Analysis Of Respiratory Signal For Anxiety Disorder Identification

H. Haritha, C. Santhosh Kumar, A. Anand Kumar

Abstract: Anxiety disorder identification (ADI) is becoming increasingly important in addressing mental health across the population. Traditionally, ECG has been found to be effective as a means to estimate stress and anxiety, and the effect of respiratory signal has been considered as undesirable. In this work, we study how respiratory signal can be effectively used for ADI. The data for this study was collected from normal population, subjects with anxiety disorders and regular meditators, at the Department of Neurology and the Department of Psychiatry, Amrita Institute of Medical Sciences (AIMS), Kerala, over a period of 1.5 years. We used respiratory rate variability (RRV) features as input to support vector machine (SVM) classifier for our baseline ADI system. We noticed that the baseline ADI gave very low classification performance, 63.88%, 83.43% and 69.23% absolute respectively, for sensitivity, specificity and accuracy. We observed large within class person specific variations (PSV) in the RRV features among the controls and the effect of these variations in the RRV features is a nuisance factor affecting the performance of the ADI adversely. To minimize the effect of PSV, we explored several techniques such as covariance normalization (CVN) and Fisher vector encoding (FVE), and on combining CVN and FVE (RFE-CVN-FVE-SVM-ADI), we obtained a sensitivity of 91.66% absolute, specificity of 95.23% absolute and accuracy of 92.30% absolute, which is an improvement of 27.78% absolute sensitivity, 11.80% absolute specificity and 23.07% absolute accuracy, over the baseline ADI. The optimum sets of features were selected using recursive feature elimination (RFE) algorithm. Respiratory signal can be effectively used in ADI. The study scientifically establishes the role of meditation and yoga in reducing anxiety and stress disorders, thus helping in the overall wellness of patients with psychiatric disorders, in their speedy recovery.

Index Terms: Anxiety Disorder Identification, Machine Learning, RRV, Respiratory Signal, SVM.

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1. INTRODUCTION

In today's hectic life style, anxiety has become an unavoidable companion to most people. Anxiety disorder identification (ADI), at present is done in a subjective manner, using questionnaires and interaction observation. These methods can be made possible only by clinical experts, who may be unavailable in a primary health centre (PHC) [1]. Also, ADI is usually associated with the psychiatric department, and this association prevents patients from taking medical counseling due to the social implications of being seen visiting a psychiatric department. Anxiety is one of the most important reasons leading to many fatal health related problems, cardiac disorders, sleep disorders, and depression. Often we do not understand the intensity of anxiety we are in, till there is a breakdown of the system or a heart attack. Hence, it would be of great importance, if we could develop an automated system for the identification of anxiety.

1.1 State-of-the-art

Recent studies [2] [3] [4] [5] [14] have reported the detection of stress and anxiety using wearable physiological sensors and smartwatch, where stress conditions were presented to healthy subjects and the variation in the physiological signals like electrocardiogram (ECG) signal, skin conductance, electromiogram (EMG) of trapezius muscles, galvanic response and body temperature, were considered. In [3], Ciabattoni et.al. developed a real-time detection of mental stress system, in which, stress is classified using a K-NN (K-nearest neighbor) classifier and an accuracy of 84.5% was observed. In [4], Martin et.al. proposed a method, consisting of activity recognizer, laboratory and context-based stress detector, for identification of stressful events using the data provided from a commercial wrist device. The method gave a classification accuracy of 92% for continuous stress detection. In [7], Gustavo Lenis et.al. explored the effect of respiratory signal on heart rate variability (HRV) and suggested that decoupling HRV from its respiration driven part could provide new information. In [7], the coupling between HRV and respiration was quantified using Granger's causality and the decoupling was then performed with a linear filter. In [6], Jongyoon Choi and Ricardo Gutierrez-Osuna, reported that the removal of respiratory influences from heart rate gives a leftover signal, in which the effects of stress becomes more prominent. It is observed that the research till date had considered the respiratory signal and its influence on other physiological signals, as a nuisance attribute in monitoring stress and anxiety.

Intuitively, it is well known that RRV [12] [13] will be moderate for normal population, low for people with psychiatric disorders and high for regular meditators. In autonomic nervous system (ANS), only respiratory signal can be regulated by human, where the other vital signs such as ECG, blood pressure (BP) and oxygen saturation are not in our control. Any effort to regulate the breathing pattern can help a person relax and regulate his anxiety [18]. However, no scientific study in this direction is been explored till date.

1.2 Proposed Study

In our study, we emphasize the usefulness of respiratory signal in ADI [20]. The study was carried out at the Department of Neurology and the Department of Psychiatry, AIMS, Kerala, in context with an ongoing work on analyzing the role of meditation and yoga in improving the wellness of patients with psychiatric disorders [15]. We selected 20 controls from normal population, 11 controls with anxiety disorders and 10 regular meditators for checking the effectiveness of the respiratory signal analysis for ADI. It may be noted that we chose the controls from the extreme cases: patients with psychiatric disorders and regular meditators. In this work, time and frequency domain (TaFD) features derived from the RRV, along with an SVM [8] classifier is used in developing the ADI system. The best performance for SVM-ADI system was

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63.88%, 83.43% and 69.23% absolute respectively, for sensitivity, specificity and classification accuracy. We then investigated different approaches to enhance the performance of ADI system. To optimize the ADI system performance, recursive feature elimination (RFE) algorithm was used for the selection of optimum set of RRV features. We obtained 75.00% absolute sensitivity, 85.71% absolute specificity and 76.92% absolute accuracy for the RFE-SVM-ADI system. It may be noticed that there exists PSV in the feature vectors of the respiratory signal that affects the performance of ADI adversely. In order to minimize the effect of PSV on the input features, we used covariance normalization (CVN) on the input feature vector. Alternatively, to further reduce the effect of PSV, we used Fisher vector encoding (FVE) to express the input features in a person independent feature space using Gaussian mixture models (GMM) trained person independently. Subsequently, we used CVN followed by FVE, to further minimize the effect of PSV. We obtained a sensitivity of 91.66% absolute, specificity of 95.23% absolute and classification accuracy of 92.30% absolute for RFE-CVN-FVE-SVM-ADI, which is an improvement of 27.78% absolute sensitivity, 11.80% absolute specificity and 23.07% absolute accuracy, over the SVM-ADI system.

2 DATASET

The study was organized at the Department of Neurology and the Department of Psychiatry, AIMS, Kerala. The study included 41 participants - 20 normal subjects, 11 regular meditators trained in Integrated Amrita Meditation Technique (IAM Tech) [17], and 10 patients with psychiatric disorders diagnosed based on DSM-V criteria [16]. Ethical issues were considered and a written consent was taken from all the study participants. After the diagnostic interview, the subjects received an individual appointment for a non-invasive set-up procedure in a non-threatening context of the neurophysiology lab at the Dept. of Neurology, AIMS, starting at 8.00 AM in the morning. The participants were encouraged to do their normal everyday activities after leaving the laboratory, and were asked to stop the recordings and take off the sensors the next morning at 8.00 AM, so that the physiological data was recorded for a complete period of 24 hours. The respiratory signal was collected using an ambulatory device called Embletta [21]. Embletta employs respiratory inductance plethysmography (RIP) bands [19]. It is battery operated and weighs around 150 grams, and therefore can be used in an ambulant setup.

3 SYSTEM DESCRIPTION

The respiratory signal of three different classes: normal, abnormal (patients with anxiety disorders) and meditators were collected and the ADI system was developed, considering the RRV features. TaFD features extracted from the RRV were given as input to an SVM backend classifier. The system architecture of SVM-ADI is shown in Fig. 1.

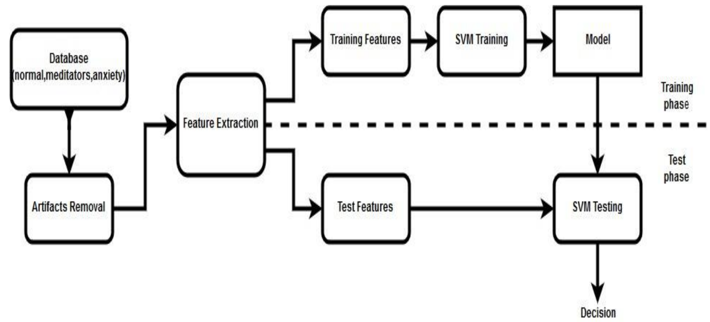

***Fig. 1**. Baseline System*

3.1 Signal Preprocessing

There were artifacts present in the respiratory signal, which may be due to missed beats or lung ectopy. These artifacts that can lead to performance deterioration of the system were detected and removed.

3.2 Features

In our study, TaFD features have been extracted from the respiratory rate (RR) interval series [11]. Time domain features: The time domain analysis [1] is often classified into two: statistical measures and geometric measures. Statistical measures are calculated directly from the Inter-Beat-Interval (IBI) and geometric measures are based on computations from a geometric pattern who's basis lies with the IBI series. The geometric pattern used in this work is the histogram of IBI [11]. Table 1 shows the time domain features used in the ADI system.

Table 1
Time domain features

Feature Abbreviation	Description
Mean	Mean of Inter-Beat-Interval (IBI) series
Median	Median of IBI series
SDNN	Standard deviation (SD) of NN interval
SDANN	Computes the mean IBI of each segment and returns the SD of all mean
NNx	Number of successive differences, greater than x milliseconds
pNNx	Percentage (%) of total intervals that successively differs by more than x milliseconds
RMSSD	Root mean square of the successive differences of the IBI series
SDNNi	Computes the SD of each IBI segment and returns the mean value of SDs
meanRR	Mean value of respiratory rate
sdRR	Average SD value of respiratory rate
RRVTi	Respiratory rate variability triangular index
TINN	Triangular interpolation of NN histogram

Mean IBI, median IBI, SDNN, SDANN, NNx, pNNx, RMSSD, SDNNi, meanRR and sdRR are the statistical measures, and the geometric measures include RRVTi and TINN. The statistical measures SDANN and SDNNi are computed as given by (1) and (2) respectively.

$$\text{SDANN} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}[meanIBI(i) - \overline{meanIBI}]^2} \quad (1)$$

$$\text{SDNNi} = \frac{1}{N}\sum_{i=1}^{N} SDNN(i) \quad (2)$$

Frequency domain features: The method adopted in this work for frequency domain analysis is Fast Lomb method. Table 2 shows the frequency domain features used in the ADI system.

Table 2
Frequency domain features

Feature Abbreviation	Description
VLF	Very low frequency power (0 Hz-0.04Hz)
LF	Low frequency power (0.04Hz-0.15Hz)
HF	High frequency power (0.15Hz-0.4Hz)

3.3 Techniques used for improving the performance of ADI

3.3.1 Recursive Feature Elimination (RFE): Recursive Feature Elimination (RFE) [9] is an iterative procedure, in which each iteration includes training the classifier, calculating the scores for all features and eliminating the features with smallest scores[10]. In RFE, the model is trained using all the features present in the input feature set. Subsequently, the effect of each feature is considered, based on which a score is generated. The features are ranked based on the generated score and the features with the least scores get eliminated. Let X be a set of ordered sequence (X1 > X2 > X3... > XN), which represents the features used in the generation of the model. At each iteration of the RFE algorithm, the Xi top ranked features are kept, the model is refit using these optimum set of features and the model accuracy is assessed.

3.3.2 Covariance Normalization (CVN): In ADI system, there exits an intrinsic dependency relationship between the different features considered. This relationship is considered and we find the dependencies between the features using a covariance matrix. The PSV in the respiratory signal features is treated as noise. CVN minimizes the PSV and helps in the reduction of noise, thus by improving the performance of the system. The covariance matrix is found as given in (3):

$$C = \frac{1}{M}\sum_{ij}^{M}(x_i - \mu_1)(x_k - \mu_2)^T \quad (3)$$

We use Cholesky decomposition to decompose the matrix C. The covariance estimates are usually noisy, and hence to reduce the noise in the estimation, we use smoothing, as given in (4).

$$S = \lambda * C + (1-\lambda) * I \quad (4)$$

where, S : smoothed covariance matrix, λ : smoothing factor (value ranging from 0 to 1), I : unit matrix.

3.3.3 Fisher Vector Encoding (FVE): In FVE, we express the input features in a person independent feature space using Gaussian mixture models (GMM) trained person independently. In FVE, a generative probabilistic model is used to derive a gradient vector for characterizing the features and is given to a discriminative classifier. We use GMM for probabilistic modelling of the training data. Expectation maximization (EM) algorithm is used for iteratively solving the maximum likelihood problem for training the GMMs. It is based on fitting the GMM to the feature vectors and then encoding the derivatives of log-likelihood of the model with respect to its parameters. The gradient of the log-likelihood, Fisher score, describes the direction in which parameters should be modified to fit the data. The EM algorithm of GMM uses posterior probabilities for soft assignment of the feature to each mixture component.

Let X1,..,XN be set of input vectors, wi be the weight vector, and qik, represented as in (5), be the soft assignments of the N feature vectors to G Gaussians, where k=1,2,..,G and i = 1,2,..,N.

$$q_{ik} = \frac{p(x_k|\Sigma_k)w_k}{\sum_{j=1}^{K} p(x_i|\Sigma_j)w_j} \quad (5)$$

For each k=1,2,..,G, the mean features u_k and covariance features v_k is calculated as in (6) and(7), respectively:

$$u_k = \frac{1}{N\sqrt{w^k}}\sum^{N} q_{ik}\Sigma_k^{-1/2}(x_{t-}\mu_k) \quad (6)$$

$$v_k = \frac{1}{N\sqrt{w^k}}\sum_{i=1}^{N} q_{ik}[(x_{t-}\mu_k)\Sigma_k^{-1/2}(x_{t-}\mu_k) - 1] \quad (7)$$

arranging u_k and v_k as in (8).

$$f_{Fisher=}[u_1^T, v_1^T \ldots\ldots\ldots\ldots, u_K^T, v_K^T]^T \quad (8)$$

The final dimension of FVE is 2GD, where, G : number of Gaussians and D : dimension of input feature vector.

4 RESULTS

4.1 Dataset

The data used in the study was obtained from the Dept. of Neurology and Psychiatry, AIMS, Kochi. We collected respiratory signal of 20 normal population, 11 regular meditators and 10 individuals with anxiety disorders for validating the ADI system. The TaFD statistical features derived from the RRV is given as input to the system. beats or lung ectopy. These artifacts that can lead to performance deterioration of the system were detected and removed.

4.2 Evaluation Parameters

The proposed system for anxiety detection is validated in terms of sensitivity, specificity and accuracy, which are calculated as:

Sensitivity = TP / (TP+FN) (9)

Specificity = TN / (TN+FP) (10)

Accuracy = (TP+TN) / (TP+FN+TN+FP) (11)

where TP, TN, FN, and FP represents true positive (the anxiety disordered subjects identified as anxiety disordered), true negative (normal subjects identified as normal), false negative (anxiety disordered subjects identified as normal), and false positive (the normal subjects identified as anxiety disordered patients), respectively. The dataset was divided in 80:20 ratio, like 80% of the data was used as training data and the rest 20% was used as test data. Models were trained and verified using an SVM backened classifier (multi-class classification). Further, to enhance the system performance, feature mapping and feature normalization techniques were explored over the SVM baseline system.

4.3 Baseline (SVM-ADI) System

For the baseline system, we experimented with different SVM kernels: linear, polynomial, radial basis function (RBF) and sigmoid. The performance of the baseline system is shown in table 3.

Table 3

Performance of baseline (SVM-ADI) system

Kernel	Sensitivity (%)	Specificity (%)	Accuracy (%)
Linear	55.55	77.61	61.53
Polynomial	63.88	83.43	69.23
RBF	33.33	66.66	46.15
Sigmoid	33.33	66.66	46.15

It is noted that the best performance is obtained for the polynomial kernel, with a sensitivity of 63.88% absolute, specificity of 83.43% absolute and classification accuracy of 69.23% absolute.

4.4 RFE-SVM-ADI System

The optimum set of RRV features were selected using RVE and we found that the RFE-SVM-ADI gave a performance of 75.00% absolute sensitivity, 85.71% absolute specificity and 76.92% absolute accuracy, which is 11.12%, 2.28% and 7.69% absolute improvement over the SVM-ADI. The performance of the RFE-ADI system is low since there exists PSV in the input signal used. Hence, to reduce the PSV and enhance the performance of the ADI system, we used different machine learning algorithms such as CVN and FVE.

4.5 RFE-CVN-SVM-ADI System

In CVN, the PSVs were removed and the classification was done by considering only the person independent attributes. The results obtained for the RFECVN-SVM-ADI system is given in table 4.

Table 4

Performance of RFE-CVN-SVM-ADI system

Lambda (λ)	Sensitivity (%)	Specificity (%)	Accuracy (%)
0.16	66.66	82.38	69.23
0.21	83.33	91.90	84.61
0.33	77.77	88.20	76.92

From the results, we note that the system performance has significantly increased with respect to the baseline system. We obtained an improvement of 19.45% absolute in sensitivity, 8.47% absolute in specificity and 15.38% absolute in accuracy, on using CVN.

4.6 RFE-FVE-SVM-ADI System

In FVE, we tried out different GMM clusters. Table 5 shows the classification results of RFE-FVE-SVM-ADI system, using linear SVM kernel.

Table 5

Performance of RFE-FVE-SVM-ADI system

No. of GMM Clusters	Sensitivity (%)	Specificity (%)	Accuracy (%)
2	66.66	83.81	69.23
6	69.44	86.29	69.23
7	50.00	71.64	46.15

From the experiments, it is found that the FVE did not improve the accuracy of the SVM-ADI. However, FVE with GMM clusters 6 has improved the sensitivity and specificity of ADI system, by 5.56% absolute and 2.86% absolute, respectively.

4.7 RFE-CVN-FVE-SVM-ADI System

To further refine the classification predictions of the ADI system, we combined the information from CVN and FVE systems. The results of RFECVN-FVE-SVM-ADI system are given in table 6.

Table 6

Performance of RFE-CVN-FVE-SVM-ADI system

Lambda (λ)	No. of GMM Clusters	Sensitivity (%)	Specificity (%)	Accuracy (%)
0.00249	16	91.66	95.23	92.30

An improvement in the classification performance of 27.78% absolute in sensitivity, 11.8% absolute in specificity and 23.07% absolute in accuracy, was obtained over the SVM-ADI system on using FVE over CVN. The best results obtained for four different systems of ADI : baseline, FVE-SVM-ADI, CVNSVM-ADI, CVN-FVE-SVM-ADI and RFE-SVM-ADI, are shown in Fig. 2.

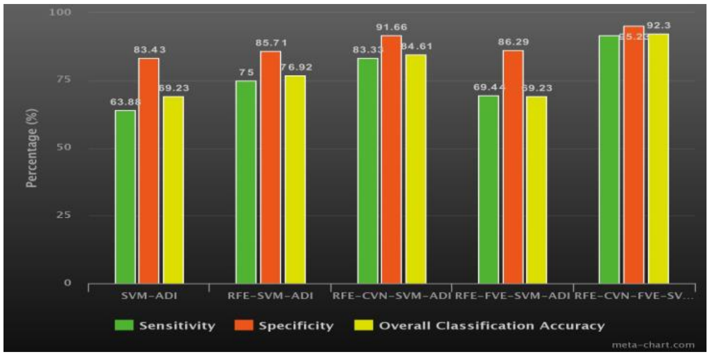

Fig. 2*. Graphical consolidation of results obtained for different ADI systems*

5 CONCLUSION

In this work, we analyzed the usefulness of respiratory signal for measuring anxiety, by developing an automated anxiety disorder identification (ADI) system using respiratory data as its input. We used data of 20 controls from normal population, 10 controls with psychiatric and anxiety disorders and 11 regular meditators, for validating the effectiveness of ADI system. TaFD statistical features extracted from the respiratory signal, is input to an SVM backend classifier in the ADI system. We obtained 63.88% absolute sensitivity, 83.43% absolute specificity and 69.23% accuracy for our baseline (SVM-ADI) system. To optimize the performance of ADI, we used recursive feature elimination (RFE) to find the optimum set of RRV features. We obtained a performance of 75.00% absolute sensitivity, 85.71% absolute specificity and 91.66% absolute accuracy, for the RFE-SVM-ADI. To further enhance the performance of ADI, we explored different machine learning techniques. We first used covariance normalization (CVN) on ADI, to minimize the person specific variations present in the respiratory signal. We then explored Fisher vector encoding (FVE), in which the input features are expressed in a patient independent feature space using Gaussians trained patient independently. Further, we combined the CVN and FVE systems to obtain RFE-CVN-FVE-SVMADI, and obtained a sensitivity of 91.66% absolute, specificity of 95.23% absolute and classification accuracy of 92.30% absolute for RFE-CVN-FVE-SVM-ADI, which is an improvement of 27.78% absolute sensitivity, 11.80% absolute specificity and 23.07% absolute accuracy, over the SVM-ADI system. This study scientifically demonstrates that respiratory signal has information within for ADI and regulating the respiratory patterns through yoga/meditation can help regulate the anxiety level of individuals.

CONFLICTS OF INTEREST

The authors of this paper do not hold any conflicts of interest.

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