# 21 Electrodermal Activity: Applications and Challenges

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**Abstract**

Electrodermal activity (EDA) is a conductance measure that can be used to assess the sympathetic nervous system arousal and for the diagnosis of stress, pain, sleepiness, seizure prediction, neuropathies, depression, and other states. EDA has potential for ambulatory research applications, as it can be collected using wearable devices, but motion artifacts are an issue. While EDA was discovered in 1879 by Vigouroux, the signal was traditionally observed in most of the studies as the mean value of the signal in response to a given stimulus, which provides static information but does not account for time-varying dynamics of the signal. The new technologies for EDA collection and the development of novel and robust signal processing algorithms have increased the interest in EDA for many new and emerging fields, including affective computing, seizure prediction, and pain monitoring. We aim to summarize the characteristics of EDA, describe current and future applications, and outline challenges when using EDA.

**Keywords: Electrodermal Activity, Physiomarkers, Motion Artifact Detection, Pain Detection, Stress and Emotion Detection, Wearable Devices and Ambulatory Monitoring, Seizure Detection and Prediction**

## Introduction

Electrodermal activity (EDA) refers to changes in the capacity of the skin to conduct electrical current resulting from the amount of sweat produced by the sweat glands. Originally discovered by Vigouroux in 1879, scientists have called it different names through history, such as galvanic skin response, skin conductance, and skin resistance. Given the relatively recent interest in EDA for biological applications, attempts to standardize the terminology and the techniques for collecting and processing the signals have been made, and EDA is currently more widely accepted (Boucsein et al., 2012).

Since its discovery, EDA has been primarily used in psychophysiological research, and most researchers have used EDA to measure the body's autonomic response to emotional and cognitive stimuli. However, given that sweat glands are controlled directly and uniquely by the sympathetic nervous system, EDA can be

used as an indication of both psychological responses and general sympathetic arousal. Furthermore, in a similar fashion to photoplethysmography, accelerometry, and skin temperature, EDA is feasible for deployment in wearable sensors. Its direct link to sympathetic arousal and its ease of collection make EDA a feasible sensor for a wide range conditions, including stress, pain, sleepiness, exercise recovery, epilepsy, neuropathies, and depression. It can also be deployed in currently hot fields like affective computing, marketing, human–computer interaction, and social-media analysis.

Advances in smart wearable devices, novel signal processing of EDA data, and the recent popularity of machine learning have been the main drivers of new insights and some impressive diagnostic capabilities in the above-mentioned applications. Hence, in this chapter we will discuss the morphology of EDA signals, popular EDA indices used as physio-markers, challenges in EDA signal processing (e.g., motion artifact detection), various applications of EDA signals in real life and clinical settings, wearable implementations, and smartphone applications for data collection and analysis. Some limitations and challenges of EDA interpretations will also be discussed.

Technically speaking, EDA refers to the variation in the electrical properties of the skin. Sweat gland activities are modulated by sympathetic stimuli (i.e., stress, pain, and emotional behavior), and the changes are captured in the EDA signal (Sato et al., 1989). As sodium and chloride (major components in sweat) are the most abundant electrolytes, they are responsible for increased conductance of the skin by creating low-resistance parallel paths along the skin surface (Poh, Loddenkemper, Swenson, et al., 2010; Sato et al., 1989). There have been multiple theories about how the sweat glands are innervated. Although it was initially thought that both the sympathetic and parasympathetic nervous systems contribute to innervating sweat glands (Boucsein, 2012), subsequent research confirmed that only the sympathetic nervous system innervates the sweat glands. Thus, sympathetic arousal due to emotion, cognition, and attention can be measured by variations in the EDA signal; they reflect the modulation of the sympathetic nervous system.

Due to their indication of the modulation of sympathetic activities, EDA measurements have been applied extensively in psychological applications such as stress detection (Gjoreski et al., 2016; Healey et al., 2010; Hernandez et al., 2011; Momin et al., 2020; Setz et al., 2010), autism examination (Prince et al., 2017; Schupak et al., 2016), panic disorder studies (Wendt et al., 2008), detection of depression (A. Y. Kim et al., 2018), and recognition of emotional states (Jang et al., 2015; Jaques et al., 2015). Diverse medical studies using EDA have included sleep monitoring (H. Kim et al., 2021; Romine et al., 2019; Sano et al., 2014), objective measurement of pain (Kong et al., 2020, 2021b, 2021a; Posada-Quintero et al., 2020; Posada-Quintero, Kong, & Chon, 2021; Sugimine et al., 2020; Susam et al., 2018), and hypoglycemia detection in diabetes (Elvebakk et al., 2018), as well as neurological applications such as seizure detection (Poh et al., 2012; Poh, Loddenkemper, & Swenson, 2010; Posada-Quintero et al., 2022), attention-deficit hyperactivity disorder (ADHD) studies (Beauchaine et al., 2015; Dupuy et al., 2014; von Polier et al., 2014), and dementia monitoring (Melander et al., 2018; Perugia et al., 2017).

## EDA Data Collection

Typically, the EDA signal is recorded using two main approaches: (1) the exosomatic method, in which a constant current or voltage is applied between two electrodes and the corresponding variation in electrical conductance is measured over time; and (2) the endosomatic approach, in which an AC voltage or current source replaces the DC voltage/current source. However, because of the simplicity of their circuit implementation, DC-source devices are generally the most popular for EDA data collection. In addition, EDA data can be collected using both wired and wireless wearable sensors, as shown in Figure 21.1. In both cases, a pair of electrodes is placed on the middle and index fingers, typically, or on the wrist. Some studies reported a low correlation of wrist EDA with finger EDA; the latter is regarded as the gold standard since there are more sweat glands on the fingers.

Two types of electrodes are widely used for EDA data collection: dry stainless steel electrodes and wet (gel) Ag/AgCl electrodes. While gel electrodes offer better sensitivity and good signal quality, they are also not feasible for long-term monitoring since the gel may degrade, get detached, or cause skin irritation. Dry electrodes, on the other hand, depend on sufficient sweat and may require a longer time to capture the signal (hydration time), especially in cold and dry conditions. The easiest

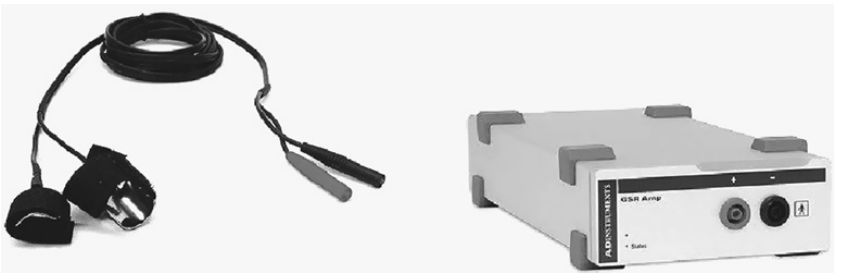


**Figure 21.1a** *EDA data collection setup for laboratory environment. (Images obtained from ADInstruments.)*

**Figure 21.1b** *Examples of wearable EDA devices. (Images obtained from Shimmer and embracePLUS.)*

way to check the quality of the EDA signal is by providing a momentary stimulus such as a deep breath and observing the corresponding change in EDA. In an ideal scenario, there should be a rise in the EDA signal corresponding to the initiation of the stimulus. In most EDA studies, baseline data is recorded for a few minutes in the beginning. During the baseline, the subjects are instructed to rest without talking. Since caffeine or any other stimulant may affect the sympathetic activities, it is often recommended that the subjects do not consume any caffeine at least 24 hours before the experiment.

Another crucial factor for EDA data collection is the electrode placement site (Hossain, Kong, et al., 2022). Because of high sweat gland density, palms and fingers are usually the primary site for EDA data collection (Frewin & Downey, 1976; Harker, 2013; Saga, 2002). However, as some applications may rule out using palmer sites or fingers, alternative sites such as the foot, forehead, wrists, and lower calves are proposed in many research papers (Hossain, Kong, et al., 2022; Kasos et al., 2018, 2020; van Dooren et al., 2012). However, when considering alternative sites for EDA data collection, hydration time (i.e., conduction time) should be considered, as some of the sites have fewer sweat pores (Hossain, Kong, et al., 2022; Kasos et al., 2020).

## Basic EDA Morphology

A raw EDA signal, plotted as amplitude versus time, is often characterized by oscillatory transient events, also known as skin conductance responses (SCRs). These SCRs are of two types: (1) event-related SCRs that are used to capture the response to some given external stimuli, and (2) nonspecific SCRs that are due to changes in the phasic signal not related to any stimuli (Theodoros, 2014). Figure 21.2 shows a typical SCR with time-based quantitative measures.

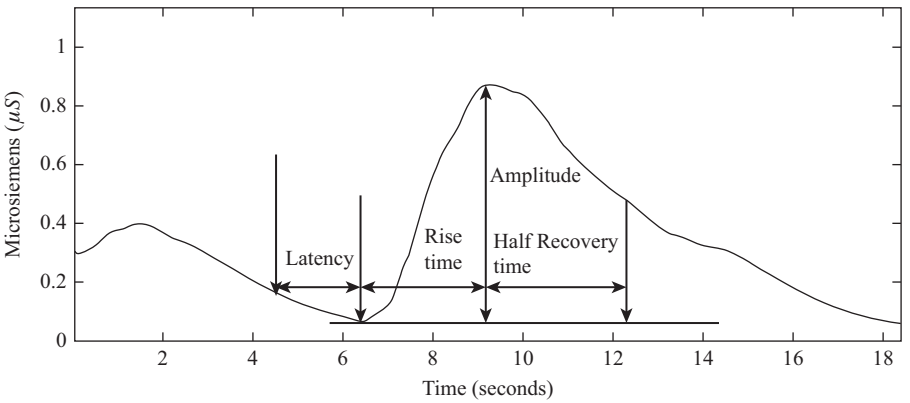


**Figure 21.2** *Morphology of typical skin conductance response (SCR).*

An ideal event-related SCR starts with a given stimulus that initiates the response in the EDA signal. The time interval between the stimulus being applied and the beginning of the SCR peak is regarded as the latency and ranges between 1 and 3 seconds (Boucsein, 2012). The amplitude of SCRs can reach several $\mu S$, and a minimum threshold of 0.05 or 0.04 is set to identify event-related or significant SCRs (Boucsein, 2012; Posada-Quintero & Chon, 2020). The time between the onset of an SCR and the peak is termed the rise time and typically ranges between 0.5 and 5 s (Theodoros, 2014). The amplitude and the rise time may vary depending on the type of stimulus being provided (Posada-Quintero & Chon, 2020). Soon after the peak, there is a slow and exponential decay in the amplitude until the phasic signal value reaches the baseline. The time interval needed for 50% decay of the peak amplitude is regarded as the half recovery time (as shown in Figure 21.2.). Typically, the half recovery period may vary between 2 and 10 s depending on the experimental conditions, such as electrode placement and the environmental temperature (Boucsein, 2012; Posada-Quintero & Chon, 2020), since EDA response can vary slightly depending on the surrounding temperature and sweat gland density of the recording site.

## EDA Signal Processing

Typically, EDA signals are decomposed into two major components. In addition to the skin conductance responses just discussed, consisting of rapid and transient events in the EDA signal that represent the dynamics of the sympathetic stimuli, there is also the skin conductance level (SCL) – the slow and smooth overall trend in the EDA signal that represents the response to tonic stimuli. The baseline value of the SCL varies within and between different individuals (Braithwaite et al., n.d.); this is why SCL is not typically used for analysis (Boucsein, 2012; Topoglu et al., 2020). However, changes in normalized skin conductance level (nSCL) can be an important indicator of the intensity of sympathetic stimuli (Munsters et al., 2012).

There are several different approaches for decomposing EDA into phasic and tonic components (see Figure 21.3). The most popular approaches include continuous and discrete decomposition analysis (Boucsein, 2012), dynamic causal modeling (Bach et al., 2011), convex optimization (CvxEDA; Greco et al., 2016), and sparse deconvolution (sparsEDA; Hernando-Gallego et al., 2018). CvxEDA models the EDA signal as the sum of three components – phasic, tonic, and additive noise. CvxEDA then uses Bayesian statistics and the convex optimization technique to obtain the phasic and the tonic components from the noisy observation data by minimizing the error. SparsEDA models the phasic component (the skin conductance response: SCR) as a standard linear convolution between a sudomotor sympathetic nervous system innervation and the response triggered by that driver. SparsEDA is known to be a computationally fast and easily interpreted method. Both cvxEDA and SparsEDA decomposition methods are open source and available online (cvxEDA, SparsEDA).

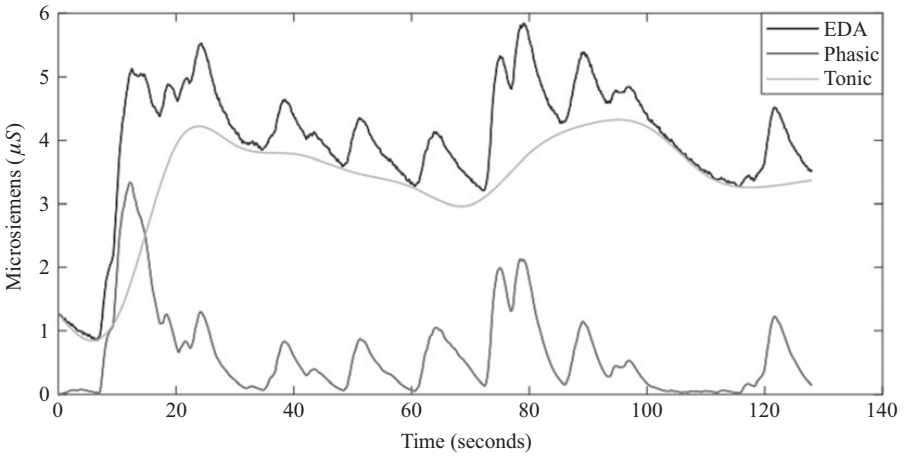


**Figure 21.3** *Decomposition of EDA into tonic and phasic components.*

## EDA Physiomarkers

There have been several EDA indices developed by researchers for different applications. These EDA indices can be broadly classified into time domain and frequency domain measures. Most EDA indices are based on the phasic and tonic decomposition of EDA in the time domain, as mentioned earlier. The time domain EDA indices include amplitudes, number of SCRs, rise time, and falling time. Moreover, a number of statistical features such as mean and median values of EDA, approximate entropy, and sample entropy are calculated from either the raw EDA signal or the phasic component calculated from the EDA signal. In addition, a number of automated sympathetic arousal tracking methods, such as the sparse decomposition approach with physiological priors (Amin & Faghih, 2021; Amin & Faghih, 2022) and marked process filtering (Wickramasuriya & Faghih, 2020), have been developed by researchers.

There have been several research projects on frequency domain and time-frequency domain EDA indices. Most of the spectral analyses of EDA have been developed recently and were motivated by spectral analyses of the heart rate variability (HRV). The high frequency content of HRV – the parasympathetic activity – typically resides in the frequency band 0.15 to 0.4 Hz. The low frequency content – in the frequency band 0.04 to 0.15 Hz – represents both sympathetic and parasympathetic activities. In the presence of different stressors, the spectral power of EDA lies in a similar frequency band as the low frequency components in HRV (Posada-Quintero et al., 2016). Based on this observation, a sensitive index, named EDASymp, was proposed by Posada-Quintero et al. (2016).

## Detection and Correction of Motion Artifacts

Despite its popularity, EDA is often affected by severe noise and motion artifacts (MA), especially when data collection involves wearable devices or is in a non-controlled setting (Boucsein, 2012). The sources of noise and motion artifacts include unstable electrode contact (Boucsein, 2012; Healey et al., 2010), environmental temperature and humidity (Boucsein, 2012; Shaffer et al., 2016), and the subject's activities (Boucsein, 2012; Kleckner et al., 2018; Zhang et al., 2017). All these factors corrupt EDA signals, thereby leading to unusable data. Typically, motion artifacts are detected using accelerometers or simple algorithms, and those corrupted portions of data segments are discarded (Posada-Quintero & Chon, 2020). There have been significant efforts toward automatic detection of motion artifacts in EDA signals. They can be broadly classified as simple rules-based (Kleckner et al., 2018) and machine-learning-based methods (Hossain, Posada-Quintero, Kong, McNaboe, & Chon, 2022; Subramanian et al., 2021; Taylor et al., 2015; Xia et al., 2015; Zhang et al., 2017). While detecting and discarding MA-corrupted data is one option, it is not always the best solution, especially when most of the data are needed. In this case, recovering a clean EDA signal from the MA-corrupted segments would be more beneficial. Unfortunately, there is little research on this topic.

Since manual handling of motion artifacts is time-consuming and inefficient, several automatic motion artifact algorithms have been developed. An automated quality assessment for EDA signals was proposed by Kleckner et al. (2018) in which the authors identified noisy EDA data based on some simple rules such as EDA out of range, EDA values changing too quickly, or thermocouples indicating that an EDA electrode was not making good contact. This method works well when there are large amplitude spikes or obvious discernible motion artifacts. Several machine-learning-based algorithms were proposed for automatic MA detection in EDA in recent years (Subramanian et al., 2021; Taylor et al., 2015; Zhang et al., 2017). Machine learning methods use different statistical features such as the mean, median, and standard deviation derivatives, maxima and minima of EDA, and spectral features calculated using wavelet transforms to assess the data quality.

The performance of machine learning methods is largely dependent on accurate labeling of EDA (e.g., clean or corrupted); this can be complicated given the aperiodic nature of EDA signals. To overcome this limitation, a reference EDA signal was suggested for accurate modeling of the EDA signal (Hossain et al., 2021; Hossain, Posada-Quintero, Kong, McNaboe, & Chon, 2022). In our recent studies, we collected reference EDA signals and used them as a supporting tool when labeling the EDA signal (Hossain et al., 2021; Hossain, Kong, Posada-Quintero, & Chon, 2022; Hossain, Posada-Quintero, Kong, McNaboe, & Chon, 2022). Independent validation on an unseen data set was performed to test the generalizability of the method. Figure 21.4 shows one example of MA detection in an EDA signal using the machine learning method (Hossain, Posada-Quintero, Kong, McNaboe, & Chon, 2022). However, this approach requires an additional EDA sensor on a different and more stable body location that is not optimal for practical implementation.

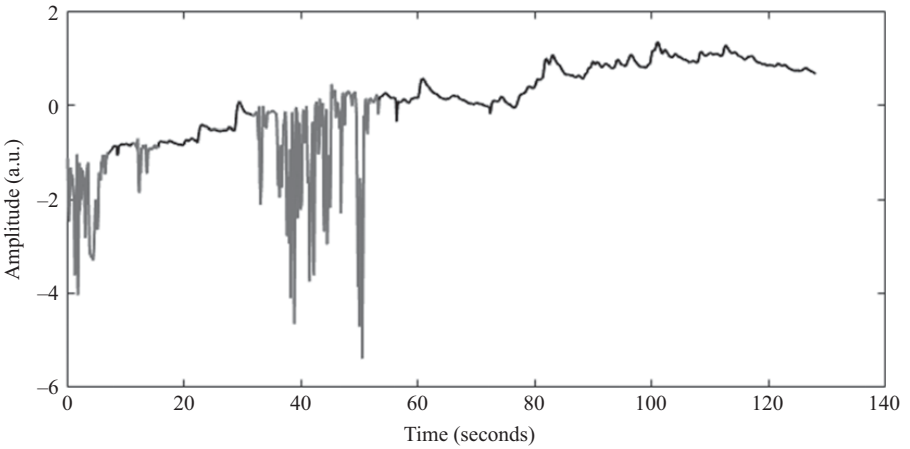


**Figure 21.4** *Motion artifact detection in EDA using machine learning method. (The B&W marked portion represents motion artifact.)*

MA detection algorithms can be of great value, especially when handling long-term EDA recordings. However, in the case of short-duration collection or limited data, it is often desirable to recover moderately MA-affected EDA data. Fortunately, automated algorithms for EDA reconstruction can recover a considerable amount of data. There are several notable automated motion artifact correction algorithms developed in recent years. Chen et al. (2015) proposed an automatic motion artifact removal technique based on the wavelet transform, in which the authors decomposed the EDA segments using the stationary wavelet transform (SWT). This approach involved modeling each wavelet coefficient using the Gaussian mixture model (GMM), computing an automated threshold using the cumulative distribution of GMM to mask the MA components in each wavelet coefficient, and finally using the inverse SWT to reconstruct a clean EDA. This method works well when the MA-corrupted data segments are relatively small and MA-corrupted values have significantly higher amplitudes than the clean signal.

The other approaches (Llanes-Jurado et al., 2021; Subramanian et al., 2021, 2022) use motion artifact detection first, remove the motion artifacts, and use linear/non-linear interpolation to replace the corrupted data portions. The main disadvantage of these methods is that they only work well when MA-corrupted segments are only a small portion of the signal. Moreover, the interpolation procedure used for replacing the MA-corrupted segments is not advisable for relatively longer artifact segments, as the linearity assumption becomes invalid.

Given the availability of large data sets and the ever-growing efficiency of computational processing, it is timely to apply advanced deep learning methods for automatic reconstruction of EDA segments corrupted with MA. In our most recent work (Hossain, Posada-Quintero, & Chon, 2022a; Hossain, Posada-Quintero, & Chon, 2022b), a deep convolutional denoising autoencoder (DCAE) has been used to automatically remove motion artifacts from EDA signals. The application of this

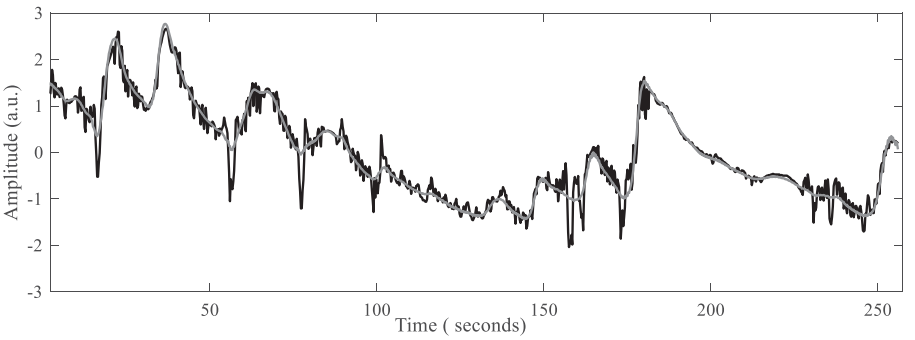


**Figure 21.5** *DCAE reconstruction of EDA signal B&W from MA-corrupted data (black).*

denoising autoencoder has led to impressive reconstruction performance on EDA signals. A denoising autoencoder is one of the state-of-the-art MA removal techniques widely used in different applications such as signal reconstruction (Vincent et al., 2010), dimensionality reduction (Wang et al., 2016), and biomedical signal denoising and classification (Chiang et al., 2019; Feng et al., 2014; Lee et al., 2019; Li et al., 2015; Reljin et al., 2020).

A representative plot of DCAE reconstruction is shown in Figure 21.5. The black line represents MA-corrupted EDA data, and the red line shows the reconstructed EDA using the DCAE network. As shown, DCAE is able to effectively remove most of the high-frequency MA dynamics.

## Applications of EDA

As previously noted, EDA has been widely used in different psychological, physiological, and neurological applications. We describe a few EDA applications in this section.

## Pain Detection

It is well established that dynamics of the sympathetic nervous system (SNS) are elevated in proportion to pain intensity (Nahman-Averbuch & Coghill, 2017; Nickel et al., 2017). Thus, EDA can be used as a pain detector since EDA is a physiomarker of SNS dynamics. Dubé et al. (2009) showed the brain activities associated with elevated EDA dynamics during acute heat pain; the authors identified brain stimulation related to the resultant EDA dynamics by modeling the predicted blood oxygen level dependent (BOLD) signal. Munsters et al. (2012) observed that changes in skin conductance can be used to detect and differentiate pain and discomfort in newborn infants. Sugimine et al. (2020) measured the number

of fluctuations (NFSC) in EDA and normalized skin conductance level (nSCL) during different pain stimuli such as heat, mechanical, and cold stimulation, and other sympathetic stimuli consisting of abrupt sound and painful images and found that both NFSC and nSCL increased during these stimulations. The authors concluded that nSCL could better differentiate than NFSC between physical pain stimuli and other sympathetic-induced responses. Similarly, Susam et al. (2018) used timescale decomposition to extract salient features from EDA signals and applied machine learning to distinguish between pain and no pain. As a result of their approach, the authors achieved a moderate level of accuracy in detecting pain, indicating the feasibility of developing medical applications in objective pain assessment, currently reliant on self-report or observation, which can be affected by personal bias.

Time-varying spectral features have been used extensively in pain detection studies and are reported to have higher sensitivity compared to time-domain indices (Kong et al., 2021a). Posada-Quintero, Kong, et al. (2020) used the time-varying spectral index (TVsymp) of EDA to quantify a multilevel pain stimulation evoked by thermal grill. This work showed that TVsymp was significantly affected by thermal grill pain-inducing stimulations. Kong et al. (2021a) collected EDA signals during different levels of electrical stimulation. This work computed several sensitive EDA indices using a derivative of the phasic EDA signal and time-varying spectral analysis. The authors also proposed modification of a previously developed time-varying spectral index (MTVsymp) that enabled more accurate detection and quantification of pain. The method showed a robust 87% balanced accuracy in classifying high versus no pain stimulations. These examples demonstrate the merits of using time-varying spectral indices for detecting and quantifying pain induced by different stimuli. Their high level of accuracy indicates that utilizing the differential characteristics of EDA enhances the detection of fast and sharp responses, such as pain. By leveraging these distinct features of EDA signals, their approach proves to be particularly effective in capturing rapid physiological changes associated with pain, potentially leading to more efficient and precise pain assessment techniques.

## Stress Detection

Stress is sensed in the amygdala of the brain, activating the sympathetic nervous system (Scharmüller et al., 2015; Yang et al., 2007). Since EDA can be used as a non-invasive surrogate marker of SNS activity, a corresponding change is expected in the EDA signal during stress. This is the motivation to use EDA for stress detection. Liu et al. (2015) found that participants showed increased SCL following stress. They also observed that sleep-deprived people had higher SCL responses to stress than did well-rested subjects. Ruiz-Robledillo and Moya-Albiol (2015) performed an interesting study comparing parents of children with autism spectrum disorder (ASD) to parents of children without ASD. The authors observed that the parents of the ASD patients showed lower EDA response to acute stress compared to the parents of the children without ASD; this could reflect an adaptive habituation of parents of the ASD patients to stress.

Setz et al. (2010) did an interesting study in which they induced mild cognitive load and two stress factors (cognitive and psychological) on the participants; cognitive stress was induced by solving arithmetic problems under time pressure and psychological stress was induced by a social-evaluative threat. Mild cognitive stress was also induced by solving arithmetic problems without a time limit. The authors obtained a classification accuracy of 82.8% between cognitive load and stress using EDA features such as peak height and instantaneous peak rate. Posada-Quintero et al. (2018) collected EDA on subjects while they were fully immersed in water and performing the Stroop test (a moderate cognitive-stress-inducing experiment; Scarpina & Tagini, 2017). This study did not observe any significant changes in time domain indices such as SCL and non-specific SCRs during cognitive stress. However, the frequency domain indices, such as EDAsymp and TVsymp, showed significant differences between baseline and cognitive stress.

Most of the stress-related experiments were performed in a controlled laboratory environment. However, there have been some studies that were performed in real-life settings. Liu and Du (2018) used electrodermal activity features with a simple linear discriminant analysis classifier to classify the stress levels on drivers. They used the MIT Media Lab driver stress database that contains EDA data from 24 drivers while they were driving in different stressful scenarios such as on highways and in a city and also during resting moments. Their machine learning method obtained a classification accuracy of 81.8%. Hernandez et al. (2011) also used EDA signals with a support vector machine (SVM) to classify stressful versus non-stressful calls in a call center and obtained a good accuracy of around 75%. Choi et al. (2012) used the heart rate variability (HRV) with EDA features in association with logistic regression to discriminate between mental stress and relaxation in an ambulatory setting.

## EDA in Sleep Applications

Since different stages of sleep and wakefulness produce different levels of SNS activation (Murali et al., 2003; Silvani & Dampney, 2013; Somers et al., 1993), EDA can be a potential tool for analyzing sleep stages. In addition, EDA can be easily collected while sleeping using wearable devices to capture information pertaining to sleep stages and sleep quality. Moreover, SNS activity reduces by more than half from wakefulness through light to deep sleep stages (Murali et al., 2003; Somers et al., 1993). These observations have motivated several sleep research studies using EDA. Most of the sleep research studies were performed in the laboratory while some were performed in natural settings such as at home. Early studies using EDA-based sleep analysis reported more frequent "storm" patterns, and elevated EDA responses, during slow wave sleep (SWS) (Koumans et al., 1968). One of the studies reported lower EDA peak frequencies during the first cycle of the night (Freixa i Baqué, 1983). Koumans et al. (1968) studied skin potential and skin resistance level and observed that those levels could differentiate between being awake and asleep.

Recently there have been several works on sleep applications using EDA. Sano et al. (2014) collected EDA data from both wrist and palmer surfaces with concurrent

polysomnography (PSG) during nighttime. The authors compared the EDA obtained from the wrist and the palm and observed higher and more frequent EDA peaks from the wrist compared to the palm. This study also compared EDA peaks across different sleep stages – N1, N2, SWS, REM – and found that 80% of the EDA peaks occurred in non-REM sleep. Herlan et al. (2019) performed a study on 48 patients with sleep disorders and 43 healthy subjects, collecting EDA signals during nighttime. The authors computed EDA-smoothed features called EDASEF, and the number of EDA peaks (EDAcounts), and compared them across wakefulness and different stages of sleep. The authors found significant differences between wakefulness and sleep stages, such as awake versus non-REM stage 1 (N1), awake versus N2, awake versus SWS, and awake versus REM. Moreover, the authors reported a significant difference in EDA counts between normal healthy subjects and patients with sleep disorder in the stage N1. Also, higher variances in EDAcounts and EDASEF were observed in the sleep-disordered group.

## Emotion Recognition

Since EDA is considered a non-invasive surrogate measure of SNS activity, it can be applied to recognize emotional arousal that is controlled by the autonomic nervous system (Dutta et al., 2022; Shu et al., 2018). Wu et al. (2010) used EDA, blood oxygen saturation, and heart rate as inputs to a random forests machine learning method to recognize five different emotions. The authors computed several statistical features such as the mean and standard deviation of EDA, number of SCRs, and the average amplitude and duration of SCRs. The machine learning method yielded an overall accuracy of 74%. Das et al. (2016) combined EDA and electrocardiogram (ECG) features to classify sad, happy, and neutral emotions. The authors concluded that features calculated using power spectral density (PSD) from both ECG and EDA were effective in classifying the happy, sad, and neutral emotions. The authors obtained maximum classification accuracy of 93.32% when differentiating opposite emotions such as sad and happy. The accuracies for sad vs. neutral and happy vs. neutral emotions were 91.42% and 90.12%, respectively. These show promise of EDA in human–brain computer interaction.

Several researchers used a publicly available data set (A Dataset for Emotion Analysis using Physiological Signals – DEAP; Koelstra et al., 2012) for emotion recognition. This multimodal data set consists of several physiological signals, including electroencephalogram (EEG), EDA, electromyogram (EMG), and ECG. The measurements were obtained while playing varied emotional content on videos to induce different emotions in the participants. For example, Ganapathy et al. (2021) used the DEAP data set and applied a multiscale deep convolutional neural network on EDA signals to differentiate various emotional states. This approach achieved an accuracy of 69.33% in classifying valence and 71.43% for classifying arousal.

Veeranki et al. (2021) used EDA signals and explored different time-frequency decomposition methods such as the short-time Fourier transform, Choi Williams

distribution, and smoothed pseudo-Wigner-Ville distribution in association with various machine learning algorithms to classify and annotate happy and sad events obtained from different publicly available data sets. The authors reported that smoothed pseudo-Wigner-Ville distribution with a random forests classifier yielded the highest F measure of 8.74%. Likewise, Shukla et al. (2019) used EDA signals from a publicly available emotion data set named AMIGOS (Miranda-Correa et al., 2021), and extracted 40 different features from the time-frequency domain of EDA. They used different feature selection techniques and machine learning to classify emotional valence and arousal. The authors reported that the Mel-Frequency Cepstral Coefficients (MFCC) outperformed other features. In summary, time-frequency features of EDA in association with machine learning can be a potentially powerful tool for automatic emotion recognition.

## Seizure Detection

Epileptic seizures cause significant changes in ANS function and often cause symptoms such as flushing, sweating, and piloerection (Loddenkemper et al., 2004; Wannamaker, 1985). Poh, Loddenkemper, et al. (2010) collected EDA data in patients and observed that epileptic seizures induced a surge in EDA amplitudes. This study also found that a generalized tonic-clonic seizure induced a massive sympathetic discharge. Their work was the first to illustrate the use of EDA for seizure detection. Meisel et al. (2020) collected multimodal data such as EDA, body temperature, and blood volume pulse from epilepsy patients' wristbands and used machine learning techniques, including 1D-convolutional neural network and long short-term memory (LSTM), to predict epileptic seizure. There have been a few other studies (Nasseri et al., 2021; van Andel et al., 2017; Vandecasteele et al., 2017) that used ambulatory EDA alone or with other modalities such as ECG and PPG for seizure prediction.

Recently our group published interesting results on prediction of seizures in rats caused by exposure to hyperbaric oxygen (Posada-Quintero et al., 2022). This study collected EDA data on rats while they were breathing 100% oxygen at hyperbaric pressure which caused central nervous system oxygen toxicity leading to generalized seizures. This study captured the EDA dynamics over time using TVsymp and observed a significant increase in its amplitude approximately two minutes before the seizure occurred, as noted by the experts. This result motivated us to explore similar predictive capability using EDA on humans. Our group performed hyperbaric oxygen experiments on human subjects until either a maximum time of 120 minutes or when the subject started showing symptoms associated with oxygen toxicity (Posada-Quintero, Derrick, et al., 2021). This study reported similar sudden and large increase in EDA amplitudes as observed in rats, about one minute prior to expert adjudication noting the symptoms associated with oxygen toxicity. These findings are exciting, as the EDA device can potentially be used for prediction of seizures related to oxygen toxicity while scuba diving after prebreathing oxygen to prevent decompression sickness.

## Challenges and Limitations of Using EDA

The main challenges and limitations of technologies based on EDA can be summarized by two factors: reduced specificity due to motion artifacts and other confounding sympathetic-induced reactions seen in EDA, and lack of validation involving large populations. First, the sensitivity of EDA to sympathetic arousal is at the same time linked to its main limitation. When a pain assessment based on EDA is examined, for example, in many instances the observed reaction in the EDA signal is also a byproduct of expectations and stress as well as pain itself. The challenge in this case is developing features based on signal processing tools that are more specifically linked to the phenomena being assessed (e.g., SCRs with abnormal amplitude, slope, spectral content) and using multimodal approaches (e.g., incorporating heart rate) to rule out other sources of sympathetic reaction using the patterns of reaction produced in different signals.

Secondly, none of the tools for pain, seizures, stress, emotions, etc., have been validated in large populations. Different scenarios can create data corruption and MA that need to be identified and corrected before the technologies can be used with confidence. Furthermore, studies involving large populations will allow better generalizability of the chosen machine/deep learning models. Finally, although there is some preliminary evidence of the production of SCRs from the innervation of sympathetic nerves, a more in-depth understanding of the functioning of the physiology behind the tonic and phasic changes of EDA is necessary to foster better acceptability and generalization of the technique.

## Conclusions

EDA has become increasingly popular over the last few decades and has found its way into many exciting applications. However, as previously discussed in this chapter, motion and noise artifacts are a big challenge in EDA analysis. With the advancement of deep learning techniques, such as the convolutional autoencoder, a significant amount of corrupted data can be recovered. Innovations should be made in terms of data collection as well. For example, finding the best recording sites and incorporating accelerometers that could be used for identifying and removing MA continue to be active research areas. Regarding EDA analysis, time-varying spectral features have been particularly useful, as the dynamics of the signal are transient and related to the duration of the stimuli. Application of machine learning has enabled more accurate classification of different psychophysiological events. With ambulatory monitoring being so popular nowadays, and allowing collection of even greater amounts of data, it is timely to explore more advanced deep learning techniques in EDA research. Moreover, given the success of EDA research over the last few years, it is also timely to develop the next generation of wearables. There have been a number of exciting developments in EDA applications involving wearables and

smartphones recently, but the number of research works is still limited. We envision that wearable and smartphone applications for EDA will be an exciting and growing research area in the coming years.

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