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Analysis of Facial Electromyography Signals Using Linear and Non-Linear Features for Human-Machine Interface*

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Abstract— **In this work, an attempt has been made to analyze the facial electromyography (facial EMG) signals using linear and non-linear features for the human-machine interface. Facial EMG signals are obtained from the publicly available, widely used DEAP dataset. Thirty-two healthy subjects volunteered for the establishment of this dataset. The signals of one positive emotion (joy) and one negative emotion (sadness) obtained from the dataset are used for this study. The signals are segmented into 12 epochs of 5 seconds each. Features such as sample entropy and root mean square (RMS) are extracted from each epoch for analysis. The results indicate that facial EMG signals exhibit distinct variations in each emotional stimulus. The statistical test performed indicates statistical significance (p<0.05) in various epochs. It appears that this method of analysis could be used for developing human-machine interfaces, especially for patients with severe motor disabilities such as people with tetraplegia.**

I. Introduction

Electromyography is a technique that is used to record the electrical activity of neuromuscular activities. They are highly non-stationary and non-linear signals produced by neuromuscular activities. Electrophysiology and the recording environment highly influence the properties of these signals [1]. Hence, there is a great challenge in analysing EMG signals [2].

Facial Electromyography (facial EMG) is a type of electromyography where electrical activities are recorded from the facial muscles of human beings. Research studies using facial EMG signals have been conducted to find emotional information. Researchers have attempted to obtain emotional information using various physiological signals individually or through two or more physiological signals. Research using physiological signals are challenging as they are complex and very subjective [3]. However, they are considered the most reliable method because of their ability to the inherent activity of the autonomous nervous system and capture the unexpressed emotions that cannot be identified visually [4, 5].

Facial EMG signals are widely used for affective computing. They are used to understand the responses to hypertension, stress, and stroke patients [3, 6, 7]. Researchers have found that the facial EMG signals recorded from facial muscles such as zygomaticus major, corrugator supercilii, frontalis, and trapezius are beneficial to understand the emotional states of a person. The predominant muscles during the expression of emotions have been identified by Anton van Voxtel [8]. It has also been identified that the signals obtained from the zygomaticus major muscle effectively differentiate the positive emotions, while the signals recorded from the corrugator supercilii muscle are effective in differentiating the negative emotions [3, 9, 10].

This paper reports our attempt to differentiate different emotional states using the facial EMG signals obtained from the DEAP dataset, using linear and non-linear features. One positive emotion (joy) and one negative emotion (sadness) are used in this analysis.

II. Methodology

A. Dataset Preparation

The DEAP Dataset is established by a research group from the Queen Mary University of London [11]. It is a publicly available dataset comprising of multiple physiological signals like electromyography (EMG), electroencephalography (EEG), electrodermal activity (EDA), and other bioelectrical signals with emotive evaluations. It is a widely used dataset used by various researchers for emotion analysis. Thirty-two healthy subjects (16 males, 16 females) volunteered for the establishment of this dataset. They were asked to watch 40 one-minute-long videos, each called a trial, which provided the video/audio stimuli with different emotive inclinations. Then, the subjects were asked to assess the video in terms of the four basic affective dimensions – arousal, valence, dominance (rated on a scale of 1 to 9) and liking (thumbs up or thumbs down). They were also asked about the familiarity of the video, which was rated on a scale of 1 to 5.

In this work, we have used the facial EMG signals recorded from the zygomaticus major muscle, available as the 35th channel in the preprocessed DEAP dataset. It contains the bioelectric signals downsampled to 128 Hz, and the duration of each trial is 63-s, segmented into pre-trial baseline signal (3-s) and trial signal (60-s). We have considered the trials based on the following two emotions for our study: (1) Positive Emotion: Joy, (2) Negative Emotion: Sadness.

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B. Pre-processing and Feature extraction

The pre-trial baseline signal (3-s) is removed, and the remaining 60-s duration of the signal is passed through a high pass filter (passband cutoff – 20 Hz) and a notch filter (50 Hz) to remove any artefacts due to external movements and machine interference. The entire duration of the signal is segmented into 12 epochs of 5 seconds each. The following features are, then, extracted from two emotions, namely joy and sadness, in each epoch for our analysis:

- Root Mean Square (RMS) [12]:

$$\text{RMS} = \sqrt{\frac{1}{M} \sum_{p=1}^{M} {x_p}^2} \qquad (1)$$

where x_p represents the filtered EMG signal in a segment *p,* and *M* denotes the length of the facial EMG signal.

- Sample Entropy (SaEn)[13]: To calculate SaEn, the scalar-time series $\{t_1, t_2, \ldots., t_n\}$ is first embedded in a delayed m - dimensional space, where the vectors are assembled as,

$$t(p) = [t(p+k)]_{k=0}^{m-1}, p = 1, 2, .., n-m+1 \qquad (2)$$

The probability that $X^m(z)$ that two sequences match for m points is calculated by counting the average number of vector pairs, for which the distance is lower than the tolerance *z*. Similarly, $Y^m(z)$ is the probability for an embedding dimensional space, m+1. SaEn is then calculated as:

$$SaEn\,(t, m, z) = -\ln(Y^m(z)/X^m(z)) \qquad (3)$$

The tolerance *z* is chosen as 0.25 * standard deviation of the segment of facial EMG signal, and the number of delayed dimensions (m) is chosen as 2 for this study.

The Wilcoxon rank-sum statistical test is then performed to check for significant differences between the two emotional states. The pipeline of the proposed methodology is shown in fig. 1.

III. Results and Discussions

Fig. 2 shows the representative facial EMG signals recorded during joy and sadness audio-visual stimuli. It is seen that the amplitude of the facial EMG signal varies with time. Specifically, each segment of the signal has varied characteristics. It is observed that the fluctuations in the joy signal are found to be higher.

Fig. 3 (a) depicts the variation of RMS feature in joy and sadness stimuli. It is seen that the amplitude of the signal decreases with the presentation duration in both stimuli. The joy signal has a higher amplitude in all segments for this subject. The variance in the joy stimuli is higher.

In fig. 3 (b), the variation of sample entropy feature with joy and sadness stimuli is shown. It is observed that the entropy values in sadness stimuli result in higher entropy values in most segments. The variance of the sadness signal is higher. A maximum percentage difference value is observed in the third segment.

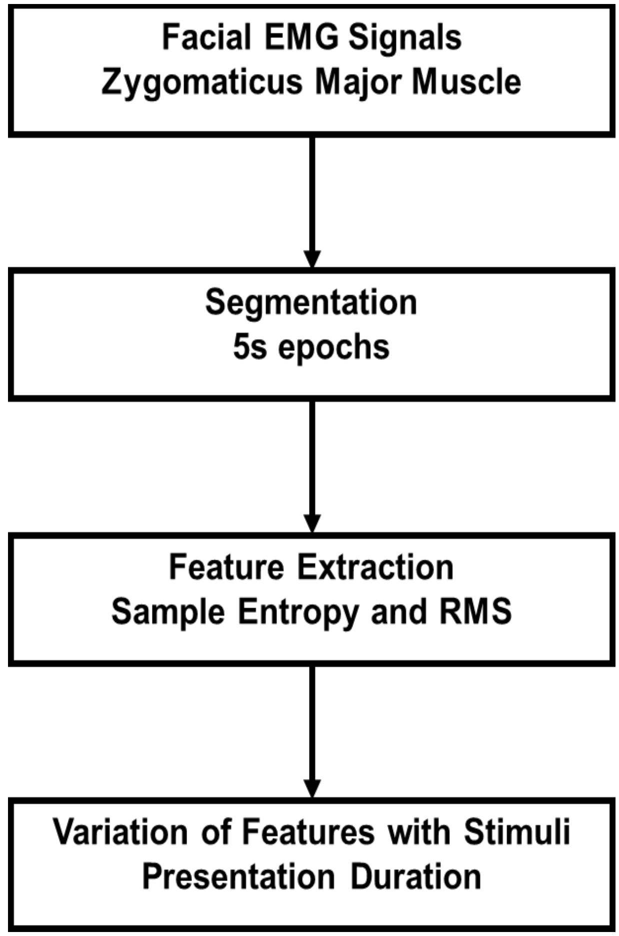
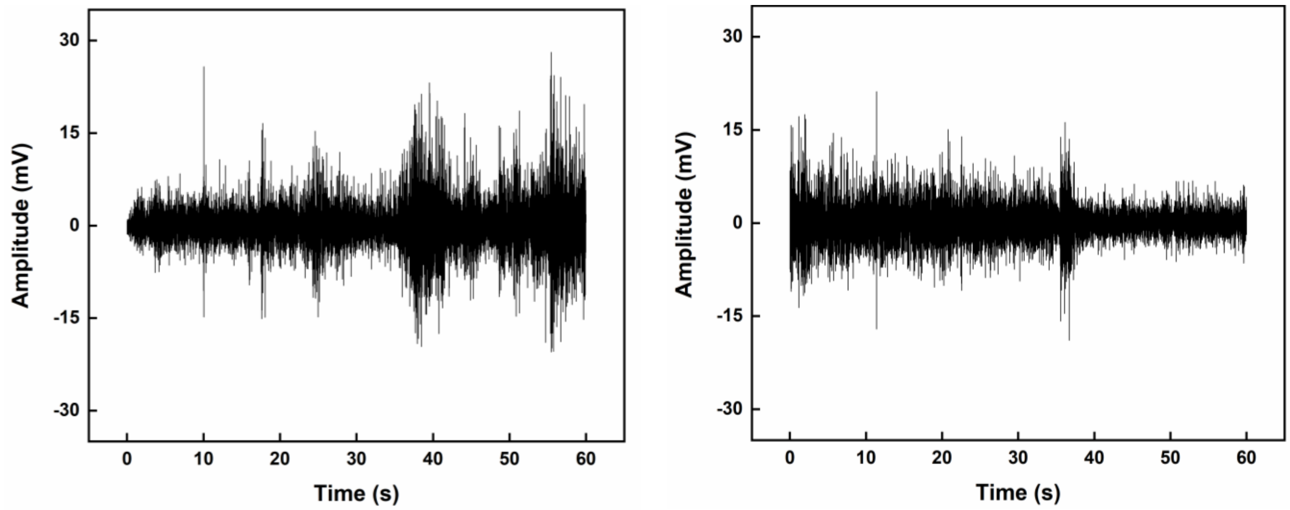


Figure. 1 Flowchart of Methodology

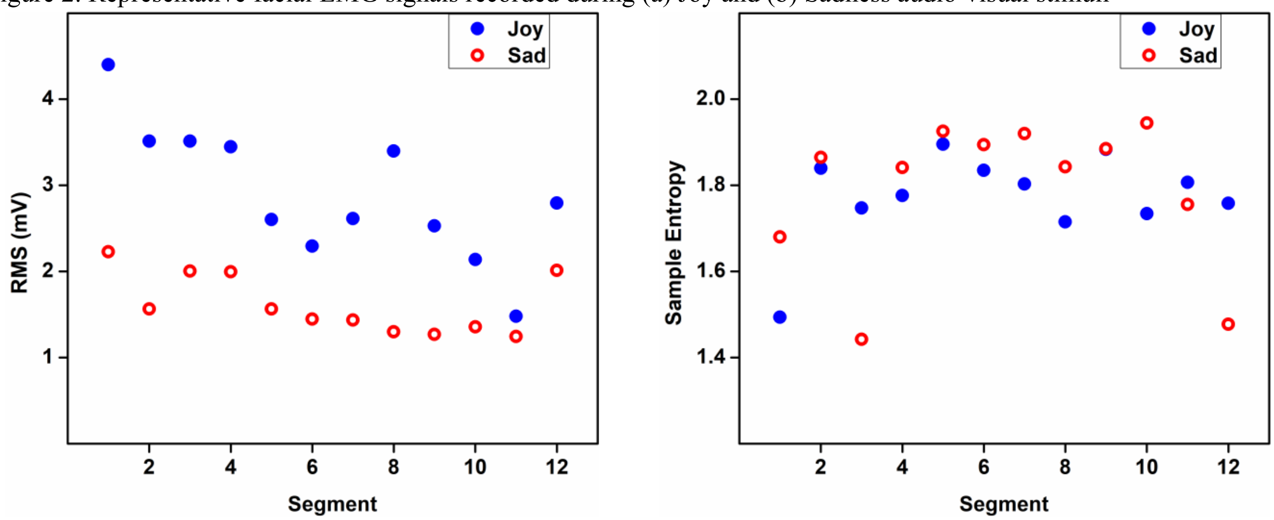
Fig 4 (a) shows the variation in the RMS in segment nine. It is seen that the median of Joy is higher than the sadness signals. It is also observed that the interquartile range of sadness is lower, which indicates a lower inter-subject variability. Further, both stimuli result in a skewed distribution.

Fig 4 (b) depicts the distribution of the sample entropy feature in segment seven. It is observed that in the joy condition, a median value of 1.78 is observed. In the case of sadness stimuli, an increase in the medial value to 1.83 is seen. These lower entropy values in joy indicate lower complexity of the signal. It might be due to the systematic activation of facial muscles to generate the expression of joy. Similar to RMS, the sadness has a lower interquartile range indicating a lower inter-subject variability.



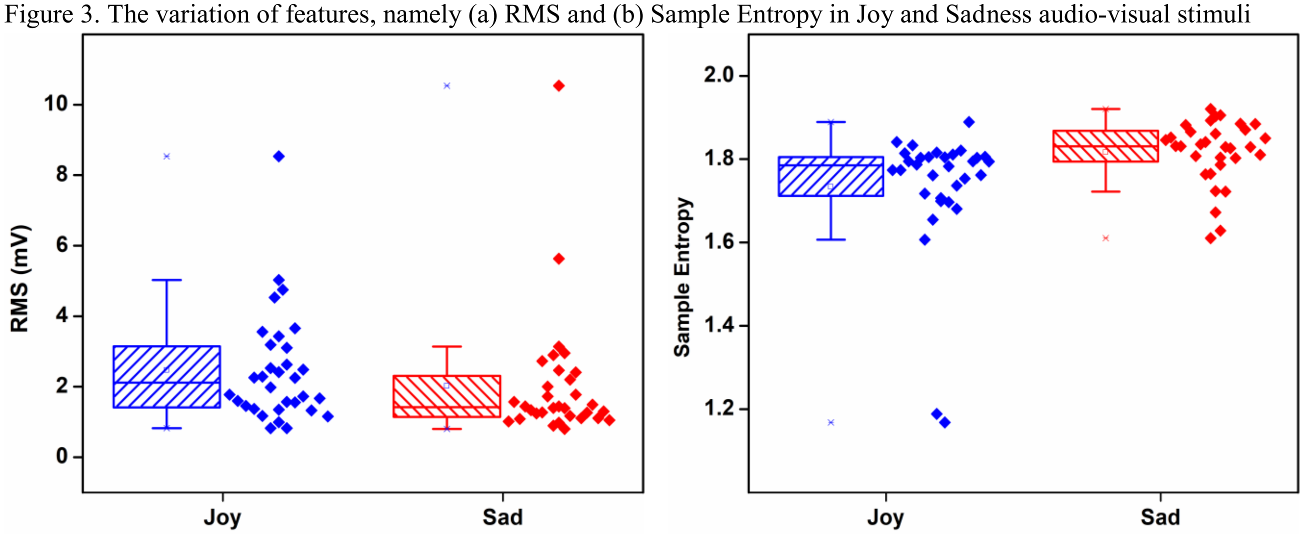
(a) (b)

Figure 2. Representative facial EMG signals recorded during (a) Joy and (b) Sadness audio-visual stimuli



(a) (b)

Figure 3. The variation of features, namely (a) RMS and (b) Sample Entropy in Joy and Sadness audio-visual stimuli



(a) (b)

Figure 4: Boxplot of (a) RMS and (b) Sample Entropy in a representative segment

TABLE I. STATISTICAL VARIATION OF THE FEATURES IN EACH SEGMENT

Segment	RMS	Sample Entropy
1	0.0709	**0.0105**
2	0.0946	0.3237
3	0.1146	0.2192
4	**0.0462**	**0.0462**
5	0.1566	0.1028
6	0.2680	0.0668
7	**0.0476**	**0.0004**
8	0.0507	0.0752
9	**0.0356**	0.3719
10	**0.0393**	**0.0333**
11	0.0730	0.2622
12	0.0894	0.2295

In table 1, the statistical variation of the features extracted to differentiate the two emotions, joy and sadness, in each segment is shown. It is seen that the features in segments four, seven, nine and ten are statistically significant ($p<0.05$) in differentiating joy and sadness. In the case of sample entropy, segments one, four, seven and ten are statistically significant ($p<0.05$). This difference in amplitude and complexity of the signal indicates that emotion is a complex process and varies with the presentation duration. It is also to be noted that the type of stimuli elicits different reactions in each individual, resulting in overlapping feature values. The complexity feature, namely, sample entropy, uses relative amplitude values compared to RMS, resulting in lower inter-subject variability.

IV. CONCLUSION

In this work, EMG signals from the zygomatic major facial muscle are analysed to differentiate various emotional states. For this, signals from the DEAP database belonging to joy and sadness audio-visual stimuli is considered. The EMG signals are preprocessed and segmented into 5-s segments and used for analysis. Features such as RMS and sample entropy are extracted from each segment. The results indicate that the facial EMG signals exhibit distinct variation in each of the emotional stimuli. Segment-wise differences are observed in both the RMS and entropy features. Specific segments of the signal exhibit statistically significant differences between joy and sadness. Specifically, in segments greater than the 30-s, these features result in more significant differences in the mean and lower overlap. This indicates that the presentation duration may have an impact on emotion elicitation. In future, EMG signals recorded from other facial muscles could be studied to classify emotions better. The proposed methodology might be helpful in developing human-machine interfaces using facial EMG.

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