AN EFFICIENT ECG BACKGROUND NORMALIZATION

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ABSTRACT

This paper presents an improved morphological approach for baseline wander correction in electrocardiogram (ECG) signals, with emphasis on preserving all required clinical information of the original signal. The algorithm consists of only one stage of morphological processing (while similar morphological filters need two stages). The morphological operators are applied to approximate the baseline drift. Then it is subtracted from the input signal to leave a corrected-baseline signal. The performance of the algorithm is evaluated with real ECGs containing artificial and real baseline drift. Compared with all existing morphological methods, there is a substantial improvement, especially in reducing distortion of the baseline waveform in any part of the signal. The experimental results prove that the proposed method is less sensitive to the size of the structuring element if a reasonable size is considered.

Keywords: Morphological filtering; ECG; weighted mediated morphological filters.

1. INTRODUCTION

When the patient moves or respires while recording his (her) electrocardiogram (ECG) signal, baseline wander (drift) is often generated which is added to the original signal. The recorded ECG signal is also distorted by 50 (60)-Hz [1] and impulsive noises (from powerline [2] and skeletal muscle contraction, respectively) [3]. These artifacts should be removed as a preprocessing stage prior to any subsequent automatic processing for clinical identification, classification, interpretation, etc, [4] -[10]. Linear filtering was first attempt to normalize the baseline ([11]). Also cubic splines baseline estimation and correction has been investigated ([4]).

An efficient morphological approach has been proposed in [5] for impulsive noise suppression and background normalization in ECGs (referenced as method 1 in this paper). Trahanias ([12]) has applied a variant of this technique for QRS complex detection. Although this approach is promising in terms of robustness and computational efficiency, it introduces distortions to the PR and QT segments and Sun et. al. confirms it as well in [6] and introduce a modification to this method, called improved morphological approach to background normalization of ECG signals (referenced as method 2 in this paper), in attempt to obtain a normalized ECG with less such distortions. Sedaaghi et. al. ([8]) have proposed a rather similar approach with the same efficiency (also called method 2 in this paper). However, in this paper the author employs the "weighted mediated morphological filters" (introduced in [13]) as a more robust and efficient tool for baseline drift correction in ECG signals compared with other morphological approaches.

The organization of the paper is as follows. Section 2 introduces ECG preprocessing. The proposed method is discussed in Section 3. Section 4 highlights the empirical results. Finally section 5 concludes the paper.

2. ECG PREPROCESSING

In method 1 ([5]), an average of open-closing and close-opening is first applied to get an approximation of the baseline wander. The size of the structuring element is greater than any important data in ECG (like QRS complexes, ST interval, P and T waves, etc.). Then, the result is subtracted from the input signal to get a signal with corrected baseline.

Generally, the baseline drift correction is achieved by estimating the baseline drift and subtracting it from the signal. Classical morphological ECG baseline drift estimation is done with the price of smoothing the ECG features such as P wave, QRS complex and T wave. Although, the ECG has particular rhythmic nature and its features are relatively specific, the morphological algorithm used in method 1 estimates the baseline without any attention to the certain geometrical structure of the ECG signal and manages the ECG features similar to noise components that do not have certain shape and order [8]. Furthermore, the QRS complex, due to its short duration and long amplitude, resembles an edge. Due to the particular nature of morphological filters, the edges and local maximum and minimum points are affected. Consequently in classical morphological baseline drift estimation, the maximum error of the estimation is in the QRS neighborhood, i.e., the location of ST segment and J point. ST segment and J point are so important in clinical observations, therefore they should not be modified by baseline drift correction procedure [8].

In method 2 ([6] and [8]), QRS complexes are first extracted by applying an average of open-closing and close-opening using a structuring element with a shorter duration. Then an estimate for the size of the structuring element of the next stage is obtained. In the third attempt, the same operators but with new structuring element is applied. Then the result is subtracted from the signal of the previous stage to correct the baseline drift. The simplified block diagram of method 2 is illustrated in Figure 1.

3. THE PROPOSED METHOD

The proposed method (also called method 3 in this paper) corrects the baseline wander only in one stage, but at the same time, more efficiently. Later, the experimental results will prove the idea.

The operators (called weighted morphological operators) are defined as follows. Let x and g denote the 1-D gray-scale input signal buried in noise and the structuring element, respectively. D_x and D_g denote their domains. Weighted mediated erosion, dilation, opening, closing, open-closing, close-opening, denoted $WTMD_{ER}$, $WTMD_{DI}$, $WTMD_{OP}$, $WTMD_{CL}$, $WTMD_{OC}$, $WTMD_{CO}$, respectively, are defined as follows [13]:

$$
\begin{aligned}
&WTMD_{ER}(x,g,w,n) = \\
&\min\{x(n+v_0)-g(v_0), \mathbb{WTMED}_0(w)\} \\
&WTMD_{DI}(x,g,w,n) = \\
&\max\{x(n-v_0)+g(v_0), \mathbb{WTMED}_0(w)\}
\end{aligned} \tag{1}
$$

where v_0 is the location of the center of g, $\mathbb{WTMED}_0(w)$ is the weighted median of x in a neighborhood defined by the size of g and the weight factor defined by w, except that $x(n+v_0)$ in calculating erosion ($x(n-v_0)$ in dilation) is replaced with the previous $\mathbb{WTMED}_0(w)$ (for the first calculation it takes a default value).

$\mathbb{WTMED}_0(w)$ is defined as follows.

$$
\begin{aligned}
&\mathbb{WTMED}_0(w) = \text{MEDIAN} \\
&[|W_0|\blacklozenge\text{sgn}(W_0)x(n),,\ldots,|W_M|\blacklozenge\text{sgn}(W_M)x(n-M)]
\end{aligned} \tag{2}
$$

where $w = \{W_1, W_2, \ldots, W_M\}$, and $W_i \blacklozenge x_i = \underbrace{x_i, x_i, \ldots, x_i}_{\text{W}_\text{i} \text{ times}}$ and

$\text{sgn}(W_i)$ denotes the sign of W_i.

The rest of the operators are similarly defined:

$$
\begin{aligned}
&WTMD_{OP}(x,g,w,n) = \\
&WTMD_{DI}(WTMD_{ER}(x,g,w,n),g,w,n), \\
&WTMD_{CL}(x,g,w,n) = \\
&WTMD_{ER}(WTMD_{DI}(x,g,w,n),g,w,n), \\
&WTMD_{OC}(x,g,w,n) = \\
&WTMD_{CL}(WTMD_{OP}(x,g,w,n),g,w,n), \\
&WTMD_{CO}(x,g,w,n) = \\
&WTMD_{OP}(WTMD_{CL}(x,g,w,n),g,w,n).
\end{aligned} \tag{3}
$$

Figure 2 illustrates the block diagram of the baseline drift correction task with weighted mediated morphological filters (method 3). A suitable structuring element is applied. This algorithm is not very sensitive to the size of the structuring element.

3.1 Properties of the operators

The operators, denoted $WTMD(x,g,w,n)$, have the following properties:

1. **Increasing:** They are all increasing:
   $x_1(n) < x_2(n) \Rightarrow WTMD(x_1,g,w,n) < WTMD(x_2,g,w,n)$
2. **Extensive:** Weighted mediated dilation and closing are extensive:
   $WTMD_{DI}(x,g,w,n) \geqslant x(n)$,
   $WTMD_{CL}(x,g,w,n) \geqslant x(n)$.
   However, weighted mediated erosion and opening are anti-extensive:
   $WTMD_{ER}(x,g,w,n) \leqslant x(n)$,
   $WTMD_{OP}(x,g,w,n) \leqslant x(n)$.
3. **Idempotent:** Weighted mediated erosion and dilation are not idempotent:
   $WTMD_{DI}(WTMD_{DI}(x,g,w,n),g,w,n) \neq WTMD_{DI}(x,g,w,n)$,
   $WTMD_{ER}(WTMD_{ER}(x,g,w,n),g,w,n) \neq WTMD_{ER}(x,g,w,n)$.
   Weighted mediated opening and closing are idempotent:
   $WTMD_{OP}(WTMD_{OP}(x,g,w,n),g,w,n) = WTMD_{OP}(x,g,w,n)$,
   $WTMD_{CL}(WTMD_{CL}(x,g,w,n),g,w,n) = WTMD_{CL}(x,g,w,n)$.

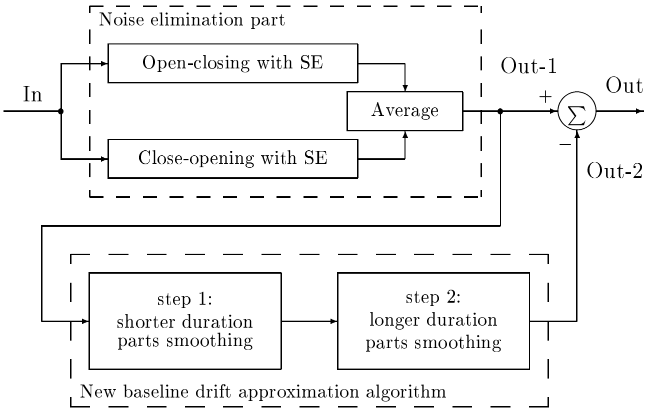

Figure 1: Simplified block diagram of ECG preprocessing (method 2).

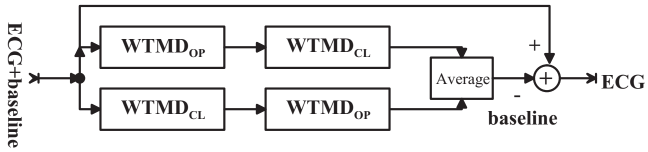

Figure 2: Block diagram of ECG preprocessing (the proposed method (3)).

These results are consistent with the established theory of mathematical morphology. For more detailed expressions about the above properties, the reader is invited to refer to the literature, e.g., [14, 15]. A morphological filter should be increasing, idempotent, and extensive or anti-extensive [14]. Therefore the weighted mediated opening, closing, open-closing, close-opening can be used to construct a morphological filter, because they possess all required properties. However the weighted mediated dilation and erosion are not considered as morphological filters, but morphological operators, as they are not idempotent.

4. EMPIRICAL RESULTS

The following definition is used to explain each of the methods:

1. Method 1: classical morphological filtering [5].
2. Method 2: improved classical morphological filtering [6].
3. Method 3: weighted mediated morphological filtering [13] (the proposed method).

Figure 3 shows the original and (artificially) corrupted ECG signal, respectively. The trend is to remove the baseline drift. Figures 4 and 5 illustrate the performance of three methods. The signals have been zoomed in Figure 5 (the first 5 seconds of the signals are presented). It is clear that the results of method 1 is not acceptable, as it causes severe distortions. Some of the problems with method 2 as well as method 1 are marked with arrows in figures. The dominance of method 3 is clear.

A real corrupted ECG signal is illustrated in Figure 6. The better performance of the proposed method have been proved in Figures 7 and 8. In Figure 7, high-frequency noise is first removed by small-size structuring element (in all three methods), and then, the baseline drift is corrected.

Figure 8 is about the situation when the attempt to higher frequency noise removal is done as the last stage. The results prove that it is better to correct the baseline wander at first and then try to remove the higher frequency noise components. This could be a valuable recommendation for similar research topics.

Also other results show that the proposed method is less sensitive to the size of the structuring element while method 2 relies on the approximation of the size of the structuring element. Due to the limitation of the paper, the results have not been illustrated as the processed signal will look the same for different structuring element sizes in method 3. We have got similar results when this size varies from 29 up to 59 for removing the the baseline drift and 3 to 7 for higher frequency components. This variation of the size of the structuring element will cause other methods to fail.

For all cases, a flat (symmetric) structuring element of size 1×3 has been applied as the small-size required (The weight parameter, w, for method 3 is $[1,2,1]$). The large size is about 1×51 (with an arbitrary values for w of the same size).

5. CONCLUSIONS

In this paper, a more efficient approach to background normalization of ECG signals has been proposed using weighted mediated morphological filters. Results with less distortion and more accurate baseline estimation were achieved while it was proved that the proposed method requires less stages for preprocessing (roughly half of the processing time required by method 2) as it does not need to remove the QRS complexes at first prior to baseline correction. Only one stage is enough. The future work is to improve the efficiency, even more, using Genetic Algorithms to design the optimum weights for the filters similar to the research as addressed in [16], and even adaptive filtering [17].

6. ACKNOWLEDGEMENT

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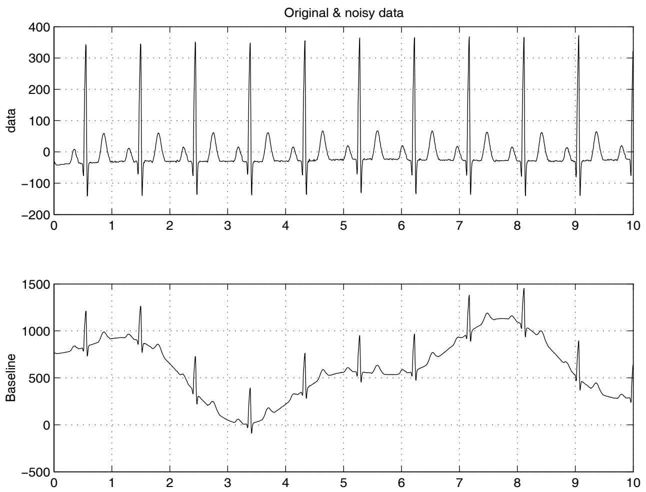

Figure 3: Original and (artificially) corrupted signal.

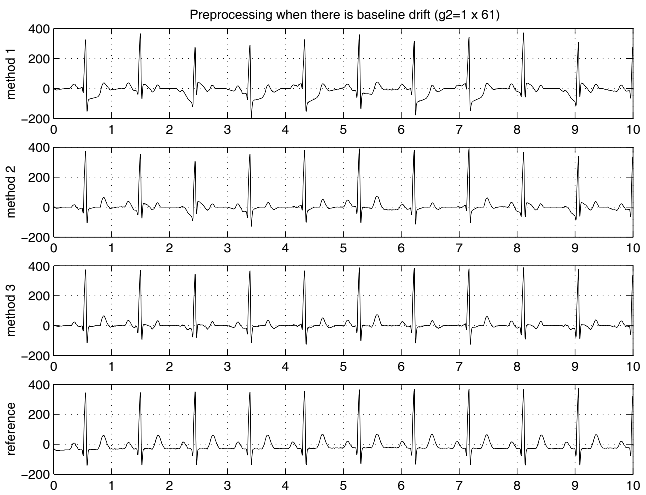

Figure 4: Baseline drift correction with three methods.

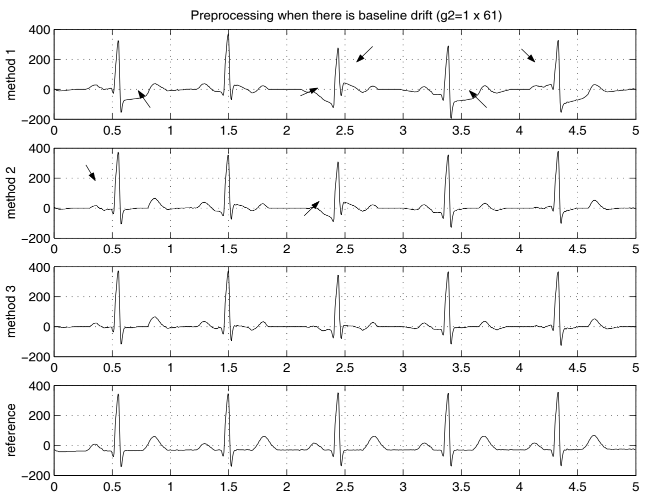

Figure 5: Baseline drift correction with three methods (zoomed).

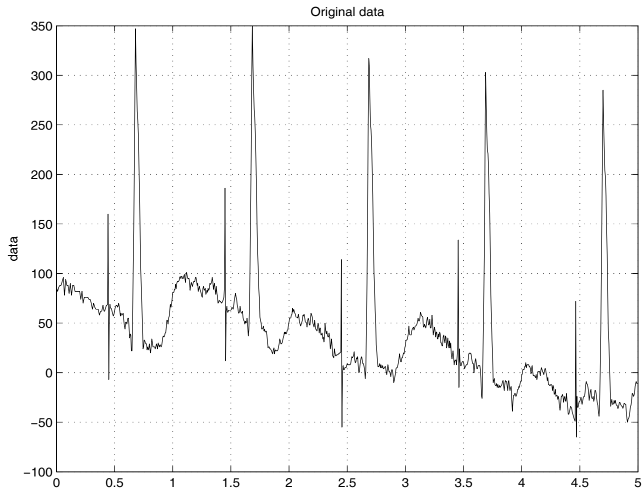

Figure 6: A real corrupted ECG signal.

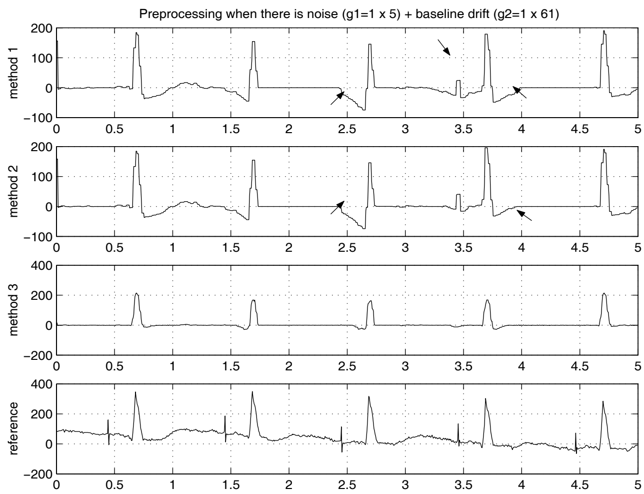

Figure 7: The preprocessing with three methods for removing high frequency noise at first and next, the baseline wander correction.

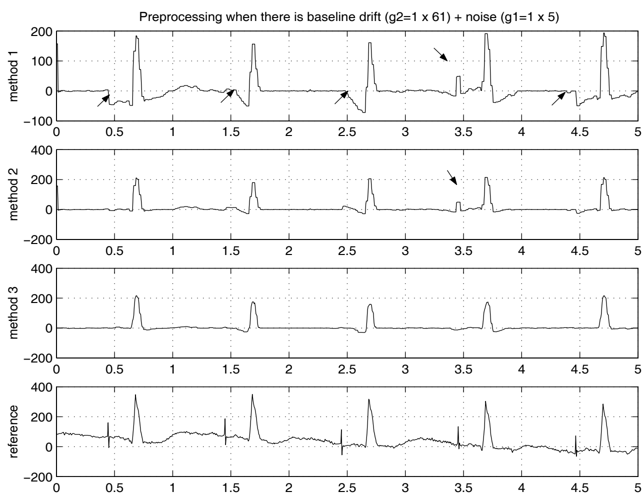

Figure 8: The preprocessing with three methods for the baseline wander correction at first and then, high frequency noise removal.