Adaptive filter to remove motion artifacts from GSR sensor embedded on handle cane

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***Abstract*—Wearable devices capable of recording physiological variables such as pulse and electrodermal activity have become popular in the form of smart watches or bracelets. The measurement is affected by the relative movement of the device with respect to the skin, generating artifacts. An alternative to watches or bracelets that can improve adherence for population groups such as elderly people may be the integration of sensors into everyday objects, such as walking sticks. In this case, the challenge of motion artifacts is particularly difficult. This paper presents a strategy based on a Notch filter that adapts its center frequency from the reading of a force sensor placed under the GSR sensor. A noticeable reduction of the interference from motion artifacts is observed.**

***Index Terms*—GSR sensors, wearables, motion artifacts**

I. Introduction

The monitoring of biomedical variables by means of wearable devices or ”wearables” integrated into objects is a field of interest linked to technological progress and security needs and to the aging of the population observed on a global scale, especially in developed countries [1]. Common devices such as wristbands or smartwatches provide physiological variables such as the Galvanic Skin Response (GSR) related to the skin conductance (also Electrodermal Activity or EDA), pulse, blood oxygen saturation, or temperature. A challenge to be addressed in the incorporation of GSR sensors in wearables is that of motion artifacts. Numerous works have been reported aimed at detecting these artifacts. In [2] statistical, model-based, and time-frequency features were extracted from the GSR signals, and different machine learning algorithms were used to classify GSR data segments as clean or corrupted by motion artifacts. To avoid incorrect adjudication due to the aperiodic nature of the GSR signals, the reference GSR signal from a channel in a motionless arm was used. The use of the stationary wavelet transform (SWT) is proposed in [3] to filter out motion artifacts. The process uses SWT to decompose the contaminated GSR signal, selecting adaptive thresholds based on a statistical estimation of the distribution of the wavelet coefficients and then applying the inverse wavelet transform to obtain the noise-free GSR signal. Finally, in [4] a learning algorithm is also used that learns to separate segments affected by artifacts and replaces them with a polynomial regression.

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The above cases are based on devices such as smart watches or bracelets. However, integration in other objects allows overcoming drawbacks and widening the range of applications. From the point of view of the acceptance of watches or bracelets, a correct reading requires a close contact between the object and the skin continuously, which often causes rejection, especially in elderly people, and motivates the research of other materials and technologies [5]. Moreover, individuals with dementia often try to remove unfamiliar objects, such as bracelets and leg bands. To address this issue, devices like GPS-enabled shoes have been developed [6].

In this sense, a cane in different versions, or a walker, equipped with sensors and embedded electronics, can be a well-accepted resource for elderly people to assist in health monitoring and stress detection associated with possible critical gait events. Likewise, in the cases of artifacts in watches and wristbands, typical aperiodic motion artifacts are usually contemplated and manual labeling is used to obtain the artifact-free training set. In the case of an GSR sensor integrated in a cane, a clear quasi-periodic interference correlated with gait is observed.

In [7], adaptive notch filters are used with the frequencies determined from a three-axis accelerometer readout. This paper proposes to explore the use of an adaptive notch filter to remove motion artifacts linked with gait. The frequency of the filter will be determined from a Force Sensing Resistor (FSR) sensor located below the GSR sensor, which detects periodic variations of the force.

II. Materials and Methods

The GSR has two components, the tonic and the phasic. The tonic is the slow-moving baseline level of skin conductance while the phasic reflects rapid fluctuations in skin conductance in response to specific psychological or external stimuli such as emotional arousal or sudden changes in the external environment. The latter is the information of interest to be collected by a wearable on a cane, with a target audience of elderly or disabled people in mind. Both components are superimposed in the frequency spectrum. To separate them it is common to make a high-pass filter to obtain the phasic, or to average in windows of between 10 and 100 seconds to obtain the tonic component and subtract it from the GSR signal to obtain the phasic. Also, the phasic information of interest is in time windows that are typically between one and five seconds [4]. In this work, the GSR signal has been filtered between 0.05Hz and 1.6Hz to obtain the phasic component information, and the resulting signal has had the motion artifact reduction strategy applied to it.

A. Instrumented Cane

The cane is equipped with a FSR sensor (FSR 402, Interlink Electronics, CA, US) and a superimposed custom GSR sensor, which is composed of two copper foils with conductive silver paint. It is placed on the upper face of the handle of the cane, as this position best characterizes the quasi-periodic walking motion artifact and improves the electrode-skin contact. Fig. 1 shows the prototype developed.

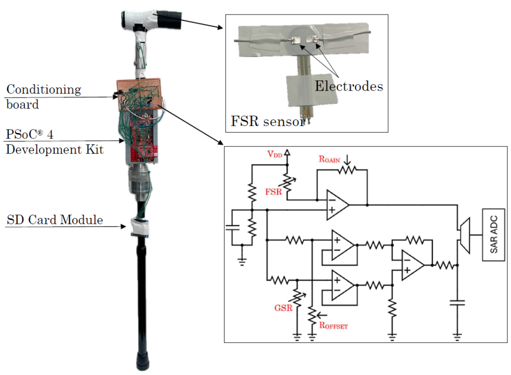

Fig. 1. Instrumented cane.

A transimpedance amplifier circuit with a gain adjustment potentiometer is used to condition the FSR sensor (see Fig. 1). For the GSR signal, a differential amplifier with manual offset adjustment is used to set the maximum skin conductivity limit, along with a low-pass filter with a cutoff frequency of 1.60 Hz. The PSoC Development Kit PSoC® 4 (Infineon Technologies AG, Neubiberg, DE) multiplexes, captures and digitizes the GSR and FSR signals at a rate of 32 Hz. All data are stored on a SD memory card using the SPI interface at 115200 Bd. For each FSR/GSR instantaneous sample pair, a Coordinated Universal Time (UTC) of 1/32 s resolution is associated, allowing post hoc synchronization with the data captured from the reference sensor which has a resolution of 1/16 s. In the post-processing stage the data from both sensors are linearly interpolated with a time vector resolution of 1 ms.

B. Adaptive Filtering for Gait Artifact

The contaminated GSR signal can be modeled as an interference (ϵ) superimposed on the clean GSR signal:

$$GSR_{cont} = GSR_{clean} + \epsilon \tag{1}$$

The FSR sensor was used to obtain information of the artifact ϵ in the GSR signal while a person walks with the instrumented cane. In this situation, ϵ can be modeled as a periodic noise whose frequency is related to the gait and whose amplitude depends mainly on the force on the skin-electrode interface and its contact area, as well as properties related to the skin. Fig. 2 shows how the periodic artifact generated by the gait at 2 km/h has a frequency clearly detectable by the FSR. This artifact is reflected in the GSR signal at the same frequency, along with its two successive harmonics. To estimate the frequency of the first harmonic of the gait artifact in Fig. 2, the FSR sensor signal is used to generate a square wave using a comparator and a reference voltage. A Gaussian filter on a 5-second sliding fixed window is then applied to the computed frequency of this signal to obtain a continuous and smooth curve (see the inset in Fig. 2). The data in Fig. 2 were collected with the instrumented cane while being used by a healthy subject on a treadmill.

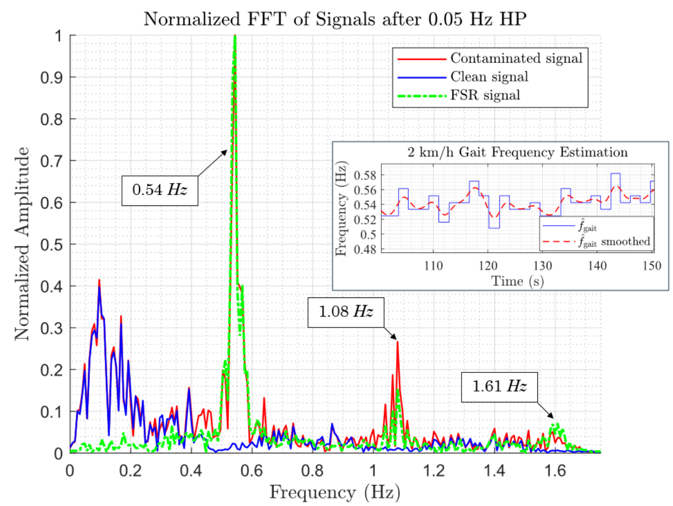

Fig. 2. FFT of the FSR and GSR signal with artifacts filtered with a high-pass of 0.05 Hz. The inset shows the estimated gait frequency $f_{\text{gait}}(t)$ for a walk at 2 km/h.

The real-time tracking of the gait frequency allows the dynamic setting of the center frequency of a triple Notch filter that filters the three harmonics of the artifact caused by the gait in Fig. 2. Fig. 3 shows the flowchart of the corresponding adaptive filter. The proposed filter is composed of three cascaded Notch filters designed with the Chebyshev equiriplet window. This work proposes a fixed rejection bandwidth of 0.15 Hz with a sidelobe attenuation of 25 dB. These values, along with the order of each Notch filter were experimentally adjusted to obtain the best results along with the system sampling frequency limitation of 32 Hz.

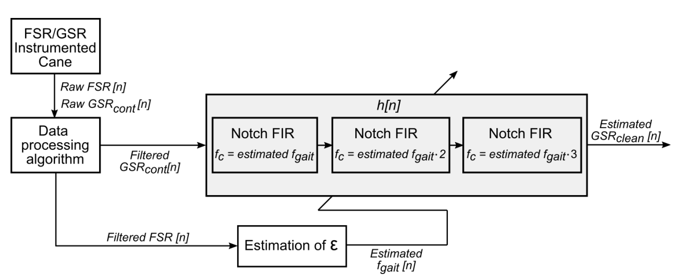

Fig. 3. Flowchart of triple Notch filter centered on $f_{\text{gait}}(t)$.

C. Protocol

Two experiments were performed using the reading of the commercial sensor *Ring* (Bitbrain®, Zaragoza, ES) as the reference signal. In the first experiment, the GSR signal was obtained from a healthy subject standing supported by the instrumented cane for 3 minutes without moving. It is supposed that the GSR signal is free of artifacts under these conditions. This experiment aims to study the relationship between the GSR signal of the palm of the hand captured with the proposed prototype and the GSR signal of the index and middle fingers taken with the reference sensor. In the second experiment, the same subject walked at 2 km/h for 3 minutes on a treadmill with the instrumented cane. In this second experiment, the reference sensor was placed on the hand that rests on the handlebar of the treadmill. It is supposed that the signal from the reference sensor is free of motion artifacts.

III. Results and Discussion

The data were processed using MATLAB. All signals were filtered below 0.05 Hz and above 1.60 Hz (see section II). Fig. 4 shows the filtered phasic signal from the GSR obtained in the second experiment. The ripple of the contaminated signal corresponds mainly to the frequency components of ϵ in (1).

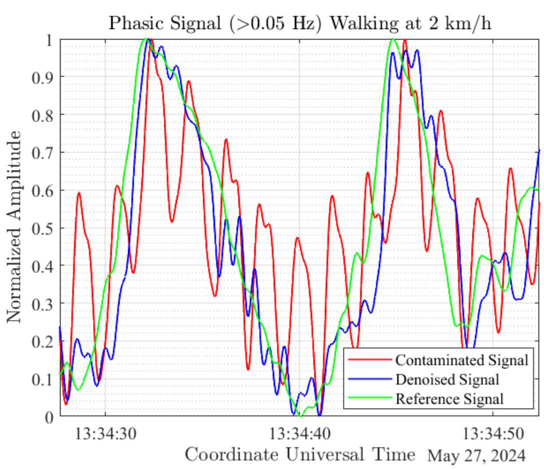

Fig. 4. Artifact noise reduction of phasic signal using the proposed algorithm.

In order to quantify the performance of the proposed strategy and compare the reference signal and the filtered one, the Artifact Power Attenuation (APA), the Average Error, and Pearson correlation are used. The APA is the ratio of the artifact power before and after the filter in dB [3]. In this paper, 20 sets of samples were extracted from the registered data of four 3-minutes sessions of the second experiment. These sets correspond to windows with a length of a gait cycle. For each set, the APA is computed as:

$$APA = 10\log_{10}\left(\frac{\sum_{n\in A_m}\text{Var}[y(n)]}{\sum_{n\in A_m}\text{Var}[\hat{y}(n)]}\right) \tag{2}$$

where A_m is the set the APA is computed for, n denotes the *n-th* sample of the signal in this set, y the GSR signal with artifacts, and $\hat{y}$ the filtered GSR signal. The APA values obtained for the 20 sets using (2) are a median of 7.63 dB, a maximum of 11.61 dB, and a minimum of 3.91 dB.

Regarding the Average Error, it is obtained as

$$\text{AvgError} = \frac{1}{N}\sum_{n=1}^{N}|y_{ref}(n) - \hat{y}(n)| \tag{3}$$

where the filtered ($\hat{y}$) and the reference signals (y_{ref}) are both normalized to fit in the range [0, 1].

Table I shows the Average Error and the correlation (p-value<0.001) for the first experiment where the subject was not moving ("Static" in the table), and for the second experiment with the subject walking on the treadmill without the proposed strategy ("Moving without filtering") and with the proposed strategy ("Moving after filtering" in the table). The data in Table I are the mean values from four consecutive sessions of the experiments.

TABLE I
Gait-Artifact Deonising Results With Proposed Method

	AvgError	Correlation
Static	0.0735	0.8833
Moving without filtering	0.1659	0.3851
Moving after filtering	0.1303	0.6889

The APA and the Average Error in Table I show that the strategy achieves a noticeable improvement. Note that the correlation is not 1 even without motion. This is mainly due to the different body parts the GSR is read in (palm of the left hand in the cane handle sensor and medium and index fingers in the case of the reference sensor). Moreover, more artifacts that are not related to the periodic gait are present in the GSR signal.

IV. Conclusions

This paper proposes a strategy to reduce the motion artifacts due to gait when a GSR sensor is embedded on the handle of a cane. The approach consists in tracking the gait frequency with a force sensor and using it as center frequency of an adaptive triple Notch filter that removes the harmonics of this motion artifact. This strategy attenuates the artifact while minimally altering range of interest in the spectrum of the phasic component. Preliminary results showed a noticeable improvement in the quality of the phasic signal. However, other non periodic artifacts with lower power are still present. In addition, experiments with a larger and more diverse sample of subjects should be performed to assess the robustness of the approach. The use of a cane allows detection of potentially critical events during gait and improves adherence in the elderly population. It also allows intimate contact between the sensor and the skin. However, much work remains to be done to have a mature device.

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