Evaluation of the ECG Derived Respiration in the Presence of Irregular Heart Beats

John F. Morales[1], Rik Willems[2], Sabine Van Huffel[1] and Carolina Varon[1,3]

***Abstract*— In this work, the performance of 5 methods to calculate the ECG derived respiration is compared when applied to ECG signals with irregular beats. The results suggest that approaches based on the R-peaks amplitude and the difference between the R and S waves are more stable when the number of irregular beats increases to more than 2. In addition, the approach based on Kernel PCA is the most affected by ectopic beats due to its sensitivity to outliers.**

I. INTRODUCTION

The respiration is frequently used to assess different health conditions. At the same time, the recording of this signal requires the use of intrusive sensors and expensive setups, complicating the continuous respiratory monitoring in ambulatory settings. An alternative to overcome these issues is to derive the respiratory signal from the electrocardiogram (ECG), known as ECG-derived respiration (EDR). In general, methods employed to compute the EDR rely on ECG signals with normal QRS complexes. This condition represents a challenge for the use of EDR in people with cardiac disorders. In this population, arrhythmias and abnormal beats result in irregular ECG recordings.

Different methods to calculate the EDR were previously evaluated in [1], in which ectopic beats where removed using a method based on the variance of the QRS complexes. However, little attention has been paid to the EDR computed using the ectopic beats or abnormalities present in the ECG. For example, an evaluation of three EDR methods applied in populations with atrial fibrillation is reported in [2]. The current paper complements these works by evaluating the performance of 5 algorithms for EDR when applied to ECG signals with irregular heart beats.

II. MATERIALS AND METHODS

A. Dataset

Full-night Polysomnographic studies from 100 subjects recorded with a Medatec acquisition system were used in this study. Lead-2 ECG and thoracic respiratory inductive plethysmography signals were acquired with a sampling frequency of 500 Hz. Fifty patients suffered from cardiovascular comorbidities associated with sleep apnea, hence, the ECGs contained irregular beats to a different extent. Approval was granted by the UZ Leuven ethical committee and each patient gave informed consent.

B. Methods

1) Preprocessing: Firstly, the ECG signals were normalized to have unit standard deviation and zero mean. Secondly, the baseline was removed using a highpass filter with a cutoff frequency of 0.5 Hz. Afterwards, the QRS complexes were detected with the algorithm described in [3]. Next, the Integral Pulse Frequency Modulation (IPFM) model was used to find the abnormal beats as in [4].

The respiratory signals were downsampled to 5 Hz and filtered to preserve frequencies in the interval between 0.05 Hz and 1 Hz using a fourth-order bandpass filter in forward and reverse direction to avoid phase distortion.

2) ECG Derived respiration methods: 5 approaches to extract the EDR signals were tested.

- *R-wave amplitude ($\hat{r}_r$)*: builds the EDR using the amplitude of the R-peaks in the ECG signal.
- *R-to-S-wave ($\hat{r}_{rs}$)*: is calculated as the difference in amplitude between the R and the S waves [5].
- *Principal component analysis ($\hat{r}_p$)*: quantifies the amplitude change of the QRS complexes. For this, segments of 60 ms before and 60 ms after the R-peaks are extracted and put together in a matrix. Principal Component Analysis (PCA) is applied to this matrix and the first principal component is used as EDR [6].
- *Kernel principal component analysis ($\hat{r}_k$)*: is the kernel version of $\hat{r}_p$. To compute it, the matrix containing the QRS complexes is first transformed into a higher dimensional space using a kernel function. Afterwards, PCA is calculated in this space. The first principal component is then projected back and used as EDR [7].
- *QRS area ($\hat{r}_a$)*: results after calculating the area under the curve of the QRS complex [8].

The EDR time series are sampled at the locations of the R-peaks. For this reason, they were interpolated using a cubic spline to have a uniform sampling frequency of 5 Hz. These signals were then filtered to preserve frequencies between 0.05 Hz and 1 Hz using a fourth-order bandpass filter. Finally, the real respiratory signals as well as EDRs were divided in 1-minute epochs without overlap and the number of irregular beats given by the IPFM model was counted on each segment. An example of the extraction of the EDR in segments with different number of irregular beats

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is shown in figure 1.

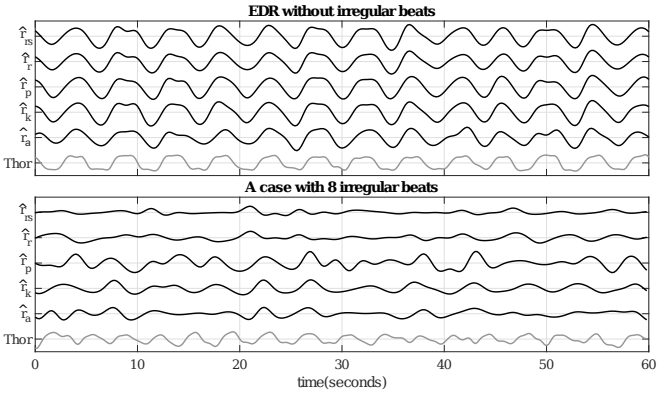


Fig. 1. Examples of 1-minute EDR segments derived using ECG epochs contaminated with a different number of irregular beats. The reference is the thoracic respiratory signal, depicted in gray in the figure.

3) Comparison of the methods: In order to compare the methods, the similarity between each EDR and the real respiratory segments was evaluated using the maximum absolute value of their cross-correlation $|\rho|$ in a window in a range ± 3 s. In addition, significant differences between the $|\rho|$ of segments containing different amount of ectopics were assessed using the Kruskal-Wallis test ($p < 0.05$) with Bonferroni correction for multiple comparisons. These comparisons were done grouping segments containing a different amount of irregular beats according to the IPFM model: 0, 1 or 2, from 2 to 7 or more than 7.

III. RESULTS AND DISCUSSION

Figure 2 displays $|\rho|$ for the segments grouped according to the number of ectopics. The *** indicate that $|\rho|$ is significantly different to the results with the other EDRs when computed in segments with the same number of irregular beats.

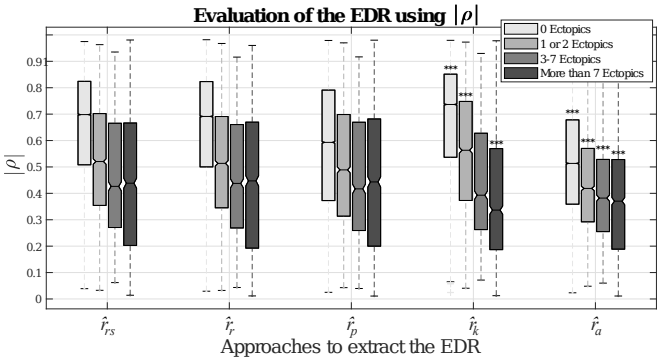


Fig. 2. Correlation coefficients between the real respiration and the different EDRs. The number of epochs were 47542, 2884, 1357 and 1510 for the groups containing 0, 1 or 2, 2 to 7 or more than 7, ectopic beats, respectively.

The figure shows that $\hat{r}_a$ always has the worst performance among the compared methods using segments with any amount of irregular beats.

The most affected EDR by the irregular beats is $\hat{r}_k$. This method produces an EDR significantly more similar to the real respiratory signal when the number of ectopic beats is smaller than 3. However, when the number of ectopics increases, its performance drops dramatically. This result is explained by the fact that irregular heart beats can be considered as artifacts or outliers to which this method is known to be particularly sensitive, as discussed in [1].

A visual inspection suggests that the performance of $\hat{r}_{rs}$ and $\hat{r}_r$ was less affected compared to the other approaches when the number of irregular beats increased to more than 2. Furthermore, it is seen that $\hat{r}_{rs}$, $\hat{r}_r$, $\hat{r}_p$ are the most similar to the real respiratory signal when the number of ectopic beats is higher than 2. It is important to highlight, however, that the median values of $|\rho|$ in this case are always below 0.5, suggesting that only a moderate to weak correlation between the real respiration and the EDRs exists.

It is also important to keep in mind that some of the ECG segments might be affected by artifacts, which would reduce the performance of the EDR algorithms.

IV. CONCLUSIONS AND FUTURE WORK

As expected, the performance of the EDR algorithms compared in this work decreases with the presence of irregular beats in the ECG signal. However, the approach based on Kernel PCA is the most affected among the compared methods due to its sensitivity to outliers. On the other hand, the methods based on the amplitude of the R-peaks and S-waves seem to be more stable when the number of irregular beats increases to more than 2. As a future work, more algorithms will be included in the comparison and the performance of the algorithms will be evaluated in a population with heart failure.

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