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Research paper

Applications of sparse recovery and dictionary learning to enhance analysis of ambulatory electrodermal activity data

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ABSTRACT

Electrodermal Activity (EDA) – an index of sympathetic nervous system arousal – is one of the primary methods used in psychophysiology to assess the autonomic nervous system [1]. While many studies collect EDA data in short, laboratory-based experiments, recent developments in wireless biosensing have enabled longer, 'out-of-lab' ambulatory studies to become more common [2]. Such ambulatory methods are beneficial in that they facilitate more longitudinal and environmentally diverse EDA data collection. However, they also introduce challenges for efficiently and accurately identifying discrete skin conductance responses (SCRs) and measurement artifacts, which complicate analyses of ambulatory EDA data. Therefore, interest in developing automated systems that facilitate analysis of EDA signals has increased in recent years. Ledalab is one such system that automatically identifies SCRs and is currently considered a gold standard in the field of ambulatory EDA recording. However, Ledalab, like other current systems, cannot distinguish between SCRs and artifacts. The present manuscript describes a novel technique to accurately and efficiently identify SCRs and artifacts using curve fitting and sparse recovery methods We show that our novel approach, when applied to expertly labeled EDA data, detected 69% of the total labeled SCRs in an EDA signal compared to 45% detection ability of Ledalab. Additionally, we demonstrate that our system can distinguish between artifact and SCR shapes with an accuracy of 74%. This work, along with our previous work [3], suggests that matching pursuit is a viable methodology to quickly and accurately identify SCRs in ambulatory collected EDA data, and that artifact shapes can be separated from SCR shapes.

1. Introduction

Electrodermal Activity (EDA) – an index of sympathetic nervous system activity – is one of the primary methods employed in psychophysiological research [4] and is widely used to quantify autonomic and psychological arousal [5]. Formally, EDA is a measure of electrical conductance on the skin surface, which changes as sweat is released by eccrine sweat glands [6]. Fluctuations in skin conductance are linked to a specific set of brain circuitry [7], and can be used to reveal when psychologically salient events occur. Using this link, EDA has been widely employed to investigate a variety of psychological states, including stress, depression, anxiety, attention, pain, and information processing [8,9,1].

EDA signals are traditionally separated into three distinct components: skin conductance level (SCL); skin conductance response (SCR); and artifacts. SCL, or tonic response, is a slowly fluctuating response that typically ranges between 2 and 20 μS and reflects general trends in level of activation. It is common to remove the tonic level from an EDA signal during analyses given that 1) it is less clear how psychological events relate to tonic changes [1] and 2) EDA baselines are rarely consistent within or between individuals due to hydration status, recording site, eccrine sweat gland density at site of recording, and psychological state [1]. In contrast, SCRs are quick responses superimposed on the tonic response that can be more directly linked to psychological events [10]. SCRs typically have a predictable shape that can be characterized by rise time, amplitude, and half recovery time. In healthy adults, rise time is

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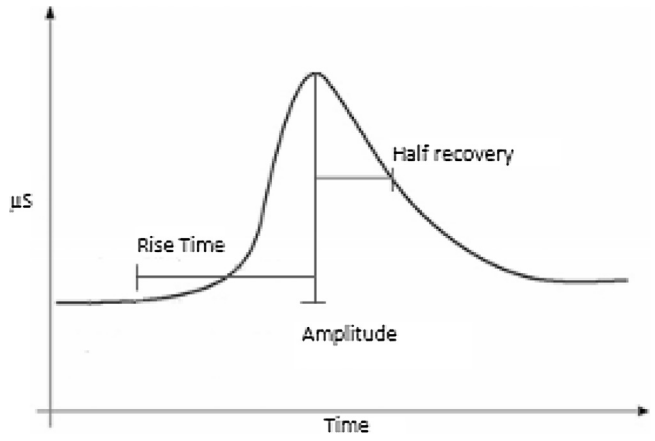

Fig. 1. Parameters used to characterize SCRs.

usually between 1 and 3 s, amplitude often varies, but a minimum is commonly set between 0.01 and 0.05 μS, and half recovery time is typically between 2 and 10 s [1]. Fig. 1 shows the typical shape and parameters that can be used to describe an SCR. A complicating factor occurs when a second SCR is elicited before the previous SCR has fully recovered. This case, referred to as compound SCRs, indicates that two separate stimuli or psychologically different events have occurred [11]. As compound SCRs may be caused by different stimuli, accurate identification of each SCR is important during analysis. Finally, a common feature in EDA data are artifacts resulting from contact changes (i.e., increased or decreased pressure of the senor on the skin), wearer movement, shifts in ambient environmental temperature, or electrical interference. While the curvature of an artifact can vary widely, they are often, and problematically, similar in shape and phase to SCRs. Due to this similarity between artifacts and SCRs, identifying artifacts using current practices is a challenging and manually intensive endeavor.

Until the early 2000s, most studies employing EDA were restricted to short-term assessments in laboratory settings [9]. The recent advent and wider availability of ambulatory recording devices has made it increasingly feasible to gather EDA longitudinally in daily life, opening the exciting possibility of evaluating unique variance across time-scales and settings. For example, a study investigating panic disorders found that SCL trends in participants with panic disorders were significantly elevated during longer ambulatory recordings than in shorter-term assessments in a laboratory setting [12]. While advances in wireless biosensing have allowed for more studies to be conducted in ambulatory settings, the challenges associated with artifact detection and robust SCR identification have hindered efficient and accurate analyses of these signals [9].

To further the utility of ambulatory EDA data, the current manuscript presents a novel strategy for automatically identifying SCRs and removing artifacts. We present the performance of our methods compared to expert manually labeled EDA data. EDA data used for testing was acquired from 55 healthy participants in a lab setting in response to a standardized set of evocative photos. While we will ultimately apply our novel approach to ambulatory data, using data collected in a lab setting provided two major benefits: 1) using standardized evocative photos as a stimulus is a well-studied and widely used approach to elicit SCRs and 2) expert human coders provided labels, coded from videos, for the responses enabling a ground truth with which to compare our method's performance. Using the expert labels as ground truth, we evaluated our method's accuracy in automatically identifying SCRs compared to a current gold-standard software, Ledalab. We also report the separability between SCR and artifact shape as a first step towards moving our method to ambulatory collected EDA data. Finally, we present the possible directions this work could take in the future work section.

1.1. Current analysis methods

1.1.1. SCR detection

Traditionally, EDA signals are analyzed by hand, and, in fact, the Society for Psychophysiological Research still recommends manual analysis for identifying SCR locations and removing artifacts [11]. However, manual analysis is time-consuming and prone to human error and inconsistency. As a first step towards more automated analysis methods, many groups have developed different models to represent the shape of an SCR. A popular model used in several recent studies is the Bateman equation:

$$b(t) = e^{\frac{-t}{\tau_2}} + e^{\frac{-t}{\tau_1}} \quad (1)$$

In (1), t is time and $\tau_1$and τ_2 are parameters that characterize the shape of the function. The Bateman function is characterized by a steep onset followed by a slow recovery period, controlled by τ_1 and τ_2 respectively [4]. Because the Bateman equation relies on only two parameters, minimal computation complexity is required to estimate optimal parameters and fit to an SCR, making it ideal for different SCR detection software [10], [13]. Using this model as the basis for an SCR shape, several groups have created software capable of analyzing EDA data and determining the location of SCRs; however, most of these methods were developed for short, laboratory-based studies and have not been optimized for longer ambulatory recordings [14]. Model-based approaches employ psychophysiological assumptions to develop mathematical models describing how an underlying process generates observed data [14]. Two model-based systems currently considered gold-standard for EDA analysis are SCRalyze and Ledalab [15,16]. However, while both systems have been shown to perform well when analyzing EDA signals collected in the lab, they may not perform well with ambulatory signals [15,17,16]. One of the major drawbacks of SCRalyze is that it relies on convolution with a driver function to locate SCRs in the signal before employing probabilistic inversion to estimate the parameters of the SCRs. This convolution and subsequent estimation relies on prior knowledge about the location of a stimulus or event that evoked an SCR [15], [14]. When this prior knowledge is unknown, for instance when EDA is collected outside of a controlled laboratory setting, these systems may not accurately locate SCRs. For further details the reader is referred to the original papers [15,17,18]. Similar to SCRalyze, Ledalab uses the Bateman equation as an impulse response that, when deconvolved with the signal, is used to identify the onsets of individual SCRs. To improve goodness of fit, Ledalab uses gradient descent to optimize the $\tau_1$and τ_2 parameters to better fit SCRs found across the signal [16]. Ledalab is slow due to its optimization process and not robust to artifacts, making it difficult to scale to longer and more artifact-laden ambulatory signals.

Another interesting automated SCR identification approach recently proposed is convex optimization. Convex optimization allows the problem to be solved efficiently using a sparse QP-solver [19]. While the algorithm appears conceptually promising, in-depth quantitative analyses of its performance is currently based on simulated data, while only an observatory analysis is provided for the SCR detection with real data [19]. Because a full quantitative analysis of non-simulated data is not provided, a true comparison between this method and our novel approach is not possible at this time. Additionally, this algorithm only considers noise as iid white Gaussian but does not consider artifacts caused by movement or touching the recording sensor [19]. Not being robust to these types of artifacts could degrade the performance of this algorithm if applied to ambulatory data and make it difficult to successfully scale analysis for ambulatory data.