

# PCA-based Finger Movement and Grasping Classification using Data Glove “Glove MAP”

Nazrul H. ADNAN, Khairunizam WAN, Shariman AB, Juliana A. Abu Bakar, Azri A. AZIZ

**Abstract:** nowadays, fingers movement and hand gestures can be used as main activities in translating by naturally and convenient way to the human computer interaction. The purpose of this paper is to analyze in depth the thumb, index and middle fingers on the hand grasping movement against an object. The classification of the fingers activities is analyzed using the statistical analysis method. Principal Component Analysis (PCA) is one of the methods that able to reduce the dimensional dataset of hand motion as well as measure the capacity of the fingers movement. The fingers movement is estimated from the bending representative of proximal and intermediate phalanges of thumb, index and middle fingers. The effectiveness of the propose assessment analysis were shown through the experiments of three fingers motions. Preliminary results of this experiment showed that the use of the first and second principal components can allow distinguishing between three fingers grasping movements.

**Index Terms:** finger movement; finger activities; hand grasping; Human Computer Interaction; Principle Component Analysis (PCA)

## I. 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 data set in which there are a large number of interrelated variables, while maintaining as much as possible in data set 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]-[3].

According to [4], the first user of PCA Sirovich and Kirby [5], [6] 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.

Manuscript published on 28 February 2013.

\*Correspondence Author(s)

**Nazrul H. ADNAN**, Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis KampusPauh Putra, 02600 Arau, Perlis, MALAYSIA.

**Khairunizam WAN**, Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis KampusPauh Putra, 02600 Arau, Perlis, MALAYSIA.

**Shariman AB**, Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis KampusPauh Putra, 02600 Arau, Perlis, MALAYSIA.

**Juliana Aida Abu Bakar**, Department of Multimedia School of Multimedia Tech & Communication College of Arts and Sciences Universiti Utara Malaysia 06010 Sintok, Kedah, MALAYSIA.

**Azri A. AZIZ**, Advanced Intelligent Computing and Sustainability Research Group, School of Mechatronic, Universiti Malaysia Perlis KampusPauh Putra, 02600 Arau, Perlis, MALAYSIA.

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an [open access](http://creativecommons.org/licenses/by-nc-nd/4.0/) article under the CC-BY-NC-ND license <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

Meanwhile Turk and Pentland [7] 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 [8]-[12].

The goal of this research is to verify all the signals that recorded from the fingers movement using Glove MAP 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 is 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 will present the results and discussion. Finally on section 7 described the conclusions and proposing some possible future work..

## II. LITERATURE REVIEW

The physical hand model that used for this research is based on the 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 structure of the human hand is important in order to clarify some significant part of the structure to measure the movement of the human fingers. Distal, intermediate, and proximal phalanges are the Osteology of the phalanges of the hand as shown in Fig. 1. According to S. Cobos et al. [15] direct kinematics is used to obtain the position and orientation at any angle fingertips together.

T. E. Jerde et al. [16] stated PCA found as a support for the existence of a motionless position synergy angle configuration. The physical figure and contour of human hand can be predicted using a reduced set of variables and postural synergies. Meanwhile Ramana et al. [17] stated that the use of PCA able to quantize and characterize the variance in hand posture of novel transformation task.



For the virtually applies, Salvador Cobos et al. [18] 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. [20] 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. [21] 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.



Fig 1: Anatomy of the hand [19]

### III. METHODOLOGIES

#### A. Calculation Analysis of PCA

Principal component analysis (PCA) is a multidiscipline statistical analysis approach of data compression and feature extraction [22]. 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  $F$  be a dimensional vector, and represent the multi-spectral observation of a finger bending. The principal component transform is defined by:

$$J = A^T F \quad (1)$$

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

$$C_j = E \{ (Y - M_y)(Y - M_y)^T \} = AC_x A^T = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & \dots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & \lambda_n \end{bmatrix} \quad (2)$$

Where  $\lambda_1 > \lambda_2 \dots > \lambda_n$  are the eigenvalues of the 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 [23]. Eigenfingers  $J$  of  $A$  and Eigenvalues  $\lambda$  can be determined as:-

$$A_j = \lambda_j \quad (3)$$

Can be simplified as:

$$(A - \lambda I)X = 0 \quad (4)$$

Where  $\lambda$  and  $A$  are calculated using Jacobi method [24], meanwhile  $I$  is an identity matrix. By using the equation 4, it is simply find the determinant of the Eigenfingers.

$$\det(A - \lambda I) = 0 \quad (5)$$

In this research the first data that obtain from the grasping fingers movement and the characteristics of the GloveMAP, the practical value of the principal components analysis provide an effective techniques for dimensionality reduction. 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 [25]. Let  $\lambda_1, \dots, \lambda_l$  denote the largest  $l$  eigenvalues and associated eigenfingers be denoted by  $Q_1, Q_2, \dots, Q_x$  respectively. The equation may write as:-

$$\bar{J} = \sum_{X=1}^l A_x Q_x \quad (6)$$

#### B. Dimensionality Reduction of Principal Components Analysis

From the respective data of fingers grasping movement, the total variance values of the  $j$ th component possibly will finalize more effective the dimensionality reduction. According to Haykin [25] data vector  $j$  that resulting from the principle components will be preserving the information content of the original data.

$$\sum_{X=1}^n \sigma_X^2 = \sum_{X=1}^n \lambda_X \quad (7)$$

Where  $\sigma_X^2$  is the variance of the  $X^{th}$  principle component of  $J^{th}$ .

### IV. MATERIAL AND METHODS

Figure 2 depicts a flow of the overall fingers grasping using the GloveMAP system where the basic system is outlined. In this study, DataGlove is assembled with a three pieces of flex sensors which was attached on the finger joint positions of the hand. When the fingers are bent, the sensors also bent and the generated outputs data was measured. Based on these output data, the fingers grasping of the hand is calculated.

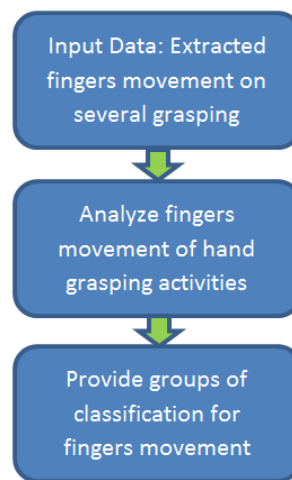


Fig 2: Fingers grasping classification using PCA

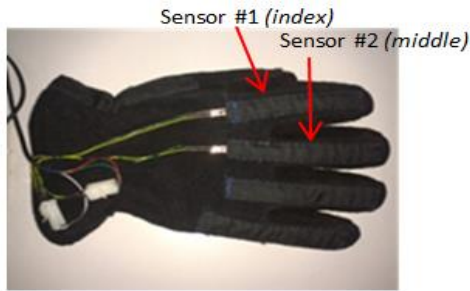


Fig 3: Resistive interface glove (GloveMAP)



Fig 4: Sample of GloveMAP grasping activities

**V. EXPERIMENT**

Experiment was carried out by using three flex sensors, and the purpose was shown the reliability of flex sensors on the sign language translation via the fingers movement and bending. By using the movement of the index finger and middle finger as well as thumb, then the resistance will be measured and evaluated by ensuring that the resulting signal can be analyzed. Then, the signal had to be sent to the microcontroller called as Arduino Uno [16] until the last signal will then be evaluated and interpreted before being sent to the self-developed programmed.

**A. Experimental Setup**

For the experimental setup, the used of GloveMAP for measuring the multiple angular finger joint positions was needed in order to measure the continuity of the grasping data. Figure 4 shows the example of grasping activities whereas the process of flex-sensors bending that attached to the hand-glove must be initiated the process. For the example, when the fingers were bent then the resistance will be fed across the flex sensor circuit. The example of GloveMAP product function can be seen in Fig. 5.

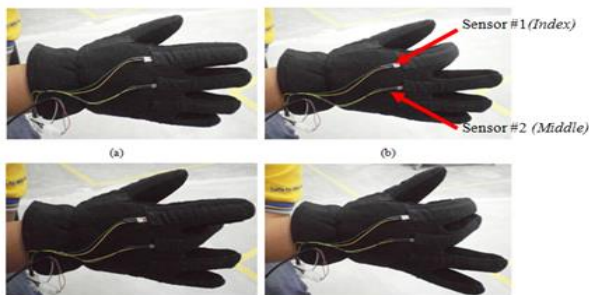


Fig 5: The example of GloveMAP Bending activities (a) straighten fingers (b) bending of index finger (c) bending of middle finger (d) bending of both fingers [27]

Five people/subjects was needed in doing this experiment for holding objects. Arrangements of GloveMAP wearer was

required to grasping some objects such as cylinder, box and round. The chosen of objects depends on the diversity of grasping for every human being was indifferently. Raju Kota et al. [28] said the idea of PCA is illustrated in Fig 6 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 orthogonality constraints; in a higher-dimensional space the selection process would continue, guided by the variances of the projections.

Each trial was limited to several seconds. The completion task was relatively successful when the subjects grasp the object till they're asking to release and all the 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 define a maximum number of samples, but a reasonable number of samples per grasping activities.

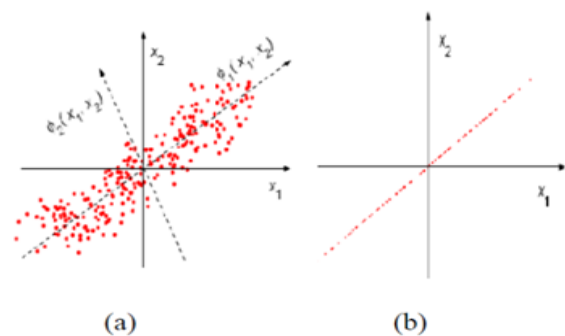


Fig 6: (a) The concept of PCA. Solid lines: the original basis; dashed lines: the PCA basis. The dots are selected at regularly spaced locations on a straight line rotated at 30°, and then perturbed by isotropic 2D Gaussian noise. (b) The projection (1D reconstruction) of data using only the first principal component [28].

**B. Definition of Correct Grasping**

Definition of the hand grasping in use of object is defined below. It is important for human to grasp bottle properly to treat bottle properly 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.

Meanwhile for the grasping analysis of the human hand has always been the same motion others even finger at the same angle, because the human hand motion data is very large and the shape of the human hand is multifarious.



VI. RESULT AND DISCUSSION

For the experiments result, all data's which has been taken will be going to be analyze using PCA methods. One of the experiments is using the bottle grasping. It is not really difficult in measuring the hand grasping if the correspondent follows the stage in section 5.2. Figure 7 shows the example of 30 distributions data which taken from bottle grasping activities. The others research were measured and evaluated three pattern hands grasping including box and ball object with use of tools for the confirmation of research evaluation method.

	1	2	3
1	1.5800	1.9800	1.5800
2	1.5900	1.9700	1.5800
3	1.5900	1.9700	1.5800
4	1.5900	1.9800	1.5800
5	1.5800	1.9800	1.5900
6	1.5800	1.9900	1.5800
7	1.5900	1.9700	1.5800
8	1.6000	1.9800	1.5900
9	1.5700	2.0200	1.6300
10	1.6100	2.1700	1.7700
11	1.6600	2.3800	1.9300
12	1.7700	2.4000	1.9500
13	1.8200	2.3900	1.9400
14	1.8200	2.3900	1.9300
15	1.8100	2.3900	1.9200
16	1.8100	2.3800	1.9200
17	1.8100	2.3600	1.9200
18	1.8100	2.3500	1.9200
19	1.8100	2.3600	1.9100
20	1.7900	2.3400	1.9000
21	1.7800	2.3500	1.8900
22	1.7100	2.3200	1.8600
23	1.5900	2.0400	1.6600
24	1.5500	1.9600	1.5800
25	1.5500	1.9500	1.5700
26	1.5600	1.9600	1.5700
27	1.5400	1.9600	1.5700
28	1.5500	1.9700	1.5700
29	1.5600	1.9600	1.5800
30	1.5600	1.9500	1.5700

Fig 7: 30 samples of original data on bottle grasping activities (Raw 1 = Thumb, Raw 2 = Index and Raw 3 = Middle)

	1	2	3
4	-1.3381	0.1750	-0.0359
5	-1.3548	0.0741	0.0038
6	-1.3602	0.0806	-0.0755
7	-1.3680	0.1946	0.0012
8	-1.2507	0.2240	0.0089
9	-1.1460	-0.1828	0.0218
10	0.0052	-0.5397	0.0670
11	1.4585	-0.9907	-0.0232
12	2.1617	-0.2575	0.0152
13	2.3569	0.1626	0.0228
14	2.3216	0.1886	-0.0194
15	2.2342	0.1396	-0.0641
16	2.2043	0.1591	-0.0271
17	2.1445	0.1982	0.0470
18	2.1146	0.2177	0.0841
19	2.1092	0.2242	0.0048
20	1.9099	0.1393	0.0316
21	1.8524	0.0709	-0.0502
22	1.2923	-0.3171	-0.0835
23	-0.8761	-0.1499	0.0794
24	-1.6061	-0.0856	0.0280
25	-1.6714	-0.0401	0.0229
26	-1.5894	0.0153	-0.0116
27	-1.6935	-0.1346	-0.0167
28	-1.6116	-0.0792	-0.0512
29	-1.5541	-0.0107	0.0306
30	-1.6193	0.0348	0.0254
31			
32			

Fig 8: 30 sample Eigenfingers data on bottle grasping activities (Raw 1 = Thumb, Raw 2 = Index and Raw 3 = Middle)

After identifying data from PCA dimensionality reduction/feature extraction, all data collection on the bottle 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 [29]. PCA is a stylish way to minimize the dimensionality of grasping data, while (supposedly) keep most of the information. PCA dimensionality reduction maintains what is common in data and it's capable to differentiate data. For the example fig. 9 shows how the collections of finger movement data from a bottle grasping were classified into three groups. Groups 1 show the maximum finger movement while group 2 show a less movement compare to group 1. Finally group 3 shows a minimum finger movement. In simple words, this situation proved that 2 from 3 groups were shows more effective movement meanwhile the other group shows less effective finger movement for hand to grasp.

For fig. 10 and 11 the same concept was applies against the grasping of object such as box and ball. All five subjects will continue the same procedure as bottle grasping. PCA will identify strongly-associated combination of many of the original variables data. Evaluation of hand grips after using the PCA has shown that each of the fingers movement was different. For the future research, the 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.

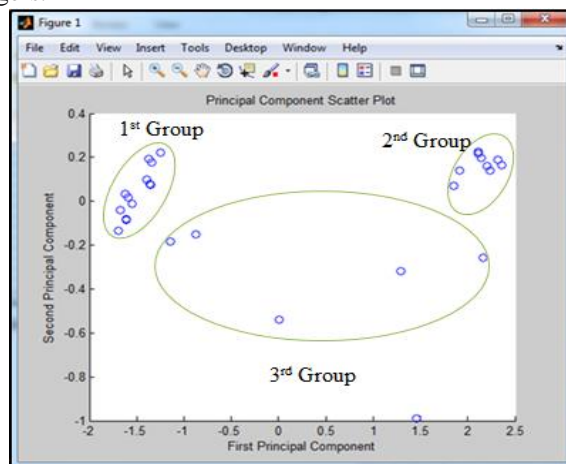


Fig 9: PCA data clustering for bottle grasping

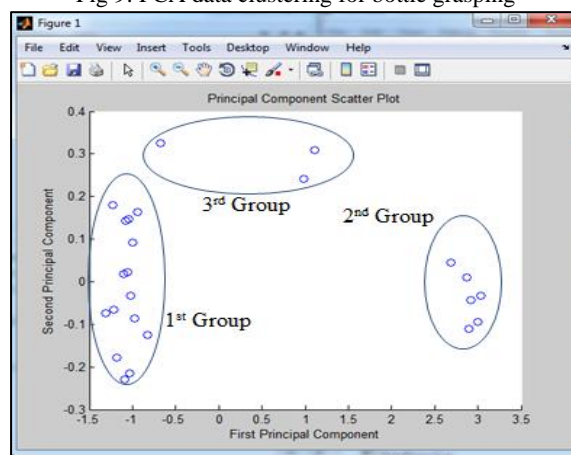


Fig 10: PCA data clustering for box grasping

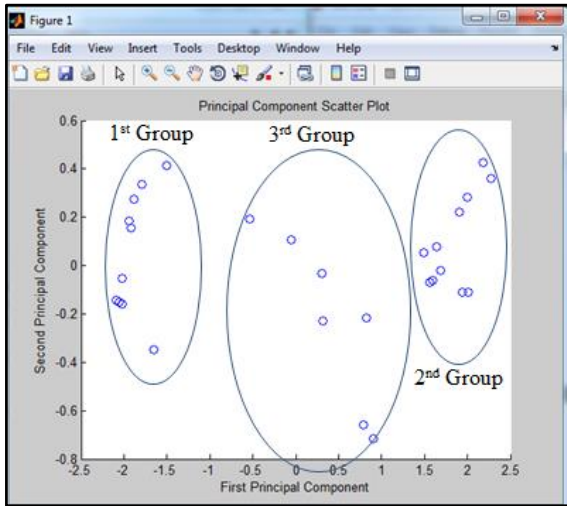


Fig 11: PCA data clustering for ball grasping

### VII. CONCLUSION

In this paper, a new development of a low cost DataGlove “GolveMAP” by using the flexible bend sensor which is able to recognize the human fingers activities is presented. The goal of this research is to analyze the accurateness of the GloveMAP which is able to assist the minimum and maximum data of the fingers movement between thumb, index and middle finger using the principle component analysis (PCA). With use of PCA concept, every act or activity is 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. From the PCA analysis, value of data will be represented as the number of sensor bending that located on the GloveMAP. The values of data show the amount of movement that could be representing which finger signified more to grasp the object. Finally, from the experiments result we conclude that PCA capable to translate 100% finger movement classification and Eigenfingers can be put into practice for fingers classification in variety application.

### VIII. ACKNOWLEDGMENT

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 is supported by the ScienceFund Grant by the Ministry of Science, Technology and Innovation to Universiti Malaysia Perlis (01-01-15-SF0210).

### REFERENCES

1. 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.
2. 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.
3. 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.

4. 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.
5. L. Sirovich and M. Kirby, “Low-Dimensional Procedure for Characterization of Human Faces”, *J. Optical Soc. Am.*, vol. 4, pp. 519-524,1987.
6. 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, no. 1, pp. 103-108,1990.
7. M. Turk and A. Pentland, “Eigenfaces for Recognition”, *J. Cognitive Neuroscience*, vol. 3, no. 1, pp. 71-86,1991.
8. 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.
9. M.A. Grudin, “On Internal Representations in Face Recognition Systems”, *Pattern Recognition*, vol. 33, no. 7, pp. 1161-1177,2000.
10. G.W. Cottrell and M.K. Fleming, “Face Recognition Using Unsupervised Feature Extraction”, *Proc. Int'l Neural Network Conf.*, pp. 322-325,1990.
11. 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.
12. 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.
13. Laurent Vigouroux, Jérémy Rossi, Matthieu Foissac, Laurent Grélot, Eric Berton, “Finger force sharing during an adapted power grip task”, in *Neuroscience Letters*, 504: 290– 294.2011.
14. 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.
15. S. Cobos, M. Ferre, M.A. Sánchez-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.
16. 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.
17. Ramana Vinjamuri, 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.
18. 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.
19. Information on <http://www.yalemedicalgroup.org/stw/Page.asp?PageID=STW023547>
20. 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.
21. 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.
22. R. Valavi and H. Ghassemian, “A fusion Approach of Multi-Sensor Remote Sensing Data Based on Retina Model”, *Proceedings of 12th Iranian Conference on Electric Engineering*. 2004.
23. Information on [http://en.wikipedia.org/wiki/Eigenvalues\\_and\\_Eigenvectors](http://en.wikipedia.org/wiki/Eigenvalues_and_Eigenvectors)
24. 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.
25. Simon Haykin, *Neural Networks and Learning Machine*. Pearson, 2009.
26. Information on <http://arduino.cc/en/Main/arduinoBoardUno>
27. Nazrul H. ADNAN, Khairunizam WAN, Shahriman AB, SK Za’ba, Shafriza Nisha BASAH, Zuradzman M. Razlan, Hazry Desa, M. Nasir Ayob, Rudzuan M. Nor and Mohd Azri Abd 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.

28. 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.
29. Information on <http://blog.explainmydata.com/2012/07/should-you-apply-pca-to-your-data.html>

### AUTHOR PROFILE



**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 Bac. 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 collaborativetasks 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. AbuBakar** 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.



**Azri A. AZIZ** received his B. Eng degree in Mechatronics from International Islamic University Malaysia (IIUM) from 2005 – 2009. He is currently a teaching engineer at University Malaysia Perlis and undergo his post graduate study (Master degree of Mechatronic). He has registered as graduate engineer of Board of Engineer. His research interest is in Human Computer Interaction (HCI), Gesture Recognition and Image processing.