Apnea MedAssist: A Personalized Low-Cost Sleep Apnea Monitor

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INTRODUCTION

We have developed a personalized low-cost sleep apnea monitoring system capable of recognizing Obstructive Sleep Apnea (OSA) episodes [1] with a high performance and accuracy. The fully automated system uses patient's single-channel Electrocardiogram (ECG) during sleep to extract large set of features [2], and uses Support Vector Classifier (SVC) [3] to detect apnea episodes. The implementation is done as a downloadable software module on a smart-phone making it low-cost and widely available. Another version is implemented on a server that uses simpler cellular phone as a gateway. This has wide ranging applications such as pre-surgery assessment, drug-effect studies, CPAP treatment verification etc.

ARCHITECTURE AND METHODS

The *"Apnea Med-Assist"* architecture with various components and functionalities is shown below. The machine learning algorithm considers a large set of features extracted directly from Heart Rate Variability (HRV) and the ECG-derived respiration signal (EDR). Optimization of number of support vectors (SVs) and input features to reduce classifier complexity is the key to the application development on a smart phone.

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RESULTS

The system was tested using 35 subjects' sleep studies obtained from PhysioBank's Apnea-ECG database with a total of about 14000 minutes divided between apnea and non-apnea. The system performance *F-measure* (a combining factor for both sensitivity and specificity) and accuracy (Acc) are investigated under different classifier models, kernel types and feature selections from the ECG and EDR signals. Table-1 shows the results for the subject-dependent (personalized) support vector classifier (SV-SD) used here. The fully automated real-time system achieves a classification F-measure of 90% and a sensitivity of 96%. The higher sensitivity and accuracy achieved here are due to the personalized machine learning algorithm used.

TABLE 1
Comparison of SV-SD classifiers: linear [3] versus one implemented here (radial basis function). C and γ are optimization parameters

Linear classifier				Classifier used here			
C	Sens Spec	Acc	F	C/γ	Sens Spec	Acc	F
0.45	96.88 83.42	88.40	89.65	0.8/ 0.4	96.05 84.98	89.08	90.18
0.50	96.85 83.54	88.47	89.70	0.9/ 0.3	96.17 84.76	88.98	90.10
0.55	96.83 83.57	88.48	89.71	1.0/ 0.3	96.05 84.88	89.02	90.12
0.60	96.77 83.62	88.49	89.71	1.0/ 0.5	95.10 85.90	89.30	90.26

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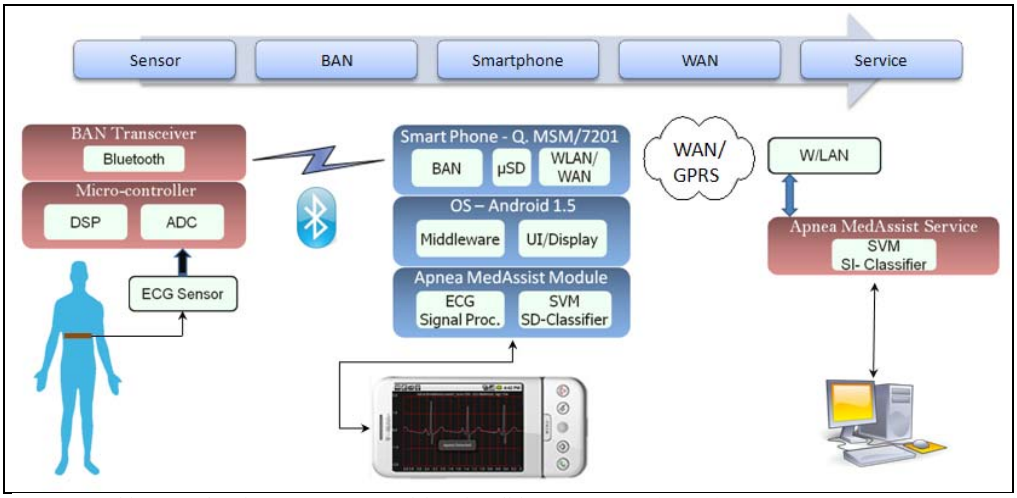

System Architecture showing components and functionalities. *DSP-Digital signal processor, ADC- analog to digital converter, BAN-body area network, WAN-wide area network, SVM-support vector machine, SI-subject independent.*