ARL-TR-10051 ● JAN 2025

Validation of a Signal-Processing Pipeline for Electrodermal Activity Responses in Multimodal Paradigms

by Thomas Rohaly, Leah Enders, Alex Stauff, and Michael Nonte

NOTICES

Disclaimers

ARL-TR-10051 ● JAN 2025

Validation of a Signal-Processing Pipeline for Electrodermal Activity Responses in Multimodal Paradigms

Thomas Rohaly, Alex Stauff, and Michael Nonte
DCS Corporation

Leah Enders
DEVCOM Army Research Laboratory

REPORT DOCUMENTATION PAGE

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED	
		START DATE	END DATE
January 2025	Technical Report	5 December 2022	17 May 2023

4. TITLE AND SUBTITLE
Validation of a Signal-Processing Pipeline for Electrodermal Activity Responses in Multimodal Paradigms

5a. CONTRACT NUMBER	5b. GRANT NUMBER	5c. PROGRAM ELEMENT NUMBER
5d. PROJECT NUMBER	**5e. TASK NUMBER**	**5f. WORK UNIT NUMBER**
ARL-22-150		

6. AUTHOR(S)
Thomas Rohaly, Leah Enders, Alex Stauff, and Michael Nonte

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)	8. PERFORMING ORGANIZATION REPORT NUMBER
DEVCOM Army Research Laboratory ATTN: FCDD-RLA-FC Aberdeen Proving Ground, MD 21005	ARL-TR-10051

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
DISTRIBUTION STATEMENT A. Approved for public release: distribution unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Situational awareness (SA) is considered a foundational skill for Soldiers, and maintaining SA is critical to reduce errors and casualties during combat. Soldiers are exposed to high levels of stress not only at work but also in their daily lives, negatively impacting their ability to maintain SA and overall job performance and safety. Advances in wearable technology and mixed reality have allowed us to increase our understanding of how stress conditions impact job performance for in-lab scenarios. Specifically, including multimodal sensors to jointly capture physiological responses (e.g., electrodermal activity and heart rate) and kinematics (e.g., joint position and movements) provides a comprehensive view of SA maintenance and job performance. However, many hurdles remain before we can feasibly use these types of sensors to capture stress responses in mobile, in-field operating paradigms. The purpose of this study was to develop a signal-processing pipeline for electrodermal activity signals to be used as an in-house standard. In this study, participants navigated through a desktop-based virtual environment and completed a visual search task. During this task, surprising flashbang events occurred intermittently and the team collected isolated electrodermal activity responses. Data collected from the task was then utilized to develop a processing pipeline for cleaning and formatting data for analysis, such as using standardized signal decomposition models. Results from this study conclude that the developed pipeline is a feasible option for cleaning and preparing electrodermal activity signal for analysis and encourage its use in future paradigms to further test and refine the pipeline.

15. SUBJECT TERMS
Humans in Complex Systems, electrodermal activity, signal processing, processing pipeline, Python, visual search

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES
a. REPORT	b. ABSTRACT	C. THIS PAGE		
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED	UU	36

19a. NAME OF RESPONSIBLE PERSON	19b. PHONE NUMBER *(Include area code)*
Thomas Rohaly	(410) 278-7747

STANDARD FORM 298 (REV. 5/2020)
Prescribed by ANSI Std. Z39.18

Contents

List of Figures

List of Tables

1. Introduction, Study Purpose, and Aim

Soldiers are often in environments where they are required to keep constant situational awareness (SA) of their surroundings while completing mission objectives. The frequent co-occurrence of high levels of stress in their daily lives and jobs can negatively impact their ability to maintain SA (Kerick and Allender 2004; Scribner et al. 2007). The Department of the Army has listed SA as a foundational skill and states that maintaining a high level of SA is integral for the reduction of human errors and combat causalities (DOA 2021). As such, research over the past few decades has focused on efficiently implementing SA-specific training to help Soldiers develop superior SA skills (Salas et al. 1995; Endsley et al. 2000; Strater et al. 2001; Salmon et al. 2006; Enders et al. 2024) as well as quantifying metrics of SA in military settings for both individuals and teams (Endsley et al. 2000; Salmon et al. 2006). Even with Soldiers receiving SA-specific training, the introduction of stress/increased cognitive load can have negative impacts on performance and attention (Chèrif et al. 2018; Smith et al. 2019; Buckley et al. 2022; Enders et al. 2023, 2024). Furthermore, certain health conditions that often coexist with military experience (e.g., posttraumatic stress disorder) also impact SA, performance, and arousal states in both active duty and civilian populations (Roy et al. 2022). Many physiological signals such as heart rate and electrodermal activity (EDA) can be used to infer periods of increased stress load and therefore have the potential to be used as indicators of when a Soldier's SA may be compromised. One problem space is that these signals can be temperamental and require complex processing and filtering methods to make their output interpretable. Historically, it has been difficult to capture these types of signals in mobile settings, which limits military application as mobility is often fundamental to Soldier tasking. The purpose of this study is to develop and demonstrate the validity of a methodology to extract, clean, and model EDA data for the purpose of identifying stress response features. The end goal of this work is to expand the flexibility and usage of EDA signals to capture stress response features in complex study paradigms so they can be used in further analyses to make inferences about constructs like a Soldier's SA.

Over the past few decades, the feasibility of measuring impacts of stress on SA in the field has increased greatly given recent improvements in wearable sensors, ML tools, and deep learning models (e.g., Sánchez-Reolid et al. 2019; Han et al. 2020; Tronstad et al. 2022), as well as newer signal-processing techniques (Posada-Quintero and Chon 2020). These methodologies can be made to be portable (i.e., computationally light), be integrated with newer wearable sensors, and create new possibilities for measuring physiological signals to predict Soldier states like stress.

Furthermore, technological advancements in mixed reality (e.g., virtual and augmented reality) have pushed our capabilities of creating novel and realistic environments, opening the door for mobile test-beds to measure physiological responses in controlled, mobile, and safe environments. Together, the advancements in physiological measurement integrated into wearable technology and mobile mixed reality increase our capabilities to conduct research and preserve naturalistic movement capabilities, producing more ecologically valid results. However, these new methods also present novel obstacles to overcome for successful integration and implementation and depend on selection of the best viable physiological response signals to incorporate.

Physiological measures of stress response include changes in heart rate, respiration, and thermoregulation, all controlled by the autonomic nervous system (ANS). The ANS can be broken down into two different systems: the sympathetic system, which controls the body's fight-or-flight response; and the parasympathetic system, which controls the body's anabolic homeostatic activities such as digestion, rest, and repair. Researchers have found that both systemic diseases (e.g., diabetes and heart failure) and individual states (e.g., stress and fatigue) can be detected/measured via sympathetic nervous system activity (Posada-Quintero 2016). Heart rate variability (HRV) is a historically popular and noninvasive way to try to capture sympathetic activity. A spectral analysis of HRV allows an inspection of ANS activity. However, HRV reflects both sympathetic and parasympathetic activity (Posada-Quintero et al. 2016), with no reliable way of parsing that information apart. In addition, HRV is more reliable when measurement occurs over longer time periods (e.g., at least 5 min of measurement time) with research finding poor reliability in short-term HRV measurement (e.g., less than 5 min), especially in clinical populations (Sandercock et al. 2005; Pinna et al. 2007). Both issues make HRV an unreliable measure of pure sympathetic activity.

EDA is an alternative, noninvasive method for capturing sympathetic-specific activity over fairly short periods of time. It is a physiological signal that reflects changes in the electrical conductance of the skin due to sweat secretion, and variations in this signal can capture changes in stress/arousal levels (Boucsein 2012). EDA is a pure measure of sympathetic nervous system activity as there is almost no parasympathetic innervation of the skin (Kleckner et al. 2018), although there are external factors (e.g., position of electrodes on the body, how dry the skin is, external temperature, and humidity) that can affect EDA measurements. Being able to collect a signal that contains only sympathetic activity should allow researchers to more accurately capture true sympathetic responses to external stimuli (e.g., a stress response to a startling event). EDA can be broken down into two main components: a slow varying tonic component and a fast-varying phasic component (Boucsein 2012). The tonic component represents the overall arousal of an individual, whereas the phasic component reflects reactions/responses to stimuli in the environment (e.g., a loud sound) (Boucsein 2012). In previous work, EDA has been used to assess arousal (Greco et al. 2017), understand emotional experiences (Christopoulos et al. 2019), predict assessments that measure posttraumatic stress disorder severity (Gramlich et al. 2021), index cognitive load (Shi et al. 2007), and detect stress (Kurniawan et al. 2013; Stržinar et al. 2023). Overall, measuring EDA offers a potential low-cost, noninvasive route for accurately measuring sympathetic activity in isolation and has a high sensitivity to psychological processes (Babaei et al. 2021).

The advantageous characteristics of EDA make it an attractive method to capture stress responses due to its relatively fast reflection of changes in an individual's attentional state, with a phasic response usually 1–3 s after stimulus onset, and its ability to be readily integrated with other response measures in test-beds such as visual search tasks. Visual search tasks are ubiquitous in a military context and are well-structured to probe the current state of SA. With the addition of mixed reality, visual search tasks allow researchers the unique opportunity to examine stress response in new problem spaces that increase complexity and allow for the possibility of natural movement. EDA has previously been used to examine arousal in static, visual search tasks. Some examples of EDA being used in a visual search task include EDA differing as a function of task (Posada-Quintero and Bolkhovsky 2019), estimating anxiety and examining responses to distractor stimuli (Naveteur et al. 2005), and using EDA as a tool to discriminate between visual attention states (Momin and Sanyal 2019). Thus, measurement of an EDA signal during visual search tasks can be a useful tool to capture physiological response to stress (Kurniawan et al. 2013; Gramlich et al. 2021). EDA could be used to capture stress responses while Soldiers maintain SA during a visual search task in a military environment with military-like stressors (e.g., enemy fire, flashbangs) and, by integrating mobile mixed-reality technology, the ecological validity of using such paradigms to examine Solider capabilities can be increased. Since recent research has also investigated the feasibility of using wearable sensors to collect EDA (van der Mee et al. 2021), there is prime opportunity to integrate EDA-measuring wearable technology into such a relevant military testing scenario.

Two major hurdles remain in integrating EDA as a wearable testing measure into our future work with mobile mixed-reality, military-relevant scenarios. The first hurdle is signal noise caused by external factors (e.g., signal spikes caused by movement) and the second is the development of a data-processing pipeline that can standardize how we treat the EDA signal before decomposing it into its phasic and tonic components, for stimulus-based responses and overall arousal levels, respectively, while maintaining the capability to be integrated into reliable, wearable designs. As can be expected with these mobile, wearable designs, motion artifacts in the EDA data are a prevalent issue. Recent research has focused on methodologies like unsupervised learning models (e.g., Zhang et al. 2017; Subramanian et al. 2021), anomaly detection (Sunny et al. 2022), ML for automatic detection (Taylor et al. 2015), and other methods like efficient wavelet-based artifact removal (Shukla et al. 2018). However, unlike other physiological signals like electroencephalography (EEG) (Bigdely-Shamlo 2015), there is currently no standardized method for removing artifacts or processing EDA signals and separating them into individual components. Most models have only examined EDA components post hoc and with mixed success. Some of these models include cvxEDA (Greco et al. 2016), sparsEDA (Hernando-Gallego et al. 2018), and Continuous Decomposition Analysis (CDA) and Discrete Decomposition Analysis (DDA) from Ledalab (Benedek and Kaernbach 2010a, 2010b), among others. A recent meta-analysis gave an overview of different processing techniques for EDA signals as well as the EDA quality in previous literature (Posada-Quintero and Chon 2020). Importantly, Posada-Quintero and Chon (2020) observed that all four of these models listed above produced different estimations of tonic and phasic components, but cvxEDA and sparsEDA have a low computational cost and could be implemented into wearable devices. Additionally, it was noted that cvxEDA and sparsEDA models require setting a group of parameters and, if they are kept at their default values, the decomposition results could vary widely depending on the individual participant and the application in which the model is being used (Greco et al. 2016; Hernando-Gallego et al. 2018). These factors limit EDA signal efficacy in mobile paradigms and the development of portable models to integrate with wearable sensors. While there are potential options for portable models (e.g., Greco et al. 2016; Hernando-Gallego et al. 2018) there are still drawbacks to the implementation of these models. Further work is needed to form best practices for cleaning and processing EDA data.

The main purpose of our study was to demonstrate a reasonable methodology to extract, clean, and model EDA signals to allow for meaningful detection of stress responses during a desktop visual search task and minimize artifacts. To accomplish this, we developed a study where we asked participants to navigate and search a desktop virtual environment (VE) for a specified target while EDA signals were simultaneously collected via a 64-channel BioSemi Active II. A startling stimulus (e.g., flashbangs) occurred while participants navigated the desktop environment to elicit stress responses. To time-sync the EDA signals with game-state VE data, we used Lab Streaming Layer (LSL) (Kothe 2014). Although LSL allowed us to link corresponding events in the data layers, the combination use with

BioSemi presented several initial hurdles. The BioSemi's proprietary software (e.g., ActiView) that normally enables signal preprocessing (e.g., signal demodulation, combining multiple data streams), could not run simultaneously to LSL. Additionally, the signal output from LSL required rescaling as LSL was designed for use with EEG signals and assumes very small magnitudes (i.e., microvolts). Thus, our **Aim 1** was to develop code to address these limitations. Next, the preprocessing of this signal type is very dependent on the experimental setup. Therefore, in our **Aim 2** we sought to develop a preprocessing pipeline to both clean and remove artifacts (e.g., motion) from EDA signal data. Since one of the overarching goals of this work is to provide an in-house method for EDA signal processing that is usable to other researchers with a range of signal-processing experience, the preprocessing pipeline had to be easy to implement and capable of automatically assessing different aspects of the EDA signal. Finally, in **Aim 3** of this study, we tested the output of our in-house preprocessing pipeline, developed in Aim 2, by running the preprocessed data through two different models (cvxEDA and sparsEDA) and compared the resulting tonic and phasic components to results from similar work found in literature.

The outcomes of this study are as follows: an EDA signal-processing pipeline that could be used as an in-house standard, and a method for correcting errors in the raw signal collection (see details below) and properly rescaling the signal to allow for further processing for those collecting EDA signals using the BioSemi Active II in conjunction with LSL.

2. Methods and Results

2.1 Participants

A total of 12 individuals participated in this study. One participant was excluded due to an error where only a partial dataset was recorded. All participants were recruited from personnel working for the U.S. Army Combat Capabilities Development Command Army Research Laboratory's Humans in Complex Systems competency at Aberdeen Proving Ground, Maryland. Participants were all at least 18 years old, had corrected-to-normal vision, and were fluent in English. This study was approved by the DEVCOM Army Research Laboratory Institutional Review Board (ARL-22-150) as nonhuman subjects research.

2.2 Procedure

2.2.1 Aim 1: Replication of Signal Processing

Researchers addressed several key issues related to Aim 1. First, researchers corrected a scaling error that is caused by the LSL app for BioSemi. Specifically, the app treats all BioSemi auxiliary channels as if they were EEG sensors (i.e., microvolt units) and performs incorrect scaling on the EDA signal when it is included. Next, researchers used guidance from the BioSemi support forums (Eric42 2014) to determine what corrective processing steps needed to be applied to the signal to replicate what the proprietary software normally applies (Table 1). Table 1 shows a list of all steps taken for corrective processing of the EDA signal over LSL, as well as correcting the scaling error. A comparison between the original signal from the LSL stream and the same signal after corrective processing can be seen in Figure 1.

Table 1. List of steps taken for the signal recorded over LSL to match preprocessing automatically conducted on the signal when recorded over proprietary software, as well as address scaling changes that occur in LSL.

Step No.	Step description
1	Correct the scaling factors applied to data in the LSL app
2	Compute the difference of auxiliary 1 and 2 to get the EDA signal
3	4th order lowpass filter 1-dB passband ripple with a 16-Hz cutoff frequency
4	Apply a scaler of 13.3
5	Decimate signal by a factor of 16
6	Divide data into 128 data-point windows and calculate (max to min) for each window
7	Apply byte shift by dividing the signal by 8192
8	Convert the signal from Ohms to Siemens
9	Convert the signal from Siemens to MicroSiemens
10	Up-sample signal back to the EEG sample rate

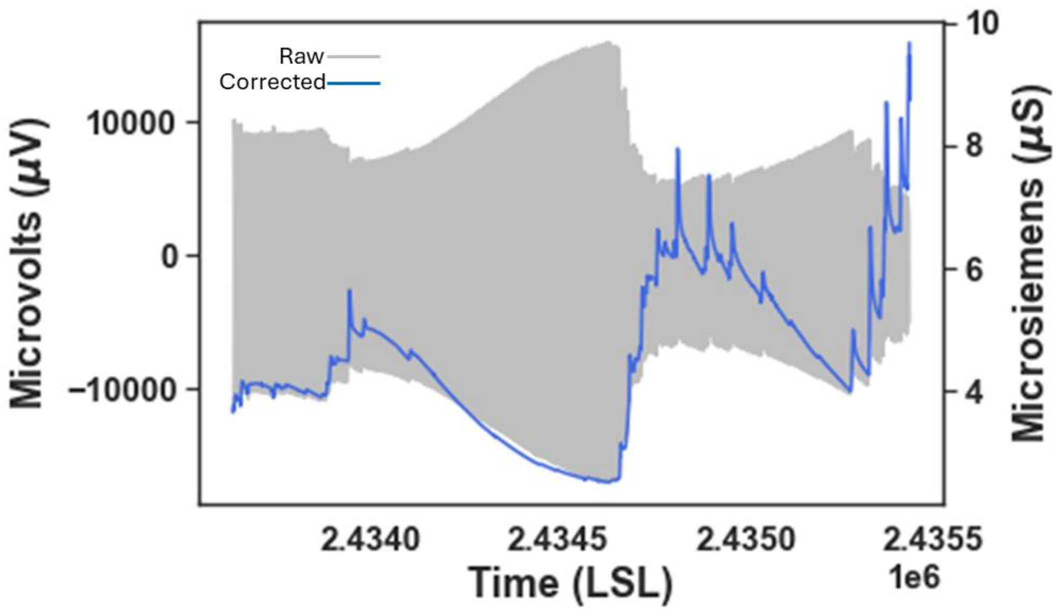

Figure 1. The gray signal represents the raw signal (μV) saved by LSL. The blue line represents the signal (μS) after the corrective script is applied.

A Python script was developed to process the EDA signal using all steps listed in Table 1. To test the effectiveness of this script, researchers conducted a resistor test where data was saved via both LSL and ActiView to compare the resulting signal from our corrective processing to ground truth values collected in ActiView. Resistors were tested at 4.7, 10, 47, and 91 kΩ as the resistance of human skin is usually between 1 and 100 kΩ (Fish and Geddes 2009; Abe and Nishizawa 2021). A minute's worth of data was collected for each resistor and then the median resistance was compared between each recording method to ensure that, after the corrective processing, the LSL recordings matched the ground truth signal collected via ActiView.

2.2.2 Visual Search Task

To validate EDA preprocessing methods and test tonic/phasic decomposition models (Aims 2 and 3, respectively), we recorded EDA on human subjects in a VE with sparse known stimuli. This allows us to measure phasic EDA features in isolation from the complexity of the experimental simulation task and verify that phasic responses can be detected using the cleaning and detection methods developed under Aim 2.

Upon arrival, participants were given a verbal COVID-19 screening questionnaire. After a successful screening, two electrodes were placed on the palm of the participant's hand to record EDA data. The electrodes were placed on the participant's left hand and EEG common mode sense active electrode and driven right leg passive electrode were affixed to the scalp per the standard EEG setup procedures. Electrode gel was applied to the electrodes to reduce skin–electrode impedance, and electrodes were in place for at least 5 min before the start of the main visual search task to ensure acclimation of the electrode to the participant's body temperature. After equipment setup, there was a 2-min baseline where participants were asked to relax and remain as still as possible with the electrodes attached to their palm.

In the visual search task, participants were asked to navigate through the desktop VE while mentally counting the number of targets (Figure 2) they saw in the environment. To validate which targets were seen or missed, participants were asked to click the left mouse button as soon as they saw a target. Participants were exposed to stimulus events while navigating through the VE (see below for details). Participants did not need to respond to these stimulus events in any way other than to continue searching for and counting targets. Participants navigated the VE using the "W," "A," "S," and "D" keys on the keyboard with their left hand (allowing unrestricted movement) and directed the camera view with their right hand on the computer mouse. Navigation of the VE was self-paced but took approximately 25 min in total to finish. Upon finishing the main task, all sensors were removed, and participants verbally reported how many targets they counted. Overall, experimental sessions lasted approximately 40 min.

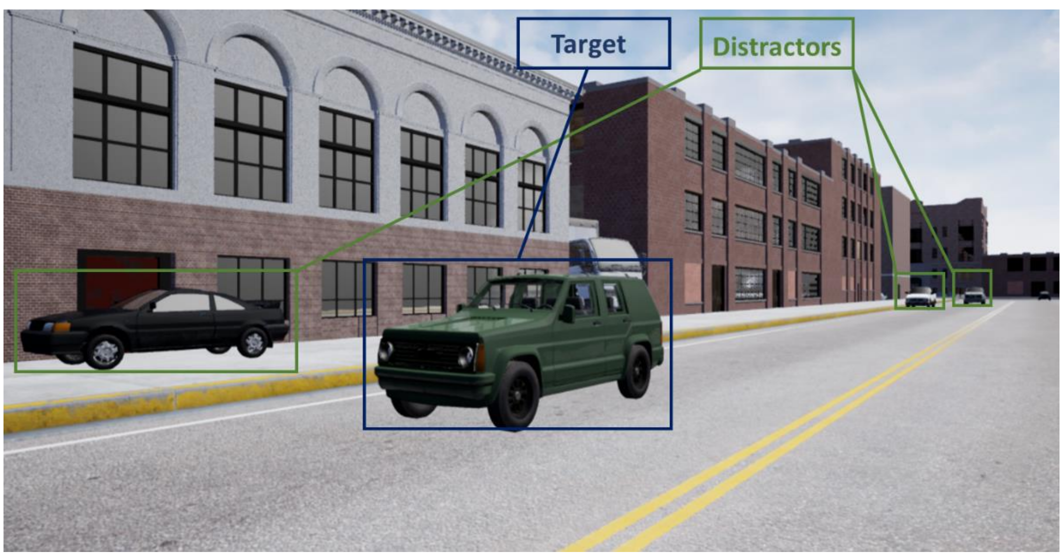

Figure 2. A still image showing the VE, one of the targets used (all identical), and several distractors (different types and colors of vehicles).

2.3 Virtual Environment

The desktop VE for the visual search task was created with the Unreal Engine 4, version 4.27 (Unreal Engine c2024). This environment consisted of an urban city filled with 20 targets (green jeeps), numerous distractors (other vehicles), and 38 stimulus events (flashbangs/auditory bangs). Of the 38 stimuli, 26 were flashbang stimuli, where the screen would briefly flash white, and a loud banging sound occurred. The final 12 stimuli were the audio effect of the flashbangs without the visual component included. Stimulus events were triggered when the participant reached certain locations following the path in the environment (positionally triggered, not triggered at a specified time spent in the environment). Although the task was self-paced and varied slightly with each participant, a stimulus event occurred every 40 s on average (±15 s). There was only one path available for participants to navigate through, with all other paths (e.g., side streets and alleyways) being physically blocked off. The UETack software suite was used during data collection to capture both human sensing and game state data (Touryan et al. 2023).

2.4 Equipment for EDA Signal Collection

The EDA signal was collected using the BioSemi Active II. The EDA signal itself was measured via two passive Nihon Kohden electrodes, and two EEG electrodes were used as the ground for the EDA signal. EDA data was collected at 16 Hz and up-sampled to 2048 Hz when saved out by the device, with the output saved as Ohms (not microSiemens).

2.5 Aim 2: Proposed EDA Signal-Processing Pipeline

Currently, there is no standardized method in the field for preprocessing the EDA signal prior to implementation of the signal into the decomposition models (that will decompose the signal into tonic and phasic components) that was appropriate for our experimental setup. The following five-step EDA preprocessing pipeline was developed over multiple iterations and the finalized pipeline reported here yielded the highest quality of preprocessed EDA signal compared to other iterations. A Python pipeline leveraging the following steps elicited a reasonably clean, processed EDA signal: 1) Signal Conversion, 2) Cut-off Threshold, 3) Windowing, feature engineering, and Isolation Forest algorithm, 4) Noise Filtering, and 5) Interquartile Range Cutoff Threshold (Figure 3). In the Signal Conversion step (Step 1), all EDA data was converted to µS and resampled back down to 16 Hz. This was necessary, as the BioSemi Active II had previously saved the data in a unit of Ohms and up-sampled the data to 2048 Hz automatically. Next, in Step 2, a Cutoff Threshold was applied to the data. This was based on measures of central tendency and removed any extreme outlying values ±3 standard deviations (SDs) from the mean. In Step 3, the EDA signal data was portioned into 0.5-s windows and for each window, 12 features were generated (Table 2). These signal features were input into the Isolation Forest algorithm (Liu et al. 2008) to identify any anomalous data. The Isolation Forest algorithm method was successfully used by Subramanian et al. (2021) to process EDA signal data. In Step 4, a 16-point smooth median filter was applied to the signal to remove noise and smooth the data. Finally, in Step 5, a cutoff threshold with the interquartile range (IQR) was applied to the signal to remove any last outliers that were not detected in the previous steps. IQR was calculated as the difference between the upper quartile (Q3) and lower quartile (Q1) of the signal. Throughout the preprocessing pipeline, all removed data was replaced via linear interpolation. There were cases, at the ends of the signal, where linear interpolation could not be used on the missing data due to not falling between valid values. In these cases, backward/forward filling of the data, using the nearest value, was used after linear interpolation.*

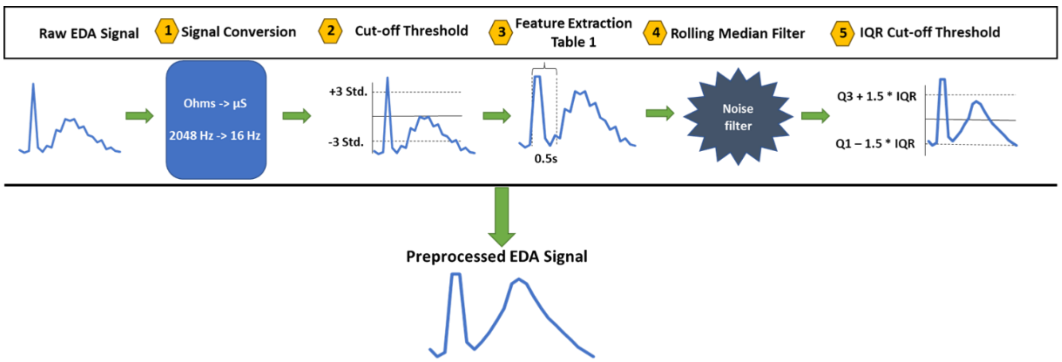

Figure 3. The five-step EDA signal preprocessing pipeline was developed in-house, removed outliers and anomalous data, and produced a clean and reasonable EDA signal.

Table 2. List of features used for the Isolation Forest algorithm (Subramanian et al. 2021) in Step 3 of the proposed processing pipeline.

Feature No.	Feature description
1	Range of the signal
2	SD of the signal
3	Mean of the first derivative
4	Median of the first derivative
5	SD of the first derivative
6	Min of the first derivative
7	Max of the first derivative
8	Mean of level 4 Haar wavelet coefficients
9	Median of level 4 Haar wavelet coefficients
10	SD of level 4 Haar wavelet coefficients
11	Min of level 4 Haar wavelet coefficients
12	Max of level 4 Haar wavelet coefficients

*Code for the correcting the signal and the processing pipeline can be found at https://github.com/trohaly/EDA_Processing_Pipeline

2.6 Aim 3: Decomposition Model Testing

To test the output of our processing pipeline, the resulting signal was run through both the cvxEDA and sparsEDA models. This allowed for a comparison between the tonic and phasic components between models, the processed signal, and with previous literature. For both models, we used the default settings for their parameters, even though that can vary estimates, to give an example of baseline performance of each model without having to tweak the model for each individual participant.

3. Results

3.1 Resistor Test

The corrective script was created using Python (version 3.11) and the outcome values were compared to the Ground Truth resistor values. Values had some deviance from the ground truth and this disparity appears to increase as resistance increases (Figure 4). Additionally, the ground truth values did not deviate from the resistor values, indicating that there were no hardware issues associated with recording of the EDA signal.

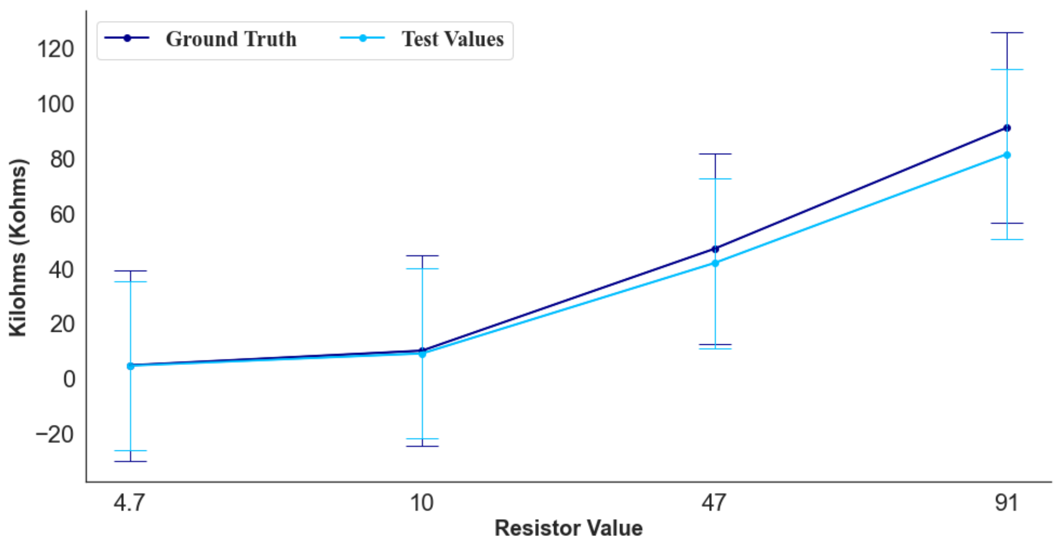

Figure 4. A comparison of test values to ground truth values across multiple different resistors

3.2 Preprocessing Pipeline

3.2.1 Overall Signal Quality

To assess the quality of the signal resulting from our pipeline, a comparison was made with the raw signal (Figure 5). Extreme peaks in the data were flagged in the signal and either reduced or removed entirely. For example, in Figure 5 (the region of interest shown in the inset), peaks were flagged (light blue signal), then removed and interpolated (dark blue signal). The interpolated signal in this example is shown to maintain the overall shape of the raw signal, but the amplitude is reduced. Additionally, when examining the amount of data lost cleaning the signal, it was found that an average of 16.4% (4:06 min, with a SD of 4.7% [1:11 min]) of data was removed from the signal. Given that participants took approximately 25 min to complete the visual search task, this means that an average 20 min and 54 s of data were considered usable.

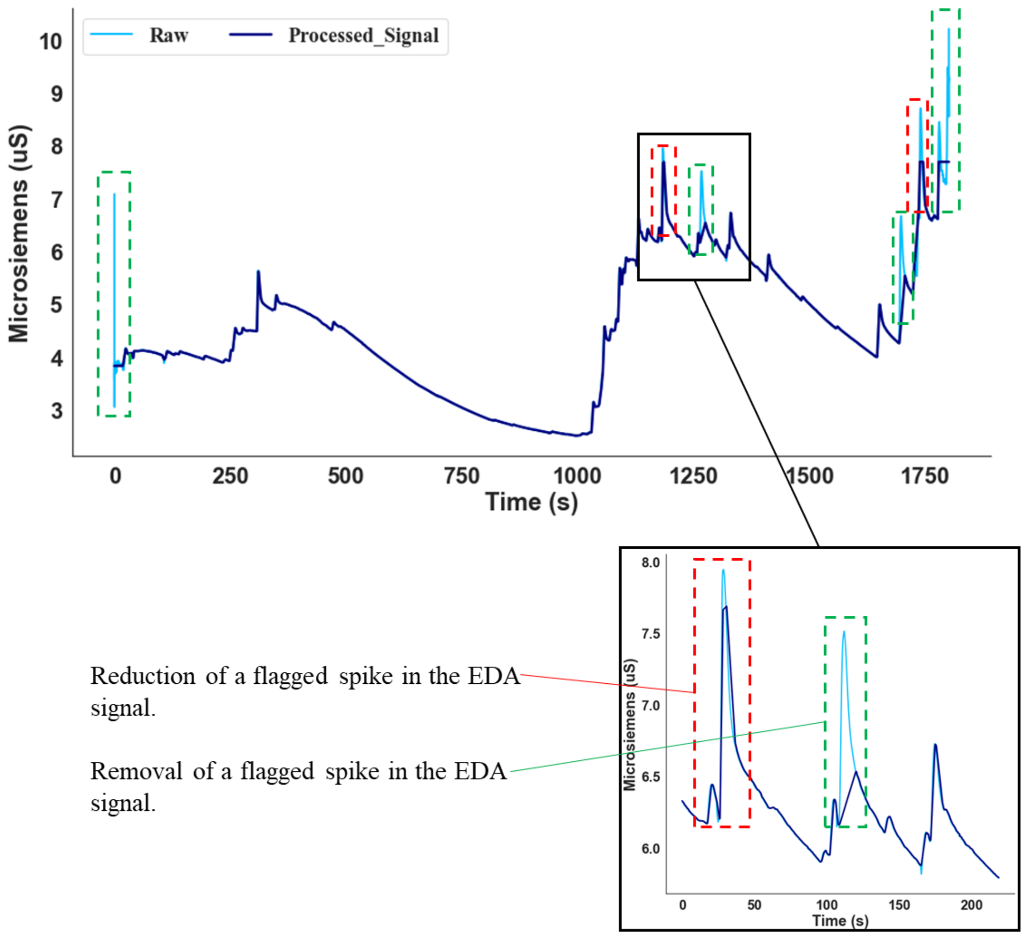

Figure 5. Comparison of an example raw EDA signal data over an entire run and the pipeline processed outcome signal to demonstrate the effectiveness of the pipeline removing artifacts. Red boxes indicate when a signal spike was reduced and green boxes indicate where a spike was removed.

3.2.2 Stimulus Event Signal Quality

One important consideration for the preprocessing pipeline is determining whether stimulus events within the signal, processed through the pipeline, could be preserved. One potential issue is that startling events could lead to artifacts in the data that obscure the actual physiological response. For example, flashbangs are sudden events that may cause an individual to both physiologically and physically react (i.e., jump scare). While it is possible that a strong EDA response occurred to that event, it is also possible that the physical response introduced noise resulting in an artifact. If the signal processing were too conservative, this event would be flagged as an erroneous movement instead of a valid EDA response (spike) and removed as an artifact. If the pipeline were too liberal, the opposite problem would occur, and signal artifacts could be preserved as a true physiological response. To ensure the processing pipeline did not erroneously filter this response data, graphs were generated for each stimulus event in the paradigm. Each graph was visually inspected and included a 12-s window of the EDA response data starting 2 s prior to the stimulus event and 10-s poststimulus event, a sufficient amount of time to allow for a response onset, rise time, and decay (e.g., Figure 6).

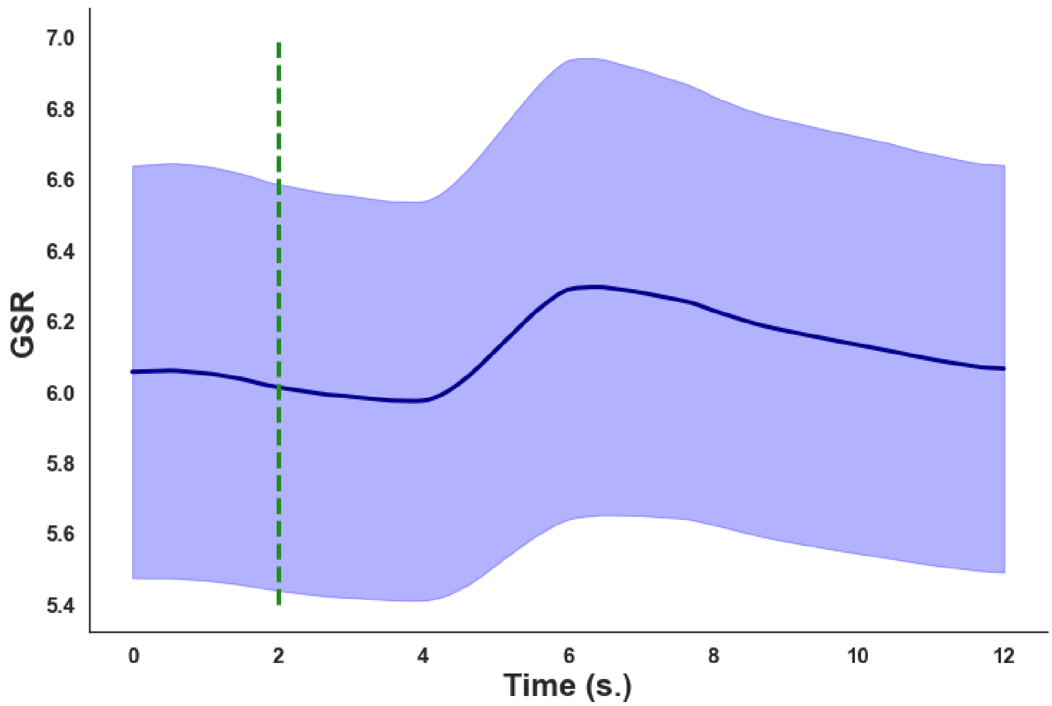

Figure 6. The average response of the first five stimulus events collapsed across six of the participants. The dark blue line represents the average response, the shaded-blue area represents the standard error of the response, and the vertical, green dashed line indicates event onset.

To assess any lack of a response to a given event, there were two methods employed. The first was grabbing a time window around the stimulus event onset and checking the percentage of data that was classified as bad in that window. We took a 10-s window around each event onset (5 s before and after onset) and checked the classifications to get a count of how many windows had over 20% data loss. In this sample, we found that about 3% of events across participants exceeded 20% data loss. The second method was to visualize the EDA signal alongside markers for both stimulus event onsets and data classified as bad (Figure 7).

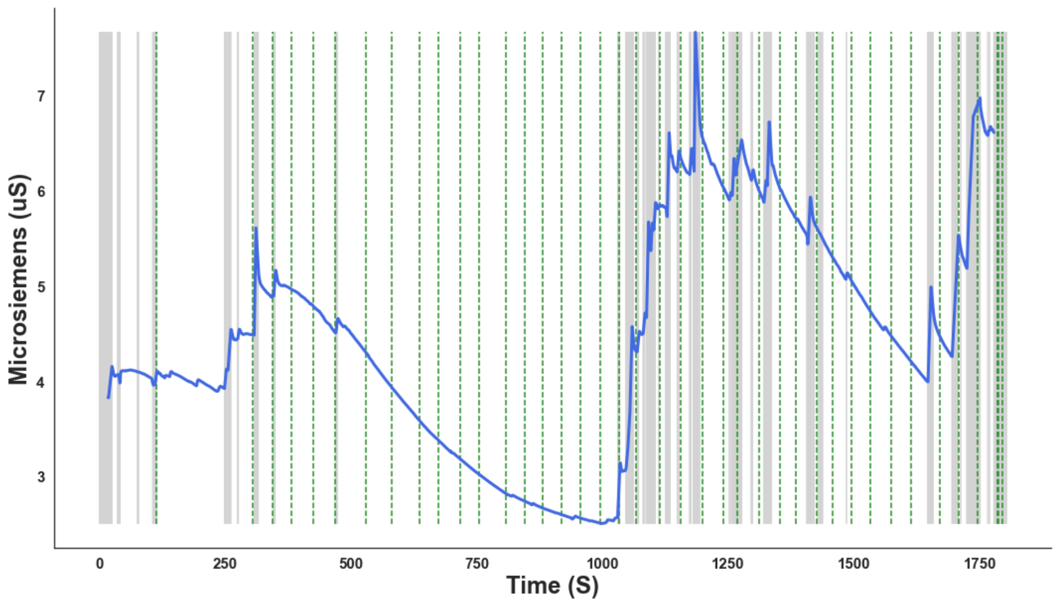

Figure 7. **An inspection of the signal in comparison to stimulus event onsets and data flagged as artifacts. The blue line represents the EDA signal. The vertical, dashed-green lines represent stimulus event onsets. The vertical, gray lines represent where data was removed and interpolated.**

3.3 Feature Extraction

Using the cvxEDA and sparsEDA models, the processed EDA signal was decomposed into its phasic and tonic components to validate the resulting input compared with that found in literature. Tonic components of each model were compared with each other and the original, processed signal (Figure 8A) and phasic components for each model were compared with each other (Figure 8B). Only a portion of the full run is shown (1000–1300 s from Figures 5 and 7) to give a more detailed view of the signal. Visual inspection of the decomposed signals shows that the computed tonic component for both models is a fair approximation of the overall shape of the original, processed signal. Additionally, while the phasic component also seems to be a fair approximation with both models, there are differences in the resulting component when comparing cvxEDA and sparsEDA with each other. Specifically, the cvxEDA model tends to have larger phasic peaks and less noise across the overall signal.

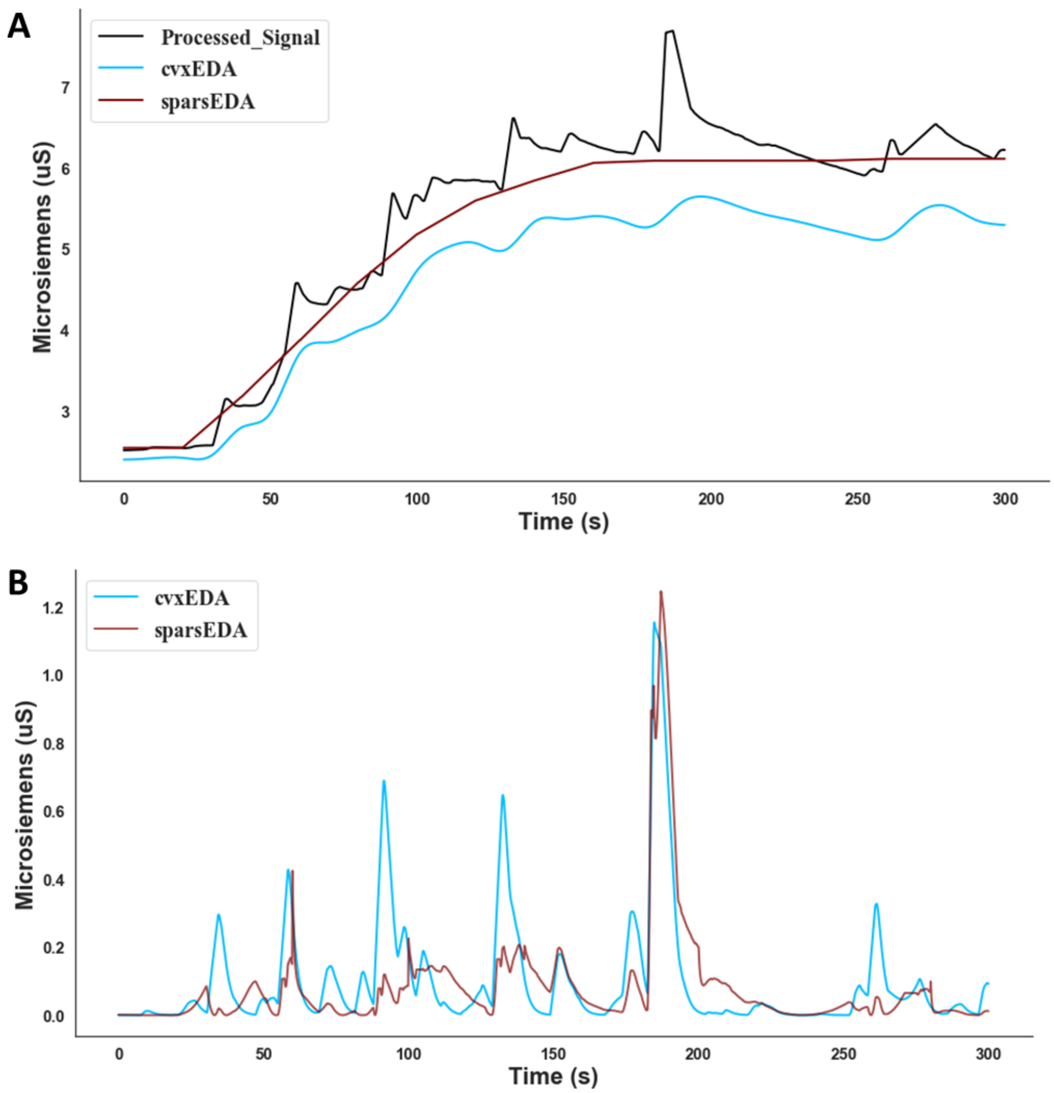

Figure 8. A comparison of cvxEDA and sparsEDA output to the original, processed data between the 1000 and 1300 s marks from Figures 5 and 7. A) comparison of the tonic components of the two models with each other as well as the original signal. cvxEDA tonic was linearly transformed by adding a constant (+4) to make comparison with other signals easier. B) comparison of phasic components between the two models.

4. Discussion

Overall, the corrective script to use with the LSL and preprocessing pipeline was successful in producing a usable and reliable EDA signal. Furthermore, we were able to successfully use two established EDA decomposition models (cvxEDA and sparsEDA) to extract tonic and phasic components, producing results comparable to those found in literature. This work was important for future in-house data collections for two reasons: 1) any study using LSL for the simultaneous collection of multiple data streams and collecting EDA signals via the BioSemi now has a solution for correcting the signal and preparing it for processing and analysis; and 2) regardless of the equipment used to record EDA signals, this work provides a general guide to others who may require an adaptation to the collection and processing pipeline for EDA signal analysis.

4.1 Development of Initial Processing for Data Streamed over LSL

The corrective script to duplicate the initial processing of ActiView and fix the issues with the BioSemi LSL app produced values comparable to Ground Truth resistors, with deviations within acceptable limits. One source of discrepancy likely lies with how the preprocessing is being calculated, giving slightly different results compared to the ground truth. Several other potential contributors to these deviations include 1) each resistor has a certain tolerance to account for fluctuation, 2) environmental noise introduced by nearby equipment, and 3) resistors tend to drift over time and with temperature changes. For our study, drift caused by temperature is assumed to be limited as the room was indoors and constant over the course of the resistor tests. Small amounts of time drift, however, could have been a factor as ground truth values were always recorded first and test values recorded second. Despite the small SDs (expected) noted, the resulting script applied all required filtering steps and produced a signal that was similar in resistance (kOhms) to the ground truth. Given these results, this filtering method should be usable in future studies to replicate EDA signals that are recorded on a BioSemi Active II and saved over LSL as if they were saved by the hardware's proprietary software.

A secondary reason for conducting this test was to ensure that the hardware was functioning properly. If the data recorded via Actiview did not approximately match the kOhms of any of the given resistors, then researchers could conclude that there may be some hardware issue that would interfere with data collection. Since these values were equitable, it can safely be assumed that the hardware was functioning properly and resulting signals from the device could be trusted.

4.2 Robust Development of Preprocessing Pipeline for EDA Signal Data

The preprocessing EDA signal pipeline developed in-house (Aim 2) for cleaning data produced reasonably clean output signals. In the example shown in Figure 2, it can be observed that the EDA preprocessing pipeline was successfully able to identify spikes in the signal and either reduce or remove them. The resulting signal from our pipeline is comparable to other examples in literature (e.g., Greco et al. 2016; Posada-Quintero and Chon 2020). These examples show a similar absolute range in the signal compared with the data recorded in this study along with equivalent phasic changes over time. Similar comparisons can be made when considering work that has focused on artifact removal (e.g., Taylor et al. 2015). Examples in literature show that only the most extreme values/patterns (e.g., spikes) tend to get labeled artifacts, though this is not true 100% of the time. Based on this comparison to previous literature, we argue that the output of our processing pipeline is comparable in terms of generating a signal that resembles EDA previously seen as well as flagging extreme artifacts. Additionally, our pipeline flagged, on average, had 16.4% data loss. As a comparison to this data, EDA and eye-tracking were collected in a different study in our laboratory (ARL 21-104), which measured these signals in four different trials of a similar paradigm that lasted ~5–7 min. Data loss across all participants and total trials for the eye-tracking signal was 10.36% (SD = 19.12%). Any participant (N = 3) with data loss over 50% had their eye-tracking removed from analysis. For EDA data from the ARL-21-104 study, average data loss across all participants and total trials was 20.73% (SD = 3.71%). Any participant (N = 3) with overall data loss over 30% was removed from the data. Their average data loss seems to be fairly consistent and does not seem to deviate too much from data loss from other physiological signals (i.e., eye-tracking). As mentioned previously, signal quality is dependent on lots of external factors such as study paradigm (e.g., stationary vs. mobile), temperature, dryness of the skin, and even sensor placement. The expected percentage of artifacts in the data can vary widely and expectations should be drawn based on a study-by-study basis. The core of our data-processing pipeline, the feature engineering and unsupervised learning method, has been previously established in literature as an effective means for identifying and removing artifacts (Subramanian et al. 2021). However, this could be a limitation in other applications, depending on study design. Although this droppage may be excessive for some paradigms that require stricter analysis needs, it is well within the reasonable expectations when collecting physiological signals. Furthermore, we would expect such droppage to be less with shorter paradigms, because this would also reduce chances of shifts in the lead placement itself.

When considering stimulus events in the paradigm, there are a few things to bear in mind. First, when considering a skin conductance response (SCR) to a stimulus, literature generally agrees that the SCR response occurs 1–3 s after stimulus onset, has a curved shape that is a steep incline followed by an exponential decay, and has a typical peak magnitude of anywhere from 0.01 to 1.0 μS (Dawson et al. 2007; Taylor et al. 2015; Shukla et al. 2018). Based on visual inspection of the data

(Figure 6), our processed SCR responses appear consistent with typical SCR responses found in literature (Dawson et al. 2007; Taylor et al. 2015; Shukla et al. 2018; Posada-Quintero and Chon 2020).

There were some stimulus events where there was no EDA response. This could be explained in several ways. First, because there were N = 38 stimulus events, participants may have habituated to the stimuli after repeated exposure, having a reduced or undetectable SCR response, especially later in the testing session. To inspect this further, we plotted the habituation by looking at the classification output to see if data was removed during the stimulus event (see Section 3.2.2. for how we implemented this). Another method of verifying habituation as a cause would be to plot early versus late responses to stimuli after ensuring that events used did not have data loss and comparing the resulting waveforms. Additionally, one could plot the EDA signal, stimulus event onsets, and data classified as artifacts to visually inspect which stimulus events co-occur with artifacts (Figure 7). Second, the participant's response resulted in an actual artifact (e.g., jerked their hand) and was flagged and subsequently appropriately removed from the data. Third, the participant had a normal SCR for the stimulus event, but it was erroneously flagged and removed. In the current and future work, the second and third ways could be reduced by building in data checks in the pipeline when such stimulus events are not responded to and checking the raw output and visually inspecting the signal segment in question. Other physiological measures (e.g., eye-tracking) could provide a more holistic picture of the individual's state, especially if collected in conjunction with EDA. Having several time-synced signals (via LSL) allow for redundancy while collecting data, where if one signal has an artifact at a particular time point, other signals may not. This would give researchers a more informed view of participant responses to the task and the presented stimulus events.

The goal of this preprocessing pipeline is to offer a standardized method for cleaning and formatting EDA signals for further analysis. Given the results of this study, specifically the examination of percentage of data loss, the impact of data cleaning on events, as well as the test of running the resulting signal through a phasic/tonic decomposition model, we conclude that the established five-step pipeline was fairly robust for preprocessing and cleaning EDA signal data in our current study (Aim 2 of our study). Future use of the pipeline, especially when collecting EDA signals via a BioSemi and streaming over LSL, is encouraged.

4.3 Model Comparison for EDA Signal Component Extraction

In Aim 3 of our study, we tested two different EDA decomposition models to verify that good estimations of tonic and phasic features could be pulled from data processed with the pipeline from Aim 2. While both decomposition models produced different phasic/tonic components, they both produced good representations of the original signal (Figure 8) and are also comparable to previous literature (Greco et al. 2016; Posada-Quintero and Chon 2020). When considering the tonic component of the models, there is the question of what an actual increase in an individual's baseline arousal is, and what is drift in the signal over time. Looking at Figure 8 over the 5-min segment of the run, the tonic component steadily rises before eventually plateauing. When looking at the entire signal as well (Figures 5 and 7), you can see several instances of the EDA signal rising and falling. Drift could be contributing to how much the signal rises or falls. In the current implementation of the processing pipeline, drift removal is not included and would need to be addressed independently. There are two things to note when considering this step in EDA data processing. First, both cvxEDA and sparsEDA have parameters that can be tweaked to better fit the data. However, in this study we used the default parameters to have a more automated pipeline in this study. If researchers wanted to take the time to adjust the model parameters for each participant, even better results could be achieved with the phasic/tonic decomposition. Second, while this test only focused on two models of EDA decomposition, there are other options to achieve this (e.g., Benedek and Kaernbach 2010a, 2010b), as well as other methods of analyzing EDA data that do not involve phasic/tonic decomposition (Posada-Quintero and Chon 2020).

4.4 Limitations

There are a couple of key limitations to this study, both pertaining to data collection methodology. First, the sample size is small. Care should be given before generalizing the results of the preprocessing pipeline to larger populations. Additionally, this sample was not controlled for potential confounding variables (e.g., age, medication use). It is possible that there are individual variables that are not evenly distributed across this sample and could have influenced results. Thus, further validation of this processing pipeline using larger samples that are controlled for multiple moderative variables, like age (Bari et al. 2020), is suggested.

Second, this paradigm did not explicitly vary the amount of noise found in the signal. For this study participants ran through the desktop visual search task, which is expected to produce fairly low levels of noise in the signal, compared with a more mobile paradigm, unless the participant is frequently moving their left hand (where EDA electrodes are placed). A further test of our preprocessing pipeline would be to test on multiple different tasks that vary in the amount of noise present in the signal. For example, a desktop-based task might be considered a low-level noise task, while a walking task would be considered a high-level noise task. There is currently no data to indicate how well our preprocessing will work on a signal with large amounts of noise.

Third, this pipeline does not currently account for electrode drift. Especially during longer recordings of EDA signals, it is expected that there will be some drift in the tonic component of the EDA signal, making it more difficult to attribute an increase in that component to overall arousal changes versus drift in the electrodes. Future work that uses this pipeline will want to include a process for removing drift from the signal before inputting that signal into a model.

Finally, while the models we tested with, sparsEDA and cvxEDA, are listed as being good options for processing EDA signals in real time (Posada-Quintero et al. 2016), there are other options and not all are based on tonic/phasic decomposition. For example, spectral analysis has been growing in popularity over recent years. This study did not test the efficacy of our pipeline's output with models beyond EDA decomposition. Some examples of other options that could be tested in future work include ML (e.g., Veeranki et al. 2021), deep learning (e.g., Machot et al. 2019), convolutional neural networks (e.g., Sánchez-Reolid et al. 2022), and biophysical modeling (e.g., Tronstad et al. 2022).

5. Conclusion

The main purposes of this study were to 1) develop a corrective script to fix signal errors caused by the BioSemi LSL app and replicate processing conducted in ActiView when recording EDA data, 2) establish an in-house standardized EDA signal-preprocessing pipeline, and 3) test the output of the preprocessing pipeline with phasic/tonic decomposition models to verify that the resulting signal resembles EDA phasic and tonic components from previous literature. The aims of this study were primarily applicable to our current and developing paradigms but could be applied to a broader audience or researchers who wish to quantify EDA signals in visual search paradigms. Given the results of this study, we make two conclusions/recommendations when analyzing EDA data. First, because the preprocessing pipeline performed well in this study, we recommend that future research consider using the same five-step preprocessing pipeline for cleaning their EDA signal data. While more testing is needed and there are other options for cleaning data, like other ML techniques or wavelet-based approaches, our pipeline is automated and simple to implement. Second, considering the results running our processed data through both sparsEDA and cvxEDA, the output from our preprocessing pipeline appears to clean data well enough to get good estimates of phasic and tonic features from the signal. The processing pipeline above provided a solution to apply necessary corrections and remove artifacts in an automated and standardized fashion for our EDA analysis. This was vital to interpret how stressful events impacted our EDA event responses in related, in-house research paradigms. The processing pipeline has external applications and can be adapted to broader applications of physiological signal processing, especially EDA data that is collected via BioSemi and LSL.

6. References

Abe Y, Nishizawa M. Electrical aspects of skin as a pathway to engineering skin devices. APL Bioeng. 2021;5(4):041509. https://doi.org/10.1063/5.0064529

Al Machot F, Elmachot A, Ali M, Al Machot E, Kyamakya K. A deep-learning model for subject-independent human emotion recognition using electrodermal activity sensors. Sensors (Basel). 2019;19(7):1659.

Babaei E, Tag B, Dingler T, Velloso E. A critique of electro-dermal activity practices at CHI. In: Kitamura Y, Quigley A, Isb-ister K, Igarashi T, Bjørn P, Drucker S, editors. CHI '21: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems. 2021 May 8–13; online. ACM; c2021. p. 1–14. https://doi.org/10.1145/3411764.3445370

Bari DS, Yacoob Aldosky HY, Martinsen ØG. Simultaneous measurement of electrodermal activity components correlated with age-related differences. J Biol Phys. 2020;46(2):177–188. https://doi.org/10.1007/s10867-020-09547-4

Benedek M, Kaernbach C. A continuous measure of phasic electrodermal activity. J Neurosci Methods. 2010a;190(1):80–91.

Benedek M, Kaernbach C. Decomposition of skin conductance data by means of nonnegative deconvolution. Psychophysiol. 2010b;47(4):647–658.

Bigdely-Shamlo N, Mullen T, Kothe C, Su K-M, Robbins KA. The PREP pipeline: standardized preprocessing for large-scale EEG analysis. Front Neuroinform. 2015;9. https://doi.org/10.3389/fninf.2015.00016

Boucsein W. Electrodermal activity. 2nd ed. Springer; 2012. https://doi.org/10.1007/978-1-4614-1126-0

Buckley S et al. Cognitive load impairs time to initiate and complete shooting tasks in ROTC members. Mil Med. 2022;187(7–8):e898–e905. https://doi.org/10.1093/milmed/usab276

Chérif L, Wood V, Marois A, Labonté K, Vachon F. Multitasking in the military: cognitive consequences and potential solutions. Appl Cogn Psychol. 2018;32(4):429–439. https://doi.org/10.1002/acp.3415

Christopoulos GI, Uy MA, Yap WJ. The body and the brain: measuring skin conductance responses to understand the emotional experience. Organ Res Methods. 2019;22(1):394–420. https://doi.org/10.1177/1094428116681073

Dawson ME, Schell AM, Filion DL, Berntson GG. The electrodermal system. In: Cacioppo JT, Tassinary LG, Berntson G, editors. Handbook of

Psychophysiology. 3rd ed. Cambridge University Press; 2007. p. 157–181. https://doi.org/10.1017/CBO9780511546396.007

[DOA] Headquarters, Department of the Army. Advanced situational awareness. Headquarters, Department of the Army (US); 2021 Apr. Training Circular TC 3-22.69. https://armypubs.army.mil/epubs/DR_pubs/DR_a/ARN34875-TC_3-22.69-000-WEB-1.pdf

Enders LR et al. Evidence of elevated situational awareness for active duty soldiers during navigation of a virtual environment. PLoS One. 2024;19(5):e0298867. https://doi.org/10.1371/journal.pone.0298867

Enders LR et al. Impacts of posttraumatic stress disorder on eye-movement during visual search in an open virtual environment under high and low stress conditions. J Vis. 2023;9:5691.

Endsley MR, Garland DJ, Wampler RL, Matthews MD. Modeling and measuring situation awareness in the infantry operational environment. Army Research Institute for the Behavioral and Social Sciences (US); 2000 Jan. Report No.: 1753. https://doi.org/10.21236/ADA372709

Eric42. Accessing GSR data using C code. BioSemi support forum; 2014 Feb 17 [accessed 2023 Sep 20]. https://www.biosemi.nl/forum/viewtopic.php?t=808

Fish RM, Geddes LA. Conduction of electrical current to and through the human body: a review. Eplasty. 2009;9:e44.

Gramlich MA et al. Psychophysiology during exposure to trauma memories: comparative effects of virtual reality and imaginal exposure for posttraumatic stress disorder. Depress Anxiety. 2021;38(6):626–638. https://doi.org/10.1002/da.23141

Greco A, Valenza G, Citi L, Scilingo EP. Arousal and valence recognition of affective sounds based on electrodermal activity. IEEE Sens J. 2017;17(3):716–725. https://doi.org/10.1109/JSEN.2016.2623677

Greco A, Valenza G, Lanata A, Scilingo E, Citi L. cvxEDA: a convex optimization approach to electrodermal activity processing. IEEE Trans Biomed Eng. 2016;63(4):797–804. https://doi.org/10.1109/TBME.2015.2474131

Han HJ, Labbaf S, Borelli JL, Dutt N, Rahmani AM. Objective stress monitoring based on wearable sensors in everyday settings. J Med Eng Techno. 2020;44(4):177–189. https://doi.org/10.1080/03091902.2020.1759707

Hernando-Gallego F, Luengo D, Artes-Rodriguez A. Feature extraction of galvanic skin responses by nonnegative sparse deconvolution. IEEE J Biomed Health. 2018;22(5):1385–1394. https://doi.org/10.1109/JBHI.2017.2780252

Kerick SE, Allender LE. Effects of cognitive workload on decision accuracy, shooting performance, and cortical activity of soldiers. Proceedings for the 24th Army Science Conference; 2004; Orlando, FL.

Kleckner IR et al. Simple, transparent, and flexible automated quality assessment procedures for ambulatory electrodermal activity data. IEEE Trans Biomed Eng. 2018;65(7):1460–1467. https://doi.org/10.1109/TBME.2017.2758643

Kothe C. Lab Streaming Layer (LSL) - a software framework for synchronizing a large array of data collection and stimulation devices. 2014 [accessed 2021]. https://github.com/sccn/labstreaminglayer

Kurniawan H, Maslov AV, Pechenizkiy M. Stress detection from speech and galvanic skin response signals. Proceedings of the 26th IEEE International Symposium on Computer-Based Medical Systems; 2013 June 20–22; Porto, Portugal. IEEE; c2013. p. 209–214. https://doi.org/10.1109/CBMS.2013.6627790

Liu FT, Ting KM, Zhou Z-H. Isolation Forest. Proceedings of the 2008 Eighth IEEE International Conference on Data Mining (ICDM); 2008 Dec 15–19; Pisa, Italy. IEEE; c2008.

Momin A, Sanyal S. Analysis of electrodermal activity signal collected during visual attention oriented tasks. IEEE Access. 2019;7:88186–88195. https://doi.org/10.1109/ACCESS.2019.2925933

Naveteur J, Buisine S, Gruzelier JH. The influence of anxiety on electrodermal responses to distractors. Int J Psychophysiol. 2005;56(3):261–269. https://doi.org/10.1016/j.ijpsycho.2004.12.006

Pinna GD et al. Heart rate variability measures: a fresh look at reliability. Clin Sci (Lond). 2007;113(3):131–140. https://doi.org/10.1042/CS20070055

Posada-Quintero HF et al. Power spectral density analysis of electrodermal activity for sympathetic function assessment. Ann Biomed Eng. 2016;44(10):3124–3135. https://doi.org/10.1007/s10439-016-1606-6

Posada-Quintero HF, Bolkhovsky JB. Machine learning models for the identification of cognitive tasks using autonomic reactions from heart rate variability and electrodermal activity. Behav Sci (Basel). 2019;9(4):45. https://doi.org/10.3390/bs9040045

Posada-Quintero HF, Chon KH. Innovations in electrodermal activity data collection and signal processing: a systematic review. Sensors (Basel). 2020;20(2):479. https://doi.org/10.3390/s20020479

Posada-Quintero HF. Electrodermal activity: what it can contribute to the assessment of the autonomic nervous system [dissertation]. University of Connecticut; 2016.

Rao Veeranki Y, Ganapathy N, Swaminathan R. Electrodermal activity based emotion recognition using time-frequency methods and machine learning algorithms. Curr Dir Biomed Eng. 2021;7(2):863–866. https://doi.org/10.1515/cdbme-2021-2220

Roy H et al. Posttraumatic stress disorder and differences in eye gaze during a visual search task with cognitive load. Proceedings of the Annual Meeting of the Cognitive Science Society. 2022 July; Toronto, Canada. 44:2094-2100).

Salas E, Prince C, Baker DP, Shrestha L. Situation awareness in team performance: implications for measurement and training. Hum Factors. 1995;37(1):123–136. https://doi.org/10.1518/001872095779049525

Salmon P, Stanton N, Walker G, Green, D. Situation awareness measurement: a review of applicability for C4i environments. Appl Ergon. 2006;37(2):225–238. https://doi.org/10.1016/j.apergo.2005.02.001

Sánchez-Reolid R, López De La Rosa F, López MT, Fernández-Caballero A. One-dimensional convolutional neural networks for low/high arousal classification from electrodermal activity. Biomed Signal Process Control. 2022;71:103203. https://doi.org/10.1016/j.bspc.2021.103203

Sánchez-Reolid R, Martínez-Rodrigo A, Fernández-Caballero A. Stress identification from electrodermal activity by support vector machines. In: Ferrández Vicente JM, Álvarez-Sánchez JR, De La Paz López F, Toledo Moreo J, Adeli H, editors. Understanding the brain function and emotions. Vol. 11486. Springer; 2019. https://doi.org/10.1007/978-3-030-19591-5_21

Sandercock GRH, Bromley PD, Brodie DA. The reliability of short-term measurements of heart rate variability. Int J Cardiol. 2005;103(3):238–247. https://doi.org/10.1016/j.ijcard.2004.09.013

Scribner DR, Wiley PH, Harper WH, Kelley TD. The effects of workload presented via visual and auditory displays on Soldier shooting and secondary task performance. Army Research Laboratory (US); 2007. Report No.: ARL-TR-4224.

Shi Y, Ruiz N, Taib R, Choi E, Chen F. Galvanic skin response (GSR) as an index of cognitive load. CHI EA '07: Extended Abstracts on Human Factors in Computing Systems. 2007 Apr 28–May 3; San Jose, CA. ACM; c2007. p. 2651–2656. https://doi.org/10.1145/1240866.1241057

Shukla J, Barreda-Ángeles M, Oliver J, Puig D. Efficient wavelet-based artifact removal for electrodermal activity in real-world applications. Biomed Signal Process Control. 2018;42:45–52. https://doi.org/10.1016/j.bspc.2018.01.009

Smith CD et al. Sleep restriction and cognitive load affect performance on a simulated marksmanship task. J Sleep Res. 2019;28(3):e12637. https://doi.org/10.1111/jsr.12637

Strater LD, Jones D, Endsley MR. Analysis of infantry situation awareness training requirements. Army Research Institute for the Behavioral and Social Sciences (US). 2001 Nov. Report No.: Technical Report 1123.

Stržinar Ž et al. Stress detection using frequency spectrum analysis of wrist-measured electrodermal activity. Sensors (Basel). 2023;23(2):963. https://doi.org/10.3390/s23020963

Subramanian S. Tseng B, Barbieri R, Brown EN. Unsupervised machine learning methods for artifact removal in electrodermal activity. 2021 43rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2021 Nov 1–5; Mexico. IEEE; c2021. p. 399–402. https://doi.org/10.1109/EMBC46164.2021.9630535

Sunny JS et al. Anomaly detection framework for wearables data: a perspective review on data concepts, data analysis algorithms and prospects. Sensors (Basel). 2022;22(3):756. https://doi.org/10.3390/s22030756

Taylor S et al. Automatic identification of artifacts in electrodermal activity data. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2015 Aug 25–29; Milan, Italy. IEEE; c2015. p. 1934–1937. https://doi.org/10.1109/EMBC.2015.7318762

Touryan J et al. UETack: software tools for multiplayer experimentation using the unreal engine. DEVCOM Army Research Laboratory (US); 2023. Report No.: ARL-TR-9646.

Tronstad C, Amini M, Bach DR, Martinsen ØG. Current trends and opportunities in the methodology of electrodermal activity measurement. Physiol Meas. 2022;43(2):02TR01. https://doi.org/10.1088/1361-6579/ac5007

Unreal Engine. Epic Games. c2024. https://www.unrealengine.com van der Mee DJ, Gevonden MJ, Westerink JHDM, de Geus EJC. Validity of electrodermal activity-based measures of sympathetic nervous system activity from a wrist-worn device. Int J Psychophysiol. 2021;168:52–64. https://doi.org/10.1016/j.ijpsycho.2021.08.003

Zhang Y, Haghdan M, Xu KS. Unsupervised motion artifact detection in wrist-measured electrodermal activity data. ISWC ’17: Proceedings of the 2017 ACM International Symposium on Wearable Computers; 2017 Sep 11–15; Maui, HA. ACM; c2017. p. 54–57. https://doi.org/10.1145/3123021.3123054

List of Symbols, Abbreviations, and Acronyms

ANS	autonomic nervous system
CDA	Continuous Decomposition Analysis
DDA	Discrete Decomposition Analysis
EDA	electrodermal activity
EEG	electroencephalography
HRV	heart rate variability
IQR	interquartile range
LSL	lab streaming layer
SA	situational awareness
SCR	skin conductance response
SD	standard deviation
VE	virtual environment

1 (PDF)	DEFENSE TECHNICAL INFORMATION CTR DTIC OCA
1 (PDF)	DEVCOM ARL FCDD RLB CI TECH LIB