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Efficient wavelet-based artifact removal for electrodermal activity in real-world applications

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ABSTRACT

Online monitoring of electrodermal activity (EDA) may serve as an economical and explicit source of information about actual emotional state and engagement level of users during their interaction with information and communications technologies (ICT) applications in *real-world* situations. In such contexts, however, EDA signal is affected by motion artifacts that introduce noise in the signal and can make it unusable. As the scope of movement minimization during EDA data acquisition is limited, this scenario demands online methods for detection and correction of artifacts with low computational cost. We propose an efficient wavelet-based method for artifacts attenuation while minimizing distortions, using a stationary wavelet transform (SWT) modeling the wavelet coefficients as a Laplace distribution. The proposed method was tested on EDA recordings from publicly available driver dataset collected during real-world driving, and containing a high number of motion artifacts, and the results were compared to those of three state-of-the-art methods for EDA signal filtering. In addition, the proposed method was tested for the online filtering of EDA signals collected while 12 volunteers conducted tasks designed to elicit various stress states. The results evidenced that the prediction of arousal states can be significantly improved after motion artifacts removal, and that the proposed method outperforms existing approaches and it has a lower computational cost. Taken together, these results evidence the effectiveness of the proposed method for online EDA filtering in real world scenarios.

1. Introduction

Electrodermal activity (EDA) refers to the changes in conductivity in the skin, which is affected by the activity of the sympathetic branch of the autonomous nervous system and is usually considered as a correlate of psychological processes such as emotional arousal, stress, or cognitive effort ([3], Chapter 3) [10]. It is commonly measured by placing two electrodes in palmar sites of the hand, although also other alternative locations, such as the wrist [28], have been proposed.

Due to its low-cost and easy-to-collect nature, EDA measurement has been commonly used in research in psychology [10] and as a tool for the assessment of user's experience in a variety of contexts such as recreational and serious games [12,26], driving [16], visual discomfort with 3D media [2], internet browsing [1], or patient–robot interaction [31].

EDA signal is a non-stationary signal, with mean levels usually ranging between 2 and 20 μS, and varying within a range between 1 and 3 μS for an individual. Its values typically show a slow decrease over time when the subject is at rest, and increase more rapidly when novel stimulation is introduced, and, once the stimulation is over, gradually decrease again [10]. EDA signal is considered to have two components: a tonic, or general, level, and a phasic component, characterized by more rapid and momentary changes in EDA levels. Such momentary changes, usually associated to the presence of arousing stimuli, are called Skin Conductance Responses (SCRs). SCRs can be seen as peaks over imposed to the tidal drifts in the general EDA levels.

The availability of wearable devices able to measure online EDA provide the opportunity for real world data collection in a comfortable manner in real-life scenarios outside the lab. This allows broadening the scope of EDA analysis from simply gathering information on user's psychological state to the online adaptation of the system according to the user's cognitive and emotional states.

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The advantages of such online adaptation are especially remarkable in the cases of the users with acute problems to identify, report, and regulate their emotions, such as children or individuals with intellectual developmental disabilities (IDD). In this sense, novel cognitive stimulation systems based on the robots or virtual reality may greatly benefit from an online input of the user emotional state from EDA signal (e.g. [23]).

However, compared to laboratory studies, the online collection and analysis of EDA signals in real-life context involves new challenges related to signal processing. While in lab experiments the participants are usually asked to not to move the hand to which the electrodes are attached, hand's movement can be hardly controlled in real-life settings. As a consequence of such movement, partial detachment of the electrodes or pressure over them may occur, leading to the appearance of artifacts in the signal [3]. If these artifacts remain in the signal when it is analyzed they can easily be misinterpreted and skew the analysis [32]; for example, they may be mistaken for a SCR indicating an increased stress, especially when the analysis is conducted automatically. Even in a context in which not much movement should be expected, the presence of such motion artifacts can be critical in the case of users whose ability to control the level of movement is limited (e.g. individuals with IDD).

The remainder of the paper is structured as follows. Section 1.1 discusses the previous researches related with denoising of the EDA signal. Section 2 details the techniques used in this research for wavelet based artifact removal of EDA signals. Section 3 discusses the computational advantages of the proposed method and Section 4 presents the analysis of the method on the publicly available driver dataset. Section 5 discusses the online validation of the proposed method via an experiment involving stress eliciting tasks. Finally, Section 6 concludes the article by summarizing this work and highlighting the future steps.

1.1. Related work

Methods used in previous research to correct artifacts mainly consist of exponential smoothing [17] and low-pass filtering [24]. Over the last two decades, wavelets have already proven their significant value in signal processing and image. Wavelets have also been found suitable for EDA activity modeling, given its non-stationary behavior [22]. Wavelet based sophisticated de-noising of motion artifacts have been widely used in research [19,25,31,6] and has offered better results due to the good localization property of the wavelet transforms [25]. On the other hand, other sophisticated methods, not based in wavelets, have also been proposed. Recently, Greco et al. [14] proposed a deconvolution based approach (called cvxEDA) using Maximum a Posteriori (MAP) estimation and convex optimization which provided a decomposition of the EDA that is robust to noise.

However, the aforementioned techniques present several important limitations when used for online filtering of the EDA signals, such as the following:

1. Exponential smoothing [17] and low pass filtering based denosing [24] methods are not able to atone the unexpectedly occurring artifacts which have higher values than EDA and undiscriminated filtering of the whole signal also distorts the EDA signals without artifacts [6].
2. Denoising with the traditional DWT wavelet transform [31] can exhibit visual artifacts due to lack of translation invariance and "pseudo-Gibbs" oscillations are especially pronounced in the vicinity of discontinuities [9].
3. Estimation of the noise level σ as proposed by Swangnetr and Kaber [31] is based on the data collected during the rest period. This type of noise level estimation is an off-line and static measure and is an overhead cost on denosing. Moreover, as the actual nature of noise in the noisy signal is dynamic, hence the noise level estimation needs to be done online.
4. Gaussian mixture based modeling for the distribution of the wavelet coefficients [6] requires estimation of three model parameters, γ_j the mixture parameter, σ_j^2 and $c^2\sigma_j^2$ the variances of the two Gaussians (Eq. (1)) which demand employment of iterative algorithms such as Expectation Maximization (EM) algorithm. These algorithms have high computational complexity of $O(n+2n^2)$ for 2 mixture of Gaussians of one dimensional data as in the current case, where n is the number of data samples [7].

$$\tilde{d}_j \sim \gamma_j N(0, \sigma_j^2) + (1-\gamma_j) N(0, c^2\sigma_j^2) \tag{1}$$

5. The cvxEDA method (Eq. (2)) depends on convex Quadratic Programming (QP) [14] which demands polynomial time algorithms, such as interior point algorithms, for solution. The time complexity of convex QP solving algorithms is $O(n^3)$ [4], where n is the number of data samples. Denosing in online scenarios can be limited by the computational complexities of Chen et al. [6] and Greco et al. [14] methods.

$$y = Mq + Bl + Cd + \epsilon \tag{2}$$

Whereas in the offline analysis of EDA signals visual inspection allows identifying and removing the parts of the recording containing artifacts, online adaptation of systems based on EDA signal requires automated methods for such purpose. These methods not only need to be accurate enough to provide a good signal quality, but also need to be computationally affordable enough to work online.

The aim of the proposed work is to present a wavelet based method for filtering motion artifacts in EDA signal that fits these requirements. Experimental results described in Sections 3, 4.3 and 5.3, demonstrate the benefits of the algorithm through a comprehensive comparison with Swangnetr and Kaber [31], Chen et al. [6] and Greco et al. [14] methods.

2. Method

De-noising with the traditional wavelet transforms can exhibit visual artifacts due to lack of translation invariance [9]. Stationary Wavelet Transform (SWT) is redundant, linear and hence shift invariant in comparison to the Discrete Wavelet Transform (DWT) [27]. SWT also provides better sampling rates in the low frequency bands compared with a standard DWT [27].

The literature suggests that the selection of the mother wavelets can be done based upon their resemblance to either the shape of the signal [15] or the shape of the typical motion artifact [20]. Since EDA signals have asymmetric nature, asymmetrically shaped Daubechies (dbN) wavelets have been used to analyze them [21]. Swangnetr and Kaber [31] suggests that *db*3 is the most appropriate choice of the mother wavelet to represent the EDA signal. *Haar* wavelet has also been used for detecting edges and sharp changes, commonly seen in motion artifacts [6]. In addition, Chen et al. [6] suggests that *Coiflet*3 wavelet can have potential as the basis function, since it resembles the shape of the typical motion artifact. Hence, to analyze the effects of the different basis functions, we examine the *db*3, *haar* and the *coiflet*3 wavelets separately, as a mother wavelet during EDA signal denosing.

As explained in Section 1.1, EDA artifacts may result from the recording procedure or from the physiological responses, hence, artifact removal in EDA for above types is discussed separately.