Hybrid Fusion Techniques For (Face And EEG) Based Emotion Recognition

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Abstract- *This paper proposes two multimodal fusion methods between brain and peripheral signals for emotion recognition. The input signals are electroencephalogram and facial expression. The stimuli are based on a subset of movie clips that correspond to four specific areas of valance-arousal emotional space (happiness, neutral, sadness, and fear). For facial expression detection, four basic emotion states (happiness, neutral, sadness, and fear) are detected by a neural network classifier. For EEG detection, four basic emotion states and three emotion intensity levels (strong, ordinary, and weak) are detected by hybrid algorithms like LSTM AND RNN, respectively. Emotion recognition is based on two decision-level fusion methods of both EEG and facial expression detections by using a sum rule or a production rule. Twenty healthy subjects attended two experiments. The results show that the accuracies of two multimodal fusion detections are achived better results comparatively existing SVM and NN algorithms. The combination of facial expressions and EEG information for emotion recognition compensates for their defects as single information sources.*

Keywords- electroencephalogram, emotion, emotion recognition, LSTM-RNN, affective computing.

I. INTRODUCTION

Humans make use of face as an important clue factor for identifying people. Hence, face recognition technologies have been associated generally with very costly top secure applications. The face recognition, as one of the most representative applications of image analysis and understanding, has received a significant interest, due to wide range of applications such as video surveillance, biometric identification, and content-based video indexing/search. One"s everyday communication is highly influenced by the emotional information available to one about people with whom he/she communicates with. Understanding the emotions and knowing how to react to people"s expressions also greatly enrich the interaction. Thus, recognition of facial expression is highly relevant for human–computer interaction and may gain broad applications in video annotation, situation analysis of social interactions. Furthermore, recognition of facial emotion is more essential that one should be aware of the current emotions of the person; he/she is interacting, and the situation analysis of social interactions and contextual analysis. Facial expression is the most effective form of non-verbal communication and it provides a clue about emotional state, mindset, temperament and intention (Ekman 2001). Frequently, all humans express their emotions through their facial expressions. A facial expression is a gesture executed with facial muscles, which convey the emotional state of the subject to observers. Six important facial emotions are accepted in the set of measurements such as happiness, sadness, anger, fear, surprise and disgust as suggested by Ekman et al. (1978). The six facial expressions" functional role is shown in Figure 1.

Figure 1 Samples of six facial expressions from RML database

- **Happiness:** usually involves a smile - both corner of the mouth rising and wrinkles appear at eyes corners. This expression represents the happiness and smile.
- **Sadness**: involves stretching down of lip corners, and the inner side of eyebrows is raised. Generally, this expression will intend to be the reason for even crying.
- **Fear:** involves wide eyes and sometimes open mouth. The process of opening the eyes in a wide manner results in helping the visual field to be increased.
- **Disgust**: involves crumpled nose and mouth. In a few conditions even it involves tongue advent out. This expression reveals a person who has tasted bad food and wants to spit it out, or smelling foul smell.
- **Surprise**: looks like an expression of fear. Perhaps, an astonishing situation can scare everyone for a short moment, and then it continues depending on whether the surprise is a good or bad one.

- **Anger**: involves three main features - teeth exposing, eyebrows down and inner side stiffening, squinting eyes. The emotion anger expresses ready for defend.

Face Recognition system is thus, much more effective than any other biometric measurements. Human face supplies a diversity of different communicative functions such as identification, gender recognition and the perception of emotional expression which helps in authentication process and on different affective domain based applications. Initially, for face, gender and emotion recognition, there is a need to detect the location and the scale of the face region in image/video sequences. Face detection detects the facial features only and neglects other background details such as buildings, trees and bodies (hands, neck). The outline sketch of the proposed research work is shown in Figure 2.

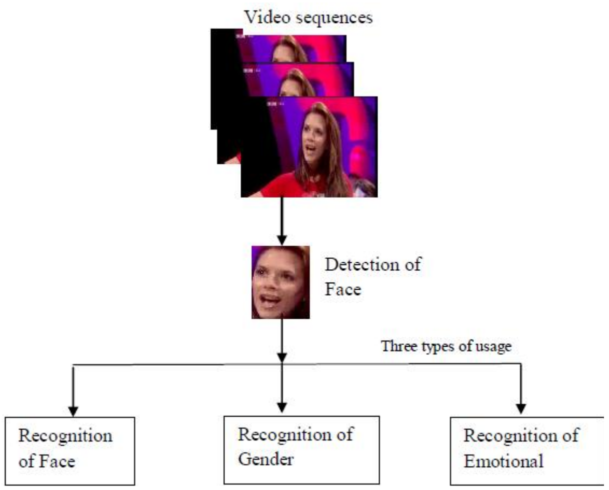


Figure 2 Outline sketch of the proposed research work

The rest of the proposed paper is referred as follows: - A review of existing works is done in Section II. Section III includes the proposed technique. Simulation results and performance analysis is done in Section IV.. Section includes the network model and proposed energy harvesting technique. Simulation results and performance analysis is done in Section V

II. LITERATURE REVIEW

In this section various literature works on face, gender and emotion recognition systems are outlined. Face detection is the initial stage of face, gender and emotion recognition system, as a face has to be located in the input image with various objects.

Human are often more emotional, than we wish to be, and our feelings influence the way we work, play and interact with computers. Effective computing is a domain that focuses on user emotions while interacting with computers for such applications [1, 2]. As emotional state of a person may influence concentration, task solving and decision making skills, effective computing vision is to make systems able to recognize and influence human emotions in order to enhance productivity and effectiveness of working with computers [3, 4]. Emotion recognition and effective intervention are nowadays well recognized desired features of intelligent tutoring systems [5], with primary focus on such learner effective states as flow, boredom or frustration. Another areas of effective computing methods applications include: testing driver stress, psychological diagnosis and training, neurobiofeedback etc. Recognition of facial expression results in identifying the basic human emotion like anger, fear, disgust, sadness, happiness and surprise. These expressions can vary in every individual. Researchers [1,6] have found that 7% of message is conveyed by spoken words, 38% by voice intonation while 55% of message is conveyed by facial expression. Facial expressions [5] are produced by movement of facial features. The basic mechanisms of the emotion detection system are as follows [7]

First step is face detection. First the machine takes an image, then by skin color segmentation it detects human skin color and then it detects human face. Then background need to be separated so as to obtain the region of interest of the captured image. So second is normalization phasethat remove the noise and normalize the face against brightness and pixel position. In third phase features are extracted and irrelevant feature are eliminated. In the final step basic expressions are classified into six basic emotions like anger, fear, disgust, sadness, happiness and surprise. Emovoice [8] is a comprehensive framework for real time recognition of emotion from acoustic properties of speech. It has been recently integrated as toolbox into the social signal Interpretation (SSI) framework which is also from the Lab for multimedia concept and application. There are several types of classifiers such as ANN [9][10] Hidden Markov models (HMM) [11], statistical tools etc and modeling problems. One of the main advantages of HMMs is their ability to model non-stationary signals or events. Dynamic programming methods allow one to align the signals so as to account for the non-stationarity[9]. However, the main disadvantage of this approach is that it is very timeconsuming since all of the stored sequences are used to find the best match of emotion expression, the signal is the measurements of the facial motion. Again the efficiency of a statistical classifier is poor as it cannot classify samples with minor differences. However researchers have found the ANN as one of efficient classifier for stationary as well as nonstationary signals. ANNs are non-parametric prediction tools that can be used for a host of pattern classification and speech recognition purposes. It is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information [9]. The fundamental information-processing unit of the operation of the ANN is the McCulloch-Pitts Neuron (1943)

III. SYSTEM DESIGN

Proposed design used to collection of EEG signal dataset get it from kaggle dataset, and a Logitech camera (25 FPS, 800 × 600 image size) was used to capture facial expressions. According to the standard 10–20 system, the EEG signals are referenced to the right mastoid. The EEG signals used for analysis were recorded from the "Fz" electrode. For our proposed system, the EEG and facial expression detectors were designed separately. The EEG and image data were fed into the two detection procedures simultaneously

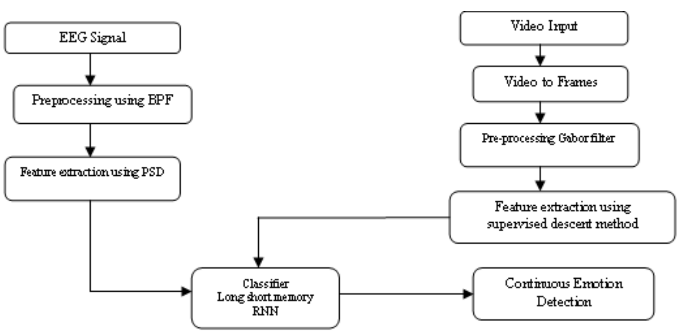


Figure 3 block diagram for proposed system design

Figure 1 shows the data processing procedure. The analysis methods and algorithms used in this study are described below. The location of the eye and the mouth regions are used for facial emotion recognition. Each pixel within the eye and mouth region contains (□□□□) 32-dimensional Gabor features. The block of temporal features which are extracted from the signature of the eye and mouth region is explained below. Initially, the training set is formed in the database-4 ( ) 4 *DB* using the temporal Gabor signatures from the collection of training videos having happiness, sadness, fear, anger, surprise, disgust and neutral expressions. During the temporal feature extraction stage, each training set contains 910 temporal features. To learn discriminative features for better facial expression classification, a form of multi-class classifier is required. Hybrid LSTM-RNN algorithm is a well-known method of constructing a combination of classifiers, and has shown good performance. Multi-class algorithms involve steps of LSTM-RNN multiclass weak classifiers including computationally costly process such as decision trees and have high potential for overfitting. A novel method is proposed to instantaneously detect the emotions of video viewers' emotions from Electro encephalogram (EEG) signals and facial expressions. Long-short-term-memory recurrent neural networks (LSTM-RNN) and Continuous Conditional Random Fields (CCRF) were utilized in detecting emotions automatically and continuously.

IV. RESULT AND DISCUSSIONS

Fractal and power spectral features are used to analyze RNF and LSTM-RNN classifier yielded classification accuracy is very efficient. To assess the performance of the proposed Emotion detection system used to combinational features of EEG and facial. It is obtained by auto facial image camera with a resolution of 1504x1000 pixels in the RGB mode. The simulation of the proposed system first phase emotion detection system is done in MATLAB R2013a and tested on Intel architecture under the windows operating system. From figure 1 describe the input images of facial and corresponding EEG signal.

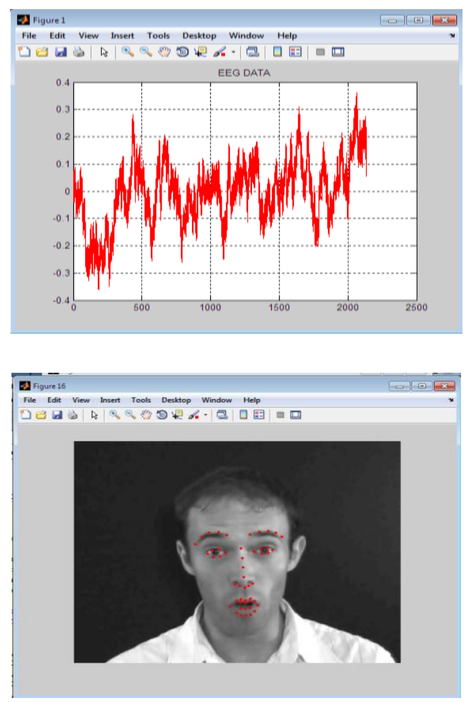
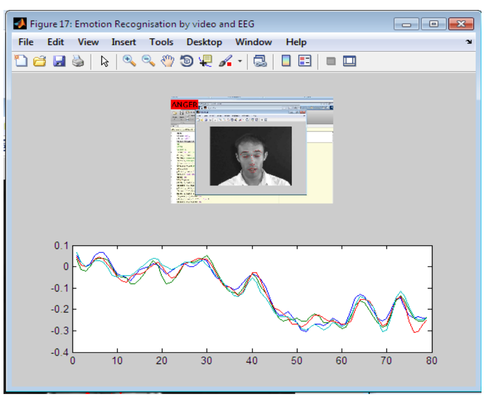
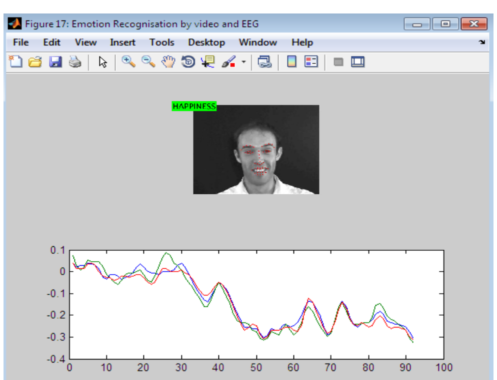


Figure 4 Input Data a) EEG Data b) Facial Data

Figure 4 describe the input dataset selection image acquisition, This proposed fusion technology combined with facial expression recognition technology and EEG emotion recognition technology. The stimuli are based on a subset of movie clips that correspond to four specific areas of valance-arousal emotional space (happiness, neutral, sadness, and fear). The four emotion states are detected by both facial expression and EEG. Emotion recognition is based on a decision-level fusion of both EEG and facial expression detection.

For the decision-level fusion, the classifier selection for facial expression and EEG detections is also important. Several properties have to be taken into consideration, such as the long term variability of facial expression signals and the availability of small data sets of EEG signals. First, the neural network-based methods are found to be particularly promising for facial expression recognition, since the neural networks can easily implement the mapping from the feature space of face images to the facial expression space. Second, a neural network model generally requires a large amount of high-quality data for training. In this study, the EEG signals recorded by a one-electrode mobile device could lack sufficient training data for the neural network-based method. Third, LSTM-RNN is known to have good generalization properties and to be insensitive to overtraining and to the curse-of-dimensionality, especially in the small data set. It should be noted that LSTM-RNN classifier was widely used in the EEG-based brain computer interface in practice. Furthermore, some modified Long short-term memory methods had the advantage of using a regularization parameter to control the number of support vectors and margin errors. For example, Gu and Sheng developed a modified LSTM formulation based on a sum-of-margins strategy to achieve better online accuracy than the existing incremental RNN algorithm





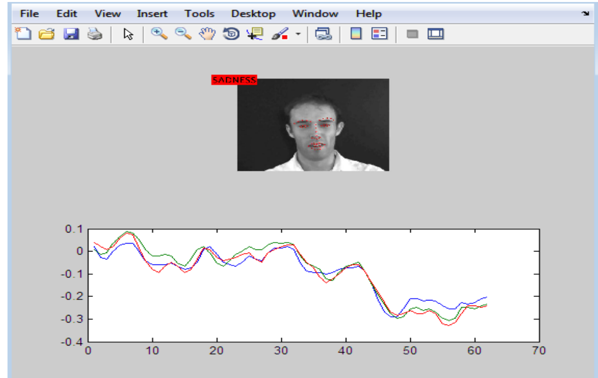


Figure 5 simulation results for **a)** angry detection b) happiness detection c) sadness detection

Figure 5 describe the results obtained different emotion detected by the corresponding different datasets. They further proposed a robust RNN method based on lower upper decomposition with partial pivoting, which results in fewer steps and less running time than original one does. From the below diagram figure 6 implementation of phase two hardware setup done by phython software for following library files tensorflow, opencv, keras, and numpy. Software algorithm effectively used by cnn.

Figure 6 Hardware implementation for emotion detection

Figure 6 rael time face detection and emotion detection results below implementation result conclude to find each emotion percentage which emotion is most percentage result of hardware implementation displayed comparatively simulation results hardware implementation results very effective and python platform are security concern in future development.

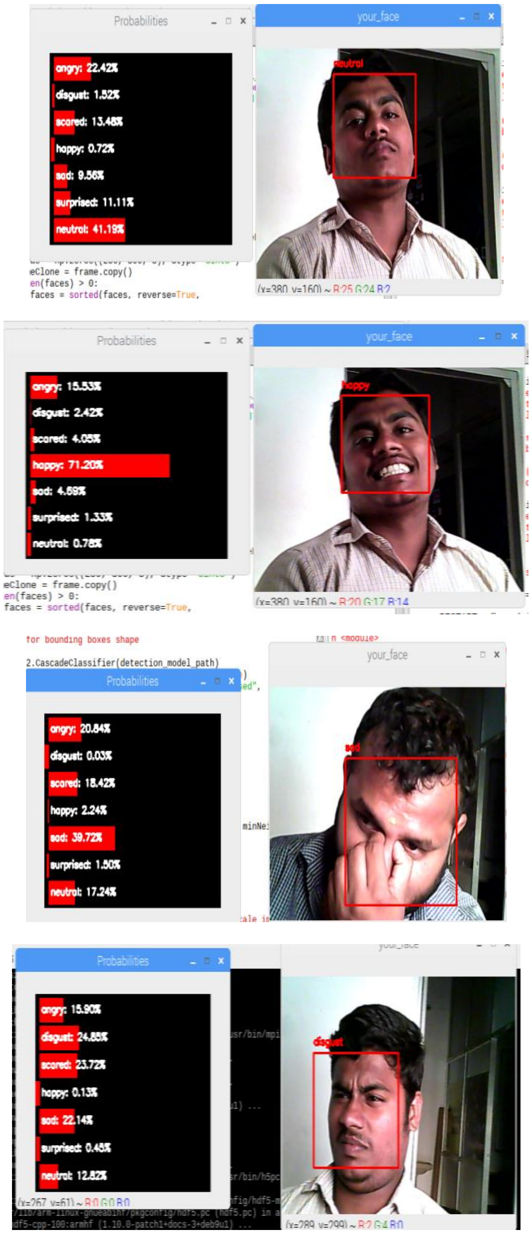


Figure 7 proposed system real time emotion prediction results

Taken together, the neural network classifier was used for the facial expression detection, and the LSTM-CNN classifier was used for EEG detection in this study.

V. CONCLUSION

Two multimodal fusion methods are proposed in this study. For the first fusion method, Hybrid LSTM-RNN classified the EEG signal into the four types of emotion, and fusion is performed using a sum rule. For the second fusion method, Hybrid LSTM-RNN classified the EEG signal into three intensity levels (weak, moderate, and strong), and fusion is performed using a production rule. It is interesting to note that the second fusion method combining type of emotion and intensity level yields comparable average accuracies with the first fusion method. Indeed, it might very well be what humans do for emotion recognition: for example, an expression of weak happiness is typically answered with neutral, whereas a strong expression of sadness usually evokes fear. This study still has open issues that need to be considered in the future. At this present stage, the image data set we obtained is very limited, and the EEG signals used for analysis were recorded from only one electrode. In the future, however, we will collect more image data from more subjects and use a more complicated model to train our data to yield a classifier with better performance. Furthermore, we could consider an EEG device with more electrodes to obtain higher-quality data.

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