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Research Article

Emo-Gem: An Impacted Affective Emotional Psychology Analysis through Gaussian Model using Amigos

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ABSTRACT

Analysis of human affect (feelings) that directly release on human emotions is mandatory to rival many psychological impacts. Human emotions are more precious and real. The history of Effect Theory implies on the idea of detecting the feelings and emotions seem needful to predict behaviour. The proposed research work is based on predicting the real emotion using a robust model with neurophysiological data. Any change in the emotional affect directly triggers the physiological signals. The presented system utilizes the concept of Gaussian mixture models to create a novel prediction algorithm named the Gaussian Expectation Maximization technique (GEM) using the amigos dataset. The dataset considered physiological signals such as Electrocardiography (ECG), Electroencephalography (EEG), Galvanic Skin Response (GSR). The statistical response after the processing of the data, measurable results on emotion labels those coincidence responses with training samples directly impacts the obtained results. The presented system is comparatively discussed with a state-of-the-art approach in terms of statistical parameters like standard deviation, the population mean etc. The comparative analysis on various participants and their unique covariate points are extracted for deep emotion analysis. The proposed system achieves the detection of emotional affects such as anger, contempt, disgust, happiness and sadness. Based on various iterative learning with improved expectations and maximization value extraction, the proposed system detects the emotion with minimum iterations of 5.

Keywords: Affective computing; Emotion analysis; Subject identification; Machine learning; Artificial intelligence; Emotional psychology

INTRODUCTION

Need for affective computing

The sociology of emotions has a long history of identifying the effect produced from human emotions better in terms of formulating contagious questions and self-assessment tests. The conscious and unconscious forms of emotion directly impact human behaviour. Subjected to psychological facts affective computing is the challenging area of research that created with many ideological Pathways. Audio signals can clearly define the emotional impact since the variations in the pitch determine the emotional factor. Many cross-modal emotion embedding systems incorporate audio and video correlations to determine the actual emotion explode by the subject through the ensemble learning process [1].

Depression and anxiety are chronic mental disorders that start small and continue to affect human emotion in a large span. Affect sensing is a wide area of challenging research. While discussing the effect scenario, it is obvious to include the term called emotion contagion. Emotional contagion is a kind of social contagion that transits the emotions and related behaviors from one person to another. This convergence of expressed emotions can happen to reflect from one person to another in a certain environment [2]. Emotions are the outcome of serial events. Reactions of a series of events enable the person to behave differently at irrelevant times [3].

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Technology support

The emerging growth of artificial intelligence technology creates a way for much interactive analysis to understand the emotions of people through various sources. Standard datasets are available for research purposes and many publicly available data are used for the research work. Speech signals are used to determine the emotional impacts. Changes in pitch, tone are the direct reflectors of emotional change or affect notification. Neuro-fuzzy logic-based resilient evaluations are used to recognize the speech patterns that change concerning emotional affect [3].

The face is the foremost mirror of emotional impacts. Expressions are a common principle for all. It is clear to understand the emotion through facial expression. Often in certain cases, hidden emotions are difficult to find out based on face emotions only. Virtual facial vectors and landmark extractions are another way of expression formulation [4]. The growth of Machine learning technology manipulates the existing difficulties in neural networks toward improved algorithms creation. Linear Discriminant Analysis (LDA) models are used to evaluate the large set of feature vectors created from subject analysis data. After the number of trials, emotion analysis results are getting improved with LDA [5].

Multi-label learning algorithms help analyzes the emotional effects in various modalities. Major polarity concerns the happiness and sad expressions, where multiple modality scenarios offer to extend the emotional impact factors to different angles [6].

Dimensions of emotions

Emotion is the real expression of feedback from the brain on a given input. It directly expresses the spontaneous feeling in the given instance. In terms of dimensionality, the emotion model can be classified into two types, such as 2D or two-dimensional models and 3D or three-dimensional models. In the 2D model, the most impactful emotion lies within the Valance and arousal dimension, whereas the 3D model contains the major emotion as Valence, arousal Dominance etc. (Figures 1a and 1b).

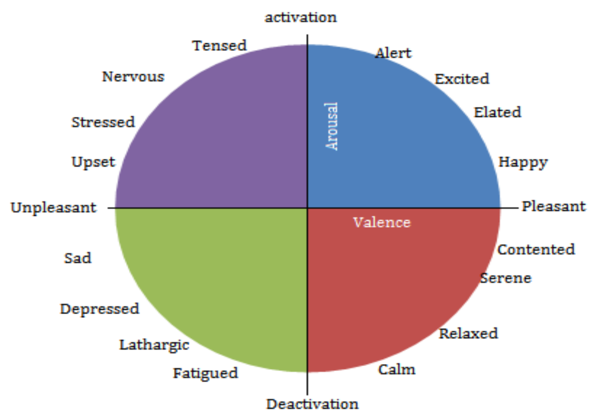

Figure 1a: 2D model of emotion.

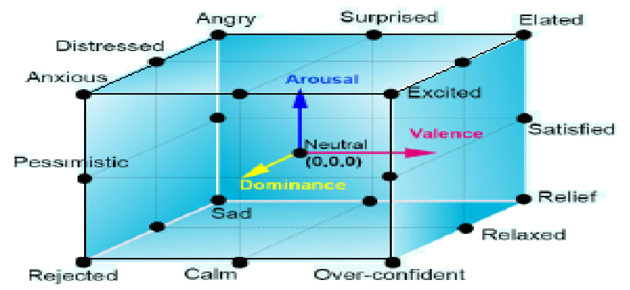

Figure 1b: 3D model of emotions.

Existing research works, the drawbacks and guidelines are summarized in Sec II. On Background study to further proceed with the model selection and design constraints evaluation in Sec III. The proposed methodology, data collection and algorithm are discussed. Describe the system architecture and Sec V. Describe the results and further discussions.

BACKGROUND STUDY

Few authors studied multi-step enabled deep emotion detection framework is used to detect multiple polarities about emotions. Based on publicly collected databases, videos and physiological signals are extracted using Deep Neural Networks (DNN). Pattern comparison is done concerning training features and testing features [7].

Few authors studied multi-task cascaded neural network with primary agent stream to detect the posture, face and reasoning stream detection using a virtual semantic module is evaluated. The reasoning stream is extracted using a Multi-Level Perceptron (MLP). Exotic dataset with modeled heat stream maps is involved to improve the detection mechanism [8].

Few authors studied emotion detection is the process of detecting and expanding the mental state of the individual. Deep learning and shallow learning-based spontaneous feeling detection and comparison are implemented. ECG and EEG signals are incorporated to reveal the correlated performance on emotion identification. The technique of prisma which includes identification, screening, eligibility is considered for detailed analysis [9].

It presented a system, where the Mahnob dataset is used to analyze the emotion using weighted Multi-Dimensional Discrete Wavelet Transform (MD-DWT) and the K-Nearest neighbor algorithm is applied. Video clips of various emotions are ensemble together and after the levels of training iterations, a Meta classifier detects the final emotional affect. Using different simulations using MD-DWT, 9 emotions are highlighted [10].

Due to frequent interaction with smartphones, an android application-based emotion identification system is presented. The combination of Convolutional Neural Network (CNN) with Recurrent Neural Network (RNN) is evaluated to create a strong model for emotion detection. CNN attains an accuracy of 65% and RNN attains an accuracy of 41% respectively. The presented recommendation platform is used for new content etc. [11].

Few authors presented a system based on a self-supervised learning approach in which unlabeled data are mapped to the bias weights based on the iterative learning and feedback updating. ECG based emotion recognition system is evaluated using the hardware sensors collected with various temporal properties. Considering the standard emotion dataset namely Amigos, Swell, Wesad and Dreamer the maximum accuracy achieved was 97% [12].

Scholarly articles

Many existing implementations are considered for algorithm selection. Self-supervised learning models act as an intermediate approach between supervised learning and unsupervised learning. The beneficial thing in the self-supervised learning approach is the learning scenario of many unlabeled data. Because of these unlabeled data, the biased weights are continuously updated and enable the downstream version of raw data [13]. Deep belief networks are considered as the robust method in analyzing complex data connections. Multi-Feature analysis models need complex structures that rely on unique combinations of data [14]. Convolutional Neural Network (CNN) algorithms are considered as the automated feature mapping blocks that can be tuned to attain deeper analysis. By changing the preceding layers of the CNN structure, an adaptive network is created. Selection of filter blocks, improvising the feature selection blocks such as fully connected layers, ReLu layer and Max-pooling layers, adaptive design is formed [15]. Gaussian mixture models find out all probabilistic data that is generated from the finite Gaussian distribution of data in the random space. The model converges the relative data into the grouped structure to make the regression better [16].

Datasets available

OMG emotion dataset: One-Minute Gradual (OMG) emotion behaviors a dataset consists of category information of volunteers with emotional classifications are 12567 videos from Youtube and an average length of 1 minute. These videos are divided into various emotion-based classifications such as happiness, sadness, surprise, fear and disgust. The dataset consists of standard 1-minute videos that triggered the emotion mentioned above. OMG emotion dataset used as one of the standard emotion grabbing models [17]. Instead of emotion rating, the keyword tagging based emotion identification standard module is available in the dataset. The collection of 24 participants is involved in organizing the dataset in which they are allowed 20 different brain-stimulating videos to prevail their real emotions [18].

The proposed methodology considers the drawbacks of similar polarity in decision making and evaluated a Gaussian mixer model-based ensemble algorithm to improve the prediction quality.

METHODOLOGY

Data collection

Amigos is a standard data set used for affect personality and mood research done with the individuals and groups of peoples based on personality profiles and external annotations created neurophysiological recordings such as ECG, EEG, and GSR signals are recorded from the individual during the test. During the test short and long video experimental videos are given to the volunteers. 40 volunteers watched a set of 16 different effective videos that trigger the brain stimulus deals concerning the emotions namely valance, arousal dominance, familiarity and liking. Selected basic emotions such as neutral, happiness, sad, surprise, fear, anger, and disgust that they feel during the videos. Based on this information and the kinematics of patients the evaluation of emotion needs to be determined. Amigo is a robust recorded dataset, validated with a self-assessment test. In the proposed system ECG, EEG, GSR signals are considered from the Amigos data set.

GEM algorithm

The expectation-maximization algorithm is based on the Gaussian mixture model that is not advertised of probabilistic clustering model allows describing the given selected data into equivalent groups. Each observation and density of the given groups validates a set of classes. It has the capability of grouping the concentrated main of data that belongs to the same class. The Gaussian Expectation-Maximization (GEM) algorithm is an iterative way to find maximum-likelihood estimates for model parameters when the data is inadequate with misclassified data feature points or has some Eigen variables. GEM initiates from any random values for the missing data points and evaluates a new set of data. These new values are then recursively used to learn and find out the better covariate data, by filling up missing points, until the values get fixed.

These are the two basic steps of the GEM algorithm, namely E Step or Expectation Step or Estimation Step and M Step or Maximization Step. The initial process starts with the Normal distribution analysis discussed below.

Normal distribution

In a Gaussian space, the expectation-maximization algorithm enables the initiation the random location to pick the covariate points from the given data. The iterative loops tend to continue to search for the newly obtained data from the statistical measures like standard deviation of the initiated pattern, and variance, mean of the population.

RESULTS AND DISCUSSION

The iterations are repeated for different participants to analyze the unknown labels. The formulated results are tabulated for verification. The Figure 2 shows the unique covariate points of a single participant under test analyzed using the GEM algorithm [19]. These points are unique and extracted from the overall distributed random data. The points are extracted after the errorrate reaches the minimum from the given iterations. The iterations are initially started with maximum error and u value gets organized according to error rate until the expectation algorithm search for the maximum value [20]. The complete process provides easy capturing of unique points from the large dataset. The difference between the expected value and the obtained maximum value enables the system to iteratively learn and run for the new data search. The complete process takes a maximum of 500 million seconds to finish the complete given test data [21]. The training process forms the working model concerning the initial maximization value obtained. The proposed model classifies the given test data such as anger, contempt, disgust, happy and normal.

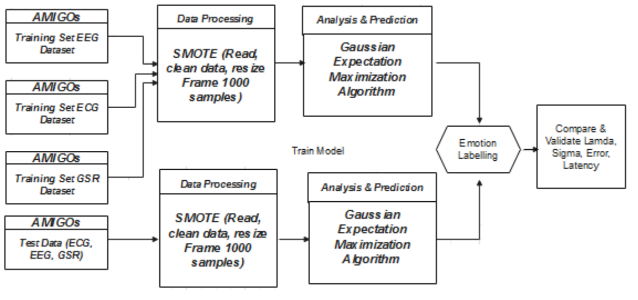

Figure 2: System architecture of proposed Emo-Gem model.

CONCLUSION

Emotion identification through the Gaussian expectation-maximization algorithm is evaluated here. Amigos dataset is considered for analysis. Physiological signals such as ECG, EEG and GSR is considered for analysis. The proposed research work is focused on detailed analysis and creating a lightweight model for emotion analysis that produce less latency comparatively is evaluated here. The participants are selected randomly and tested with ECG, EEG, GSR data covariance analysis using Emo-Gem and Gaussian expectation-maximization model that depends on the regression of the data. The higher the processing depth-wise convergence that produces equality in data size, produce unique correlation points to determine the emotions. The proposed model achieves less latency of approximately 435 mSec for the overall processing with 0%error to the maximum iterations. The statistical measures highlighted as Mean=0.62, SD=0.88, concerning the detection of emotions like anger, contempt, disgust, happy and normal. Further, the system needs to be classified using a deep learning model to find the detailed variations etc.

CHALLENGES

The main challenge of the presented work is the big data handling and processing latency consumed for training and testing. The Gaussian expectation-maximization model determines the relative convergence of grouped data through probabilistic distribution and similarity mapping. The system model needs to be focused on improvising the preprocessing stage and feature extraction steps to scale the data before processing.

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