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Validation of Spectral Indices of Electrodermal Activity with a Wearable Device*

Riley Q. McNaboe, *Member, IEEE,* Md-Billal Hossain, *Member, IEEE*, Youngsun Kong, *Member, IEEE*, Ki H. Chon, *Senior Member, IEEE*, Hugo F. Posada-Quintero,

***Abstract*— Electrodermal activity (EDA) has been found to be a highly sensitive, accurate and non-invasive measure of the sympathetic nervous system's activity and has been used to extract biomarkers of various pathophysiological conditions including stress, fatigue, epilepsy, and chronic pain. Recently, various robust signal processing techniques have been developed to obtain more reliable and accurate indices that capture the meaningful characteristics of the EDA using data collected from laboratory-scale devices. However, EDA also has the potential to monitor such physiological conditions in active ambulatory settings, for which the developed tools must be deployed in wearable devices. In this paper, we studied the feasibility of obtaining the highly-sensitive spectral indices of EDA using a wearable device. EDA signals were collected from left hand fingers using a wearable device and a laboratory-scale reference device, while N=18 subjects underwent the Head up Tilt test and the Stroop test to stimulate orthostatic and cognitive stress, respectively. We computed two time-domain indices, the skin conductance level (SCL) and nonspecific skin conductance responses (NS.SCRs), and two spectral indices, the normalized sympathetic components of the EDA (EDASympn), and the time-varying EDA index of sympathetic control (TVSymp). The results showed similar performances for EDASympn and TVSymp indices across both devices. While spectral indices obtained from both devices performed similarly in response to orthostatic and cognitive stress, time-domain exhibited large variation when obtained by the wearable device. Further research is required to develop and refine such devices, as well as the indices used to analyze EDA results.**

***Clinical Relevance*— This study proves the feasibility of obtaining spectral indices of EDA using a wearable device, which can be used to develop wearable tools to detect pain, stress, fatigue, between others.**

I. Introduction

Electrodermal activity (EDA) has recently increased in popularity due to its sensitivity as a measure of sympathetic activity. In measuring changes in the conductance of skin, EDA acts as a method for evaluating the state of the autonomic nervous system in addition to the cognitive activity of a subject [1]–[5]. Obtained in a noninvasive and direct process, EDA has proven to be an accurate and useful metric in studies observing a range of conditions including emotional arousal [6], pain [7] and stress [8],[9]. However, the majority of research utilizing EDA signals is conducted with large, laboratory designed devices that limit the potential EDA has to be used as a measure in ambulatory settings. By incorporating EDA functionality into wearable devices, it is possible to provide sensitive, accurate, and real-time metrics similar to those currently produced in research laboratories in an unobtrusive and practical manner.

High sensitivity measures of a subject's sympathetic tone are needed, as they provide means of monitoring and treating various conditions related to the impairment of sympathetic control [10]. Traditionally, the analysis of EDA has been in the time domain [1], using two highly variable measures, skin conductance level (SCL) and nonspecific skin conductance responses (NS.SCRs) [11]. Recent studies have also used a normalized time-invariant frequency domain analysis of EDA (EDASympn) which has demonstrated lower variability compared to SCL and NS.SCRs, but still only marginally acceptable consistency in results [11].

Recently, we have created a technique to improve upon these metrics by accounting for the time-varying characteristic of the sympathetic tone using a time-varying analysis of EDA referred to as TVSymp [12]. This index was developed using a variable frequency complex demodulation, a time-frequency spectral analysis technique and a high time-frequency resolution to develop and index of sympathetic tone. TVSymp is the mean spectral amplitudes in the frequency band associated with the sympathetic tone of the EDA signals. When compared to the time-domain and time-invariant indices such as heat rate variability, SCL, NS.SCRs, and EDASympn, TVSymp proved to be the most sensitive to applied stimuli.

TVSymp has proven to be a reproducible index of EDA activity in various applications [13] including dental pain [14], dehydration [15], stress [16]. In accurately quantifying various forms of sympathetic activity, its promising results not only demonstrates consistency but enables future applications and studies with EDA. An accurate understanding of the autonomic nervous system's dynamics can lead to improved treatment and interventions related to the performance and health of patients with related conditions. Wearable devices are one of the most obvious implementations of such a sensitive and versatile measure like EDA. Several studies have looked into collecting EDA data from wearable devices, such

R. McNaboe, H.F. Posada-Quintero, M-B. Hossain, Y. Kong, and K.H. Chon are with the Department of Biomedical Engineering, University of Connecticut, Storrs, CT 06269 USA (corresponding author to provide phone: 959-777-2623; e-mail: riley.mcnaboe@uconn.edu, h.posada@uconn.edu, md.b.hossain@uconn.edu, youngsun.kong@uconn.edu, ki.chon@uconn.edu).

as exploring its ability to treat anxiety [17] or reduce risk on construction sites [18]. Similar studies could benefit from a more reliable form of EDA analysis for wearable devices such as TVSymp.

TVSymp was developed using data acquired by an industry standard device (ADINSTURMENTS GSR Module) and digitized with a standard module (PowerLab). Given that the resulting TVSymp index has provided consistent results on data from standard references devices, it is important to see its ability to serve as a metric for EDA data produced by a wearable device. We hypothesized that when compared to those obtained using an industry standard device, the spectral indices derived from EDA data produced by a wearable device would show equally accurate and sensitive results.

To test our hypothesis, we obtained EDA data from subjects using an industry standard device for a reference as well as a wearable device. From the outputs of these two devices we computed an array of traditional time-domain and spectral EDA indices; SCL, NS.SCRs, EDASympn, and TVSymp. The differences in mean index values and the variability of the different indices were compared between the two devices.

II. Methods and Materials

A. Subjects

All of the procedures were approved by the Institutional Review Board (IRB) for human subject research at the University of Connecticut. Eighteen healthy volunteers (8 males, 10 females) of ages ranging from 19 to 36 years old were enrolled in this study. No gender related differences have been reported for EDA or sympathetic function. Consent was given by subjects after reviewing the subject protocol approved by the Institutional Review Board at the University of Connecticut.

B. Protocol

The experiment was conducted in a quiet, moderately lit room with an ambient temperature of 26-27 ºC. To induce a variety of sympathetic arousal types, the subjects underwent two isolated tests. The first test was the 70° Head up Tilt (HUT) stand test to simulate orthostatic stress. The second test administered was the Stroop task to simulate cognitive stress. Before each test, the subject was in supine position for 2 minutes to establish a baseline reading. For the HUT test, after the baseline was established, subjects were tilted from 0 to 70° and remained in the angled position for 2 minutes. Once returning back to supine position to reestablish the baseline for an additional two minutes, a computerized version of the Stroop test [19] was administered for a final two minute period. The tests were conducted in the same order using the same protocol for each subject.

TABLE I. Protocol Summary and Selected Data

Duration (s)	Data Selected (s)	Activity	Remarks
120	Last 90	*PreTilt:* Flat table, relaxing with eyes closed	Baseline
30	-	Start table tilt	Orthostatic Stress
120	First 90	*PostTilt:* Subject remains in titled position	
150	Last 90	*PreStroop:* Subject returns to supine, relaxation	Baseline
120	First 90	*PostStroop:* Perform Stroop task	Cognitive Stress

C. Materials

EDA signals were simultaneously recorded throughout the experiment using two devices: a laboratory-scale device (ADINSTRUMENTS GSR module), and a wearable device (Shimmer3+ GSR Unit). EDA data were collected from the left hand of the subject using the two different devices. Two stainless steel electrodes from the standard device were placed on the index and middle fingers. Additionally, two stainless steel electrodes from the wearable device were attached to the ring and middle fingers. The EDA data from both the reference device and the wearable device were sampled at a frequency of 1000Hz. Both sets of data were later down sampled to 8 Hz as the majority of the desired signals in EDA data consists of low frequency components [11].

C. Data selection and processing

To compute the EDA indices, the raw data were passed through a zero phase lowpass FIR filter (cut-off frequency = 1 Hz). To analyze the various indices for each of the two stress stimuli, the raw EDA data from both of the devices were split into sections corresponding to each test. These two sections were then subdivided into two periods representing a relaxation state which consisted of the hemodynamic stabilization (baseline), and a stress state (test), for each test. The 2 portions of the HUT test data consisted of 90 seconds of baseline activity prior to the table tilt and 90 seconds of activity starting from the subject arriving in a tilted position. As outlined in Table 1, the Stroop consisted of 90 seconds of baseline activity before the start of the Stroop and 90 seconds of activity starting from the presentation of the Stroop task.

EDA signals are decomposed into tonic and phasic components [20]. The SCL and NS.SCR for each portion of data were calculated using a tonic/phasic decomposition of the data based on non-negative sparse deconvolution algorithm referred to as SparsEDA [22] which has proven to be faster and more efficient than alternatives [4]. SCL (expressed in microsiemens, μS) is a measure related to the slow shifts of EDA, computed as a mean of the tonic component of each EDA segment. The skin conductance responses (SCRs) are those rapid transient events contained in the EDA signals (Fig. 1). The non-specific SCRs (NS.SCRs) are the number of SCRs in a period of time, expressed as the number of responses per minute [20].

EDASympn and TVSymp were calculated for the data using the processes outlined in previous works, using time-invariant (power spectral density) and time-varying (variable frequency demodulation) approaches, respectively [11], [12]. EDASymp comprises the power of EDA in the range 0.045–0.25 Hz, and TVSymp uses the components of EDA in the range 0.08–0.24 Hz. The mean index value for every data period over both devices was computed from each subject's individual resultant indices. These values are shown Table 2

along with the mean coefficient of variation (CV) computed as the ratio between the standard deviation and the mean, for each index.

III. Results

The raw EDA output for a given subject can be seen in Fig. 1 for the duration of both tests administered in the experiment for both the reference device and the wearable. Note that during the periods prior to the application of a test (indicated by the yellow lines) there were no positive SCRs as the subject remains relaxed. Once both the HUT test and Stroop tests began, there was a clear response observed as the amount of NS.SCRs dramatically increased. This pattern remained constant throughout all of the subjects.

The SCL, NS.SCRS, EDASymp, and TVSymp values of all subjects for both wearable and reference devices are presented in Table I. The SCL values showed a significant difference ($p<0.05$) between the baseline period and test period for both devices during the HUT and Stroop test. The mean values for the NS.SCRs also showed a significant difference between the baseline and the test data, however only for the HUT test. The TVSymp values followed the same pattern. The indices for EDASympn had significant difference in both devices for the Stroop task but did not indicate a difference for the HUT test results.

To assess the variability of the indices between the reference and wearable outputs, the mean CV for each index is presented on the bottom row of Table 1 and Fig. 2. The CV values for the mean SCL and NS.SCRs showed a significant difference between the reference device and the wearable device. The mean CV for the wearable SCL was 2.08 times larger than the mean CV value for the reference of the same index. Reversely, the mean CV values for both EDASympn and TVSymp indices were relatively similar to one another for both the wearable and reference devices. The difference in CV between the wearable and reference was less than 0.1 for TVSymp.

IV. Discussion

The presence of significant differences in mean values between rest and test values for all four indices demonstrate that all can capture the sensitivity of EDA to cognitive and orthostatic stress using either a laboratory-scale or a wearable device. Specifically, SCL, NS.SCR and TVSymp indices showed sensitivity to the orthostatic stress induced by the HUT test. Similar sensitivity has been seen for a range of tests in many EDA related studies that measure time-varying and spectral EDA indices [4], [23]. It is also important to note that although there was an increase in the mean values of NS.SCR and TVSymp, the lack of a significant differences in response to the Stroop Task could be attributed to the short recovery period after the HUT. This could have prevented subjects from reestablishing an accurate baseline reading before the following test as previous studies have used 2-5 minutes [8][11].

The similarities in statistical difference appear in pairs for both wearable and reference devices and supports our initial hypothesis that the wearable device would perform in a similar manner to reference device. This is further supported by the CV values for the two spectral indices EDASympn and TVSymp that showed the same amount of variation for both types of devices. While the wearable CV values were distinctly higher for SCL and NS.SCR indices than those of the reference device, these values can be attributed to the inherent variant

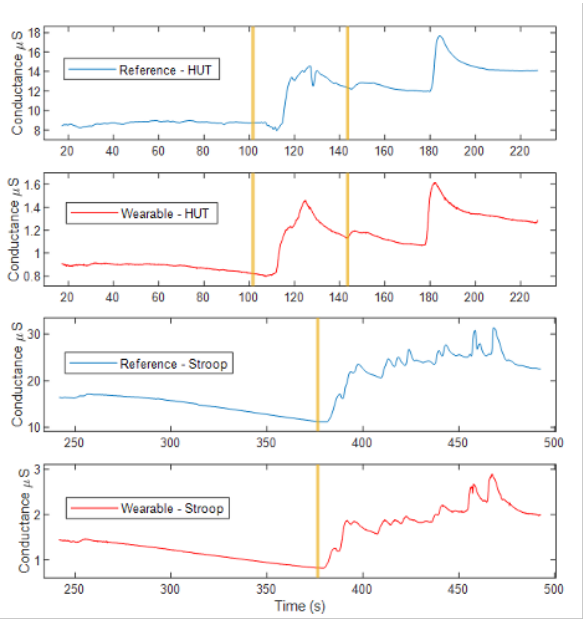

Figure 1. Raw EDA data from a given subject. For HUT test data portions, the yellow lines mark the start and end of the subject being tilted, this data is not included in the analysis. For Stroop test the yellow line marks start of the test.

TABLE II. Results for EDA indices

		SCL		NS.SCRs		EDA Sympn		TVSymp	
Task	*Stage*	*Reference*	*Wearable*	*Reference*	*Wearable*	*Reference*	*Wearable*	*Reference*	*Wearable*
Stroop	**BL**	6.18 +/- 4.2	2.81 +/- 3.87	1.06 +/- 0.639	0.889 +/- 0.719	0.129 +/- 0.157	0.0813 +/- 0.135	0.661 +/- 0.41	0.699 +/- 0.37
	Test	9.35 +/- 4.98*	3.37 +/- 4.51*	1.47 +/- 1.28	0.861 +/- 1.1	0.245 +/- 0.201*	0.227 +/- 0.187*	0.959 +/- 0.5	0.869 +/- 0.544
HUT	**BL**	8.56 +/- 6.25	3.16 +/- 4.27	1.11 +/- 0.948	0.472 +/- 0.581	0.166 +/- 0.199	0.13 +/- 0.163	0.589 +/- 0.41	0.513 +/- 0.37
	Test	12.8 +/- 7.41*	3.91 +/- 4.63*	2.78 +/- 1.75*	1.94 +/- 1.63*	0.254 +/- 0.181	0.181 +/- 0.127	1.32 +/- 0.313*	1.34 +/- 0.416*
Mean CV		0.630	1.312	0.739	1.037	0.986	1.110	0.500	0.522

Values are expressed as means +/- SD. *Significant difference compared to baseline stage ($P<0.05$). TVSymp, time-varying index of sympathetic skin conductance level; NS.SCRs, nonspecific skin conductance responses; EDASympn, normalized sympathetic component of the EDA; SCL, skin conductance level ---- BL, baseline reading period; Test, applied stress test period; CV, Coefficient of variation

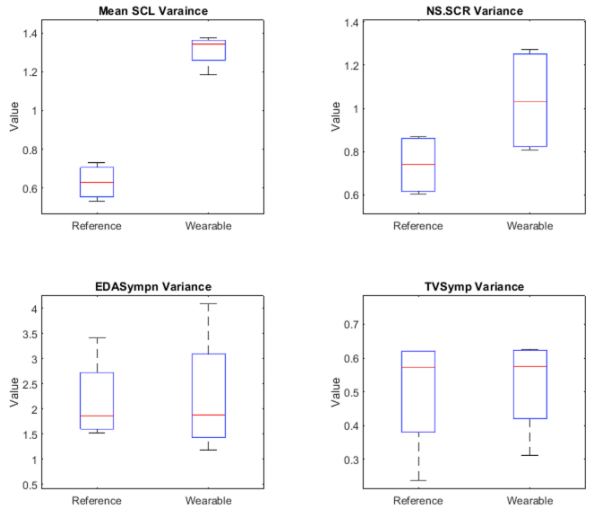

Figure 2. Coefficient of variation (CV) for reference (laboratory-scale) device and wearable devices for SCL, NS.SCRs, EDASymp, and TVSymp.

behavior of these indices that was extenuated by characteristics of the wearable technology such has susceptibility to noise and motion artifacts [17], [24]. The difference that arises in CV values between SCL, NS.SCR and EDASympn, TVSymp are important to note moving forward as they demonstrate that the latter indices are more accurate at reading EDA data from the wearable device.

The main goal of this work was to determine if a wearable device is able to produce similar results to a laboratory-scale reference device when comparing the spectral EDA indices derived from the data. Traditional time-domain indices, SCLs and NS.SCRs, were included in the analysis to provide a more thorough analysis of the indices of EDA obtained from a laboratory-scale and a wearable device. The low variation of the spectral indices between a wearable and reference device provided promising results that spectral analysis of EDA could provide the means to capture the signal's full potential in a wearable format. However, one of the most important points of interest to note from this work is that the wearable devices consistently had higher variations than the references. Combining this trend with the lack of sensitivity for the spectral indices across one of the two tests administered, it is clear that further development and refinement is still required. For wearable devices which utilize EDA to be considered practical and relevant, it is crucial that they are designed to perform just as accurately and efficiently as the laboratory-scale devices used in foundational EDA research where such accurate indices were developed.

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