The Identification of Respiratory Phase Using Support Vector Machines and Extreme Gradient Boosting

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INTRODUCTION

Respiration is often monitored by direct airflow measurement. Indirect approaches of monitoring breathing can be used when direct airflow access is inconvenient or impossible. Respiration tends to affect the seismocardiographic signal (SCG). Hence, SCG signals may be used to derive the respiratory phases noninvasively. In portable settings where SCG signals are readily available, the use of SCG would eliminate the need for direct airflow measurements. Previous studies [1]-[6] extracted respiratory phases from different physiological signals using traditional signal processing and machine learning techniques/methods. Solar et.al. [7] classified SCG events using support vector machine (SVM) algorithm, but only lung volume classes (i.e., Low and high lung volumes) were considered. The current study investigated both lung volume and inspiratory/expiratory phases and compared the performance of two methods (namely, SVM and extreme Gradient Boosting (XGBoost)).

DATA COLLECTION

15 healthy subjects were recruited after IRB approval. Subjects were asked to lay supine on a bed tilted to 45 degrees head facing forward with their feet extended horizontally. The SCG signals were recorded using a tri-axial accelerometer (Model: 356A32, PCB Piezotronics, Depew, NY) which was attached to the chest surface near the left lower sternal border of the 4th intercostal space. A recent study [8]-[11] also used accelerometers to measure acoustic signals. A biopotential recorder (IX-B3G, IWorx Systems, Inc., Dover, NH) was used to record the ECG signal. It also allows simultaneous acquisition of chest galvanic skin response (GSR) signal by attaching two separate electrodes under subject's right clavicle and next to left abdomen.

FEATURE COLLECTION, SELECTION AND SCALING

ECG R-peaks were used to detect and segment SCG events. Each SCG event was selected to start 0.1 seconds before the R peak of the corresponding ECG and ends at 0.1 seconds before the next R peak. The SCG features used in this study were the waveform amplitudes (voltage) during every 4 milliseconds since an earlier study [2] suggested the utility of this feature. Figure 1 shows how the features are collected by dividing the signal into bins then calculating the average amplidute in each bin. Based on the SCG timing in the respiratory cycle, segmented SCG beats were classified into inspiratory and expiratory beats, as well as high and low

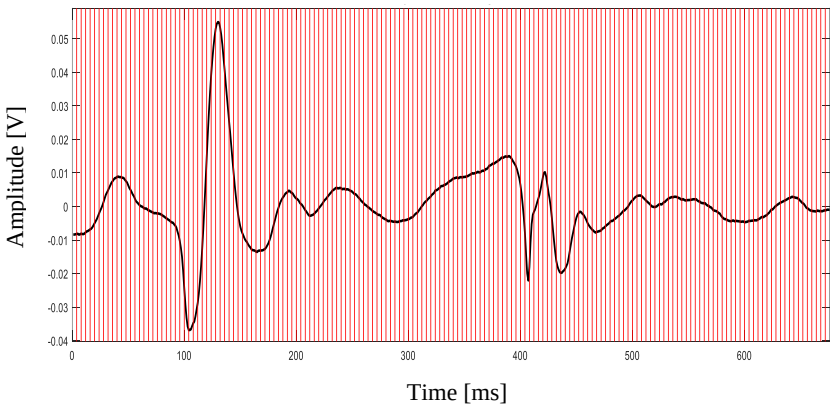

Figure 1. Feature selection from segmented SCG waveform. Here, the average amplitude during each 4 ms window (interval between the red lines) was chosen as a feature.

lung volumes (relative to the mean lung volume). The features were normalized before splitting for training and testing. Subject-specific (SS) training and testing was done using SVM and XGBoost (i.e., both training and testing were done for each subject separately). Here, 70% of the data was used for training and 30% for testing of each subject. Table 1 shows the number of data points used for training and testing for each subject.

MACHINE LEARNING FRAMEWORK

Support vector machine (SVM) and extreme Gradient Boosting (XGBoost) were utilized to extract respiration phases. When SVM was used, a hyperplane was found in the "features space" [12] that maximizes the margin between classes (i.e., respiration phases). Linear kernel function was used to train the SVM. For the XGBoost [13] model, the number of gradient boosted trees was 100, the maximum tree depth for base learners was 6 and boosting learning rate was 0.7. K-fold cross-validation [14] (k=10) was performed for both models. Table 1 shows the validation accuracy for each subject. The validation accuracy was 89 ± 6 % for inspiration/expiration, 85 ± 6 % for HLV/LLV detection using SVM. For XGBoost the validation accuracy was 90 ± 4 % for inspiration/expiration and 85 ± 3 % for HLV/LLV detection.

Table 1. Subject specific training samples, testing samples, validation accuracy, testing accuracy, sensitivity/recall, specificity, precision, F1 score for detecting HLV/LLV and Inspiration/expiration phases using SVM and XGBoost

Subject No		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Training samples		22088	29116	23845	28112	26857	21084	19327	21084	21586	20080	17570	20080	22590	23343	26857
Testing samples		9500	12500	10250	12000	11750	9250	8250	9000	9500	8750	7500	8750	9750	10000	11750
SVM: Inspiration/Expiration	Validation accuracy	81	87	93	87	95	88	86	92	87	86	99	79	96	92	93
	Testing accuracy	95	88	90	88	94	95	85	94	82	89	100	77	95	98	96
	Sensitivity/ Recall	100	79	89	95	100	94	78	93	86	95	100	72	93	100	90
	Specificity	91	100	91	81	86	95	93	95	76	79	100	82	100	96	100
	Precision	89	100	89	80	90	94	93	93	82	87	100	81	100	93	100
	F1 score	94	88	89	87	95	94	85	93	84	91	100	76	97	96	95
XG Boost: Inspiration/ Expiration	Validation accuracy	89	87	85	91	94	92	86	94	86	87	97	83	95	90	92
	Testing accuracy	92	90	98	90	89	92	82	97	84	86	97	80	97	93	94
	Sensitivity/ Recall	90	96	96	95	86	100	82	95	89	86	96	89	100	100	88
	Specificity	94	84	100	85	92	85	81	100	79	86	100	69	93	88	97
	Precision	95	86	100	84	90	85	82	100	81	90	100	77	96	84	94
	F1 score	93	91	98	89	88	92	82	98	85	88	98	83	98	91	91
SVM: HLV/ LLV	Validation accuracy	93	85	83	87	81	88	92	87	84	89	84	71	86	74	88
	Testing accuracy	76	96	88	88	87	81	76	86	92	91	80	80	87	90	94
	Sensitivity/ Recall	88	100	91	88	81	81	68	79	95	89	78	86	89	95	91
	Specificity	57	89	84	88	92	81	91	94	89	92	86	71	86	85	96
	Precision	78	94	87	88	89	85	94	94	90	80	95	82	84	86	95
	F1 score	82	97	89	88	85	83	79	86	92	84	86	84	86	90	93
XG Boost: HLV/ LLV	Validation accuracy	88	87	85	89	84	88	85	87	82	86	80	79	81	83	88
	Testing accuracy	89	90	90	83	85	86	85	92	89	86	83	86	82	88	91
	Sensitivity/ Recall	86	96	95	91	92	95	100	95	100	78	89	93	92	79	92
	Specificity	94	84	85	76	77	75	71	87	81	94	73	80	67	95	90
	Precision	95	86	87	78	82	83	76	91	81	93	85	78	81	94	92
	F1 score	90	91	91	84	87	89	86	93	89	85	87	85	86	86	92

RESULTS AND CONCLUSIONS

The subject-specific testing accuracy, sensitivity/recall, specification, precision, F1 score [15] for detecting HLV/LLV and inspiration/expiration phases using SVM and XGBoost are shown in Table 1. Results showed that the average testing accuracy, sensitivity/recall, specificity, precision, F1 score were 91 ± 6 %, 91 ± 9 %, 91 ± 8 %, 91 ± 7 %, 91 ± 6 %, respectively for inspiration/expiration and 86 ± 6 %, 87 ± 8 %, 85 ± 10 %, 88 ± 6 %, 87 ± 5 %, respectively for HLV/LLV detection using SVM. For XGBoost, these parameters were 91 ± 6 %, 93 ± 6 %, 89 ± 9 %, 90 ± 7 %, 91 ± 5%, respectively for inspiration/expiration and 87 ± 3 %, 92 ± 7 %, 82 ± 9 %, 85 ± 6 %, 88 ± 3 %, respectively for HLV/LLV detection.

This pilot study suggests that SCG signals combined with machine learning procedures may be able to detect respiratory phases accurately in normal subjects. The respiratory rate can also be monitored using this information. Future studies may explore increasing the accuracy of the XGBoost model by optimization of other hyperparameters. In addition, jackknife test and leave one subject out (LOSO) schemes would be performed to further test the robustness of the proposed methods. Moreover, the findings of this study need to be verified in a larger sample size of healthy subjects and heart disease patients. Further studies may also test other machine learning techniques including artificial neural networks, random forests and k-nearest neighbor analysis.

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