ABSTRACT

Electroencephalogram (EEG) is one of the most reliable physiological signal for emotion detection. Being non-stationary in nature, EEGs are better analysed by spectro temporal representations. Standard features like Discrete Wavelet Transformation (DWT) can represent temporal changes in spectral dynamics of an EEG, but is insufficient to extract information other way around, i.e. spectral changes in temporal dynamics. On the other hand, Empirical mode decomposition (EMD) based features can be useful to bridge the above mentioned gap. Towards this direction, we extract two novel features on top of EMD, namely, (a) marginal hilbert spectrum (MHS) and (b) Holo-Hilbert spectral analysis (HHSA) based on EMD, to better represent emotions in 2D arousal-valence (A-V) space. The usefulness of these features for EEG emotion classification is investigated through extensive experiments using state-of-the-art classifiers. In addition, experiments conducted on DEAP dataset for binary emotion classification. The effective features for EEG emotion classification in both A-V space, reveal the efficacy of the proposed features over the standard set of temporal and spectral features.

Index Terms— EEG, Emotion Recognition, Wavelet, Hilbert-Huang Transform, Empirical Mode Decomposition, Holo-Hilbert spectral analysis

1. INTRODUCTION

Human emotion has recently emerged to bridge the gap between humans-robot and human-computer interactions [1]. Even though facial expression and speech signals are two conventional modalities to recognize human emotions, both have several limitations in terms of social and cultural dependency of the subjects. Every psychological reactions which stimulates the human emotion, produces a physiological reaction as well. These physiological signal being involuntary and insusceptible to external environment, can assist in better and reliable understanding of subject’s underlying responses to any external stimuli. It has been explored through cognitive science and psychological experiments that electrical activity generated by brain plays a vital role in expressed emotions. Hence, Electroencephalogram (EEG) is one of the reliable physiological signal, which is commonly used to recognize emotion [2].

In the literature, EEG-based emotion recognition task have been focused in various areas, such as feature extraction, classification, selecting channels, artifacts filtering etc. [3]. A variety of features have been studied from time domain [4][5], frequency domain [6][7], and time-frequency domain for which two of the most common techniques used in the literature are Discrete Wavelet Transformation (DWT) [8][9] and Empirical Mode Decomposition (EMD) [10][11]. The work in [12] investigated the autoregressive (AR) features by using a Burg’s method, followed by a classification using K-nearest neighbor (KNN). The authors in [13] explored a wider set of emotion types by combining mutual information based feature selection methods and kernel classifiers. The work in [14] conducted the bi-spectral analysis of EEG using a arousal-valence (A-V) emotion model.

Although the work in [8][9][15] shows a remarkable segment-level recognition accuracy in EEG-based emotion recognition, but the common drawback in all is that segments from the same trial have been used in both training and testing. Consequently, the performance of same systems degrade drastically when tested on segments from unseen trials. Hence, in this paper we address trial independant binary classification. In this work, we explore the effectiveness of data-driven, adaptive, non-linear signal representation, EMD technique. Besides analysing the Intrinsic Mode Functions (IMFs) extracted from EMD at Marginal Hilbert Spectrum (MHS) level, we here explored one of the most recent technique developed to represent the non-linear signal, known as Holo-Hilbert spectral analysis (HHSA). To best of our knowledge, this is the first attempt to use HHSA for recognizing emotion in EEG. Further, we extract the multi-domain feature extraction based on DWT, EMD along with several other temporal and spectral features. We hypothesise that both DWT and EMD being complementary in terms of their ability to provide the temporal changes in spectral domain and vice-versa result in much more informative representation. The effective features for EEG emotion classification are investigated by an extensive experiments with three state-of-the-art classifier, namely, Support vector Machine (SVM), Random Forest (RF) and KNN. To utilise the complementary information provided by each feature set, we fuse the posterior of models trained with each of them, which improved the recognition accuracy. Our proposed approach with RF as a
classifier achieved weighted F1-score and accuracy of 67.2% and 68.8% on valence and 66.6% and 67.5% on arousal, respectively.

2. EEG BIOMARKERS FOR EMOTION RECOGNITION

In this section, we discuss the biomarkers explored for EEG emotion classification.

2.1. Spectro Temporal Features

2.1.1. Discrete Wavelet Transformation (DWT)

In DWT, the time-frequency representation is obtained by repeatedly filtering. Precisely, DWT decomposes the signal into two parts at each stage, (i) approximation and (ii) detailed signal. In the subsequent stages, the approximation signal is again decomposed into new approximation coefficient (AC) and the detailed coefficient (DC). This step is repeated which produces set of approximation signal at different detail levels and a final approximation of the signal. Here, we use ‘db4’ wavelet due to their efficient time-frequency localization properties. Moreover, it’s waveform is similar to EEG waveforms. The compact representation provided by extracted DWT waveforms shows the energy distribution of the EEG signal in both time and frequency domain. The DCs for signal sampled at 128Hz results into decomposed frequency bands of 4-8Hz, 8-16Hz, 16-32Hz, 32-64Hz, corresponds to standard EEG frequency bands (brainwaves) i.e. Theta (θ), Alpha (α), Beta (β), Gamma (γ), respectively. The initial DC i.e 64-128Hz corresponds to noise and is dropped. We extract entropy and energy for each of the frequency bands [8].

2.1.2. Empirical Mode Decomposition (EMD)

EMD is an adaptive algorithm that decomposes a signal into IMFs through an iterative process, known as sifting. Each IMF must satisfy the following two conditions [16]:

1. The number of maxima and minima are either equal, or differ at most by one.
2. The mean value of the local envelope defined by the local maxima and local minima is zero.

At each sifting iteration, highest frequency component present in the residue is extracted. The process terminates when residual signal either becomes a constant or signal with a single extremum from which no further IMF can be extracted. Thus, on the completion of EMD, original signal \( x(t) \) can be represented as the sum of \( K \) IMFs (\( I_i \)) and a residue \( res_K(t) \)

\[
x(t) = \sum_{i=1}^{K} I_i(t) + res_K(t)
\] (1)

The biggest advantage of the IMFs are well-behaved Hilbert transforms that allows the extraction of physically meaningful instantaneous frequencies. Unlike Wavelet Transform (WT) and Short Time Fourier Transform (STFT), IMFs have large time-bandwidth products that avoid the limitations of the uncertainty principle. Furthermore, EMD being data-driven doesn’t require apriori knowledge (time windows, mother wavelets etc.) about the signal that makes it more efficient to analyse the highly non-linear and complex EEG signals. After IMF computation, each of them are converted into analytic signal with Hilbert–Huang transform (HHT) to extract the instantaneous frequency (\( \omega \)) and instantaneous amplitude (a). We analyse these IMFs at three levels:

I. IMFs based temporal and spectral features [17]: For each IMFs \( I_i \), for \( i=1..K \), we compute set of five features, namely, IMF energy, spread \( (SP_{(I_{TED}))} \) and deviation \( (D_i(I_{TED})) \) of the instantaneous temporal energy density, spread \( (SP(\omega_i)) \) of the values of \( \omega \) and deviation \( (D_i(I_{ISED})) \) of the instantaneous spectral energy density [17].

II. MHS [16]: After applying HHT, once we have the instantaneous values \( (\omega_i, a_i) \) for each IMF \( I_i \), we compute Hilbert–Huang Spectrum \((H[\omega, t])\) that provides the time-frequency-amplitude distribution and is expressed as Eq. \( \text{2} \). From \( H[\omega, t] \), we compute the marginal spectrum \((h[\omega])\) that gives the total energy distribution within specified frequency bins over a whole signal length, as expressed in Eq. \( \text{3} \). These frequency bands are defined by minimum frequency \((freq_{min})\), maximum frequency \((freq_{max})\) and number of frequency steps \((n_{bins})\).

\[
H[\omega, t] = \text{Re} \sum_{i=1}^{K} a_i(t) e^{j \omega t} dt
\] (2)

\[
h[\omega] = \sum_{i=1}^{N} H[\omega, t]
\] (3)

where, \( N \) is the length of the time samples.

III. HHSAs [18]: This is one of the most recent spectral analysis technique for nonlinear systems that overcome the deficiencies of conventional spectral analysis and give a full informational representation of nonlinear signal. So far, the best possible way to analyse the non-linear signals was to use the time-frequency representations, in which the amplitude (or energy density) variation is still represented in terms of time. However, the non-linear signals often have the presence of intrinsic amplitude and frequency modulations which were left untreated by traditional spectral methods. HHSAs technique uses a nested EMD and HHT approach to identify these intrinsic amplitude and frequency modulations. Holomorphic prefix in HHSAs symbolizes a multiple dimensional representation with both additive and multiplicative capabilities [18].

The amplitude modulations described by the \( a \) are itself oscillatory. Thus, frequency information of these amplitude modulation signal can be described with another EMD. This process is called second-level sift in which \( a_i \) (per IMF \( I_i \)) extracted from first-level sift is further decomposed into another set of IMFs. Thereafter, the second-level frequency stats \( a_i \) and \( \Omega_i \) are computed. Now the holospectrums are computed
that describes the distribution of signal power as a function of both frequency of the carrier wave (first-level frequency stats) and the frequency of amplitude modulations (second-level frequency stats).

### 2.2. Temporal and Spectral Features

In temporal domain, we extracted four types of features [19], namely, (1) Fractal dimension with Higuchi and Petrosian algorithms; (2) Hjorth mobility and complexity parameters; (3) Detrended Fluctuation Analysis (DFA); (4) Hurst Exponent. The spectral features are extracted from the following frequency bands, namely, $\theta$ (4-8Hz), $\alpha_{low}$ (8-10Hz), $\alpha_{high}$ (10-13 HZ), $\beta$ (13-25Hz) and $\gamma$ (25-40Hz). The raw EEG signal is first transformed into frequency domain using fast Fourier transformation (FFT). Thereafter, 3 types of features [19][20] are extracted, namely, (1) Power Spectral Density (PSD); (2) Relative Intensity Ratio (RIR); (3) Spectral Entropy.

### 3. EXPERIMENTS

#### 3.1. EEG Database and Data Preprocessing

In this work, we use the Database for Emotion Analysis using Physiological signals (DEAP) which is having valence-arousal-dominance-liking emotion dimensions labeled [21]. One-minute long music video clips are used as a audio-visual stimuli to elicit emotions. There are 32 subjects, where each subject was shown 40 clips (trials), and for each trial 7 physiological modalities were recorded. Each trial has physiological recording of 40 channel in which first 32 channels correspond to EEG. Each subject has self rated the trial between 1 to 9 for each of dimensions. Here, we have used the preprocessed version [21] of data in which each trial (signal) data is downsampled from 512Hz to 128Hz and then band pass filtered (4.0-45.0Hz). Originally, each trial has 63sec of data which includes 3sec of pre-trial. In this work, we have taken only 60sec data, dropping the 3sec pre-trial.

In this paper we address the binary classification task which results by applying threshold ($\lambda$) on the self-assessments provided in [21]. The affective label will be set to high if the rating is $> 4.5$ and low if rating $\leq 4.5$. Thus for each trial, two labels were generated. V+ (high valence) or V- (low valence); and A+ (high arousal) or A- (low arousal) to get the affective level in valence and arousal space, respectively. We addressed the recognition in two dimensions, A-V, as two independent tasks and present them as a two-class problem.

#### 3.2. Feature Extraction

In this work, we used five different toolbox for extracting the features discussed in section [2]. We categorize them in six different sets as follows:

1. **set_A** contains temporal features plus PSI, RIR and Spectral entropy which are extracted using PyEEG [19]. All the features computed using PyEEG are at the trial-level without any frame-level computation.
2. **set_B** contains PSDs of 5 frequency bands as mentioned in section [2.2] and is computed using BioSPPy Toolbox [20] with 4sec windows and 2sec overlap.
3. **set_C** contains spectro temporal features computed using DWT as discussed in section [2.1.1] with 4sec windows and 2sec overlap, followed by decomposition of each window into 5 levels with PyWavelets tool [22] and thus, retaining all frequency components as 4 frequency bands (excluding the first detailed component as noise) as discussed in section [2.1.1]. Finally, energy and entropy are computed in each band.
4. **set_D** contains IMFs based temporal and spectral features. We use PyEMD tool [23] for decomposing each trials into IMFs. As EM is data-driven, the number of IMFs varies among trials, we got 10 as the least number of IMFs. So, to maintain the uniformity, 10 IMFs per 1280 trials are considered and then 5 features (as discussed in section [2.1.1]) per trial are extracted.
5. **MHS and HHSA**: We use end [24] python tool to compute the two spectrums, with $freq_{min}$ and $freq_{max}$ as 5Hz and 45Hz to match with standard EEG frequency band limit. For $n_{bins}$, we experimented with values ranging from 4 to 128 (higher value gives better frequency resolution). $n_{bins}=64$ and $n_{bins}=5$ performed the best for MHS and HHSA respectively. It returns a 2D matrix with dimension of $K\times n_{bin}$ for MHS and $n_{bin}^{1}\times n_{bin}^{2}$ for HHSA. Here, $n_{bin}^{1}$ and $n_{bin}^{2}$ corresponds to first-level and second-level frequency bins as discussed in section [2.1.2].

The default frequency bands in PyEEG are modified as BioSPPy’s 5 frequency band to make the feature extraction uniform. All the features in set_B and set_C are first computed at the frame-level and later averaged to give the trial-level features.

#### 3.3. Features and IMF Selection

Concatenating the features from all 32 channels, results in high dimensional complexity and information redundancy. Thus, we performed the feature selection for each of the feature sets discussed in section [3.2]. We evaluated each individual features and all possibles subsets of the same. The only subsets performing best or almost similar to the overall set are retained. Also, EMD technique decomposes a signal
in a way such that initial IMFs contains the higher oscillation frequencies and it keeps reducing down with further decomposition. Hence, we analysed the contribution of each IMFs by considering IMFs in incremental fashion, starting with IMF-1 to IMF-10. We found that higher IMFs are more informative and performance starts degrading or saturates as we keep increasing the lower level IMFs. Based on performance, we selected top 4 IMFs for valence and top 3 IMFs for arousal for further experiments.

### 4. RESULT AND ANALYSIS

In all experiments, we use stratified 5-fold cross-validation, to maintain the imbalance ratio across each folds. The imbalance ratio for both arousal and valence is quite high with a distribution of \((A_{high}=818, A_{low}=468)\) and \((V_{high}=808, V_{low}=472)\). In order to overcome the biased learning, we incorporated the class weights using python’s `sklearn` utility. Table 1 represents the features selected from each of four sets followed by bands (/IMFs) selection, and reduced feature dimension. For MHS and HHSA, we considered first 4 IMFs as discussed in section 3.2, followed by flattening the output 2D-matrix to feed the classifiers used. Thus, MHS and HHSA resulted into vector of dimension \(4^*64^*32=8192-D\) and \(5^*5^*32=800-D\). We further reduced the dimension of MHS by taking only 10 frontal channels \(8\), giving the vector of 2560-D.

The hyperparameter of classifiers (KNN, SVM, RF) are tuned using `GridSearch`, where we found KNN with \(K=3\) to be best among \(K=3, 5, 8\). For SVM, `rbf` kernel performed best. We tuned RF with grid of parameters `estimators` and `depth` with a set of values where former varying from 50 to 300 with an increment of 50 and latter varying from 6 to 18 with an increment of 2 w.r.t each feature set. From the results presented in Table 2, we found the PSDs with RF (\(estimators=120\), \(estimators=8\)) and set A features with RF (\(estimators=210\), \(estimators=8\)) to be performing best in terms of weighted F1-score of 67.02% and 65.73%; Classification Accuracy (CA) of 67.42% and 66.56%, on valence and arousal, respectively.

It is to be noted that DWT and EMD-based features; HHSAs specifically, trained on RF, performs competitively as compared to the best ones. Hence, we perform late fusion on the posteriors of best performing models, trained individually on each feature set. As shown in Table 2, RF performs best for all the feature sets on both arousal and valence, except set A in valence for which SVM worked best. Fusing posteriors further improved the performance, with weighted F1-score of 67.02% and 66.66%; CA of 68.8% and 67.5% (as shown in Table 3), on valence and arousal, respectively.

Due to varied experimental setting in terms of evaluation method, classification task, dataset etc., we couldn’t directly compare the earlier EMD based work in EEG Emotion Recognition [10, 11]. In Table 3 we compare our approach with existing state-of-the-art work on Emotion Recognition using DEAP data with similar settings as ours i.e subject-dependent and binary class classification. Our approach performed best among all for the valence. For arousal, while [26] performs better by 0.8%, it is important to be noted that segments used in train and test are from same trials which degrades drastically if tested on unseen trials. Whereas our evaluation method (like [23,27]) is trial-independent.

### 5. CONCLUSION

In this paper, we address trial-independent EEG-based emotion recognition in A-V space. We explored the richness of EMD by analysing MHS and HHSA. Further, we extract the multi-domain feature extraction based on DWT, EMD along with several other temporal and spectral features. Both DWT and EMD being complementary, result in boosting the performance. To investigate the effectiveness of these features with several other temporal and spectral features for emotion classification using EEG, an extensive experiment has been performed. Experiments conducted on DEAP and comparison made with earlier work indicates the efficacy of our proposed approach. To best of our knowledge, this is the first attempt to use HHSA for recognizing emotion in EEG. In future efforts, tempo-spatial deep models shall be investigated to capture the 2-D HHSA representation more efficiently.

**Table 2.** Weighted performance on different sets with feature selection (F1: F1 score, CA: Classification Accuracy)

| Feature set | Valence | Arousal |
|-------------|---------|---------|
|             | RF      | SVM     | KNN     | RF      | SVM     | KNN     |
| set A       | 65.52   | 65.31   | 65.80   | 66.24   | 64.53   | 65.07   | 65.73   | 66.86   | 62.83   | 63.41   | 65.33   | 64.93   |
| set B       | 67.02   | 67.42   | 61.50   | 61.32   | 61.10   | 61.87   | 64.84   | 65.31   | 36.64   | 57.09   | 62.35   | 60.96   |
| set C       | 65.56   | 65.93   | 67.22   | 60.15   | 59.18   | 59.76   | 65.53   | 64.92   | 60.70   | 61.40   | 61.88   | 60.69   |
| set D       | 66.24   | 67.26   | 62.70   | 63.91   | 62.67   | 63.51   | 64.70   | 65.85   | 58.28   | 59.07   | 63.12   | 61.95   |
| MHS          | 65.52   | 66.71   | 67.90   | 64.83   | 63.51   | 64.06   | 65.17   | 66.33   | 59.77   | 60.37   | 61.09   | 59.85   |
| HHSA         | 66.56   | 67.33   | 58.80   | 58.20   | 62.37   | 62.73   | 64.91   | 65.46   | 60.55   | 61.18   | 59.84   | 58.63   |

**Table 3.** Comparison results for emotion recognition on DEAP dataset

| Features                | Classifiers     | CA       |   |   |
|-------------------------|-----------------|----------|---|---|
| DBN features [25]       | SVM             | 58.4     | 64.2 |
| Multiband Feature Matrix [25] | CapsNet      | 66.7     | 68.3 |
| Empirical Wavelet Transform [27] | SVM           | 64.3     | 67.3 |
| Our approach (with late fusion) |                | 68.8     | 67.5 |
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