Potential of Electrocardiogram-Derived-Respiration based on QRS slopes and R-wave angle for Discriminating Apneic from Non-Apneic Segments

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***Abstract*—A first study on the potential of electrocardiogram(ECG)-derived respiration (EDR) signals based on QRS slopes and R-wave angles for sleep apnea detection is been presented. This EDR techniques have been previously validated with a wearable ECG armband for respiratory rate estimation. Furthermore, the amplitude of the oscillations in these EDR signals was observed to be related to the tidal volume in a previous pilot study.**

The hypothesis of this work is that that relation can be exploited for sleep apnea detection. A public data set (Physionet Apnea-ECG) composed of 105 polysomnography recordings was analyzed. A linear discriminant analysis was used using features related to the amplitude of the EDR oscillations.

The classifier obtained an area under the curve from 0.74 to 0.82 when using the different analyzed features sets, suggesting that the relation between tidal volume and the amplitude of the EDR signals based on QRS slopes and R-wave angles can be exploited for sleep apnea detection. These results allow us to think of a sleep apnea screening tool based on the wearable armband and these EDR techniques, which would have both social and economic advantages.

***Index Terms*—ECG-derived respiration, EDR, sleep apnea**

I. Introduction

The sleep apnea-hypopnea syndrome (SAHS) is a sleep disorder characterized by repetitive periods of interruption or considerable reduction of respiratory flow, having serious consequences for the health that have a big socioeconomic impact that can be reduced by adequate treatment. The reported prevalence of this condition among adults varies from 9% to 36%, and some studies suggest that this prevalence may be underestimated in the literature because its symptoms are not always apparent [1]. However, most of the patients from SAHS remain undiagnosed, and thus, untreated. In fact, some studies estimate that the percentage of undiagnosed patients of SAHS is between 80% and 90% [2]. The Gold Standard for SAHS diagnosis is supervised polysomnography (PSG), which consists of an overnight recording of a large number of biomedical signals. Thus, PSG requires an overnight stay in a sleep laboratory and supervision by experts, so it remains a cumbersome process with high costs associated, not being convenient for screening and leading to the mentioned SAHS underdiagnosis.

The social consequences of this underdiagnosis include an increased cardiovascular risk [3] and an elevated risk of traffic accidents [4]. In addition, this underdiagnosis also has an important cost because people with undiagnosed SAHS usually have more healthcare costs in comparison with diagnosed (and treated) patients [5], and their productivity is lower [6]. Thus, a SAHS screening based on a wearable device would have both social and economic advantages.

In recent times, several devices have been proposed for sleep monitoring in a less invasive way, aiming to move the sleep studies from the sleep laboratories in clinical settings to home environments. This transition has two main objectives. On one hand, to improve the quality of records by increasing user comfort during sleep monitoring and so reducing the effects of the measurement process on the quality of the sleep (the measurement target). On the other hand, to overcome the limitation of reduced number of sleep laboratories, reaching a broader population.

Some respiratory information can be obtained from the ECG, based on its morphology and/or the occurrence of heartbeats through a phenomenon known as respiratory sinus arrhythmia. Algorithms for deriving respiratory information from the ECG are usually referred as ECG-derived respiration (EDR) techniques. One of the morphology-based EDR techniques in the literature exploits the variations in the QRS slopes and R-wave angle. This technique outperformed others in different terms and data sets, including during sleep [7]. In addition, it has been validated for respiratory rate estimation with an ECG-based wearable armband [8]. Thus,

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the combination of this EDR technique and the this ECG-based wearable armband may be interesting for SAHS monitoring. However, to the best of our knowledge, the potential of QRS slopes and R-wave angles for sleep apnea/hypopnea detection has been never analyzed. In this paper, a first assessment of this potential is performed by applying this EDR technique with a public PSG data set: Apnea-ECG [9].

II. Methods

A. Materials

The data analyzed in this study is publicly available on Physionet [10] under the name Apnea-ECG [9]. This data set is composed of a training set of 70 PSG records and an additional test set of 35 records. These records include (among other signals) ECG with a sampling rate of $f_s = 100$ Hz, QRS automatically detected, and apnea annotations in a 1-min basis.

B. ECG artifact detection

ECG artifact detection was performed based on the ratio of powers proposed in [11]. ECG was spitted into segments of length of 1 min, similarly to the apnea annotation criterion. The percentage of power of the kth ECG segment within the frequency band between 5 Hz and 20 Hz, with respect to the total power of the same ECG segment was computed:

$$r_{\mathrm{P}}(k) = \frac{\displaystyle\int_{5\mathrm{Hz}}^{20\mathrm{Hz}} \left|X_{\mathrm{ECG}}^{k}(f)\right|^2 df}{\displaystyle\int_{0}^{f_s/2} \left|X_{\mathrm{ECG}}^{k}(f)\right|^2 df}, \tag{1}$$

where $X(f)$ is the spectrum of the kth 1-min-length ECG segment.

In general terms, the percentage of power within the 5-20 Hz band is higher in a clean ECG segment than in an ECG segment corrupted by movement and/or electromyogram artifacts, which usually show significant power in higher frequencies. In this study, an empirical threshold of 50% was used for considering clean ($r_{\mathrm{P}}(k) \geq 0.5$) or corrupted ($r_{\mathrm{P}}(k) < 0.5$) ECG segment. Those segments considered corrupted by this criterion were discarded for further analysis.

C. ECG derived respiration

Three EDR signals were analyzed in this study, based on QRS slopes (upslope and downslope) and the R-wave angle [8]. R peak of the ith QRS complex n_{R_i} was set as the point where the ECG is maximum within a time window of 80 ms centered in the ith QRS annotation provided by the data set (see Section II-A). Subsequently, Q and S peaks (n_{Q_i} and n_{S_i}) were set as the points where the ECG is minimum within a window of 40 ms before and after n_{R_i}, respectively. Then, the time instants with maximum ECG variation from n_{Q_i} to n_{R_i}, and from n_{R_i} to n_{S_i} were computed:

$$n_{\mathrm{U}_i} = \underset{n \in \left(n_{\mathrm{Q}_i}, n_{\mathrm{R}_i}\right)}{\arg\max} \left\{|x'(n)|\right\} \tag{2}$$

$$n_{\mathrm{D}_i} = \underset{n \in \left(n_{\mathrm{R}_i}, n_{\mathrm{S}_i}\right)}{\arg\max} \left\{|x'(n)|\right\}, \tag{3}$$

where $x'(n)$ denotes the first derivative of the ECG signal.

Then, the slope around n_{U_i} is estimated as the slope of a straight line fitted by least squares within 8 ms centered in such point. This slope is denoted $\mathcal{I}_{\mathrm{US}}$ in this paper. On the other hand, $\mathcal{I}_{\mathrm{DS}}$ denotes the estimated slope around n_{D_i}, estimated in a similar way. Besides of generating EDR signals, these slopes were used also for computing the R-wave angle, which was also used for generating an additional EDR signal:

$$\Phi_{\mathrm{R}_i} = \arctan\left(\frac{\mathcal{I}_{\mathrm{US}_i} - \mathcal{I}_{\mathrm{DS}_i}}{0.4\left(6.25 + \mathcal{I}_{\mathrm{US}_i}\mathcal{I}_{\mathrm{DS}_i}\right)}\right). \tag{4}$$

The three series described above were considered EDR signals:

$$d^{u}_{\mathrm{US,\,DS,\,\Phi}}(n) = \sum_i \left\{\mathcal{I}_{\mathrm{US}_i}, \mathcal{I}_{\mathrm{DS}_i}, \Phi_{\mathrm{R}_i}\right\} \delta(n - n_{\mathrm{R}_i}), \tag{5}$$

where the superscript u denotes that these EDR signals are unevenly sampled, as the heartbeats do not occur evenly. An outlier-rejection rule based on median-absolute-deviation (MAD) was applied. Note that there should be a valid parameter ($\mathcal{I}_{\mathrm{US}_i}$, $\mathcal{I}_{\mathrm{DS}_i}$, and Φ_{R_i}) estimation per heartbeat. A too low number of estimates was considered as a sign of presence of noise. Thus, every 60-min segment with less than 45 parameters estimations was not considered for further analysis.

Then, the outlier-rejected series were evenly sampled at 4 Hz by cubic splines interpolation. Subsequently, these evenly-sampled signals were bandpass filtered with cutoff frequencies of 0.075 Hz and 1 Hz, considering such band as the respiratory band. The resulting signals are denoted without the superscript u in this paper ($d_{\mathrm{US,\,DS,\,\Phi}}(n)$). Figure 1 shows an example of these EDR signals.

D. ECG segment classification

1) Classifier: A classification strategy based on linear discriminant analysis (LDA) was used.

2) Features: The amplitude of these EDR signals may be related to the tidal volume [12]. The standard deviation of each EDR signal during each ECG segment was computed as estimation of the amplitude of these oscillations. These standard deviations were normalized by the intra-subject mean of the corresponding series in order to minimize the inter-subject variations.

3) Training: Segments from the 70 PSG recordings that compose the training set of the data set (see Section II-A) were used in the training procedure. The number of elements in the two classes (apnea present/not present) were balanced by using k-means to reduce the number of elements in the larger class while maintaining a good representation of the data. A 5-fold validation strategy was used during training stage.

4) Test: Segments from the 35 PSG recordings that compose the training set of the data set (see Section II-A) were used in the training procedure. No balancing of classes was performed in the test set.

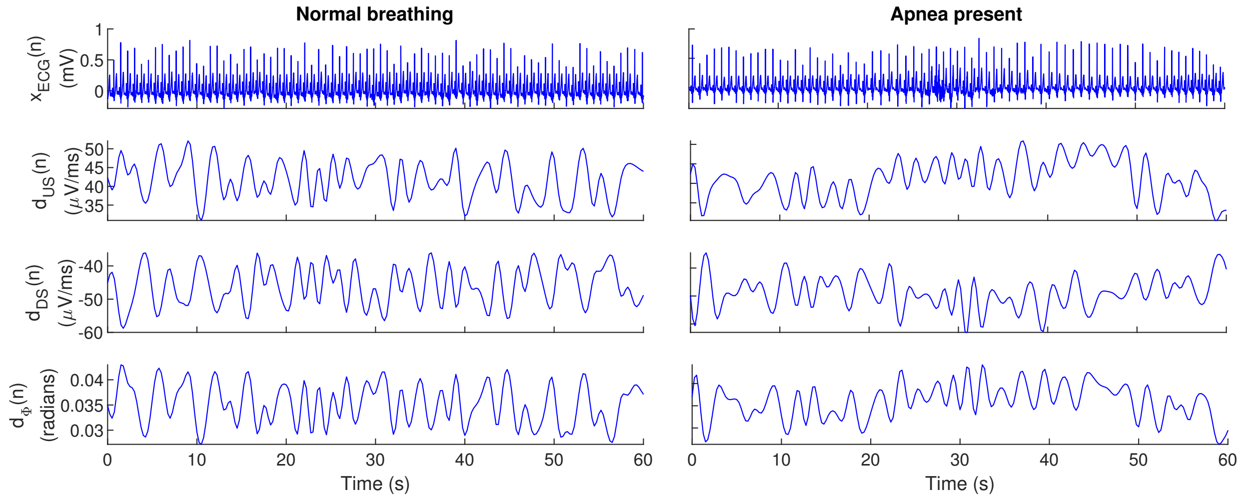

Fig. 1. Example of ECG ($x_{\text{ECG}}(n)$) and EDR signals ($d_{\text{US}}(n)$, $d_{\text{DS}}(n)$, and $d_{\Phi}(n)$) during a 60-seconds segment labeled as 'normal breathing' (left), and during a 60-seconds segment labeled as 'apnea present' (right).

III. Results

A total of 8786 ECG segments (4393 labeled as 'apnea' and 4393 labeled as 'normal') were used for training. This number was obtained after discarding ECG segments based on the ECG artifact detection and the EDR MAD outlier rejection rule, and after class balancing based on k-means. Table I shows the obtained accuracies, sensitivities, specificities, and areas under curve (AUC) obtained for the test set for the different analyzed feature sets. Figure 2 shows the best obtained receiver operating characteristic (ROC) curve in terms of AUC, which was for $d_{\text{R}}(n)$.

TABLE I

Obtained accuracies (Acc), sensitivities (Se), specificities (Sp), and areas under the curve (AUC) obtained for the test set for the different analyzed feature sets. Last row ("ALL") refers to the combination of features from the three EDR signals

EDR	Acc	Se	Sp	AUC
$d_{\text{US}}(n)$	74.6%	0.85	0.58	0.82
$d_{\text{DS}}(n)$	71.5%	0.86	0.49	0.75
$d_{\text{R}}(n)$	74.1%	0.86	0.52	0.78
ALL	71.1%	0.85	0.49	0.74

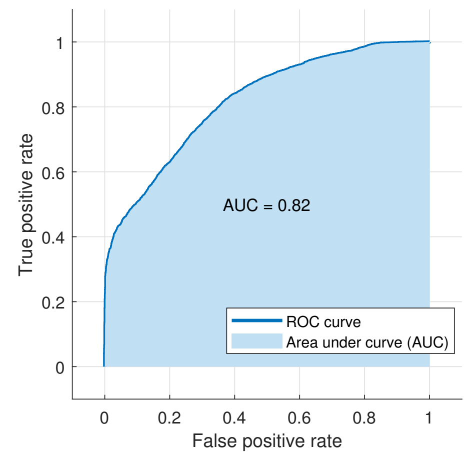

Fig. 2. Receiver operating characteristic (ROC) curve obtained for $d_{\text{R}}(n)$.

IV. Discussion

A first study on the potential of EDR signals based on QRS slopes and R-wave angles for sleep apnea detection has been presented. This EDR technique was chosen because it outperformed others in different terms and data sets (including during sleep) [7], and because it has been previously validated with an ECG-based wearable armband [8] that results very interesting for SAHS monitoring. A pilot study showed that there is a relation between the tidal volume and the amplitude of the oscillations in these EDR signals [12].

The hypothesis of this work is that that relation can be exploited for sleep apnea detection. The amplitude of the oscillations of the EDR signals was estimated by using their standard deviation within the studied segment, normalized by the mean in of the series in the entire recording. This normalization tries to minimize the effect of the differences in the amplitude of the EDR oscillations among different subjects.

Obtained AUCs suggest that the amplitude of the oscillations of the three analyzed EDR signals have potential for sleep apnea detection. Best EDR in terms of both accuracy and AUC was $d_{\text{US}}(n)$ (Acc=74.6% and AUC=0.82), followed by $d_{\text{R}}(n)$ (Acc=74.1% and AUC=0.78). $d_{\text{DS}}(n)$ obtained slightly lower values n(Acc=71.5% and AUC=0.75). Obtained Acc and AUC when combining the three analyzed EDR signals were slightly lower (71.1% and 0.74, respectively). This observation may be explained by the high redundancy between the features, as all of them were thought to be related to the tidal volume. These results suggest that the combination of them adds more noise than non-redundant information to the LDA classifier.

A similar analysis was performed in [13] for EDRs based on QRS area and principal component analysis (PCA). Reported results (AUCs of 0.92 and 0.78 for QRS area and PCA, respectively) in [13] should not be used with those results reported in this paper for a direct comparison of EDR techniques, for several reasons. First, the whole 105 recordings of the Physionet Apnea-ECG were used in this work, using the separation of training and test data proposed by the data set. However, respiratory impedance pneumography was needed for the analysis presented in [13]. This signal is available for only 8 recordings in the Apnea-ECG data set, resulting in a much more limited data set where a cross validation approach was performed. Furthermore, two temporal-optimization methods were used in [13] based on time overlapping and taking into account the relation between consecutive segments. None of these methods were used in the first exploration study presented in this work, which is not focused on classification performance.

As a first exploration study, some decisions were made based on simplicity and may not be optimal from the point of view of performance results. For example, the features are based on standard deviation of the EDR signals, which is a simple measure of the amplitude of the EDR oscillations. Thus, hypothesizing that this amplitude is related to the tidal volume, it is expected that it is lower during apnea events than during normal breathing. However, the data is not labeled as apnea event or normal breathing. Instead, the labels are on a 1-min basis, and they indicate whether there is at least one apnea event or not within each one of the segments. Therefore, a 1-min segment labeled as 'apnea' can contain up to 50 seconds of normal breathing. On the other hand, those segments may contain one or more recover-from-apnea events, which are usually characterized by a deeper breathing (instead of a shallower breathing during apnea). In this way, an approach based on estimating the variations in tidal volume through the envelope of the EDR signals could obtain a better performance in this data set. Furthermore, future studies focused on classification performance should include other features complementing the information of features based on EDR-based tidal volume estimation. Those features may include ECG-derived autonomic nervous system markers, such as those based on heart rate variability.

Moreover, a simple technique for ECG artifact detection was used, based on a ratio of powers [11]. The threshold for considering a 1-min ECG segment as an artifact or as a clean segment was empirically set after a visual inspection of recordings. In addition, a median-absolute-deviation outlier-rejection rule is applied to the EDR series. However, the ECG artifact detection approach has a big room for improvement. Future studies focused on performance should include other ECG signal quality indexes complementing the information of the ratio of powers, and thresholds optimization.

V. Conclusion

Obtained results suggest that the relation between tidal volume and the amplitude of the EDR signals based on QRS slopes and R-wave angles can be exploited for sleep apnea detection. These EDR methods have been previously validated for respiratory rate estimation using an ECG-based wearable armband, and their relation with tidal volume was observed also using this device. Therefore, these results allow us to think of a SAHS screening tool based on the wearable armband and these EDR techniques, which would have both social and economic advantages. Future studies focused on classification performance should include a better ECG artifact detector and additional features that may complement the information of the amplitude of the EDR signals, e.g., features based on heart rate variability.

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