Modeling of Motion Artifacts in Contactless Heart Rate Measurements

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Abstract

While contactless vital sign monitoring technologies provide the great opportunity of fast and simple measurements, all these technologies have the unavoidable drawback that they suffer from strong motion artifacts. These motion artifacts may severely disrupt the signal of interest, which could lead to false peak detections and hence, result in false conclusions or diagnoses. Extensive and robust signal processing is needed for a reliable detection of these artifacts. In this work, a mathematical model of the motion artifacts is derived based on capacitive ECG measurements, as an example for contactless heart rate estimation. Thus, for the first time, it is possible to generate an arbitrary large database of heavily distorted capacitive ECG signals to test and verify algorithms for the robust detection of motion artifacts.

1. Introduction

In recent years contactless or unobtrusive vital sign monitoring has gained more and more interest in research as well as in industry, as it provides several promising opportunities such as e. g. a zero preparation time. The applied physical sensor principles are, especially in case of heart rate monitoring, manifold and range from camera based systems over high frequency magnetic induction systems to force sensors [1].

However, all these methods suffer from severe motion artifacts which is a fundamental property of all contactless measurement technologies. Although methods exist, which try to compensate these motion artifacts with additional sensors and special signal processing [2–4], this may not always be possible, e. g. if the motion artifact is kind of chaotic and not linearly related to the motion. Hence, signal processing is needed to detect the intervals which are distorted by artifacts to exclude or to compensate them. Since the fraction of the distorted intervals may be very large, very robust artifact detection algorithms need to be developed.

To provide an arbitrary large database of heavily distorted signals for the development of these algorithms, a mathematical model is derived in this paper. Here, a capacitive ECG measurement is analyzed, but other own measurements show, that the model can easily be adapted to other sensor principles by slight adaption of its parameters. To the authors best knowledge, this is the first publication which analyzes and models the severe motion artifacts in contactless heart rate measurements.

2. Measurement setup

As already mentioned, the analyzed measurement system is a capacitive ECG system. Such a system is similar to a standard conductive ECG with wet electrodes with the sole and main difference, that the coupling between the electrodes and the patient is capacitive and thus forms a high-pass filter. Therefore, an active electrode with a high impedance buffer is required in order to achieve a low cut-off frequency lower than 1 Hz [5]. Since no conductive connection is needed, measurements through clothes are possible. It has been shown, that capacitive systems may achieve similar or even better results than standard ECG system [6]. However, due to the large resistances, they are on the other hand very prone to generate electrostatic charges which cause chaotic non predictable severe motion artifacts [6, 7].

In order to acquire data for modeling, a typical capacitive ECG system was installed in a mattress pad, which was positioned on a bed. Ten of the authors laid on this pad for around 10 min with the task to perform typical movements as during sleep, e. g. small, strong, short and up to one minute long movements. The height of the subjects was $(1.8 \pm 0.1)\,\mathrm{m}$ with a body mass index of $(24.2 \pm 4.0)\,\mathrm{kg/m^2}$. A MP70 Philips patient monitor was used to deduce a reference ECG.

3. Modeling

The measurement signal is denoted as $y(t)$ and is composed of the undistorted signal of interest $x(t)$ with additive superimposed gaussian noise $n(t)$ and artifacts $o(t)$:

$$y(t) = x(t) + n(t) + o(t). \qquad (1)$$

The signal of interest $x(t)$, may be any quasi-periodic signal with a time varying period $T(t)$

$$x(t) \approx x\left(t + T(t)\right). \tag{2}$$

In this specific case it is the QRS-complex or a QRS-complex similar shape, which is not important at this point for the analysis of the artifact but later on for the generation of the synthetic artifact distorted signal.

To allow a deeper insight into the motion artifacts and to provide a possibility to analyze and model the artifacts, following steps were performed:

1. Peak detection in all signals and the reference with the open source ECG peakdetector OSEA [8].
2. Calculation of the peak-to-peak heart rate from the capacitive ECG (HR) and the reference ECG (HR_{ref}).
3. Extraction of all time intervals of $y(t)$, in which the absolute difference $|HR - HR_{\text{ref}}|$ is greater than 5 BPM, with the assumption that these intervals are distorted by artifacts.

These extracted artifacts can now be analyzed regarding their amplitude distribution and their frequency spectrum, which can then be used to generate artificial motion artifacts.

Figure 1 shows the histogram of the amplitudes of the extracted time intervals. Since the supply voltage is an up-

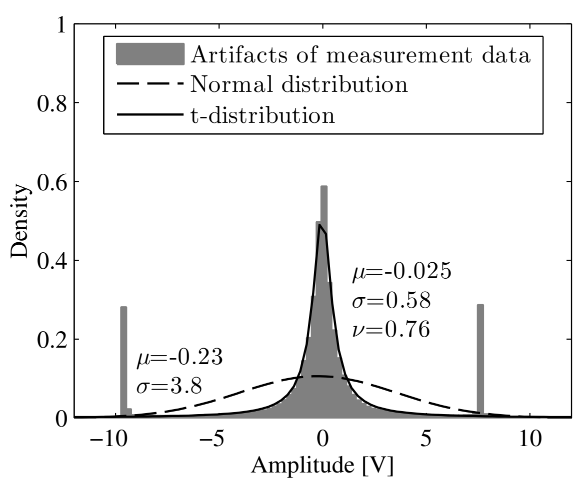

Figure 1. Histogram of the extracted motion artifacts.

per limit of the maximum and minimum voltage, all voltages above ± 9 V are cropped, which is clearly seen at both ends of the histogram. Interestingly, the distribution of the artifacts does not follow a normal distribution, but a so called t-location-scale distribution. The probability density function $p(o|\mu, \nu, \sigma)$ of a t-location-scale distribution is described by

$$p(o|\mu,\nu,\sigma) = \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})\sqrt{\pi\nu}\sigma} \left(\frac{\nu + \left(\frac{o-\mu}{\sigma}\right)^2}{\nu} \right)^{-\frac{\nu+1}{2}} \tag{3}$$

and is a standard t-distribution with its parameter ν for the degrees of freedom and an additional location and scale parameter μ and σ. The gamma function is denoted with Γ. The parameters in Figure 1 of the normal and the t-location-scale distribution for an optimal fitting of the measured data, were calculated with MATLAB and its distribution fitting tool.

The t-distribution is used in robust statistical modeling, as it better reflects the higher number of large elements due to its higher tails compared to the normal distribution [9]. This is probably also the explanation why the motion artifacts of unobtrusive measurements follow a t-distribution, as there are many small amplitudes but also a lot of arbitrary large amplitudes.

Another important property is the spectrum of the artifacts, which is shown in Figure 2. The slope of the

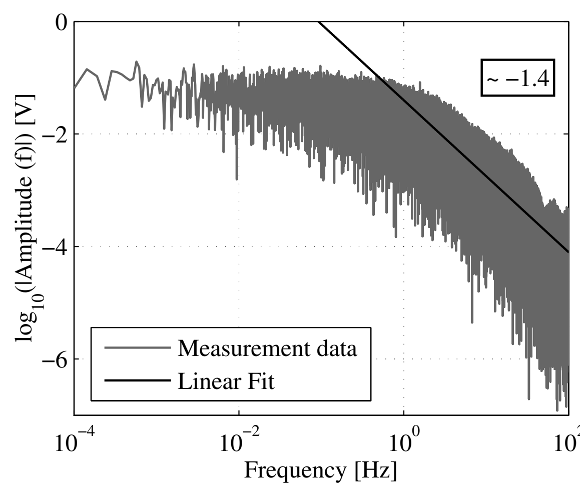

Figure 2. Spectrum of the extracted motion artifacts.

spectrum follows an inverse linear frequency behaviour of $1/f^{1.4}$ in a logarithmic scale. The duration γ of the extracted artifact intervals can be described by an exponential distribution

$$p(\gamma|\lambda) = \begin{cases} \lambda \mathrm{e}^{-\lambda\gamma} & \gamma \geq 0 \\ 0 & \gamma < 0 \end{cases}, \tag{4}$$

as it is clearly visible in Figure 3. Both the spectrum and the distribution of the durations can be explained with a consideration of energy. Strong and long lasting movements require more energy than small and short ones, and hence, these will probably less frequently occur.

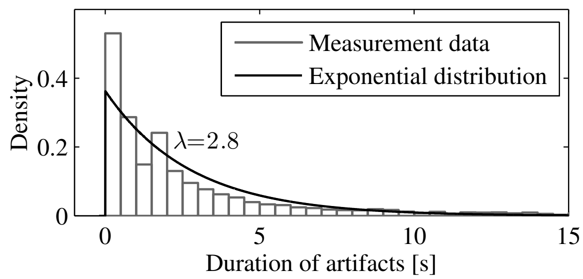

Figure 3. Distribution of the duration γ of the extracted artifact intervals.

4. Generation of an artificial artifact distorted signal

After the analysis of the artifacts a synthetic signal shall be generated. At first the quasi-periodic signal $x(t)$ of length l is generated. Since the physiological heart rate variability is an important property, a public script to generate an artificial ECG is taken [10]. However, instead of using the complete script, only the time points of the peaks are taken, at which then an own pattern is placed. This is done for further analyses if, for example, an artificial distorted optical pulse signal shall be generated. Here, a short triangle pulse is used as a model for the QRS-complex. Since the pulse shape does neither affect the r-peak detection of the ECG peak detector, nor the artifacts, it is an acceptable simplification.

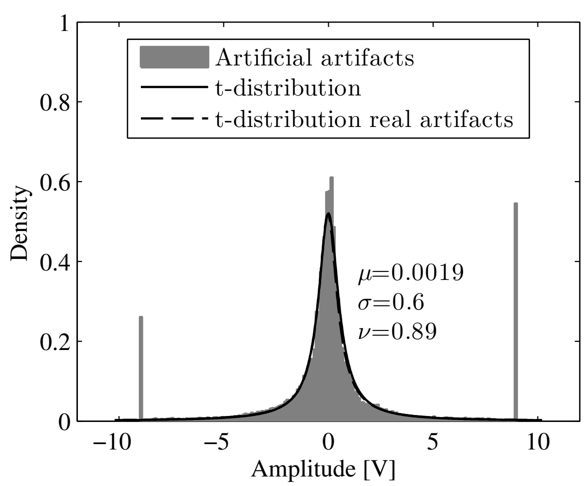

Figure 4. Histogram of the artificially generated motion artifacts.

The artificial artifacts $o(t)$ are taken from a t-location-scale distribution and low-pass filtered to achieve the right frequency behavior. The parameters for the distribution and the filter are optimized in order to fit the results from the analyses of the preceding section. The histogram of the generated artificial artifacts is shown in Figure 4. Although the parameters μ, σ and ν of the artificial t-distribution are slightly different, they almost perfectly match the distribution of the measured artifacts.

The spectrum of the artificial artifacts is given in Figure 5. It has the same qualitative behavior at low and high

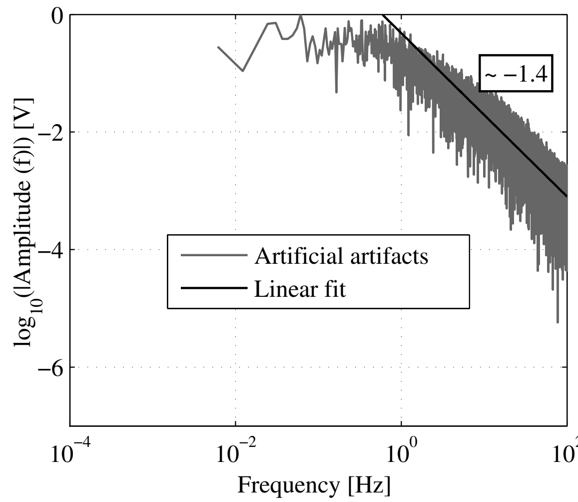

Figure 5. Spectrum of the artifical motion artifacts.

frequencies as the spectrum of the real artifacts. However, it is slightly shifted upwards. This might be due to a non perfect artifact extraction in the analysis of the real artifacts, which also include only slightly distorted time intervals. Additionally, the extracted intervals may also contain QRS complexes and other not modeled noise sources which might influence the spectrum accordingly.

The final artificial distorted capacitive ECG signal is generated by distributing the artificial artifact intervals randomly along the artificial quasi-periodic signal $x(t)$. The duration of the artificial artifact intervals is taken from an exponential distribution with $\lambda = 2.8$.

As a final example Figure 6 shows a small time interval of a real measured capacitive ECG and Figure 7 shows a small time interval of an artificially distorted quasi-periodic signal. The distorted intervals are shaded grey and they look pretty similar in the real data and the artificially generated signal. There are very large artifacts and also small artifacts in both signals. It can be seen in the real measured data, that other noise sources and variations such as the T- and P-wave exist between the R-peaks. These are not modeled here, as they do not influence the R-peak detection.

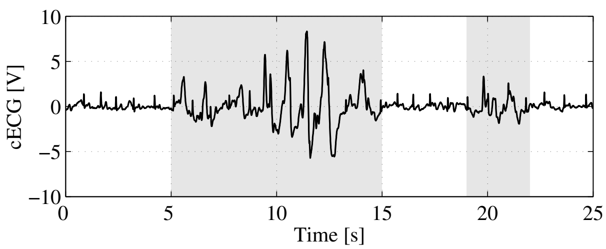

Figure 6. Example of a real measured capacitive ECG signal with artifacts.

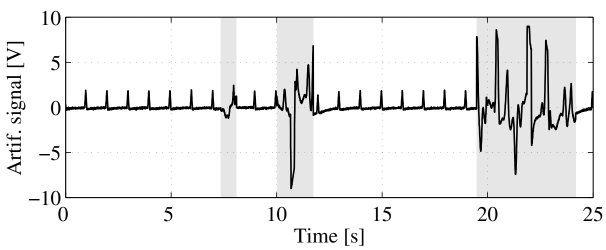

Figure 7. Example of an artifical generated quasi-periodic signal with artificial artifacts.

5. Conclusion

For the first time a mathematical model was derived to model the severe motion artifacts in capacitive ECG measurements. The amplitude distribution of the artifacts follow a t-location-scale distribution with a spectrum which follows an inverse linear frequency behavior of $1/f^{1.4}$. Although the statistical parameters of the artificially generated artifacts do not perfectly match the statistics of the measured data, the resulting artificial artifacts look equal to the measured ones. However, it is not important to meet the statistical parameters very exactly, as they may anyway slightly change depending on the actual measurement conditions. However, it will always be a t-location-scale distribution with a spectrum which follows an inverse frequency behavior.

The derived model can be used to generate an arbitrary large database to develop robust artifact detection algorithms. As the positions of the artifacts are known a priori, a gold standard is available to evaluate the algorithms with typical classification quality criteria.

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