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EEG Based Emotion Recognition: A State of the Art Review of Current Trends

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ABSTRACT:

Human existence depends on emotions, which also significantly influence thought. Emotion is frequently associated with logical judgement, perception, interpersonal communication, and, to some extent, human intellect. With the growing interest of the scientific community in the establishment of some important "emotional" exchanges between people and computers, there is a need for reliable and practical methods for the identification of human emotional states. Since consumer-grade wearable EEG devices may provide a cheap, portable, and simple way to identify emotions, the scientific community has taken a particular interest in recent developments in electroencephalography (EEG) for emotion recognition.This cutting-edge review discusses the components of study size, EEG hardware, machine learning classifiers, classification approach, and emotion stimuli kind and presentation strategy. Based on this state-of-the-art review, we suggest a number of areas for further study, including a novel technique for presenting the stimuli as virtual reality (VR). An additional portion that is specifically dedicated to reviewing solely VR publications within this study subject is presented as the explanation for this proposed novel method using VR as the stimuli presentation technology.

Keywords- EEG, sensors, human emotion, motion analysis, wireless communications, Internet of Things, wearable sensors, physiological parameters monitoring

INTRODUCTION

The Electroglottograph (EGG) as an emotion recognition system, by measuring differences in pitch. Our aim is to improve current emotion recognition systems that still have limitations. The goal is to find out if there is a relationship between the pitch, in terms of vibrationaround the neck, as to the emotion felt by a person, and if extroverts and introverts would have different pitches for the same emotion. There are various applications for our proposed emotion recognition system. Firstly, it can be enhanced lie detector to detect discrepancy between emotional and verbal messages. Secondly, it can identify social-emotional problems in toddlers. Thirdly, automatic emotion recognition can improve human-machine interactions and human computer interactions, such as in humanoid robots, car industry, call centers, mobile communication, and computer tutorial applications.

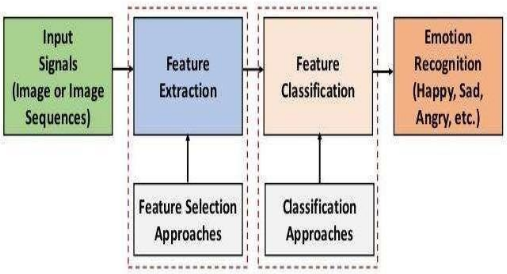


Fig 1: A simple process involved in the human emotion recognition system

The brainwave signal of a humanbeing produces insurmountable levels of neuron signals that manage all functionalities of the body.human brain stores the emotional experiences that are gathered throughout their lifetime. By tappingdirectly into the brainwave signals, we can examine the emotional responses of a person whenexposed to certain environments. With this information provided from the brainwave signals, it canhelpstrengthen and justifythe person is physicallyfit or maybesufferingfrom mental illness.

TECHNICALDETAILSOFTHEPAPER

There is a standardized procedure for the placements of these electrodes across the skull, and theseelectrode placement procedures usually conform to the standard of the 10–20 international system.The actual distances between the adjacent electrodes either 10% or 20% of the total front to back orright to the left of the skull. Additional electrodes can be placed on any of the existing emptylocations. The electrode positions placed according to the 10–20 international system. Depending onthe architectural design of the EEG headset, the positions of the EEG electrodes may differ slightlythan the standard 10–20 international standard. EEG headsets with a higher number of channels willthen add electrodes to the temporal, parietal, and occipital lobe such as the 14-channel Emotive EPOC+ and Ultra cortex Mark IV. Both these EEG headsets have wireless capabilities for datatransmission and therefore have no lengthy wires dangling around their body which makes it feasiblefor this device to be portable and easy to setup. Furthermore, companies such as Open BCI provide3Dprintable designs and hardware configurations for their EEG headset which provides unlimitedcustomizationto their headset configurations.

Fig 2: The Position of electrodes CapKit

SENSORS FOR HUMANE MOTION RECOGNITION

Recognizing human emotion is considered a fascinating task for data scientists. Studying human emotion needs appropriate sensors to deploy for collecting the right data. These sensors are generally used for automatic emotion collection, recognition, and making intelligent decisions. The key centralnervous system (CNS) emotional-affective processes are,

- Primary-process
- Secondary-process
- Tertiary-process

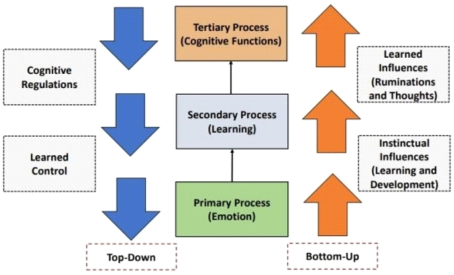


Fig 3: Studyinghumanemotionstogeneratedecisionsbasedoncontrolandcognitiveregulations

Emotion recognition using text is widely used when it comes especially for human machine interaction. In this case, textual information e.g, books, newspapers, contents of different websites, etc. are taken into consideration as a rich source of content for human emotion detection. Cameras are sued for performance monitoring by detecting the facial expressions of the individuals. Similarly, facial emotion recognition is an important part that helps to determine human emotion using different visual communication systems. Cameras are, in general, used to detecting these emotions. In addition, robots are used to communicate with human beings using AI technology. It helps to capture both logical and emotional information. Commonly, this technique includes various movements of the cheek, chin, eyes, wrinkles and mouth. Another widely used technique is speech. It contains information not only limited to what the person is saying but also holds the information of the speaker including their emotions, real-time interactions, and various meanings. It has great potential to recognize human emotion in a human machine interaction setting both for communication and interaction. The practical applicability is vast, for instance, in call centers to analyze the customers' needs and the given feedbacks, in specific, the kind of emotions an individual transmits. With the rapid improvement of sensing technologies and different IoTenabled wearable and flexible sensors, there is an improvement towards the sensing performance, accuracy in measurement, light-weight in carrying capacity and efficiency in the obtained results. The next common physiological parameter that is considered for human emotion recognition is body movements and gestures. Emotions can be featured by the whole-body posture and movement quality.

WHY IS EEG BASED EMOTION RECOGNITION IMPORTANT

EEG is considered a physiological clue in which electrical activities of the neural cells cluster across the human cerebral cortex. EEG is used to record such activities and is reliable for emotion recognition due to its relatively objective evaluation of emotion compared to non-physiological clues(facial expression, gesture, etc.) Works describing that EEG contains the most comprehensivefeatures such as the power spectral bands can be utilized for basic emotion classifications. The hypothalamus handles the emotional reaction while the amygdala handles external stimuli that is to process the emotional information from the recognition of situations as well as analysis of potential threats. Studies have suggested that amygdala is the biological basis of emotions that store fear and anxiety. Finally, the hippocampus integrates emotional experience with cognition. In daily life, human beings encounter various conditions and events that generated different stimuli that interfere with their emotions. Research shows that human emotions are strongly associated with the cognitivejudgment that direly impacts social and cultural behavior and communication. There have been various attempts made to classify the emotions and categorize them based on different parameters e.g., mood, feeling, and affect. In Ekman classifies human emotion based on facial expressions.

Audio Signals

Similarly, to the affect recognition from bio signals, the most commonly employed strategy in automatic dimensional affect recognition from audio signals is to reduce the recognition problem to atwo-class problem (positive vs. negative or active vs. passive classification) or a four-class problem (classification into the quadrants of 2D arousal-valence (A-V) space; e.g. As far as actual continuous dimensional affect prediction (without quantization) is concerned, there exist a number of methods that deal exclusively with speech. The work by Wollmer et al. uses the SAL Database and Long Short-Term ¨ Memory neural networks and Support Vector Machines for Regression (SVR). Grimm and Kroschel use the Vera am Mittag database and SVRs, and compare their performance to that of the distance-based fuzzy k-Nearest Neighbors and rule-based fuzzy-logic estimators. The work by Espinosa et al. also use the Vera am Mittag database and examine the importance of different groups of speech acoustic features in the estimation of continuous PAD dimensions. Another pioneering attempt is that of INTERSPEECH 2010 Paralinguistic Challenge featuring the Affect Sub-challenge with a focus on dimensional affect.

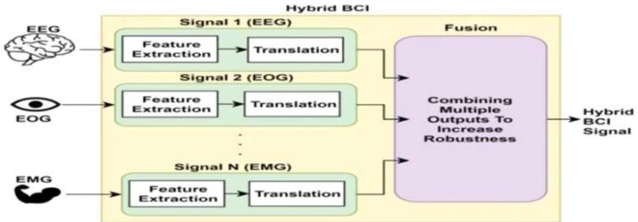
METHODOLOGY

25 participants were chosen with a variety of gender, personality types and age. The participants include17 females and 8 males, among them 17 were introverts and 8 were extroverts. Their age ranged from 15 to 40 years old. For our results to be representative of the population, each sample point should represent the attributes of a known number of population elements. In our experiment, we conducted random sampling, and choosing of a sample unit is based on chance so every element of the population has a non-zero probability of being chosen. Hence, we can obtain representative samples by eliminating voluntary response bias and guarding against under coverage bias. Typically, the larger the number of participants, the smaller the margin error is. A good approximation of the margin of error (or confidence interval) where N is the number of participants. This means that a 90% confidence level would have a 10% probability of the results differing from the actual population mean. For our experiment, our margin for error is 0.2, which means there can be a 20% deviation in the results obtained. There were two parts to our data collection..

Fig 4:Proposed Methodology

III. KEY COMPONENTS FOR THE EMOTION RECOGNITION

The combination of electrocardiography (ECG) and photoplethysmography (PPG) is used to capture real-time human emotions. The method is commonly known as pulse transit time (PTT).The idea of PPT is to calculate the time difference between the simulation of the heart (detected by the EEGsignals) and the arrival of the corresponding blood pulse wave to a certain area, e.g., arm wrist (detected by the PPG signals). To make emotion recognition more immersive and realistic, VR scenes (e.g., using VR glasses) are used with traditional EEGbased applications. A combination of EEG, EMG, and EOG signals for emotion recognition. EEG signals help to recognize inner emotion, and EMG and EOG signals are used to remove artifacts. Fig 3.1 shows a hybrid braincomputer interface combined with EEG, EOG, and EMG signals



The EEG signals of emotions vary from person to person, and there is no unique pattern for the signals. Therefore, EEG-based emotion recognition models are, in general, subject dependent. Several proposals study the need for subject independent emotion recognition based on EEG signals.It shows significance where the EEG of emotions of the subjects is not available to compose an emotion recognition model. For instance, a subject independent emotion recognition model has been reported based on variational mode decomposition (VMD) and deep neural network (DNN). VMD isused for feature extraction, and DNN is employed as the classifier for classifying emotions captured by the EEG data. It presents an EEGbased emotion recognition approach addressing the challenges of subject-dependencies in emotion recognition. The convolutional neural network (CNN) model has been proposed for human emotion recognition. It is a popular model that has been used for human emotion recognition based on a class of deep neural networks. For instance, the proposal presents an architecture for emotion detection that uses CNN. The proposed architecture is developed for user engagement estimation in entertainment applications. In CNN is used to estimate emotions from the partially covered human face images by wearing a head-mounted display (HMD). Work presented in discusses a framework that can capture emotional expressions and predict the mood of a person, perceived by other persons.

IV. OVERALL ARCHITECTURE

Channel-wise Attention:

Attention plays an important role in human perception. For example, humans can exploit a sequence of partial glimpses and selectively focus on salient parts to better capture a visual structure. Inspired by the human attention mechanism, spatial attention mechanisms have been proposed for various vision tasks, e.g., semantic attention, multi-layer attention and channel- wise attention. Channel-wise attention demonstrates superior performance because it can change the weight of different channels to explore the information of a feature map; thus, it can extract more important information about channels. Generally, channel-wise attention can squeeze the global spatial information and generate channel-wise statistics. In addition, it is trainable with CNNs, thus, it can be integrated into CNN architectures.

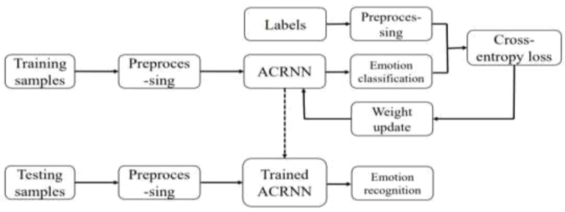


Fig 5: Neural network on EEG-based emotion recognition

Self Attention It is an intra-attention mechanism that relates different positions of a single sequence to encode sequence data based on an importance score. The self-attention mechanism is popular because it canimprove long-range dependency modeling. An attention function can be described as mapping a query and a set of key value pairs to an output, where the query, keys, values, and output are all vectors. The output is computed as a weighted sum of the values, where the weight assigned to each value is computed by a compatibility function of the query with the corresponding key. Self- attention has been demonstrated to perform well on simplelanguage question answering and language modeling tasks. For example, an attention-based architecture for machine translation, and Senegal. proposed the directional self-attention network to focus on the attention between elements in an input sequence. In EEG recognition tasks, to augment the amount of training samples, one EEGtrial is often segmented into several input samples. However, many methods ignore the importance of different EEG samples. Inspired by self-attention, we adopt this technique to further explore the time dependence between EEG samples.

The State Of The Art

In this section, we review the existing novel deep neural networks designed for FER and the related training strategies proposed to address expression specific problems. We divide the works presented in the literature into two main groups depending on the type of data: deep FER networks for static images and deep FER networks for dynamic image sequences. We then provide an overview of the current deep FER systems with respect to the network architecture and performance. Because some of the evaluated datasets do not provide explicit data groups for training, validation and testing, and the relevant studies may conduct experiments under different experimental conditions with different data, we summarize the expression recognition performance.

Deep FER networks for static images

A large volume of the existing studies conducted expression recognition tasks based on static images without considering temporal information due to the convenience of data processing and the availability of the relevant training and test material. We first introduce specific pre-training and fine-tuning skills for FER, then review the novel deep neural networks in this field. For each of the most frequently evaluated datasets, the current state-of-the-art methods in the field that are explicitly conducted in a person-independent protocol (subjects in the training and testing sets are separated).

Data Accuracy

Analysis of emotions based on facial expressions may not be accurate, as facial expressions can slightly vary among individuals, may mix different emotional states experienced at the same time (e.g. fear and anger, happy and sad) or may not express an emotion at all. On the other hand, there are emotions that may not be expressed on someone's face, thus inference based solely on facial expression may lead to wrong impressions. Additional factors can add to the ambiguity of the facial expressions, such as contextual clauses (sarcasm), and socio-cultural context. In addition, technical aspects (different angles of the camera, lighting conditions and masking several parts of the face) can affect the quality of a captured facial expression. Furthermore, even in the case of accurate recognition of emotions, the use of the results may lead to wrong inferences about a person, as FER does not explain the trigger of emotions, which may be a thought of a recent or past event. However, the results of FER, regardless of accuracy limitations, are usually treated as facts and are input to processes affecting a data subject's life, instead of triggering an evaluation to discover more about their situation in the specific context.

V. ADVANTAGES

1. Security and healthcare purposes. 2. For detecting stress and emotions. 3. Easy and simple detection of human feelings at a specific moment without actually asking them. 4. Measures heart rate and brain activity.

VI. FUTURE SCOPE

1. With the advancement in human computer interactions technology, digital learning platforms, e- commerce sectors, IoT and smart technologies, and other wearable technologies (including low-cost, energy-aware and portable sensors development), the proliferation to the marketplace for emotion recognition systems is becoming significant in our everyday life. The motion-sensing technology is no more in its experimental stage, it has become a reality. It is even used to understand the mental health of a person using various available mood-tracking apps in the market place. 2. Emotion recognition systems are becoming more sophisticated with the development of advancedwearable and processing technologies. However, attention must be paid to the efficient collection of physiological signals from sources. Suitable emotion detection models must be chosen. For this, signal processing techniques, feature extraction methods, and relevant classifiers should be employed

VII. CONCLUSION

We have presented a review of the development and progress in human emotion recognition systems and technologies. We have provided a detailed discussion on the various available mechanisms in the context of human emotion recognition comprehensively and systematically. We noted that biosensors are used widely for capturing human emotions in a more sophisticated way. We observed that there is a significant potential for Artificial Intelligence (AI) and Machine Learning (ML) technologies to contribute to next generation human emotion technologies that can operate without any human interventions. However, there are significant challenges in integrating various systems and technologies in a decentralized way to build a robust and scalable embedded human emotion recognition system. In addition, security, privacy, trust, find-grained access control, and scalability are major concerns towards the development of an efficient human recognition monitoring system.

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