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Automatic Detection of Sleep Apnea from ECG Signal

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***Abstract*—**This paper exhibits a technique for the programmed discovery of rest apnea from single-lead ECG. In this we utilizes two well known features in heart rate variability analysis, to be specific the standard deviation and the serial relationship coefficients of the RR interval time arrangement. The primary novel component utilizes the key parts of the QRS complexes, and it portrays changes in their morphology brought about by an expanded thoughtful movement during apnea. The second novel element separates the data shared in the middle of breath and heart rate utilizing orthogonal subspace projections. Respiratory data is taken from the ECG by method for three best in class calculations, which are executed and thought about here. All components are utilized as info to a support vector machine (SVM) classifier. Separation between the sleep apnea and normal recording is achieved.

Keywords*—Sleep Apnea, , ECG Morphology, SVM Classifier;*

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I.INTRODUCTION

Sleep apnea is commonly defines as the cessation of breathing during sleep. Sleep apnea is a rest related breathing issue that influences around 10% of moderately aged grown –ups[1] . Moreover, it is viewed as a danger variable for dreariness and mortality because of its long term impact on the cardiovascular system .This impact is identified with various physiological instruments like systemic hypertension and expanded thoughtful regulation that in a long term bargains the well-working of the heart. In this setting, this study proposes a basic calculation for the programmed discovery of rest apnea from the ECG signal. Likewise, two unique components catch profitable data identified with apneas are proposed. One portrays changes in the morphology of the ECG, and one registers the data shared in the middle of breath and heart rate, by method for orthogonal subspace projections.The first EDR calculation depends on the R-peak sufficiency which has been broadly utilized for apnea recognition, the second one uses central part examination and the last one uses its kernal version kPCA. All the elements got from the heart rate and from the EDR signs are utilized as information to various classifiers, to be specific, linear discriminant examination (LDA), support vector machines (SVM), and least squares support vector machines (LS-SVM).A last calculation is then proposed and tried on two diverse datasets.
will be improved and power consumption and delay will be reduced.

II METHODS

A. Datasets

The database of the Apnea-ECG signal from the physionet on the internet. This datasets we have taken contain five ECG sleep apnea signals sampled at 100khz.Each ECG signal was manually annoted by an expert on a minute-by-minute basis,for sleep apnea using additional signals such as respiration and oxygen saturation. And also we collected the healthy persons five ECG signal database for comparision from the physionet.

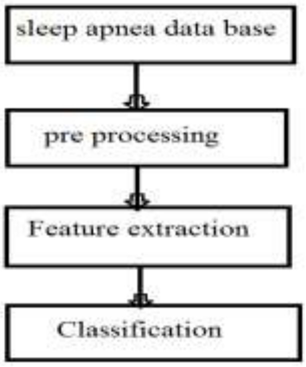

Figure 1. Schematic diagram

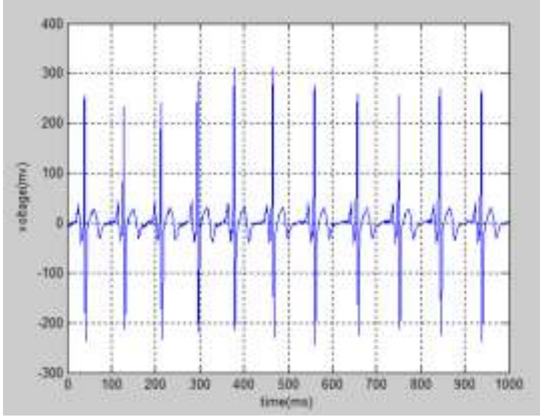

Figure 2.Sleep apnea ecg signal

B.ECG Derived respiration(EDR)

The respiratory occasions can be identified utilizing an ECG determined breath (EDR).[5]. The determination of this approximated respiratory sign is conceivable because of the mechanical association between the respiratory developments and the morphology of the ECG.. Here, three distinct approaches to process the EDR sign are actualized, and they will be depicted beneath.The exhibitions of the calculation utilizing each EDR will be evaluated and looked at against the one acquired utilizing the genuine, reference

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respiratory signs. This is done all together to decide the additional estimation of every philosophy on the discovery of sleep apnea from convenient ECG-based checking frameworks.

i) R-peak amplitude (Ramp): This system, initially depicted in utilizes the abundancy of the R-crests in a standard adjusted ECG signal. The pattern is registered by method for two middle channels, to be specific one of 200ms that evacuates the QRS complexes and P-waves, and one of 600ms that evacuates the T-waves. The subsequent gauge is then subtracted from the first ECG, and the amplitudes of the R-peaks make up the EDR. In the staying of this report, this EDR will be meant by Ramp. Here we used Rpeak.

ii).Principal component analysis(PCA): The EDR signal

figured utilizing PCA considers not just the varieties of the R-peak sufficiency, additionally the tweak of the entirety QRS complex because of respiratory developments. Here, all QRS edifices are sectioned utilizing a symmetric window of 120ms around the R-peak. The length of this window was chosen in light of the width of an ordinary QRS complex: 100ms±20ms Next, all windows are adjusted to regard to the R-peak in a grid. Since the amplitude of all points around the R-peak are modulated by respiration, a mean variety is inferred by method for PCA. This mean relates to the R peak pca, which is the primary vital segment got from the eigen decomposition of the covariance network of X: = XX^t .

3.Kernel principal component analysis (kPCA): In [6] it was demonstrated that a non-straight form of PCA, i.e., kPCA, accomplishes better approximations of the genuine respiratory sign, at the point when contrasted and the two past approaches. In this case, a non-direct change of the data space is performed by method for a RBF piece capacity, which permits to consider direct and non-straight collaborations between breath and the morphology of the QRS edifices. The information space compares to the 120ms windows that were fragmented around the R-tops, and the new, changed space is known as the component space. It is in this new space the customary straight PCA is performed.

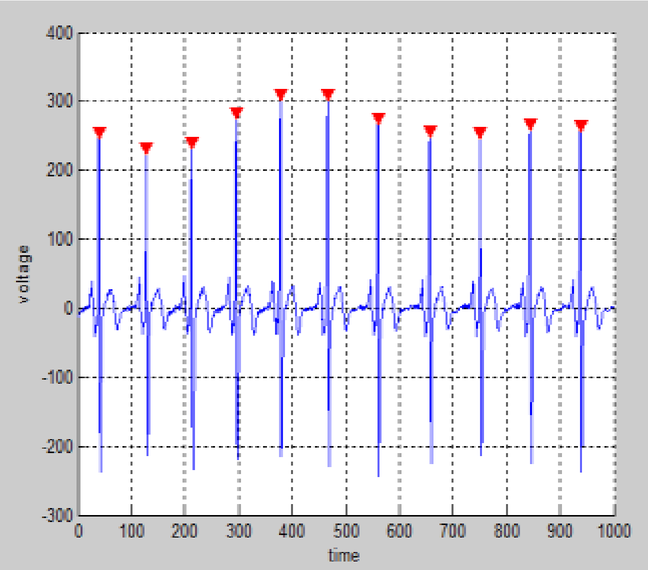

Figure 3.Rpeak of the sleep apnea ECG signal

III.FEATURE DERIVED

It is surely understood that varieties in heart rate are balanced by varieties in breath through the physio logical system called respiratory sinus arrhythmia (RSA) Hence, the data contained in the heart rate signal could on a fundamental level be part into two distinct segments, one identified with respiratory changes, and one identified with physiological systems unique in relation to respiration .Given are two physiological signs X and Y , where X is the RR interim time arrangement RR (resampled at 5Hz), and Y compares to one of the accompanying respiratory signals. These different elements relate to the standard deviation of the RR interim time arrangement (apena), standard deviation of the respiratory sign R (apnea),These different elements compare to the standard deviation of the RR interim time arrangement (normal), standard deviation of the respiratory sign R (normal).

TABLE I

S no	patient	Mean of R	Standard deviation of R	Mean of RR	Standard deviation of RR
1	Apnea	89.8	25.4757	269.0706	5.2451
	Normal	79.0667	15.7008	513.8241	1.831
2	Apnea	178.6	4.2601	109.9221	84.3819
	Normal	124.2222	36.4742	252.7101	1.5635
3	Apnea	76.1538	28.1505	440.7423	0.8006
	Normal	79.6667	18.5225	587.9398	2.0237
4	Apnea	102.667	25.8366	444.4885	4.5
	Normal	82.8571	28.5961	341.396	1.7478
5	Apnea	136.333	16.972	121.5684	53.5786
	Normal	80.4	18.1964	332.3112	0.9103

Table I: calculations for RRinterval and Rpeak

IV. CLASSIFICATION

There are different types of classifiers are classified they are:

1) Linear Discriminant Analysis (LDA) .

2) Support Vector Machines (SVM) utilizing straight, polynomial also, RBF parts.

3). Least-Squares SVM (LS-SVM) using linear ,polynomial and RBF kernels.

Here in this paper we use the SVM classifier. Support vector machines (also support vector networks) are supervised

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learning models with associated learning algorithms that analyze data used for classification and regression analysis.

SVM Algorithm:

1).we have given the training values of both normal and sleep apnea person using different parameters.

2).Label the values for the apnea signal and normal signal.

3).From the given parameters take any value to test whether the signal is apnea or normal.

4).Train the SVM classifier with the training set.

5).By using svm classifier we classify the apnea and normal signal.

6).plot the graph.

V. STIMULATION RESULT ANDDISCUSSION

This section presents the comparison of the sleep apnea person and the normal person. A comparison between different parameters extracted from the ECG signal taken from the physionet. We used SVM classifier and a final algorithm to classify sleep apnea was identified. This study had three main objectives namely the evaluation of the two novel features for the detection of sleep apnea. Here the features are derived from the RR interval time series. The classifiers used in this work only discriminated between the normal and the sleep apnea person. In this absolutely programmed calculation of ECG around 80 to 85% were accounted for in on the Physionet dataset. All analysis were done in MATLAB R2010.

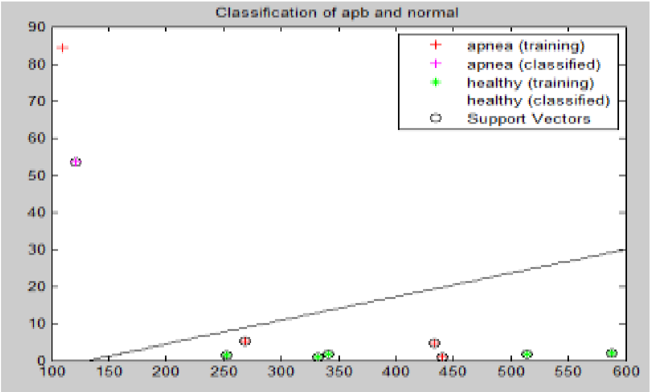

Figure 4.Comparison of Apnea and Normal signal

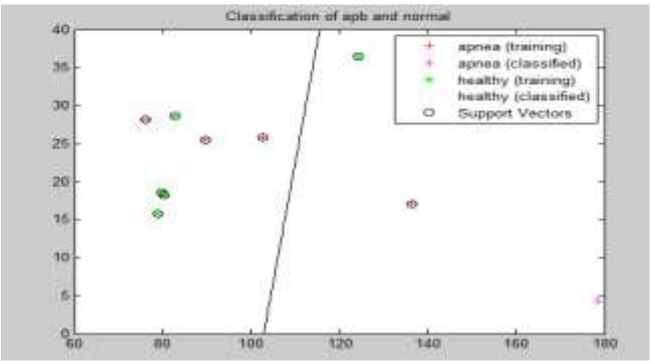

Figure 5. Comparison of Apnea and Normal signal

VI. CONCLUSION

A methodology fir the automatic detection of sleep apnea from ECG was introduced. Two novel components were proposed. These two elements together with two surely understood parameters utilized in HRV, to be specific the standard deviation and the serial connection coefficient permitted to separate apneas from ordinary action. This discrimination was performed utilizing a SVM classifier.. The exactness's accomplished in this study are practically identical to the best results reported for completely computerized calculations, to be specific in the extent somewhere around 80% and 85%. Another contribution of this work was the comparison of algorithms to derive respiratory information from the ECG. Different parameters computed from the respiratory signals were used for the detection of sleep apnea

REFERENCES

[1] P. E. Peppard et al, "Increased prevalence of sleep-disordered breathingin adults," AM J Epidemiol, vol. 177, no. 9, pp. 1006–1014, May 2013.

[2] S. M. Caples et al, "Sleep-disordered breathing and cardiovascular risk,"Sleep, vol. 30, no. 3, pp. 291–303, Mar 2007.

[3] Task Force AASM, "Sleep-related breathing disorders in adults:recommendations for syndrome definition and measurement technique[sin clinical research." Sleep, vol. 22, no. 5, pp. 667–689,Aug 1999.

[4] T. Penzel et al, "The apnea-ecg database," in Proc. Computers inCardiology, 2000, pp. 255–258.

[5] M. Bsoul et al, "Apneamedassist: real-time sleep apnea monitor usingsingle-lead ecg," IEEE Trans. Inf. Technol. B., vol. 15, no. 3, pp. 416–427, May 2011.

[6] P. De Chazal et al, "Automated processing of the single-lead electrocardiogramfor the detection of obstructive sleep apnoea," IEEE Trans.Biomed. Eng., vol. 50, no. 6, pp. 686–696, Jun 2003.

[7] K. Kesper et al, "Ecg signal analysis for the assessment of sleepdisordered breathing and sleep pattern," Med. Biol. Eng. Comput.,vol. 50, no. 2, pp. 135–144, Feb 2012.

[8] T. Penzel et al, "Systematic comparison of different algorithms forapnoea detection based on electrocardiogram recordings," Med. Biol.Eng. Comput., vol. 40, no. 4, pp. 402–407, Jul 2002.

[9] S. Boudaoud et al, "Corrected integral shape averaging applied toobstructive sleep apnea detection from the electrocardiogram," EURASIPJ. Adv. Sig. Pr., vol. 2007, no. 1, p. 032570, 2007.

[10] P. Langley et al, "Principal component analysis as a tool for analyzingbeat-to-beat changes in ecg features: application to ecg-derived respiration,"IEEE Trans. Biomed. Eng., vol. 57, no. 4, pp. 821–829, Apr 2010