IOSR Journal of VLSI and Signal Processing (IOSR-JVSP)
Volume 11, Issue 6 (Nov. - Dec. 2021), pp.46-51
e-ISSN: 2319-4200, p-ISSN: 2319-4197
www.iosrjournals.org

Stress Detection Using Facial Recognition and ECG Analysis

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Abstract:
Detection of stress using real time capture analysis is performed in this paper. ECG is captured using AD8232 ECG module. This paper is inspired by the work of various other Convolutional Neural Network for emotional recognition and takes an inference for stress from detected emotions. This paper gives a unique implementation for detection of P wave, which uses a single moving average filter instead of two moving average filters. Detection of QRS Complex, ST Segment slope and P wave segment were done for ECG Signal processing and analysis. By combining the results of facial recognition and ECG analysis prediction of stress is shown. For the results, subjects are chosen from the random group of students and the results were obtained which gives the overall accuracy of 96%.
Key Words: *Stress; Facial features; Emotions; ECG; QRS Complex; ST Segment slope; P Segment; Pan Tompkins Algorithm; AD 8232 ECG Module; NodeMCU.*

I. Introduction

Stress is a menace to our life. Those who can't handle situations will often get stressed. There may be many reasons for stress such as in students who are worried about their academic scores, being the sole money maker of the family, divorced couples, taking care of own family and friends, and lots of other situations too[1]. Due to stress, adrenaline increases the heart rate, which in turn elevates blood pressure. Cortisol elevates sugars of the bloodstream, thereby enhancing the usage of brain's glucose and availability of substances increases which repair tissues. Cortisol also restricts functions which would be non-essential in difficult situations. Cortisol also alters the response of immune system and damages the digestive system, the reproductive system and growth processes. This also communicates with the brain regions that control motivation, mood and fear[2].

It is better to take precautions in the earlier stage which is why this paper show why the idea of detecting stress. The process involves two important stages which are Image Processing and ECG analysis. Emotion detection with the help of facial expression is not an easy task with computer algorithm. Image processing block performs facial recognition which is done by capturing images from camera. In order to categorize emotions, CNN (Convolutional Neural Network) is used[1]. In comparison to other image classification algorithms, CNNs use lesser pre-processing. With the help of Max-pooling method[2], facial features such as wrinkles around the nose, eyebrows, raised cheeks and others can be extracted using which facial emotions such as angry, sad, happy, surprised, disgust, fear, neutral are classified. ECG signal is an electrical visualisation of the movements of the human heart and plays a prominent role in identifying several types of cardiac diseases. The analysis is done using small electrode patches that are attached to the skin of the subject. These electrodes are used to record electrical activity of heart rhythms. In ECG analysis block, ECG signals are obtained from the ECG leads which are placed on the subject. It is necessary to detect QRS complex widening, ST wave, P wave, and isoelectric level for stress detection using ECG[3]. This paper processes the data with the help of Pan-Tompkins Algorithm from which QRS complex is detected. It recognizes QRS complexes on the basis of digital analyses of slope, amplitude, and width[4]. The resultant module now combines both outputs and provides a final stress level of the subject.

Several methods for analysing the stress using facial recognition have been used. Analysing facial emotions using Convolutional Neural Networks (CNNs) and Image recognition is done[1]. It makes use of 3 modules, which are creation of images dataset, making of model trained by the dataset, and enabling a camera taken picture for testing the image for the output. The focus is on stress recognition by the capture of pupil videos using the camera which supports detection of subjects who are under mental stress levels. Detection of the emotional status of a subject through analysing of facial expression by capturing real-time videos of the subject is the main objective for our image processing[5]. The python framework Theano is used as a deep learning algorithm. It aims at improving the execution time and development time of the linear regression model. The FERC is designed using a two-part convolutional neural network[2]. To determine Depression Anxiety Stress Scale levels by the means of analysing the facial expressions using Facial Action Coding System is done by Mihail Gavrilescu, et al. This makes use of three layer architecture, in the first layer, Active Appearance Models and a set of Support Vector Machines. In second layer, a matrix is constructed, which contains the intensity levels of the Action Units.

In the third layer, an optimal feedforward neural network is used to analyse the matrix from the second layer, thereby predicting the DASS levels.

The four features which are required to detect stress using ECG is discussed[3]. This method includes de-noising of the ECG signal to increase the accuracy of stress recognition by designing an optimal filtering technique. The algorithm to detect the P peaks of the ECG signal is a unique approach which was implemented in this paper. Pan Tompkins Algorithm is developed to detect the QRS complexes of ECG signals[4]. This recognises QRS complexes which performs analysis of slope, amplitude, and width. A special digital bandpass filter is used to lower the false detections caused by the interference present in ECG signals. The presence of ischemia can be identified by the elevation or depression of the ST segment[8]. This technique determines changes in ST segment by measuring the slope of ST segment and inspecting the variation.

II. Methodology

Image Processing:

To train the emotional model we have used fer2013 dataset available in Kaggle website .This data set has 35887 gray scale images classified for 7 types of emotions. We reduce the size of the image to 48x48 size images for further processing .For further preprocessing we normalize the images between 1 and -1 by dividing the total pixels by 255

$x = (x - 0.5) * 2$, where $x \neq \phi$

The training and testing data are split with 20% of the data size for the testing and the remaining for the training, the data selection is done randomly. The batch size is set to 32 and done for 400 epochs.The data is generated from the input images with zoom range of 0.1 and l2 regularization of 0.01.We use two different types of model for training and these 2 models are used over 5 layers. The first layer used is 2D Convolution layer with an activation function set to relu, for the rest of the 4 layers we use separable Convolution 2D layer with relu activation function. We use SoftMax activation function at the output. These models have a adam optimizer Here we are using _mini_Xception model for training.

2D Convolution Equation:

$$\mathrm{G}[\mathrm{m},\mathrm{n}] = \sum_{\mathrm{j}} \sum_{\mathrm{k}} \mathrm{h}[\mathrm{j},\mathrm{k}]\mathrm{f}[\mathrm{m}-\mathrm{j},\mathrm{n}-\mathrm{k}]$$

where f is input image, h is kernel, m and n are Row and Column from the filter matrix

Separable 2D Convolution Equation is given as

$$\mathrm{y}[\mathrm{m},\mathrm{n}] = (h_1[\mathrm{m}]\,.\,h_2[n]) * x[m,n]$$

The eye brow distance is found from the facial data of the person from the live data which is given at the input. The distance is found by calculating the Euclidean distance between the left eye and the right eye. The emotions are used to find the status weather the person is emotionally stressed or not .The dataset used to find location of the facial features like the eyebrows, eyes,etc. from "shape_predictor_68_face_landmarks" from "dlib" website.

ECG Processing:

Bandpass filtering reduces the interference of muscle noise, 60Hz interference, baseline wander and T-wave interference. The desirable passband to maximise the QRS energy is approximately 0.5-10 Hz[4]. Normalizing the input value is done by dividing the input value sequence to the maximum input value.

The Low-Pass filter is designed for the cut-off frequency of 11 Hz, and the gain is 36[4]. The filter processing delay is six samples. The filter co-efficients will be as

b= [1 0 0 0 0 0 -2 0 0 0 0 0 1]

a= [1 -2 1]

The convolution is performed between the Low-Pass filter and the previous stage output is performed. The high-pass filter is given by the cut-off frequency of as 5 Hz, the gain is of 32, and the delay is 16 samples[4]. The filter co-effficients will be as

b = [-1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 32 -32 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1];

a= [1 -1]

The convolution is performed between the High-Pass filter and the previous stage output is performed. After filtering, the signal is differentiated to provide the QRS-complex slope information[4]. A five-point derivative is used with the transfer function as

$H(z) = (1 / 8T)(-z^{-2} – 2z^{-1} + 2z^{1} + z^{2})$

The frequency response of this derivative filter is nearly linear between dc and 30 Hz. The delay is two samples[4]. The filter co-efficient after solving the equation will result in

h= [-1 -2 0 2 1]

The convolution is performed between the Derivative filter and the previous stage output is performed. After differentiation, the signal is squared point by point[4]. The equation of the squaring function is given by

$y(nT) = [x(nT)]^2$

Where T is the sampling period. This makes all data points positive and does nonlinear amplification of the output of the derivative emphasizing the higher frequencies[4]. The purpose of moving-window integration is to obtain waveform feature information in addition to the slope of the R wave. The equation of the moving-window integration is given by

$y(nT) = (1 / N) [x(nT – (N – 1) T) + x(nT – (N -2) T) + …. + x(nT)]$

Where N is the number of samples in the width of the integration window, and T is the sampling period. The filter co-efficient is given as

h = (1/31) (1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1)

The convolution is performed between the Moving-Window Integrator and the previous stage output. The width of the window should be almost the same as the widest possible QRS Complex. The width of the window is determined empirically. The sample rate is 3000 samples/second. The window is 30 samples wide (10 milliseconds).

R peak is found by the maximum peak present between the start and end points of the window. Q peak is found by the minimum peak present between the start point of the window and the R peak. S peak is found by the minimum peak present between the R peak and end point of the window. The heart rate is the difference between the successive R peaks. Then the heart rate is given by 60 multiplied by the sampling frequency and divided by the difference found earlier. The average heart rate range is 60-100 beats per minute. The difference between the Q and S peak's position (time) gives the QRS Complex window in milliseconds. The average QRS Complex Window is of 100 milliseconds.

The duration of ST segment is usually 120 msec[8]. The length equals to approximately 36 samples. This is given by the product of the sampling frequency and the ST Segment window. Experimentally it is observed that the ST segment starts from the 30th sample after R peak. From this point till the 55th sample after R peak gives the ST Segment. The ST Segment's elevation is found out the inverse tan of ratio of difference between the first and last points of ST Segment and the number of samples in the ST Segment[8].

P peak is found out by removing the QRS Complex and Moving Average Filter or Moving-Window Integration[7]. The Moving Average Filter is of 5 milliseconds or 15 samples. The convolution is performed between the Moving Average Filter and the removed QRS Complex of the filtered input signal. The threshold is obtained by the median of the convolved signal and the maximum amplitude of the convolved signal. The start and end of the P wave finding window is found first. Initially the peaks in the convolved signal are found out by the window created earlier. The peaks are found by the maximum peaks found between the start and end of the window. The R peak values and the peak values found earlier are concatenated. The actual P peaks are found by the peaks before the R peaks. P Segment start and end points are found by the minimum peaks found between the windows. The P peak values and the segment values are concatenated. The P segments are found out by the segment values before and after the P peak. The P segment window is found out. The average value of P segment window is 130 milliseconds.

By having the average values of Heart Rate, QRS Complex Window, ST Segment elevation, and P wave window known beforehand, we can predict if the given subject is stressed or not. If the found-out values are above average we can declare that the given subject is stressed. We finally use the given ECG and Image processing results together to find the final result of the overall stress level. Firstly, the image processing gives whether the person is really stressed or not, while the ECG Processing part is to identify the level of stress they are undergoing.

Hardware Setup for ECG Signal Capturing:

The input waveform is captured by the help of AD 8232 ECG Module interfaced with NodeMCU. The AD8232 is an integrated signal conditioning block for ECG and other bio-potential measurement applications. It performs extract, amplify, and filter operations for small bio-potential signals. Due to fact that the distance from heart and electrodes is small, the ECG signal acquired is strong and thus causes low muscle artifact interference. It is assumed that the subject remains still during the measurements making unwanted noises associated with the ECG Signals less of an issue.

The cables are color-coded for proper placement. The red coloured cable is placed on the forearm, yellow cable to the left forearm, and the green cable is placed on the right leg ankle[10]. The baud rate is set at

115200 bits per second. Using “serial” library in Python, the data is acquired. The timeout is set to 10 seconds. The serial port is set accordingly. In the programming part of the ECG Data acquisition used in the delay of NodeMCU is set for 1 millisecond. The serial data reading done by the Python language takes in 3000 samples, which corresponds to 3 seconds of ECG Data. This is done to quickly verify the Facial Recognition result.

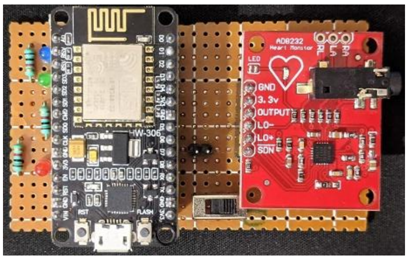

Figure 1: Hardware setup for ECG Signal Capture

III. Results and Discussions

The model trained for emotional dataset is trained to 75% accuracy. The overall accuracy for identifying the cumulative facial stress is around 80% accurate. The final output is found by compiling all the outputs from the live video feed and the final output is based on the max count of the output obtained from the video.

A group of 14 male students were chosen at random of age 22. The ECG data is acquired for a time interval of 60 seconds. After the data acquisition from the hardware, the processing done as mentioned in the methodology. The waveforms which will be displayed would be the original waveform captured by the hardware, bandpassed signal, QRS Complex detection, ST Segment detection, and P wave and segment detection. After the processing of the input ECG signal is performed, the values of the features extracted will be shown. The features which will be shown are Heart Rate (beats per minute), QRS Complex (milliseconds), ST Segment’s slope, and P segment (milliseconds). The subjects are chosen randomly from the group of students for testing our model. Since MIT-BIH Arrythmia is a standard database, this model was trained using this data.

In Figure 3, the emotions classified in the Image processing module are shown. The emotions shown here are happy, scared, neutral, surprised, sad and angry. The Fig. 4, 5 and 6 shows the ECG data with the aforementioned peaks and segment detected. Their corresponding accuracy is given in Table no 1. The accuracy is the measure of detected peaks to the true peaks.

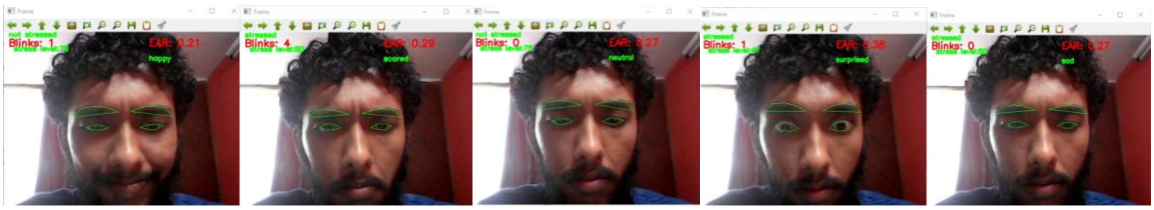

Figure 2: Different emotions detected

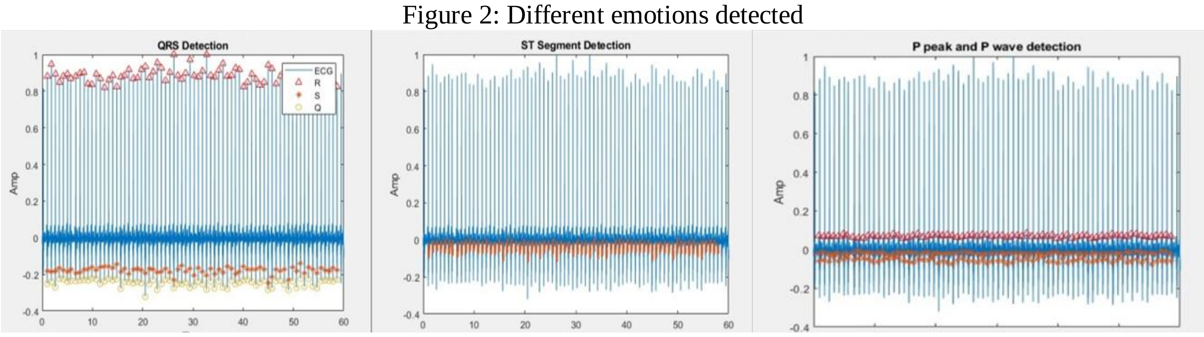

Figure 3: ECG Readings for Patient A

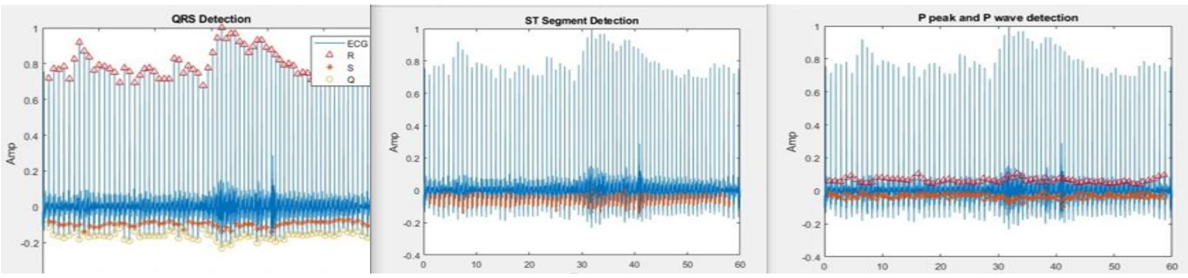

Figure 4: ECG Readings for Patient B

Table no 1: Accuracy for detecting the peaks and segment

Subject	**QRS Complex**	**ST Slope**	**P Segment**
A	100	99	100
B	100	95.89	87.67
C	100	91.3	94.2
D	81.2	100	98.75
E	85.6	96.66	98.48
F	100	86.66	94.44
G	100	98.52	100
H	100	98.11	100
I	100	98.38	98.38
J	100	76.56	100
K	100	100	100
M	100	97.91	97.91
N	100	85.54	90.36
O	100	98.07	100
Average	97.63	94.47	97.16

As Table no 1 shows the accuracy of detecting the features of ECG Signal, it is accurately predicted stress, or in this case verify the result of the Image Processing Block, it is highly reliable to extract the features using the proposed method. The overall accuracy of our method is 96.42%. This considerably better than 87% of Supriya Goel, et al.

The output for this paper can be further improved by increasing the amount of data used for training the emotional model and the live stress level from the video can be more accurate if a greater number of facial features are considered for the level. Adding wrinkle detection for certain areas of the face can easily increase the overall accuracy of the detected stress from the video.

IV. Conclusion

Stress detection using Facial recognition and ECG analysis is performed. Making use of emotions and ECG features stress is detected. By combing all the features and comparing the averages of those values we predict the stress of any given subject. The unique approach in the P wave detection helps us to reduce the complexity and increase the computational speed of detection. This is an enormous benefit to anyone and is not specific to a certain group of people.

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