INTERNATIONAL JOURNAL OF COMPUTER ENGINEERING & TECHNOLOGY (IJCET)

ISSN 0976 – 6367(Print)
ISSN 0976 – 6375(Online)
Volume 4, Issue 2, March – April (2013), pp. 79-93
© IAEME: www.iaeme.com/ijcet.asp
Journal Impact Factor (2013): 6.1302 (Calculated by GISI)
www.jifactor.com

IJCET

©IAEME

PRINCIPAL COMPONENT ANALYSIS FOR THE CLASSIFICATION OF FINGERS MOVEMENT DATA USING DATAGLOVE "GLOVEMAP"

Nazrul H. ADNAN [1], Khairunizam WAN [2], Shariman AB [3], Juliana A. Abu Bakar [4]

[1](Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis KampusPauh Putra, 02600 Arau, Perlis, MALAYSIA, BahagianSumberManusia, Tingkat 17 & 18, IbuPejabat MARA Jalan Raja Laut, 50609 Kuala Lumpur, MALAYSIA)
[2,3](Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis KampusPauh Putra, 02600 Arau, Perlis, MALAYSIA)
[4](Department of Multimedia School of Multimedia Tech & Communication College of Arts and Sciences Universiti Utara Malaysia 06010 Sintok, Kedah)

ABSTRACT

Nowadays, many classifier methods have been used to classify or categorizehuman body motions of human posture including the classification of fingers movement. Principal Component Analysis (PCA) is one of classical method that capable to be used to reduce the dimensional dataset of hand motion as well as to measure the capacity of the fingers movement of the hand grasping.The objective of this paper is to analyze thehuman grasping feature between thumbs, index and middle fingers while grasping an object using PCA-basedtechniques. The finger movement dataare measured using a low cost DataGlove"GloveMAP" which is based on fingers adapted postural movement (or EigenFingers) of the principal component. The fingers movement is estimated from the bending representative of proximal and intermediate phalanges of thumb, index and middle fingers. The effectiveness of the proposed assessment analysis is shown through the experimental study of three fingers motions. The experimental results showed that the use of the first and the second principal components allows for distinguishing between three fingers grasping and represent the features for an appropriate manipulation of the object grasping.

Keywords: EigenFingers; finger movement classification; hand grasping; Human-Computer Interaction; Principle Component Analysis (PCA)

1. INTRODUCTION

Many approaches for effective Human-Computer Communication have been proposed such as voice, face and gesture recognition systems.One approach involves the use of special devices, like sensor gloves to translating hand functionand finger movement activities for rehabilitation process (eg. DataGlove) [1][2]. Nakada et al. classified hand motion in use of chopsticks by classification method proposed by Kamakura [3][4]. The advantage of this method is it makes separations of each finger pattern clear. Several researches have proved that there are systematic coordinated motions in the human hand [5]-[10].By using the mathematical tool which transforms a number of correlatedvariables into a several uncorrelated variables, the statistical properties (PCA) are chosensuch that the transformation highlights the importance of data elements. Thus, the transformed data can be used for classification by observing important components of data. 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 [11], PCA analysis methods are capable to identify and expressing all dataset in such a way that differentiate their similarities and differences. PCA has been used formerly on hand poses such as [12][3]. According to [14], the first user of PCA Sirovich and Kirby [15], [16] 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 [17] 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 [18]-[21].

The goal of this research is to verify all signals that are recorded from the fingers movement using *GloveMAP* and the performance of data gathered to be determined by data analysis method. This method could be used as the main classifier to the raw output data commencing the fingers movement. 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. In this research, the use of PCA will provide groups of classification principle component of the fingers grasping.

This research paper is structured as follows: Section 2 addresses the literature review of the related researches to the several approaches, applications and problems of recognizing the fingers grasping movement. Section 3 describes the methodologies of the system. Section 4 describes the material and methods. Experiment will be described on section 5 including the experimental setup. Section 6 presents the results and discussion. Finally sections 7 conclude the paper as above proposes and proposing possible future work.

2. LITERATURE REVIEW

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. [22] 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. [23] 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. 1. According to S. Cobos et al. [24] direct kinematics is used to obtain the position and orientation at any angle fingertips together.T. E. Jerde et al. [25] 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 when graspingthe object can be predicted using a reduced set of variables and postural synergies.

Fig 1: Anatomy of the hand [30]

Meanwhile Ramana et al. [26] stated that the use of PCA able to quantize and characterize the variance in hand posture of novel transformation task. For the virtually applies, S. Cobos et al. [27] stated that PCA capable to explore in some depth of the physical human hand for kinematic behavior, in order to get a simplified model of the human hand with the minimum number and the optimum degree of freedom (DOF), and thus achieve an efficient manipulation tasks. Saggio G. et al. [28] used 15 sensors in order to develop a biomedical glove that able to measure the surgery classify activities and then evaluate the skill of the surgeon potential. Oz et al. [29] used artificial neural networks (ANNs) to translate ASL words into English. The system uses a sensory glove called the Cyberglove™ and a Flock of Birds® 3-D motion tracker to extract the gesture features. A glove designed has 18 sensors, which measure the angle of bend fingers at various positions. Frequency of distribution data could be up to 150 Hz.

3. METHODOLOGIES

3.1 Calculation Analysis of PCA

PCA has been found useful in many applications, such as, data analysis, process monitoring and data rectification [31]. PCA is a dimensionality reduction technique in terms of capturing the variance of the data and it accounts for correlationamong 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$\boldsymbol{X \epsilon R^{p \times q}}$. 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:

$$C_j = AC_X A^T = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots \\ 0 & \dots & \dots & \lambda_n \end{bmatrix}; \text{Where} C_X = \lambda_i t_i; A^T A = A^T \tag{3}$$

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 requisite. 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 [32]. Eigenfingers$J$ of A and Eigenvalues λ can be determined as:-

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

Can be simplified as:

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

Where λ and A are calculated using Jacobi method [33], 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 may reduce the number of features needed for effective data representation by discarding the bending data. Equation 6 shows only small variances and retain only those terms that have large variances [34]. Let ,…., denote the largest *l* eigenvalues and associated eigenfingers be denoted by , ,…., respectively. The equation may write as:-

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

3.2 Dimensionality Reduction of Principal Components Analysis

From the respective data of fingers grasping movement, the total variance values of the *jth*component possibly will finalize more effective the dimensionality reduction. According to Haykin [34] data vector *j* that resulting from the principle components will be preserving the information content of the original data.

$$\sum_{X=1}^{n} \sigma_X^2 = \sum_{X=1}^{n} \lambda_X \tag{8}$$

Raju Kota et al. [36] said the idea of PCA is illustrated in Fig 2 corresponds to the direction of maximum variance and was chosen as the first principal component. In a 2D case, the second principal component was then determined uniquely by the orthogonally constraints; in a higher-dimensional space the selection process would continue, guided by the variances of the projections.

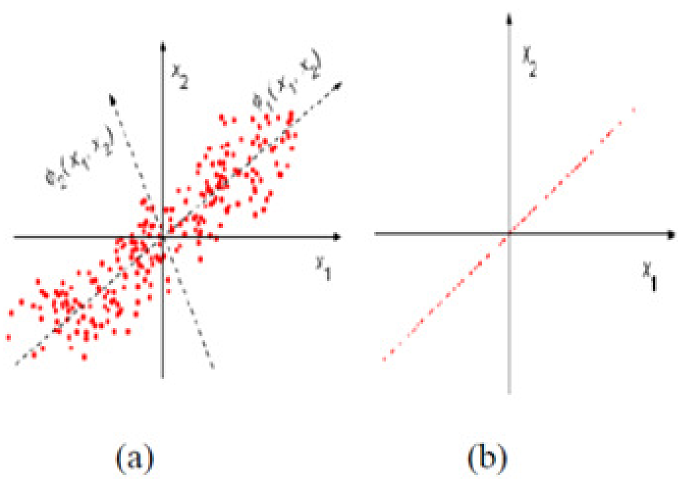

Fig 2: (**a**) The concept of PCA. Solid lines: the original basis; dashed lines: the PCA basis. The dots are selected at regularly spaced locations on a straight line rotated at 30^0, and then perturbed by isotropic 2D Gaussian noise. (**b**) The projection (1D reconstruction) of data using only the first principal component [36].

4. MATERIAL AND METHOD

Figure 3 depicts a grasping method on the three main objects book and glass of the overall fingers grasping using the *GloveMAP* system where the basic system is outlined. The types of hand grasping object were depending on two types of object grasping; power grasps and precision grasps [35]. Figure 3 also describe the graphical representation of the different hand gestures during object manipulation whereas the reality representations of the object grasping were same. For the example fig. 3a and3b were representing the way of *GloveMAP* wearer grasp a book and glass. This procedure is designed to develop a set ofgrasping feature data so that the grasping feature will be easily to be clustering using the principal components. In this study, the development of the DataGlove is assembled with a three pieces of flex sensors which are attached / build on the finger joint positions of the hand. When the fingers are bent, the specific sensors also bent and the generated outputs data ware measured. Based on these output data, the fingers grasping of the hand could be analyzed.

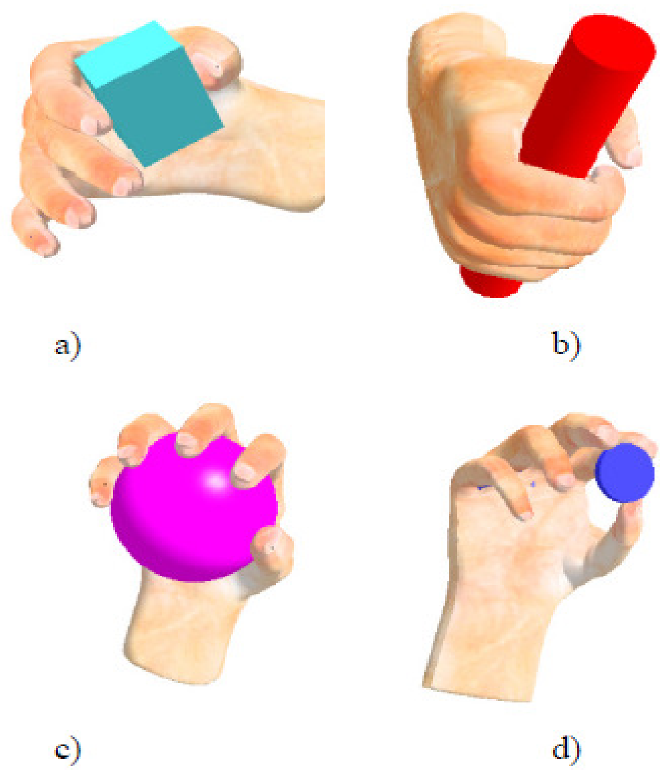

Fig 3: Example of Gestures used for this experiment. **a**) Prismatic precision, **b**) Prismatic power, **c**) circular power and d) circular precision [35]

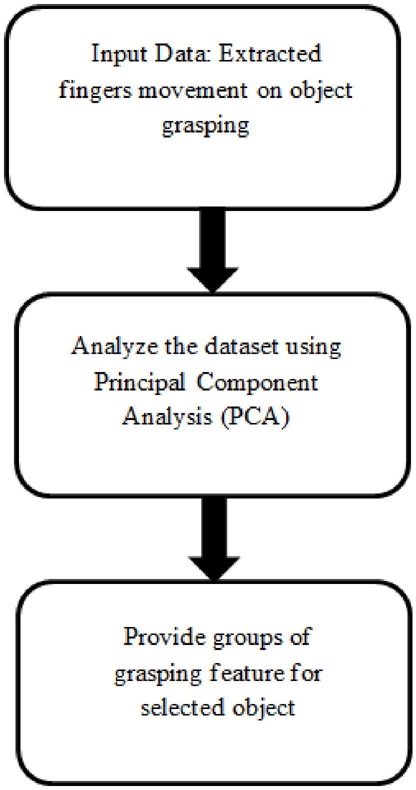

Fig 4: Fingers grasping classification using PCA

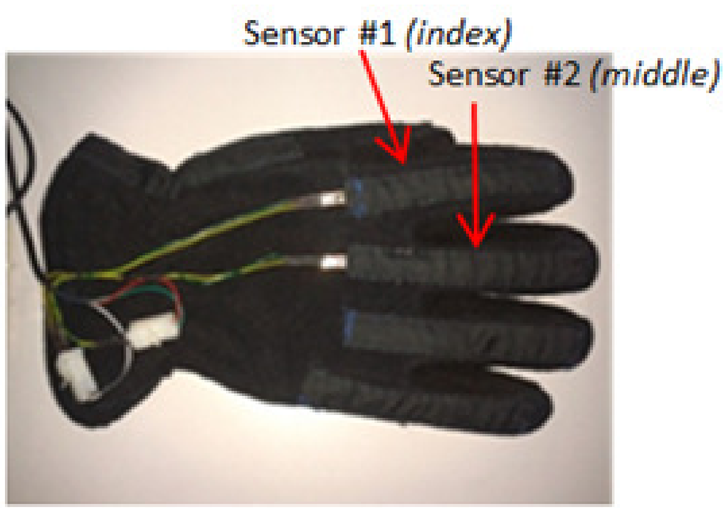

Fig 5: Resistive interface glove (*GloveMAP*)

Fig 6: grasping activities

5. EXPERIMENT

The experiment was carried out using real objects manipulated by a GloveMAP. Five people/subjects were needed 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 Nazrul et al. [37][38] the way of wearing the GloveMAPwill lead to the correct grip objects and it has already proved by the classification of finger grasping data. Figure 7 shows the sample of fingers movement using the GloveMAP.

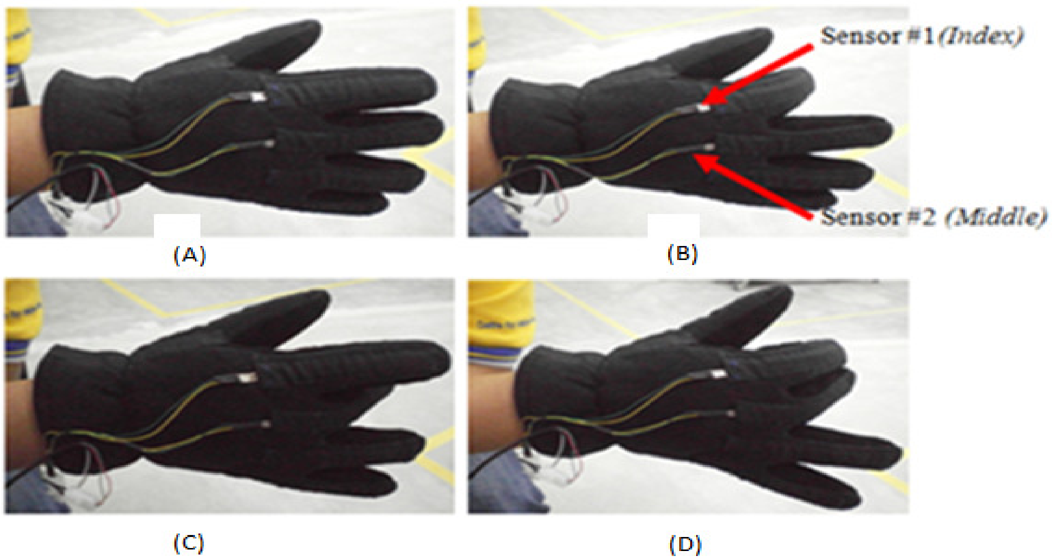

Fig 7: The example of *GloveMAP* finger movement activities (**A**) straighten fingers (**B**) bending of index finger (**C**) bending of middle finger (**D**) bending of both fingers [37]

Each experiment was limited to several seconds. The completion task was pretty successful when the subjects grasp the object till they're asking to release and the entire measurement end. During the task subjects wore the *GloveMAP* on the right hand. Sensor values of the glove were sent through MATLAB engine into MATLAB®SIMULINK where they were transformed into data coordinates. The number of data configurations was determined accordingly to the grasping duration for each group. It may seem trivial at first sight, since one could just fix a maximum number of data and divide it by the number of groups. For this research, we propose not to justify a maximum number of samples, but some reasonable number of samples per grasping activities.

6. RESULT AND DISCUSSION

In this study, subjects under various grasping objects were captured by aMATLAB®SIMULINK using *GloveMAP* and the sample results of the fingers movement data of hand grasping are shown in fig 8 and 9.By using PCA analysis, it is possible to determine how many variables are needed to represent the data information of finger movement including the EigenFingers data. The purpose of this experiment was to classify fingers movement characteristics of object grasp (book and glass) in order to identify whichever fingers move more while grasping. Figure 10 and 11 shows the sample of EigenFingers data through the PCA process for book and glass grasping activity. PCA is a stylish way to minimize the dimensionality of grasping data, while (supposedly) keep most of the information.

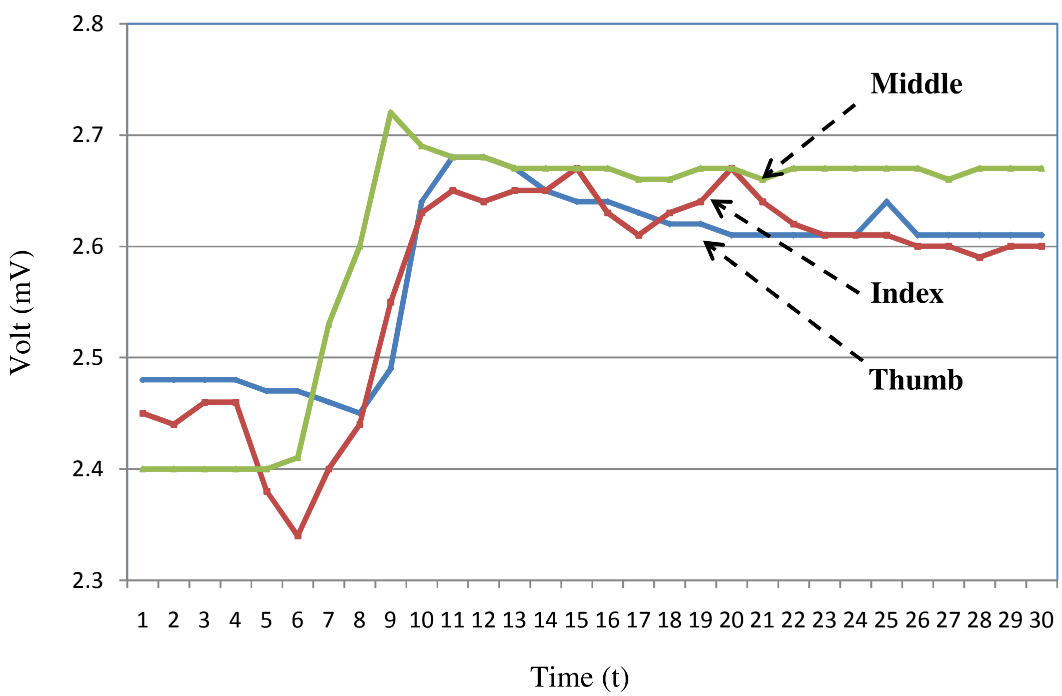

Fig 8: 30 samples of original finger movement data for book grasping

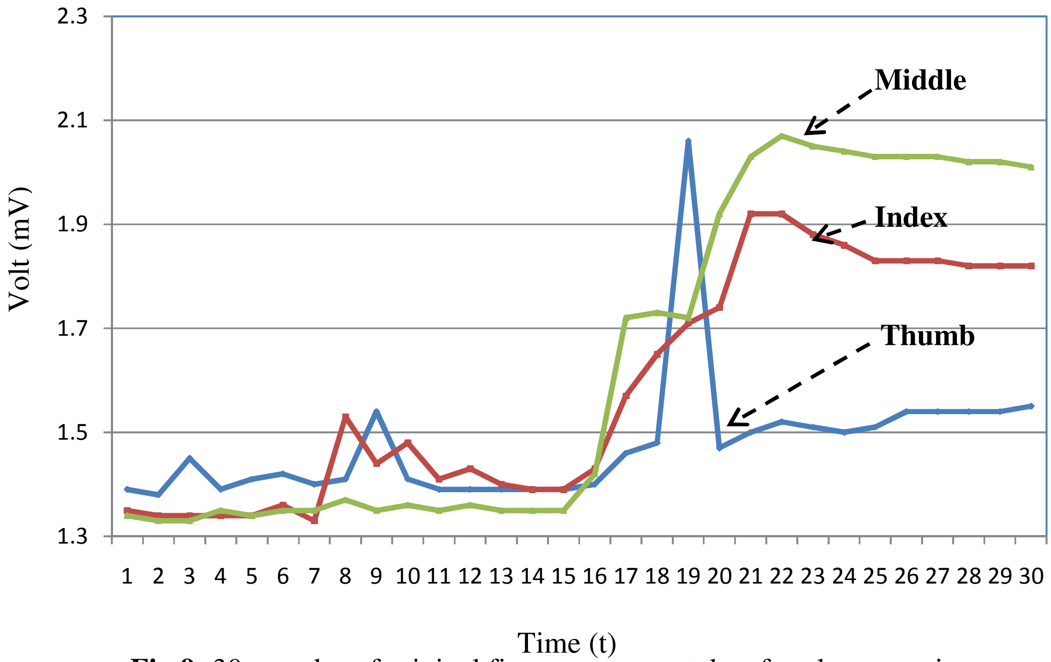

Fig 9: 30 samples of original finger movement data for glass grasping

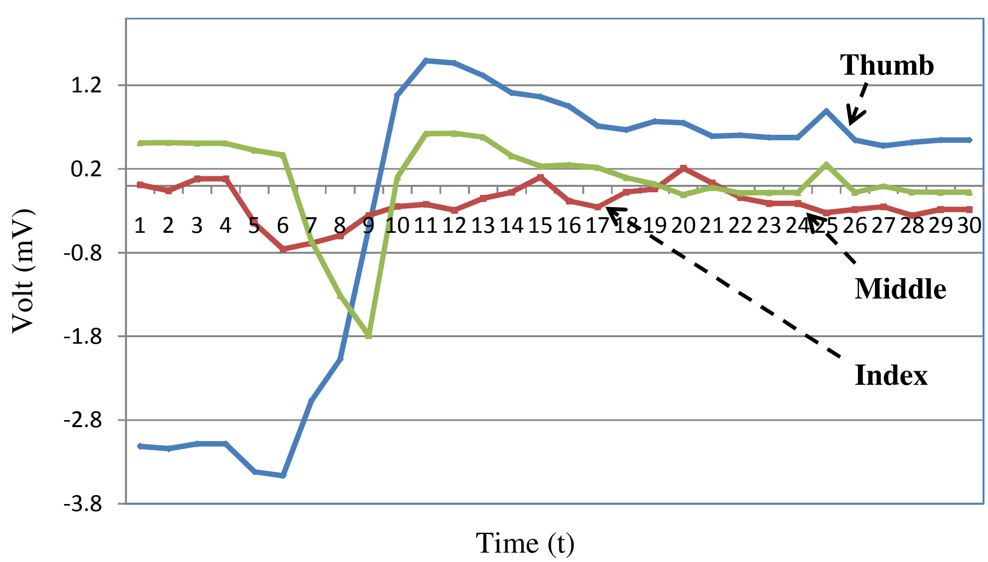

Fig 10: 30 samples of EigenFingers data for book grasping

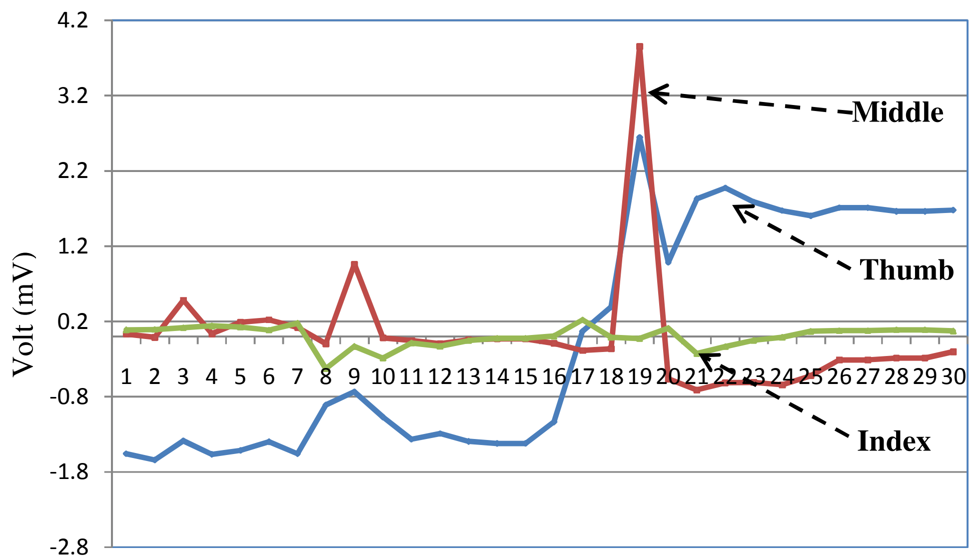

Fig 11: 30 samples of EigenFingers data for glass grasping

PCA dimensionality reduction maintains what is common in data and it's capable to differentiate data.The PCA is started by modeling the fingers movement while grasping the object using collected sample quality of characteristics data then all the datacan beanalyze into newly collected process data (including covariant, eigenvalues as well as EigenFingers), and finally all the data's were manipulated using the MATLAB®SIMULINK clustering approaches to overcome the correlation between the fingers movement data of principal components and the object grasp by the DataGlove "*GloveMAP*". All the detection fingers movement will be exceeds to the maximum stage to do the process stability judgment.

6.1 Clustering Analysis

After identifying data from PCA dimensionality reduction/feature extraction, all data collection on the object grasping activities will be through the process of clustering analysis. Cluster analysis is the task of the group of each object in such a way that the object in the same group [39].Clustering is useful medium in several exploratory pattern-analysis, grouping, decision-making, and machine-learning situations, including data mining, document retrieval, image segmentation, and pattern classification. However, in many such problems, there is little prior information available about dataset, and the decision-maker must make as few assumptions about the data as possible [40].

The most challenging step in clustering the fingers movement was feature extraction or pattern representation. In classification the objects were assigned to pre-defined groups, whereas in clustering the groups were also to be defined. However to achieve the partitioned indifferently for several applications dataset then clustering analysis was the best option. Figure 10, 11 and 12 shows the clustering groups of fingers movement while grasping the objects such as book and glass.

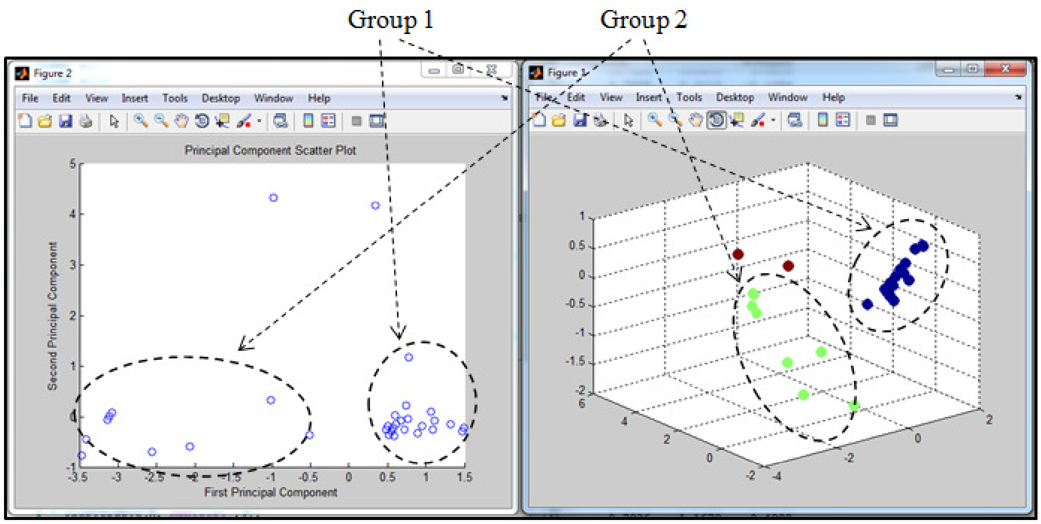

Fig 12: PCA data clustering for book graspingactivity (A) training data using PCA projected on a two-dimensional space (B) training data using three dimensional space. It deserves to be specially noted that Group 1represent main grasping features for index finger movement. While Group 2 represent middle finger data contain.

From the distribution of group data stated that the amount of data structures was determined accordingly to the grasping duration for each group. It may seem trivial at first sight, since one could just fix a maximum number of data and divide it by the number of groups. For this research, we propose not to define a maximum number of samples data, but a reasonable number of samples per grasping activities.

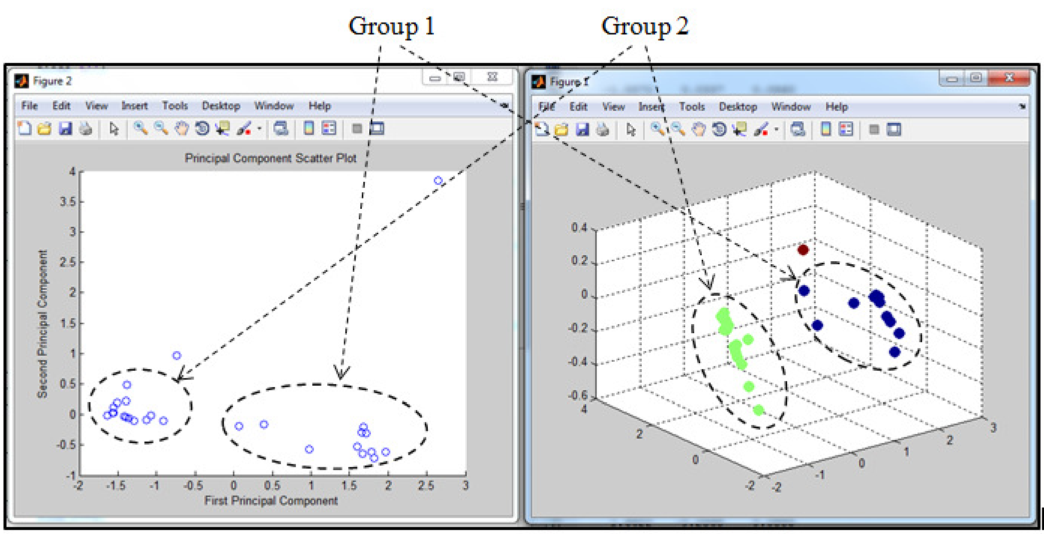

Fig 13: PCA data clustering for glass graspingactivity (A) training data using PCA projected on a two-dimensional space (B) training data using three dimensional space. It deserves to be specially noted that Group 1represent main grasping features for index finger movement. While Group 2 represent middle finger data contain.

By referring to fig. 12 and 13 the collections of finger movement data from a book andglass grasping were classified into three groups. Groups 1 show the finger grasping feature that the data for each grip is formed while group 2 show a less movement compare to group 1but the data still can be defined as a reference. The other data could be form as a group 3 shows a minimum finger movement and it could be ignore/eliminated in order to simplify the grasping features. 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.

7. CONCLUSION

In this paper, a new method of analyze finger movement of human hand grasping by using a low cost DataGlove "GloveMAP" which is able to recognize the fingers features activities was presented. The aim of this research was to recognize the maximum movement of fingers grasping while grasp the object.With use of PCA concept, every act or activity was capable to simplify the finger movement using the classification of data collection. Collection of data that measure from the hand grasping or finger movement was measured by using GloveMAP and the advantages of the measurement could be perform by the characteristic values of one dimensional data of hand grasping.The results from these experiments show that PCA capable to simplified and classified various fingers movement for many applications. Not limited to the gaming but GloveMAP also capable for education, medication as well rehabilitation purpose.

8. ACKNOWLEDGEMENTS

Special thanks to all members of UNIMAP Advanced Intelligent Computing and Sustainability Research Group and School Of Mechatronics Engineering, Universiti Malaysia Perlis (UNIMAP) for providing the research equipment's and internal foundations. This work was supported by the ScienceFund Grant by the Ministry of Science, Technology and Innovation to Universiti Malaysia Perlis (01-01-15-SF0210).

REFERENCES

[1] SilvestroMicera, EttoreCavallaro, Rossella Belli,Franco Zaccone, Eugenio Guglielmelli,Paolo Dario, Diego Collarini, Bruno Martinelli, Chiara Santin,Renzo Marcovich, Functional Assessment of Hand Orthopedic Disorders Using a Sensorised Glove:Preliminary Results, Proceeding of the 2003 IEEEinternational Conference on Robotics & Automation, September 14-19, 2003, pp. 2212-2217.

[2] Manjula B. Waldron and Soowon Kim, Isolated ASL Sign RecognitionSystem for Deaf Persons, IEEE Transactions on Rehabilitaron Engineering, Vol. 3, No. 3, September 1995, pp. 261-271.

[3] Noriko Kamakura, Hand Forms and Hand Movements [in Japanese],IshiyakuPublichers. Inc., 1989.

[4] Mayumi Nakada, Noriko Kamakura, KyoukoOtaki and Kaori Miura,Patterns for Holding and Handing Chopsticks with Normal Hands,Trans. of Japanese Association of Occupational Therapist, vol. 12,No. 2, pp. 137–145, 1993.

[5] Salvador Cobos, Simplified Human Hand Models based on Grasping Analysis, The 2010 IEEE/RSJ International Conference onIntelligent Robots and Systems, October 18-22, 2010, pp. 610-615.

[6] M. Santello, M. Flanders, and J. Soechting, Postural hand synergies for tool use, Journal of Neuroscience, 1998, vol 18, pp. 10105–10115.

[7] M. Ciocarlie and P. Allen, Hand Posture Subspaces for Dexterous Robotic Grasping, The International Journal of Robotics Research, 2009, vol 28, pp. 851-867.

[8] A. Tsoli and O. Jenkins, 2D subspaces for user-driven robot grasping. RSS Workshop on Robot Manipulation: Sensing and Adapting to the RealWorld, Atlanta, GA. 2007.

[9] J. Rosell, R. Suárez, C. Rosales, J. A. García and A. Pérez,MotionPlanning for High DOF Anthropomorphic Hands, in Proc. of the IEEEInt. Conf. on Robotics and Automation, 2009, pp. 4025–4030.

[10] S. Cobos, M. Ferre, M. A. Sánchez-Urán, J. Ortego and R. Aracil, Human hand descriptions and gesture recognition for object manipulation, Computer Methods in Biomechanics and Biomedical Engineering, Vol. 13, No. 3, pp. 305 - 317.

[11] Y. Endo, S. Kanai, T. Kishinami, N. Miyata, M. Kouchi, and M. Mochimaru, A computer-aided ergonomic assessment and product design system using digital hands, Digital Human Modeling, HCII 2007, V.G. Duffy (Ed.): LNCS 4561, pp. 833-842.2007.

[12] M. Santello, M. Flanders, and J. F. Soechting, Postural Hand Synergies for Tool Use, The Journal of Neuroscience, December 1, 18(23):10105–10115, 1998.

[13] Vo Dinh Minh Nhat, and SungYoung Lee, Two-dimensional Weighted PCA algorithm for Face Recognition, IEEE International Symposium on Computational Intelligence in Robotics and Automation, pp 219-223, 2005.

[14] L. Sirovich and M. Kirby, Low-Dimensional Procedure for Characterization of Human Faces, J. Optical Soc. Am., vol. 4, pp. 519-524, 1987.

[15] M. Kirby and L. Sirovich, Application of the KL Procedure for the Characterization of Human Faces, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12,1no. 1, pp. 103-108, 1990.

[16] M. Turk and A. Pentland, Eigenfaces for Recognition, J. Cognitive Neuroscience, vol. 3, no. 1, pp. 71-86, 1991.

[17] A. Pentland, Looking at People: Sensing for Ubiquitous and Wearable Computing, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, no. 1, pp. 107-119, 2000.

[18] M.A. Grudin, On Internal Representations in Face Recognition Systems, Pattern Recognition, vol. 33, no. 7, pp. 1161-1177, 2000.

[19] G.W. Cottrell and M.K. Fleming, Face Recognition Using Unsupervised Feature Extraction, Proc. Int'l Neural Network Conf., pp. 322-325, 1990.

[20] D. Valentin, H. Abdi, A.J. O'Toole, and G.W. Cottrell, Connectionist Models of Face Processing: a Survey, Pattern Recognition, vol. 27, no. 9, pp. 1209-1230, 1994.

[21] J. H. Ahroni, E. J. Boyko, R. Forsberg, Reliability of F-Scan In-Shoe Measurements of Plantar, Pressure in Foot and Ankle International, 9, 10 pp. 668-673. October 1998.

[22] Laurent Vigouroux, Jérémy Rossi, MatthieuFoissac, Laurent Grélot, Eric Berton, “Finger force sharing during an adapted power grip task”, in Neuroscience Letters, 504: 290– 294. 2011.

[23] Gregory P. Slota, Mark L. Latash, Vladimir M. Zatsiorsky, Grip forces during object manipulation: experiment, mathematical model, and validation, in Exp Brain Res 213:125–139, 2011.

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

[25] T. E. Jerde, J. F. Soechting, and M. Flanders, Biological constraints simplify the recognition of hand Shapes, IEEE Trans. Biomed. Eng., vol. 50, pp. 265–269, 2003.
[26] RamanaVinjamuri, Mingui Sun, Douglas Weber, Wei Wang, Donald Crammond, Zhi-Hong Mao, Quantizing and Characterizing the Variance of Hand Postures in a Novel Transformation Task, 31st Annual International Conference, pp. 5312-5315, 2009.
[27] Salvador Cobos, Manuel Ferre, Rafael Aracil, Simplified Human Hand Models based on Grasping Analysis, International Conference on Intelligent Robots and Systems, pp. 610-615, 2012.
[28] Saggio G., Bocchetti S., Pinto C.A., Orengo G, Wireless DataGlove System developed for HMI. ISABEL, 3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies, Rome, Italy, November 7-10, 2010.
[29] Oz, C., Leu, M.C, American Sign Language word recognition with a sensory glove using artificial neural networks, Engineering Applications of Artificial Intelligence 24, 1204–1213, 2011.
[30] Information on http://www.yalemedicalgroup.org/stw/ Page.asp?Page ID=STW023547
[31] Jae-Kuk Lee, Kyung-Hun Kim, Tae-Young Kim, and Won-Ho Choi, Non-Linear Principle Component Analysis Using LocalProbability, Proceedings of the 7th Korea-Russia International Symposium, KORUS 2003, pp. 103-107.
[32] Information on http://en.wikipedia.org/wiki/Eigenvalues_and_ Eigenvectors
[33] Yu Kinoshita, Daisuke Takeda, Akinori Sasaki, Hiroshi Hashimoto, Chiharu Ishii, Archive and Instruction of Hand Motion: Analysis and Evaluation of Hand Motion, IEEE, pp. 3030-3035, 2006.
[34] Simon Haykin, Neural Networks and Learning Machine. Pearson, 2009.
[35] Salvador Cobos, Rafael Aracil, and Manuel Ferre, Low Dimensionality Space for Controlling Human Hand Models, Proceedings of the 2010 3rd IEEE RAS & EMBSInternational Conference on Biomedical Robotics and Biomechatronics, September 26-29, 2010. pp. 203-208.
[36] Solomon Raju Kota, J.L.Raheja, Ashutosh Gupta, ArchanaRathi and Shashikant Sharma, Principal Component Analysis for Gesture Recognition using SystemC, International Conference on Advances in Recent Technologies in Communication and Computing, pp 732 – 737, 2009.
[37] Nazrul H.ADNAN, Khairunizam WAN, Shahriman AB, SK Za'ba, ShafrizaNisha BASAH, Zuradzman M. Razlan, HazryDesa, M. NasirAyob, RudzuanM. Nor and MohdAzriAbd Aziz, Measurement of the Flexible Bending Force of the Index and Middle Fingers for Virtual Interaction, International Symposium on Robotics and Intelligent Sensors 2012 (IRIS 2012), Procedia Engineering 41, 388 – 394. 2012.
[38] Nazrul H. ADNAN, Khairunizam WAN, Shariman AB, Juliana A. Abu Bakar, Azri A. AZIZ, PCA-based Finger Movement and Grasping Classification using Data Glove "Glove MAP", International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278-3075, Volume-2, Issue-3, February 2013, 66-71.
[39] Information on http://blog.explainmydata.com/2012/07/should-you-apply-pca-to-your-data.html
[40] A.K. Jain, M.N. Murty, and P.J. Flynn, Data Clustering: A Review, ACM Computing Surveys, Vol. 31, No. 3, September 1999, 264-322.
[41] Ms.Shaikh Shabnam Shafi Ahmed, Dr.Shah Aqueel Ahmed and Mr.Sayyad Farook Bashir, "Fast Algorithm for Video Quality Enhancing using Vision-Based Hand Gesture Recognition" International journal of Computer Engineering & Technology (IJCET), Volume 3, Issue 3, 2012, pp. 501 - 509, ISSN Print: 0976 – 6367, ISSN Online: 0976 – 6375.