTM) since 2004 and 2010 respectively. After graduated in Bachelor Engineering he joined Majlis Amanah Rakyat (MARA) as Teaching Engineer where he worked as a lecturer to Mechatronics, Electronics and Mechanical Diploma students. He was currently a PhD student in Universiti Malaysia Perlis. His research interest is in Human-Computer Interaction (HCI), Product Design, Artificial Intelligence, and Machine Design.

Khairunizam WAN received his B. Eng. degree in Electrical & Electronic Eng. from Yamaguchi University and Ph.D. in Mechatronic Eng. from Kagawa University, in 1999 and 2009 respectively. He is currently a Senior Lecturer at School Of Mechatronic Engineering, University Malaysia Perlis. He is member of Board of Engineer and Institute of Engineer, Malaysia. His research interest is in Human-Computer Interaction (HCI), Intelligent Transportation System, Artificial Intelligence and Robotics.

Shahriman A.B. received the B.Eng, M.Eng, and PhD in Mechanical engineering from Mie University, Mie, Japan in 1997 2004, 2010 respectively. After graduating from his bachelor degree he joined NEC Semiconductors (Malaysia) where he worked as machine engineer to supervise engineering team in order to improve equipments performance and efficiency. He did his Ph.D. studying human and robot collaborative tasks in senses and ergonomics. He is currently a senior lecturer in UniMAP, Perlis. His current research interest is in Medical Engineering, Industrial Agriculture Automation and sustainable energy.

Juliana A. Abu Bakar currently lectures virtual reality and multimedia technology courses at University Utara Malaysia (UUM). She received B.Eng. degree in Electronic Engineering from University of Leeds, UK in 1999 and MSc. degree in Information Technology from UUM in 2003. She was awarded Ph.D from International Islamic University Malaysia in 2012 where her Ph.D thesis covers a complete cycle of design, development, and user evaluation of a virtual reality application for architectural heritage learning. She is passionate in virtual reality research and development projects since her first involvement in the academic world and has secured several national grants and published many articles in the area.