Application of Multivariate Empirical Mode Decomposition in EEG signals for Subject Independent Affective States Classification

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***Abstract*—Physiological signals, EEG in particular, are inherently noisy and non-linear in nature which are challenging to work with using conventional linear signal processing methods. In this paper, we are adopting a new signal processing method, Multivariate Empirical Mode Decomposition, as a preprocessing method to reconstruct EEG signals according to its instantaneous frequencies. To test its effectiveness, we applied this signal reconstruction technique on EEG signals for a 2-dimensional affect states classification application. To evaluated the proposed EEG signal processing system, a three-class classification experiment were carried out on the Emobrain dataset from eNTERFACE'06 with K-nearest neighbours (KNN) and Linear Discriminate Analysis (LDA) as classifiers. A leave-one-subject out cross validation process were used and an averaged correct classification rate of 90.77% were achieved. Another main contribution of this paper was inspired by the growth of non-medical grade EEG headsets and its potential in advanced human-computer interface design. However, to reduce cost and invasiveness, consumer grade EEG headsets have far less number of electrodes. In this paper, we used emotion recognition as a case study, and applied Genetic Algorithm to systematically select the critical channels (or sensor locations) for this application. The results of this study provide much needed insights on sensor configuration for future consumer-grade EEG headset design.**

***Index Terms*—Multivariate empirical mode decomposition, EEG, Genetic Algorithm, Affective signal processing, Human-Computer Interfaces**

I. Introduction

Affective states classification has become an important part of the Human-Computer Interface (HCI) study. Affective states are the physiological expression of emotion, but unlike emotion itself, which is typically a very personal experience that is influenced by many factors such as, one's past experience, education and cultural background, affective expressions can be measured and quantized. There are many theories for emotion modeling and representation, but the most recognized is the circumplex model of emotion, which represents emotional states as continuous points on a two or three dimensional space, e.g., a 2-D model shown in Fig. 1. In this dimensional theories of emotion, emotional states have unique physiological and neural profiles that distinguish them from one another, and are represented as a combination of more fundamental dimensions, such as emotional arousal (strength or intensity of emotion) and emotional valence (degree of pleasantness or unpleasantness). For example, fear emerges as a combination of negative valence and high arousal.

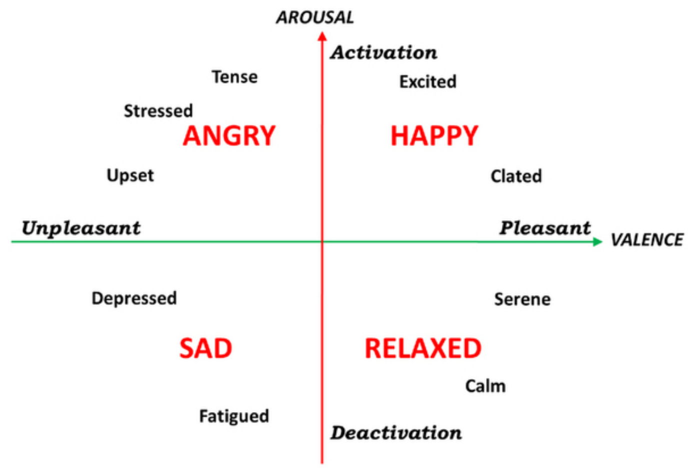

Fig. 1: Dimensional Representation of Emotion [1]

In recent years, many studies of physiological signals, e.g. heart rate, blood pressure, galvanic skin response and respiration rate, though generally more invasive than facial image or voice based modalities, have delivered substantially more accurate results on the estimation of affective states. However, these physiological signals, can also vary due to non-emotional factors such as, physical activity or environmental (temperature) changes, which cast great doubt on the practical applications of these signals. Electroencephalogram (EEG) signals, on the other hand, are generated from the Central Nervous System (CNS) and directly reflect the brain activity, which can potentially overcome these challenges.

The EEG is a measurement of the electrical activity within the brain [2] that is produced by synchronous neural activities. Extra-cranial EEG signals are captured using multiple electrodes resting on the scalp that are spatially located according to a specific system known as the 10-20 system [3]. EEG signals are time series indicating the oscillatory nature of the brainwaves. EEG signals are non-linear, non-stationary and usually contaminated with substantial amount of noise caused by thermal fluctuations, artefacts (muscle movements, electrodes movements) and technical interference (power line). It is very challenging to infer EEG signals in its raw time-domain format without any signal processing procedures. It is also a challenging signal processing problem since EEG signal violates the stationary assumption that are assumed in many

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conventional time-series analysis methods.

This paper is divided into five parts. First, an overview on the concept of emotion/affect recognition is introduced. Then the multivariate empirical mode decomposition (MEMD) as a preprocessing method for EEG signal is presented and discussed, particularly on its application as an instantaneous frequency (IF) based filter bank, which can reconstruct the signal components of interesting with least distortion. The third part is a discussion on using EEG signal as a modality for affective states classification, as well as the challenges faced by such systems. In the forth part, due to the increasing diversity of non-medical grade EEG headsets, a channel selection method, Genetic Algorithm, is introduced to systematically select the critical channels for affect detection purposes. In the last part of the paper, two experiments designed to examine the proposed system and their simulation results are discussed and compared to the results in the literature.

II. EEG Based Affective Signal Processing System

There are three main components for such affect classification systems using physiological (e.g., EEG) signals, the preprocessing step, the feature extraction and selection (optional) step and the classification step. Each step has its own challenges, for example, EEG signal is prone to noises, such as muscle movement, eye-blinking,especially for the signals collected over the scalp. However, due to the fact that the neural signals are sourced from a non-linear process, action potential at the individual neuron level, traditional linear signal processing methods are less effective to eliminate or reduce the non-informative components.

Another challenge lies in the selection of a suitable feature extraction and/or selection method.This challenge is imposed by practical constraints, for example, for such stochastic learning systems, the number of samples available usually are much smaller than the dimension of the features. This is due to the fact that data collection is labor intensive, the requirements of manual labeling of input data, the experimental setup is often preventative of every large data set (both in terms of number of subjects and number of individual trials). We start by ensemble four sets of features that were well studied in the literature for this study. Due to the high dimension of features and the challenge of sample sizes, genetic algorithm (GA) is utilized as a feature selection algorithm. Genetic Algorithm is a non-ranking global optimization method that maximize a set optimization criterion, for this study, we have chosen the correct classification rate as a fitness function.

III. Signal Reconstruction using MEMD as a Filter Bank

Empirical mode decomposition is a time-frequency analysis method that were proposed in recently years. EMD has been shown to be effective in analyzing non-linear and non-stationary signals through the use of Instantaneous Frequency (IF) obtained using Hilbert-Huang Transform (HHT) [4]. In this method, a multi-component (spectral) signal is reduced into a set of mono-component functions, which is referred to as Intrinsic mode functions (IMFs), through the construction of analytical signals or Hilbert transform [5]. Multi-component refers to the cases that there are multi-extremas between two consecutive zero-crossings for a oscillating signal, which indicates the coexisting of multiple frequency components at any given time instance.

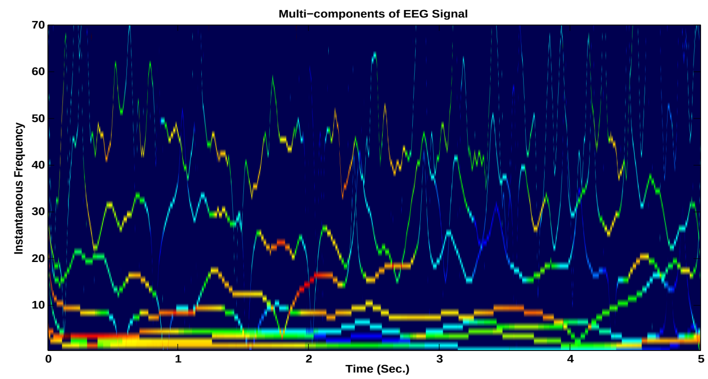

Fig. 2: Multicomponent Characteristics of the EEG signals

As shown in Fig. 2, a multiple component signal has a spectrum where multiple intrinsic frequencies super-imposed at each time instance.

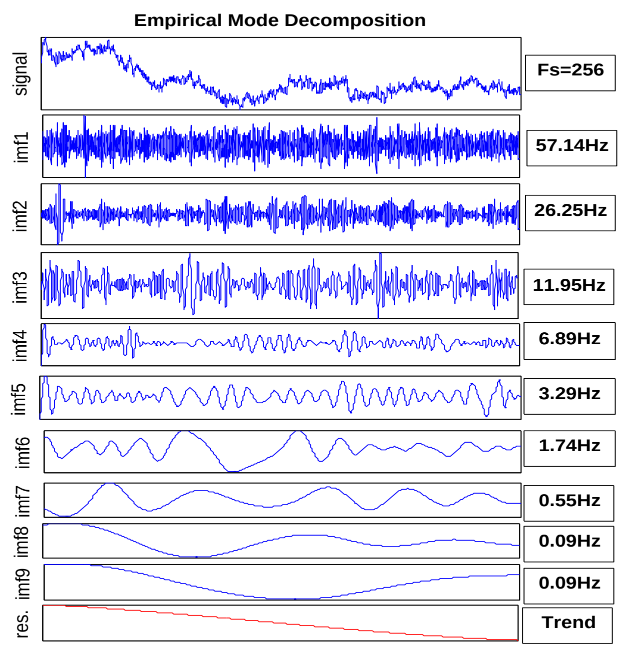

Fig. 3: Instantaneous Amplitude and Averaged Frequency of the IMFs

EEG signal is reconstructed based on its Instantaneous Frequencies at each time instance, without the requirement of any information at other time instances. To do so, EEG signal is first decomposed into a series of IMFs, as shown in Fig. 3, each with its own instantaneous frequency (IF). The IMFs within the desired frequency range will be summed to obtain the reconstructed signal. This is very different from the conventional filtering process, since the filtered result is adaptive, and is able to extract signal components that are over-lapping both in time and frequency. This is mainly due to the fact that the result is not influenced by a set of a priori basis and no convolution procedure required. Other methods, such as wavelet analysis, a predetermined basis, is convolved with the multiple component signal in time and to re-fine the frequency resolution, the 'mother' wavelet is scaled at each decomposition level (expand by a factor of α in time will result a $\frac{1}{\alpha}$ change is the frequency domain).

Empirical Mode Decomposition (EMD) has been used in emotion recognition study using EEG and shown promising results. However there are many unsolved challenges in terms of the application of this method on multi-channel inputs, first of all, since this decomposition method is entirely data-driven, and the decomposition level depends on the time domain local characteristics, the number of decomposition levels varies between channels, recording scenario (trials and sessions). Therefore, to define a common feature space is very challenging or impossible. This prompt the adaption of multivariate version of the EMD, which ensures the same number of IMFs across all multi-variables (or channels), and also the mode alignment problem (see Fig. 4). Mode alignment in multivariate data corresponds to finding a set of common scales or modes across different components (variables) of a multivariate signal, thus ensuring that the IMFs are matched both in the number and in scale properties.

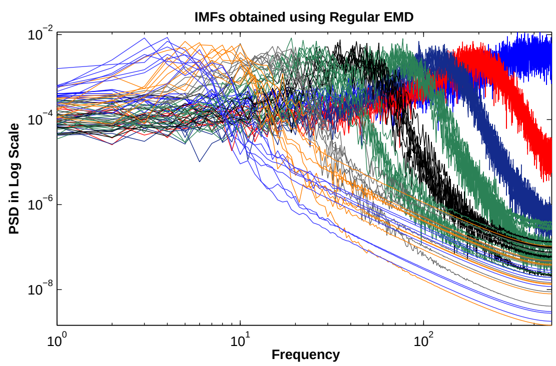

Fig. 4: Mode alignment problem when using regular EMD as a filter bank

MEMD is an analysis method that in many aspects gives a better understanding of the physics behind the signals [5]. Because of its ability to describe short time changes in frequencies that cannot be resolved by Fourier spectral analysis, it can be used for nonlinear and nonstationary time series analysis. Each extracted signal admits well-defined instantaneous frequency (see Fig. 5). Due to the above stated properties, MEMD can be used effectively as a filter bank to extract frequency components of interest for EEG signal analysis. As stated in Sec. I, physiological signals like EEG is very noisy and denoising such signals is one of the most important step. Effective filtering process will enable better understanding of the underlying physiological process and the intrinsic characteristics or sources more accessible.

In [6], $3-5$ IMFs were selected for each channel to reconstruct the EEG signal. However, we found that the number of IMFs and the instantaneous frequency of each IMF

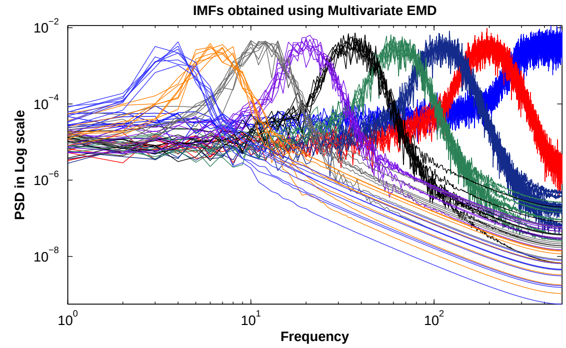

Fig. 5: Well-defined instantaneous frequencies for each IMF when using MEMD as a filter bank

can vary between EEG segments and recordings, particularly from different subjects. Therefore, to simply summing IMFs by their decomposition level is not feasible. Furthermore, if we naively summing up IMF components that within the desired frequency band, we might potentially cause discontinuity or spurious effect in the reconstructed EEG. One possible solution, as discussed in [7], was to use a weight matrix to optimize the selection of IMF components and maintain the continuity of the background components.

We now consider a unique reconstruction method based on the Hilbert-Huang spectrum which we refer to as Hilbert-Huang (HH) reconstruction. To do this, we first calculate the instantaneous frequency of each IMFs, as shown in Fig. 2, and given a signal d(k), we propose to remove any unwanted frequency information outside of the (spectral) region of interest, and reconstruct a signal, d(k), that retains only desired frequency characteristics from d(k).This is achieved by first decomposing d(k) into a set of N IMFs, $c_i(k)$, and determining the instantaneous frequencies. $f_i(k)$ denotes the instantaneous frequency of the ith IMF at time instant k. Given the scenario where it is required to retain frequencies greater than $f_{low}$and lower than f_{high}, we have

$$\tilde{c}_i(k) = \begin{cases} c_i(k), & if\ f_{low} < f_i(k) < f_{high} \\ 0 & otherwise \end{cases} \tag{1}$$

Essentially all values of $c_i(k)$ that do not fall within the desired frequency range are set to zero. We can construct $\tilde{d}(k)$ by summation of the IMF values that fall within the desired frequency range, to obtain

$$\tilde{d}(k) = \sum_{i=1}^{N} \tilde{c}_i(k) \tag{2}$$

A. Feature Extraction

Two types of features were extracted from the reconstructed time-domain EEG signal. One is the features based on the statistical features of the time-domain signal, and the other, higher order crossing, is to examine the oscillatory mode or complexity of the time-domain signal.

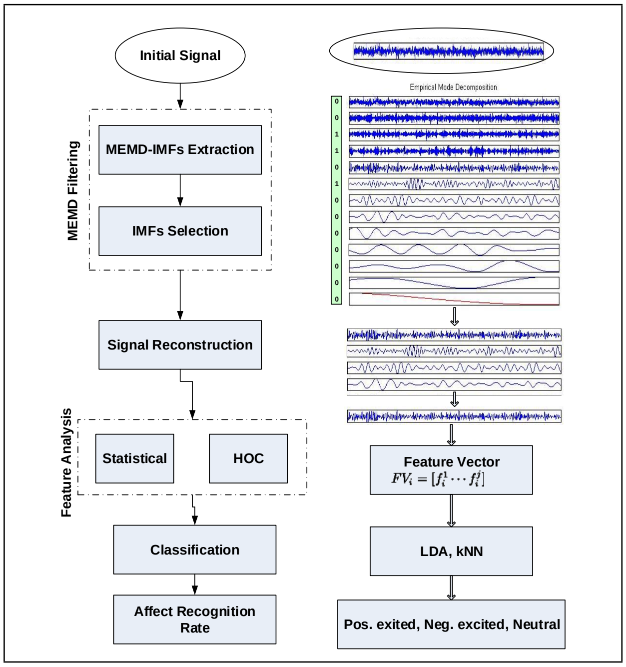

Fig. 6: MEMD for Signal Reconstruction and Feature Analysis

1) Statistical-based Features: The statistical features proposed by Picard [8] for physiological signals were used here to form the proposed FVs, which were defined as ($X_t, t = 1, ..., N$ is the raw N-sample EEG signal) given in the following. The mean of the raw signals μ_x, the standard deviation of the raw signals σ_x, the mean of the absolute values of the first differences of the raw signals δ_x, the mean of the absolute values of the first differences of the normalized signals $\overline{\delta}_x$, the mean of the absolute values of the second differences of the raw signals γ_x, and the mean of the absolute values of the second differences of the normalized signals $\overline{\gamma}_x$.

2) Higher Order Crossings: Observed time series of physiological signals such as EEG, display both local and global up and down movements. Characteristics of the oscillatory mode process discrimination powers and can be extracted as features for classification purpose.The oscillation behavior, seen in a finite zero-mean time series $Z_t, t = 1, ...N$ can be expressed through the zero-crossing count. When a specific sequence of filters is applied to a time series, the corresponding sequence of zero-crossing counts is obtained, resulting in the so-called HOC sequence [9]. Let $Z_1, Z_2, ..., Z_N$ be a zero-mean stationary time series, the zero-crossing count in discrete time is defined as the number of symbol changes in the corresponding clipped binary time series [9]

$$X_t = \begin{cases} 1, if Z_t \geq 0 \\ 0, if Z_t < 0 \end{cases} \tag{3}$$

The number of zero-crossings, denoted by D, is defined in terms of X_t

$$D = \sum_{t=2}^{N} [X_t - X_{t-1}]^2, 0 \leq D \leq N - 1 \tag{4}$$

B. Genetic Algorithm

Due to the large number of IMFs produced after the decomposition along with a large number of EEG channels present, there is much redundancy in the features directly extracted from all IMFs. There are two problems present due to the high dimension of feature space, first of all, it is the computation complexity and secondly, a very large number of samples are required to produce a meaningful statistical model [10]. Since we have a small number of observations comparing to the dimension of the features, also the uncertainty of which electrodes provides more information in terms of discriminating one emotion class from the other. Generic Algorithm is applied to reduce the number of channels and the number of IMFs for feature extraction analysis. The objective here is to use GA on the collection features in hope to reduce the feature dimension and also discover the main class-specific features, to boost classification performance.

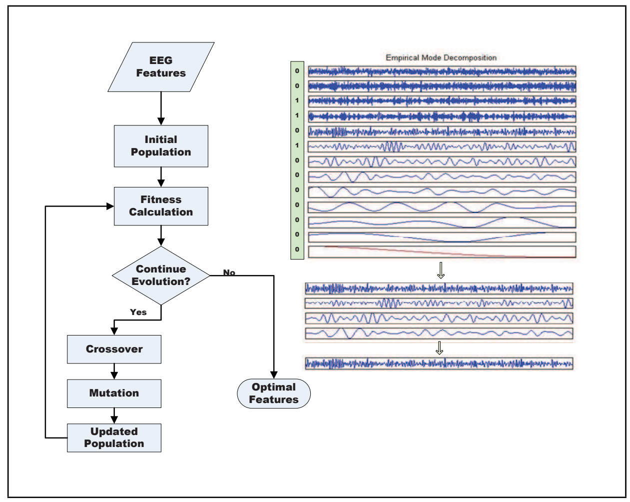

Fig. 7: The block diagram for Genetic Algorithm

Generic algorithm is a non-ranking, global optimization algorithm that was introduced in [11]. The optimization process is mimicking the natural selection from a large population members. It iteratively modifies (mutates) a population of individuals (variables of the features space) to maximize a fitness criterion. At each step, genetic algorithm tries to select the best individuals, which will be used to allow the generation of offsprings (with set crossover rates). Over successive generations, the generation evolves towards an optimal solution. The algorithm terminates when maximum generation is reached. The selection of maximum generation is typically chosen when the fitness criterion (or performance0 stabilizes.

There are mainly three parameters that governs the process at each step (see Figure. 7):
1. Select the individuals (parents) to generate next generation
2. Crossover rules applied to combine two parents to form children for the next generation
3. Mutation rules apply random changes to individual parents to form children

Related papers [12], [13] have shown that genetic algorithms, from the nonranking group, can be successfully applied to feature selection. When using ranking methods such as Principle Component Analysis (PCA) the chosen feature vectors can contain features that are correlated with each other and at the same time do not bring in significant new information for the classifier. When use the correct classification rate as a fitness measure, Genetic algorithm will choose features that are most representative to the class labels. Another major advantages of Genetic Algorithm is the fact that we are able to represent our features and electrodes in binary form to for feature reduction, which differs greatly from the conventional, ranking based methods such as Principle Component Analysis (PCA) or Linear Discriminate Analysis (LDA).

On the other hand, the main disadvantage is the fact the fitness criterion is calculated based on a large number of samples, population at each generation times the number of generations, which can take a long time to compute before a result can be obtained. Also due to the randomness of mutation and crossover at each generation, each run of genetic algorithm creates slightly different set of features. Since the features are not ranked, in general, we do not know which feature is more significant in the classification process later on. Therefore, to elevate the above two shortcomings and to learn the importance of each features, multiple runs of genetic algorithm is proposed and the features with higher frequencies in appearance are considered to be more significant and are selected in the channel reduction process. It also enables us to determine where to place the electrodes and which frequencies of EEG spectrum are the most important.

C. Fitness Functions

Fitness function as a selection criterion is to conserve some of the characteristics of EEG signal in the feature reduction process. Previously, methods to best preserve the characteristics of EEG signals, such as the energy (event-related potential) and complexity (Fractal Dimension) have been used in the literature. For example, fractal dimension method has been used in the analysis of epileptic seizure using EEG [14]. However, such selections of fitness function gives no consideration of the association of features with class labels or anything beyond each individual samples. Since the objective of my study is to find the most discriminating channels and frequency range, a different fitness function has be to be considered. Here the correct classification rate is used as a fitness measure for the GA.

The aim of the genetic algorithm is to maximize the fitness function. As soon as the corresponding IMFs have been chosen, with the inverse EMD algorithm, a new signal is constructed only by the selected IMFs. Figure 7 demonstrates the GA feature selection process in an EEG signal which corresponds to the emotion of positively excited.

D. Emobrain Dataset

To examine the performance of the designed EEG-based affective signal processing system with MEMD as a preprocessing method, Emobrain dataset from the eNTERFACE'06 workshop [15] were used during the experiment. Five subjects participated emotions were elicited in subjects using images from the IAPS (International Affective Picture System) [16]. It consists emotionally-driven physiologically signals from both the peripheral (galvanic skin response, respiration and blood volume pressure) and central nervous system (EEG and frontal fNIRS). Since our study is focused only on brainwaves, we have only used the EEG recordings. More details can be found in [17].

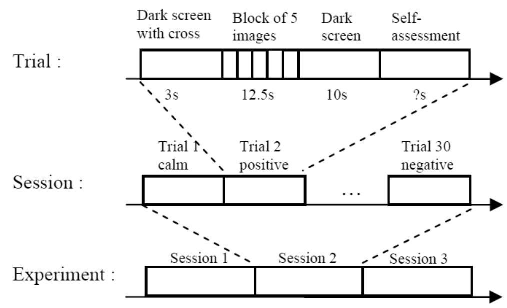

Fig. 8: Protocol description for eNTERFACE06-EMOBRAIN database

EEG data were collected from 5 participants, aged from 22-38, for three different sessions with 30 trials per session. The experimental protocol is detailed in Fig. 8. For each session, participants were stimulated using images selected from the International Affective Picture System (IAPS) [16]. The images were divided into three categories: negatively excited, neutral and positive excited based on their valence and arousal scores. These thresholds were imperially defined according to the circumplex model shown in Fig.1. Each trial consists of a block of five images selected for the same affect class, this to insure stability of the emotion over time. Each picture was displayed on the screen for 2.5 seconds leading to a total of 12.5 seconds per block. Blocks of different classes were displayed in random order to avoid participant habituation. The total number of observations obtained was $5 \times 3 \times 30 = 450$. Biosemi active II headset was used during the experiment, which has 64 channels, however, due to the parallel recording of the fNIRS signals, only 54 EEG channels were actually present in the dataset.

IV. Results and Discussions

For the selected Emobrain database, there were 30 trials for each session and three sessions in total for each subject. However, upon further investigation, samples of subject one collected during session 1 were excluded due to the different sampling rate as well as the missing information on the IAPS images used for this session, particularly after the discovery that the eliciting images listed for this session was a duplicate of session 2, which raised concerns on the validation of these samples. Samples from subject 2 session 1 were also excluded due to inconsistency in recording setting comparing to other trials. Due the randomness of crossover and mutation process, each run of genetic algorithm may result in a slightly varying set of features. To solve this problem genetic algorithm was applied ten times on the original set of features. Features were ranked according to their averaged selection rate, as shown

TABLE I: Overview of the dataset

subject	Used sessions	Total trials	Pos. Trials	Neg. Trials
S1	sess2,3	300	100	100
S2	sess2,3	300	100	100
S3	sess1,2,3	450	150	150
S4	sess1,2,3	450	150	150
S5	sess1,2,3	450	150	150

in Fig. 9. Final set of features were selected by applying a threshold value on the averaged selection rate.

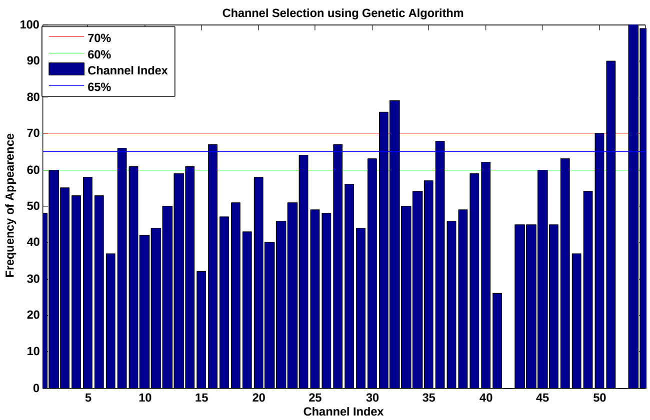

Fig. 9: Channels selected through Genetic Algorithm

The following are the channels selected after 10 runs of genetic algorithm. Channels of 18,10 and 6 were presented here.

TABLE II: Channels selected using GA algorithm

Frequency of Appearance	Number of Channels	Channels Selected
$\geq 60\%$	18	$Ft7$, $Fc3$, $Fc1$, Fcz, $C3$, $C1$, Poz, $Af3$, $P2$, $Fc4$, $Cp4$, $Cp6$,$Tp8$, $Fc4$, Iz, $O1$, $P10$, $Ft8$
$> 65\%$	10	$Ft7$, $Ft8$, $Fc3$, $Fc4$, Fcz, $Tp8$, $P2$, $P10$, Poz, Iz
$> 70\%$	6	$Ft7$, $Ft8$, $Fc3$, $Fc4$, $P2$, $P10$

For the subject independent affective classification problem, 10-fold leave-one-subject out cross validation process were used. Table III shows the correct recognition rates for three affective states: positively excited, neutral and negatively excited. Two simple classifiers were used here, the k nearest neighbour (kNN) and the linear discriminate analysis (LDA). Euclidean distance were used as a ranking metric for both classifier and 5 neighbor were used for KNN.

The results shown that HOC is much more effective in discriminating the affective states of the subjects. Also, by reducing the channels from 18 to 6, system performance degrade very slightly and gradually, which indicates that there is definitely more informative channels existing for this pattern classification problem. This finding provides very positive confirmation on the possibilities towards the design and application of EEG signals on non-medical (emotion recognition) applications.

TABLE III: Emotion Recognition rates using electrodes selected using GA

Number of Channels	Classifier	Statistical	HOC
18	5NN	80.97	90.21
	LDA	48.92	62.05
10	5NN	79.74	88.77
	LDA	43.03	56.31
6	5NN	76.46	89.79
	LDA	40.82	53.21

Following the thought on the critical channel selection on the system performance and also on the potential emotion recognition applications using consumer-grade EEG headsets. We further reduced the number of channels using GA as well as reference the current setup to a well-known in-market EEG headset, the Emotiv Epoch [18]. The correct recognition rate using KNN classifier shown in Table IV are very close when the number of electrodes were significantly reduced from 54 to 10, then 6. More importantly, when we selected 8 of the 14 channels present in a consumer-grade EEG headset, Emotiv Epoc, very promising results were obtained again. These results provided evidence on the feasibility of consumer grade headsets for real-time, emotion recognition in mobile applications. However, the recognition rate using LDA decreases dramatically, this indicates that the samples of the reduced channels are not linearly separable in the projected feature space.

TABLE IV: Recognition rates of emotion using channels selected by GA

Method	Number of Channels				
	All 54 channels	8*channels	Channel selected using GA		
			18	10	6
5NN	90.77	89.64	89.23	88.77	89.79
LDA	79.64	43.13	62.05	56.31	53.21

* - Referenced to commercial device: Emotiv Epoc with 14 channels and having 8 channels in common with the current setup

V. Conclusion

In summary, we have designed and implemented an EEG-based affective signal processing system using a novel time-frequency signal processing method, Multi-variate Empirical Mode Decomposition (MEMD) as a preprocessing method. Like wavelet methods, MEMD method will decompose the original time series into a set of oscillatory modes, termed as Intrinsic Mode Functions (IMFs), but unlike wavelet, we are not restricted to a fixed, predefined set of wavelets, which could be challenging to determine the most appropriate basis for a particular application, or under the stationary or piece-wise stationary assumption as required by other conventional signal processing methods (e.g., Fourier based methods), but is violated by most biomedical signals. A correct recognition rate of 90.77% were achieved using HOC features and kNN classifier on five subjects. Genetic algorithms were also implemented to examine the critical channels present for this affective classification problem. Very promising results were maintained when the number of channels were reduced from 54 to 18, 10 as well as 6.

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