Motion-artifact reduction in capacitive heart-rate measurements by adaptive filtering

Citation for published version (APA):

Xu, L., Rabotti, C., Zhang, Y., Ouzounov, S., Harpe, P. J. A., & Mischi, M. (2019). Motion-artifact reduction in capacitive heart-rate measurements by adaptive filtering. *IEEE Transactions on Instrumentation and Measurement*, 68(10), 4085-4093. [8573141]. <https://doi.org/10.1109/TIM.2018.2884041>

DOI:

[10.1109/TIM.2018.2884041](https://doi.org/10.1109/TIM.2018.2884041)

Document status and date:

Published: 01/10/2019

Document Version:

Accepted manuscript including changes made at the peer-review stage

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

[Link to publication](#)

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license above, please follow below link for the End User Agreement:

www.tue.nl/taverne

Take down policy

If you believe that this document breaches copyright please contact us at:

openaccess@tue.nl

providing details and we will investigate your claim.

Motion-artifact reduction in capacitive heart-rate measurements by adaptive filtering

L. Xu, *Member IEEE*, C. Rabotti, *Member IEEE*, Y.J. Zhang, S. Ouzounov, P.J.A. Harpe, *Senior Member IEEE* and M. Mischi, *Senior Member IEEE*

Abstract—Electrocardiography (ECG) measurements are essential components in clinical diagnosis and monitoring. Conventional ECG measurements produce discomfort to the patients due to the use of gel and direct skin contact. Capacitive electrodes can measure ECG signals through an isolation layer; they are especially suitable for long-term ambulatory monitoring. However, capacitive ECG measurements are severely affected by motion artifacts (MAs) due to variable coupling distance. Adaptive filtering has been widely used for MA reduction in ECG measurements. Unfortunately, a reference signal recorded by additional sensors is required for the existing adaptive-filtering methods, limiting their applicability in ambulatory settings. In the present study on capacitive ECG recordings, a novel adaptive-filtering method is proposed for MA removal, where the reference signal is extracted from the power-line interference (PLI). PLI is particularly evident in a capacitive ECG due to unbalanced coupling capacitance. Along with MAs, electrode movement causes variations in the PLI amplitude. By demodulating the PLI, a reference signal reflecting variations in the coupling capacitance can be extracted for adaptive MA removal. The proposed method was evaluated both by simulations and real data, and compared with acceleration-based adaptive-filtering method. Comparable or higher ECG signal-to-noise ratio was achieved by the proposed method with a computational cost of $79 \mu\text{s}/\text{iteration}$, indicating effective MA removal. The proposed method may, therefore, lead to improved analysis of capacitive ECG signals in ambulatory settings.

Index Terms—Capacitive sensor, ECG measurement, Adaptive filter, Motion artifacts, Power-line interference.

I. INTRODUCTION

Electrocardiography (ECG) is an important physiological signal reflecting the cardiac condition of a person. The importance of the ECG led to an increased interest in ECG measurements not only in clinical settings but also in many other applications, e.g., sleep and driving monitoring [1]–[3]. For some applications, especially for long-time ambulatory monitoring, conventional ECG measurements using wet or dry electrodes are unsuitable or uncomfortable due to the use of gel or the direct contact with the skin [4].

Considering the limitations of wet and dry electrodes, capacitive sensors have been introduced a couple of decades ago and further developed in recent years [5], [6]. Capacitive sensors enable ECG measurements through insulating layers, e.g., clothes. Studies suggested the quality of the ECG signal measured by capacitive electrodes to be comparable to that measured by contact wet electrodes [6]. In addition, studies have demonstrated the possibility to integrate capacitive sensors in daily objects, such as a bed, a chair, a car seat, and even a neonatal incubator [2], [3], [7], [8].

Despite their promise, several studies have indicated a critical sensitivity of capacitive sensors to motion artifacts (MAs), which has been identified as the main challenge hampering the development of a robust capacitive ECG measurement system [4], [6], [9], [10]. MAs may distort or mask the desired ECG signals and even saturate the measurement circuit, causing information loss. Therefore, MAs need to be addressed prior to adopting a capacitive ECG measurement system for clinical diagnosis or monitoring.

The origin of MAs in a capacitive ECG system has been associated to longitudinal and lateral movements of the electrodes [4]. The longitudinal movement causes variations in the coupling distance, changing in the coupling capacitance. The lateral movement produces friction and thus triboelectricity at the body-electrode interface [9], [10].

Several methods for MA reduction in capacitive ECG measurements have been suggested in the literature. Ottenbacher and Heuer proposed a theoretical model to investigate the artifacts caused by variation in the coupling distance and reconstructed the ECG signal by solving the inverse system function [9]. However, their reconstruction needs knowledge of all the model parameters, which are often not available. To overcome this problem, Serteyn *et al.* used an injection signal to estimate the model parameters and the MAs caused by variation in the coupling distance [11]. However, this method showed effective MA reduction only on simulation and controlled lab data but not on real data [11].

Adaptive filtering has been widely used for MA reduction in conventional biopotential measurements with wet electrodes [12]–[15]. An adaptive filter estimates the transfer function between a reference signal and the MAs; any signal correlated to the reference signal is then removed from the raw signal. A recent study also applied adaptive filter to capacitive ECG signals for MA reduction by using a 3-D acceleration signal as reference [16]. Other studies suggested the use of an auxiliary capacitive sensor to track the change in the coupling impedance as a reference signal for the adaptive filter [17]. The main limitation of these methods is the requirement of additional sensors in order to measure a reference signal that correlates with motion. This solution may increase the complexity and power consumption of the recording system, and is therefore unsuitable for ambulatory monitoring, which is the main goal of capacitive ECG measurements.

In addition to MAs, power-line interference (PLI), with a frequency equal to 50 Hz in Europe and 60 Hz in the United States, is a major noise source in any ECG measurement system and especially evident in capacitive ECG measurements.

In general, PLI is mainly caused by a displacement current coupling either into the measurement system or into the subject body, and present in the final recordings due to unbalanced electrode impedance [18], [19]. Active guarding is usually implemented in a capacitive sensor, preventing the displacement current from coupling into the measurement system [9]. In addition, dedicated hardware design such as a driven-right-leg circuit and neutralization can further reduce the PLI [20]–[22]. However, after implementing these reduction techniques, considerable PLI may remain in the final recordings due to the large and unbalanced coupling impedance of the capacitive electrodes.

Previous studies on wet electrodes showed high correlation between MAs and PLI variation [19]. An adaptive filter for MA reduction in wet ECG measurements was then evaluated using a reference signal extracted from the PLI, and significant MA reduction was observed [19]. However, the mechanisms generating MAs in capacitive electrodes are quite different from those in wet electrodes. In addition, the transfer function between MAs and body movement in capacitive electrodes is nonlinear due to the inverse relation between coupling capacitance and coupling distance. Finally, triboelectricity may introduce additional high-amplitude MAs in capacitive ECG measurements. As a result, MA reduction in capacitive ECG measurements is much more challenging than in wet electrodes. In the present study we aim at investigating the feasibility and performance of the adaptive-filtering method described in [19] for MA removal in capacitive ECG measurements.

A feasibility study of the proposed method has been reported in [23]; more extensive evaluation was carried out in the present study. To this end, dedicated simulations with different PLI amplitudes were implemented to assess the influence of the PLI amplitude on the performance of the proposed method. In addition, 5 *in-vivo* measurements were performed, in which a 3-D accelerometer was employed to measure electrode movement and two wet electrodes were used to record a clean ECG signal, providing a reference to evaluate the accuracy of the proposed method in real measurements. The proposed method was then compared with the traditional adaptive-filtering method using the 3-D acceleration signal as reference. The signal-to-noise ratio (SNR) defined in [24] was used to assess the performance of both methods. Moreover, in order to evaluate the accuracy of the proposed adaptive-filtering method, R-R intervals of the adaptively filtered signals were detected and compared with those detected from the clean ECG signal using Bland-Altman analysis [25].

II. METHOD

A. Capacitive measurement system

1) *System model*: In a typical capacitive sensor, a plate electrode is coupled to the body and connected to a buffer with very high input-impedance, as shown in Fig. 1 (a). In order to reduce the influence of PLI, active guarding is usually implemented to prevent environmental electric field coupling into the measurement system. A voltage difference, v_{diff} , is present between the body virtual ground and the measurement-system reference.

Fig. 1. Capacitive ECG measurement system: a) physical model; b) equivalent model.

The capacitive sensor shown in Fig. 1 (a) can be represented by an equivalent model as shown in Fig. 1 (b). The electrode together with the body surface can be modeled by a capacitor $C_c(t)$, whose capacitance is proportional to the area of the electrode surface and inversely proportional to the distance between the electrode and the body surface, as given by

$$C_c(t) = \frac{\epsilon_r A}{x(t)}, \quad (1)$$

where ϵ_r is the dielectric constant, A the area of the electrode surface, and $x(t)$ the distance between the electrode and the body. The gap between the electrode and the body surface can be pure air or some cloth-like insulators, e.g., cotton.

The input impedance of the buffer is modeled as a resistor R_i in parallel to a capacitor C_i , both assumed to be time-invariant. The biopotential to be measured, e.g., the ECG, is represented by $v_{ecg}(t)$. Three components are considered in the voltage difference v_{diff} : the DC voltage that comes from the electrodermal voltage (skin potential) v_{dc} , the accumulation of static charges due to triboelectric effects $v_{tri}(t)$, and the PLI $v_{pli}(t)$. In general, a time-varying electric field may cause displacement current coupling either into subject body or into the measurement system [18], [19]. However, as shown in Fig. 1 (a), an active guarding is usually implemented in a capacitive sensor to prevent the displacement current from coupling into the measurement system. Therefore, $v_{pli}(t)$ is mainly caused by displacement current coupling into the subject body rather than into the cables.

2) *System behavior*: Since $C_c(t)$ and $v_s(t)$ are time-varying due to relative movement at the body-electrode interface, the behavior of the capacitive system is analyzed in dynamic condition. The equivalent circuit of the capacitive sensor

shown in Fig. 1 (b) can, therefore, be mathematically described in the time domain by a differential equation describing the balance of electrical currents as

$$\frac{d[(C_i + C_c(t)) \cdot v_o(t)]}{dt} + \frac{v_o(t)}{R_i} = \frac{d[C_c(t) \cdot (v_{ecg}(t) + v_{pli}(t) + v_{dc} + v_{tri}(t))]}{dt}, \quad (2)$$

where $v_o(t)$, $C_c(t)$, $v_{ecg}(t)$, $v_{pli}(t)$, and $v_{tri}(t)$ are time varying. Being a linear system, the output signal $v_o(t)$ should contain the superimposition of four components, which are the output due to $v_{ecg}(t)$, $v_{pli}(t)$, v_{dc} , and $v_{tri}(t)$. By using standard techniques for differential equations with time-varying coefficients [11], [26], we can solve (2) and obtain

$$v_o(t) = v_{o,ecg}(t) + v_{o,dc}(t) + v_{o,tri}(t) + v_{o,pli}(t), \quad (3)$$

where

$$v_{o,ecg}(t) = A(t) \int_0^t \frac{d[C_c(u) \cdot v_{ecg}(u)]}{du} e^{-\int_u^t f(s)ds} du, \quad (4)$$

$$v_{o,pli}(t) = A(t) \int_0^t \frac{d[C_c(u) \cdot v_{pli}(u)]}{du} e^{-\int_u^t f(s)ds} du, \quad (5)$$

$$v_{o,dc}(t) = v_{dc} \cdot A(t) \int_0^t \frac{dC_c(u)}{du} e^{-\int_u^t f(s)ds} du, \quad (6)$$

$$v_{o,tri}(t) = A(t) \int_0^t \frac{d[C_c(u) \cdot v_{tri}(u)]}{du} e^{-\int_u^t f(s)ds} du, \quad (7)$$

with

$$A(t) = \frac{1}{C_i + C_c(t)}, \quad f(t) = \frac{1}{R_i[C_i + C_c(t)]}. \quad (8)$$

Equations (3)-(8) indicate that each component in $v_o(t)$ is a function of the coupling capacitance $C_c(t)$ and the corresponding source, i.e., $v_{ecg}(t)$, $v_{pli}(t)$, v_{dc} , and $v_{tri}(t)$. It is clear that variations in $v_{o,pli}(t)$ reflect the modulation effects of $C_c(t)$ on $v_{pli}(t)$; therefore, $v_{o,pli}(t)$ can be used to extract a reference signal for an adaptive filter in order to estimate the additive MAs $v_{o,dc}(t)$ and $v_{o,tri}(t)$.

B. Adaptive filtering for MA reduction

An adaptive filter is able to remove any additive noise correlated to a given reference signal from the raw (noise-contaminated) signal. The reference signal is, therefore, of key importance for an adaptive filter. In the present study, the PLI is exploited to extract the reference signal for adaptive MA

removal in an ECG signal recorded by capacitive electrodes. Figure 2 shows the scheme of the proposed adaptive filter, in which all the signals are expressed in the discrete domain as sampled ECG data are typically used.

In the upper branch in Fig. 2, a low-pass filter (< 40 Hz) is applied to the raw ECG signal in order to remove the high-frequency noise and the PLI. For ambulatory heart-rate monitoring, an ECG bandwidth up to 40 Hz is sufficient for the detection of the R peaks in the ECG [11]. The filtered signal, $x[n]$, contains a distorted version of the desired ECG signal and additive MAs, as given by

$$x[n] = v_{o,ecg}[n] + v_{o,dc}[n] + v_{o,tri}[n]. \quad (9)$$

In the lower branch in Fig. 2, a band-pass filter with a central frequency equal to the frequency of the PLI (f_p) is applied to the raw ECG signal in order to extract $v_{o,pli}[n]$. Studies have suggested that the movement-induced MAs are mainly below 10 Hz [27], [28]; therefore, a pass band of $f_p \pm 10$ Hz is adopted. The band-pass filtered signal is then demodulated (DM) to obtain a reference signal $r[n]$, reflecting variation in the coupling capacitance caused by sensor movement.

An adaptive finite-impulse-response filter $\underline{W}[n]$ is employed to estimate the transfer function between the reference signal and MAs. The desired signal $\hat{v}_{o,ecg}[n]$ is then obtained by subtracting the estimated MAs, $\hat{v}_{o,dc}[n] + \hat{v}_{o,tri}[n]$, from $x[n]$. A normalized least mean square (NLMS) algorithm is employed to estimate and remove the movement-induced MAs in $x[n]$ [14]. The adaptive filter is designed such that the squared error $|\hat{v}_{o,ecg}[n]|^2$ is minimized [29]. The NLMS algorithm is then given as

$$\begin{aligned} \underline{W}_{NLMS,opt} &= \arg \min_{\underline{W}} |\hat{v}_{o,ecg}[n]|^2 \\ &= \arg \min_{\underline{W}} |x[n] - r[n] \cdot \underline{W}[n]|^2. \end{aligned} \quad (10)$$

The initial value of $\underline{W}$ is an empty matrix $\underline{0}$. The update of the NLMS algorithm is described as

$$\underline{W}[n+1] = \underline{W}[n] + \alpha \cdot \underline{r}^t[n] \cdot \hat{v}_{o,ecg}[n] / \sigma^2, \quad (11)$$

$$\hat{v}_{o,ecg}[n] = x[n] - r[n] \cdot \underline{W}[n], \quad (12)$$

$$\sigma^2 = \underline{r}[n] \cdot \underline{r}^t[n] / M + \varepsilon, \quad (13)$$

where α is the adaptive factor, M the length of the filter, σ the time varying step size, and ε a small constant to avoid σ to be zero.

C. Validation

1) *In-silico experiment:* To evaluate the performance of the proposed adaptive-filtering method, a numerical dataset was simulated in Simulink (Matlab 2016a, The Mathworks, Natick, MA, USA) based on equation (2). A clean ECG signal recorded by wet electrodes (Fig. 3) was employed to represent the biosignal $v_{ecg}[n]$. In order to assess the influence of the PLI amplitude on the performance of the proposed adaptive filter, the PLI $v_{pli}[n]$ was simulated by a 50-Hz sinusoidal signal with different amplitudes: 50, 10, 1, and 0.1 mV, which are chosen based on the PLI amplitude observed in our preliminary measurements, i.e., around 20 mV. The DC

Fig. 2. Scheme of the proposed adaptive filter.

Fig. 3. The clean ECG representing the biosignal $v_{ecg}[n]$.

Fig. 4. Real ECG measurement.

voltage v_{dc} was set to 10 mV, in line with previous studies [9]. A transversal chirp motion ranging from 0.2 to 10 Hz, which covers the full frequency range of body movement [27], was adopted to mimic the electrode movement. An air gap with distance of 1 mm and a variation of ± 0.3 mm was assumed between the capacitive electrode and the body surface. In line with our real application, where the variation in the coupling distance was limited, the variation adopted in our simulation was slightly lower than that adopted by previous authors [9]. The static charges due to triboelectric effect, $v_{tri}[n]$, were assumed to be zero as the simulated motion was transversal. The surface of the capacitive electrode was set to 1 cm², the same as that used in real measurements (II-C2). The input impedance was 1000 G Ω and 2 pF for R_i and C_i , respectively [9].

2) *In-vivo experiment*: Real ECG signals were also recorded on the chest of five male subjects in order to evaluate the feasibility of the proposed method. A capacitive ECG signal was recorded by two square capacitive electrodes (Plessey Semiconductors Ltd, Plymouth, UK), whose scheme was similar to the typical sensor shown in Fig. 1 (a). The gain of the capacitive sensor was 10 while the surface was 1 cm². The subject was sitting in a chair and wearing a cotton shirt approximately 0.5-mm thick, as shown in Fig. 4. A 3-D

accelerometer was placed next to one electrode. The sensors were maintained against the chest by an elastic belt. The patient ground was connected to the index finger of the subject through a conductive foam. In addition, two wet electrodes were placed on both forearms of the subject to obtain a clean ECG signal, providing a reference to evaluate the accuracy of the proposed adaptive-filtering method. 60-s ECG signals were recorded simultaneously with the wet and capacitive electrodes by a Porti amplifier (TMS International, Enschede, The Netherlands) at a sampling frequency of 2048 Hz. The experiment was performed in a lab with stable PLI.

In order to generate different levels of MAs, the subject was instructed to perform two types of test. The first test was performed while sitting on a chair with the subject's trunk straight (Fig. 4), in which sensor movement was mainly induced by breathing. The second test was performed with random body movement during the 60-s recording. The subject was instructed to sit on the chair and move his trunk forward and backward by approximately ± 15 degrees. The subject's arms were relaxed on the arms of the chair to avoid any movement and thus obtain a clean ECG signal (Fig. 4).

3) *Motion-artifact removal*: The proposed adaptive NLMS filter (Fig. 2) was evaluated on both simulated and real data. The data in the time interval from 20 to 50 s was used for the analysis. Two 4th order Butterworth filters were implemented for the low-pass and band-pass filters shown in Fig. 2. The pass bands were 0-40 Hz and 40-60 Hz, respectively. In order to obtain the reference signal for the adaptive filter, local maxima of the band-pass (40-60 Hz) filtered signal, $v_{o,pli}[n]$, were first detected and then re-sampled by spline interpolation to obtain the same sampling frequency as the original signal.

For the simulation, the results $\hat{v}_{o,ecg}[n]$ were compared to the theoretical signal $v_{o,ecg}[n]$, which was obtained by setting v_{dc} and $v_{pli}[n]$ to zero during the simulation. In addition, the results of the proposed method on real data were compared to the classical adaptive-filtering method shown in Fig. 5, in which the acceleration signal $acc[n]$ was employed as a reference.

For the aforementioned comparisons, SNR was employed as a quantitative metric. In general, SNR is determined by

$$SNR = 10 \cdot \log \frac{P_s}{P_n}, \quad (14)$$

where P_s is the signal power and P_n the noise power. However, for an ECG signal, the signal power will be proportional

Fig. 5. Scheme of classical adaptive filter using acceleration as a reference.

to the heart rate and thus such a measure has no relation with R-peak detection, which is the main focus in ambulatory monitoring. A modified definition of SNR, as described in [24], is therefore employed in the present study in order to assess the R-peak detectability. To this end, the R peaks of the adaptively filtered data were first detected using the algorithm described in [24]. The SNR was then calculated as

$$SNR = 20 \cdot \log \frac{v_{pp}}{v_n}, \quad (15)$$

where v_{pp} is the maximum value of each R peak, and v_n is the maximum value in two surrounding intervals. For an R peak located at time $t(i)$, the surrounding two intervals are defined as $[t(i-1) + 300 \text{ ms}, t(i) - 75 \text{ ms}]$ and $[t(i) + 75 \text{ ms}, t(i) + 250 \text{ ms}]$, where $t(i-1)$ is the time of the previous R peak [24]. This is the maximum-length segment without QRS complex, considering a maximum heart rate of 200 bpm [24]; by this choice, heart rate ranging from 30 to 200 beats per minute can be detected.

Furthermore, for the real data, the accuracy of the proposed adaptive-filtering method was assessed by comparing all the R-R intervals detected from the adaptively filtered capacitive ECG signals, denoted as RRi_{cap} , with those detected from the reference ECG signals recorded by the wet electrodes placed on the forearms of the subjects, denoted as RRi_{wet} . The Bland-Altman analysis was employed to evaluate the agreement between those two R-R intervals [25].

All the analysis was implemented in Matlab® 2016a (MathWorks, Natick, MA). The adopted computer was an HP Compaq Elite CMT PC, with an Inter(R) Core(TM) i5-2500 CPU @ 3.30 GHz processor. The execution time was also tested to provide an indication of the computational complexity of the proposed algorithm.

III. RESULTS

A. Results on in-silico data

An example of the results obtained on the simulated data (PLI = 50 mV) were shown in Fig. 6. Figure 6 (a) shows the signals in the lower branch of the adaptive scheme, including the raw signal $v_o[n]$, the estimated output due to the PLI, $v_{o,pli}[n]$, and the demodulated signal $r[n]$ after re-sampling. It is clear that the reference signal $r[n]$ varies over time similar to the simulated chirp motion ranging from 0.2 to 10 Hz. Figure 6 (b) shows the results after applying the proposed adaptive-filtering method to the data showed in Fig. 6 (a). Before adaptive filtering, the R peaks in the low-pass filtered signal, $x[n]$, are not visible, while they become clear after adaptive filtering ($\hat{v}_{o,ecg}[n]$). The SNR of $\hat{v}_{o,ecg}[n]$, as defined by equation (15), is 2.2 dB, while it is 1.8 dB for the theoretical signal $v_{o,ecg}[n]$, obtained by setting $v_{dc}[n]$ and $v_{pli}[n]$ to zero during the simulation.

All the simulation results with different PLI amplitudes are shown in Fig. 7. With decreased PLI amplitudes, the R peaks in $\hat{v}_{o,ecg}[n]$ are less visible and for PLI amplitude equals to 0.1 mV, the R peaks are masked by the artifacts generated by the chirp motion. The SNRs of $\hat{v}_{o,ecg}[n]$ are 2.2, 1.6, 1.5, and -4.1 dB for PLI equals to 50, 10, 1, and 0.1 mV, respectively.

Fig. 6. Results on the simulation data: a) signals in the lower branch of the adaptive scheme in Fig. 2; b) signals in the upper branch of the adaptive scheme in Fig. 2.

B. Results on in-vivo data

Figure 8 shows an example of the results obtained on real data recorded during normal breathing without body movement. The breath-induced MAs cause a baseline wander presenting in the low-pass filtered signal $x[n]$, resulting in difficult R-peak detection. After the proposed adaptive-filtering algorithm using the demodulation of the PLI as a reference, all the R peaks are clearly visible in $\hat{v}_{o,ecg}[n]$. Similar results are obtained by the acceleration-based adaptive-filtering method, as shown in x_{acc} in Fig. 8 (c). For all the five subjects, the average SNRs, defined by equation (15), are 8.9 ± 3.5 dB and 8.8 ± 3.7 dB for $\hat{v}_{o,ecg}[n]$ and x_{acc} , respectively.

An example of the results obtained on real data recorded with the subject's trunk moving forward and backward are shown in Fig. 9. Due to the body movement, the baseline wander is much larger compared to the one caused by breathing. In addition, high-amplitude MAs due to triboelectricity can be observed in the recorded signal. As a result, the R

Fig. 7. Simulation results with different PLI amplitudes.

peaks are not visible in $x(n)$. After the proposed algorithm, MAs are significantly reduced and all the R peaks are clearly visible and can be detected by the algorithm described in [24], as shown in $\hat{v}_{o,ecg}[n]$. The results obtained by the acceleration-based adaptive-filtering method are comparable with our results. The average SNRs are 6.3 ± 2.9 dB and 5.0 ± 3.9 dB for the proposed method and the acceleration-based method, respectively.

For all the 10 datasets (30 s for each), 337 RRi_{cap} and RRi_{wet} are detected by the algorithm described in [24]. Figure 10 shows the Bland-Altman plot indicating the agreement between RRi_{cap} and RRi_{wet} . The average of the difference between RRi_{cap} and RRi_{wet} is 0.99 ms. The upper 95% limit of agreement (LOA) is 136 ms while the lower 95% LOA is 138 ms. For a 30-s signal with a sampling frequency of 2048 Hz, the average execution time of the whole algorithm shown in Fig. 2 over the 10 data-sets is 4.86 ± 0.03 seconds.

IV. DISCUSSION

In the present study on capacitive ECG measurements, we hypothesize that the PLI in the recorded data may reflect movement-induced variation in the coupling capacitance and may, therefore, be used to extract a reference signal for adaptive MA removal. Our hypothesis is first evaluated by a dedicated simulation, in which a chirp motion ranging from 0.2 Hz to 10 Hz is employed in order to cover the full frequency range of body movement [27], [28]. Effective MA removal is obtained on the simulation data by the proposed adaptive-filtering method (Fig. 6).

Our hypothesis has also been tested with real data recorded during breathing with and without body movement. For the data recorded without movement, the proposed method achieves excellent artifact removal. For the data recorded with body movement, high-amplitude MAs may be present due to the effect of triboelectricity, which is not considered in our simulation. As shown in equation (7), $v_{o,tri}[n]$ results from the combined effects of triboelectricity and variation in the coupling capacitance. The reference signal extracted from

Fig. 8. Real measurement data during normal breathing without additional body movement: a) signals in the lower branch of the adaptive scheme in Fig. 2; b) results of the proposed method together with the results using the acceleration signal as reference.

the PLI can track variation in the coupling capacitance but not in the triboelectricity. As a result, some MAs remain in the adaptively filtered data. However, all the R peaks in the processed data are still clearly visible and can be detected by the algorithm described in [24].

The adaptive filter is designed to remove additive noise, e.g., $v_{o,dc}[n]$. However, as shown in Fig. 6, the ECG signal is also distorted due to multiplicative noise in $v_{o,ecg}[n]$. Our results (Fig. 6) suggest the proposed adaptive filter to also suppress the multiplicative noise component in $v_{o,ecg}$. In principle, an adaptive filter can remove any signal that correlates to the reference signal. As indicated in equation (4), the multiplicative noise in $v_{o,ecg}$ is also due to the variation in the coupling capacitance and, therefore, can be removed by the proposed adaptive filter.

In order to evaluate the performance of the proposed adaptive-filtering method, SNR is employed as a quantitative metric. In general, SNR is defined as the ratio between the signal power and the noise power. However, the main focus of the present study is ambulatory monitoring and thus the R-peak detection. The standard definition of SNR has no relation

Fig. 9. Real measurement data during normal breathing with additional body movement: a) signals in the lower branch of the adaptive scheme in Fig. 2; b) results of the proposed method together with the results using the acceleration signal as reference.

with R-peak detection since the signal power of an ECG signal is proportional to the heart rate. As a result, a modified SNR definition, as described in [24], is employed to assess the detectability of the R-peaks in the adaptively filtered signal.

As compared to the acceleration-based adaptive filtering method, our method achieves comparable or even better results as indicated by the SNRs. This can possibly be explained by the following mechanism. As shown in equation (6), MAs are mainly generated by variation in the coupling capacitance, which is nonlinearly correlated to the variation in the coupling distance $x(t)$. Consequently, the transfer function between the MAs and motion is nonlinear. Using acceleration as a reference, the adaptive filter can only remove MA that is linearly correlated to the acceleration (motion). However, demodulation of the PLI reflects variation in the coupling capacitance $C_c(t)$ rather than the coupling distance $x(t)$ and thus can remove all MAs correlated to $C_c(t)$. This hypothesis is further confirmed by the different SNR improvements between the two different recording conditions: with and without body movement. For the measurement with body movement, larger nonlinear effects may be expected and, therefore, higher

Fig. 10. Bland-Altman plot indicating the agreement between RRI_{cap} and RRI_{wet} .

improvement in the SNR (6.3 dB *vs* 5.0 dB) is achieved compared to no body movement (8.9 dB *vs* 8.8 dB).

It should be noted that, since movement-induced MAs are mainly below 10 Hz [27], [28], a 10-Hz analog high-pass filter might be helpful in the removal of MA. However, such high-pass filter also cancels some useful information in the desired ECG signal. Furthermore, although the proposed method is evaluated by ECG measurements in the present study, it can also be applied to other biopotential measurements in which the signal of interest may be in the frequency band between 0 and 10 Hz; a relevant example is provided by electrohysterography [30], [31]. In this case, a 10-Hz high-pass filter is not suited. Finally, the implementation of an analog filter increases the complexity and power consumption of the hardware and thus is not suitable in ambulatory monitoring model.

The presence of the PLI is essential for the proposed adaptive filtering method. In general, active guarding is implemented in a capacitive sensor in order to reduce the PLI [9]. Moreover, dedicated hardware design such as driven-right-leg circuit and neutralization can further reduce the effects of PLI [20]–[22]. However, even after implementing these solutions, a considerable amount of PLI remains in the output signal due to the large and unbalanced coupling impedance. This permits the extraction of the reference signal from the PLI for adaptive MA removal. Our dedicated simulations with different PLI amplitudes show that the proposed method works with PLI amplitudes above a lower threshold that in the order of few mV. The PLI amplitudes observed in all our measurements are much larger than this low threshold, which confirms the applicability of the proposed method.

On the other hand, in the present study, we focus mainly on adaptive MA removal. Although it is not the objective of this study, the PLI also needs to be removed after obtaining the reference signal. A low-pass filter was therefore implemented in the present study to remove the PLI from the signal of interest. A cutoff frequency of 40 Hz was adopted given that

an ECG bandwidth up to 40 Hz is sufficient for ambulatory monitoring [11]. For applications that need higher ECG bandwidth, the PLI can be removed by a notch filter or dedicated algorithms such as those described in [32].

It is also important to note that our measurements are performed in a laboratory with stable PLI. The proposed adaptive scheme is indeed based on the assumption of stable PLI. In case of a fast changing electrical environment, the PLI may show variation in its amplitude. As a consequence, besides the variation in the coupling impedance, the reference signal extracted by demodulating the PLI may also contain components reflecting variation in the PLI amplitude, producing an overestimation or underestimation of the MAs. In this case, a more stable signal, such as an injected signal [11], may be needed to achieve accurate MA cancelling.

V. CONCLUSION

In conclusion, the present study proposes a novel adaptive-filtering method for MA reduction in capacitive ECG recordings. The mathematic analysis indicates that variation in the PLI can reflect variation in the coupling capacitance and, therefore, be used to extract a reference signal for adaptive MA removal. Evaluation on both simulation and real data show effective MA removal by the proposed method, as evidenced by high SNR in the filtered signal and the low computational cost. This method requires no additional sensors to measure a reference signal for the adaptive filter, enabling reliable analysis of heart rate in ambulatory settings.

REFERENCES

- [1] M. B. Weil, M. Oehler, M. Schilling, and L. S. Maier, "First clinical evaluation of a novel capacitive ECG system in patients with acute myocardial infarction," *Clinical Res Cardiol*, vol. 101, no. 3, pp. 165–174, 2012.
- [2] T. Wartzek, B. Eilebrecht, J. Lem, H. J. Lindner, S. Leonhardt, and M. Walter, "ECG on the road: Robust and unobtrusive estimation of heart rate," *IEEE Trans Biomed Eng*, vol. 58, no. 11, pp. 3112–3120, 2011.
- [3] Y. G. Lim, K. K. Kim, and K. S. Park, "ECG recording on a bed during sleep without direct skin-contact," *IEEE Trans Biomed Eng*, vol. 54, no. 4, pp. 718–725, 2007.
- [4] Y. M. Chi, T. P. Jung, and G. Cauwenberghs, "Dry-contact and noncontact biopotential electrodes: Methodological review," *IEEE Rev Biomed Eng*, vol. 3, pp. 106–119, 2010.
- [5] A. Lopez and P. C. Richardson, "Capacitive electrocardiographic and bioelectric electrodes," *IEEE Trans Biomed Eng*, vol. BME-16, no. 1, pp. 99–99, 1969.
- [6] Y. M. Chi, P. Ng, E. Kang, J. Kang, J. Fang, and G. Cauwenberghs, "Wireless non-contact cardiac and neural monitoring," in *Wireless Health 2010*, New York, NY, USA, 2010, pp. 15–23.
- [7] Y. G. Lim, K. K. Kim, and S. Park, "ECG measurement on a chair without conductive contact," *IEEE Trans Biomed Eng*, vol. 53, no. 5, pp. 956–959, 2006.
- [8] L. Atallah, A. Serteyn, M. Meftah, M. Schellekens, R. Vullings, J. W. M. Bergmans, A. Osagiator, and S. B. Oetomo, "Unobtrusive ECG monitoring in the NICU using a capacitive sensing array," *Phys Meas*, vol. 35, no. 5, pp. 895–913, 2014.
- [9] J. Ottenbacher and S. Heuer, *Motion Artefacts in Capacitively Coupled ECG Electrodes*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 1059–1062.
- [10] T. Wartzek, T. Lammersen, B. Eilebrecht, M. Walter, and S. Leonhardt, "Triolectricity in capacitive biopotential measurements," *IEEE Trans Biomed Eng*, vol. 58, no. 5, pp. 1268–1277, 2011.
- [11] A. Serteyn, R. Vullings, M. Meftah, and J. Bergmans, "Motion artifacts in capacitive ECG measurements: reducing the combined effect of DC voltages and capacitance changes using an injection signal," *IEEE Trans Biomed Eng*, vol. 62, no. 1, pp. 264–273, Jan 2015.
- [12] M. Baig, H. Gholamhosseini, and M. Connolly, "A comprehensive survey of wearable and wireless ecg monitoring systems for older adults," *Med Biol Eng Comput*, vol. 51, no. 5, pp. 485–495, 2013.
- [13] S. Pongponsoi and X.-H. Yu, "An adaptive filtering approach for electrocardiogram (ecg) signal noise reduction using neural networks," *Neurocomputing*, vol. 117, pp. 206 – 213, 2013.
- [14] L. Xu, C. Rabotti, and M. Mischi, "Novel vibration-exercise instrument with dedicated adaptive filtering for electromyographic investigation of neuromuscular activation," *IEEE Trans Neural Syst Rehabil Eng*, vol. 21, no. 2, pp. 275–282, 2012.
- [15] H. Kim, S. Kim, N. V. Helleputte, A. Artes, M. Konijnenburg, J. Huiskens, C. V. Hoof, and R. F. Yazicioglu, "A configurable and low-power mixed signal soc for portable ecg monitoring applications," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 8, no. 2, pp. 257–267, 2014.
- [16] B. Eilebrecht, T. Wartzek, J. Willkomm, A. Schommartz, M. Walter, and S. Leonhardt, "Motion artifact removal from capacitive ECG measurements by means of adaptive filtering," in *5th Europ Conf Int Fed Med Biol Eng*, 2012, pp. 902–905.
- [17] G. Peng and M. F. Bocko, "Non-contact ecg employing signal compensation," in *2013 IEEE Biomedical Circuits and Systems Conference (BioCAS)*, 2013, pp. 57–60.
- [18] J. C. Huhta and J. G. Webster, "60-Hz interference in electrocardiography," *IEEE Trans Biomed Eng*, no. 2, pp. 91–101, 1973.
- [19] L. Xu, M. J. Rooijakkers, C. Rabotti, J. Peuscher, and M. Mischi, "Use of power-line interference for adaptive motion artifact removal in biopotential measurements," *Physiol Meas*, vol. 37, no. 1, pp. 25–40, 2015.
- [20] E. Spinelli and M. Haberman, "Insulating electrodes: a review on biopotential front ends for dielectric skinelectrode interfaces," *Physiol Meas*, vol. 31, no. 10, 2010.
- [21] A. M. Van Rijn, A. Peper, and C. Grimbergen, "High-quality recording of bioelectric events," *Med Biol Eng Comput*, vol. 28, no. 5, pp. 389–397, 1990.
- [22] C. Guld, "Cathode follower and negative capacitance as high input impedance circuits," *Proc IRE*, vol. 50, no. 9, pp. 1912–1927, 1962.
- [23] L. Xu, C. Rabotti, Y. Zhang, M. Meftah, P. Harpe, and M. Mischi, "Adaptive motion-artifact reduction in capacitive ECG measurements by using the power-line interference," in *13th Annual IEEE International Symposium on Medical Measurements and Applications, Rome, Italy, July, 2018*.
- [24] M. J. Rooijakkers, C. Rabotti, S. G. Oei, and M. Mischi, "Low-complexity r-peak detection for ambulatory fetal monitoring," *Physiol Meas*, vol. 33, no. 7, pp. 1135–1150, 2012.
- [25] G. D., "Understanding bland altman analysis," *Biochemia Medica*, vol. 25, no. 2, pp. 141–151, 2015.
- [26] T. M. Apostol, "Calculus: One-variable calculus, with an introduction to linear algebra," *Wiley New York*, 1967.
- [27] H. W. Tam and J. G. Webster, "Minimizing electrode motion artifact by skin abrasion," *IEEE Trans Biomed Eng*, no. 2, pp. 134–139, 1977.
- [28] D. P. Burbank and J. G. Webster, "Reducing skin potential motion artifact by skin abrasion," *Med Biol Eng Comput*, vol. 16, pp. 31–38, 1978.
- [29] B. Widrow, J. R. Glover, and J. M. McCool, "Adaptive noise canceling: principles and applications," *Proc IEEE*, vol. 63, no. 12, pp. 1692–1716, 1975.
- [30] M. Mischi, C. Chen, T. Ignatenko, H. de Lau, B. Ding, S. G. Oei, and C. Rabotti, "Dedicated entropy measures for early assessment of pregnancy progression from single-channel electrohysterography," *IEEE Trans Biomed Eng*, vol. 65, no. 4, pp. 875–884, 2018.
- [31] M. J. Rooijakkers, C. Rabotti, S. G. Oei, R. M. Aarts, and M. Mischi, "Low-complexity intrauterine pressure estimation using the teager energy operator on electrohysterographic recordings," *Physiol Meas*, vol. 35, no. 7, pp. 1215–28, 2014.
- [32] S. M. Martens, M. Mischi, S. G. Oei, and J. W. Bergmans, "An improved adaptive power line interference canceller for electrocardiography," *IEEE Trans Biomed Eng*, vol. 53, no. 11, pp. 2220–2231, 2006.