Physiological Detection of Anxiety

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Abstract— **Anxiety detection from physiological signal has great significance in the healthcare application. Anxiety has negative valence and it keeps individual concentrated on negative emotions. Physiological features of Electrocardiogram signal quantify the anxiety response in individuals. Pan Tompkins algorithm is used for detecting the R peaks in the signal and then determines the interbeat intervals or R-R intervals. Support vector machine (SVM) and Kalman filter are used to detect anxious and non-anxious data. System performance is evaluated on ECG signals from the database for both methods. The system detects physiological changes related to the anxiety stimuli. From the results it can be concluded that the system can detect anxiety state with an accuracy of 71.1 % and 69.35 % using SVM classifier and Kalman filter respectively. The system detects anxiety and it can support individuals with anxiety disorders.**

Keywords— ***Physiological signal, feature extraction, R-R interval, SVM classifier, Kalman filter.***

I. Introduction

Emotion is a state of mind that occurs impulsively without of any endeavour and accompanies physiological changes and formed by subjective feelings, behavioural reactions, cognitive process, motivational tendencies and physiological arousal. Emotions result in psychological and physical changes. These changes influence our behaviour and interact with the mathematical, verbal and perceptual intelligence linked with the human brain. At a physiological level of emotions, both autonomic and central nervous system play a central role and responsible for specific internal reactions.

Anxiety has negative valence and it keeps individual concentrated on negative emotions. Automatic detection of anxiety finds application in numerous fields including human-computer interaction, intelligent transportation systems, security and access control, workload assessment, health monitoring, geriatric nursing and clinical anxiety treatment programs.

Anxiety disorder plays a significant role in occurrence and succession of cardiovascular disease (CVD). Anxiety also triggers CVD by the effects of repetitive emotional events. Cumulative effects of anxiety lead to physiological variations that increase risk of disease (direct effects) or because anxiety influences health relevant behaviours like smoking, diet, or physical activity over time, which in turn influence risk of CVD (indirect effects).Measurement of arousal linked with anxiety supplement treatment programs for many population. These populations have problem in communication, introspection and emotion recognition. The individual with ASD (Autism Spectrum Disorder) is an example of such a population.

Autism Spectrum Disorder (ASD) is a pervasive neurodevelopment disorder [1]. The individuals with ASD have difficulties in social and communication skills, and they show restricted and repetitive behaviour. Children who are suffering from ASD and intellectual disability have scarcity in communal and emotional skills, which may be one of several contributing risk factors to the very high prevalence of mental health issues in this population. Thus, promoting interventions to communal and emotional skills provide an opportunity to support the mental health and welfare of children with ASD and intellectual disability.

The rest of this paper is organised as follows: The related works on anxiety classification proposed in recent years are summarised in section II. The methodology of the whole system is included in section III. The concepts of feature extraction, emotion classification and Kalman filtering are described in methodology. The subsequent section, section V includes the obtained test results. Finally, we conclude this paper in section VI.

II. RELATED WORKS

Gestures, speech and facial expression are the main audio-visual channels used for automatic recognition of emotions [2]. These modalities have higher results and researched widely and all this approaches are prone to social masking. An emotion that is not conveyed, emotion communicated differently or slight emotional variation that is concealed to the eye cannot be traced.ANS activities are reflected in physiological signals and it helps to identify the inherent emotions. Physiological signals are the most powerful method for recognizing inner emotions even if there is social mask.

Power mean values and statistical features from ECG, EMG, Skin Conductivity were used to classify emotions (Joy, anger, sadness, pleasure) using pseudo inverse linear discriminate analysis [3] with accuracy of 70 and 95 percentage for subject-independent and subject-dependent respectively. Murugappan et al. [4] uses discrete wavelet transform for extracting statistical feature from ECG signal. Happiness, disgust, fear, sadness, and neutral emotions are classified using LDA and KNN (k-nearest neighbour) with maximum accuracy of 50.28 percentages for sadness using LDA.

A fuzzy logic system was proposed by Jerritta S et al. [6] to classify happiness, sadness, fear, surprise, disgust and neutral using ECG signal. Rescaled range statistics (RRS) and finite variance scaling (FVS) methods are used to find Hurst exponent. Hurst exponent is a nonlinear feature derived from QRS complex. The authors reported detection accuracies above 70 percent.

Support vector machine (SVM) iswidely used by researchers for classifying thefeaturesextracted from

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physiological signals [5, 7, 9, and 10]. In [5], the statistical time and frequency domain features extracted from ECG, skin conductance, and PPG are fed to SVM, CART and LDA classifiers to obtain an accuracy of more than 90 percentages.

Hany Ferdinando et al. [8] proposed kNN classification to solve 3-class problem (low-medium-high) for emotion classification in valence and arousal levels. 168 features are calculated by representing statistical distribution of dominant frequencies (DFs) from intrinsic mode Functions (IMF) after applying the Bivariate empirical mode decomposition (BEMD) to short-time ECG. Along with kNN classifier, Discriminate function analysis (DFA) is used to classify sadness, anger, surprise, fear, frustration by deriving minimum, maximum, mean values of Galvanic skin response, heart rate, and temperature [11].

Integrated system was proposed by Katsis et al [12]. It provides a monitoring system for the patients who have anxiety in therapeutic sessions. The system can recognize patient's emotional state such as neutral, relaxed, apprehensive, startled and very apprehensive. Physiological signals like Heart rare (HR), Blood volume pressures (BVP), respiration and Galvanic skin response were collected via non-invasive sensors. Artificial Neural Networks (ANNs), Support Vector Machines (SVM), Random Forests (RF) and a Neuro-Fuzzy System was used for classification. The overall classification accuracy is about 84.3%.

An optimal algorithm was proposed by Park et al. [13].the algorithm classifies the emotions happy, anger, sad, stress, surprise, fear and disgust based the on features extracted from physiological signals. Four channels of physiological signal, that is, Electrocardiogram, Skin temperature, Photoplethysmograph, and Electrodermal activity were recorded and analyzed.

In the work [14], analyzed various physiological signals (ECG, EEG and respiratory signals) were analyzed to detect the stress of an automobile driver under different conditions. Two features are extracted to get different levels of stress. SVM classifier is used for classification.

Valenzi et al [15] proposed offline and computer aided experiment for emotion classification. Video clips are used to elicit emotional states (sad, amused, sad and disgusted) and corresponding EEG signal is measured. Different supervised and clustering algorithm is used to classify emotions. The highest accuracy is for SVM.

Wanhui Wen et al [16] proposed evaluation system for social anxiety. Eleven Heart rate features from ECG signal is used for detection of low and high level anxiety. SVM, KNN (K-nearest neighbour), LDA (Linear Discriminant analysis), QDA (Quadratic Discriminant analysis) and NB (Naive Bayes) classifiers are used. Range of local hurst exponent is the most excellent feature for each classifier.

A multimodal database [17] which includes eye gaze data, audio signals, face videos, and physiological signals is used for emotion recognition. ECG, respiration amplitude, GSR and skin temperature are used as physiological signals. A total of 102 features are extracted from physiological signals. Fusions of EEG and eye gaze modality have high classification accuracy of 76.1%.

III. METHODOLOGY

The objective of this work is to measure the correlation between R-R interval and anxiety, and to detect anxiety related arousal from baseline condition. The block diagram of the anxiety detection is shown in below figure. The main steps are QRS detection, feature extraction and detection. Two methods are used for detection of anxiety related arousal.

The physiological signal, ECG changes with anxiety and it is the input to the system. The signal is processed to get features that are related to anxiety stimuli. Pan Tompkins algorithm is used for feature extraction. Then, the extracted features serve as the input to SVM classifier and Kalman filter. Classifier and Kalman filter decides the data belong to anxious or non-anxious stimuli.

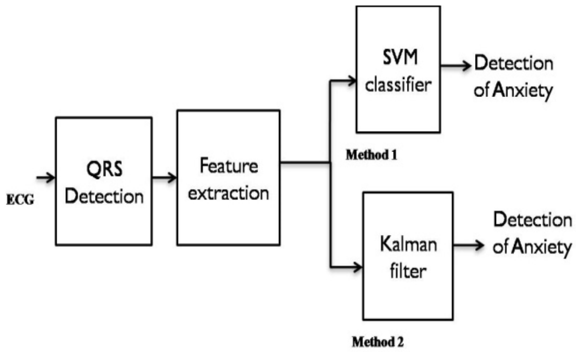

Fig 1: Block diagram of proposed system

A. *Feature Extraction*

Physiological, subjective, behavioural and cognitive are the interrelated dimensions of anxiety. Physiological changes related to anxiety can be measured by various non-invasive techniques. Stimuli related to anxiety sense and infer as a risk in the central nervous system structures. To respond to anxiety stimuli, endocrine and peripheral system stir up the body's resources and it is intertwined with physiological changes. The cardiac effect can be measured by the duration between consecutive heartbeats, known as inter-beat interval or R-R interval. Anxiety stimuli cause decreased R-R interval time and increased heart rate.

Pan Tompkins algorithm [18] is used for feature extraction by detecting QRS complex from ECG signal. The algorithm detects QRS by analyzing amplitude, slope, and width of QRS complex. The algorithm has the highest accuracy for detecting R peaks compared to other methods. The main steps in the algorithm are low pass and high pass filtering, derivation, squaring, integration, adaptive thresholding, and search procedures.

The filtering stage removes the power line interference at 50 Hz, muscle noise and baseline wandering. Derivation phase yields complex slope formation of QRS. Squaring phase makes all the data positive and to highlight the higher ECG frequencies. Integration phase employing a moving window to find the slope of R wave and also for finding feature information, followed with setting of thresholds and detection of QRS complexes [18].

B. *Classification*

SVM classification is a supervised learning method. Classification is used to map the feature vectors and to learn the pattern through a training model. In this classification algorithm, each data item is plotted as a point in dimensional space. The dimension is decided by the number of features selected. Then the algorithm locates the hyperplane that separates the two classes. The hyperplane is also called the functional margin that has a prime distance to the nearest trained data item of any class.

Selected features for SVM classification are the average R-R interval, a minimum value of R-R interval and a maximum value of R-R interval. Data from 15 subjects are used for classification. Seven signals for training and three signals for testing from each subject are used.

C. Kalman Filtering

Kalman filter is an unsupervised algorithm. It uses state dynamics of R-R intervals to detect anxiety. Kalman filter uses small variation model of R-R interval to detect anxiety related arousal [19].Kalman filter operates in two phases, in the prediction phase, state equation is used for modeling and in the update phase, measurement equation is used for refinement [1]. The Kalman filter assumes a linear model of R-R interval with the inclusion of additive white gaussian noise.

$$x_k = x_{k-1} + w_k \tag{1}$$

$$y_k = x_k + v_k \tag{2}$$

where x_k is the ideal slow varying R-R interval and y_k is the average R-R interval. The system and measurement noise processes w_k and v_k are zero mean white gaussian noise with known covariances $Q_k$and $R_k$respectively.

IV. PERFORMANCE MEASURE

The performance of SVM classifier and Kalman filtering was calculated using accuracy, specificity and sensitivity as defined below.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \tag{4}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TP+FN}} \tag{5}$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+TN+FP}} \tag{6}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{7}$$

where true positives (TP) and false negatives (FN) indicatescorrectly and incorrectly identified anxious states. True negatives (TN) and false positives (FP) indicates non-anxious states that are correctly and incorrectly identified, respectively.

V. RESULTS

The results of each stage of Pan Tompkins algorithm is depicted in below figures.First, the signal is filtered with a digital bandpass filter. Cascade combination of low pass and high pass filter is used for bandpass filtering. The filtering stage removes the noises in the ECG signal.

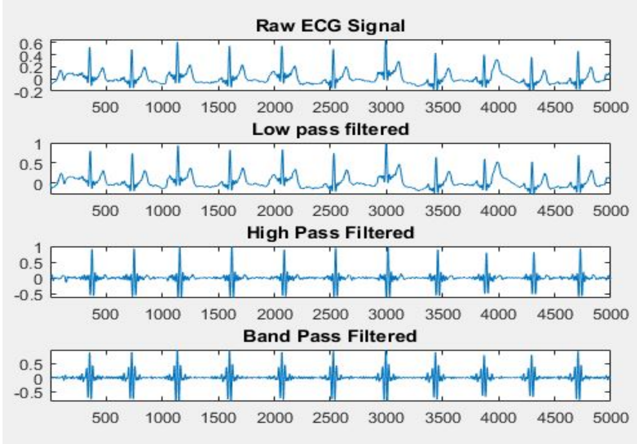

Fig 2: Raw ECG signal and filtered signal

The derivative stage intensifies the slope of the QRS complex. Squaring enhances the slope and helps to avoid the peaks sourced by T waves. Moving-window integrator filter produces a smoothed signal that contains the information about width and slope of the QRS complex signal. At last, the R peaks are identified by adaptive thresholding and search back process.

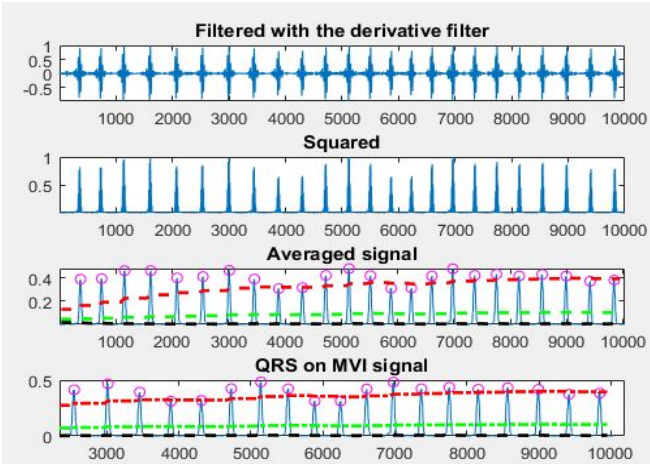

Fig 3: Filtered, squared, and integrated and QRS detected signal

R-R intervals are acquired by the difference of consecutive QRS complex using Pan-Tompkins algorithm. The ECG signals are sampled at a high rate compared to the QRS complex. So R-R intervals are interpolated at 2 Hz to get more samples.

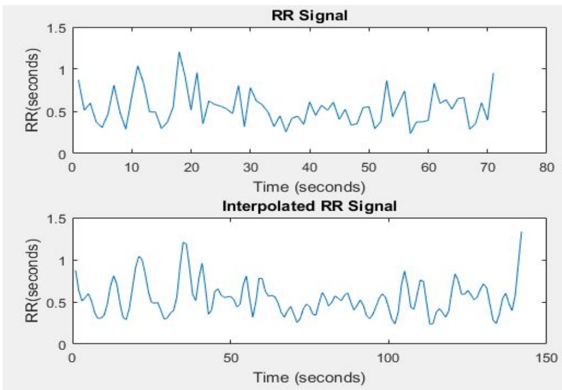

Fig 4: R-R Signal and interpolated R-R interval

The extracted features are given to the SVM classifier and kalman filter. Average R-R interval,maximum value of

R-R interval and minimum value of R-R interval are the selected features for classification. Kalman filter uses R-R signal as input.Classifier required a training stage and testing stage.but filtering algorithm have only testing stage.

The Kalman filter assumes a linear model of R-R interval with the inclusion of additive white gaussian noise. It estimates the R-R intervals. The diffrence in real and estimated R-R interval is affected by the noise covariance of measurement noise which is depicted in Fig 6 and 7.The performance of system improves with decreasing the value of noise covariance of measurement noise.

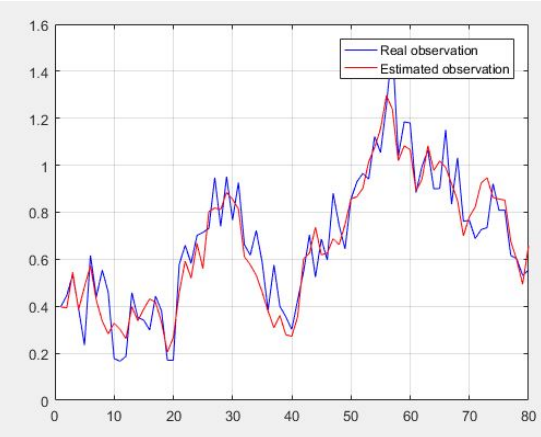

Fig 5: Kalman filter output for R=0.01

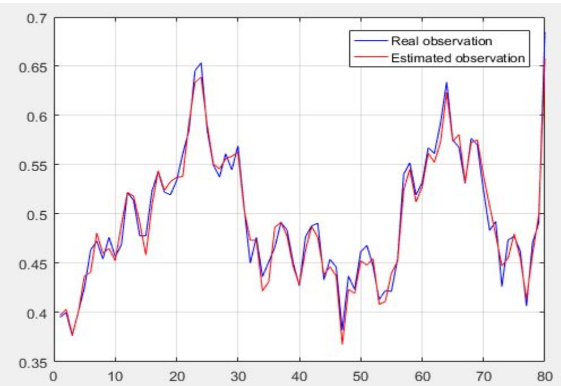

Fig 6: Kalman filter output for R=0.0001

Data from 15 subjects are used for detection of anxious and non-anxious states. Seven signals for training and three signals for testing from each subject are used for SVM classification. Kalman filter requires only testing state. Three samples from each subject are used to calculate the performance measures of the algorithm. The obtained performance measures of the classifier and Kalman filter are included in Table 1 and Table 2.

TABLE 1 PERFORMANCE COMPARISON FOR TRUE POSITIVE RATE

Performance Measure	SVM Classifier	Kalman filter
Accuracy	0.711	0.6935
Sensitivity	0.733	0.5484
Specificity	0.689	0.8387
Precision	0.7097	0.7727

TABLE 2 PERFORMANCE COMPARISONS FOR TRUE NEGATIVE RATE

Performance Measure	SVM Classifier	Kalman filter
Accuracy	0.711	0.6935
Sensitivity	0.689	0.8387
Specificity	0.733	0.5484
Precision	0.7143	0.6500

VI. CONCLUSION

RR interval obtained through ECG is used as a physiological measure of arousal and RR intervals shows significant anxiety-related changes. Anxiety arousal increases the heart rate and decreases R-R interval. Supervised and unsupervised algorithms can be used for detection of anxiety. System performance is sensitive to the choice of the noise covariances in kalman filtering algorithm. Kalman filter shows improved detection of anxiety arousal compared to SVM classifier. Cardiac activity along with electrodermal activity can be used for effective detection of anxiety. Real-time detection of anxiety can be done with kalman filter algorithm in clinical treatment programs.

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