Australian Journal of Basic and Applied Sciences, 8(4) Special 2014, Pages: 219-223

AENSI Journals

Australian Journal of Basic and Applied Sciences

ISSN:1991-8178

Journal home page: www.ajbasweb.com

Extracting Features of Fingertips Bending by Using Self-Organizing Map

[1,2]H.A. Nazrul, [1]W. Khairunizam, [1]A.B. Shahriman, [3]A.A.B. Juliana

[1]*Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis, Kampus Pauh Putra, 02600 Arau, Perlis, Malaysia.*
[2]*Bahagian SumberManusia, Tingkat 17 & 18, IbuPejabat MARA Jalan Raja Laut, 50609 Kuala Lumpur, Malaysia.*
[3]*Department of Multimedia School of Multimedia Tech &Communication College of Arts and Sciences Universiti Utara Malaysia 06010 Sintok, Kedah, Malaysia.*

ARTICLE INFO

Article history:
Received 20 November 2013
Received in revised form 24 January 2014
Accepted 29 January 2014
Available online 5 April 2014

Keywords:
Human Grasping; Grasping Features; Self-Organizing; SOM neural networks

ABSTRACT

In this paper the method of Self-Organizing Maps (SOM) is introduced to analyze the human grasping activities of human fingertips bending using the low cost DataGlove called as GloveMAP. The research shows that the proposed approaches capable to utilize the effectiveness of the SOM for creating the grasping features of the bottle object. After the iterative learning of net-trained, all data of the trained network will be simulated and finally self-organized. The final result of the research study shows the fingertips features extraction were generated from the several grasping activities and verify the validity of the analysis through simulation with human grasp data captured by a GloveMAP.

To Cite This Article: H.A. Nazrul, W. Khairunizam, A.B. Shahriman, A.A.B. Juliana., Extracting Features of Fingertips Bending by Using Self-Organizing Map. ***Aust. J. Basic & Appl. Sci.,*** *8(4): 219-223, 2014*

INTRODUCTION

Many scientists have been exploring and developing new interaction paradigms for human computer interaction such as EMG (Cipriani, C. *et al*., 2008), DataGlove (Hager-Ross C. and Schieber M.H., 2000, Todorov, E., Ghahramani, Z., 2004; Nazrul H.A., Khairunizam W., Shariman A.B. and Juliana A.A.B., 2013) and humanoid hand (Taisuke S., Genki, F., Hiroyasu, I. and Shigeki, S., 2010). This research describes human hand grasping using low cost DataGlove called GloveMAP meanwhile SOM functioning to visualized and clustering based on a neural network viewpoint. Fingertips grasping are more on the fingers (thumb, index and middle fingers) motions in order to analyse the fingertips movement style and grasping stability.

Nowadays, many researchers study the classification of hand grasping using many methods such as EMG (Cipriani, C. *et al*., 2008), DataGlove and humanoid hand. Nazrul *et al*. classified human grasp into several grasping feature using new and low cost development DataGlove called "GloveMAP" for classification of human fingertips objects grasp. The objective of this research is to verify the entire finger bending movement / motion signals that recorded by using GloveMAP and the clasification of grasping feature to be determined by Self-Organizing Mapping (SOM). SOM method is an effective approach for high dimensional data analysis and processing.

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.

MATERIALS AND METHODS

SOM classifier functioning as a neural network method used for computer applications such as data analysis, dimension reduction of features. This method is a special instance between the clustering method reducing the amount of data and the nonlinear projection method projecting data onto lower dimension. Mantyla *et al*. present a system for static gestures recognition using a self-organizing mapping scheme, while a hidden Markov model is used to recognize dynamic gestures. While in 2007, Guido Heumer used the Sammon Map and SOM method to visualize and compare the result of the grasp recognition experiments in their research. The kinematic posture/structure of the human hands is important in order to be clarifying using some significant part of the fingers structure to the human hands.

Corresponding Author: H.A. Nazrul, Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis, Kampus Pauh Putra, 02600 Arau, Perlis, Malaysia.

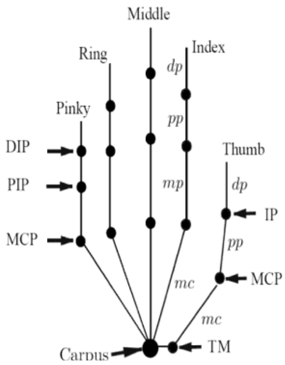


Fig.1: Anatomy of the hand.

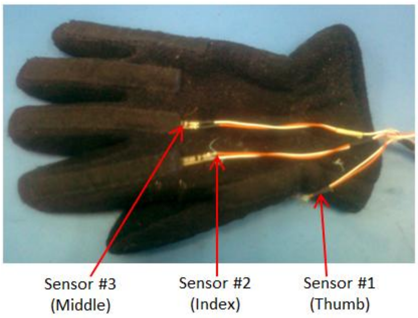


Fig. 2: Resistive interface glove (*GloveMAP*).

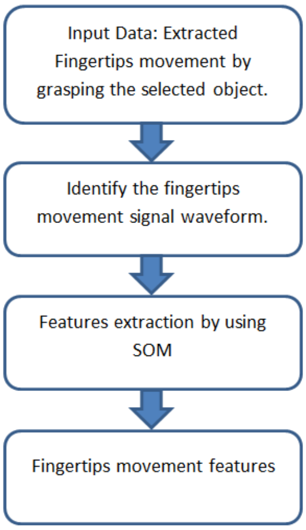


Fig. 3: Flow chart of proposed works.

Distal, intermediate, and proximal phalanges are the bone structure of the phalanges of the hand as shown in Fig. 1. According to S. Cobos *et al*. direct kinematics is used to obtain the position and orientation at any angle fingertips together. In this research, the flexiforce sensors are attached to the thumb, index and middle fingers of the *GloveMAP* as shown to Fig. 2. Meanwhile Fig. 3.shows the flow chart of the proposed works. According to SOM is a neural network method used for computer applications such as data analysis, dimension reduction of features. Figure 3 shows the SOM map-structure, whereas the structure of SOM is structured by a one-layer network consisting of the two layers (called as the input and competitive layer). The original structure of the input layer of map structure is structured by single-dimensional called as *P* nodes, and the competitive layer can either one or two-dimensional with *T* nodes.

Australian Journal of Basic and Applied Sciences, 8(4) Special 2014, Pages: 219-223

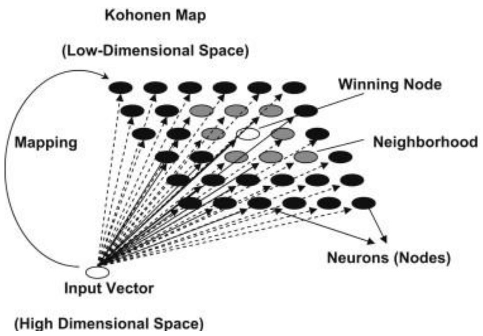


Fig. 4: Illustration of the winning node and its neighbourhood in the Kohonen Self-organizing Map.

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. Below are the training steps over the iteration of SOM:

- Weight of each node that has been initiated.
- A vector randomly selected from the training data set and presented to the lattice.
- Each node is examined to calculate which is the best weights are most similarly to the input vector. The winning node or neuron is basically known as the Best Matching Unit (BMU).
- After the neighbourhood of the BMU has been calculated. Whereas the node starts large, what is the author set more on the 'radius' of the lattice, but reduces each time-step. Any nodes found within this radius are estimated to be the BMU's neighbourhood.
- Each neighbouring node's (the nodes found in step 4) weights are adjusted to be more likely to the input / original vector. The closer a neuron node is to the BMU, the more its weights get improved.
- Retry step 2 for next P 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 Principal Component Analysis (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 Eq. 1.

$$\|x(t) - w_c(t)\| = min_i \|x(t) - w_i(t)\| \qquad (1)$$

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 $i \epsilon \Theta$ $(i^*{}_q)$ are adjusted as Eq. 2.

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

Where $\alpha(q)$ is a monotonically decreasing learning coefficient and $p(q)$ is the input vector.

RESULT AND DISCUSSION

A. Experimental Setup:

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. Figure 4 shows the experiment activity involved in this research. Each subject should follow the step to extract the hand grasping data reading as follow:

- 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.
- 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

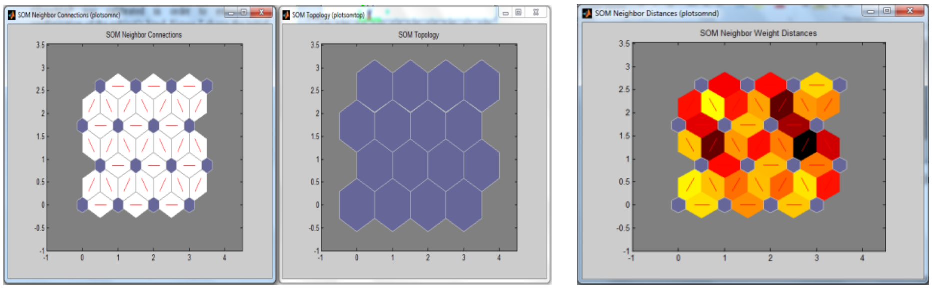
Australian Journal of Basic and Applied Sciences, 8(4) Special 2014, Pages: 219-223

Fig. 5: Bottle Grasping Activity.

B. Experimental Results:

In this section, the research present and discuss based on the simulations through MATLAB engine into MATLAB®SIMULINK where all the dataset were transformed into fingertips group of features as shown in Fig. 5. This experiment was done by letting the SOM algorithm create a topological mapping from the high-dimensional attribute space to a one-dimensional output space. The principal goal of an SOM is to transform an incoming signal pattern of arbitrary dimension into a topologically ordered fashion. According to, 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).

Fig. 6 and 7 show the winning neuron or weight centre of *GloveMAP* grasping in order to justify the bottle grasping feature. Figure 6 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. 7. However the complexity of the topological structure depends on the output space dimensions of the SOM network, thereupon, more neurons will be generated.



(a) (b)

Fig. 6: (a) SOM neighbor and topological mapping of *GloveMAP* (b) SOM Neighbor Weight Distances of *GloveMAP*.

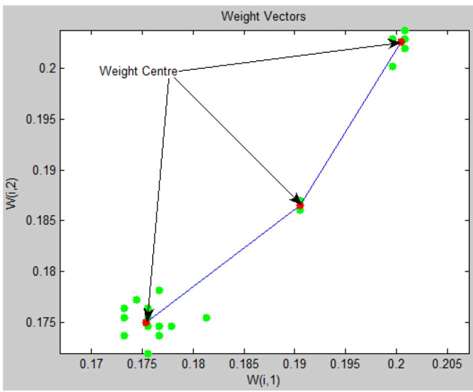


Fig. 7: SOM weight vectors.

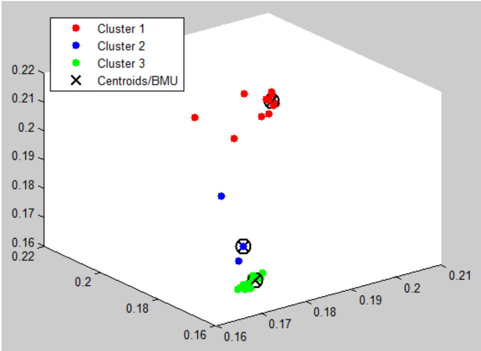


Fig. 8: SOM weight centroid /BMU.

Conclusion and Future Works:

In this research paper, we proposed the method to classify the hand grasping feature for bottle grasp using low cost DataGlove called GloveMAP. Self-Organizing Map (SOM) has proved that the grasping features capable to be initialized and identifying the object grasping at the same time one of the main methods of determining the bottle grasp. For a future work, we would like to seek methods for describing full fingers movement not limited only to thumb, index and middle fingers but the other fingers (ring and little). From this result also the further analysis from these experiments could be transforms into various application / purposes such as education, medication as well as the hand rehabilitation.

REFERENCES

Cipriani, C. *et al*., 2008. “On the Shared Control of an EMG-Controlled Prosthetic Hand: Analysis of User-Prosthesis Interaction”, *IEEE Transactions on Robotics*, 24-1: 170-184.

Cobos, S., M. Ferre, M.A. Sanchéz-Urán, J. Ortego and C. Peña, 2008. “Efficient Human Hand Kinematics for manipulation Task”, *IEEE/RSJ International conference on intelligent Robots and Systems*, pp: 2246-2250.

Hager-Ross C. and M.H. Schieber, 2000. “Quantifying the independence of human finger movements: Comparisons of digits, hands and movements frequencies”, *The Journal of Neuroscience*, 20: 8542-8550.

Heumer, G., H.B. Amor, M. Weber and B. Jung, 2007. Grasp recognition with uncalibrated data gloves - a comparison of classification methods. In Virtual Reality Conference, 2007. VR ’07. IEEE, pp: 19-26.

Information on http://www.computer.org/csdl/trans /th/2013/01 /tth2013010106-abs.html.

Jin, S., Y. Li and W. Chen, 2010. “A novel dataglove calibration method”. In*2010 5th International Conference on Computer Science and Education (ICCSE)*, pp: 1825-1829.

Kohonen, T., 1982. “Self-organized formation of topologically correct feature maps”, *Biological Cybernetics*, 43(1): 59-69.

Mantyla, V.M., J. Mantyjarvi, T. Seppanen, E. Tuulari, 2000. Hand Gesture Recognition of a Mobile Device User., Multimedia and Expo, 2000, ICME 2000, 2000 IEEE International Conference on, 1: 281-284.

Nazrul H. Adnan, W.A.N. Khairunizam, A.b. Shariman and Juliana A. Abu Bakar, 2013. “Principal Component Analysis For The Classification Of Fingers Movement Data Using DataGlove *“GloveMAP””*., *International Journal of Computer Engineering & Technology (IJCET)*, 4(2): 79-93.

Nazrul H. Adnan, W.A.N. Khairunizam, A.b. Shariman, Juliana A. Abu Bakar, Azri A. Aziz, 2013. “PCA-based Finger Movement and Grasping Classification using DataGlove *“GloveMAP*””, *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, ISSN: 2278-3075, 2(3): 66-71.

Nazrul H. Adnan, W.A.N. Khairunizam, A.b. Shariman, Juliana A. Abu Bakar, 2013. “Classification Of Finger Grasping By Using PCA Based On Best Matching Unit (BMU) Approach”, *International Journal of Advanced Research In Engineering And Technology (IJARET)*, ISSN 0976 - 6480 (Print), ISSN 0976 - 6499 (Online), 4(2): 92-105.

Taisuke Sugaiwa, GenkiFujii, Hiroyasu Iwata and Shigeki Sugano, 2010. “A Methodology for Setting Grasping Force for Picking up an Object with Unknown Weight, Friction, and Stiffness”, *IEEE-RAS International Conference on Humanoid Robots*, pp: 288-293, DOI: 10.1109/ICHR.2010.5686331.

Todorov, E., Z. Ghahramani, 2004. “Analysis of the synergies underlying complex hand manipulation”, *Proceedings of the 26th Annual International Conference of the IEEE EMBS*, pp: 4637-4640, DOI: 10.1109/IEMBS.2004.1404285.

Yang Ke-ming, Xue Zhao-hui, Li Hong-wei, Cui Li, Ran Ying-ying and Zhang Yong-jie, 2011. “Clustering Analysis on Disease Severity of Wheat Stripe Rust Based on SOM Neural Network”., *IEEE Seventh International Conference on Natural Computation*, pp: 421-425.