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Easy and Precise Classification of Implicit Communication signals from Data Gloves

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ABSTRACT

This experimental work is conducted to find the best paradigms for emergency czommunication systems that are developed in disabled and patient health care. The system must be proficient in avoiding adverse effects due to any misinterpretation that may arise in mis-classification of input. The proposed system works well with the suggested paradigms for the extraction of signals from a wearable hand glove. Each extracted signal spectrum represents the corresponding and precise paradigm feature, suitable for efficient classification. The application of Fast Fourier Transformation on signals to extract these features along with the Linear Discriminant analysis (LDA) resulted in faultless results. The wider differentiation is found in paradigms that depend on finger bustle, and are found less in false acceptance and false rejection in turn in equal error rate. Hence the experimental results prove the feasibility of constructing the efficient and simplified emergency response system for the sick, elderly and the disabled using the well differentiated paradigms.

Introduction

The present situation in taking care of the disabled and the bed ridden are highly challenging. Also the miscommunication leads to adverse effects. Similarly a person cannot be spending all the time with the disabled and the elderly despite with their work schedule. So, a simple wearable device may be highly helpful for the better communication between the elderly and disabled with the health aiders. The proposed system provides a novel technique for the communication of the bed ridden in case of emergency. The experimental results prove to be efficient for the emergency response to the call of the disabled. The data gloves are used for many purposes like communication, forgery detection, signature verification, etc and here we use it for monitoring the elderly and disabled.

The human and computer interaction technologies increasingly provide natural ways to operate and communicate with machines [12]. Ranging from speech to vision, all the standalone to wearable interaction technologies help to change the way how people operate computers. With all these interaction methods, gesture recognition takes an important and unique role in human communication with Machines [1]. The usage of motion trackers for communication is an expensive approach and American Sign Language (ASL) is an idea in which the computer has to interpret the gestures of the ASL. The problem in this is that ASL should be taught prior to the elderly and the disabled which is difficult [2]. Moreover such ASL based hand activity functions are difficult during unbearable pain and emergency.

The usage of this emergency health care responsive system provides digital translation of hand glove signals from the hand movements of the user. This system is designed with a group of small electrode sensors embedded in a wearable hand glove which quantifies the dimensions of the fingers and their associations. The purpose of this system is to keeping it active 24/7 by which it can eradicate the limitations of human's aid such as tiredness and lack of timely service in the health care environments. This can also break the barrier of the elderly, sick, injured and disabled towards operating any complex mechatronic and robotic system for assistance. The glove is worn to the right hand of the subjects and the data are transmitted through the wireless transmission to the core system.

Though the system idea is novel and efficient in operation and simplicity, there exists a problem of ambiguity. The signals originated from the same hand and dimensions. To interpret and distinguish every action from other, the paradigms of gestures should be organized in a unique way. The ASL is difficult for everyone to learn and it is time and cost consuming. The remedy is to design the paradigms in such a way that they are reflected with well deviated boundaries when quantified. As an endeavor to find such paradigms this research work identified a set of paradigms which are easy for the intended users to handle, and identified the most distinguishable paradigms from each other [13] [14]. This is to adopt such long distance paradigms to be a part of the future system's design. The mathematical modeling and classification tools are discussed in the next section of the paper and the results were supported with the tables and diagrams in results section.

Methods and Materials

Data Gloves

The data glove used by the researchers for recording consists of 22 sensor wireless cyber glove 2. These sensors are located mainly at the joint positions and measure its amount of bending around one axis [5].

The data glove used here is a conventional glove which is used to find the size, position and orientation of the hand. The gloves are size independent [15].

It is a new dimension in the medicinal field, health care for rehabilitating [2]. The glove is used to capture the gestures efficiently and facilitates in sensing and fine motion control in robotics with various degrees of sensors embedded in it [3]. The

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data glove offers multiple degrees of freedom; permits the user to communicate to the computer to greater extent than most other input devices [6].

The 5DT data glove is designed to satisfy the requirements of modern motion capture and animation professionals. The glove is made up of black stretch lycra material with flexure resolution of 12 bit A/D. Fourteen flexure fiber optics sensors, as 2 sensors per finger, 1 sensor for knuckle, 1 for first joint abduction and sensors between fingers with an USB interface using kaydara MOCAP, Discreet 3D studio Max, Alias Maya, SofImage XSI, SDK and Glove Manager Utility software. The sampling rate of this glove is minimum 75Hz [7].

Fig 1. 5dt data glove ultra5

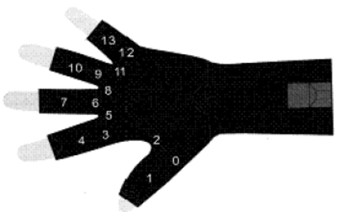


Fig 2. Data glove with electrode positions

Table 1. Description of electrode positions

Sensor	Description
0	Thumb flexure (lower joint)
1	Thumb flexure (second joint)
2	Thumb-index finger abduction
3	Index finger flexure (at knuckle)
4	Index finger flexure (second joint)
5	Index-middle finger abduction
6	Middle finger flexure (at knuckle)
7	Middle-ring finger (second joint)
8	Middle-ring finger abduction
9	Ring finger flexure (at knuckle)
10	Ring finger flexure (second joint)
11	Ring-little finger abduction
12	Little finger flexure (at knuckle)
13	Little finger flexure (second joint)

Electrode positions during the experimental setup

The glove used in this experiment consists of 14 electrodes to capture the signals from the hand. The positions of the electrodes are given as in Tab 1.

The data glove signals are captured for 5 healthy subjects, including 2 female subjects. The average age of the subjects taken into consideration is 19.5 years. For all 5 subjects their right hand is dominated, the glove is worn in it [1].

The subjects are allowed to capture signals from

- A soft material (sponge)
- A hard material (iron) and
- A coin

10 samples are captured for each paradigm – sponge light hold, sponge hard hold, iron material light hold, iron material hard hold, coin light hold, coin tight hold respectively denoted as SL, SH, HL, HT, CL, CT. The size of each sample matrix for its row is 265 – 266

Fig 3. Various action paradigms used in the experiment for extraction of signals

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,

$$S = \{s_i^k, s_{i+1}^{k+1}, \dots \dots s_N^K\} \qquad \text{----->}\ (1)$$

The FFT of set S can be calculated as,

$$FFT\ (S) = \{A, B\} \qquad \text{----->}\ (2)$$

here,

$$A = a + bw_N^k \qquad \text{----->}\ (3)$$

And

$$B = a - bw_N^k \qquad \text{----->}\ (4)$$

Where,

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

FFT with first order butterfly values

The FFT value is calculated using MATLAB function as

$$\mathbf{Y = fft(X, N)} \qquad \text{----->}\ (5)$$

Where,

X→ data

Y→ number of values

Linear Discriminant analysis

LDA is used to classify objects in to groups depending on the set of features taken [9]. Here, we use multi-class LDA to classify multiple unknown data glove signals into multiple classes (SL, SH, HL, HT, CL, CT).

The mathematical calculation for LDA is as –

- Two sets are taken as k1, k2.
- Mean of each set is calculated as $mu1 = mean(k1)$ -----> (6)
- Average of mean is taken as $mu = \frac{mu1 + mu2}{2}$ -----> (7)
- Center of the data (data – mean)

$$d1 = k1 - repmat(mu1, size(k1,1), 1) \qquad \text{----->}\ (8)$$

- Within class variance (SW) is calculated $s1 = d1' * d1$ -----> (9)

$$sw = s1 + s2 \qquad \text{----->}\ (10)$$

$$invsw = inv(sw) \quad \text{-----}\rightarrow (11)$$

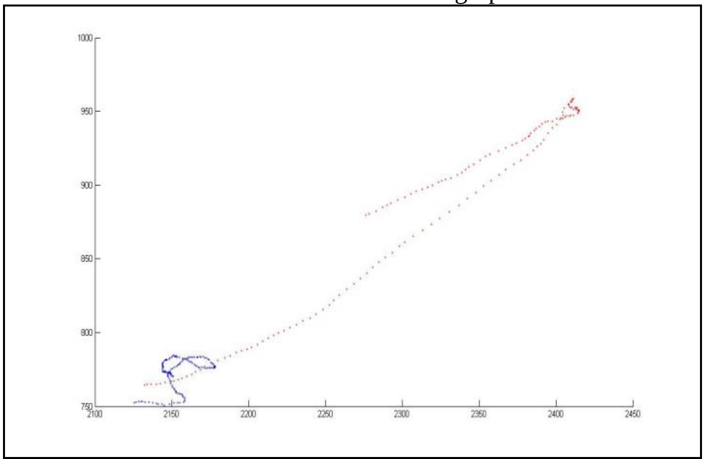
$$v = invsw * (mu1 - mu2)' \quad \text{-----}\rightarrow (12)$$

- Find eigen value and eigen vector of v

$$[evec, eval] = eig(v) \quad \text{-----}\rightarrow (13)$$

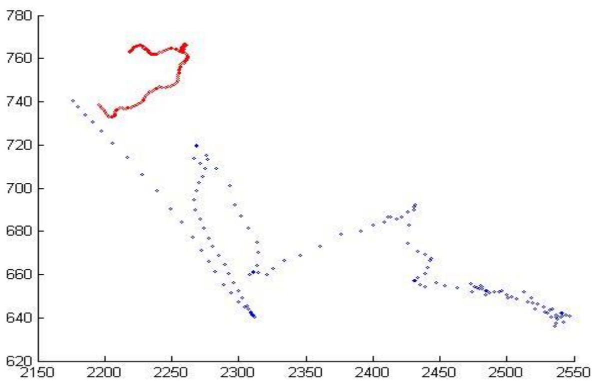
Results

The FFT features are classified using the Linear Discriminant Analysis and the classification between SH FFT features and HL FFT features is shown in graph 1.



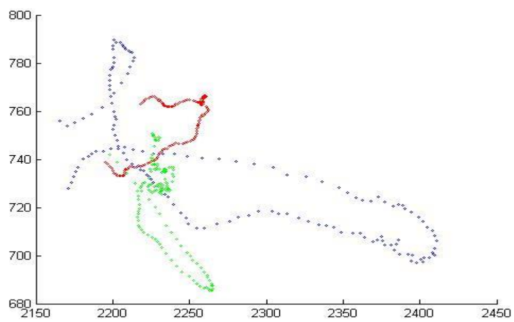
Graph 1. The LDA classification of SH features and HL features derived from Data glove signals by FFT

Graph 2 explains about the classification between SL FFT features and CT FFT features by using the LDA classifier. There are no overlaps when these two paradigms are classified. Because the SL features differs a lot from the CT features.



Graph 2. The LDA classification of SL and CT features derived from Data glove signals by FFT

Graph 3 explains the classification between 3 paradigms SL, HT, CL. These paradigms have the most misclassified objects and their error rates are higher when compared to other combinations of paradigms used in this work. The overlaps in the graph below show the misclassifications for these 3 paradigms.



Graph 3. The LDA classification of SL, HT and CL features derived from Data glove signals by FFT

The Table 2 consists of the FAR, FRR and ERR of various combinations in percentage (%) values by using Naïve Bayes Classifier [11].

The formulae are given as follows –

$$FAR = \frac{total\ number\ of\ accepted\ features}{total\ number\ of\ tested\ features} X\,100$$

$$FRR = \frac{total\ number\ of\ rejected\ features}{total\ number\ of\ tested\ features} X\,100$$

$$ERR = \frac{(FAR + FRR)}{2}$$

Table 2. FAR, FRR and ERR of all paradigms by Naïve Bayes Clasifier

Sl. No:	Combinations		FAR %	FRR %	ERR %
1	SL – CT	CT	0	4.5	2.25
		SL	0	0	0
2	SH – CT	CT	0	3.007	1.50
		SH	0	0	0
3	HL – CT	CT	0	1.48	0.74
		HL	0	0	0
4	HT – CT	CT	19.13	19.13	19.13
		HT	17.18	17.18	17.18
5	CL - CT	CT	11.2	9.6	10.4
		CL	8.82	10.29	9.55
6	SL – SH - HL	SL	0	0	0
		SH	13.33	0	6.665
		HL	0	15.38	7.69
7	HL – HT - CL	HL	2.68	0.67	1.675
		HT from HL	0.83	0	0.415
		HT from CL	12.5	0	6.25
		HT to HL	0	3.33	1.665
		HT to CL	0	21.66	10.83
		CL from HT	19.25	0	9.625
		CL to HT	0	11.11	5.555
8	SH – HT - CL	SH to HT	0	20.96	10.48
		HT to CL	0	20.96	10.48
		HT from SH	20.96	0	10.48
		HT from CL	12.096	0	6.048
		CL from HT	19.259	0	9.6295
		CL to HT	0	11.11	5.555
9	SL – HT - CL	SL from HT	29.82	0	14.91
		SL from CL	13.15	0	6.575
		SL to HT	0	7.01	3.505
		SL to CL	0	24.56	12.28
		HT from SL	8.16	0	4.08
		HT from CL	13.26	0	6.63
		HT to SL	0	34.69	17.345
		HT to CL	0	18.36	9.18
		CL from SL	22.95	0	11.475
		CL from HT	14.75	0	7.375
		CL to SL	0	12.29	6.145
		CL to HT	0	10.65	5.325

Table 3. explains about the average ERR of the all the paradigms in percentage (%)

Table 3. Average ERR of all paradigms

Sl. No:	Paradigms	Average ERR (%)
1	SL	7.4958
2	SH	3.3325
3	HL	2.7575
4	HT	6.7919
5	CL	10.0471
6	CT	6.804

Discussions

It is interestingly seen from the average EER results from Table 3 that the light holds are prone to much overlaps than the tight holds it is seen from the case of CT and SH. As controversial result and acceptable HL posses less EER than HT and naturally it is due to the reason that the hard material cannot be pressed or squeezed more as in the case of light material and a coin. This explains the very good reasoning of arranging the paradigms with the hard materials or uses the hard hold of other materials. The light hold of soft materials can be complemented with the hard hold or hard materials to reduce the error.

Conclusion

Here in our work we used reduced number of data by deploying limited electrodes which comes to a total of 14 for the whole hand and in the work [5] the number of electrodes used were 22 sensor wireless Cyberglove. The FFT features resulted in better realizations while classifying them, which helped us in identifying the best distinguishable paradigms from each other that provided good results. From the Table1 and Table 2 shown in results section the minimum FAR is found in the HT from HL paradigm as 0.83% and minimum FRR 0.67% is found in the HT to SL and the minimum ERR is in HT from HL as 0.415%. Similarly, the maximum FAR is found in SL from HT paradigm as 29.82 and the maximum FRR in HL as 34.69 and maximum EER in CT as 19.13% paradigm. Therefore the paradigms that can be combined for the proposed user interface should be like SH, HL and CT and should not be like SL, HT, and CL.

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