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Emotion Classification Using Physiological Signals

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Abstract

The interpretation of an individual's conduct is significantly influenced by their emotions, or affects. It plays an important role in our daily life because it greatly aids in cognitive functions such as perception, interaction, problem-solving, and decision-making. It is a complex psychological state that involves a behavioral reaction, a physiological reaction, and a subjective journey (the individual's feelings). Affect recognition is a technique that aids in determining the kind of emotion a person is experiencing. Affective Computing (AC) is a well-established field within computer science that seeks to identify, model, and synthesize human emotions by utilizing technical tools and approaches to bridge the gap between computing systems and human affect. It is clear in the field of AC that a person's personality, character, and mood are among the many other personal characteristics that impact their emotions (Park et al., 2007). Predicting these variables, with a focus on personality, is important for a variety of applications, including social media, entertainment, healthcare, education, and virtual worlds, to enhance people's everyday activities.

Keywords: Emotion, Classification, Deep Learning.

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Introduction

The first step in each research project is to define and review the phenomenon being studied. It is necessary to describe the different characteristics of emotions and their reactions because the current research focuses on the investigation of human emotions (Kim & André, 2008). Emotional behavior and social cognition are the main topics of social psychology. As much as possible, the psychological component of the social-psychological investigation utilizing electrical and electronic equipment must be clearly specified and characterized. The cause and effect of emotions have been characterized differently by many theorists. Social psychologists contend that emotion has a significant impact on perception, memory, problem solving, judgment, task performance, and other areas (Kim et al., 2004). According to Breckler & Wiggins, (1993), emotions are also a significant factor in changes in attitudes. Undoubtedly, understanding how emotions are communicated through expressive behavior is incredibly fascinating. Additionally, a number of psychologists have suggested that emotions are crucial in the formation and maintenance of social bonds like friendships and marriages (Sim et al., 2007). Therefore, it is clear that emotion is a key component supporting the social-psychological phenomenon. Emotions must be studied because human survival depends more on them than on material luxuries. It might be wise to define emotion before continuing. The EEG and FNIRS Acquisition System shown in Fig. 1.

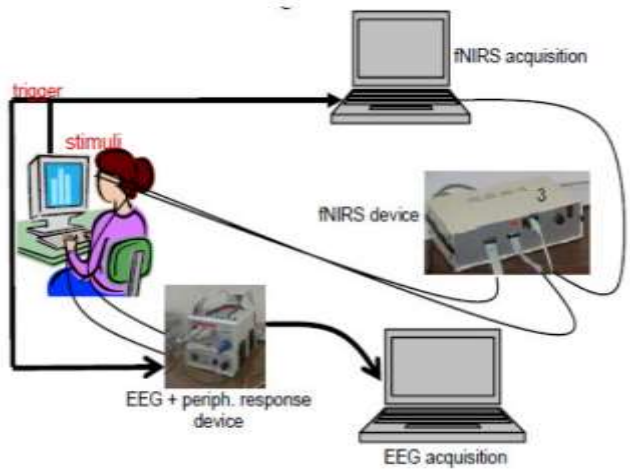

Fig. 1: The EEG and FNIRS Acquisition System

Literature Review

The thorough description of this period's study is shown in Table 1 below, with a special emphasis on the classification of various emotions using physiological data. Similar to many other areas of biosignal processing research, early efforts in emotion recognition primarily employed a user-dependent approach, which heavily relied on specific individuals as subjects. Nonetheless, there has been a shift in emphasis towards the recognition of emotions without reliance on specific users, utilizing novel physiological data for assessment. Notable achievements have been reported in the case of user-dependent systems, with a peak accuracy rate of 95% in recognizing four emotions (Joy, Anger, Sadness, Pleasure) and 92% in recognizing six emotions (Amusement, Contentment, Disgust, Fear, Sadness, Neutral) as described in references and (Rani & Sarkar, 2006). The user-independent method, on the other hand, has also produced encouraging results, with reported classification accuracy of 86% for two emotions (joy and sadness), 70% for four emotions (joy, anger, sadness, and pleasure), and 50% for nine emotions (anger, interest, contempt, disgust, distress, fear, joy, shame, and surprise).

Even though research by Gross and Levenson shows that audio-visual stimuli, like movie snippets, are more efficient at evoking emotions, the categorization accuracy is still only 86% when compared to other methods of emotion elicitation. It's worth noting that the feature extraction techniques used in audio-visual emotion elicitation are relatively straightforward (as mentioned in reference (Park et al., 2007). This implies that even simple algorithms can achieve significant classification accuracy in audio-visual emotion elicitation. Therefore, the adoption of enhanced feature extraction and classification algorithms has the potential to yield improved results. Certain researchers have taken advantage of the MIT Media Lab database to induce emotions via the auditory channel, particularly through

music, and have achieved an impressive classification accuracy of 95%, as documented in reference (Raouzaiou et al., 2003).

Conceptual Methodology

Emotion Elicitation Stimuli

For emotion detection systems to advance, a top-notch dataset comprising physiological signals is required. Unlike image and audio recognition, where non-experts can assess data quality based on visual or auditory cues, evaluating the quality of physiological data is not straightforward. Researchers use a variety of methods to elicit emotions from study participants, especially those pertaining to the autonomic nervous system (ANS), in order to guarantee the accuracy of the physiological data that is gathered.

Pre-Processing

Prior to any further processing, it is necessary to eliminate this noise and these artifacts from the raw physiological data. Different kinds of low-pass filters, including adaptive, elliptic, and Butterworth filters, are frequently used in the preprocessing of raw physiological signals, including ECG and facial EMG (Kessous et al., 2010). Overall Conceptual View shown in Fig. 2.

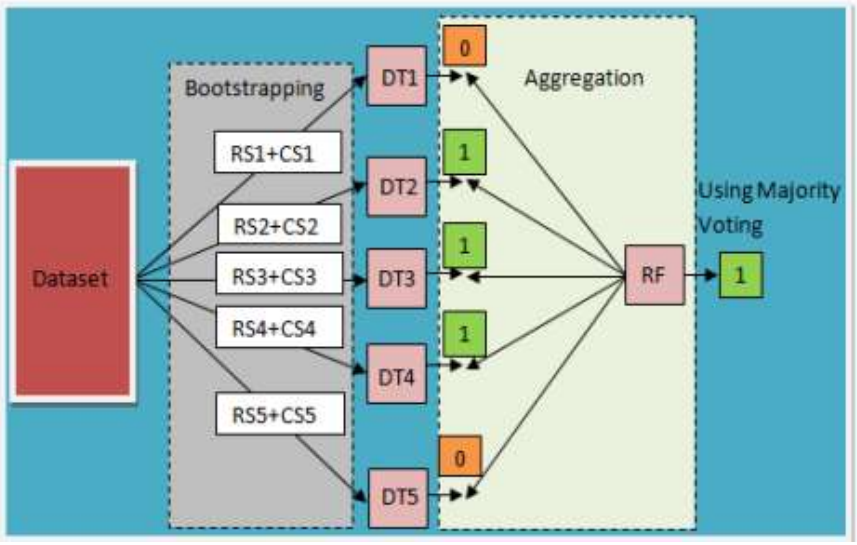

Fig. 2: Overall Conceptual View

Feature Extraction

Numerous physiological signals can yield a wide range of properties, including time, frequency, statistics, and time-frequency parameters. Up to 110 characteristics were retrieved from four physiological signals (ECG, EMG, skin conductance, and respiratory signal) in a study (Bal et al., 2010). Traditional statistical measures within time series, frequency-domain parameters, geometric analysis, power measurements, multiscale sample entropy, sub-band spectra, and more were among these aspects. Moving mean, sliding mean, moving median, sliding median, and other dynamic and sliding characteristics were used by Honig et al. While sliding features imitate the behavior of moving features without depending on historical sample data, moving features are calculated iteratively inside the analysis window and rely on the prior feature value. These sliding features are especially well-suited for emotion classification algorithms with memory limitations because they use less memory.

Feature Reduction

The extracted features from different bio-signals may or may not have a connection to emotions. Hence, it is essential to eliminate characteristics that do not exhibit correlations across different emotional states. The performance of classifiers can be adversely affected by the presence of unrelated features (Picard, 2003).

Classification

It is vital to use these attributes for the training of a classifier after choosing the pertinent traits connected to emotional states. However, comparing these different classification algorithms can be challenging due to variations in the training and testing datasets used by different systems, as well as differences in the methods of eliciting emotions. It has been observed that when all physiological signals are utilized for classifying various emotions from the same database, the classification accuracy is higher. On the other hand, if one depends exclusively on a single physiological signal (EMG), there is a tendency for the classification accuracy to decrease.

Results and Discussion

However, it's important to acknowledge that emotional changes within these physiological signals occur within a short timeframe, typically ranging from 3 to 15 seconds. Therefore, collecting data precisely at the moment when emotions are elicited in the subject has the potential to yield superior results. Performance Evaluation shown in Fig. 3.

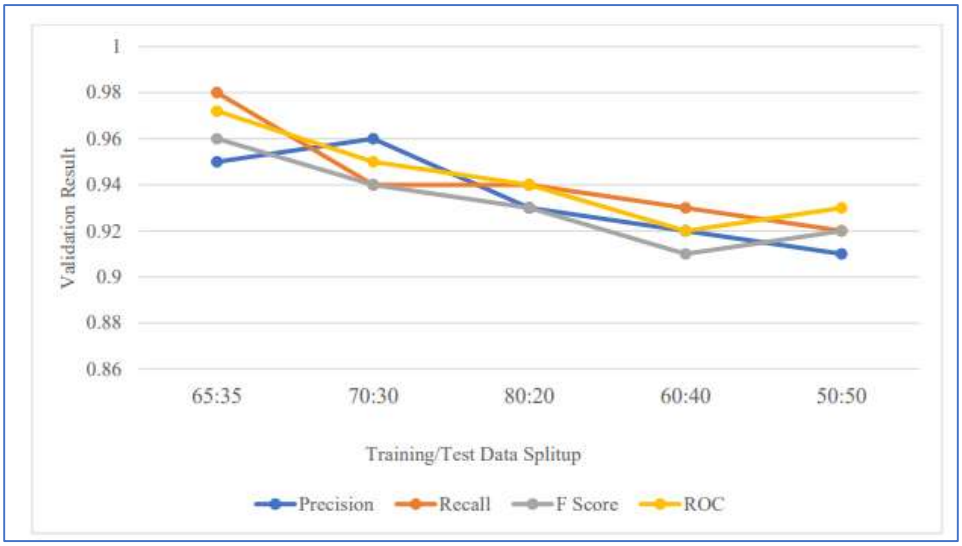

Fig. 3: Performance Evaluation

In order to achieve this, it is crucial to utilize a windowed approach when handling diverse physiological signals. Performance Comparison Using Different Brain Regions shown in Fig. 4.

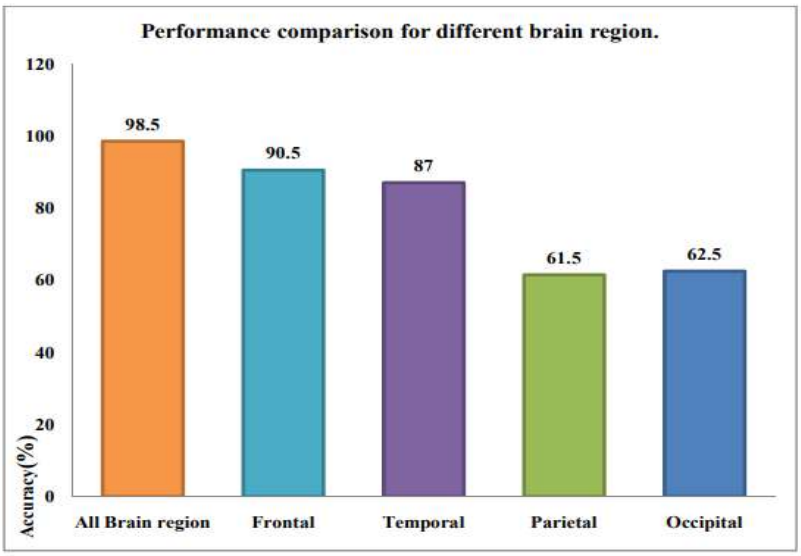

Fig. 4: Performance Comparison Using Different Brain Regions

Through the examination of physiological signals, we have carefully investigated and clarified the several phases of human emotion recognition in this work. It is clear that the science of using physiological cues to recognize emotions in real time is still in its infancy.

Conclusion

Through the examination of physiological signals, we have carefully investigated and clarified the several phases of human emotion recognition in this work. It is clear that the science of using physiological cues to recognize emotions in real time is still in its infancy. Given the inherently subjective character of emotions, creating a universally adaptable framework for classifying all fundamental emotions continues to present a noteworthy obstacle. The majority of existing systems created to date lean on individual users, and user-independent systems typically encounter diminished accuracy. To establish a dependable and resilient emotion recognition system that isn't bound to a specific user, a considerable volume of physiological signal data is imperative.

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