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Current trends and opportunities in the methodology of electrodermal activity measurement

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Conflicts of interest

ØGM is member of the board for Biogauge AS, Norway.

Abstract

Electrodermal activity (EDA) has been measured in the laboratory since the late 1800s. Although the influence of sudomotor nerve activity and the sympathetic nervous system on EDA is well established, the mechanisms underlying EDA signal generation are not completely understood. Owing to simplicity of instrumentation and modern electronics, these measurements have recently seen a transfer from the laboratory to wearable devices, sparking numerous novel applications while bringing along both challenges and new opportunities. In addition to developments in electronics and miniaturization, current trends in material technology and manufacturing have sparked innovations in electrode technologies, and trends in data science such as machine learning and sensor fusion are expanding the ways that measurement data can be processed and utilized. Although challenges remain for the quality of wearable EDA measurement, ongoing research and developments may shorten the quality gap between wearable EDA and standardized recordings in the laboratory. In this topical review, we provide an overview of the basics of EDA measurement, discuss the challenges and opportunities of wearable EDA, and review recent developments in instrumentation, material technology, signal processing, modeling and data science tools that may advance the field of EDA research and applications over the coming years.

1. Introduction

1.1. What is EDA?

Electrodermal activity may be defined as a common term for all electrical phenomena in skin, including all active and passive electrical properties that can be traced back to the skin and its appendages

(Boucsein W, 2012). As sweat contains mostly water and electrolytes, the electrical conductance of the skin is increased through sweating. Sweat secretion not only leads to changes in skin conductance (SC), but also other electrical properties such as skin potential (SP) and capacitance. Due to the high density of sweat glands in the hands and feet, the EDA phenomenon is particularly evident in those areas (Shields SA *et al.*, 1987; Van Dooren M *et al.*, 2012). The primary function of sweat glands is thermoregulation, however sweat glands are also responsive to psychologically significant stimuli (Cacioppo JT *et al.*, 2007). As sweat glands are innervated by the sympathetic branch of the autonomic nervous system, EDA can be a useful measure of the sympathetic nervous system activity (Boucsein W, 2012).

1.2. Historical background

Studies of the electrical properties of the human skin dates back to more than 100 years ago. Various electrical phenomena have been described by terms such as psychogalvanic reflex, galvanic skin response, skin resistance response, skin conductance response, skin potential response, and electrodermal activity (Boucsein W, 2012). In 1849, the very first EDA experiments were performed by du Bois-Reymond (Neumann E and Blanton R, 1970). In 1878, Hermann and Luchsinger showed for the first time that there is a connection between sweat gland activity and flow of current in the skin. In 1879, Vigouroux found that EDA is related to psychological factors. In 1881, Hermann repeated the du Bois-Reymond experiment, which had been performed 30 years earlier. They found that due to higher concentration of sweat glands in palms and fingers, skin current was higher than on wrist and elbow (Neumann E and Blanton R, 1970). In 1888, Féré, and in 1889 Tarchanoff performed pioneering EDA studies: Féré observed reduced skin resistance as the result of external direct current in hysterical patients following emotional stimulation (Neumann E and Blanton R, 1970; Sequeira H *et al.*, 2021). Later, Tarchanoff was able to measure changes in skin electrical potential between two electrodes, that were connected to the skin surface without the application of any external stimuli (Neumann E and Blanton R, 1970; Sequeira H *et al.*, 2021). In 1928 and 1929, Gildemeister and Rein investigated the source of endosomatic EDA by injuring the skin under one electrode and in this way restricting skin potential origin to only one of the recording sites (Neumann E and Blanton R, 1970). In 1930, McClendon and Hemingway identified the sweat glands as the seat of “psychogalvanic phenomena” (McClendon JF and Hemingway A, 1930). In the same year, Wang and Lu defined a palmar galvanic test for testing sweat secretion (Wang GH and Lu TW, 1930). In 1966, Johnson and Lubin introduced electrodermal activity (EDA) as general term for all electrical phenomena in skin (Johnson LC and Lubin A, 1966). In 1971, Edelberg established an electrical model for the skin, in which polarization capacitance as well as the psychophysiological aspects of EDA were included (Edelberg R, 1971). In 1972, after more than a decade of EDA research, Edelberg focused on improvement and evaluation of the EDA recordings and introduced new EDA components such as the rise time and recovery times of the EDR (Edelberg R, 1972). Since then, EDA has mostly been used as one of several sensor methods in psychophysiological research. More detailed information about the historical background of EDA is provided in Boucsein 2012, sections 1.1.2 and 1.1.3. Although EDA has become a well-established measurement today, there are still ongoing efforts to improve the methodologies of recording, evaluation, and interpretation, of EDA signals.

1.3. Physiology and anatomy behind EDA

The most superficial layer of the skin (the epidermis) consists of several sub layers where the stratum corneum is the outermost layer consisting of keratinized skin cells. This stratum corneum has a high electrical impedance as it comprises dead cells without nuclei embedded in a dense lipid matrix with a low moisture content and narrow transport channels (Agache P and Varchon D, 2017; Baker LB, 2019). The skin contains two main types of sweat glands: apocrine and eccrine. The apocrine glands

(mainly in the axillae and the genitals) open into hair follicles and play only a negligible role with respect to the total amount of sweating (Boucsein W, 2012). Eccrine sweat glands are found in most parts of the body and are mainly responsible for thermoregulation (temperature control). They are innervated by sudomotor nerves activated by cholinergic transmission, which forms part of the sympathetic nervous system. When the sweat glands are stimulated, activation of the glands can be detected by a change in skin conductance before the corneum becomes hydrated and subsequent surface sweating (Gerrett N *et al.*, 2018). For further details on the physiology of different types of sweat glands, a recent overview can be found in Baker 2019 (Baker LB, 2019).

Firing bursts in the sudomotor nerves normally produces sweating in palms and soles (Wilke K *et al.*, 2006). All eccrine sweat glands are responsive to cognitive activity, emotion and temperature, but because the palmar and plantar regions have higher densities of eccrine sweat glands, they appear more responsive to emotional stimuli compared to the trunk and limbs (Shaffer F *et al.*, 2016). When the sweat ducts of the stratum corneum are filled with sweat, ionic transport pathways are created and consequently the electrical impedance of the epidermis decreases (Grimnes S, 1984). In addition, transport of sweat from the ducts to the surrounding epidermis results in hydration of the corneum and consequently decreases its impedance (Fowles DC, 1986).

EDA is generated by activity of sudomotor nerve fibres, which are part of the sympathetic nervous system. The sympathetic nervous system receives direct and indirect afferents from various brain areas, mainly via the hypothalamus (Critchley HD, 2002). Consequently, electrical stimulation in various brain areas elicits SCR in humans (Mangina CA and Beuzeron-Mangina JH, 1996) as well as other species (e.g. amygdala in cats (Lang H *et al.*, 1964). Stimulation in amygdala, hippocampus, and cingulate cortex, with presumably more direct projection, elicits predominantly ipsilateral SCR (Mangina CA and Beuzeron-Mangina JH, 1996).

1.4. Conductance, admittance, and more

Electrodermal activity can be theoretically described using electrical components in a circuit as shown in figure 2. The term conductance either refers to the ability of a material to conduct direct current (DC) or the real part of the ability of a material to conduct alternating current (AC). In the DC case, the current will simply be in the form of free ions (including protons) moving in the electric field. For an AC system, the underlying process is more complicated. The current will be phase shifted from the applied sinusoidal voltage (or vice versa) and is hence represented with a complex term for the conduction ability, called admittance. This admittance has a real (in phase) term called conductance and an imaginary term (90 degrees out of phase) called susceptance. Furthermore, the susceptance can be due to capacitive or inductive properties. Biomaterials are predominantly capacitive. It is worth noticing that the AC conductance is dominated by free ions in the low frequency range, but as the frequency increases, the contribution from dielectric loss will dominate. This dielectric loss is mainly due to vibrating ions causing heat dissipation. Ions have finite mobility and when the frequency starts to exceed their relaxation time, their movement is restricted causing vibration. Since dielectric loss is not directly related to sweat secretion, it follows that EDA can be measured with either DC or low frequency AC. For completeness it can be mentioned that the inverse of admittance is impedance, that can be decomposed into resistance (real part) and reactance (imaginary part) (Grimnes S and Martinsen ØG, 2015).

1.5. Endosomatic and exosomatic EDA

EDA recordings are generally categorized into endosomatic and exosomatic measurements. In endosomatic measurements, no external source of current is applied and only the potential (voltage) generated by the skin is measured. In contrast, for exosomatic recordings, an external source is applied to the skin, that either is an alternating current (AC) or direct current (DC). Applying constant DC voltage or current makes it possible to measure the passive electrical properties of skin (skin conductance or skin resistance, respectively) through Ohm's law. Applying AC constant voltage or current provides measurement of skin admittance or skin impedance, respectively. Although measurement of endosomatic potential is the simplest approach, exosomatic DC measurement by means of constant voltage is the most widely used method. While exosomatic electrodermal responses are monophasic, endosomatic responses can be monophasic positive and negative, biphasic, or triphasic. This makes the process of scoring and interpretation of endosomatic results more complicated and is one of the reasons for limited use of endosomatic devices (Boucsein W, 2012; Posada-Quintero HF and Chon KH, 2020).

1.6. *Characterization of EDA signals*

Skin conductance and skin potential are the main physical properties measured in EDA, presented in the units of conductance (microsiemens) and voltage (millivolts) respectively. Both change at different time scales, conventionally simplified into two components: tonic (electrodermal level - EDL) and phasic (electrodermal response - EDR) (Boucsein W, 2012), summarized in figure 1. EDL can refer to skin conductance level (SCL) or skin potential level (SPL) - the magnitude of the skin conductance or potential in the absence of sudomotor nerve activity. In contrast, EDR refers to rapid skin conductance responses (SCRs) or skin potential responses (SPRs) as direct result of a sudomotor burst. EDR is typically recognized by a sharp rise to a peak and a slower decline to the baseline, and can be characterized by an onset, rise time, amplitude and the recovery time. The recorded skin conductance signal may be represented as the sum of tonic (SCL) and phasic (SCR) components, and signal-processing tools can be used to decompose the recording into estimates of these components. Summary statistics over defined recording periods (such as the mean of the skin conductance signal) may be used as a tonic EDA parameter. However, it may be important to note that this approach mixes EDL and EDR, possibly affecting the specificity of analysis.

In laboratory experiments, EDRs are regarded as either specific or non-specific, depending on whether they are triggered by distinct experimental events, or occur spontaneously due to internally generated sudomotor bursts. With respect to EDA characterization, the frequency of non-specific responses over a period of time is often considered a tonic parameter (Nikula R, 1991). This parameter is not dependent on the amplitude of EDRs (provided that they are detected), and may offer a better predictor of psychological arousal compared to amplitude-dependent parameters (Bach DR *et al.*, 2010c).

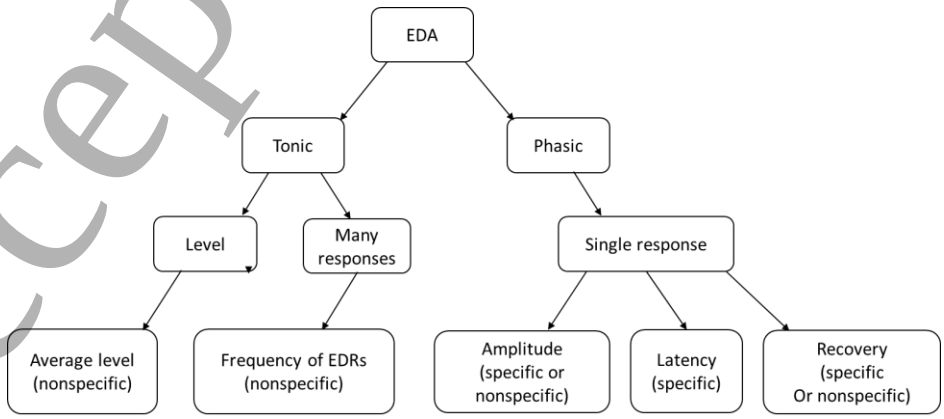

Figure 1. Overview of components of EDA and conventional parameters used to characterize electrodermal levels and responses.

1.7. The origin of EDA

Comparing EDL and EDR, both have been used frequently in research and applications of EDA, where the most common measures are SCL and SCR. Because the electrodermal skin conductance is usually measured with DC or low-frequency AC excitation, the SCL represents the ability of the skin to transport ions between the electrodes due to a static or slow-varying electrical field. Because the stratum corneum is highly resistive at low frequencies (Martinsen ØG *et al.*, 1997), the SCL measurement is dominated by the properties of this skin layer, in which the layer thickness and moisture content are likely the most influential properties. Hence, the SCL may naturally vary between subjects, days, environments, skin sites and even the choice of electrode type, unrelated to the sympathetic nerve activity (SNA) or arousal level that is typically the target of measurement. While the SCL reflects these properties of the stratum corneum, it is also indirectly related to sudomotor activity as a result of transport of sweat into the stratum corneum following expulsion of sweat from the glands. Changes in SCL have sometimes been thought to reflect changes in autonomic arousal, but we argue that this association is indirect where increases in SCL are rather a result of precursory sweating. There is little empirical evidence that cognitive processes can be specifically inferred from SCL independently from phasic responses.

In contrast, the generation of SCRs is more straightforward. SCRs are caused by the filling of ducts with sweat, thus creating electrical shunts through the highly resistive epidermis, which produce a rapid increase in the conductance of the skin area below the electrode, adding contributions from all active sweat ducts below the electrode area. This rise is followed by a slower recovery part that is thought to be ascribed to ion reabsorption in the duct (Baker 2019), diffusion of sweat away from the periductal area (Benedek and Kaernbach 2010) and a possible poral closure (Edelberg R, 1993). A typical SCR shape is illustrated in figure 2, together with an electrical equivalent circuit describing both exogenous and endogenous EDA. According to theory (Edelberg R, 1993), the shape of the SCR is also influenced by a pore opening and closure mechanism that is governed by the balance between the intraductal pressure versus the hydration-dependent pressure of the surrounding stratum corneum. Variation in pore opening may thus also explain variation in the SCR shape (Benedek M and Kaernbach C, 2010b). Therefore, there is also a possible dependency between SCL (in relation to hydration) and SCR. Extreme hydration and swelling of the corneum may impede pore opening and weaken the SCR, while a very dry corneum may limit the measurement sensitivity to sweating that reaches the skin surface (Boucsein W *et al.*, 2012).

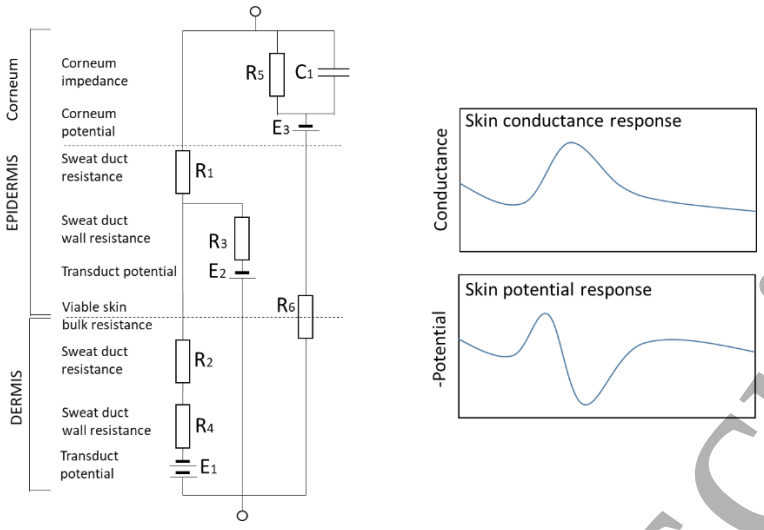

Figure 2. A simplified electrical model of the main parts contributing to endogenous and exogenous electrodermal activity based on the skin electrical properties and the sweat duct. The model is based on Fowles 1986 (Fowles DC, 1986) but slightly modified to also include AC measurement. Illustrations of typical responses in skin conductance and skin potential as a result of sweat duct filling is shown to the right. Note that the skin potential response is shown on a negative vertical axis.

EDA is typically used to provide a measure of the degree of arousal to a stimulus that activates the sympathetic branch of the autonomic nervous system. In addition to experimental factors and the degree of arousal, there are several other sources of variation in electrodermal levels and responses:

- Passive properties of the skin (stratum corneum thickness, skin hydration)
- Density of sweat ducts below the electrode
- Electrode size and material (gel properties, occlusion effects)
- Measurement technique (electronics and instrumentation)
- Electrolyte concentration in sweat
- Functioning of the neural pathway and sudomotor nerves
- Skin physiological variations (temperature, blood flow)
- Environmental temperature and humidity

In addition, as skin properties may differ between groups of different demographic characteristics (ages, gender and ethnicity) these variables may indirectly explain some variation in EDA measurement (Boucsein W, 2012). All of these factors can make it difficult to compare some parameters of EDA such as SCL and SCR between subjects and experiments. Some parameters such as the frequency of nonspecific responses may be more robust, by increasing the amount of variation from experimental conditions compared to between-subject variations (Van der Mee DJ *et al.*, 2021). EDA is a very sensitive measurement for many purposes, but the specificity is low unless confounders are reduced through careful experimental design, and reproducibility of experiments depends strongly on standardized methods. Currently EDA measurement is transitioning from the laboratory to wearable applications where it is not always possible to follow standards, but at the same time this is creating new opportunities and innovations in data collection from real-life settings.

1.8. *Applications*

EDA measurements provide valuable information about sudomotor activity and the response of the autonomic sympathetic nervous system to a wide range of stimuli and events. Psychologically, EDA

measures are considered as reflecting changes in autonomic reactivity elicited by psychosocial events associated with emotions, task demands, motor responding, workload, stress etc. (Turpin G and Grandfield T, 2007). EDA signals are considered to be purely produced by the sympathetic branch of the autonomous nervous system as there is no parasympathetic innervation of eccrine sweat glands (Critchley HD, 2002), and EDA measurements are considered to be useful in studying stress and anxiety in comparison to other physiological measurements such as heart rate, respiration rate and skin temperature. Studies have shown that changes in the amplitude of SCR, increases in SCL and frequency of non-specific response are known to be associated with increasing response to stress (Cacioppo JT *et al.*, 2007; Turpin G and Grandfield T, 2007). Psychology, physiology and neurology are some main areas where EDA is applied either in research or clinically, and some examples from these fields are given below:

Psychology

- Quantification of aversive learning (Bach DR and Melinscak F, 2020)
- Stress detection (Setz C *et al.*, 2010; Hernandez J *et al.*, 2011; Ruiz-Robledillo N and Moya-Albiol L, 2015; Martínez-Rodrigo A *et al.*, 2016; Momin A and et al., 2020)
- Teaching and learning effectiveness (Pijeira-Díaz HJ *et al.*, 2016; Potter L *et al.*, 2019)
- Autism examination (Hubert BE *et al.*, 2009; Schupak BM *et al.*, 2016; Prince EB and et al., 2017)
- Recognizing emotional states and emotional sensing (Westerink J *et al.*, 2009; Jang EH *et al.*, 2015; Jaques N *et al.*, 2015)
- Detecting the orienting response (Boucsein W *et al.*, 2012)
- Studies on panic disorder (Roth WT *et al.*, 1998; Wendt J *et al.*, 2008)
- Detection or differentiation of depression (Straub R *et al.*, 1985; Straub R *et al.*, 2003; Kim AY *et al.*, 2018)
- Schizophrenia prognosis (Dawson ME and Schell AM, 2002; Schell AM *et al.*, 2005)
- Cognitive research (Tranel D, 2000)
- Affective computing (Lanatà A *et al.*, 2012; Henriques R *et al.*, 2013)

Physiology

- Studies on pain mechanisms or detection (Storm H, 2008; Dubé AA *et al.*, 2009; Munsters J *et al.*, 2012; Susam BT *et al.*, 2018; Sugimine S *et al.*, 2020)
- Sleep studies and monitoring (Johnson LC and Lubin A, 1966; Sano A *et al.*, 2014; Romine W *et al.*, 2019; Kim H *et al.*, 2021)
- Hypoglycemia detection in diabetes (Johansen K *et al.*, 1986; Elvebakk O *et al.*, 2019)
- Assessment of hyperhidrosis (Tronstad C *et al.*, 2014; Ho AVT *et al.*, 2020)

Neurology

- Seizure detection (Poh MZ *et al.*, 2010a; Poh MZ *et al.*, 2012)
- Parkinson's disease monitoring (Esen F *et al.*, 1997; Lagopoulos J *et al.*, 1997; Lagopoulos J *et al.*, 1998)
- Studying traumatic brain injury (O'Keeffe FM *et al.*, 2004)
- Dementia monitoring (Perugia G *et al.*, 2017; Melander CA *et al.*, 2018)
- Biofeedback for epilepsy mitigation (Nagai Y *et al.*, 2019)
- Attention-deficit hyperactivity-disorder (ADHD) studies (Iaboni F *et al.*, 1997; Dupuy FE *et al.*, 2014; Von Polier GG *et al.*, 2014; Beauchaine TP and et al., 2015)

- Study on autism spectrum disorder (Hubert BE *et al.*, 2009; Schupak BM *et al.*, 2016; Prince EB and et al., 2017)

1.9. *Devices on the market*

Previously EDA could only be measured and recorded in a laboratory setting and in a controlled manner, but recent developments have made it possible to use mobile or wearable devices to record EDA out of the lab. Today, there are many wearable or mobile EDA devices on the market that are listed in Table 1. Recently, short-term EDA measurement and analysis has been implemented in one of the most popular smartwatches (Fitbit Sense, Fitbit Inc).

Table 1. List of commercially available wearable or mobile devices for continuous EDA measurement (not exhaustive).

Device name	Developer	Sensors	Type	Skin site (intended use)	Website
EdaMove 3 & 4	Movisens GmbH	• EDA • Motion • Angular rate • Barometric air pressure • Temperature	Wearable	Wrist, Ankle	Movisens.com
E4 wristband	Empatica	• PPG • EDA • Temperature • Motion	Wearable	Wrist	Empatica.com
Feel emotion sensor wristband	Sentio Solutions	• PPG • EDA • Temperature • Motion	Wearable	Wrist	Myfeel.co
Moodmetric smart ring	Moodmetrics	• EDA • Motion	Wearable	Finger	Moodmetric.com
EmotiBit	OpenBCI	• PPG • EDA • Motion • Temperature	Wearable	Optional	Openbci.com
Biosignalsplux EDA sensor	PLUX	• EDA	Mobile	Fingers, optional	Biosignalsplux.com
Mindfield eSense skin response	MINDFIELD BIOSYSTEMS	• EDA	Mobile	Fingers	Mindfield.de
Shimmer GSR+	Shimmer	• EDA • PPG • Motion	Mobile	Fingers, optional	Shimmersensing.com

Sudologger (version 3)	Biogauge	• EDA • ECG • Motion	Mobile	Four channels for optional skin sites	Biogauge.no

2. Instrumentation:

Electrodermal activity can be measured either by application of a current between electrodes (exosomatic measurement) or by only measuring the electrical potential difference between electrodes (endosomatic measurement). The current applied in exosomatic measurement can either be direct or alternating, and require different types of instrumentation. Figure 3 provides an overview of possible methods for EDA measurement.

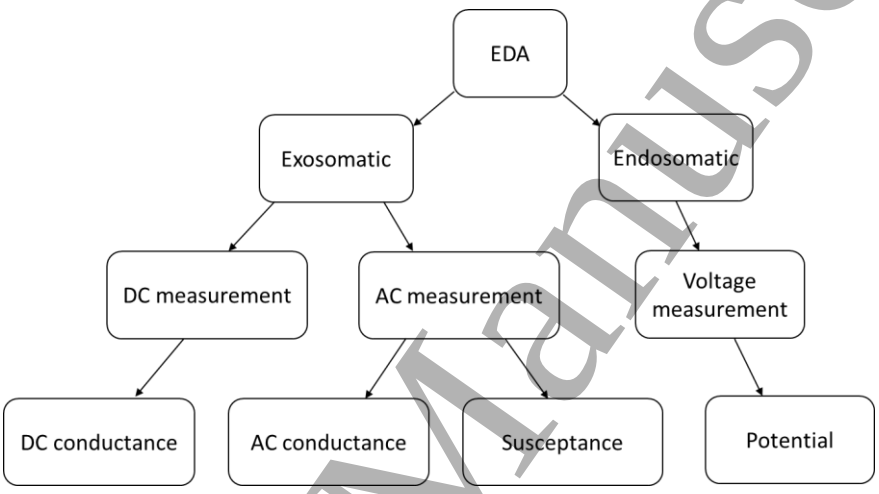

Figure 3. Overview of possible types of measurement of electrodermal activity

2.1. *AC vs DC recording in exosomatic EDA*

Both DC current and voltage sources can be used for exosomatic EDA recordings, but due to its simplicity, DC voltage is most commonly used (Boucsein W, 2012). However, one main disadvantage of using DC excitation sources is the electrode polarization phenomena, that occur even if non-polarizing electrodes are used (Posada-Quintero HF and Chon KH, 2020). Electrode polarization is virtually eliminated when AC measurement is used (Boucsein et al., 2012), but the approach requires a more sophisticated setup, and the sampling rate is limited by the excitation frequency. When an AC voltage source with constant voltage amplitude is used, EDA is recorded as skin admittance from which both skin conductance and susceptance can be calculated (Tronstad C *et al.*, 2008). In addition, the AC method allows simultaneous recording of endosomatic and exosomatic EDA by signal decomposition (Grimnes S *et al.*, 2011). Pabst et al. 2017 did a systematic comparison of DC and AC measurement, finding an excellent agreement between the AC method (using 20Hz excitation frequency) and a standard DC method, supporting the validity of the AC methodology that was employed (Pabst O *et al.*, 2017).

2.2. *Differences between types of EDA measurement*

While the AC and DC conductance measurements provide very similar signals, the skin potential signal is typically different from skin conductance measurement. Not only are their units and scales different,

but their response waveforms often differ in shape (Tronstad C *et al.*, 2013). While the SCR is always monophasic, the SPR can be monophasic (in both directions), biphasic or triphasic (Boucsein W, 2012). Current knowledge suggests that these variations in SPR shapes are not due to neural effects, but rather the biophysics of the sweat duct as first explained by Fowles 1986. Earlier models of the electrodermal system introduced by Edelberg in 1968 and 1993 that incorporate both the skin potential and conductance changes (the voltage divider model and the poral valve model) agree with later data on SCR and SPR measured simultaneously at the same skin site (Tronstad C *et al.*, 2013). Following this reasoning, filling of the sweat duct causes the conductance through the skin to increase while the skin potential at the surface becomes more negative as the electrical resistance through the duct decreases with filling of sweat (see figure 2). As the duct is filled with sweat, the change in conductance reaches a peak while the (negative) deflection of the potential may also peak as the electrode has gained more access to the more negative potential in the dermis through the sweat duct. However, if sweat secretion continues after the duct has reached its limp capacity, increased hydraulic pressure on the duct walls may promote diffusion of sweat and a decrease in the electrical resistance from the duct to the peritubular corneum, that in turn produces a skin potential deflection in the positive direction according to the voltage divider model, as the epidermal potential is more positive than the dermal potential where the sweat gland resides. In addition, the poral valve model (Edelberg R, 1993) explains that the orifice of sweat ducts may open and close depending on the balance between intraductal pressure (contributing to opening), and the corneum hydration (contributing to closure). In this way, sweat secretion may lower the corneum resistance and cause a deflection in the skin potential at a time that is different from the complete pore opening and the skin conductance peak. Thus, the SPR can be biphasic or triphasic at the same time as the SCR is monophasic, depending on the state of the sweat duct at the onset of the response, and earlier SPR peaking compared to SCR peaking may represent the time when the corneum begins to become hydrated before the pore has completely opened (Tronstad C *et al.*, 2013). This also suggests that the SCR is a better measure of the magnitude of a sudomotor response than the SPR, being unconfounded by the processes driving the response in opposite directions. The SP could still be useful in research on the electrodermal phenomenon, while it is still unclear whether the measurement of SP together with SCR may provide additional information of significance. This theory and implications of waveform differences are also relevant for measurement of the skin sympathetic response in neurology, that is essentially the same as the SPR.

Skin susceptance is a parameter that is rarely used in electrodermal measurements, but is inherently provided as a component of the electrical admittance measurement when the AC method is employed. It represents the ability of the skin to let current flow capacitively, and is strongly dependent on the excitation frequency used for the measurement. Low-frequency susceptance has been found to be a good indicator of skin hydration (Martinsen ØG *et al.*, 1995), verified by in vitro calibration of skin samples (Martinsen ØG *et al.*, 2008). Moreover, earlier research suggests that the sweat ducts are not capacitive and therefore the skin susceptance may not represent filling of sweat ducts such as the skin conductance and partly the skin potential (Martinsen ØG *et al.*, 1993). Nevertheless, skin susceptance responses have been reported in several studies (Quiao ZG *et al.*, 1987; Greco A *et al.*, 2016a; Bari DS *et al.*, 2018) and could be due to changes in hydration during and following a sudomotor response. The potential role of skin susceptance in EDA is not yet defined and is a topic for further research.

2.3. Simple circuits

Compared to other methods in electrophysiology or psychophysiology, the instrumentation required for EDA recording is simple. In principle, the measurement requires only a voltage applied between

two electrodes and a reading of the current that passes through them in order to measure the conductance. However, more sophisticated solutions are needed for measurements of high quality, and there are different approaches in EDA instrumentation that will be discussed below. Nevertheless, the simplicity of EDA measurement makes it very suitable for miniaturization in wearable applications or for integration with other sensors. There are few basic parts needed to complete an EDA measuring system, depending on the method:

- Electrodes
- Controlled current or voltage source (exosomatic measurement)
- Differential amplifier (controlled current exosomatic measurement, endosomatic measurement)
- Transimpedance amplifier (controlled voltage exosomatic measurement)
- Filters (low-pass noise removal)
- Phase-sensitive rectifier (AC exosomatic measurement)

Today, a microcontroller with a few external components can cover most of these parts. A phase-sensitive rectifier not only converts the AC signal magnitude to a DC level that is proportional to the electrical admittance being measured, but also selectively extracts the signal component at a chosen phase and frequency, thereby also working as a narrow band-pass filter. Using two phase-sensitive rectifiers can provide both the real (conductance or resistance) and imaginary (susceptance or reactance) parts of the immittance, in addition to the phase angle. With modern microcontrollers the complete tasks of double phase-sensitive rectification can be done in firmware following sampling of the AC signal (Tronstad C *et al.*, 2008). Over the recent years, application-specific integrated circuits for impedance measurement such as the AD5933 and the AD5940 (Analog Devices) have made it even easier to develop compact electronics for AC EDA measurement.

2.4. Controlled current vs controlled voltage

The skin potential is the simplest measurement with respect to instrumentation required, and may be recorded with other equipment such as an EMG amplifier. Exosomatic measurement can be done either by application of a controlled voltage or current while the resulting current or voltage difference between the electrodes is measured, respectively, providing a calculation of conductance as current divided by voltage. For most purposes, controlled voltage provides the simplest instrumentation as a constant current source is not needed, and the circuitry for reading the resulting current is very simple. In some cases, such as the solution for simultaneous measurement of skin potential and skin conductance (Grimnes S *et al.*, 2011), a controlled current is required to pick up both endogenous potentials and exogenous signals simultaneously. The choice of voltage or current strength is a compromise between signal quality and linearity of measurement. Too strong excitation may make the measurement non-linear in the sense that the measurement (through electrical excitation) changes the electrical properties to be measured. While higher currents may provide a higher signal-to-noise ratio, the excitation current may produce biophysical effects in the skin (through electro-osmosis) at excitation voltages as low as 0.4V for DC or very low frequency alternating current (Pabst O *et al.*, 2018). Excitation voltages below 0.1V can still provide EDA recordings of good quality. Whether to use controlled current or voltage in this regard is debatable, but it can be argued that controlled current offers better limitation of local current densities upon variation in skin impedance.

2.5. Electrode systems

The simplest and most commonly used electrode system for EDA measurement is the two-electrode system, where two electrodes of the same size and material are placed at similar and electrodermally active skin sites such as the tips of two fingers, or at the thenar and hypothenar eminences of the

palm. With this configuration, the skin below both electrodes are contributing equally to the measurement, and the conductance increase during a response depends on the sum of resistance decreases below both electrodes. If a monopolar measurement is desired (one skin site dominating), the contribution from one of the electrodes can be reduced or made negligible using an electrode that is sufficiently large compared to the other electrode. For skin potential measurement, an active electrode is placed at an electrodermally active site such as the hypothenar while the other electrode, serving as a reference, has to be placed on a comparably inactive site such as the volar surface of the forearm or the apex of the elbow.

In addition to the basic two-electrode configuration, certain properties can be gained by adding an additional electrode together with modified circuitry. One solution (Grimnes S, 1983) is to use a reference electrode in a feedback connection with an operational amplifier as shown in figure 4a. This circuit provides individual measurement of the impedance (or EDA) through the skin below a selected electrode, and has the added benefit of automated cancellation of external ground-referenced noise that is capacitively coupled to the body (Grimnes S *et al.*, 2009). Qiao et al. demonstrated that this circuit also can be modified to provide endosomatic EDA measurement simultaneously at the same electrode (Quiao ZG *et al.*, 1987).

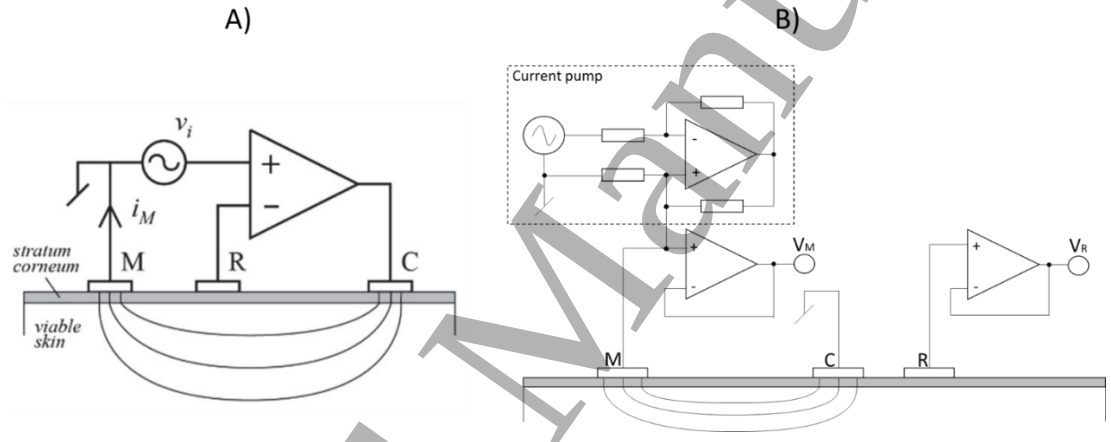

Figure 4. Three-electrode systems for unipolar measurement of skin admittance (A) and three-electrode system for simultaneous measurement of skin admittance and skin potential (B). In A), the excitation voltage (Vi) is directed to the tissue below the reference (R) electrode by the op-amp feedback, cancelling the contribution from the current injection (C) electrode and making the measurement dominated by the stratum corneum below the M electrode. In B), a constant AC current is applied between the M and C electrodes, while the voltage difference between the M electrode (placed at an electrodermally active site) and the R electrode (at an electrodermally inactive site) contains both an impedance signal and the skin potential, which can be demodulated into skin admittance (conductance and susceptance) and skin potential. A) is reproduced from Martinsen et al. 2015 (Martinsen ØG *et al.*, 2015).

Another three-electrode solution that can be used to measure both exosomatic and endosomatic EDA uses constant AC current applied between two of the electrodes while the third electrode serves to provide the skin potential at an electrodermally inactive site such as the elbow (Grimnes S *et al.*, 2011) as shown in figure 4b. The voltage difference between the current injection and the reference electrodes then contains an AC impedance signal on top of the skin potential difference, and is decomposed into exosomatic and endosomatic components by signal processing. Further details on this circuit can be found in Grimnes et al. 2011, Tronstad et al. 2013 and Martinsen et al. 2019. Several studies have employed this method to compare exosomatic and endosomatic parameters for research purposes (Tronstad C *et al.*, 2013; Bari DS *et al.*, 2018), but any application of the method is not yet determined.

2.6. *Choice of excitation frequency in AC measurement*

For the AC method of exosomatic recording, it is recommended to use a low excitation frequency (5-100Hz) for the measurement (Boucsein W, 2012), and the rationale for this is to keep the sensitivity of measurement dominated by the stratum corneum. As demonstrated by Martinsen et al. 1999 (Martinsen ØG *et al.*, 1999), the measuring depth depends on excitation frequency due to the differences in frequency dependence of the electrical properties of the skin layers. When the excitation frequency increases above the kHz range, the measurement is no longer dominated by the stratum corneum but rather by the deeper viable tissue, except for electrodes that are very thin and narrowly spaced that confine the current path superficially. Due to the frequency-dependent part of the skin conductance, the SCL increases with increasing frequency as shown in Martinsen et al. 2015 (Martinsen ØG *et al.*, 2015). There is a lack of systematic studies on how SCR depends on excitation frequency, but two examples are provided in figure 5. Figure 5a shows normalized EDA at different frequencies when measured with solid gel electrodes. Although the SCL changes markedly with frequency, SCRs are well preserved up to a few kHz although their magnitudes also vary. Figure 5b provides an example of EDA measured with a bipolar dry electrode with 1mm gap between electrodes that confines the measurement to the superficial skin. In this example, clear SCRs are preserved even up to 100 kHz. The advantage of using higher excitation frequencies is that higher sampling rates can be reached, as this is limited by completion of whole cycles of the excitation signal. Although systematic studies on EDA frequency dependency is lacking, these examples show that EDA can be acquired over a broad frequency range, and at frequencies sufficient for high sampling rates also when using the AC method. As shown, this depends on the electrode, and will also likely depend on the skin below it. It must be noted that the SCL measured with low and high frequencies represent different skin properties and cannot be directly compared.

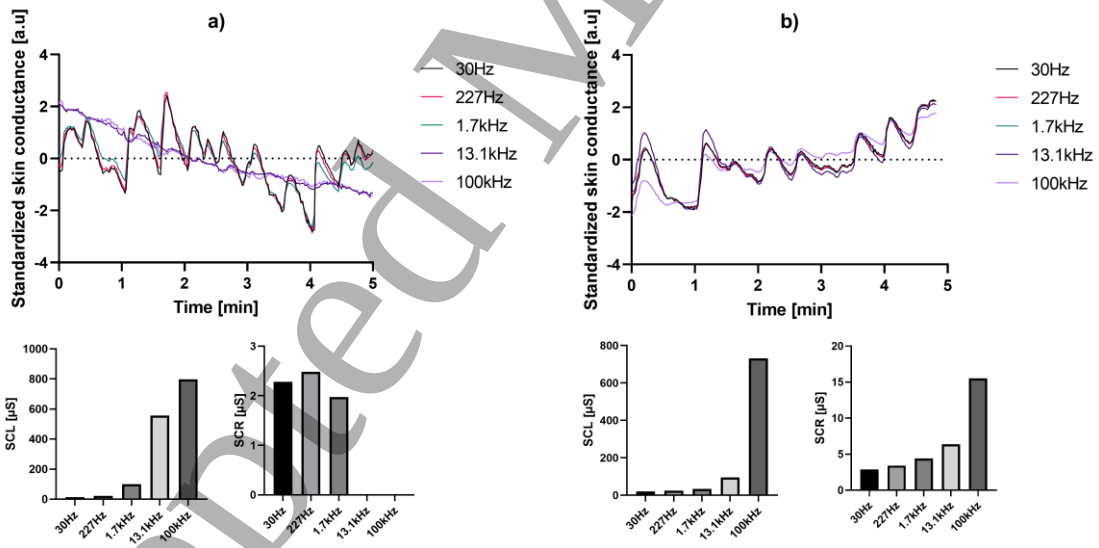

Figure 5. Examples of AC skin conductance measured with multiple excitation frequencies from 30Hz to 100 kHz on a logarithmic scale. In a) a measurement between the index and middle fingers using solid hydrogel electrodes, and in b) a measurement using a bipolar dry silver electrode (1mm gap) on the thumb. The plots show values that are standardized by z-score transformation. The SCL (initial value) and SCR (amplitude of the most prominent response) for each frequency are displayed below.

2.7. Multi-site measurement

Measuring and comparing EDA at different skin sites can be of interest for physiological studies such as investigations on conduction delay, bilateral differences or skin site comparisons (Van Dooren M *et al.*, 2012). While modern miniaturized devices can be used in conjunction to achieve multi-site recordings, there are also instrumentation approaches that enable multi-site measurement by the same measurement circuit. As first described by Martinsen et al. 1993 (Martinsen ØG *et al.*, 1993), the three-electrode system (Grimnes S, 1983) allows simultaneous multi-site measurement by simply adding electrodes and current reading circuitry as shown in figure 6. This electrode system also has the attractive properties of providing a true unipolar measurement and cancellation of any external ground referenced noise signal capacitively coupled to the body (Grimnes S *et al.*, 2009).

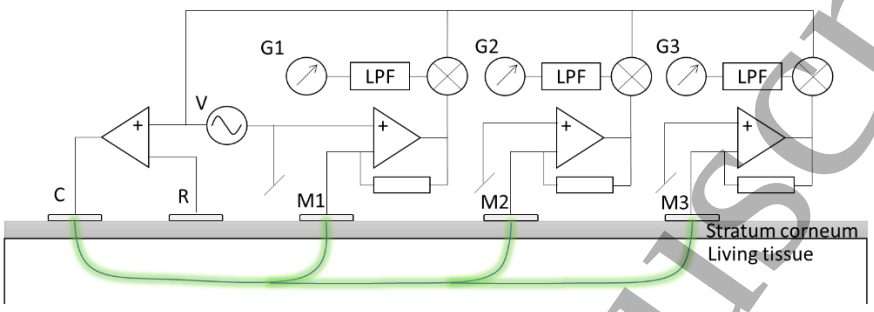

Figure 6. Extension of the three-electrode system for multichannel skin AC conductance measurement. The feedback sensing by the R electrode ensures that the excitation voltage (V) is applied to the living tissue below all measuring (M) electrodes, given that the stratum corneum impedance is much larger than that of the living tissue. The conductance at each site is acquired by the transimpedance amplifiers followed by phase-sensitive rectification extracting the in-phase component and low-pass filtering to obtain voltages (G1-G3) that are proportional to the AC conductances at the skin below each M electrode.

2.8. Signal quality

Regardless of whether exosomatic or endosomatic recording is used, the EDA signal has a bandwidth and magnitude that is manageable with basic signal acquisition methods. In case of low signal-to-noise ratio in exosomatic measurement, the voltage or current used for excitation can be increased. However, care must be taken to keep currents below limits of electrical safety and to avoid nonlinear effects (Pabst O *et al.*, 2018) and for DC measurement the undesired polarization effect will also increase with stronger excitation. For endosomatic recording, the magnitude of responses is typically several or up to tens of millivolts, providing stronger signals compared to other measures such as ECG. The frequency range of the EDA signal ranges from DC up to a few Hertz and is well below the 50/60Hz mains noise, enabling improvements in signal quality with a simple low-pass filter. Due to the low-frequency signal bandwidth, the sampling rate may also be low without losing much of the signal variance. Depending on the application, sampling rates around 5Hz may sufficiently preserve the relevant EDA signal information, especially for long-term recordings of spontaneous EDA. Other applications such as event-related latency analysis or the use of mathematical modeling approaches can require higher sampling rates of up to the kHz range for accurate timing and waveform representation. A particular consideration for exosomatic EDA measurement is the dynamic range. As the skin impedance can vary greatly from dry to moist skin, and due to skin anatomical variations between subjects and skin sites, the instrumentation needs to handle a wide dynamic range while also retaining sufficient resolution for the acquisition of weak responses. As described in Boucsein 2012 (Boucsein W, 2012), the use of AC-coupled amplifiers or separate circuitry for electrodermal levels and responses may be used to enhance the resolution of responses. This is no longer needed with modern high-resolution analog-to-digital converters (ADCs), and the range can be enhanced by using

non-linear or programmable gain of the amplifier. If cheaper ADCs are desired, or the ADCs built into microcontrollers that typically have lower resolution, digitally controlled gain adaptation may be used to optimize the measurement range and precision (Banganho et al.2021). When the electrodermal level is not important, the signal can be high-pass filtered into an easier manageable signal by squeezing the dynamic range. In order to facilitate testing of measurement quality, an EDA patient simulator has recently been proposed, capable of simulating both levels and responses of skin conductance (Geršak G and Drnovšek J, 2020). In addition to the instrumentation, the electrodes and skin contact are major factors in electrodermal signal quality and will be discussed in the next chapter.

3. Electrodes

The electrodes are an essential part of EDA measurement, and can be the most important component with respect to the quality of a recording. Conventionally EDA is recorded in the laboratory using gel-based electrodes, but dry electrodes based on different materials have recently emerged for wearable applications, giving a wide variety of electrode types as shown in figure 7.

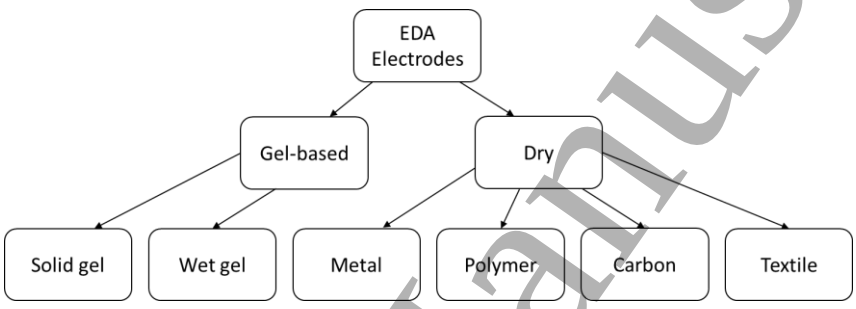

Figure 7. Overview of different types of electrodes relevant for EDA measurement

3.1. *Gel electrodes*

Gels are applied to both rigid and flexible electrodes to provide better contact and charge transfer between the metal part of the electrode and the skin. Gels used for this purpose are designed to mimic the salt concentration of sweat and help with decreasing the electrode-skin interface impedance and thus increase the signal quality (Posada-Quintero HF and Chon KH, 2020). Electrode gels may be solid or wet, and have different electrolyte compositions. Comparison of different gel types for skin conductance measurements suggests that solid hydrogel electrodes provide more stable measurements over time, while wet gels may cause more drift in the measurement and be more susceptible to pressure artifacts (Tronstad C *et al.*, 2010). When it comes to choosing the proper gel for EDA electrodes, an electrolyte concentration that matches the NaCl concentration in skin surface sweat is preferred (Boucsein W *et al.*, 2012). Other factors to consider include the mechanical stability and viscosity of the gel and how it interacts with the skin over time. Therefore, the time between electrode placement and the start of recording is of importance, as it can take time for the water content of the stratum corneum to match that of the electrode and to stabilize, and fixation of the electrodes for at least 5-10 minutes before recording is recommended (Boucsein W, 2012). It is important to use the same type of material for two EDA electrodes, in particular for endosomatic measurement or exosomatic DC measurement, due to possible potential differences introduced between different metals. Applying gels and adhesives for better adherence of the electrodes to the skin can be uncomfortable if the electrode is to be worn for a long time (Haddad PA, 2018). Application of gels can influence the skin and lead to changes in the skin conductance level over time based on the properties of the gel and its free water content (Tronstad C *et al.*, 2010). With respect to shelf life

of the hydrogel electrode and potentially also for long-term recording, degradation of the gel layer with time can impair the EDA signal quality due to a higher impedance and increased sensitivity to motion artifacts and noise (Posada-Quintero HF and Chon KH, 2020).

3.2. Dry electrodes

Dry electrodes do not provide the electrolyte that facilitates ionic transport between the skin and electrode surface, and the charge transfer is more capacitive which makes the electrical impedance of this interface more dependent on the excitation frequency. In addition, dry electrodes typically do not provide the same physical contact with the skin by lacking adhesion and conformity to uneven surfaces. Without a wet contact, the roughness of skin introduces pockets of air that can result in a higher electrical impedance, and the electrical impedance of skin measured with a dry electrode can therefore vary greatly with even slight changes in the pressure of electrode contact (Heikenfeld J *et al.*, 2018). Dry electrodes on the other hand prevent signal degradation issues of the hydrogel electrodes as they do not degrade over time. In addition, dry electrodes do not have a shelf life and can be used to obtain better long-term recordings (Boucsein W, 2012; Posada-Quintero HF and Chon KH, 2020) and the elimination of electrode gel may also enhance wearable comfort and reduce the risk of skin irritation (Wu H and et al., 2021). The skin-electrode contact tends to improve over time, as the impedance is decreased through buildup of moisture from perspiration between the electrode and skin surfaces (Posada-Quintero HF and Chon KH, 2020).

As for metal-based electrodes, Anusha et al. (Anusha AS *et al.*, 2018) compared four metals (stainless steel, brass, silver and gold) for EDA measurement on the wrist, and found that silver electrodes worn at the dorsal surface separated by 4cm performed consistently well on all study participants. In addition, they found that the average time needed for stable measurement was about 27 minutes for this electrode. Standard metal electrodes for EDA are rigid and may decrease the effective contact with the uneven skin surface. Flexible electrodes produced with materials such as Ag/AgCl are attractive alternatives for wearable EDA electrodes and the design for optimization of such electrodes has been researched in recent studies. In addition, electrodes fabricated of Ag/AgCl help with minimizing the electrode polarization as well as the bias potential between the electrodes (Haddad PA *et al.*, 2017; Kaipu SVR *et al.*, 2017).

Dry electrodes based on carbon may also be suitable for EDA measurement. Posada-Quintero et al. 2017 (Posada-Quintero HF *et al.*, 2017) demonstrated the suitability of a novel dry carbon/salt adhesive electrode by comparison to Ag/AgCl hydrogel electrodes, also having the advantages of consistently low impedance and no shelf life limitations without the use of a hydrogel layer (Posada-Quintero HF *et al.*, 2015).

Electrodes made from conductive polymer-based dry foam have been shown to provide EDA measurement in good agreement with gel-based reference measurement, and in addition has the attractive properties of high flexibility and resilience (Kim J *et al.*, 2014). The polymer mixture of PEDOT:PSS has recently been explored for EDA electrodes (Sinha SK *et al.*, 2020), having attractive properties such as the capability to conduct both ionic and electronic current. Using screen-printing technology, custom electrodes can be manufactured using commercially available inks based on conductors such as silver, carbon or polymers. In addition to the conductor material, the substrate is also an important part in the manufacturing and for the performance of the electrode. Nittala et al. 2020 (Nittala AS *et al.*, 2020) compared five different substrates for the production of skin-conformal electrodes and assessed their correlations to a commercial electrode for EDA measurement. Kim et al. 2021 (Kim H *et al.*, 2021) used a novel printing fabrication process to produce both flexible electrodes and electronics integrated into a soft silicone elastomer, providing a wireless, soft

electronic system that can measure EDA on the wrist. Textile electrodes have lately been developed and studied for this purpose (Haddad PA *et al.*, 2018; Sinha SK *et al.*, 2020). In addition to being flexible, textile electrodes have the attractive property of being breathable, that may provide more inert measurement of skin electrical properties with no gel influence and a reduced occlusion effect. With respect to signal quality, the impedance of the electrode material and of the electrode-skin interface (polarization impedance) is usually not a concern, as the skin impedance will under normal circumstances be much higher unless the electrode is very small. The physical contact between the electrode and skin surfaces plays a more important role in the signal quality.

3.3. *The influence of the electrode on the measurement*

An electrode gel can influence the EDA measurement over time, depending on factors such as the electrolyte strength, sorption properties and fluid properties of the gel in addition to the skin at the measurement site. As shown in Tronstad et al. 2010 (Tronstad C *et al.*, 2010), a wet-gel ECG electrode may provide quite different changes in SCL over time compared to a solid-gel electrode, and could even produce negative SCRs in certain cases due to the properties of the gel. Mechanical stability is also an important factor of electrode gels, where solid gels are less prone to pressure artifacts. While the reaction between the gel and skin may alter the EDA measurement when using gel electrodes, the dry electrode measurement is influenced by occlusion of the skin after contact. This means that the measurement will be unstable for some time after attaching electrode while the buildup of sweat and moisture increases the galvanic contact with the skin. Figure 8a gives an example of skin conductance changes within the first ten minutes after electrode attachment, comparing a gel-based electrode and a dry silver electrode. For wrist-based measurement, about half an hour has been suggested to obtain sufficient contact and measurements that are comparable to gel electrodes (Anusha AS *et al.*, 2018). Because the skin conductance is an extrinsic property (as opposed to the intrinsic conductivity of the skin), the measurement also depends on the size of the electrode. The area of the skin in contact with the electrolyte influences the conductance level and amplitude of the measured signal. Therefore, it is important to make sure that this area is constant during the whole measurement independent of the method used for fixing the electrode on the skin, and that the gel or cream is free from air. Any kind of seepage of the gel or the cream can change the contact area dimensions and cause errors in the measurements directly dependent on the diameter of the electrode (Venables PH and Christie MJ, 1980). The potential error due to seepage increases by the decrease in contact area, and consequently the conductance levels and response amplitude decrease. According to Fowles et al. the contact area between the skin and the electrode should be at least 1 cm^2 to prevent any kind of errors in the measurements (Fowles DC *et al.*, 1981). Figure 8b gives an example of simultaneous bilateral measurement with the same type of electrode but with different effective electrode areas. A monotonic, linear relationship between EDA and electrode size has been found in earlier studies (Mahon ML and Iacono WG, 1987), and dividing the measured conductance by the effective area of the electrode to represent the skin surface conductance density may provide a more comparable measure between studies.

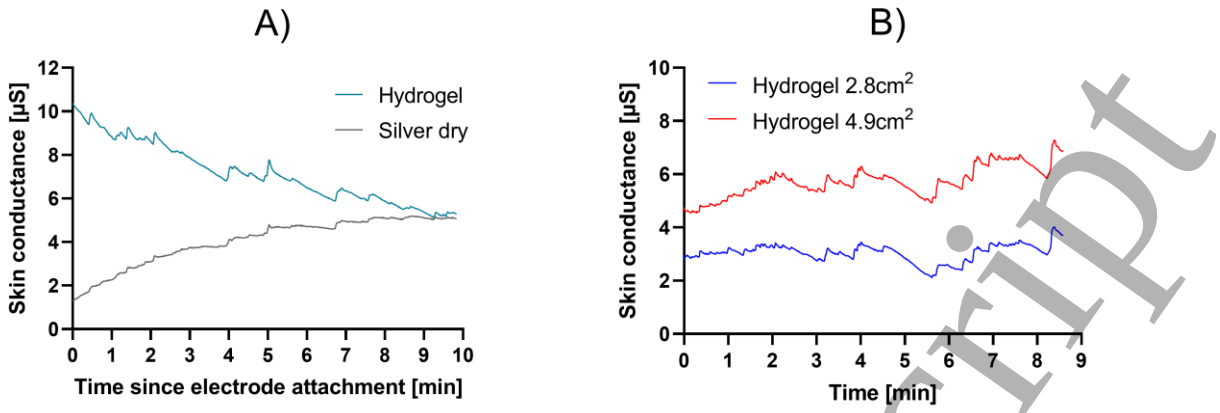

Figure 8. A) Example measurement of DC skin conductance during the first 10 minutes after electrode attachment, comparing a gel electrode (Kendall ARBO 1050NPSM) and a dry silver electrode of the same size, measured simultaneously on both wrists. B) Example measurement of DC skin conductance from the thenar eminence of both hands using the same type of hydrogel electrode, but with different electrode sizes. The measurements were done with two Shimmer3 GSR+ units (Shimmer Research Ltd).

3.4. *Measurement site*

The response to emotional stimuli varies based on the site of measurement, due to variations in sweat gland density (Kreyden OP and Scheidegger EP, 2004; Boucsein W, 2012). In 2012, Van Dooren et al. compared 16 different sites in the body to study sweating as the result of emotional stimuli and found out that it is possible to record emotional sweating on body sites other than palmar and plantar regions, however with much lower amplitude and activation level (Van Dooren M *et al.*, 2012). Another interesting feature with respect to sites of measurement is the concept of asymmetry on different sides of the body (Picard RW *et al.*, 2016), where differences in recordings from right and left hands might be the result of functional differences in the left and right lobes of the brain, and in some cases due to pathological reasons (Banks SJ *et al.*, 2012). With respect to finger locations, measurements from the distal phalanx of all fingers on the palmar side of the hands have shown stronger EDA signals in comparison to the median and proximal phalanges, that may be due to the higher concentration of sweat glands distally (Poh MZ *et al.*, 2010b; Valenza G *et al.*, 2010; Haddad PA *et al.*, 2018).

4. Modeling and analysing electrodermal activity

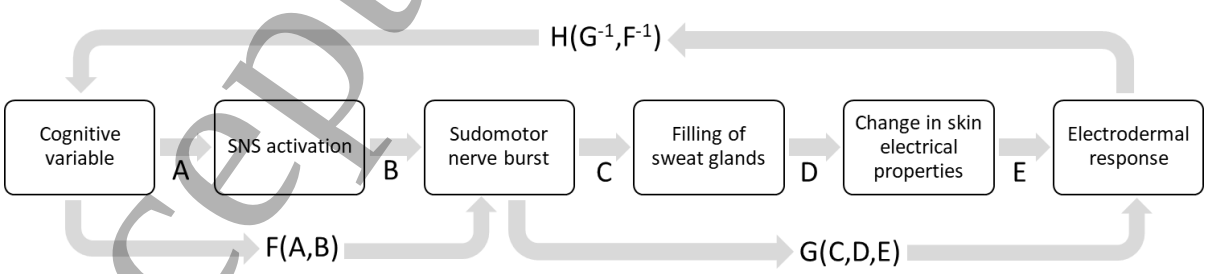

Figure 9. An illustration of the cascade of events involved from cognitive process to a measured electrodermal response, represented in steps with respect to modeling of EDA. F and G represent forward models of neural and peripheral parts respectively. H represents the inverse inference on a cognitive variable based on the measured electrodermal response.

Explanatory models are an important foundation both in understanding the electrodermal measurement and for the development of applications. Going from a cognitive variable that an experimenter wants to infer to the resulting electrodermal response, there are several important events involved in series, where one simple representation is provided in figure 9. With respect to modeling, different factors influence the events described in the figure: Mental state (A), condition of peripheral nerves (B), skin anatomy and condition of sweat glands (C), epidermal electrical properties and electrodes (D) and the measuring technique, electronics and signal processing methods used (E). This cascade can be divided into two forward models: a neural model representing the brain and nervous system (F), and a peripheral model (G) representing the sweat glands and the changes in skin electrical properties and electrical measurement. Inverse forms of these models can then be applied to estimate the cognitive variable based on the electrodermal measurement (H). A complete explanatory model of EDA that details all these events and influencing factors has not yet been developed. A simpler approach is to collapse all steps into one or two models without regard to influencing factors that often are unknown, allowing a more direct fit to the data. In some applications, inference on sudomotor nerve bursts or the degree of sweating may be of interest, and may be performed through inversion of a peripheral model only, leaving out the neural part.

4.1. *Biophysical models*

Typically, the skin and electrodes are represented as a combination of electrical components (with resistors, capacitors and batteries as illustrated in figure 2) that allows for a simple model of the active and passive electrical properties of skin, and also the role of the electrodes contributing to the measurement. Most of the work in biophysical models of EDA was done in the 1970s to the 1990s mainly by Fowles and Edelberg introducing the voltage divider and poral valve models which are still applicable today. With current trends such as dry electrodes for wearable devices and AC recording, these models may be expanded to account for electrode effects and AC phenomena in order to describe the measurement more completely. Newer techniques such as multi-parameter recording (skin conductance, potential and susceptance) (Grimnes S *et al.*, 2011; Tronstad C *et al.*, 2013), non-linear measurement (Pabst O *et al.*, 2018), multi-frequency AC measurement or multi-sensor approaches may provide new angles for testing and developing biophysical models, facilitated by modern computational methods for fitting unknown model parameters from empirical data. Because skin impedance is strongly dependent on excitation frequency, using impedance spectroscopy over wide frequency ranges can provide data with enough information to test different electrically equivalent models through data fitting.

While there is a current trend for black-box approaches such as machine learning in extracting relevant patterns from raw data, biophysical models can increase the understanding of the measurement and may assist in optimization of the measurement such as choice of electrodes and instrumentation. One example is the introduction of new electrode materials, that may behave electrically different than conventional electrodes when connected in series with the skin. A complete biophysical model may also be used to simulate cases of interest (such as the minimal limit of electrode sizes), and biophysical models of the processes governing EDA may be integrated in signal processing of EDA recordings (Tronstad C *et al.*, 2015). For more information on electrical equivalent models and analysis, see Grimnes and Martinsen 2015, chapter 9 (Martinsen ØG *et al.*, 2015).

Even though the relationship between sympathetic nerve activity, sweat gland filling and subsequent evaporation is well established, an accurate model describing the complete process from sudomotor nerve burst to the EDA measure is lacking. This is partly due to the challenge in obtaining recordings

of sudomotor nerve traffic while measuring EDA and perspiration at the same time. In 1992, Kunimoto et al. (Kunimoto M *et al.*, 1992) combined intraneural recordings with skin resistance and water vapour partial pressure recorded simultaneously in the same innervation zone, obtaining new knowledge on variations in sweat responses due to local skin and nerve factors, and found that irregular sudomotor nerve traffic evokes more sweat than for regular impulses. More recently, Gerster et al. 2018 (Gerster S *et al.*, 2018) reanalyzed the same data in order to test assumptions of linear time invariant models of EDA, confirming that LTI systems can reliably represent the relationship between sudomotor nerve activity and skin conductance responses as long as stimulation frequency corresponds to typical psychological or cognitive experiments (below 0.5Hz). Comparing intraneural stimulation under regional anesthesia with intraneural recordings, the former appeared as a more sensitive method to test the validity of LTI model assumptions.

4.2. Descriptive models

Although biophysically constrained or motivated models can reproduce qualitative data features, their free parameters have not yet been systematically fit to empirical data. However, as will be explained below, the explanatory power of biophysical models is less relevant for applications in SCR scoring, and descriptive models of the SNA-SCR relationship are sufficient to this end.

All model-based SCR scoring schemes use (approximately) linear time-invariant (LTI) models of the SNA-SCR relationship (function G in figure 9) (Alexander DM *et al.*, 2005; Bach DR *et al.*, 2018; Bach DR and et al., 2009; Benedek M and Kaernbach C, 2010b; Greco A *et al.*, 2016b). The first characteristic feature of an LTI system is that the response to the same input (under the same initial conditions) is assumed to be always the same. This response is fully characterized by the system's impulse response function (RF), the response to an infinitely short input. The second characteristic feature is linearity: the response does not depend on the baseline, and so the response to two subsequent inputs is just the sum of the responses to the individual inputs.

Notably, these assumptions often do not appear to be met for raw SC data. Following the poral valve theory, precursory sweating and hydration may influence the hydraulic pressure needed to expulse sweat through the opening of the duct, causing a possible interaction between electrodermal levels and responses (Edelberg R, 1993). Also, sweat expulsed after a sudomotor burst can lead to tonic changes in the SCL through hydration of the corneum, with later dehydration processes partly independent from the initial hydration. To render EDA data amenable to LTI models, they are usually high-pass filtered, which removes tonic changes.

LTI assumptions can be tested indirectly or directly. Indirect tests make the additional assumption that brief external events generate a constant-latency SNA burst, or in other words, that the function F in figure 9 is also described by an LTI system. Such tests have shown that an LTI system explains 60% of the variance in EDA for various external stimuli (aversive white noise bursts, aversive electric stimulation, aversive pictures, deviants in an auditory oddball task, visual targets in a detection task), and that the baseline EDA variance in the absence of external events is higher than the residual variance not explained by an LTI system (Bach DR *et al.*, 2010b). This suggests that this residual variance is caused by internally generated (spontaneous) SCR and measurement noise, rather than violations of the LTI principle. It was also shown that SCR amplitude to white noise bursts (after subtracting the zero-input response) does not depend on the baseline, when baseline was manipulated by preceding white-noise bursts at different intervals (Bach DR *et al.*, 2010b). Direct tests rely on intraneural stimulation or recordings from the sudomotor nerve and have shown that under regional anesthesia, which removes any spontaneously generated sudomotor activity, an LTI system accounts for around 95% of the EDA variance (Gerster S *et al.*, 2018).

These results motivate using an LTI model to describe the SNA-SCR relationship. The existing data suggest that the RF differs between individual participants or recording sites (Bach DR *et al.*, 2010b), and they may also differ between electrode types. However, it can be hard to estimate the true RF for single participants, and if this estimation is imprecise, then the benefit of using a tailored RF for scoring purposes is reduced (Bach DR *et al.*, 2010b; Bach DR *et al.*, 2013; Staib M *et al.*, 2015). Hence, all model-based scoring schemes provide a generic "canonical" RF across participants; the software PsPM additionally allows to use participant-specific RFs.

To determine the canonical RF, unconstrained descriptive models currently offer a more precise fit to empirical data than biophysically constrained models. Specifically, a Gaussian smoothed bi-exponential function showed a good fit on the first principal component of 1278 externally generated SCRs from 64 individuals (Bach DR *et al.*, 2010b). This canonical model is visibly different from the biophysically motivated models used in some scoring schemes, which were not fit on empirical data, (Benedek M and Kaernbach C, 2010b, a; Greco A *et al.*, 2016b) and do not match the empirical data used for the development of the descriptive model discussed above. Interestingly, the shape of externally and spontaneously generated EDA appears to be slightly different, as shown by comparing the aforementioned data to 1153 semi-automatically detected non-specific SCR from 40 male participants (Bach DR *et al.*, 2010c). Whether this is due to differently shaped SN bursts or stochastic variation between the different samples is currently unclear.

4.3. Model inversion

Equipped with a canonical or participant-specific RF, it is possible to infer cognitive or neural input from the data. Two common approaches are used for this (Bach DR *et al.*, 2018).

The first approach is termed psychophysiological modelling (Bach DR *et al.*, 2018). It is based on a generative model that consists of two parts (F and G in figure 9): an LTI model of the SNA-SCR relation together with a model of how the cognitive process generates SNA. The cognitive process can be parametrized in different ways, depending on the application. Sometimes, an LTI model is assumed here as well, and only the amplitude of a cognitive variable (e.g. arousal) is estimated based on matrix pseudoinversion (Bach DR and et al., 2009). In other applications, latency and dispersion of the SNA are free parameters as well, and the parameters are estimated using non-linear optimization (Bach DR *et al.*, 2010a; Bach DR *et al.*, 2011).

The second approach may be seen as a hybrid of model-based analysis and peak scoring. In a first step, one of several deconvolution schemes is used to estimate the most likely SNA time series, given SCR data and the RF. This SNA time series is then searched for peaks close to external events. Various deconvolution schemes in this approach differ in how and how much they constrain the SNA time series, for example to be non-negative, or to be composed of sparse bursts (Benedek M and Kaernbach C, 2010b, a; Greco A *et al.*, 2016b). Recently, characterization of EDA through the statistical nature of interpulse intervals has been proposed as a different approach to modeling the SNA time series (Subramanian S *et al.*, 2020).

A recent development in this field is the formulation of a biophysically motivated model that allows simultaneous estimation of sparse neural impulses and biophysical model parameters (Amin MR and Faghih RT, 2021). As yet, this approach has not been fully developed into a scoring scheme, and has only been applied to relatively straightforward types of laboratory experiments. However, in theory it holds promise if it can be computationally solved for more complex types of data.

4.4. Tools for Scoring

Many scoring tools exist in parallel. It is desirable to compare them by rational criteria. A concept common in psychological research is based on general measurement principles: a latent variable has a true score, and the purpose of measurement is to approximate this true score as closely as possible (Cronbach LJ and Meehl PE, 1955).To instantiate this concept in a process termed calibration, a psychological experiment is performed to instantiate several true scores for a given cognitive variable. Measurement approaches are compared by how well they reproduce the intended true score, a metric termed "retrodictive validity" (Bach DR *et al.*, 2020). To calibrate SCR scoring schemes, the most common experimental approaches have been to generate different levels of sympathetic arousal by presenting aversive and non-aversive external events (Bach DR and et al., 2009; Bach DR *et al.*, 2013; Bach DR, 2014), or by learning to predict aversive and non-aversive events (Bach DR *et al.*, 2010a; Staib M *et al.*, 2015; Privratsky AA *et al.*, 2020).

In general, there are three types of scoring approaches: psychophysiological modelling, hybrid approaches, and scoring the SCR data directly (e.g. peak-scoring, area under the curve, or counting of non-specific fluctuations). Direct comparison has shown that for analysing responses generated by brief (<1 s) aversive events, or short-interval (<4 s) prediction of aversive events, psychophysiological modelling has higher retrodictive validity than peak-scoring or hybrid approaches (Bach DR and et al., 2009; Bach DR *et al.*, 2010a; Bach DR *et al.*, 2013; Bach DR, 2014; Staib M *et al.*, 2015; Privratsky AA *et al.*, 2020).

The following softwares implement these approaches:

- PsPM (https://github.com/bachlab/PsPM): full psychophysiological modelling scheme for estimating phasic arousal in different experimental situations, as well as tonic arousal (Bach DR *et al.*, 2013; Bach DR *et al.*, 2018). The software repository is being actively maintained and provides user support.
- Ledalab (http://ledalab.de/software.htm): hybrid scoring scheme for generating an estimated SN time series by non-negative or continuous deconvolution, and peak-scoring in this time series (Benedek M and Kaernbach C, 2010b, a). The most recent major activity on the software repository was in 2016.
- cvxEDA (https://github.com/lciti/cvxEDA): hybrid scoring scheme for generating an estimated SN time series by convex optimization, and peak-scoring in this time series (Greco A *et al.*, 2016b). The most recent major activity on the software repository was in 2015.
- Breathe Easy EDA (http://github.com/johnksander/BreatheEasyEDA): peak-scoring scheme with specific tools for integration of respiration data (Ksander *et al.*, 2018). The most recent major activity on the software repository was in 2020.
- Autonomate (https://dibs-web01.vm.duke.edu/labar/autonomate.html): peak-scoring scheme with support for overlapping SCR (Green SR *et al.*, 2014). No code repository is provided.

5. Challenges and solutions for wearable EDA:

Transitioning from a laboratory setup to wearable solutions allows more relevant data to be collected in the field and opens up for numerous new applications, but it can be difficult to obtain the same quality of measurement when standards such as recommended experimental conditions and electrode placement can no longer be followed. The main challenge with wearable EDA is the variable electrode contact or pressure upon movement causing artifacts in the measurement. In addition to discussing the challenges with wearable EDA, we also review recent works that may provide solutions to these problems.

5.1. *Sources of artifacts*

When variations in the recorded signal are caused either as a result of the recording process or from physiological sources other than the electrodermal activities of interest, they are defined as artifacts (Boucsein W, 2012). Physiologically, studies have shown that speech activity, deep inhalations, breath holding, changing the respiratory pattern are all activities that would evoke EDR (Stern RM and Anschel C, 1968; Hygge S and Hugdahl K, 1985). Whether EDA variations caused by these sources are to be interpreted as artifacts or as relevant signals is up to the investigator (Boucsein W, 2012). Technically, the electrode-skin connection can be another source of recording based artifacts. This can be either due to an increase in the resistance between the skin and the electrode or detachment of the electrode from skin, or problems from the cables and their contacts to the electrodes (Boucsein W, 2012). Movement is the most important physiological source of artifact in EDA measurement, either disturbing the contact between the skin and the electrode or influencing the electrical properties due to changing pressure. Studies have shown that pressure to the skin would result in decrease in sweating that might be because of increase in ductal reabsorption while the sweat gland continues its activity (Millington PF and Wilkinson R, 1983; Boucsein W, 2012).

5.2. Other Sources of error

Environmental factors can also influence the EDA recordings. The hand temperature may lower or raise EDA values (Venables PH and Christie MJ, 1980), and very high temperatures can cause sweating as the results of thermoregulatory responses that may be regarded as artifacts by not being the result of psychophysiological activity of the subject (Peek CJ, 1987). A recent study suggests that ambient humidity influences the recording of EDA levels in particular (Bari DS *et al.*, 2018). Therefore, it would help preventing these types of unwanted variation if consistency is followed with regards to the temperature and humidity of the room (Stern RM *et al.*, 2001; Shaffer F *et al.*, 2016), but this is rarely possible in applications of wearable devices. Because movement and environmental effects (temperature and humidity) can be main sources of error (either as artifacts or confounders), wearable EDA systems may benefit from including sensors that provide information on these sources of variation, facilitated by the availability of miniaturized accelerometers, temperature and humidity sensors that are available today.

Electrical noises affecting the signal quality and statistical power of wearable electrophysiological recordings mainly include intrinsic body noise, skin-electrode interface noise and environment noise (Heikenfeld J *et al.*, 2018). Among these, the skin-electrode interface is the most important issue in wearable EDA, as intrinsic body noise (such as muscle potentials and cardiovascular activity) is weak compared to endosomatic EDA or the voltages involved in exosomatic EDA, and environmental noise (such as powerline interference and surrounding electronics) is not overlapping the EDA signal frequency range and can be easily filtered within the device.

5.3. Artifact handling

Manual artifact handling is too time-consuming for wearable devices, and in order to streamline processing of longer recordings, automated tools for identification of artifacts have been developed. Taylor et al. developed a machine learning algorithm for this purpose, obtaining a high accuracy in distinguishing artifacts from normal physiological responses (Taylor S *et al.*, 2015). Zhang et al. (Zhang L *et al.*, 2020) demonstrated that motion artifacts can be detected by unsupervised learning with competitive performance as supervised algorithms. In a recent study by Gashi et al. (Gashi Sh *et al.*, 2020) using more than 100 hours of labeled data to train their algorithm, they demonstrated a high accuracy (97%) in identifying artifacts for data collected in-the-wild, which is a significant step towards eliminating the need for human annotators. As an alternative to machine learning methods where the

decision making of the algorithm by default is unavailable or uninterpretable, automated rule-based procedures have demonstrated excellent agreement with consensus ratings in labeling invalid data from ambulatory EDA (Kleckner IR and et al., 2018). If EDA is recorded from more than one similar skin site, their signal similarity may be exploited to identify movement artifacts (Thammasan N *et al.*, 2019). For applications where EDA is used to detect and alert physiological changes such as painful events, epileptic seizures or hypoglycemia, real-time artifact handling can be crucial. To the best of our knowledge, real-time implementation of artifact handling methods in wearable devices is yet to be demonstrated and validated scientifically.

5.4. Skin sites for wearable devices

For EDA measurement in wearable devices, standard skin sites such as the palm are less practical, except for sensors that are built into gloves (Lee Y *et al.*, 2010; Valenza G *et al.*, 2010; Lanatà A *et al.*, 2012). The most popular skin site for practical reasons is the wrist. Sano et al. (Sano A *et al.*, 2014) compared wrist and palmar recordings during sleep and found higher skin conductance levels and larger, more frequent peaks when measured on the wrist. Kasos et al. 2020 (Kasos K *et al.*, 2020) compared bilateral skin conductance measurement from traditional and alternate measurement sites recorded during breathing exercises, arousing and neutral stimuli, and found moderate correlations (Pearson's r=0.33 and 0.30) between the wrists and the left fingers as a reference. The wrists were less responsive and showed smaller amplitudes compared to the fingers. Similarly, Van der Mee 2021 (Van der Mee DJ *et al.*, 2021) found modest but significant within-subject correlations between palm-based and wrist-based EDA (r=0.31 for SCL and r=0.42 for non-specific SCRs). Vavrinsky et al. (Vavrinsky E *et al.*, 2017) developed an "EDA ring" for integration into smart clothes, and Torniainen et al. (Torniainen J *et al.*, 2015) demonstrated that a small ring sensor could obtain recordings similar to a laboratory-grade finger EDA measurement, obtaining an average cosine similarity of 83%. For sensor applications integrated into shoes or socks, EDA at the feet correlate well with palmar EDA (Kappeler-Setz C *et al.*, 2013; Kasos K *et al.*, 2019; Sanchez-Comas A *et al.*, 2021). Other skin sites such as the calves may become comparable to the wrists in response frequency, magnitude and correlation, given sufficient hydration time (Kasos K *et al.*, 2019). Other possible candidate skin sites for wearable EDA are the forehead (Tronstad C *et al.*, 2008; Krönert D *et al.*, 2019; Geršak G and Drnovšek J, 2020) for a possible EDA cap/headband and the nose for EDA eyewear (Zheng YL and et al., 2014). It is however important to consider that EDA from alternative skin sites may have different pathways of innervation (governed by different branches of the spinal nerve), and that similarity to standard skin sites such as the palm may be dependent on conditions of central regulation in addition to the density and activation of the sweat glands.

5.5. Long-term monitoring

For long-term recordings, the user comfort, power requirements and data storage needs particular consideration. Relevant advances in this area includes on-chip data compression for reduction of memory and connectivity requirements as developed by Pope et al. 2019 (Pope GC and Halter RJ, 2019), and sparse representation of EDA signals based on a compressed sensing approach by Iadarola et al. 2021 (Iadarola G *et al.*, 2021), obtaining high compression rates without affecting detection of peaks. Long-term recordings also depend on electrodes that can provide stable measurements over days, preferably without gel that may dry out or cause allergies over time. For long-term use, some degree of moisture transport and minimal thermal load is desired, either through the use of thin backing materials that themselves are water permeable or through the introduction of physical microperforations (Heikenfeld J *et al.*, 2018). Dry electrodes for long-term monitoring have been developed for other bioelectrical signals such as ECG (Chi M *et al.*, 2019) and EMG (Li J *et al.*, 2020), that may also be suitable or relevant for long-term EDA recording. For recordings over days to weeks,

the accumulation of dead skin cells from the stratum corneum can be a limiting factor degrading the electrical and mechanical properties of the electrode interface (Heikenfeld J *et al.*, 2018).

5.6. Signal processing

Signal processing for cleaning of signals, decomposition and calculation of scores or features have traditionally been done as a post-processing task after raw data collection. With wearable devices there is often a need for real-time processing in order to provide direct feedback to the user, creating more demand on the microcontroller. Several recent works have addressed this issue by developing more computationally efficient methods of signal processing. Shukla et al. 2018 (Shukla J *et al.*, 2018) demonstrated computationally efficient EDA filtering using wavelet transformation. Caldas et al. 2020 (Caldas OI *et al.*, 2020) proposed a simplified algorithm for the purpose of online extraction of skin conductance features. Hernando-Gallego et al. 2018 (Hernando-Gallego F *et al.*, 2018) developed a faster variant of the hybrid analysis approach of nonnegative deconvolution with immediate extraction of the skin conductance level and response. Kelsey et al. 2018 (Kelsey M *et al.*, 2018) presented an approach combining sparse recovery and dictionary learning for improved computational efficiency of analysis and decreased run time while maintaining a high degree of accuracy in detecting responses. Methods for signal smoothing and calculation of features may be improved and customized for ambulatory EDA, as presented by Coffman et al. 2020 (Coffman DL *et al.*, 2020). With sensors that are interfaced with mobile phones, signal processing can also be done by the mobile phone or through cloud computing. When using model-based approaches, it may be important to develop specific response functions for the different types of sensors used.

6. New opportunities in EDA research and development

General developments in electronics, material technology and data science has led to new opportunities in the research on EDA and further developments in the methodology. Below we list some examples of recent works in selected areas that are currently in development.

6.1. ***Electrodes***

Late developments in material technology for wearable dry electrodes has solved many of the drawbacks with dry electrodes such as lack of flexibility, stretchability, adhesion and high electrode-skin impedance. Developments over the last decade has provided great advancements in performance optimization and function extension of on-skin electrodes (Wu H and et al., 2021) and introduced electronic systems with thickness, elastic moduli, bending stiffness and areal mass densities matching the epidermis (Kim DH and et al., 2011), where excellent skin surface conformity has been obtained for skin surface electronic systems (Ershad F *et al.*, 2020). These may laminate and adhere directly to the skin via the action of van der Waals forces alone, capable of accommodating the motions of the skin without any mechanical constraints (Yeo WH *et al.*, 2013). One recent example is the dry conductive polymer electrode developed by Zhang et al. 2020 (Zhang L *et al.*, 2020) that has high conductivity, self-adhesiveness, mechanical flexibility/stretchability and biocompatibility. For measurement of the inert electrodermal activity, the influence from the electrode on the measurement should be minimized. Ideally, the electrodes should be breathable to prevent occlusion effects. Examples of recent developments in this area is the transparent breathable epidermal electrode developed by Fan et al. 2018 (Fan YJ and et al., 2018) and the highly sweat breathable, conformable and stretchable epidermal electrode presented by Wang et al. 2020 (Wang Y *et al.*, 2020).

6.2. Multi-site measurement

Previous studies have compared skin conductance signals from up to 16 different skin sites, using a self-developed hardware platform (Van Dooren M *et al.*, 2012). Smaller wireless devices and multichannel devices have made it easier to measure EDA at different skin sites. In addition to comparing different skin sites with respect to suitability for EDA recording, associations between EDA signals from different sites may be studied with respect to innervation and central control. Among the new opportunities are bilateral recordings of EDA for studies of lateralization (Picard RW *et al.*, 2016; Kasos K *et al.*, 2018; Bjørhei A *et al.*, 2019; Kasos K *et al.*, 2020), and combining measurements from different dermatomes in studies of physiological reactions (Elvebakk O *et al.*, 2019). These solutions may also support the evaluation and comparison of different recording sites for wearable applications.

6.3. Multi-person measurement

With miniaturized EDA loggers available today, many devices can be time-synchronized for the purpose of data collection from many participants measured simultaneously (Kasos K *et al.*, 2019). This facilitates research avenues on collective phenomena in large audiences such as the cinema (Silveira F *et al.*, 2013; Kaltwasser L *et al.*, 2019). New insights may be gained by the synchrony of physiological measurements between subjects over time. As an example using EDA, EEG and heart rate sensors, Stuldreher showed that interpersonal physiological synchrony can support the detection of attentionally engaging events over time (Stuldreher IV *et al.*, 2020). Van Beers et al. 2020 (Van Beers JJ *et al.*, 2020) compared laboratory and wearable sensors (ECG and EDA) in the context of physiological synchrony, and found no significant difference in classification accuracies between the laboratory and wearable sensors.

6.4. Long-term recordings

With modern wearable devices and sufficient data storage, EDA can be recorded over longer periods and patterns in variation seen over days or longer can now be analyzed. Vieluf et al. in 2021 (Vieluf S *et al.*, 2021) investigated 24-hour patterns of EDA and found that circadian patterns are reflected in EDA recordings, and Kim et al. 2018 (Kim J *et al.*, 2018) found a significant circadian rhythm in EDA data from participants hospitalized for two nights. More data from longer durations may improve understanding of reproducibility and cyclic variability in electrodermal patterns, and facilitate development of improved prediction models with possibilities for personalization.

6.5. Machine learning

As the field of machine learning has evolved over the last decade, these algorithms have been used to train models for predicting various outcomes based on EDA data or multi-sensor data including EDA. Examples from works published within the last few years include classification of epileptic seizures (Zsom A and et al., 2019), differentiation of sensory responses for children with autism spectrum disorder (Raya MA *et al.*, 2020), identification of cognitive tasks (Posada-Quintero HF and Bolkhovsky JB, 2019), pain assessment (Susam BT *et al.*, 2018; Posada-Quintero HF *et al.*, 2021; Aqajari SAH *et al.*, 2021), emotion recognition (Al Machot F *et al.*, 2019; Sharma V *et al.*, 2019; Ganapathy N *et al.*, 2020), assessment of emotional engagement (Di Lascio E *et al.*, 2018), Stress detection (Amalan S and et al., 2018; Zontone P *et al.*, 2019; Pakarinen T *et al.*, 2019; Anusha AS *et al.*, 2020; Sánchez-Reolid R *et al.*, 2020; Greco A and et al., 2021), cognitive load measurement (Romine WL *et al.*, 2020), detection of major depressive disorder (Kim AY *et al.*, 2018), and arousal detection from music (Bartolomé-Tomás A *et al.*, 2020). Among these studies, high performances in classification accuracies have been reported ranging from 64% to 95% depending on the dataset, classification problem and difficulty

(binary classification is for instance less challenging than multiple levels of stress). Sample sizes (in number of participants) range from seven to 147 (median of 32), indicating that generalizability of models could benefit from larger datasets in many studies. Although there are many promising results, generalizability is yet difficult to determine due to a lack of external validation of new models. External validation may be especially important in the EDA field due to possible bias coming from differences in measurement techniques and conditions as described earlier.

With bigger datasets, *deep learning* methods may further improve performance and possibilities in prediction based on sensor data. While deep learning has demonstrated outstanding performance in several applications such as speech recognition (Nassif AB *et al.*, 2019) and computer vision in medicine (Esteva A and et al., 2021), these methods have been developed based on massive amounts of training data at a scale that is far above the size of most studies on EDA. One increasingly popular approach in the field of machine learning is *transfer learning*, where knowledge from developed models trained in one domain can be employed to another, and in this way may offer a technical solution to the challenge of small datasets (Yang F *et al.*, 2020). While transfer learning has been used widely in other areas such as image recognition, its application in physiological time-series is limited. Recently, studies have demonstrated possibilities and potential advantages of applying transfer learning to time-series of physiological time-series (Li X *et al.*, 2020; Radhika K and V Ramana MO, 2020; Bizzego A *et al.*, 2021). With more advanced models, the mechanisms behind their decision-making become increasingly difficult to understand. Different methods have recently been introduced to provide interpretability and explainability of machine learning models (*explainable AI*) in order to deal with the "black-box" problem of complex models (Adadi A and Berrada M, 2018). In addition to the potential for improving insight and trustworthiness of developed models, these methods may also help determine which signal features are important and explain patterns that are uncovered by the machine learning process. While these methods have demonstrated promising results in the aid of ECG classification (Rjoob K *et al.*, 2020; Jo YY *et al.*, 2021), we could not find any published works on explainable AI methods applied on EDA data at the time of this review.

6.6. Sensor fusion

While EDA is not a very specific measurement for most applications, more accurate predictions may be obtained by combining EDA measurement either with sensors that help adjust for confounders such as movement (accelerometer) or temperature, or by combining EDA parameters with other sensors that provide more or less independent predictors of the target variable. One such example of complementary sensors is EDA and EEG, where the combination of these has shown superior classification performance to either single modality in an emotion recognition model (Yasemin M *et al.*, 2019). Using a large multimodal dataset including EDA, skin temperature, accelerometer data together with mobile phone data, Umematsu et al. 2019 (Umematsu T *et al.*, 2019) demonstrated the possibility to forecast the high/low binary stress level of the next evening based on data from previous days. Sensor fusion may also improve robustness against physical activity artifacts as demonstrated by Tiwari et al. (Tiwari A *et al.*, 2020).

6.7. Large datasets

Research in EDA and in particular the development of prediction models would benefit from more open data and bigger datasets, allowing more input for model training and stronger validation of developed models. However, as EDA results may vary due to conditions of experiments and recording technique, it is important to carefully match data sources that are compatible or follow a high degree of standardization. Less control and standardization in ambulatory experiments using wearable

devices implies a need for larger sample sizes to obtain the same effect sizes as in controlled laboratory experiments. An ecosystem model for EDA data that includes open data, open source, application programming interface and software development kit has been proposed by Jussila et al. (Jussila J *et al.*, 2018). Concepts for integrating physiological sensors together with big data analysis and cloud computing is already described (Chen M *et al.*, 2016). Availability of open data is growing on resources such as Physionet. Large datasets from other wearable devices including sensors such as photoplethysmography and accelerometers combined with machine learning has demonstrates possibilities in detecting important conditions such as atrial fibrillation from only smartwatch data (Tison GH *et al.*, 2018), and the future may tell what will be possible for applications relevant for EDA developed using larger datasets.

6.8. Expanded measures of EDA

Using the AC technique, the skin conductance, skin potential and skin susceptance can be measured at the same time (Grimnes S *et al.*, 2011). Although these measures have been compared in a few studies (Tronstad C *et al.*, 2013; Bari DS *et al.*, 2018), their relationship and implications in EDA is yet not fully understood. Furthermore, the exogenous EDA can be measured at different frequencies of voltage or current excitation, possibly providing more information on the dynamics of skin electrical properties in relation to sudomotor activity. Multi-frequency measurements over time provides a more complete representation of the skin electrical properties, estimation of Cole parameters for mathematical modeling, and a hypothesis is that this approach has potential to improve ambulatory measurement quality. Lately, measurement of non-linear properties of skin admittance have been introduced, where it has been found that low frequency AC excitation voltages down to 0.4V can reversibly change the skin admittance due to electro-osmosis (Pabst O *et al.*, 2018). This excitation-dependent effect on the skin admittance may be quantified from the voltage-current response during few cycles of AC excitation, calculating a non-linearity parameter for the skin below an electrode that is assumed to be related to the properties of the sweat ducts and the surrounding tissue, the stratum corneum (Pabst O *et al.*, 2018). Together, these options in measurement may expand the information that can be collected on the electrical properties of skin, and the activity and properties of sweat glands with respect to interpretation of EDA.

6.9. Theoretical developments

Even though new data science methods improve the scope and performance of EDA applications through data-driven approaches, the understanding of the electrodermal mechanism will always remain a topic of interest and importance. Further advances in all parts of EDA modeling may not only improve knowledge on EDA as a phenomenon, but also lead to more accurate inferences and predictions through inverse modeling. The biophysical part of EDA, relating sudomotor nerve activity to the electrodermal signal is yet incomplete, and would benefit from models that are able to explain more of the signal variance under different conditions. Such development could potentially provide better inferences or predictions between subjects by specific extraction of relevant variance or adjusting for irrelevant variance by additional measurements. We believe that this development must be based on statistical fitting of models to data collected under controlled experimental conditions where as many as possible of variables are known.

6.10. Summary

Recent research in the methodology of measurement and data interpretation has advanced the applications of EDA both in the laboratory and for wearable devices. While standards for high-quality recordings are difficult to meet in ambulatory measurement, recent and ongoing developments in electrodes and signal processing may shorten this gap. Along with current trends in electronics,

material technology and data science, several opportunities for research and further development of EDA methodologies and applications are emerging. We highlight the following areas of particular interest or importance for the future progress in the EDA methodology and applications:

- Artifact handling for wearable devices in real time
- Skin conformal, stretchable and breathable dry electrodes for long-term wear
- Further development and validation of models for inferring cognitive, sympathetic or sudomotor nerve activity from EDA recordings
- Long-term EDA data collection and analysis
- Larger datasets of standardized recordings for development in machine learning approaches
- Integration of EDA in multisensory systems with sensor fusion
- Increased understanding of EDA through a complete biophysical model of the dynamical skin electrical properties
- Understanding and optimization of the information that can be acquired from different methods of EDA measurement
- More complete mapping of different skin sites for suitability of EDA measurement under different conditions

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