Mutual Information Between Inter-Hemispheric EEG Spectro-Temporal Patterns: A New Feature for Automated Affect Recognition

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***Abstract*— Automated electroencephalography (EEG) based affect recognition has gained a lot of interest recently, with clinical (e.g., in autism), human-computer interaction (e.g., affective brain-computer interfaces), neuromarketing, and even multimedia (e.g., affective video tagging) applications. Typically, conventional EEG features such as spectral power, coherence, and frontal asymmetry have been used to characterize affective states. Recently, cross-frequency coupling measures have also been explored. In this paper, we propose a new feature set that combines some of these aforementioned paradigms. First, the full-band EEG signal is decomposed into four subband signals, namely theta, alpha, beta, and gamma. The amplitude modulation (or envelope) of these signals is then computed via a Hilbert transform. These amplitude modulations are further decomposed into 10 cross-frequency coupling patterns (e.g., gamma-beta coupling pattern). The mutual information between each of these ten patterns is then calculated for all inter-hemispheric EEG electrode pairs. To gauge the effectiveness of the newly-proposed feature set, the so-called DEAP database was used. Experimental results show the proposed feature set outperforming conventional ones for estimation of arousal, valence, dominance, and liking affective dimensions. Gains of up to 20% could be achieved when the proposed features were fused with spectral power and asymmetry index features, thus suggesting complementarity between spectral and spectro-temporal features for automated affective state recognition.**

I. INTRODUCTION

Automated affective state recognition has gained increased interest lately, particularly in clinical [1], human-computer interaction (HCI) [2], and multimedia/advertising quality-of-experience perception [3], [4] applications. To this end, both wearable sensors (e.g., galvanic skin response, heart and breathing rates) and neuroimaging (e.g., electroencephalography, EEG and near-infrared spectroscopy, NIRS) devices have been explored, with EEG emerging as one of the most prominent modalities [5]. The basic premise behind this so-called 'affective computing' field is to provide humans and machines with emotional intelligence that would otherwise not be available. In the former scenario, it can provide relatives and/or caregivers of e.g., children with autism spectrum disorders or individuals with emotional and behavioural disorders cues about their emotional states, or vice-versa, as well as multimedia services providers and ad agencies of the emotional impact of their delivered content [4]. In the latter setting, it can provide machines with cues that will allow them to be perceived as more social, thus potentially improving their popularity.

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With the advances in brain-computer interface (BCI) technologies witnessed over the last decade, tools have emerged enabling so-called 'affective BCIs' [2]. The aim of affective BCIs is to detect in real-time the affective states of its users and use that information for either offline or online feedback. In the latter setting, for example, existing applications for affective BCIs include the monitoring of the user's stress level while using a brain speller or a robotic interface and adjust the system's response time accordingly, or the user's engagement level while playing a videogame and adapting the game difficulty accordingly [6].

As mentioned previously, the use of EEG has been prominent within the scope of affective BCIs and conventional features have been widely used, such as EEG subband frequency powers [7], wavelet coefficients [8], and spectral coherence [9]. Moreover, frontal asymmetry [10] has also been shown to be a useful indicator of emotional states, particularly dispositional mood, temperament and reactivity to emotionally provocative events. On the other hand, alternate feature representations have been shown useful in clinical settings but have received little attention within the affective BCI community. Representative features include EEG cross-frequency coupling [11] and spectro-temporal neuromodulatory analysis [12].

In this paper, we propose to develop a new feature set that encompasses several of the key paradigms mentioned above, particularly inter-hemispheric interactions, cross-frequency coupling, subband and spectro-temporal analysis. The overarching goal is to harness the advantages of each modality into a single feature set for improved automated affective state characterization. Special emphasis is placed on the neuromodulatory aspect, motivated by the fact that "the presence of amplitude modulation in bioelectrical processes is of fundamental nature, since it is a direct reflection of the control, synchronization, regulation and interaction in the nervous and other body systems" [13]. Experiments were performed on a publicly-available EEG dataset [7] and results showed that the proposed features outperformed conventional (baseline) spectral-based features by around 15% (relative) in emotion recognition accuracy. Moreover, when the proposed features were fused with spectral power and frontal asymmetry index parameters, relative gains of up to 20% could be achieved over the baseline.

The remainder of this paper is organized as follows. Section II provides the methodology used, including a description of the proposed and baseline features. Sections III and IV describe the experimental setup and results, respectively. Lastly, Section V presents the discussion and conclusions.

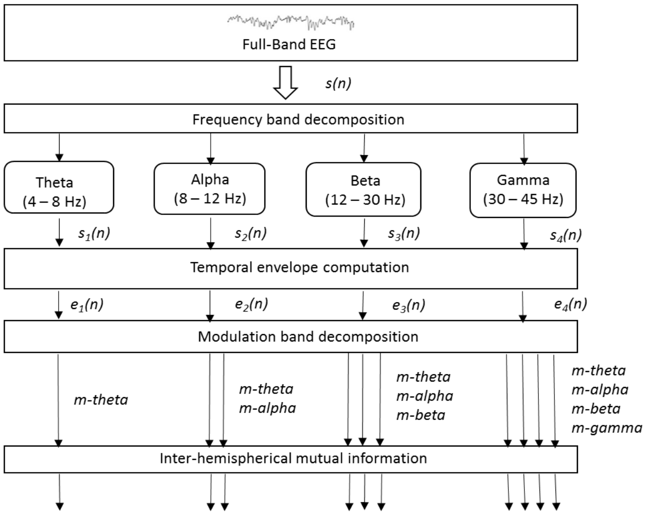


Fig. 1: Processing steps for proposed feature computation

II. METHODOLOGY

This section describes the proposed feature set and the baseline features used for performance comparison.

A. Proposed feature set

Figure 1 depicts the signal processing steps involved in the calculation of the proposed features. First, the full-band EEG signal is decomposed into four frequency subband temporal signals $s_i(n), i = 1, \ldots, 4$ (theta, alpha, beta, and gamma, respectively) using elliptic bandpass filters. Next, a Hilbert transform is used to compute temporal amplitude envelopes $e_i(n), i = 1, \ldots, 4$ for each of the four subband signals. Temporal envelopes are further decomposed into four so-called modulation frequency bands using 2nd order bandpass filters in order to obtain amplitude-amplitude cross-frequency coupling patterns as in [12]. The modulation frequency bands have been empirically calculated to coincide with the theta, alpha, beta, and gamma subbands to facilitate cross-frequency coupling analysis. To distinguish the frequency subbands from the modulation subbands, the latter is referred to as m-theta (4-8 Hz), m-alpha (8-12 Hz), m-beta (12-30 Hz) and m-gamma (30-45 Hz). According to Bedrosian's theorem, only ten of these cross-frequency coupling patterns (see Fig. 1) make mathematical sense [12]. We use the notation $A(B_i, m - B_j)$ to indicate the spectro-temporal pattern for frequency subband B_i and modulation subband $m - B_j$ for $i = 1, \ldots, 4$ and $j = 1, \ldots, 4$.

These ten spectro-temporal patterns serve as the basis for the proposed feature set. In order to incorporate asymmetry cues into the proposed features, we use the mutual information (MI) between inter-hemispheric spectro-temporal patterns. Unlike coherence, which measures only linear relationships between spectral patterns, MI provides an estimation of both linear and non-linear statistical dependencies between time series. In order to compute MI, the probability density function of the spectro-temporal patterns $A(B, m - B)$ (where indexes i and j were omitted without loss of generality) were found via 2-D histogram analysis for two given inter-hemispheric electrodes. With these probability functions available, MI can be computed, by [14]:

$$MI(X;Y) = H(X) + H(Y) - H(X,Y), \qquad (1)$$

where $H(X)$ (or $H(Y)$) indicates the marginal entropy of variable X (or Y) and $H(X,Y)$ indicates the joint entropy of variables X and Y. Here, X and Y represent $A(B_i, m - B_j)$ for two inter-hemispheric electrodes, say X and Y. In this study, the following fourteen electrode pairs were used: Fp1-Fp2, AF3-AF4, F7-F8, F3-F4, FC5-FC6, FC1-FC2, T7-T8, C3-C4, CP5-CP6, CP1-CP2, P7-P8, P3-P4, PO3-PO4, and O1-O2. For the sake of notation, we refer to one such mutual information feature as an *inter-hemispheric amplitude modulated interaction* (IAMI) feature. A total of 140 such IAMI features are extracted, corresponding to the ten spectro-temporal patterns times the 14 inter-hemispheric pairs.

B. Baseline features

As baseline features, conventional EEG subband spectral power and asymmetry indices were computed. A total of 184 baseline features were computed, including 128 spectral power features (4 subbands $\times$ 32 electrodes) and 56 asymmetry features (4 subbands $\times$ 14 inter-hemispheric electrode pairs, as described in Section II-A).

III. EXPERIMENTAL SETUP

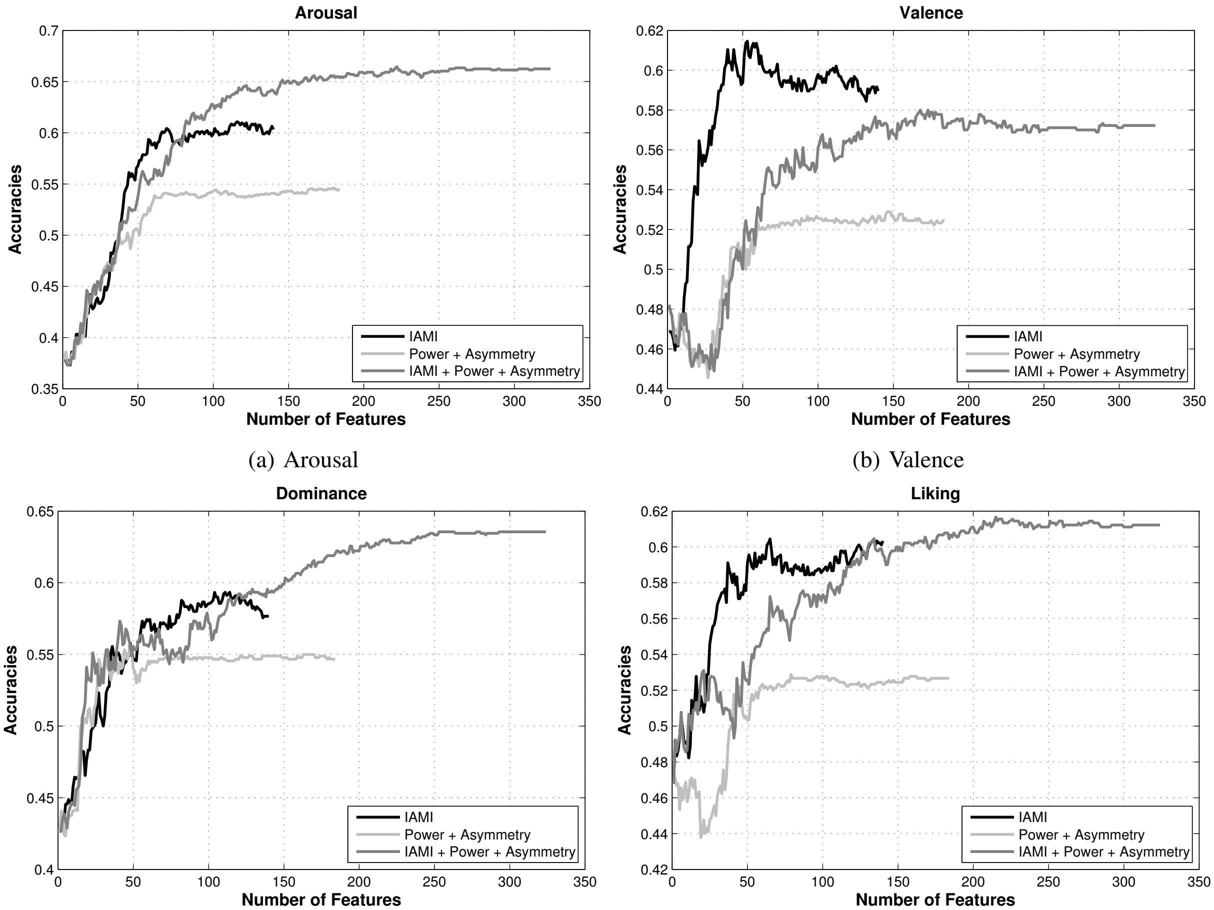
In this section, the database used, as well as feature ranking and classifiers explored are described.

A. Affective stimuli database

The DEAP database [7] was used in the experiments. The database is publicly available and is composed of EEG from 32 participants while they watched 40 1-minute long excerpts of music videos, which were hand-picked to elicit different emotional states. EEG signals were recorded using a 32-channel BioSemi Active II device using the 10-20 international electrode placement system. The pre-processed dataset was used here, where the original dataset was downsampled to 128 Hz, bandpass filtered from $4 - 45$ Hz, averaged to a common reference, and had ocular artifacts removed using principal component analysis as described in [7]. For each music clip, participants rated their levels of arousal, valence, dominance, and liking using a 9-point continuous scale.

B. Feature ranking and classifier design

Of the 140 extracted IAMI features and 184 baseline features, some may not contribute significantly to the task at hand. As such, we have ranked all features based on their importance to each of the four classification tasks using the minimum redundancy maximum relevance algorithm [15]. Feature ranking was done for the IAMI feature set alone, the baseline feature set alone and the combined feature set. For classification, a support vector classifier with default parameters (regularization coefficient $C = 1$ and $\gamma = 0.01$)



(a) Arousal (b) Valence

(c) Dominance (d) Liking

Fig. 2: Accuracy versus number of features for the baseline, proposed, and fused feature sets for the (a) arousal, (b) valence, (c) dominance, and (d) liking affective dimensions.

and a radial basis kernel was used. For analysis, 25% of the data were set aside for feature ranking and were selected such that high and low class values were represented in the set for the arousal, valence, dominance, and liking dimensions. Since a 9-point scale was used, ratings greater or equal to 5 were classified as high and those below 5 as low. The remaining 75% of the data were used, within a leave-one-out cross-validation paradigm, to train and test the classifiers to detect the low/high class values. Training was done with the proposed and baseline feature sets alone, as well as fused.

IV. RESULTS

Figures 2(a)-(d) depict the accuracy of the SVM classifiers for the arousal, valence, dominance, and liking affective dimensions, respectively, as a function of number of features used. Accuracy plots are shown for classifiers trained with only the proposed IAMI features, only the baseline, as well as the combined feature set. As can be seen, the proposed features outperform the baseline ones for all four affective dimensions, but with higher gains seen in the valence and liking dimensions. Interestingly, these were the hardest dimensions to estimate with conventional EEG features in [7].

Table I, in turn, reports the highest accuracy obtained for each feature set, along with the corresponding F1-score and number of features with which such accuracy levels were attained. Numbers within parentheses indicate the relative gains attained when compared to the baseline results. As can be seen, relative gains as high as 15% could be achieved with the proposed features for the valence estimation task and accuracy; 19% relative gain was seen in F1-score. Most importantly, it can be observed that these gains were achieved using 65% fewer features (53 vs 146). When the two feature sets were combined, the largest relative gain was seen for the arousal dimension where a 20% relative gain was seen with only 20% more features (222 vs 180).

V. DISCUSSION

As seen from Figures 2, the proposed features clearly outperform the baseline ones for all four classification tasks. The performance of classifiers trained on either the proposed or baseline feature sets tended to stabilize at around 60 features, but with the proposed feature set achieving substantially higher accuracy. This was particularly true for the valence and liking dimensions, which are typically the hardest ones

TABLE I: Performance comparison of feature fusion and single modality for the four different emotion dimensions. Numbers represented by "%" indicate the relative improvement, in percentage, over the baseline.

Dimension	Metric	IAMI (%)	Baseline	Fusion (%)
Arousal	Accuracy	0.61 (11)	0.55	0.66 (20)
	F1 Score	0.61 (11)	0.55	0.66 (20)
	No. features	115	180	222
Valence	Accuracy	0.61 (15)	0.53	0.58 (10)
	F1 Score	0.62 (19)	0.52	0.57 (10)
	No. features	53	146	168
Dominance	Accuracy	0.59 (5)	0.56	0.64 (14)
	F1 Score	0.59 (7)	0.55	0.62 (13)
	No. features	82	48	253
Liking	Accuracy	0.60 (13)	0.53	0.62 (17)
	F1 Score	0.61 (15)	0.53	0.61 (15)
	No. features	65	79	215

to classify using conventional EEG features [7]. In fact, from Table I for the valence dimension, roughly one third of the features were needed to outperform the baseline features (53 vs 146 features). Such findings highlight the benefits of the compact representation of the proposed features for reliable affective state characterization. An in-depth analysis of the top-60 selected features showed that roughly half came from alpha-band spectro-temporal patterns. For the valence and arousal dimensions, the $A(alpha, m-theta)$ pattern was the most prominent. Previous work has linked alpha-theta coupling to memory [16], which in turn has been shown to be modulated by valence and arousal [17], thus suggesting that internal (affective) references may have played a key role during the experiment. The proposed features seem to be able to characterize such memory effects, unlike conventional features, thus corroborating their complementarity.

With the fused feature set, in turn, performance stabilization occurred once approximately 150 features were used to train the classifiers. Careful analysis of these top-150 features showed that for the four dimensions, roughly 66% of the features belonged to the IAMI set, with the majority of the remaining features belonging to the EEG asymmetry index set. Channel pairs that provided the most relevant features were located in the frontal (Fp1-Fp2 and AF3-AF4) and parietal regions (P7-P8 and P3-P4), thus corroborating the importance of frontal asymmetry for affective state recognition, particularly those involving high arousal states [18]. From Table I, it can be seen that overall the combined feature set resulted in the highest relative gains compared to the baseline, with the exception of the valence affective dimension which saw the IAMI features achieving the best performance. Such findings may be an artifact of the classifier design used here. Since the goal of the study was to test the effectiveness of the proposed features at classifying four different affective dimensions (or primitives), only default SVM classifier parameters were utilized. It is expected that additional gains in accuracy and F1 scores can be achieved once the classifier parameters have been optimized via grid search strategies.

VI. CONCLUSIONS

In this paper, a new feature set was proposed for automated affective state recognition. The proposed features quantify the mutual information between spectro-temporal amplitude modulation patterns between inter-hemispheric electrodes, thus were shown to result in a more compact and accurate representation for affective state recognition. Experiments on a publicly-available EEG dataset showed them outperforming baseline features by as much as 20%.

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