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EEG Based Human Facial Emotion Recognition System Using LSTMRNN

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ABSTRACT

Emotions are phenomena of affective time varying that are result elicited. Videos and movies are made to facial emotions particular in their persons. To detecting emotions instantaneously in viewers, it can be used to find the traces of videos based on the emotion. In this paper to proposed our approach in instantaneously detecting the emotions of videos, emotions from Electro encephalogram (EEG) signals and facial expressions emotion. A set of emotion videos were shown to participants while their facial expressions emotion and physiological responses were recorded. The expressed negative to positive emotions in the videos of participants' faces was detected by five types of emotion. The Long-short-term-memory recurrent neural networks (LSTM-RNN) and the signal feature to measure using PSD, and facial feature to detection using SDM were utilized in detecting emotions automatically and continuously process. They found the results from facial expressions emotion to be superior to the results from EEG signals. To analyzed the effect of facial emotion activities on EEG signals and found that most of the emotionally valuable information data content in EEG features is as a result of this contamination. And our statistical analysis and looking that EEG signals it can be carry risk types of information data in presence of facial expressions.

Keywords: Band pass filter, Gabor filter, PSD, SDM, LSTMRNN.

1. INTRODUCTION

A major role is those facial expressions starting to check a functional and not a communicative one. I will try to measure many classical expressions with its functional initially role, Anger to involve major three features teeth revealing, eyebrows down and inner side tightening, squinting eyes. The function is clear to preparing for attack in every emotion. The teeth are ready to bite and enemies, eyes and eyebrows squinting eyes to protect. And surprise very similar to fear expression. Because a surprising situation can frighten us for a moment, and then it also depends whether the surprise is a good or a bad one. Therefore the function is similar process. Sadness is a slight pulling down of lip corners expression, eyebrows inner side is raising. Darwin exposes this expression by suppressing the will to cry. The control upper lip is greater than the control over lower lip, so the lower lip drops. When a person will cry, to protect the eyes are closed in order them from blood pressure that accumulates in the face. Happiness is usually involves a corner of the mouth Rising and smile. The squinting eyes and eyes corners wrinkles appear.

Figure 1: Facial Expression

2. BLOCK DIAGRAM EXPLANATION

The goal of emotion detection is to identify the emotional of videos, and then the ground truth should reflect the expression of facial emotions. For particular reason, to detecting the expected emotion using both continuous arousal and valence labels and when annotated directly did not have the same limitation as annotating facial expressions of emotion that made annotating arousal impossible. The EEG signal preprocessing using band pass filter, and feature extracted by using PSD algorithms. Then the emotion video converted to frames after that the preprocessing using Gabor filter, the feature extraction using SDM algorithm, and finally the signal with facial emotion result classified using LSTMRNN classifier. The results are given in figure 3.the facial results are classified to the EEG signals and fusion of two models does not outperform facial expressions. Facial expressions output to perform the EEG signals. The results are in better average of the results obtained using the expression-based emotion, this might be as a result of different types of factors that to summarize as follows. The viewers at all times feel the emotions that are expected facial expression; e.g., a person have already followed a surprising moment in a movie scene and it is surprising emotion of facial expression to her for the second type time. Often times only express or feel high level of emotion or the emotional response usually decays after this process due to the result of simulation.

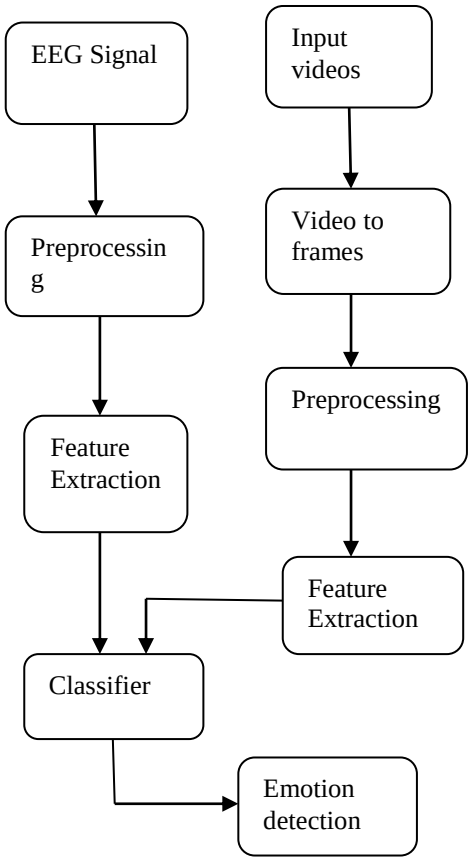

Figure 2: Block diagram of the automatic detection of the person emotion based on EEG.

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Multi-user fusion of image has been shown to detect superior results in emotional profiling of videos using physiological of EEG signals compared to single user response.

It can be to verify whether the model trained on annotations EEG based on facial expression analyses can reflect on the case without any facial expressions. It can be chose one of the videos with directional emotional highlight moments, the church scene from “Love Actually”, and took the EEG responses of the 13 participants who did not show any significant of the detection. Since these responses of the emotion did not include any visible facial expressions, they were not used for the annotation procedure of the image and were not in any form in our training data of the image. We feature extracted the power spectral features from their EEG responses and fed it into our models and the output response will accuracy better.

The output is very successful detection. The emotion can detect angry, sadness, happy, surprise. Advantages of automatic person expression detection are accuracy high. And to analyze the types of facial muscle activities on EEG signals and to detect most of the emotionally valuable information content in EEG features is as a result of this contamination. However, our statistical analysis and viewed that EEG signals it can be carry complementary information data in presence of facial expressions.

3. SIMULATION RESULT

The average valence curve, emotional trace, resulted from the EEG signals of participants who did not show any facial expressions while watching a scene from angry actually. The general facial emotion trend is correlated with the emotional moments. The result of the signal and curve figure is best seen in color.

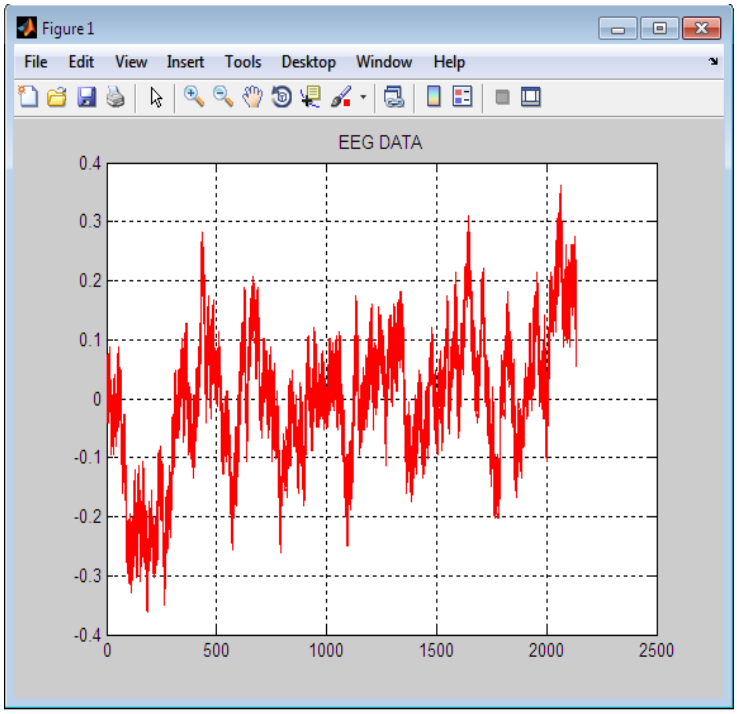

Figure 1: EEG data signal

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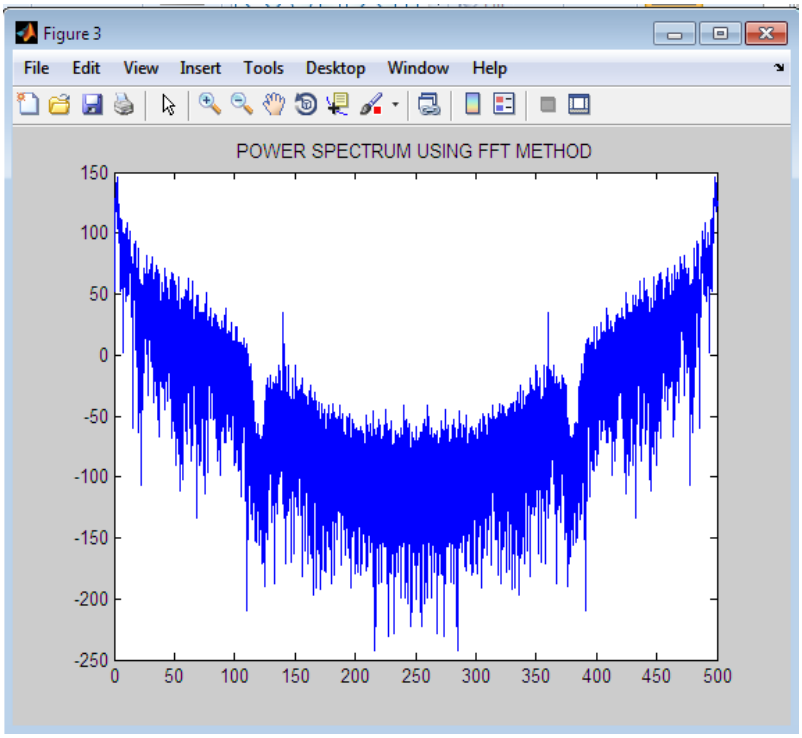

Figure 2: power spectrum of FFT signal

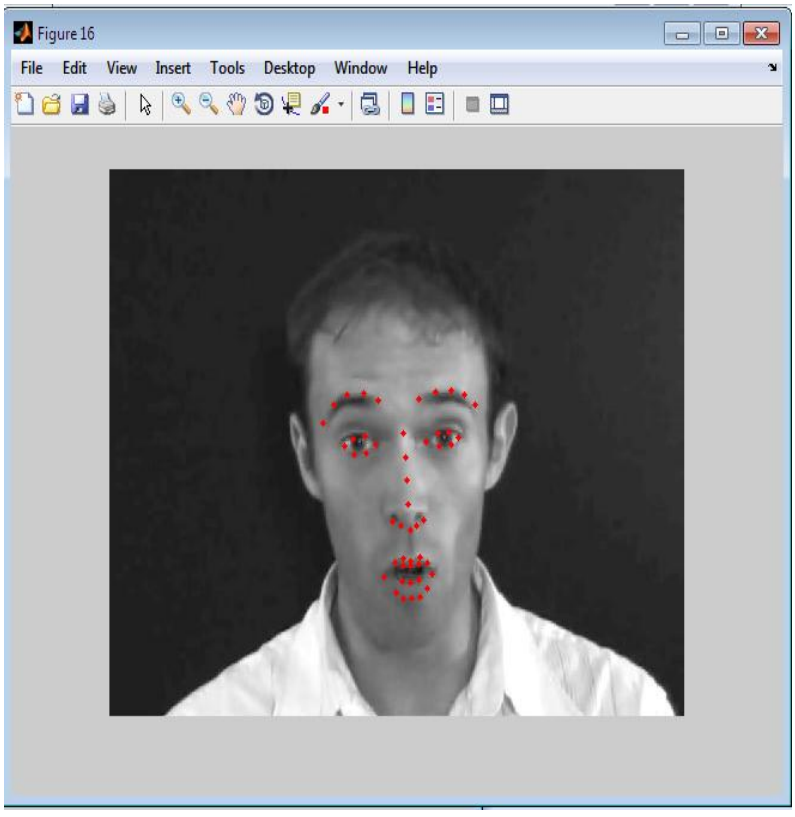

Figure 3: Facial expression detection

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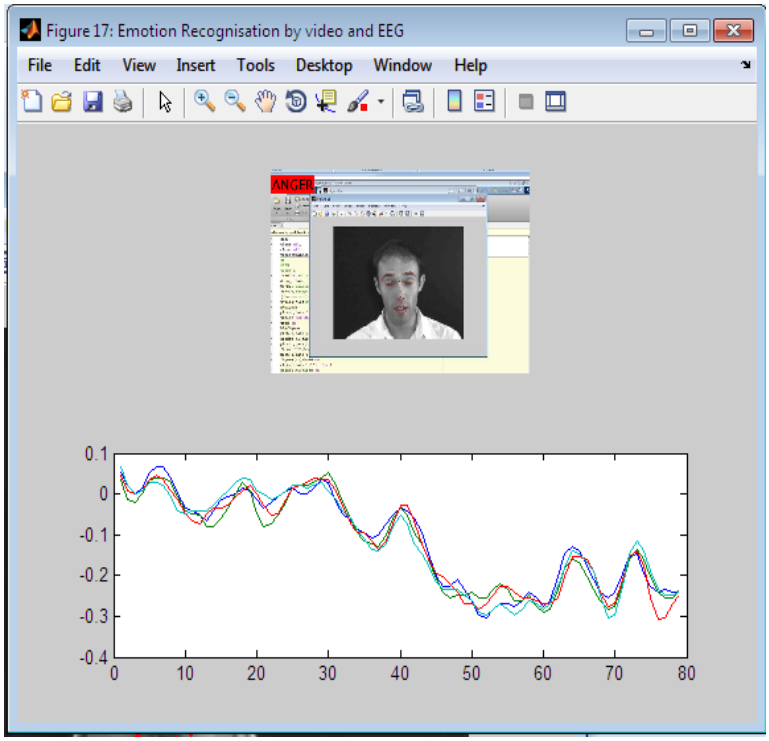

Figure 4: Facial emotion detection using EEG

4. CONCLUSIONS

These they presented a view of continuous detection of valence using EEG signals and facial expressions. Promising results were obtained from EEG signals and facial expressions. Then they expected the results from facial expressions to be superior due to the bias of the ground truth towards the expressions, i.e., the ground truth was generated based on the judgment of the facial expressions. The results from the statistical test on the linear mixed effect model showed that EEG modality carries useful information for detecting valence. The information gain data from including EEG signals improved the performance of the detection in our different fusion emotion. In the future work, it will be beneficial to record multimodal data for the sole aim of understanding the assumption and causation relationships between facial expressions and EEG signals. The recordings of the future work can include major acted and spontaneous expressions in different situations.

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