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EXPERIMENTAL AND ANALYSIS STUDY ON *GLOVEMAP* GRASPING FORCE SIGNAL USING GAUSSIAN FILTERING METHOD AND PRINCIPAL COMPONENT ANALYSIS (PCA)

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Abstract. *This research paper presents the analysis study of human grasping forces for several objects by using a DataGlove called GloveMAP. The grasping force is generated from the bending of proximal and intermediate phalanges of the fingers when touching with a surface. A flexiforce sensor is installed at the finger's position of the GloveMAP. The acquired grasping force signals are filtered by using a Gaussian filtering for the purpose of removing noises. A Principal Component Analysis technique (PCA) is employed to reduce the dimension of the grasping force signal, and follows by the extraction of its features. In the experiment, five subjects are selected to perform the grasping activities. The experimental results show that the Gaussian filter could be used to smoothen the grasping force signals. Moreover, the first and the second principal components of PCA could be used to extract features of grasping force signals.*

Keywords: Grasping force, Gaussian filter, Eigenfingers, Principal component

1. **Introduction.** Over the last decade, there are numerous literatures on grasping force analysis, grasping force optimization and grasping force stability. The key problems in the last twenty years are force analysis [1] and grip strength [2], whereas the problem occurs when multi-fingered grasping takes place. Generally speaking, many research used grasping force study for robotic grasping force [1,3,4] in order to analyze the force control and grasp stability. Another external factor influencing the finger force sharing concerns the positioning of the thumb when it opposites the other fingers (pulp grip tasks) [5]. Measuring the force along with the hand motion and understanding human force strategies are important for learning grasping and manipulation. In addition to a better understanding

of human manipulation and grasping, resulting analyses lead to better characterizations of the human haptic sense, ergonomic design criteria [6,7] and performance criteria for haptic feedback devices [8]. Principal Component Analysis (PCA) generally functions 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 [9], PCA analysis methods are capable to identify and express all dataset in such a way as to differentiate their similarities and differences. The first user of PCA [10,11] 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, other researchers used *Eigenfingers* to make the signal data more accurate. *Eigenfingers* in PCA is developed to justify the fingers movement activity accordingly to the selected grasping object [12]. In the real world applications, the signal produced by the principal component is almost effected by the signal noise. By using the Gaussian Filters Computational Algorithm all the noises could be suppressed, the noise in the grasping signal will be smoothed out and at the same time the signal noise is also distorted [13]. The author also states that propose an adaptive Gaussian filtering algorithm/Gaussian Filters Computational Algorithm in which the filter variance is adapted to both the noise characteristics and the local variance of the signal.

The aim of this research paper is to do the analysis study of fingertips grasping force during grasping the selected objects. Gaussian filter is selected to smoothen signals that contain noises. PCA in this research functions to extract features of the grasping signals, which reduce the dimension of data and follows by clustering it in two dimensional spaces.

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 fingers grasping force signals. Section 3 describes the methodologies of the proposed study. Section 4 describes the experimental studies of the research. Section 5 presents the results and discussions. Finally, Section 6 describes the conclusions and proposes some possible future works.

2. **Literature Review.** For the purpose of grasping force analysis, the basic elements of a fixture or a grasp are represented by *GloveMAP* where the development of low cost DataGlove is made by using three flexiforce sensors that are attached at the surface/palm of the thumb, index and middle fingers. Figure 1 shows the sample of flexiforce sensor that is intended for reading forces that are perpendicular to the sensor plane. According to [14], flexiforce sensor is suitable to be used for medical compression bandages (MCB) to map the pressure applied by compression products at multiple points. Flexiforce sensor is also capable to be functioned as haptic interface [15] and visual sensing systems by a virtual feel [16-18]. In multi-finger grasping, the flexiforce sensor is accomplished with both the choice of contact points and the control of contact forces through the fingers [19].

PCA characteristics are able to quantize and characterize the variance in hand/grasping posture of novel transformation task [20]. For the virtually applies, [21] states that PCA

FIGURE 1. Flexiforce sensor

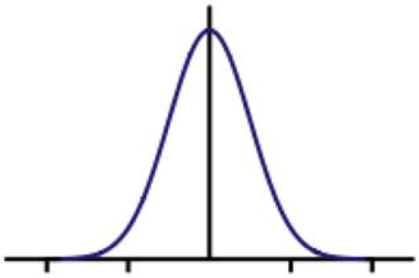

Figure 2. Shape of a typical Gaussian filter

is 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. Gaussian filtering has been intensively studied in image processing and computer vision [22]. The author also states that the famous application for Gaussian filter is for noise suppression application where the noise is smoothed out and at the same time the signal is also distorted [23,24]. Figure 2 shows the Gaussian function used in filtering process.

3. **Methodologies.** In this research, the flexiforce sensors are attached to the thumb, index and middle fingers. Figure 3 shows the flow chart of the proposed works.

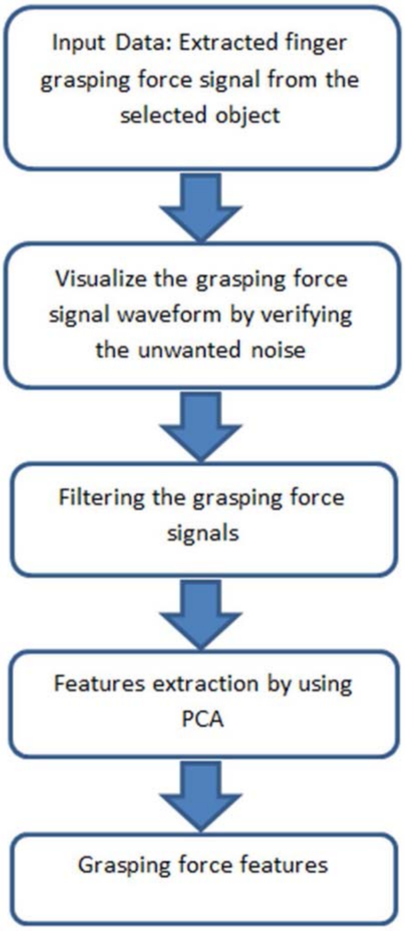

Figure 3. Flow chart of proposed work

Gaussian Filtering. The two-dimensional digital Gaussian filter can be expressed as [22]:

$$G(x,y) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{1}$$

where σ^2 is the variance of Gaussian filter, and the size of the filter kernel j $(-j \leq x, y \leq j)$ is often determined by omitting values lower than five percent of the maximum value of the kernel. The one-dimensional Gaussian filter is expressed as:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{x^2}{2\sigma^2}\right) \tag{2}$$

or

$$g(x) = \sqrt{\frac{\alpha}{\pi}} e^{-\alpha x^2} \tag{3}$$

where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis, and σ is the standard deviation of the Gaussian distribution. When the Gaussian filter is used for noise suppression, a large filter variance is effective in smoothing out noise, but at the same time, it distorts those parts of the signal where there are abrupt changes in frequency. Gaussian filter is a filter who impulses response of a Gaussian function. Gaussian filters are designed to give no overshoot to a step function input while minimizing the rise and fall time. This behavior is closely connected to the fact that the Gaussian filter has the minimum possible group delay. Mathematically, a Gaussian filter modifies the input signal by convolution with a Gaussian function. This transformation is also known as the Weierstrass transform [25].

In the application of image processing, other methods to justify the Gaussian filter are with the filter variance which adapts to the local characteristics of an image. This is based on the strategy that different parts of an image should be smoothed differently, depending on the degree of noisiness and the type of edges. Hodson et al. [36] have shown that Gaussian filtering of a signal $F(x)$, denoted as $F_g(x)$, can be expressed as:

$$F_g(x) = F(x) + \frac{F''(x)}{2}\sigma^2 + \ldots + \frac{F^{(2m)}(x)}{\prod_{p=1}^{m} 2p}\sigma^{2m} + \ldots, \tag{4}$$

where $m = 1, 2, \ldots, F''(x)$ is the second derivative of $F(x)$, and $F^{(2m)}(x)$ is the $2^{m\text{th}}$ order derivatives of $F(x)$. Omitting the higher order terms, the above equation can be approximated by:

$$F_g(x) = f(x) + \frac{F''(x)}{2}\sigma^2 \tag{5}$$

They thus defined the adaptive filter variance as:

$$\sigma^2(x) = \frac{2\varepsilon}{|F''(x)|} \tag{6}$$

where ε is the amount of pre-defined error due to Gaussian filtering process. Using this algorithm, the error due to filtering is approximately less than ε, for example $|F_g(x) - F(x) \leq \varepsilon|$. A complicated regression based method has been proposed to estimate $F''(x)$ from the noisy corrupted signal.

EigenFinger. PCA has been found useful in many applications, such as data analysis, process monitoring and data rectification [26]. PCA is a dimensionality reduction technique in terms of picking up the variance of data and it interprets for correlation among the 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 into the space of *Eigenfingers* (feature spaces). Let the dataset consisting of p observation variables and

q observations for each variable stack into a matrix $X \in R^{q \times p}$ which is expressed in Equation (7).

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ x_{q1} & x_{q2} & \dots & x_{qp} \end{bmatrix} \tag{7}$$

The principal component transform is defined by:

$$J = A^T F \tag{8}$$

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

$$C_j = AC_X A^T = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{bmatrix} \tag{9}$$

where $C_X = \lambda_i t_i$; $A^T A = A^T$.

Meanwhile, $\lambda_1 > \lambda_2 > \dots > \lambda_n$ 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 required, where Eigenvalues can be simplified as **Eigenvalues = *Eigenfingers***original data**. The analysis can be assumed to be a list of real numbers and depend on the concepts of vectors and linear transformations [27]. *Eigenfingers*, J of A and eigenvalues, λ can be determined as:

$$A_J = \lambda_J \tag{10}$$

Above equation can be simplified as:

$$(A - \lambda I)X = 0 \tag{11}$$

where λ and A are calculated using Jacobi method [28], meanwhile I is an identity matrix. By using Equation (12), it is simple to find the determinant of the *Eigenfingers*.

$$\det(A - \lambda I) = 0 \tag{12}$$

In particular, the grasping and fingers bending could be reduced in term of the features number which needed for the effective of data illustration by collecting the bending data. Equation (13) shows only a several number of small variances and preserves only those terms that have only large variances [29]. 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 be written as:

$$\bar{J} = \sum_{X=1}^{I} A_X Q_X \tag{13}$$

For the calculation of dataset reduction the use of averages and standard deviations are essential for data centering and reduction. $\bar{x}$ is the arithmetic mean of each column, and it is presented by Equation (14). The standard deviation is the square root of the variance and it is presented by Equation (15):

$$\bar{x} = \frac{1}{f} \sum_{i=1}^{f} x_i \tag{14}$$

$$\sigma^2 = \frac{1}{f} \sum_{i=1}^{f} (x_1 - \bar{x})^2 \tag{15}$$

4. **Experiments.** Five right-handed subjects participated in the experiments. Each subject was fitted with a right-handed *GloveMAP*, which recorded all 3 flexiforce sensors attached at the *GloveMAP*. The procedures of experiments were the same with our previous research [30-33]. Each subject participated in 4 experimental conditions. Figure 4 shows the *GloveMAP* installed with the flexiforce sensor the position of thumb, middle and index fingers. Figure 5 shows the selected objects used in the experiments, which are egg, cup, dice and ball. Each subject must follow several steps in the experiments as follows:

a) Subjects were instructed to generate a set of hand grasping postures, designed to reach all joint limits. Data from this condition were only used for calibrating the grasping force.

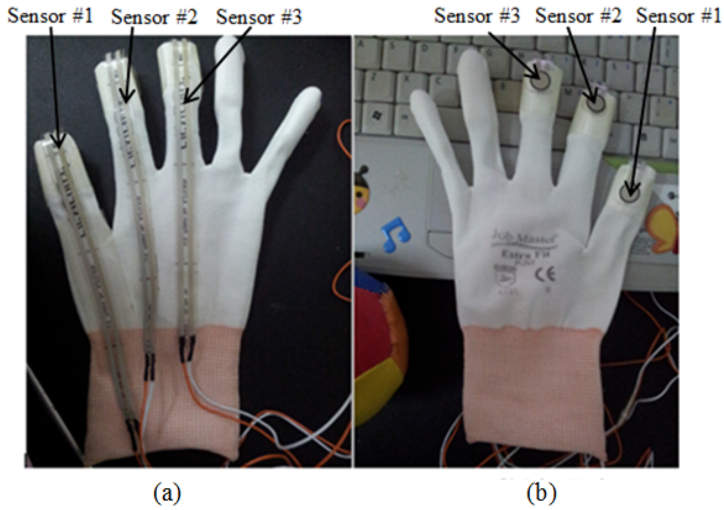

FIGURE 4. *GloveMAP* with flexiforce sensor: (a) surface and (b) palm

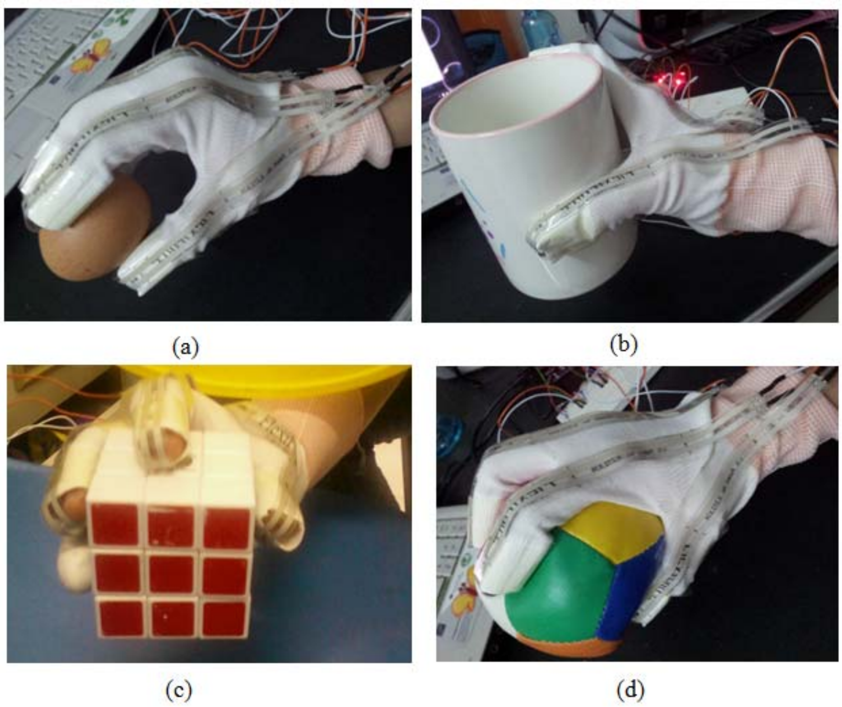

FIGURE 5. Grasping objects: (a) egg, (b) cup, (c) dice and (d) ball

b) Subjects were asked to grasp the object with their own grasping style.
c) The object was placed on a table. The subject must grasp the object in 5-6 seconds and place them back on the table.

5. **Results and Discussions.** In the experiments, all the grasping signals were analyzed by using MATLAB®SIMULINK software. Figure 6 to Figure 9 show the initial grasping force signals for the objects egg, cup, dice and ball. The graphs show acquired voltage versus the grasping time. The circles with the dot line show the signals that contains noises. The noises appear in all grasping force signals produced by all fingers for the all objects. The experimental results show that a filter was needed to remove the noises containing in the grasping force signals.

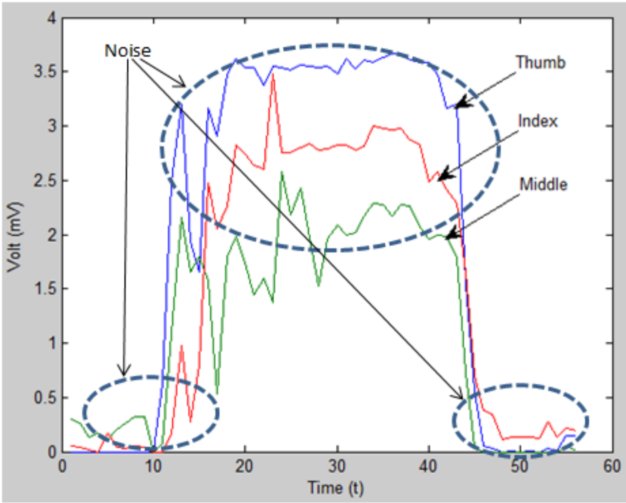

FIGURE 6. An initial grasping force signal for egg

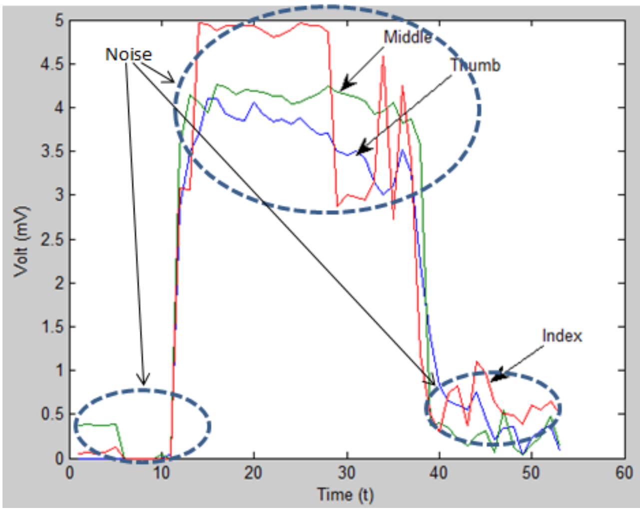

FIGURE 7. An initial grasping force signal for cup

Gaussian Filter. Figure 10 to Figure 13 show the grasping force signals after employing Gaussian filter. The grasping force signals were smoothened compared with the initial signals as shown in Figure 6 to Figure 9.
Grasping force features. After filtering the initial grasping force signals with Gaussian filter, PCA was employed to reduce dimensional of data and followed by clustering it

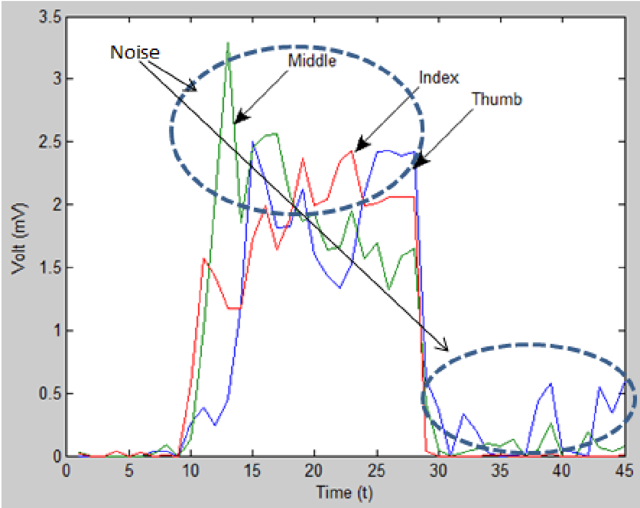

FIGURE 8. An initial grasping force signal for dice

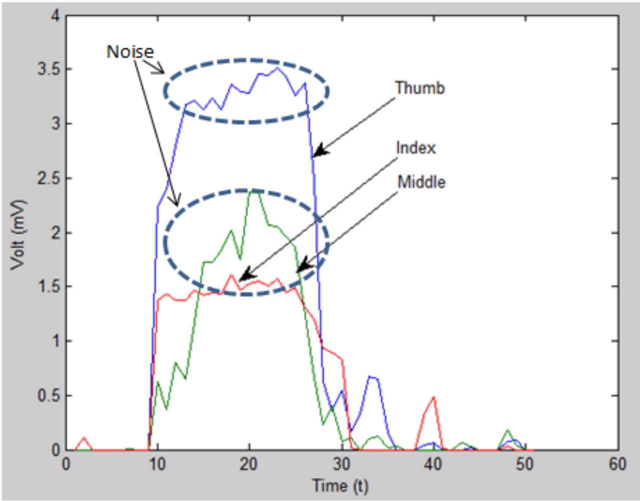

FIGURE 9. An initial grasping force signal for ball

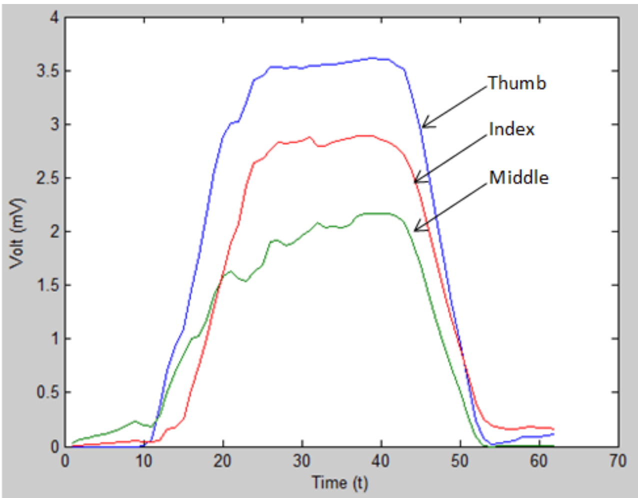

FIGURE 10. Grasping force signal for the egg after Gaussian filtering

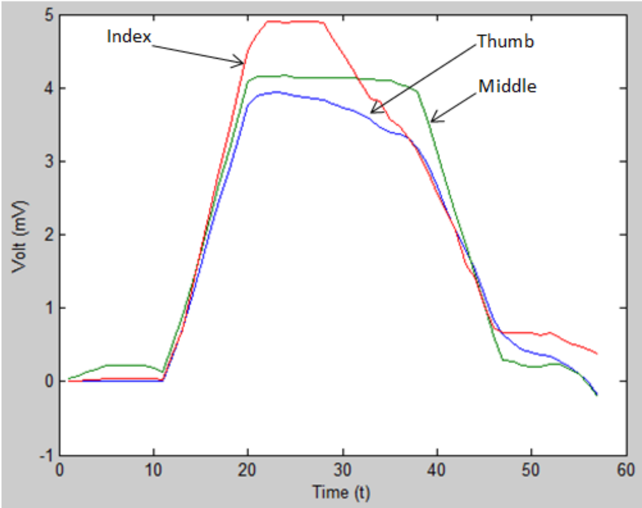

FIGURE 11. Grasping force signal for the cup after Gaussian filtering

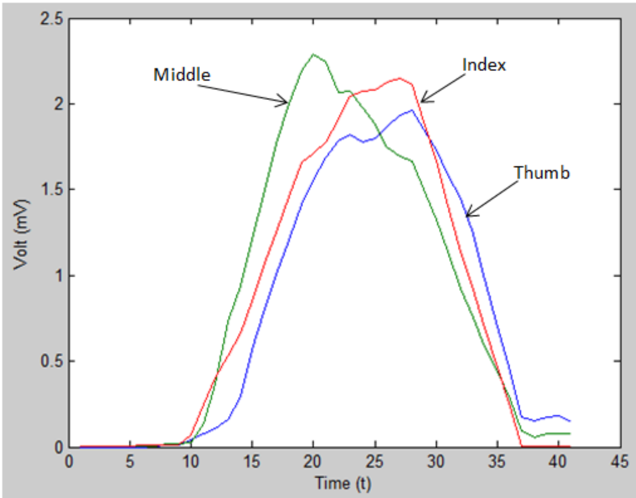

FIGURE 12. Grasping force signal for the dice after Gaussian filtering

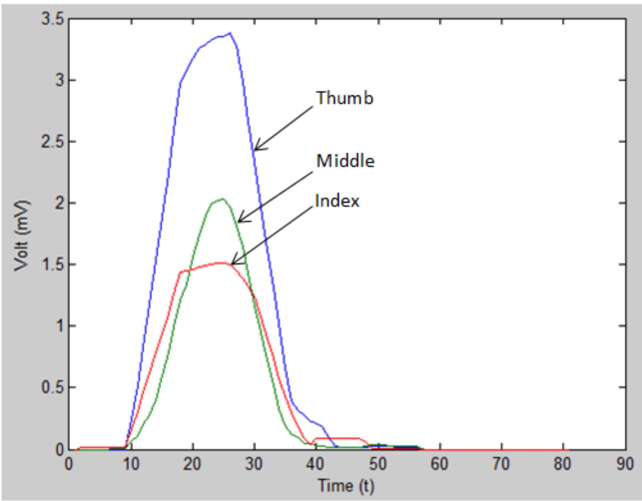

FIGURE 13. Grasping force signal for the egg after Gaussian filtering

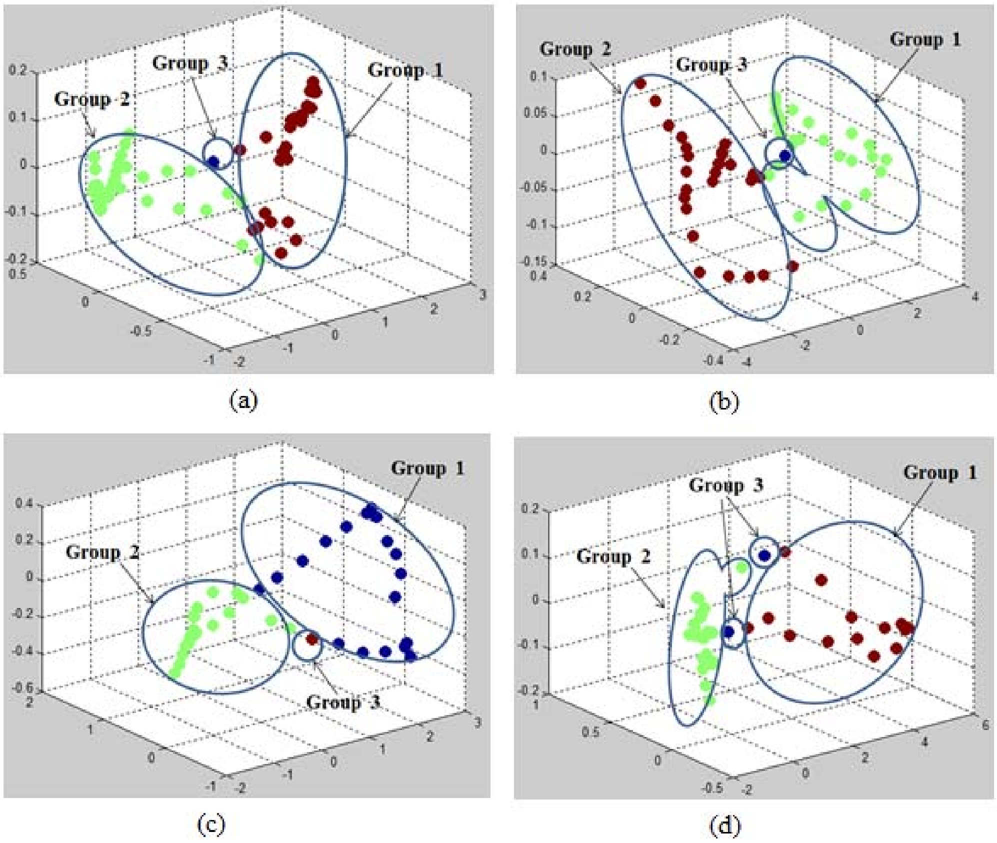

Figure 14. Gaussian data of Fingertips grasping force: (a) egg, (b) cup, (c) dice and (d) ball

to extract features. Clustering is the task of analyzing dataset in such a way and the outcome was to monitor the possibly produced the numbers of group [34]. A. K. Jain et al. [35] states that there is little prior information available about dataset, and the decision-maker must make as few assumptions about the data as possible.

Figure 14 shows the filtered grasping for signals grouped by PCA for the all objects in three dimensional spaces. Figure 14(a) shows the grasping force signal for the egg. The graph shows that it could be clustered to three groups, which were groups #1, #2 and #3. All three groups represent the grasping force signals for the egg, however, group #1 was selected as the feature. The reason was due to the volume of the distributed data in the group #1.

6. **Conclusions.** This paper presents the analysis study of the fingertip grasping force signal by using the flexiforce sensor installed to the DataGlove called *GloveMAP*. The experimental results show that the initial grasping force signals contains noises that will affect the further applications such as signal patterns, the development of gasping database and recognition of grasping patterns. The study proposes the use of Gaussian filter to remove unwanted information in the grasping force signals. Then, the filtered signals are analyzed with PCA to reduce dimensional of data and followed by the extraction of grasping force features. The experimental results show that PCA could be used to extract features of the grasping force signals. In the future, by using the proposed technique various experiments to study the sense of touch will be conducted.

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