Intact Analysis of Intra Trials On Assorted Paradigms Of Gesture Based Communication System.

Kalvina Rajendran[1], Maheswari Rajavel[1], Andrews Samraj[2]

[1]School of computing Science and Engineering, VIT University, Chennai, India
[2]Department of Information Technology, Mahendra Engineering College, India
[2]andrewsmalacca@gmail.com ,
[1]kalvina.r2011@vit.ac.in,
[1]maheswari.n@vit.ac.in

***Abstract*- The fine tuning of gesture based emergency communication for disabled and patients require more precise and pristine gestures which are recognizable without any dilemma. The acceptance for any decision making without any reservation needs a wide threshold range for every paradigm activity. The proposed research work in continuation with the previous works is set to identify such most unique paradigm activities that are to be selected for the used in such emergency gesture based response systems. The intra trial variability calculated for this purpose on all the trials of a particular paradigm with its reference gesture should be minimal to get overlaps on the reference and/or with its group components when classified. Wide difference of intra trials makes the choice of paradigm useless. This experiment uses FFT to generate features and the features are classified by LDA against the reference feature of the same subject. Performances are measured on the overlaps and minimal distance between the signal features and with their reference feature from the same subject. The findings show that the paradigms that involve more finger activities and hand pressure are intact against various trials and stands as a candidate to be used in the proposed system. This study and results reinforces our previous findings and confirms the credits of our methodology.**

***Keywords*- Data gloves, Emergency Response System, Gesture computing, Wearable computing.**

I. INTRODUCTION

The lucid and simple understanding of gesture based communication between caretakers for elderly and the disabled with their wards is absolutely essential for every fault free emergency response and communication system. The reason for ensuring it to be error free is that of taking a decision on choosing a medicine for injecting the patient. Any misinterpretation of input gestures by the support systems attached to the patients may turn fatal. The incessant refinement of the well known gesture based communication system requires a clear and wide boundary of thresholds to distinguish every response from other. The spontaneous and unstable hand movement in this activity makes it always an unachievable target for the systems while using cross boundary gesture symbols for communication. To enhance the clear command interpretation, to support the partial or fully automated robotic assistance or communication system, designing of effective gestures by choosing extremely different activity to produce highly differentiable signals are inevitable. Hence in our proposed experiment which is extended from our previous experiments [3], [4], [5], [6] using an electrodes-embedded wearable data glove to capture the different hand gestures and movements of five subjects is analyzed for suitability [2]. The aim of the experiment is to identify most different activities that can be performed by the hand gestures to differentiate symbolic representation of ‘feeling comfortable’ and ‘feeling discomfort and pain’ as well as the most uniform gesture a subject can perform. This is to ensure the definite inputs to the system from the hand glove gestures and provide wide thresholds. The wider Inter gestures and closer intra gestures provide an essential safety zone for the patients using the system.

In this experiment we focused on more uniform intra gestures which a subject may perform without deviations, so that so that the reliability ensures a wider threshold when used for inters gestures. Moreover, gesture based systems may be deployed in a elevated level tasks like controlling robots technologically an advanced equipment, poses a great demand of clarity in given commands since there involves complex interfaces and is not user-friendly [8]. The proposed experiment was carried out using a system consists of a small wearable glove which captures the gestures and hand movement activities like simple rotation movements. The reason for focusing on this work on intra trial variability is to ensure the customization towards individual needs of the elderly and disabled towards operating the robotic system or machines for assistance in future. By identifying the right and wrong combinations of gesture with more intact gesture sets of activity clusters we improved the system design with much larger and definite threshold possibilities.

II. METHODS

A. Data glove

The data glove we used is a 5DT Data Glove 14 Ultra model as shown in Figure 2a., it is embedded with 14 fully enclosed fiber optic bend sensors spread twice per finger as well as the abduction between fingers [1]. The interfacing of data Glove with the computer is done both through a cable to the platform independent USB port or through wireless by means of Bluetooth technology with up to 20m distance. This glove is fabricated with the flexible lycra material to fit to many different hand sizes unreservedly.

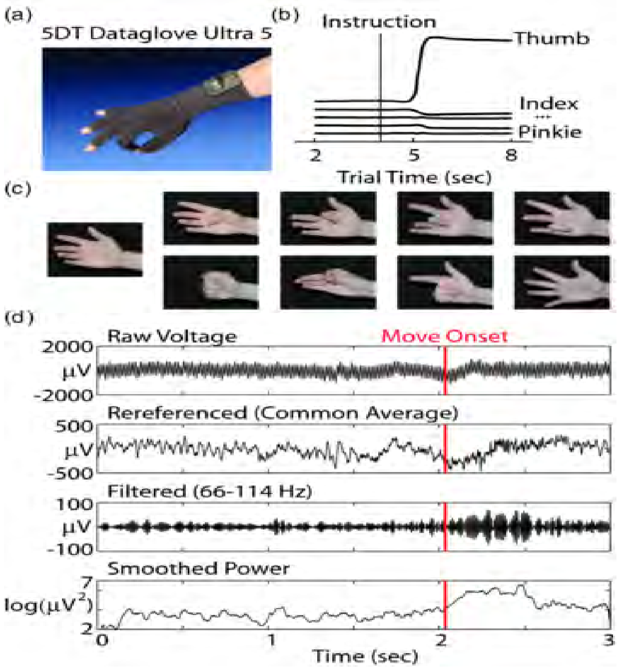

Fig 2. Data glove system Basics

Figure 2a shows the conventional data glove embedded with 14 electrodes and 2b to 2d explains the experimental data acquisition point, sample gestures and pre-processing of the captured signals [9].

B. Signal capturing

The data acquisition done through this glove is represented in 8-bit flexure resolution, at the sampling rate of minimum 75Hz [11]. The data glove is designed as a 3D input device, suitable for a wide range of applications like control and manipulation of virtual worlds, gesture and cognitive media, physiotherapy rehabilitation, control device for artists in remote controlled environments.

C. Experimental settings

The experiment is done with 5 volunteered subjects between the age 17 to 25. By calculating the average of all 10 trials the intra reference is formed for the particular gesture signal of the subject involved. The comparison of intra classification distance is the distance of reference signal against individual signals. These intra classification distances is analyzed and are found intact with minimal distances. Even though they are closer distances, than the inter gesture distances the overlaps alone are accounted as best intact points. From the signals the FFT features are taken and these features are classified using LDA.

The paradigms taken are Soft material light hold (SL), Soft material hard hold (SH), hard material light hold (HL), hard material tight hold (HT), coin light hold (CL), coin tight hold (CT).

D. Fast Fourier Transforms

Fast Fourier Transforms is used to approximate the captured data glove signals and to plot the support vectors. Let, S be the set of discrete items with N items as maximum,

$$S = \{s_i^k, s_{i+1}^{k+1}, \dots\dots s_N^K\} \quad (1)$$

The FFT of set S can be calculated as,

$$FFT(S) = \{A, B\} \quad (2)$$

Here,

$$A = a + bw_N^k \quad (3)$$

And,

$$B = a - bw_N^k \quad (4)$$

Where,

$$a = s_i^k, b = s_{i+1}^{k+1}, W_N^{nk} = e^{-j2\pi nk/N},$$

i= no: of elements in S for calculating FFT.

Here, radix-2 FFT algorithm is employed for the first two elements are taken for butterfly model, based on the stage of computation the K value varies from 0,1,2,3 and N is the total number of available data.
The FFT value is calculated using MATLAB function as,

$$Y = fft\ (X, N) \qquad (5)$$

Where,

$$X \rightarrow data$$
$$Y \rightarrow number\ of\ values.$$

This Y is the FFT with first order butterfly values.

E. Linear Discriminant Analysis

The derived FFT features of all kind were classified using Linear Discriminant Analysis (LDA). LDA is used to classify objects in to groups depending on the set of features taken. Here, we use multi-class LDA to classify multiple data glove signals against different references and the signals of other classes [7].
The mathematical calculation for LDA with two sets of signals are taken as k1, k2

Mean of each set is calculated by the formula,

$$mu1 = mean\ (k1) \qquad (6)$$

Average of mean is taken as

$$mu_A = \frac{mu_i + mu_j}{2} \qquad (7)$$

Where (i,j ε N)

Finding the Center of the data by removing mean from the data set (data – mean)

$$d1 = k1 - repmat(mu1, size(k1,1), 1) \qquad (8)$$

Within class variance (SW) is calculated

$$s1 = d1' * d1$$
$$sw = s1 + s2$$
$$invsw = inv(sw)$$
$$v = invsw * (mu1 - mu2)' \qquad (9)$$

Find eigen value and eigen vector of 'v'

$$[evec, eval] = eig(v) \qquad (10)$$
$$Y_1 = V * k1 \qquad (11)$$
$$Y_2 = V * k2 \qquad (12)$$

[10]

III. RESULTS AND DISCUSSION

The experimental results by LDA classifications of SVD features on intra subject comparisons give the best overlapped, intact classification, desired for the emergency response system. The degree of overlaps and intactness varies between paradigm actions and are shown from figures 1 to 3. Data from all the five subjects with ten trials per each gesture paradigm were taken for analysis, and found to be uniform. Samples figures are limited to different subjects to minimise explanations and space.

Fig 1a shows 96% of overlaps in FFT features classified by LDA for first subject's reference with 3rd trial signal captured from Coin tight gesture action.

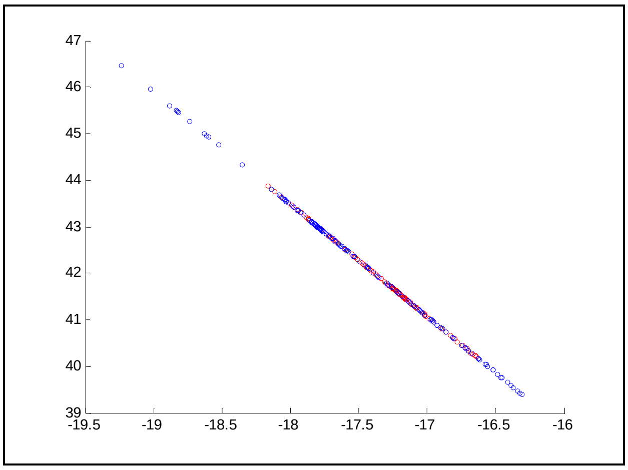

Fig.1 a intra classification of Coin Tight action of sub-1 with 96% overlaps

Fig 1b shows 90% of overlaps in FFT features classified by LDA for first subject's reference with 9th trial signal captured from Coin tight gesture action.

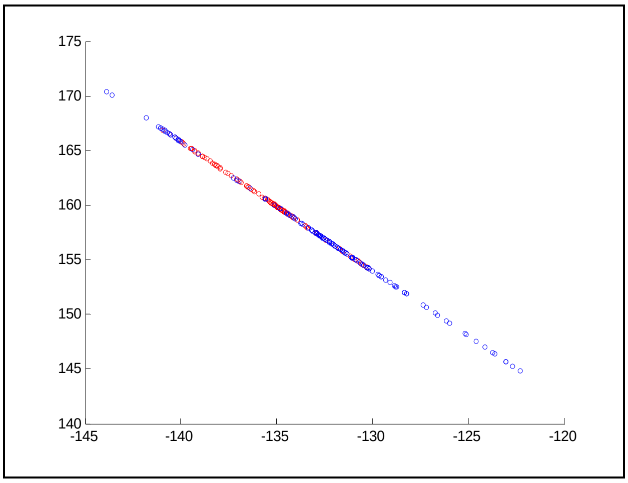

Fig.1 b intra classification of Coin Tight action of sub-1 with 90% overlaps

Fig 2a shows 95% of overlaps in FFT features classified by LDA for second subject's reference with 2nd trial signal captured from Hard material tight hold gesture action.

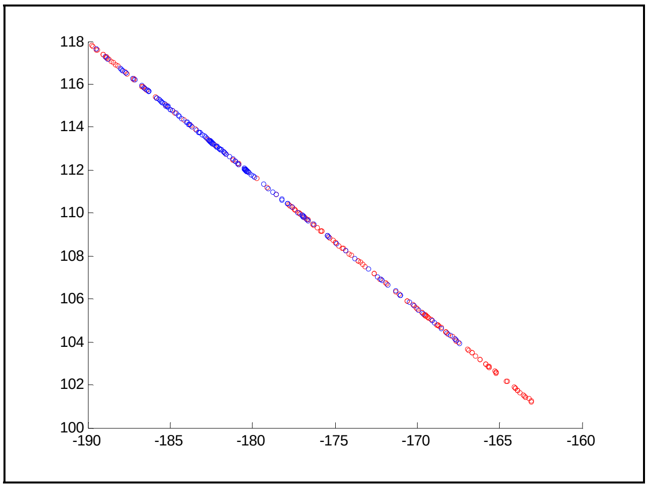

Fig.2 a intra classification of Tight hold of Hard material of sub-2 with 95% overlaps

Fig 2b shows 50% of overlaps in FFT features classified by LDA for second subject's reference with 9th trial signal captured from Hard material tight hold gesture action.

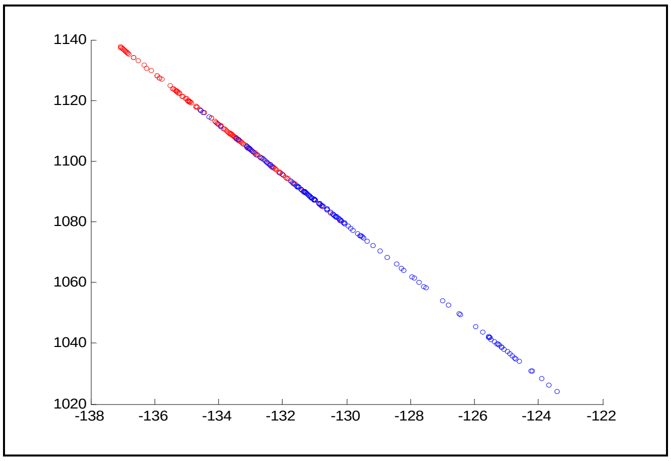

Fig.2b intra classification of Tight hold of Hard material of sub-2 with 50% overlaps

Fig 3a shows 60% of overlaps in FFT features classified by LDA for third subject's reference with 7th trial signal captured from Soft material hard hold gesture action.

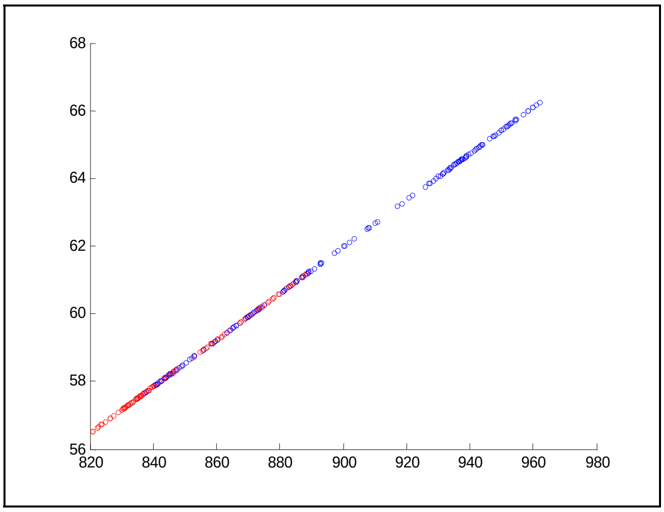

Fig.3a intra classification of Hard hold of Sponge of sub-3 with 60% overlaps

Fig 3b shows 0% of overlaps in FFT features classified by LDA for third subject's reference with 10th trial signal captured from Soft material hard hold gesture action.

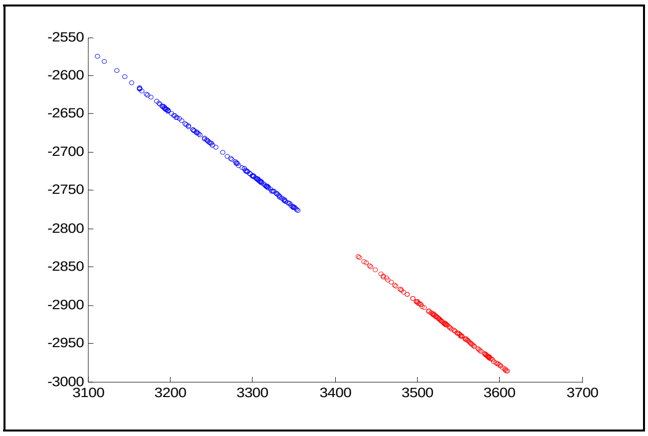

Fig.3b intra classification of Hard hold of Sponge of sub-3 with 0% overlaps

Fig 4a shows 25% of overlaps in FFT features classified by LDA for fourth subject's reference with 3rd trial signal captured from Coin light gesture action.

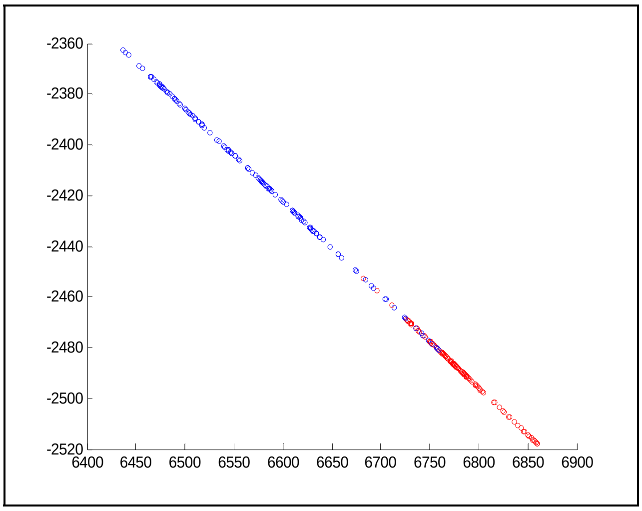

Fig.4a intra classification of coin light hold of sub-4 with 25% overlaps

Fig 4b shows 75% of overlaps in FFT features classified by LDA for fourth subject's reference with 6^{th} trial signal captured from Coin light gesture action.

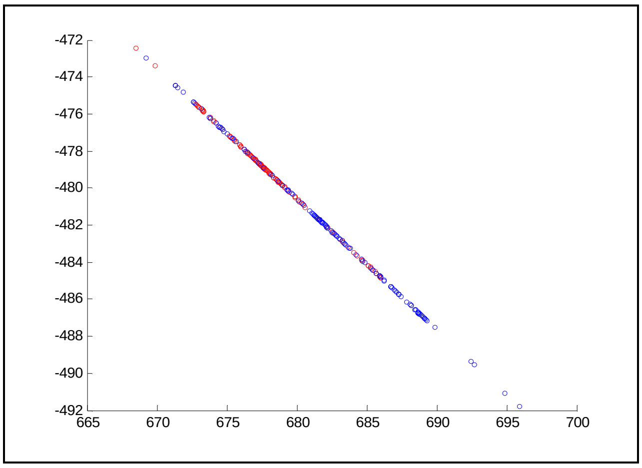

Fig.4b intra classification of Coin light hold of sub-4 with 75% overlaps

Fig 5a shows 0% of overlaps in FFT features classified by LDA for fifth subject's reference with 3^{rd} trial signal captured from Hard material light hold gesture action.

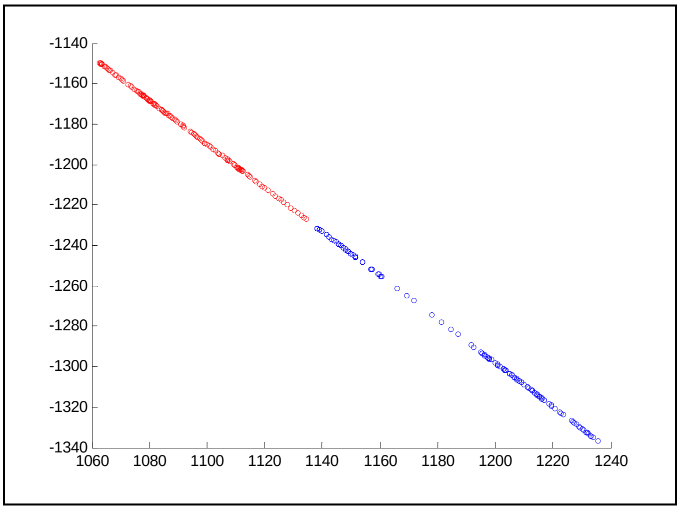

Fig.5a intra classification of Hard material light hold of sub-5 with 0% overlaps

Fig 5b shows 85% of overlaps in FFT features classified by LDA for fifth subject's reference with 10^{th} trial signal captured from Hard material light hold gesture action.

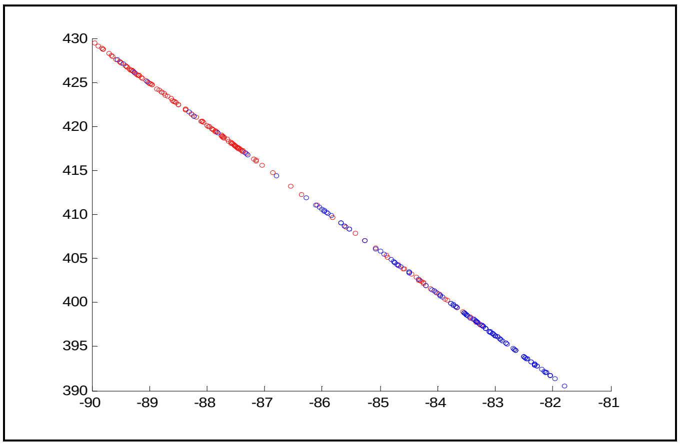

Fig.5b intra classification of Hard material light hold of sub-5 with 85% overlaps

The sample overlaps for intra classification of subject 4 for the Coin tight holding gesture is given in table1. The maximum over lap of 98 shows the best intact and the least overlap is in trial 1 and trial 9. The average overlap percentage is 93.5 which is a significant overlap we found in coin tight hold gesture action for all the subjects.

Table 1. Overlap percentage of intra signal features on the Reference feature of holding Coin Tight gesture of subject 4 by LDA classifier.

Paradigms & Signals	**Percentage of Overlap**
CT1	90
CT2	95
CT3	96
CT4	94
CT5	96
CT6	95
CT7	98
CT8	92
CT9	90
CT10	95
Average	93.5

IV. CONCLUSION

The use of intra trial variability to find the most intact gesture is proved with the best classifications in the experiments. The order of the paradigms are listed from most intact able to least intact able as CT, HT, CL, HL, SL and SH. The highest overlap is found in CT for all 5 subjects with 93.5% to 91.5%. The lowest overlap is found in SH for all 5 subjects with 30% to 40%. These results were reconfirmed intact comparisons from our earlier experiments on inter gesture classifications by resulting in high accuracy of classification.

In future this study may be further deepened by the Genetic Algorithm based selection for further fine tuning rather than trial oriented selection and enhanced with customized classifiers.

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