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Removing Cardiac Interference from the Electroencephalogram Using a Modified Pan-Tompkins Algorithm and Linear Regression*

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Abstract— **Cardiac interference can alter the results of quantitative electroencephalograms (qEEG) used for medical diagnoses. The methods currently employed for the automated removal of cardiac interference, which rely solely on the electroencephalogram (EEG), are susceptible to non-cardiac interference commonly encountered in EEGs. Methods that rely on the electrocardiogram (ECG) – besides being unreliable when non-cardiac artifacts corrupt the ECG – either assume periodicity of the cardiac (QRS) peaks or alter uncorrupted EEG segments. This paper proposes a robust method for the automated removal of cardiac interference from EEGs by identifying QRS peaks in the ECG without assuming periodicity. Artificial signals consisting only of QRS peaks and the zero-lines in between are computed. Linear regression of the EEG channels on the "QRS signals" removes cardiac interference without altering uncorrupted EEG segments. The QRS-based regression method was tested on 30 multi-channel EEGs exhibiting cardiac interference of elderly subjects (15 male, 15 female). Achieving a correction rate of 80%, the QRS-based regression method has proved effective in removing cardiac interference from the EEG even in presence of additional non-cardiac interference in the EEG.**

I. Introduction

Quantitative electroencephalogram (qEEG) measures are relevant for medical diagnoses both in neurology and psychiatry [1]. Interfering signals of technical or physiological origin can corrupt the qEEG results. Technical interference is produced by poor electrode contact, induction from the mains supply, or electromagnetic fields; physiological interference results from eye movement, muscle contraction, talking, or cardiac electrical fields caused by the heart beat [2]. Cardiac interference – even below the line of visibility – has been shown to markedly diminish the quality of qEEG measures [3].

There are a number of issues with the methods for automated removal of cardiac interference from EEGs proposed by scientific literature: methods that rely solely on the EEG are prone to non-cardiac interference occurring in the EEG [4-12]. In most clinical scenarios, an electrocardiogram (ECG) channel is recorded simultaneously. Methods relying on the ECG for interference detection [13-17] either assume periodicity of cardiac peaks (known as QRS complexes), or include irrelevant P or T waves in the removal procedure, altering uncorrupted EEG parts in the process. Besides, the methods described in literature are unreliable whenever the ECG is subject to non-cardiac artifact.

This paper describes a robust method for the automated removal of cardiac interference from the EEG using a simultaneously recorded ECG. Our algorithm is based on a modified QRS complex detection method that identifies and classifies the characteristic peaks in the ECG. Accurate correction is achieved by using real QRS complexes. By placing a zero-line in between the QRS complexes, the interference is removed without altering the rest of the EEG. This QRS-based regression method does not require periodicity of the cardiac peaks, nor is it susceptible to failure in the presence of non-cardiac artifact in the ECG.

This paper is structured as follows: Section II describes the sample data used for developing and testing, the underlying assumptions, the algorithm, and the evaluation procedure. Section III compares the performance of the algorithm with that of an alternative method. Finally, Section IV provides a conclusion and discusses the findings.

II. Materials and Methods

A. Sample Data

To develop the QRS-based regression method, EEG recordings from the databases of the Medical Universities of Graz, Innsbruck and Vienna were used. The sample consisted of EEG resting-state eyes-closed segments and simultaneously recorded ECG channels from 30 elderly subjects (aged between 57 and 87 years, 15 male and 15 female). Using alpha trace EEG, the data were recorded on 19 channels according to the international 10/20 system with sampling rate 256 Hz, connected mastoids as reference, ground electrode between Fz and Cz, and impedances < 10 kΩ. Each EEG segment was corrupted by cardiac interference of various degrees; the presence of interference was confirmed both by visual inspection, and by an automated cardiac interference detection algorithm ensuring the detection of cardiac interference both above and below the line of visibility [3].

B. Assumptions

The QRS-based regression algorithm was developed based on the following assumptions:

1) The interference peaks in the EEG signals and the QRS complexes in the ECG signal are synchronized temporally and have – up to a scaling constant – the same shape. Other cardiac waves, e.g. P and T waves, do not corrupt the EEG.
2) QRS complexes do not necessarily occur periodically
3) The median heart rate is < 180 beats per minute (bpm).

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4) QRS complexes resemble each other in appearance and duration, but their shape is not identical.
5) The ECG signal is likely to be corrupted by both high and low frequency interference from unknown sources.

No assumption of Gaussianity is required, neither for the EEG signals nor for the ECG signal.

C. *Generating QRS Signals*

First, subsidiary signals are generated which consist of estimated interference peaks and a zero-line in between. Under assumption 1 (see Section II B), the peaks are estimated by the QRS complexes in the ECG. The algorithm for detecting the QRS complexes is derived from a modified Pan-Tompkins algorithm [18]. After applying a number of filtering operations to the ECG, the QRS complexes are identified by using a set of thresholds for the heart rate and the peak shape. In the original algorithm, a dual-threshold technique is used that can only be applied in the case of a regular heart rate [18]; the QRS-based regression method was designed to be robust against irregular heart rates.

Once the QRS complexes have been located, they are classified either as *possible* or *probable*. *Probable* peaks are those that resemble each other in shape and periodicity, whereas *possible* peaks are those occurring non-periodically and/or with different shape. A *possible* peak may also be a spike-formed interference in the ECG channel. Two artificial signals are generated each consisting of QRS complexes and a zero-line in between. By using a *probable* and a *possible* QRS signal for removing cardiac interference from the EEG, the robustness of the method is enhanced in the presence of non-cardiac interference in the ECG.

Fig. 1 illustrates the procedure by a 5-second ECG sample, each window describing one step. The ECG signal – centered and scaled to have variance 1 – is shown in Fig. 1a. Seven non-periodic QRS peaks can be identified and non-cardiac interference sets in after the fourth peak.

To reduce noise, the *first step* is to apply a low pass filter to the signal. At sampling rate 256 Hz, the cutoff frequency of the filter is about 14 Hz. Fig. 1b shows the ECG signal after low pass filtering.

The *second step* is filtering the signal using a high pass filter. This reduces low frequency interference, including baseline trends. At sampling rate 256 Hz, the filter approximately corresponds to a cutoff frequency 5 Hz. Fig. 1c shows the effect of this high pass filtering – a reduction of low frequency noise.

In the *third step*, a five-point derivative filter is applied in order to enhance the information about the QRS slopes. Fig. 1d illustrates the effect of the derivative filtering.

In order to amplify the effect of derivative filtering, the resulting signal is squared in *step four* (see Fig. 1e).

In the *fifth step*, a moving average (MA) filter for amplification of the QRS shape is applied. The length of this filter is set to 38 sampling points corresponding to about 150 ms. Filtering produces a flat signal with trapezoids appearing where QRS complexes are likely to occur. The leftmost starting point of each trapezoid pinpoints the location of a Q

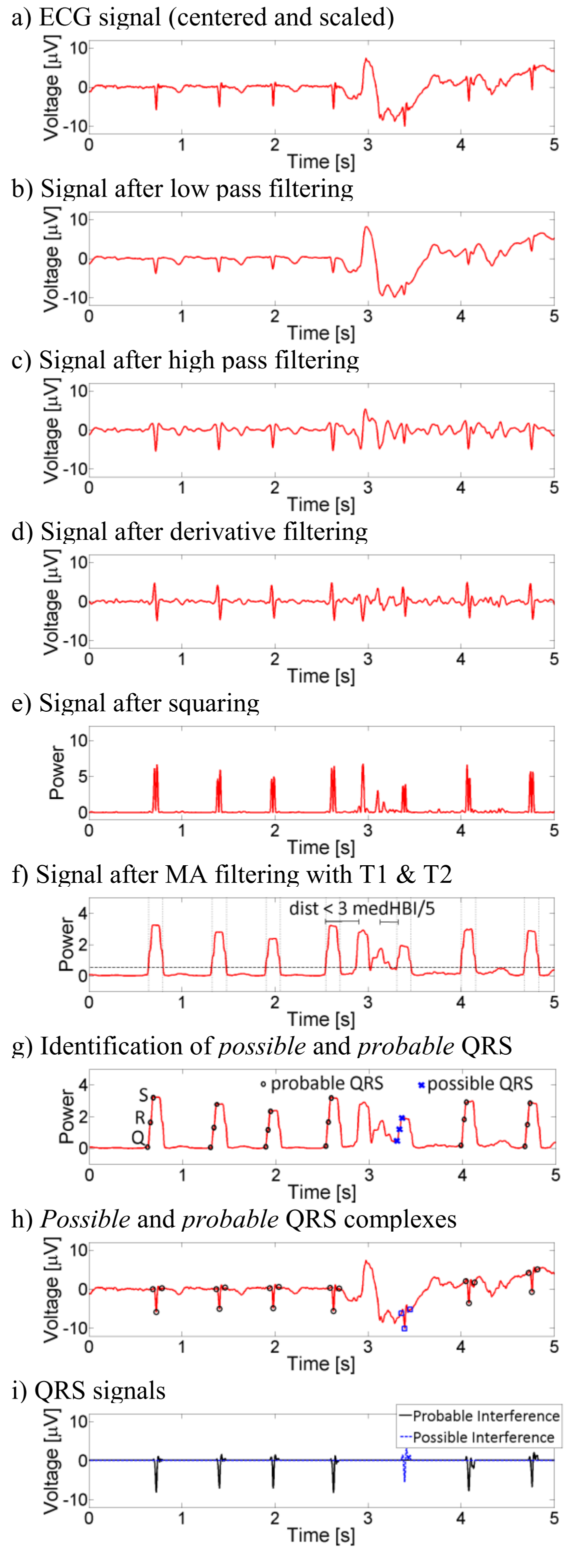

Figure 1. Illustration of processing steps for generating QRS signals.

peak, the first maximum on top of each trapezoid pinpoints the location of an S peak, and the slope in-between qualifies for the location of an R peak. The solid line in Fig. 1f shows the signal after MA filtering. For a more detailed description of steps 1 through 5, the reader is referred to [18].

To determine the time of the R peaks, the *sixth step* is to apply a set of thresholds other than those used in the dual-threshold technique suggested in [18]. Figures 1f to 1h illustrate the new thresholding procedure. The first threshold, T1, is used for the magnitude of the MA signal. The time intervals at which the MA signal exceeds T1 qualify for being the location of the R peaks. In these time intervals, the maxima of the (absolute) original ECG signal are determined. The times at which these maxima occur are the estimated points in time of the R peaks. The corresponding points in time of the Q and S peaks are then estimated by the points in time of the starting points and the maxima of the trapezoid in the MA signal. In Fig. 1f, the dashed horizontal line represents T1. The initial value for T1 was empirically determined as 5% below the mean of the MA signal:

$$T1 := 0.95 \text{ mean}(MA_{Sig}) \quad (1)$$

The median heart rate is estimated based on the median interval between estimated R peaks (medRR). As long as the median heart rate is >180 BPM, T1 is increased by 5%. Owing to its robustness, the median is used instead of the arithmetic mean.

The second threshold, T2, defines the minimum acceptable R-R span. Any R peak that follows the previous R peak within a time span of 200ms is rejected. Any R peak that follows the previous R peak after 200ms to 3/5 medRR is classified as *possible* R peak, and any R peak with a time span > 3/5 medRR is classified as *probable* R peak. At second 3 in Fig. 1f, a signal segment is shown with R-R span < 3/5 medRR. T2 is initialized as follows:

$$T2_{poss} := 200 \text{ ms}$$
$$T2_{prob} := 3/5 \text{ medRR} \quad (2)$$

Finally, the third threshold, T3, defines the acceptable height of the remaining *possible* and *probable* QRS complexes. The height of a QRS complex is defined as the absolute amplitude difference between R peak and Q peak. The height range is defined based on the medium height of estimated QRS complexes (medH). QRS complexes with a height between 0.65 medH and 1.35 medH are classified as *possible* QRS complexes, and those with a height between 0.80 medH and 1.20 medH are classified as *probable* QRS complexes (if T2 has qualified them as *probable*, too).

$$T3_{poss} := [0.65 \text{ medH}, 1.35 \text{ medH}]$$
$$T3_{prob} := [0.80 \text{ medH}, 1.20 \text{ medH}] \quad (3)$$

The height of the fifth QRS complex in Fig. 1h (second 3.3) lies in the range of $T3_{poss}$; all other QRS complexes are classified as *probable*.

After identifying the *possible* and *probable* QRS complexes, two QRS signals are generated consisting only of these complexes and zero lines in-between. Fig. 1i shows the two resulting QRS signals; all QRS complexes from the original signal are identified and no other interference – such as the low frequency artifact in Fig. 1a – is included.

D. *Two-Step Linear Regression*

Under assumption 1 (synchronized cardiac interference in the EEG and QRS complexes in the ECG), the cardiac interference is corrected by performing a two-step linear regression [19] of each EEG channel on the two QRS signals. This method enhances robustness in presence of interference in the ECG as different regression coefficients for the *probable* and *possible* QRS signals are used. Fig. 2 illustrates the cardiac interference removal: Fig. 2a shows a 2-second segment of an EEG channel (Channel Pz) corrupted by three cardiac peaks. Regression of the EEG signal on the QRS signals produced the signal in Fig. 2e. The peaks were corrected without altering the rest of the EEG.

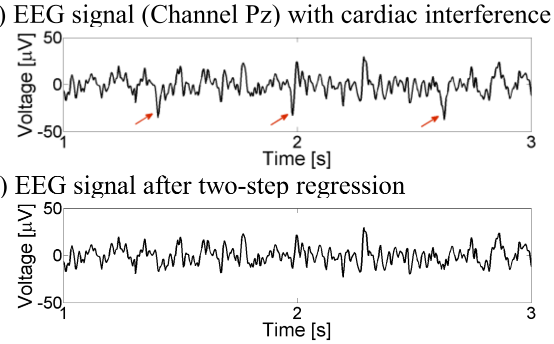

Figure 2. Illustration of the two-step linear regression.

E. *Evaluating Performance*

The performance of the QRS-based regression method was evaluated in two ways. The accuracy of the QRS detection (see Section II.C) was tested on the sample data. For this purpose, the QRS complexes in the 30 ECG channels were visually identified and tagged. In this way, the sensitivity and specificity of the peak finding algorithm was evaluated.

To evaluate the effectiveness of the QRS-based regression in removing of cardiac interference from the EEG, the method was applied on each EEG sample. Then, the HAC method [3] for finding spikes in multichannel EEG recordings was applied to assess whether the cardiac interference was still present in the EEG. The EEG was considered successfully corrected only after no remaining cardiac interference was found in any of the EEG channels. The results were compared to those of an alternative cardiac interference removal method [13]: for each EEG channel, an ensemble-average (EA) method is used to estimate the cardiac interference directly from the EEG data. The estimated interference is repeated time-locked to the QRS complexes in the ECG channel and is subtracted from each EEG channel. This method is based the following assumptions:

1) The cardiac interference in the EEG signal is time-locked to the peaks in the ECG channel.
2) The shape of the cardiac peaks is the same over time.
3) The corrupted EEG is a linear mixture of EEG and cardiac interference.
4) The EEG signal follows a Gaussian distribution.

In accordance with [13], the average signal starts 200ms before the QRS complexes in the ECG channel.

III. Results

A. *Detecting Cardiac Peaks in the ECG Signal*

Overall sensitivity of the QRS detection was 0.96 and ranged from 0.89 to 1; only one subject exhibited a sensitivity of 0, i.e. no QRS peaks were correctly identified. This was due to high-amplitude interference in the ECG channel that distorted the initial values of the threshold T1.

With the peak detection method, overall specificity was 0.80 ranging from 0.67 to 1 for the individual subjects. The lowest specificity was measured for the subject whose ECG channel had been corrupted by high-amplitude interference.

B. Removing Cardiac Peaks

To compare the performance of the QRS-based regression method and that of the EA algorithm, both were applied to the same data. The HAC method [3] was used to detect any residual cardiac interference on the corrected signals. Table 1 provides the results obtained from this procedure.

TABLE I. RESULTS OF QRS-BASED REGRESSION AND EA METHODS

Subject	**Interference left**		**Subject**	**Interference left**	
	QRS Reg	***EA***		***QRS Reg***	***EA***
1	-	-	***16***	-	-
2	-	-	***17***	-	-
3	-	-	***18***	-	-
4	-	-	***19***	-	-
5	-	X	***20***	.	-
6	-	-	***21***	X	-
7	-	-	***22***	-	-
8	-	-	***23***	-	-
9	X	X	***24***	-	-
10	-	-	***25***	-	-
11	X	X	***26***	-	X
12	-	-	***27***	X	-
13	-	X	***28***	X	X
14	-	-	***29***	-	-
15	X	-	***30***	-	-

'X' means that residual cardiac interference was detected after correction.

It is clear that the performance of the two methods is similar; both were able to correct the cardiac interference with 24 out of 30 subjects (i.e. 80%). The QRS-based regression method failed to remove the cardiac interference in the EEG recordings of 6 subjects (9, 11, 15, 21, 27, and 28). Further analyses showed that, with five of them, the cardiac interference in the EEG channels differed both in waveform and synchrony from the QRS complexes in the corresponding ECG channels. The sixth subject exhibited high-amplitude interference in the ECG channel, which diminished the quality of the QRS detection.

The EA method failed to remove the cardiac interference for the subjects 5, 9, 11, 13, 26, and 28. With these subjects, the EEG recordings contain interference of unknown origin (e.g. movement, or poor electrode contact). These artifacts altered the average signal, reducing the quality correction.

IV. DISCUSSION AND CONCLUSIONS

This paper describes a robust method for the automated removal of cardiac interference from the EEG using a simultaneously recorded ECG. Accurate correction was achieved by using real QRS complexes. Based on a sample data set of 30 EEG segments, our method was able to remove the cardiac interference in 80% of the samples. The EA method, achieving the same correction rate, performs without additional ECG.

The EA method performs well in cases when cardiac interference in EEG varies in synchrony or shape from the QRS complexes of the ECG, or when the ECG is subject to interference itself. However, the EA method is prone to other than cardiac interference in the EEG. In this common case, the QRS-method is able robustly correct cardiac interference in the EEG. Besides, a major advantage of the QRS-based method over the EA method is that, apart from the locations of the cardiac peaks, EEG signals remain unchanged. Since a simultaneously recorded ECG channel is standard clinical practice, the need for the ECG signal is justified. In summary, the QRS-based regression method has proved effective in removing cardiac interference from the EEG even in presence of additional non-cardiac interference in the EEG.

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