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Decomposition and modeling of signal shapes of single point cardiac monitoring

Abstract:

We introduce a novel method for electronic recording of cardiac signals from a single point at the skin in contrast to classical differential electrocardiography (ECG). Ultralow-noise transistor devices with an adaptable, auto-stabilizing transimpedance amplifier are able to measure tiny skin potential modulations from a single contact electrode located at an individual's wrist (single-point cardiography-SPC). Although SPC signals were highly prone to interspersed noise, they contained periodic patterns. In an electromagnetically shielded setting, we could clearly extract breathing and cardiac rhythms from the acquired SPC signals. As the reference, we measured ECG in parallel. Several signal-processing techniques like smoothening, correlation, decomposition and signal extraction showed that SPC signals contain breathing and periodic heart potential variations, which are time-correlated with ECG. In the future, we intent to use this novel technique to measure heart signals from patients in different health conditions.

Keywords: Hodrick-Prescott decomposition, ARIMA, STL, Signal Decomposition, AlGaN/GaN HEMT.

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1 Introduction

Measuring the heart activity is one of the first tests in the clinics. In modern personalized healthcare, different wearable devices were introduced for cardiac monitoring. Healthy people monitor their heart functionality at home, during their daily routines or sports. Most of the approved systems in the market, including skin patches, textile-embedded electrodes and smart watches, utilize a classical differential measurement by at least two electrodes like in classical ECG.

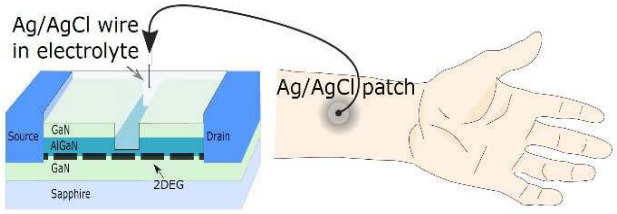

Figure 1. Illustration of a low-noise high electron mobility transistor (HEMT) device with recessed gate structure in a floating electrochemical configuration. A standard skin-patch electrode as it is usually used for ECG was connected via an electrochemical bridge to the transistor.

In the modern trend of miniaturization and digitalization, wearable devices have attracted high attention. Depending on the level of their precision, there are different methods available: 12-lead ECG, photoplethysmography (PPG), etc. There is always a trade-off between precision and comfortability. More measuring points lead to more precise medical diagnostics with the cost of lower comfortability. For decades, portable 12-lead ECG is measured by the Holter method [1]. Although this method is precise, it has several drawbacks. The high number of electrodes increases the possibility to catch artefacts and noise by body movement and environment [2]. There are also cardiac diseases such as hidden heart attacks, blockage of the arteries, undiagnosed congenital heart defects, myocardial infarction or cardiac scars [3], which are difficult to identify in ECG traces. False positive results were also reported for athletes in their ECG recordings [4]. Since SPC is using only one single point at the wrist to measure the signal, the probability of catching artefacts from multiple points decreases drastically by decreasing the wirings. In many wearable sports and fitness applications, the heart rate is monitored by optical techniques such as PPG. In many biomedical applications, routine electronic monitoring of the heart activity is in high demand for early diagnostics, where SPC might be a valuable complementary technique to ECG.

In this study, we utilized pre-processing, correlation and decomposition methods based on Hodrick-Prescott

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decomposition, Autoregression Integrated Moving Average (ARIMA) and Seasonal and Trend decomposition using Loess (STL) for signal decomposition and correlation of the recorded SPC traces. Figure 1 shows the experimental setup using a single patch electrode to contact the test persons' wrist. The ultralow-noise HEMT transistors in combination with the battery-powered amplifier pick up tiny fluctuations, which are not visible with bare skin electrodes and standard amplifier electronics.

2 Methods

2.1 Sensors and measurements

For SPC recordings, we used ultralow-noise devices based on AlGaN/GaN HEMTs [5] in a liquid-gate configuration [6] to capture tiny fluctuations at a single point of the skin. A standard Ag/AgCl skin patch electrode was connected to the wrist of a healthy individual and the lead attached to another Ag/AgCl wire, which connected an electrolyte solution. This solution formed a contact to an electrolyte-gated HEMT transistor (figure 1). HEMTs with recessed, non-metallized gates were used to increase their sensitivity [7]. The well-known, ultralow-noise level in combination with high-ohmic gate inputs of the 2-dimensional electron gas devices enable the detection of tiny skin potential fluctuations. With our adaptable, auto-stabilizing trans-impedance amplifier circuit with floating gate HEMTs, we generally cannot specify a precise amplification gain. Depending on the HEMT working point, the full amplification factor is varying. In SPC detection, the transistor current changes when a moving charge is influencing the electrochemical double layer at the input of the transistor. The amplifier automatically adapts to an appropriate gain factor to keep the output voltage always in a similar range. This switching procedure leads to sudden changes in the output signal. However, for the SPC signal analysis in this study, we only used recording periods with coarse trends as it can be seen in figure 2. In addition, since the measurements were highly prone to interspersed electromagnetic noise, we did all measurements with test persons inside a large Faraday tent (Holland Shielding Systems BV, the Netherlands). In our experiments, we measured classical ECG signals from the same individual, simultaneously, to directly correlate the remaining periodic fluctuations in SPC with ECG, which can also be used to derive the respiration rate [8]. Experiments were done on six different individuals sitting on the same chair inside the Faraday tent, while the battery-powered electronic readout was acquiring the skin potential fluctuations as shown in figure 1.

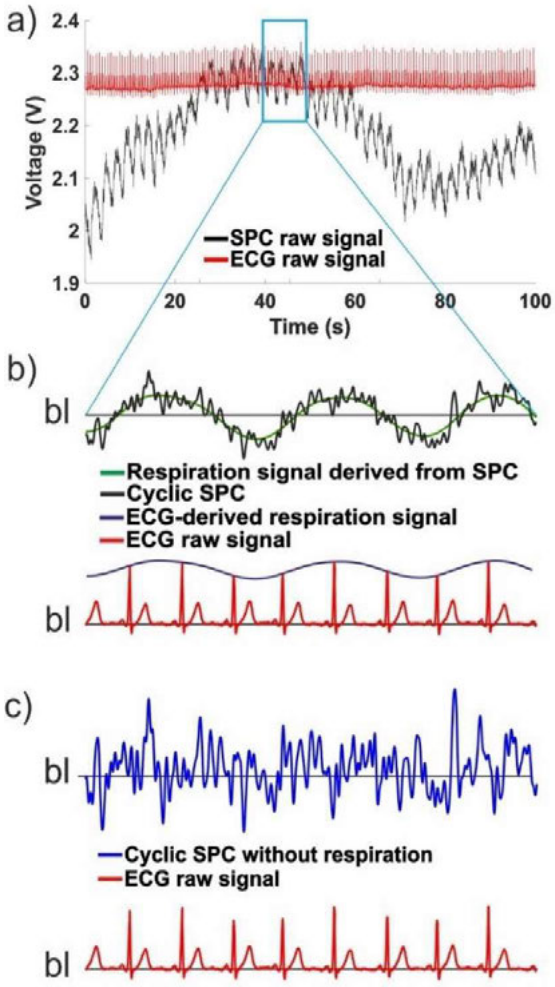

Figure 2. Overview of SPC and ECG traces in the data pre-processing procedure: a) Synchronously recorded ECG and SPC raw data using our multifunctional, battery-powered amplifier unit. b) Raw data ECG signal (red) and ECG-derived respiration modulation (blue). The remaining cyclic component of the SPC signal after the first application of the Hodrick-Prescott filter (black) and the respiration signal derived from SPC (green). It can be seen, that both breathing patterns match each other. c) Cyclic component of the SPC signal subtracted by the respiration modulation. This remaining part of the SPC is subjected to further analysis as core of this study. All filtered and processed data is shown in arbitrary voltage units (bl: baseline)

2.2 Signal processing

Since SPC signals are time series recordings including floating signals with distinct trends and cyclic fluctuations, we found linear models useful to extract the basic trends in the recordings. We used a Hodrick-Prescott decomposition algorithm to pre-process the SPC signals in order to remove coarse trends [9].

Equation 1 shows a mathematical expression of this filtering technique: The decomposition method is relating two terms of a linear model to decompose the trend and the cyclic parts. In eq. 1 and eq. 2, y_t is the logarithm of the signal, c_t is the cyclic component, τ_t is the trend component and ϵ_t denotes the error. λ defines the weight of the trend and the cyclic parts. We assume, without loss of generality, that the heart of a person is functioning repetitively in any

$$\min_{\tau}\left(\sum_{t=1}^{T}(y_t-\tau_t)^2+\lambda\sum_{t=2}^{T-1}[(\tau_{t+1}-\tau_t)-(\tau_t-\tau_{t-1})]^2\right) \quad \text{(eq. 1)}$$

$$y_t = \tau_t + c_t + \epsilon_t \quad \text{(eq. 2)}$$

environment. Therefore, the remaining cyclic part of the SPC signal after subtraction of the respiration modulation is supposed to correlate to the heart as the largest muscle in the body. In this respect, the next step in the signal processing was to use suitable mathematical models to extract the most cyclic parts of the signal. Seasonal ARIMA (SARIMA) models are usually denoted as ARIMA(p,d,q)(P,D,Q)$_m$, where m refers to the number of samples in each season, and the uppercase P,D,Q refer to the seasonal and lowercase p,d,q refer to non-seasonal autoregressive, differencing, and moving average terms for the ARIMA model, respectively.

STL is also widely used as a versatile and robust method for decomposing time series. In this method, Loess is used to estimate nonlinear relationships [10]. In this study we used an Error, Trend, Seasonal (ETS) model with the (A,N,N) configuration. Different criteria such as Akaike's Information Criterion (AIC), Akaike's Information Criterion correction (AICc) and Bayesian Information Criterion (BIC) were used to select the best model. We chose the AICc to evaluate in both of the ARIMA and STL models [11].

3 Results

Since the ultralow-noise HEMT device was operated in a floating gate configuration, the SPC raw data contained coarse trends. These trends were cancelled from the data by signal pre-processing. A first important result of our SPC analysis is that the breathing pattern of a person can be recorded by our technique electronically with only a single skin contact at the wrist. This was already discussed in figure 2 in the signal pre-processing section. We did experiments holding breath or breathing faster, which all correlated to the ECG-derived breathing rhythms as well.

After filtering the strongest cyclic part from the SPC recordings, we assumed that the remaining dominant cyclic signal is most likely time-correlated with the heart rhythm. A Hodrick-Prescott filter with $\lambda = 1600$ was applied to remove

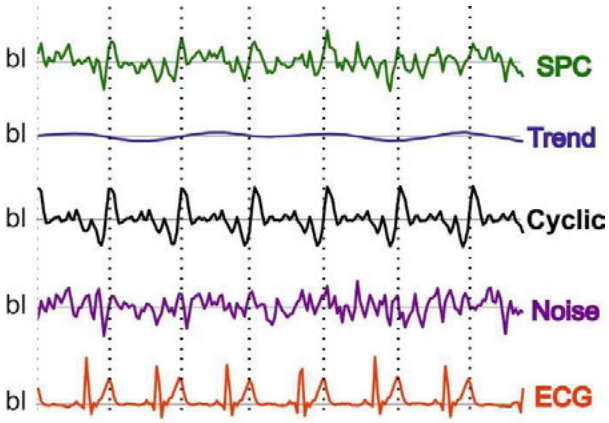

Figure 3. Signal decomposition based on the STL method. After breathing extraction, the remaining trend was very small. The cyclic part of SPC could separate from remaining noise. The cyclic pattern of SPC can be clearly time-correlated with ECG. The y-axis denotes arbitrary voltage units due to signal processing. (bl: baseline)

the coarse trend from the signals. The remaining part contains the breathing signal, the heart signal and remaining noise. Since the frequency of the breathing signal was low (1-3 Hz) in comparison to the heart signal, another additional Hodrick-Prescott filter with the much higher $\lambda \approx 10^{10}$ was applied for extraction of the breathing signal as it was already discussed in figure 2. In figure 3 it can be seen that applying the Hodrick-Prescott filtering was not 100% efficient, since a small trend was still visible as remaining baseline fluctuation correlating with breathing.

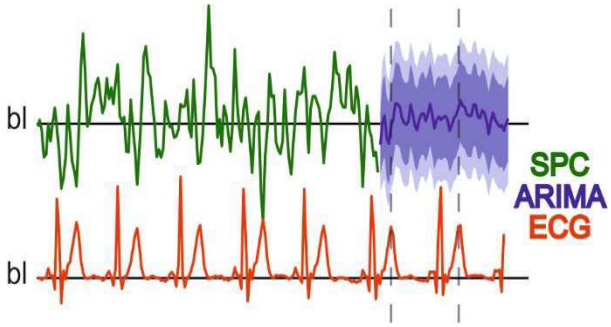

Figure 4. Overlay of the simultaneously measured ECG and SPC traces and a forecasted SPC based on the ARIMA algorithm. (bl: baseline)

Further, applying the STL method separated cyclic components and remaining noise. This noise showed normal distribution and no pattern in the ACFs. Therefore, it should mainly represent transistor and electronic noise. After decomposition, the remaining cyclic SPC trace from STL decomposition showed a clear correlation to the waveform of ECG, which is displayed in the Cyclic and the ECG traces in figure 3. Vertical dashed lines were added as guide for the eyes.

After obtaining the general waveform, we overlaid samples of 12 periods of both ECG and pre-processed SPC. Optimizing the autocorrelation factors (ACF), gave ARIMA(0,0,1)(0,0,5)$_{29}$ (a non-zero mean). The result of the remainder showed no pattern in ACFs. Therefore, we can regard the remaining part as the noise in the measurement. In figure 4, we can see the forecasted signal for the same time needed for one ECG cycle. The optimized ARIMA model is showing actually a moving average filter for both seasonal and non-seasonal terms.

Therefore, we can regard this remaining part as the noise in the measurement. The Box Cox transformation coefficient was 0.9738, which means this is nearly an additive decomposition. Other coefficients were calculated as AIC=-2354.24, AICc=-2353.82, BIC=-2323.42. In this case, we selected the best model by selecting the minimum AICc, which shows the minimum loss of data, therefore the highest quality of the model. The STL model used a Box Cox transformation coefficient, and seasonal window of 12 cycles for 29 samples per each cycle.

4 Conclusion

We introduce a novel method for the electronic recording of the heart activity by detecting tiny charge fluctuations at a single point of the skin of a person's wrist. With ultralow-noise devices and an auto-stabilizing transimpedance amplifier circuit, we were able to record periodic signals. Skin-charge modulations might stem from charged objects moving and from action of the heart muscle like in ECG. Our data analysis showed that the strongest cyclic components in the SPC traces could be clearly correlated to respiration. After removing the breathing patterns, the remaining SPC signals were strongly time-correlated to the waveforms of simultaneous ECG recordings.

Heart and lungs are the dominant charge modulating objects in the body. In our experiments, the strongest SPC signal pattern was identified as breathing, because the chest is acting as a large charged and periodically moving object. Furthermore, the strongest part of the remaining SPC traces correlated to the ECG T-wave, which reflects the repolarization of the ventricles (figure 4). At this state of the heart cycle, ventricles, the strongest muscle components of the heart, stretch and relax.

In the future, we aim to interpret the SPC signals with respect to an electrical and mechanical heart activity to understand the signal shapes and to identify potentially healthy from diseased conditions in patients.

The novel SPC technique as introduced here might complement the classical ECG techniques of cardiac monitoring in future healthcare.

Author Statement

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Conflict of interest: The authors declare the existence of a financial competing interest.

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