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Using DWT for ECG Motion Artifact Reduction with Noise-correlating Signals

Malte Kirst, Bastian Glauner, Jörg Ottenbacher

***Abstract*— Dealing with motion artifacts in long-term ECG recordings is a big issue. The frequency spectrum of motion artifacts is similar to the frequencies of the QRS complex – the wanted signal in the ECG. The deletion of motion artifacts often leads to a deformation of QRS complexes, too. These risks can be minimized by using a noise-correlating signal as a second channel for artifact reduction. This paper presents an approach using the electrode-skin impedance as a second channel for the reduction of motion artifacts. Using the discrete wavelet transform, motion artifacts can be deleted time and frequency selective. This filter approach leads to an improvement of the automatic QRS detection and decreases the number of false detections by 35 %.**

I. INTRODUCTION

The Electrocardiogram (ECG) is the most important diagnostic method for many heart diseases [1]. It predicts a lot about a patient's state of health, especially after a heart attack or contracting another heart disease. 12 lead resting ECG and stress test ECG are mostly standard, but all rare occurring dysrhythmias or syncopes need a long-term ECG for detection. This cheap and non-invasive diagnostic method is also good for screening applications.

With a period of application of several days or weeks – as it is necessary in telemonitoring scenarios – the ergonomics of the recording system get more important. The use of textile integrated ECG recorders with dry electrodes meet those requirements. Because of the skin-tolerance of dry electrodes they are the better choice for long-term applications [2]. But they pose new difficulties: Due to the necessary integration in a wearing system, the missing electrode gel and the fluctuating skin sweat dry electrodes can be more prone to motion artifacts [3]. And dealing with the occuring artifacts can be a challenging task [4].

II. MOTION ARTIFACTS

A. Origin

The signal of an ECG long-term recording is disturbed by several artifacts. Most artifacts (e. g. interferences of electrical fields or baseline wander from skin sweat) can be reduced by band-pass filters. However, the frequency spectrum of motion artifacts overlaps the spectrum of the ECG. Thus, a simple band-pass cannot remove those disturbances without changing the ECG itself. With clever electrode positions and a good hardware design motion artifacts can be minimized but can never be ruled out.

The equivalent circuit diagram in Fig. 1 shows the origin of motion artifacts. Motion artifacts are potentials that are superimposed onto the ECG signal U_{ECG}. The electrode motion on the skin produces a disturbing of the electrode/electrolyte equilibrium potential U_E. Moreover, the skin generates – due to its deformation under the electrode – a change in its skin potential U_S. Changes of the electrode-skin contact and skin deformations under the electrode lead to a change in the electrode-skin impedance Z_{ES}.

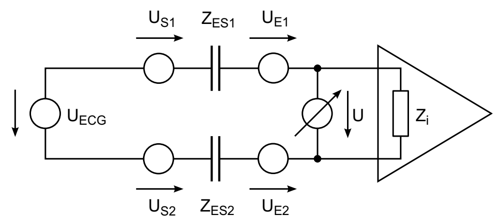

Fig. 1. Different sources of motion artifacts: The electrode and skin potentials U_E and U_S and the electrode-skin impedance Z_{ES}

B. Electrode-skin impedance as second channel

A common approach to improve artifact reduction algorithms is to use information from additional signals that correlate with the motion artifact [5], [6]. The electrode-skin impedance Z_{ES} is such a parameter: It is correlated to parts of the motion artifacts and it can be measured with a proper measurement set-up.

Figure 2 shows an ECG with motion artifacts, the electrode acceleration (vertical axis) and the electrode-skin impedance of one electrode. The similarity between the motion artifact in the ECG (above) and the changes in the electrode-skin impedance is in evidence. The cross correlation coefficient between both zero-mean signals in a disturbed ECG sequence is about 0.25 (see Fig. 3 at zero-lag).

C. Electrode acceleration as second channel

Another noise-correlating signal is the acceleration. Both [6] and [7] use the acceleration of the subject's body or of an electrode as a second channel for an adaptive artifact removal filter. They could achieve improvements of the ECG signal, but it is not known to the authors if the methods were successfully tested in the field.

Figure 4 indicates the differences between an acceleration signal and the electrode-skin impedance as noise-correlating parameter. While the correlation between electrode-skin

J. Ottenbacher is with the Institute for Information Processing Technology, Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany joerg.ottenbacher@kit.edu

M. Kirst and B. Glauner are with the FZI Research Center for Information Technology, 76131 Karlsruhe, Germany kirst@fzi.de

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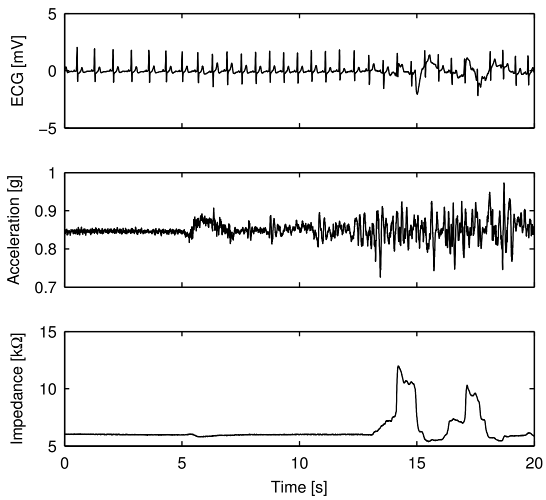

Fig. 2. ECG with motion artifacts and noise-correlating signals

impedance and disturbed ECG is in evidence (Fig. 3), there is no identifiable correlation between the electrode-skin impedance and the undisturbed ECG. The behavior of the electrode acceleration is vice versa: the correlation with undisturbed ECG is higher than with artifacts. We used for this measurements an ECG belt with two dry electrodes. A tri-axial acceleration sensor was fixed on each of the electrodes.

Two effects can explain this remarkable effect. Firstly, when the acceleration sensor is placed near the patient's heart, it will – especially by slender subjects and a good mechanical coupling to the body – record the seismocardiogram additionally. This is well correlated with the ECG signal; subject to the accelerometer axis and sensor position we could reach cross correlation coefficients of 0.8. The second effect is the physiological adaption of the heart rhythm to the human gait. A second channel signal for artifact reduction should be correlated with the noise and not correlated with the wanted signal. Because of these effects we expect not the best results by using the acceleration signal as a second channel for adaptive filters.

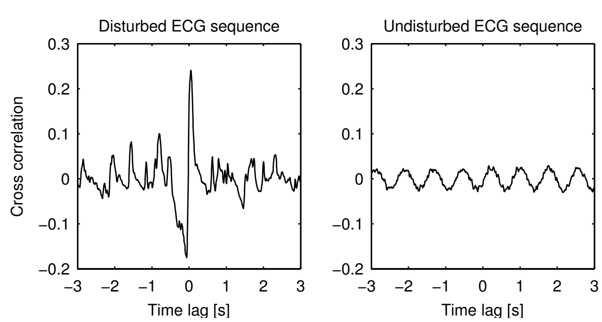

Fig. 3. Cross correlation function between ECG and electrode-skin impedance

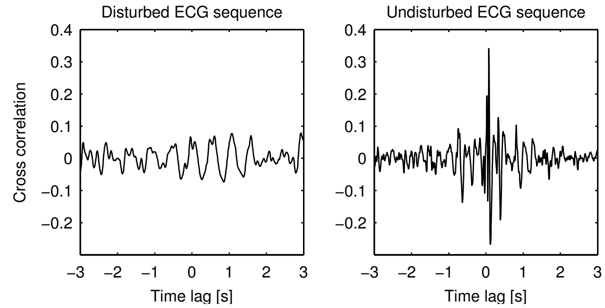

Fig. 4. Cross correlation function between ECG and electrode acceleration (mean of all axis)

III. INSTRUMENTATION AND MOBILE MEASUREMENT SYSTEM

The datasets in this work are from former recordings for testing different artifact detection algorithms [8]. The measurement system is an extension of a commercial Holter recorder. The recorder is used as a data logger and allows storing the following measured raw data on compact flash cards over several hours: The reference ECG with two bipolar channels and adhesive electrodes, a one-channel ECG with dry electrodes, integrated in a chest belt and the electrode-skin impedance of both dry electrodes.

With this system we made recordings on 14 subjects. The persons had to undergo a defined procedure with different daily life activities including activities that often provoke artifacts in ECG recordings, like climbing stairs and strong walking. The total duration of each recording was about one hour. The dry electrode chest belt was worn in the height of the sternum. The subjects were instructed to wear the chest belt only as tight as they could imagine wearing it over a very long period of time. Additionally, we recorded the Einthoven I and II leads with standard adhesive electrodes as a reference ECG. From two measurements we discarded regions in which the electrode belt came loose completely. For further evaluation we had about 14 hours of utilizable data.

All recordings got a QRS reference annotation. A software QRS detector made its annotation in a first run; afterwards the annotation was checked manually by an expert. The two reference ECG leads helped in disturbed ECG sequences. Sequences where no reliable reference annotation was possible – due to electrode lead-off or otherwise completely disturbed signal – were cut out.

IV. ARTIFACT REDUCTION ALGORITHM

A. Approach

The artifact reduction with a band-pass often leads to poor results. Either the artifacts are still present in the ECG signal or the ECG morphology is significantly changed. To avoid this set of problems we were looking for an approach filtering only ECG sequences that are disturbed. The goal was an artifact reduction without compromising the ECG itself. The electrode-skin impedance as an artifact correlating second channel should ease this goal.

A common approach for denoising a signal by means of the discrete wavelet transform (DWT) involves the following three steps [9]:

1) calculating the DWT of the signal
2) zeroing or modifying parts of the coefficients according to specific rules
3) reconstructing the signal from the modified coefficients

Step two, the zeroing of the signal, is the interesting part of this approach. We used the electrode-skin impedance for identifying the parts of the signal that should be modified.

B. Algorithm

Figure 5 shows the outline of our algorithm that follows mainly those basic steps. The sum of both impedance signals and the ECG signal are being wavelet transformed (DWT, 4 levels). All samples of all four levels of the transformed impedance signal are checked if they exceed a certain threshold. If this happens, the corresponding coefficients of the ECG's wavelet transform are set to zero. The ECG is reconstructed with an inverse DWT in a final step.

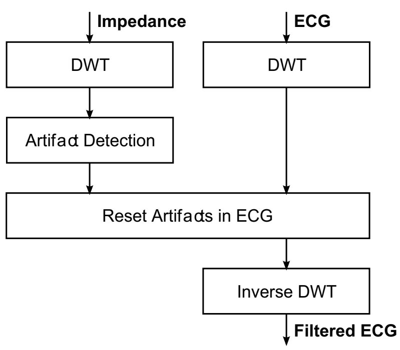

Fig. 5. Algorithm for selective artifact reduction

Setting individual levels to zero and reconstructing the signal with an inverse wavelet transform is a common approach for denoising a signal. The zeroing deletes all waveforms of a certain frequency band. In our case, we do not set the entire level to zero, but individual samples. By this way we have both a time and frequency selective artifact reduction filter.

Two main parameters influence the outcome: The threshold for detecting artifacts in the wavelet transform of the impedance signal and the baseline wander reduction by zeroing the higher levels by default. Without an extra baseline wander reduction, the ECG distortions after filtering are mainly limited to the artifact regions itself (see Fig. 6). However, the improvement of the QRS detection results is minimal. The results increase when the higher levels are set to zero.

A variation of the threshold shifts the false positive (FP) and false negative (FN) reduction rate, so the results of sensitivity and the positive predictive value of the QRS detection (Fig. 7). A lower threshold improves especially the FP rate significantly. If the threshold is too low, the FN rate increases.

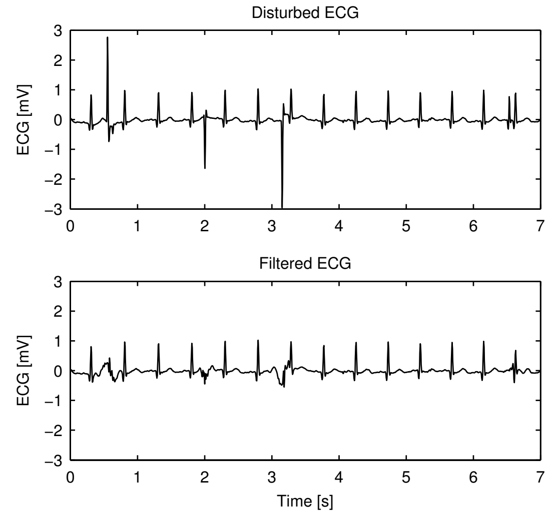

Fig. 6. Selective artifact reduction with minimal signal distortion

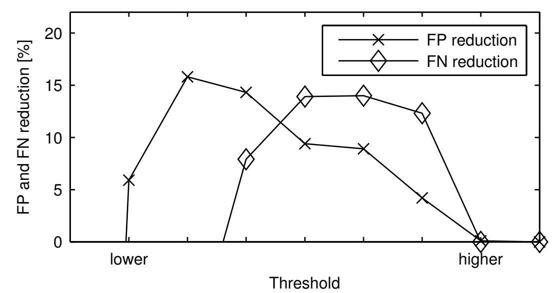

Fig. 7. A threshold variation shifts the FP and FN reduction rate

V. EVALUATION AND RESULTS

For the evaluation of the presented algorithm we measured the direct improvement of the QRS detection. The QRS detection is the most important step in automatic ECG analysis, further steps depend on a reliable detection. This is why we prefer the QRS detection as metrics. We chose the Open Source ECG Analysis (OSEA) algorithm [10] for QRS detection. The OSEA algorithm is a basic but very fast and good QRS detector in time domain.

Figure 8 shows the validation procedure. The filtered and the unfiltered ECG signal are subject to QRS detection. The detection results are compared to a reference with a beat-by-beat comparison (BxB) with a centered 150 ms window. This is the base for the calculation of the sensitivity (Se) and the positive predictive value (pP) of the QRS detection. As a result, we can get an improvement of Se and pP as well as a reduction in the number of FP and FN detections. Dependent on the threshold and the integrated baseline wander reduction, we could achieve a decrease of 10–35 % of false detections after artifact reduction. Both the sensitivity of 98.8 % and the positive predictive value of 98.5 % could be increased to more than 99 %.

Table I shows the QRS detection results. The first row contains the results with no artifact removal for comparison.

The filter with parameter set I reduces the number of false detections for about 10 %. The filter's disturbance to the ECG is minimal (see Fig. 6). The parameter set II includes a baseline wander removal by deleting the highest levels of the DWT. The reduction of the false detections is about 35 %. The filtered ECG signal itself is distorted due to the strong filtering and cannot be used for morphological diagnosis anymore.

TABLE I
IMPROVEMENT OF THE QRS DETECTION RESULTS FOR ALL DATA SETS

Algorithm	#TP	#FP	#FN	Se [%]	pP [%]
no artifact removal	98975	1457	1129	98.87	98.55
parameter set I	99125	1325	979	99.02	98.68
parameter set II	99300	888	804	99.20	99.11

We compared the artifact reduction method with other filter approaches. A 5th order IIR high-pass filter with Butterworth structure and a cutoff frequency of 5 Hz for instants leads to an improvement of about 6 % in FP and FN detection (see Tab. II). When the DWT is only used for baseline wander removal by deleting the highest levels of the ECG's wavelet transform, an improvement of 17 % is achieved. However, the filtered ECG signal is distorted and cannot be used for any morphological diagnosis.

TABLE II
IMPROVEMENT OF THE QRS DETECTION RESULTS WITHOUT USING NOISE-CORRELATING SIGNALS

Algorithm	#TP	#FP	#FN	Se [%]	pP [%]
no artifact removal	98975	1457	1129	98.87	98.55
Butterworth high-pass	99042	1367	1062	98.94	98.64
DWT baseline wander removal	99043	1073	1061	98.94	98.93

VI. DISCUSSION AND OUTLOOK

This work presents an artifact reduction algorithm with a second channel input aside adaptive filters. The algorithm has the ability to improve an automatic QRS detection that is performed after the artifact reduction. Even when a decrease of up to 35 % of false detections is a good achievement, the changes in QRS detection sensitivity and positive predictive value are minimal.

This artifact reduction algorithm shows the best results for short and steep distortions. These artifacts can occur when the electrodes slip over the skin. This can be a consequence of a loose electrode belt or strong movements.

A question to be discussed is if such an artifact reduction is worth the effort. By using the DWT and IDWT for two signals, the performance advantage of the OSEA algorithm decreases. More complex QRS detection algorithms may have good results on a disturbed ECG even without artifact reduction.

A more powerful QRS detection algorithm will probably lead to better QRS detection results as the used OSEA algorithm. The integration of the noise-correlating signal in a wavelet based QRS detection algorithm would be a promising approach for further research.

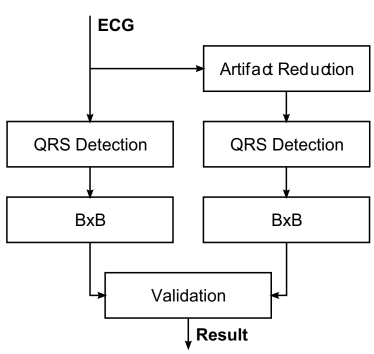

Fig. 8. Validation by the OSEA QRS detector and a beat-by-beat comparison (BxB)

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