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STUDY ON CLASSIFICATION OF TONGUE MOVEMENT EAR PRESSURE (TMEP) SIGNALS FOR HUMAN MACHINE INTERFACE (HMI)

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ABSTRACT

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Few projects on human machine interface (HMI) are already running successfully as like, power while chair, prosthetics etc. and proved to very resourceful invention for mankind with a great field for improvement. The goal of this research project is to describe pattern classification of tongue movement action by Tongue Movement Ear Pressure (TMEP) signals. The classification has been done on four tongue movement actions (up, down, left, and right). Cross validation method is used for Classifier training and testing to get a better accuracy and Bayesian classifier have been used to get better performance in real-time for hands free communications. The average classification accuracy with the real time interfering signals achieved 82.9% (Bayesian) and its shown that uni-variance Bayesian classifier performs better than multivariate classifier for this new six features mean, median, variance, kurtosis, skewness and entropy. This approach of combining the Bayesian classifier and the k-fold cross validation method provides a robust and efficient method for a real-time assistive human machine interface based on tongue-movement ear pressure signals.

Key words: *mankind, pattern, segmentation, human machine interface, tongue movement ear pressure*

INTRODUCTION

From the very beginning of human life science has proven its contribution for human life development in every step ahead of prosperity and development .Now in the golden era of science several researches are taking place regarding human disability issue (Mace *et al.* 2010). A lot of invasive and non-invasive techniques are developed to improve the life quality and to embrace people with disabilities in the development and response (Mace *et al.* 2010). Assistive devices are becoming a significant enabler in creating helpful operational environments and by the power of technology persistently science is trying to better lives of people with disabilities. Bio-signal is applied in various fields of study such as motor control, neuromuscular physiology, movement disorders, postural control, human machine interaction, and so on (Vaidyanathan *et al.* 2007). But most of them need to operate by body movement which is difficult for people who has movement disability. Processing of these bio-signals is the essential fact during each application and there still can be seen many challenges among researchers in this area (Mamun *et al.* 2012). The objectives of this research are to feature extraction and classification of Tongue Movement Ear Pressure (TMEP) signal to improve the accuracy of Assistive Human Matching Interface.

METHODOLOGY

In the present study the classification was performed between controlled movement commands and interference related tongue movement ear pressure (TMEP) signals. Tongue movement ear pressure (TMEP) signals were recorded when subjects performed six types of controlled tongue movement: moving the tongue from the neutral position to the top/front centre of the top of the mouth (‘up’), touching the tongue to the bottom/front centre of the mouth (‘down’), the front/right side of the mouth (‘right’), the front/left side of the mouth (‘left’). Six unique features have been extracted using Gaussian method and uni-variance Bayesian classifier is used to classify the features by using cross validation method for training and testing the classifier. Finally k-fold method has been used to evaluate the classifier performance.

HMI system

A Human Machine Interface (HMI) is an interface that allows humans and machines to interact. In HMI system, it takes user intention as input, processes the input and then generates a command as an output to operate a device. The tasks of HMI are to design, evaluate, and implement a system that will automate human life activity (Vaidyanathan and James, 2007).

HMI using Tongue movement

The advantage of utilizing the tongue is that it has a natural capability for fine motor control, and it has evolved to perform sophisticated motions during speech. People with limited control of their limbs, such as paraplegia or even quadriplegia can use this. The system also has the additional benefits of being simple, cheap and noninvasive (without surgery) (Mamun *et al.* 2012).

TMEP signal

Due to the connection of the oral cavity to the ear via the Eustachian tube certain tongue movements causes a change in air pressure, which can be identify by a sensor as TMEP signal (Mamun *et al*. 2012).

Pre processing

To classify the acquired bio signals, the main task is to enhance the discriminative features from raw signals (Vaidyanathan and James, 2007). This can be achievable through applying an appropriate preprocessing which is done by filtering, signal detection, signal segmentation and signal averaging.

Feature extraction

Redundant features significantly affect the pattern classification process and provide poor generalization (Vaidyanathan and James, 2007). So, maximum classification accuracy is depends on the optimal feature subset to build the classifier.

Six features are extracted here which are: mean, median, variance, kurtosis, skewness and entropy.
Mean: Unbiased estimation of the location of the amplitude distribution.
Median: An alternate measure to estimate location of the amplitude distribution.
Variance: A measure of the spread of the distribution and reflects the signal power.
Skewness: A measure of degree of asymmetry of a distribution.
Kurtosis: A measure that reflects the peak of the distribution.
Entropy: A measure that reflects amount of uncertainty carried by the distribution of samples.

Classification

The pattern classification of bio signals translates input signal features into device commands that carry out the user's intent. Generally, pattern classification algorithm consists of training and testing cycles. Training set is responsible for building the classifier while testing set is independent and does not involves in the classifier formation (Stehman 1997; Mamun *et al.* 2010). K-fold cross validation method have been used for Training and testing cycle where for each fold 90% data is assigned for training and 10% data is assigned for testing.

Bayesian classifier

A Bayesian classifier is based on the idea that the role of a class is to predict the values of features for members of that class.

Examples are grouped in classes because they have common values for the features (Mamun *et al*. 2009). The idea behind a Bayesian classifier is that, if an agent knows the class, it can predict the values of the other features.

Classifier Performance Evaluation

Classifier Performance has been evaluated by using Confusion Matrix where, Confusion value is equal to the fraction of samples misclassified. A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of this system is evaluated using the data in the matrix (Mamun *et al.* 2012).

RESULTS

All of these actions involve active participation of tongue movements, which create a pressure signal that travels through the Eustachian tube to the ear. This pressure signal causes a change in the air pressure or airflow within the ear canal and can be monitored by inserting a sensor into the ear canal (Vaidyanathan and James, 2007). The strength of this signal corresponds to the direction, speed and intensity of the movement of tongue which is unique to the respective action. This phenomenon guides us to use a tongue movement as control command for assistive HMI applications. When a human subject moves their tongue in a certain direction, the generated air pressure changes may be characterized as sound waves or vibrations within the ear. TMEP signals were recorded from five subjects with sampling frequency 2 kHz. Each of four movements (Up, Down, Left and Right) was repeated 100 times. For visual representation, segmented TMEP signals of subject 3 containing tongue movement actions of four actions are presented in below figures.

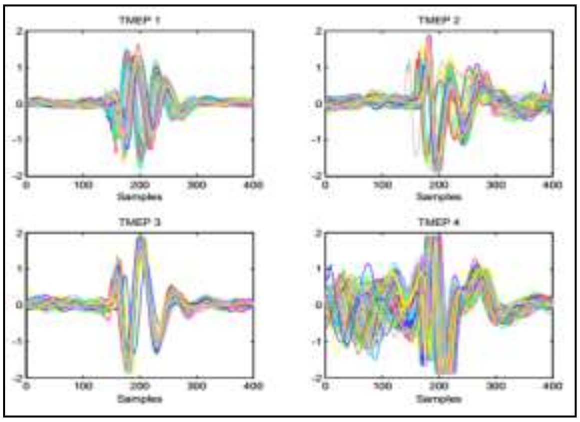

Fig. 1. Raw TMEP signals of four actions (up, down, left, and right)

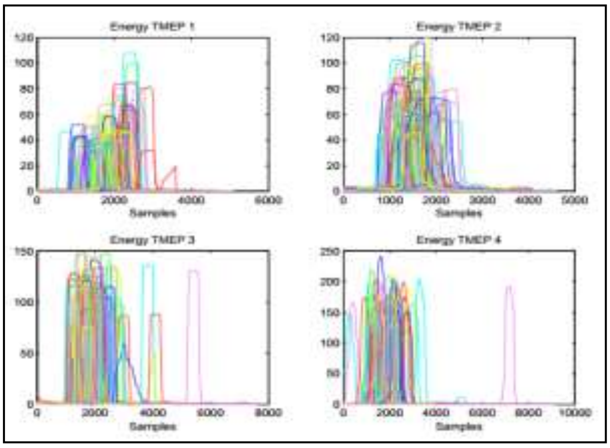

Fig. 2. Energy of main signals of four actions (up, down, left, right)

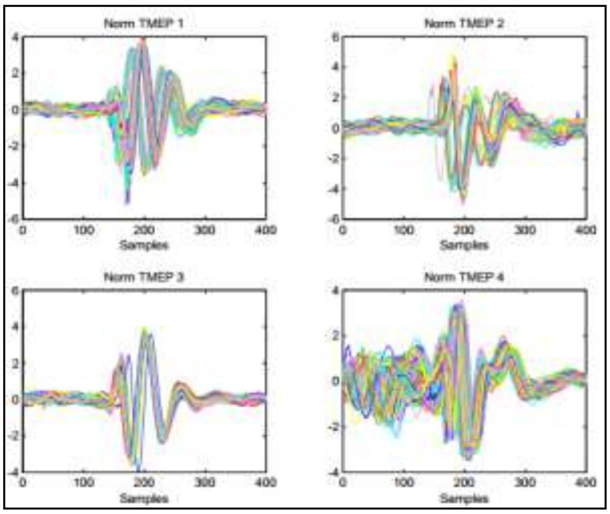

Fig. 3. Normalized main signals of four actions (up, down, left, right)

The tongue movement action classification results were obtained from six feature extraction sets and shows the averaged classification accuracy for four tongue movement actions. Averaged classification accuracy in each feature set presented in Figure 2. It was observed that the maximum average classification accuracy among all five feature sets achieved 82.9 % using Bayesian classifier.

Subjects	1	2	3	4	5	Average Accuracy is: 82.9%
Accuracy	81.4±1.5%	77.6±1.0%	97.7±0.5%	63±3.5%	84±2.0%	
Confusion Matrix	100 5 5 2	79 1 15 9	94 2 4 0	54 19 29 3	81 0 10 8	
	6 85 7 14	0 98 6 0	1 97 0 2	25 35 33 12	0 91 7 1	
	5 4 93 10	9 3 62 20	3 2 95 0	21 5 66 13	20 1 60 18	
	1 30 12 69	10 4 17 73	0 3 0 97	4 3 9 89	10 1 4 84	

Fig. 4. Accuracy measurement of five subjects

DISCUSSION

The raw signals for four action of TMEP were preprocessed and an area of interest has been normalized to get the most significant information and to enhance the discriminative features from raw signals. Six features as mean, median, variance, kurtosis, skewness and entropy were extracted and for an improved training and testing, Cross-Validation technique is used by applying k-fold (10-fold) cross-validation. After training the Bayesian classifier is used for classification to get a real time better performance. This investigated the feature extraction and classification methods for TMEP signals. When time domain feature of the TMEP signal was used, the maximum average classification accuracy obtained was 82.9% through Bayesian classifier using a large training set. According to the performance and viewpoint of real-time application, Bayesian classifier would be an optimal choice for TMEP signal classification (Mamun *et al.* 2012; Stehman 1997; Mamun *et al.* 2010). Moreover, due to the limited size of the training dataset compared to the large number of features, it was observed in the preliminary analysis that uni-variance Bayesian classifier performs better than multivariate classifier (Mamun *et al.* 2012; Stehman 1997). The inaccurate estimation of variance matrix in multivariate case may be the reason for lower performance (Stehman 1997). With larger training dataset, it can be possible to design multivariate Bayesian classifier in future that may provide better performance.

CONCLUSION

Certain Tongue Movement Ear pressure signal has been used for controlling commands and actions for developing Human Machine Interface to assist the people with mobility disorder. Six features have been extracted; and when the feature of the TMEP signal was used, the maximum average classification accuracy was obtained by 82.9% of the 5 subjects through Bayesian classifier. This research investigated the decoding ability for recognizing pattern of movement related states from tongue movement ear pressure (TMEP) signals. This research introduced a new feature selection strategy, to select optimal feature subset for pattern classification.

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