The single effector model of the sweat glands is the most generally agreed-upon model for EDA. The changes in the level and phasic shifts of the EDA are the outputs of such a model. Sweat comes through varying numbers of ducts in the sweat glands at different levels, depending on the level of sympathetic arousal. The sweat ducts can be thought of as a set of variable resistors wired in parallel, which is the principle behind the single effector model. The higher the amount of sweat rises and the more ducts that are filled up, the lower the resistance in that variable set of parallel resistors. In this manner, changes in the level of sweat in the ducts produce observable variations in EDA [11].

The neurotransmitter involved in the mediation of eccrine sweat gland activity is acetylcholine, which is the primary neurotransmitter of the parasympathetic nervous system, rather than noradrenaline, which is typically associated with peripheral sympathetic activation [12]. For that reason, at one point in history, both the sympathetic and parasympathetic branches of the ANS were thought to control EDA. However, it is currently accepted that human sweat glands have predominantly cholinergic innervation from sudomotor fibers linked uniquely to the sympathetic chain [5,13]. Studies that simultaneously recorded sympathetic action potentials in peripheral nerves and EDA provide evidence for the solely sympathetic control of EDA; a high correlation between bursts of sympathetic nerve activity and the amplitude of the rapid transient events in the EDA was shown [14].

Basics of the Signal Analysis of EDA

The most salient characteristic of an EDA signal is the occurrence of skin conductance responses (SCRs) resulting from an underlying sympathetic reaction to a stimulus. The SCRs are the rapid and smooth transient events noticeable in the EDA signal (Figure 1). At least three pathways lead to the production of SCRs: hypothalamic control, contralateral and basal ganglion influences (involves one pathway of excitatory control by the premotor cortex and another pathway of exhibitory and excitatory influences in the frontal cortex), and the reticular formation in the brainstem [13,15,16]. These pathways imply different functional roles associated with the central mechanisms: activation of the reticular formation is associated with gross movements and increased muscle tone, hypothalamic activity controls thermoregulatory sweating, amygdala activation reflects affective processes, premotor cortex activity occurs in situations requiring fine motor control, and prefrontal cortical activity is associated with orienting and attention [11,17,18]. All these processes influence the EDA signal.

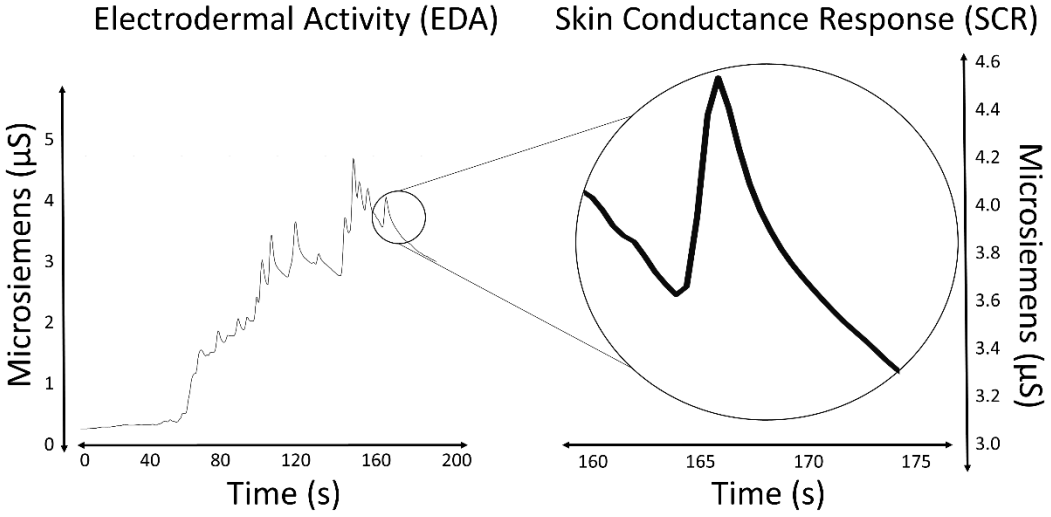

Figure 1. EDA signal and an isolated SCR.

Measures of the SCRs are used to evaluate a subject's response to event-related experiments ("startle-like" stimuli) or tonic stimuli tests (like a change in condition, workload, cognitive stress, and so forth). In event-related experiments, the occurrence of an SCR is expected after the stimulus

is applied. In such experiments, the SCRs are usually called the event-related SCRs (ERSCRs) [13]. Quantitative measures are obtained from SCRs by computing their amplitude, rise time (also referred to as onset-to-peak time), and other metrics. Figure 2 illustrates some of the quantitative measures available from an individual SCR. In the figure, time is relative to the stimulus and amplitude values are relative to the SCR onset level.

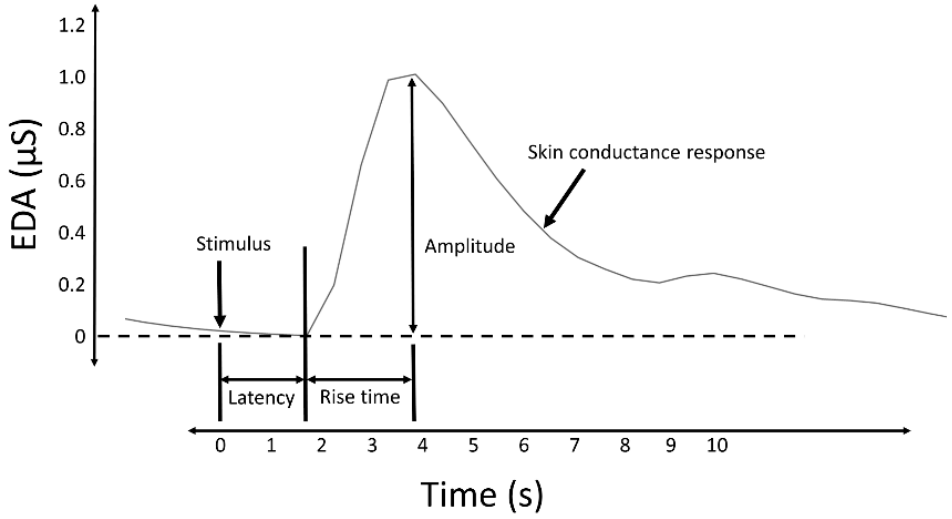

Figure 2. A typical skin conductance response (SCR) and illustration of some derived measures.

The skin conductance level (SCL) and nonspecific skin conductance responses (NSSCRs) [3] are measures obtained to assess the response to a tonic stimulus. SCL, expressed in the same units as EDA (typically microsiemens (μS)), specifically refers to the overall conductance obtained from the tonic component of EDA (Figure 3), and was conceived as a measure related to the slow shifts of the EDA. A SCL is typically computed as the mean of several measurements taken during a specific non-stimulation rest period, for example, the mean of the "tonic EDA" component shown in Figure 3. The non-specific NSSCRs are the number of SCRs in a period of time and are considered a tonic measure because they cannot be linked to a specific stimuli, but are the result of spontaneous fluctuations in EDA in the presence of an ongoing sustained stimulus over a period of time.

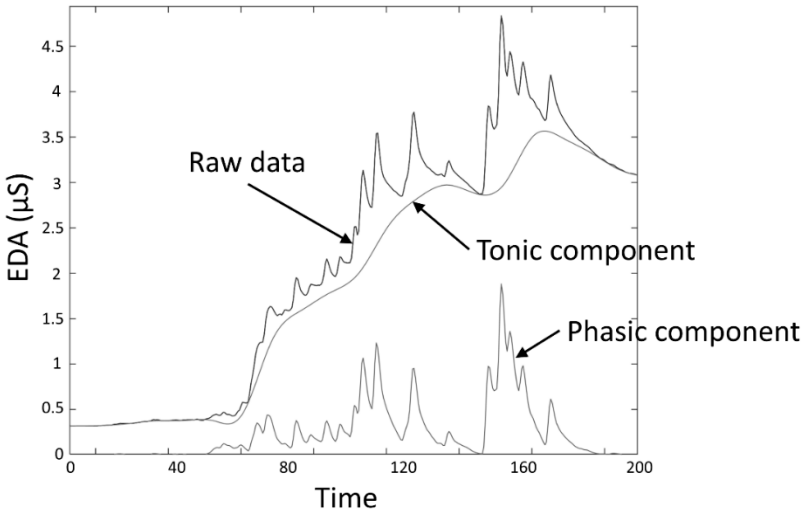

Figure 3. EDA data decomposition into tonic and phasic components.

Despite the source that caused the SCRs (specific to a stimulus or spontaneous), they are characterized by a rise from the initial level to a peak, followed by a decline [19]. When caused by

a stimulus, the onset of the SCR is typically between 1 and 5 s after the delivery of the stimulus [3]. The amplitude of the SCRs (conductance at the peak relative to the conductance at the onset) can reach several µS. A minimum of 0.05 or 0.04 µS is typically set as a threshold to define a significant SCR to avoid incorrect measurements caused by movement artifacts, the noise level of the equipment, and experimental conditions [3]. The time from the onset of the SCR to the peak, termed the rise time (Figure 2), normally varies between 0.5 and 5 s [20]. The spectral content of EDA is mostly confined to 0.045–0.15 Hz [21]. Exercise increases the spectral content of EDA, exhibiting spectral content at about 0.37 Hz when subjects perform vigorous-intensity exercise [22].

2. Methods

We reviewed advances in EDA data collection and signal processing techniques from the last 10 years. The first author searched PubMed, Web of Science (WoS), and the Scopus database to identify research articles and conference papers published in the last 10 years. As EDA is also referred to in some studies as "galvanic skin response" or "skin conductance response," these keywords were also used in the search (TITLE ("electrodermal activity" OR "galvanic skin response" OR "skin conductance") AND DOCUMENT TYPE (article) AND PUBLICATION YEAR > 2008). From the results of the search in the three databases, we extracted studies in three categories of our main interest: (1) EDA recording devices and electrodes, which included all the studies that investigated instrumentation, technologies, and sensors for EDA collection development and testing; (2) processing techniques for EDA signals, which included the signal processing techniques developed to create novel, sensitive, and quantitative measures based on the EDA; and (3) EDA quality, which included studies that evaluated the reproducibility and consistency of measures of EDA, as well as techniques for managing motion artifacts and noise.

3. Results

The search found 365 entries in Pubmed, 377 in WoS, and 417 in Scopus. From these search results, 16 manuscripts were classified as describing EDA recording devices and electrodes, 28 reported on processing techniques for the EDA, and 9 studies investigated EDA quality. For context, the previous work has been included, as described in [13].

3.1. EDA Data Collection: Recording Devices and Electrodes

3.1.1. Endosomatic versus Exosomatic Recordings

It is possible to collect EDA signals without an external source of electricity, in which case it is called endosomatic recording. In this case, the voltage between an active site and a reference electrode at a relatively inactive site is collected. Endosomatic devices are thought to be simpler as they require only a high input impedance amplifier (>10 MΩ); however, they require an amplifier gain and a floating reference to measure the potential difference between the two electrodes. The signal obtained with this method is termed the skin potential response. It has a direct relationship to SCRs [11]. However, the skin potential response can be monophasic positive, monophasic negative, biphasic, or triphasic. This complexity hinders the scoring and interpretation of the signal [3]. This has limited the use of endosomatic recordings in recent studies.

Most EDA devices use an exosomatic approach, in which an external constant current or voltage source is applied via electrodes on the skin [3]. Exosomatic devices measure the modulated current or voltage, depending on whether the constant source is a voltage (most typical) or a current, to compute the skin conductance using Ohm's law. To prevent endosomatic contamination of exosomatic measurements, the latter devices typically use a reference common to output and input that makes the voltage difference independent of a reference electrode position. The constant source for exosomatic recordings can be either a direct current (DC) or an alternating current (AC) source.

the most reproducible measurement on average (lowest coefficient of variation and highest intra-class correlation coefficient) for both types of stimuli.

4. Discussion

EDA has a long history in psychophysiological research since the studies of Vigouroux in France in 1879. During the first years of use of the technique, it was used to evaluate EDA as a response to mental (e.g., emotional, cognitive) stress. More recent observations showing that EDA varies with the state of sweat glands in the skin, which are controlled by sympathetic nervous activity, initiated the practice of using the technique as an indication of not only psychological but also general sympathetic arousal. Despite the wide acceptation of this concept, using EDA for pathophysiological assessment is rather novel.

Literature suggests the practical superiority of the constant-amplitude AC-voltage exosomatic method for reliable EDA data collection. This approach avoids the complexity of collecting signals using endosomatic approaches and the error in the EDA signal introduced by electrode polarization. Nevertheless, the constant-amplitude AC-voltage exosomatic method allows for the collection of skin potential, skin conductance, and skin susceptance (the imaginary part of admittance) at the same skin site, which is of interest for some groups attempting to assess the functioning of the sympathetic nervous system [82,83]. The constant-amplitude AC-voltage exosomatic configuration is advisable for the development of future applications based on EDA.

The development of wearable technologies capable of reliable EDA data collection and analysis is a relevant research topic. It involves the type of sensor, the measuring site, the signal conditioning, motion artifact detection and correction, and the suitability of the resulting measures of EDA. Furthermore, different scenarios, such as sleeping, exercising, driving, and others, have specific requirements, such as quality and data length, to provide the intended measures based on EDA. The feasibility of wearable devices to provide the required chain of capabilities (collection–processing–diagnosing) should be tested in such scenarios.

Tonic/phasic decomposition is the most-pursued task for EDA signal processing. The scientific relevance of tools for this task relies on their ability to detect the underlying sympathetic driver that produces a specific phasic shift. If such a task is accurately achieved using EDA, one could use the model to objectively measure subjects' reactions to specific stimuli or significant situations (e.g., public speech, advertisements, pain, and so forth). Several implementations of the tools are available. However, the main practical constraints of such methods are the feasibility of implementing the mathematical computations in wearable devices and the requirement of subject-specific tuning. In particular, the convex optimization approach (cvxEDA) and the sparse deconvolution approach (sparsEDA) are relatively fast techniques that can be implemented in a wearable device given their low computational cost. Nevertheless, both tools require setting a group of parameters (four or more). If the default values for the parameters are used, the results of the decomposition vary highly depending on the subject and the application. There is no congruency on the results between the decomposition methods. For illustration purposes, in Figure 4 we have included the tonic/phasic decomposition of a given EDA signal using the cvxEDA [57], the sparsEDA [61], the continuous decomposition analysis available in Ledalab (CDA-Ledalab) [84], the discrete decomposition analysis also available in Ledalab (DDA-Ledalab) [84], and the dynamic causal modeling available in psPM (DCM-psPM) [49]. Besides the difference in computational time, each algorithm provides a very different estimation of the tonic and phasic component. Machine learning and deep learning could help with this task. If a well-established definition of what the tonic and phasic components should be comprised of existed, a model could be trained to perform such a decomposition.

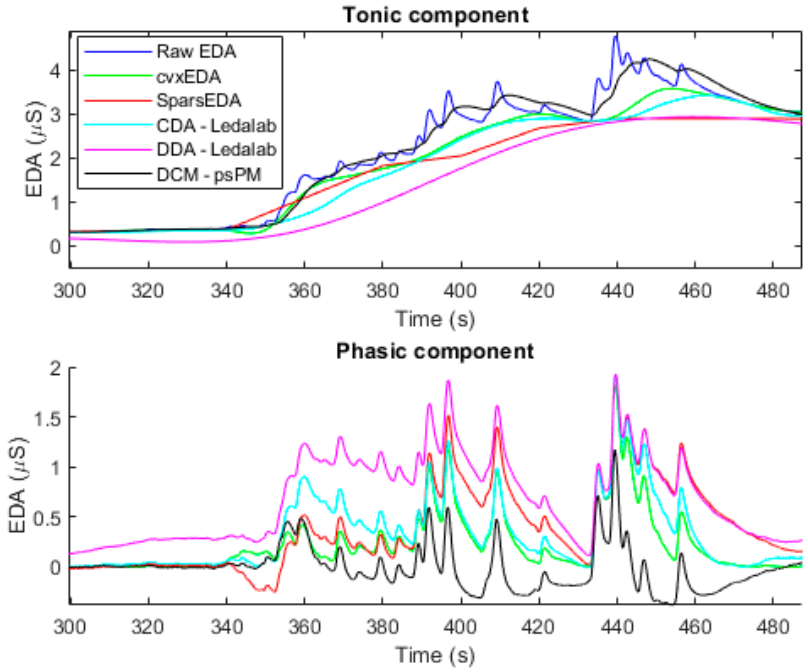

Figure 4. Tonic/phasic decomposition of a sample EDA signal using some available tools.

A potential application of EDA is to use it jointly with heart rate variability to develop indices of autonomic function. For instance, EDA can be used to adjust the bands for spectral analysis of heart rate variability under exercise. Also, adaptive filtering approaches are able to use the information in EDA to obtain more accurate, sensitive, and specific indices of autonomic control and balance. The heart rate variability is known to have a nonlinear relationship with the autonomic control [85]. For its part, the order (i.e., linear or nonlinear) of the interplay between EDA and the sympathetic tone must be determined before we can obtain suitable indices of autonomic control combining EDA and heart rate variability.

Furthermore, ways to increase the specificity of EDA for the assessment of the sympathetic nervous system in clinical applications need to be explored. The correct diagnosis of many diseases requires more sensitive and reliable measures of sympathetic function. An important example is diabetic cardiovascular autonomic neuropathy, which is present in at least 25% of diabetics. It is a remarkable example of the need for sensitive measures of sympathetic tone [85,86] because the gold standard procedure for sympathetic assessment for this disease is the cardiovascular autonomic reflex test [87], which has a low sensitivity (50%) [88]. New quantitative and accessible methods for assessment of the sympathetic nervous system are needed.

Future applications of EDA may include the multi-parameter approach (e.g., precision health) based on wearable sensors for assessing diseases that affect the autonomic control (stress, neuropathies, pain, and so forth). We envision those tools to incorporate artificial intelligence for obtaining and selecting features, as well as for estimating the level of progress of disease. A different application would be the detection of sleep drowsiness, which could be used, for example, to alert drivers when they are too tired to be driving safely because their bodies are showing low levels of responsiveness. The simplicity of the circuitry to collect the signal and the absence of parasympathetic interference make the EDA a valuable source of information and a desirable target for many applications. Several wearable devices already incorporate EDA sensors [89] but their use is limited to functions like detecting whether the user is wearing the device, or basic analysis, such as merely computing the conductance level.