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A Survey of Affective Computing for Stress Detection

Evaluating technologies in stress detection for better health.

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As we become more aware of the connection between emotional states and physical health, affective computing continues to rise as a field of interest. Affective computing uses both hardware and software technology to detect the affective state of a person. It is an active research area that has seen much growth in technology geared toward affective state analysis. Its origin is credited to Dr. Rosalind Picard of the Massachusetts Institute of Technology (MIT) when she published her 1995 article on affective computing [1]. It has since become a modern branch of computer science for human–computer interfaces [2], [3]. This stem of computer science has two main veins: 1) detection and recognition of emotional information and 2) simulation of emotion in computational devices. The focus of the current survey is the detection and recognition of emotions as affective states.

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Affective states are psychophysiological constructs that influence behavior. These constructs are generally divided into three categories: arousal, valence, and motivational intensity [4]. The majority of technology-related research in affective computing surrounds arousal because of its objective measurement of physiological activity. Arousal is directly tied to the autonomic nervous system (ANS), at which it can be measured in numerous ways via physiological sensors. Measuring arousal enables the assessment of both valence and motivational intensity of emotions to influence human behavior. Valence is the rating of positive, negative, or neutral affect, whereas motivational intensity is the measure of how likely an affect will elicit activity in response to stimuli presented to an individual.

The technology used in affective computing exploits both physiological and physical manifestations of one's affective state to determine current emotion. Six basic emotional states are deduced in affective computing: joy, anger, surprise, disgust, sadness, and fear. In addition to these basic emotions, other affects such as frustration and stress can be computed. This technology is evaluated here for its potential use in research on stress in humans of varying ages.

This article focuses particularly on physiological and physical measures of psychophysiological stress using technology commonly used for affective computing. We first examine some background of psychophysiological stress and its effect in the human body. The discussion continues by exploring the physiological and physical measures of stress and the technology used to make those measurements. This includes assessment and comparison of current products being used for research and in business.

The physiological measures of stress and their corresponding technologies can be classified as follows:

- brain activity → electroencephalography (EEG)
- heart activity → electrocardiography (ECG)
- skin response → galvanic skin response (GSR) and electrodermal activity (EDA)
- blood activity → photoplethysmography (PPG)
- muscle activity → electromyography (EMG)
- respiratory response → piezoelectricity/electromagnetic generation.

Physical measures of stress and their corresponding technologies can be classified as follows:

- facial expression → automated facial expression analysis (AFEA)
- eye activity → infrared (IR) eye tracking
- body gesture → automated gesture analysis (leveraging AFEA).

In this survey, the current literature of psychophysiological stress and its effect on the human body is reviewed. We then examine physiological and physical measures of stress and the technology used to make those measurements. We conclude with a comparison of current products used for research and commercial endeavors. From here on, psychophysiological stress is synonymously referred to as *stress*.

BACKGROUND

Managing stress is a major health concern for populations around the world. Stress exists in two main forms: acute and chronic. Every person experiences stress at some point in his or her life, most commonly as acute stress. According to the American Psychological Association, acute stress is the result of demands and pressures of the recent past as well as those anticipated in the near future [5]. This can derive from instances such as athletic challenges, test taking, or anxiety when meeting new people. Chronic stress, on the other hand, is due to long-standing pressures and demands including those experienced as a result of socioeconomic conditions, difficulties in interpersonal relationships, or an unsatisfying career [5]. If left unmanaged, chronic stress can have detrimental consequences on those experiencing it. Psychophysiological stress can manifest into physical and physiological symptoms that can affect one's health if the stress becomes chronic [5], [6]. These symptoms can be measurably observed in numerous ways that are explored in this article. Much focus is placed on acute stress because this allows researchers to study the short-term effects of stress, which are more easily observable. In addition, due to the short-lived nature of acute stress, there is an expected lower risk to the research participant when stress is induced for the purpose of research [5]. However, extrapolating from current data, more needs to be discerned when studying the effects of long-term stress.

Stress, whether chronic or acute, has effects on one's physical condition. In acute stress, symptoms may include emotional distress, muscular ache and tension, digestive tract issues, and overarousal [5]. The more serious of these concerns relate to overarousal, which can lead to heart attacks, arrhythmias, and possible sudden death in those with preexisting heart conditions [7]. Less serious concerns include headache, back pain, heartburn, stomach

ache, elevated blood pressure, and rapid heartbeat [5]. Chronic stress can exhibit the same symptoms as acute stress, but with more extensive damage. Chronic stress is identified as a risk factor for hypertension and coronary disease [7], [8], irritable bowel syndrome, gastroesophageal reflux disease [9], generalized anxiety disorder, and depression [10]. If chronic stress is allowed to proliferate, ongoing symptoms may reduce the quality of life for those experiencing this stress.

Early stress-detection methods relied heavily on self-reports in response to a standardized list of questions. Examples of these early methods include the Perceived Stress Scale 10 or 14 and the Depression Anxiety and Stress Scale 21, which were based on questionnaires regarding life events [15]. Although these methods have been validated, there is still the concern of subjective response bias from the individual that may introduce additional skewness into the assessment of stress. Hence, there is a need for objective measures with a basis in physical and physiological domains. Because stress also presents itself via biomarkers and physical expression, it can be measured objectively and observed.

The classic standard for a physiological measure of stress has been the assessment of cortisol levels produced by the hypothalamic-pituitary-adrenocortical (HPA) axis. This assessment involved cortisol extractions from various sources: hair, saliva, blood (serum), and urine. These measurements were invasive and/or involved a laborious process for analysis [16], [17]. As a result, the discovery of alternative means of measurement via wearable, as well as noncontact, sensors produced resulted in alternatives that are now more commonly used.

In the following sections, predominant traditional and contemporary methods for measuring stress via physiological and physical means are discussed. Traditional methods include ECG and EEG. However, the current trend in affective computing, particularly in stress detection, is leaning more toward noninvasive methods of measurement dealing with skin conductance and PPG (optical sensing).

PHYSIOLOGICAL STRESS-BASED AFFECTIVE COMPUTING

Several indicators provide physiological measures of stress. The most prevalent include heart activity (ECG), brain activity (EEG), skin response (GSR/EDA), blood activity (PPG), respiratory response (piezoelectricity and electromagnetic generation), and muscle activity (EMG). Each of these are examined more closely in the following sections.

HEART ACTIVITY AND ECG

HEART ACTIVITY

A predominate factor examined for stress across many studies involves heart rate (HR) and heart rate variability (HRV). When stress is induced in an individual, HR becomes elevated. This is part of the fight-or-flight response that is often referenced in high-stress situations. HRV provides more information than HR alone. HRV is the measure of standard deviation in interbeat intervals of successive R waves in a heart beat [18]. A typical heart beat consists of four main components: baseline, P wave, QRS complex, and T wave. The R spike of the QRS complex is most commonly used for evaluation of HRV because it is the most predominant spike in the waveform [21].

In stressful situations, HRV is a product of change in autonomic nerve activity, which is composed of sympathetic and parasympathetic modulation. The function of the sympathetic nervous system (SNS) as it relates to the heart is to speed HR to provide an increase in blood supply to the body. This queues the fight-or-flight rush that comes with stress. After the stressor has been removed, the parasympathetic nervous system (PNS) kicks in to slow HR. Examining the relationship of these two nervous systems provides insight into the stress state of an individual [20], [18]; HRV provides such insight. The waveform of a heart captures activity, and HRV further enables the analysis of activity across multiple heart beats. This allows monitoring of how quickly the body responds to stress, how long the stress response lingers after the stimulus, and how rapidly the PNS can act to reduce stress. When combined with other methods of stress assessment, HRV can pinpoint corresponding physiological and physical markers associated with stress in an individual.

ECG

One of the most heavily used stress-detection methods uses ECG (alternatively appearing as EKG) for heart activity such as HR and HRV. ECG devices use electrodes that are strategically placed on the body to measure electrical signals produced by depolarization and repolarization of the heart [41]. There are a few different configurations of this setup based on ECG lead polarity and electrode placement. The most common configuration is the standard limb, bipolar lead setup illustrated in Figure 1(a). Figure 1(b) shows the Einthoven's triangle, which translates lead placements to axial references in the electrical signals recorded by each electrode.

HRV data extracted from ECG measurements can be filtered by frequency content and then analyzed. Frequency content is generally divided into two bands: low frequency (LF) and high frequency (HF), with LF at 0.04–0.15 Hz and HF at 0.15–0.4 Hz [40]. It also may be common to see three-frequency bands comprised of LF (0–0.08 Hz), midfrequency (0.08–0.15 Hz), and HF (0.15–0.5 Hz) [39]. Alternatively, these may be labeled as very LF (VLF), LF, and HF, respectively. This separation of frequency content is useful because SNS activity is associated with LF content, whereas PNS activity is associated with HF content [40]. The analysis involved in assessing HRV lies in the energy ratio of LF to HF content—in other words, the ratio of SNS to PNS activity. This is usually modeled as [39]

$$\text{Power Ratio}_{\text{ECG}} = \frac{\text{Power}_{\text{LF}}}{\text{Power}_{\text{HF}}}.$$

The power values are typically extracted from power-spectral density (PSD) which uses fast Fourier transforms (FFTs) to convert time-domain data into frequency-domain data [40]. Alternatively, power densities may be normalized to total power using the following models:

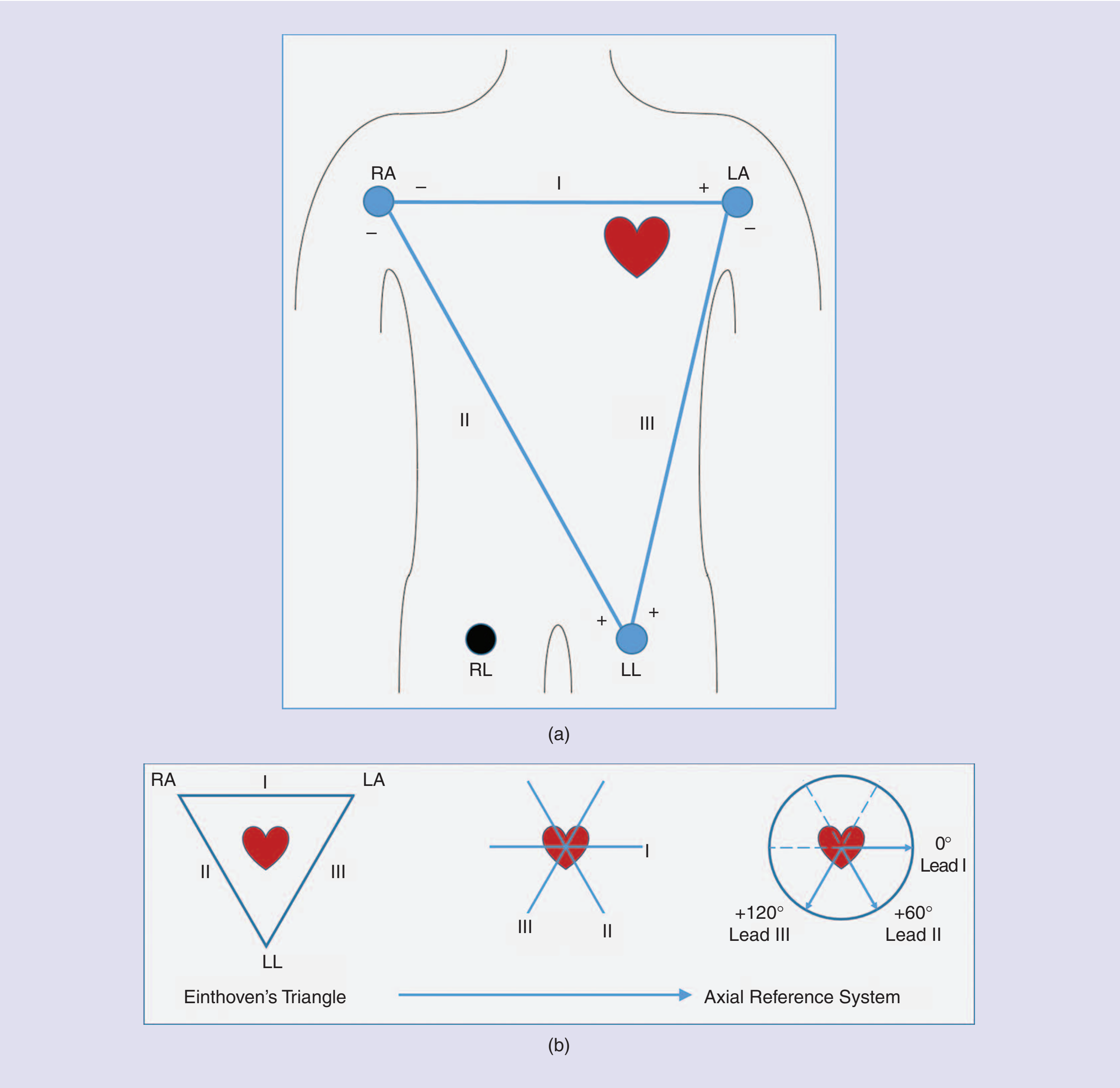

FIGURE 1. (a) The standard three-lead bipolar ECG setup. (b) Einthoven's triangle translated to axial references [42].

$$\text{Total Power}_{\text{LF}} = \frac{\text{Power}_{\text{LF}}}{\text{Power}_{\text{HF}} + \text{Power}_{\text{LF}}} \times 100$$

and

$$\text{Total Power}_{\text{HF}} = \frac{\text{Power}_{\text{HF}}}{\text{Power}_{\text{HF}} + \text{Power}_{\text{LF}}} \times 100.$$

ECG is the current gold standard for heart monitoring, with Biopac Systems, Inc. as a leader in producing reliable ECG recording systems. Biopac offers an acquisition system (MP150) equipped with an ECG amplifier. The system comes with a software suite called AcqKnowledge that offers online and offline tools for real-time analysis (see Table 1). A number of studies have cited Biopac's MP150 and MP35 (its educational system variant) for having high-precision R-R interval timing [45].

One of Biopac's main competitors in research development products is Shimmer Sensing, which offers its Consensys ECG Development Kit that comes with a wireless, wearable ECG Shimmer device, a charging base, straps, leads, and electrodes. The hardware is also accompanied by the Consensys software suite, which allows for wireless real-time synchronization and analysis. Additionally, the Shimmer unit comes with nine degrees of freedom (9 DoF) sensing (accelerometer, gyroscope, and magnetometer), with the capability of measuring up to two channels of EMG data [46]. The system is expandable to up to 15 units per kit.

Table 1. A comparison of ECG systems.

ECG System	Software	Real Time	Lead Count	Connectivity	Portable	Additional Features
Biopac MP150[a] + ECG2-R Bionomadex TX/RX [43]	AcqKnowledge	Yes	2 (ECG) + 1 (GND)	Wireless (2.4-GHz digital RF)	No	• Lead III data can be inferred based on lead I and lead II data • Can be used simultaneously with other Biopac modules
Shimmer3 + Consensys Base [46]	Consensys	Yes	3 (ECG) + 1 (GSR) + 1 (EMG)	Wireless (Bluetooth)	Yes	• EMG add-on • 9DoF sensor

[a]Biopac MP150 is considered to be the ECG gold standard.
EEG: electroencepholagraphy, ECG: electrocardiography, EMG: electromyography, GSR: galvanic skin response, 9DoF: nine degrees of freedom.

BRAIN ACTIVITY AND EEG

BRAIN ACTIVITY

The brain is the epicenter of all nerve stimuli. Thus, monitoring brain activity is complimentary to detecting stress response. Stress response originates in the amygdala, which communicates with the hypothalamus to initiate an ANS response [28]. This stimulation of the ANS provokes subsequent physiological and physical manifestations of stress. Evoked potentials at the cerebral cortex correspond to signals sent between the amygdala and hypothalamus making it possible to record brain activity at the scalp [29]. Specifically, the frontal cortex is examined, usually by means of EEG.

EEG

Several different technologies are used for measurements of direct brain activity including positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and EEG. Both PET and fMRI use blood flow as indicators of brain activity, whereas EEG uses electrical potentials. Although both PET and fMRI are effective means for measuring brain activity with high spatial resolution, both are very slow in response and involve expensive equipment [50]. Therefore, our focus here is on EEG technology.

EEG measurements involve a matrix of electrodes placed on the head that record event-related potentials at the occurrence of brain stimulation. These electrodes are most commonly fitted into a cap according to the international 10/20 system. This system is based on 19 electrode placements spaced at 10% and 20% intervals across the cranium. Each percentage is of the total length of the cranium either front to back or ear to ear. The nasion (bridge of the nose) and inion (occipital protuberance) are used as boundary markers for the perimeter of the electrode system. [51]. The system is used to allow for a comparison of results from research conducted all over the world [50], [51]. Figure 2 shows the top view of the 10/20 system (see the Figure 2 caption for more details on electrode labeling).

Similar to ECG analysis, measurements are filtered into frequency bands and can be analyzed according to power through a technique that calculates power spectrum ratios. The extracted frequency bands are categorized across a range of approximately 30 Hz as delta band (δ, 0.5–4 Hz), theta band (θ, 4–8 Hz), alpha band (α, 8–13 Hz), and beta band (β, 13–30 Hz) [55]. When using the power spectrum ratio technique for accessing EEG data, filtered measurements are then translated to PSD via FFT. An energy spectrum density can then be calculated by dividing the PSD area of each band by the respective frequency range of each band [55].

Among the systems frequently used in research are the B-Alert X10 by Advanced Brain Monitoring (ABM); the EPOC+ from Emotiv; and the gold standard, the wired ActiveTwo EEG system by BioSemi. The Emotiv EPOC+ and ABM B-Alert are both highly ranked wireless EEG systems that are commercially available. The two have been compared against the gold standard several times and have proven to be comparable [52]–[54] (see Table 2).

SKIN CONDUCTANCE AND GSR

SKIN CONDUCTANCE

More recent research focuses on skin measurements for stress detection because they provide an easy interface for instrumentation. The skin response primarily focused on is EDA, more commonly known as GSR, which measures skin conductance. Skin conductance is the susceptibility of the skin to conduct electricity. This conductivity is based on sweat gland activity that often activates in response to high stress or fight-or-flight situations [24]. During increased stress, perspiration increases, causing resistance to current flow to drop, inversely affecting conductivity of skin. This relationship is the reason that conductance is used as opposed to resistance. Conductance has a directly proportional relationship to the increase in perspiration and is indicative of increased stress. Although GSR has been used to detect stress, it is also worthwhile to note that GSR, like other biomarkers, is a response to arousal, which could be positive (e.g., elation) or negative (e.g., fight or flight) [25].

GSR

GSR, which relies on conductivity of skin in response to stimuli, measures skin conductance level while monitoring activity change. Skin conductance naturally increases over time (especially in humid environments), so transient increases are targeted for EDA [59]. The natural rise in conductance is called tonic skin response. This should be noted as a reference point, but it is generally not used for marking significant activity; instead, phasic responses are targeted. These are the rapid transient peaks that occur due to stimuli, such as a stressor. Recorded values are typically in the range of microsiemens (μS), although units of resistance (kΩ–MΩ) are often referred to both in measurement and defining a range of sensing [24].

GSR measurements have become a more popular form of stress detection because they generally require a less cumbersome setup as opposed to EEG and ECG setups. GSR measurements are typically taken at the finger, but some research has measured GSR at the wrist with good correlation to finger measurements [56], [57], making wrist measurements a viable alternative to increase wearability. Another convenience factor is that finger- and wrist-worn GSR electrodes, unlike those of EEG and ECG, do not always require gel for conductivity. Although some systems recommend them based on the type of electrode used, it is not always

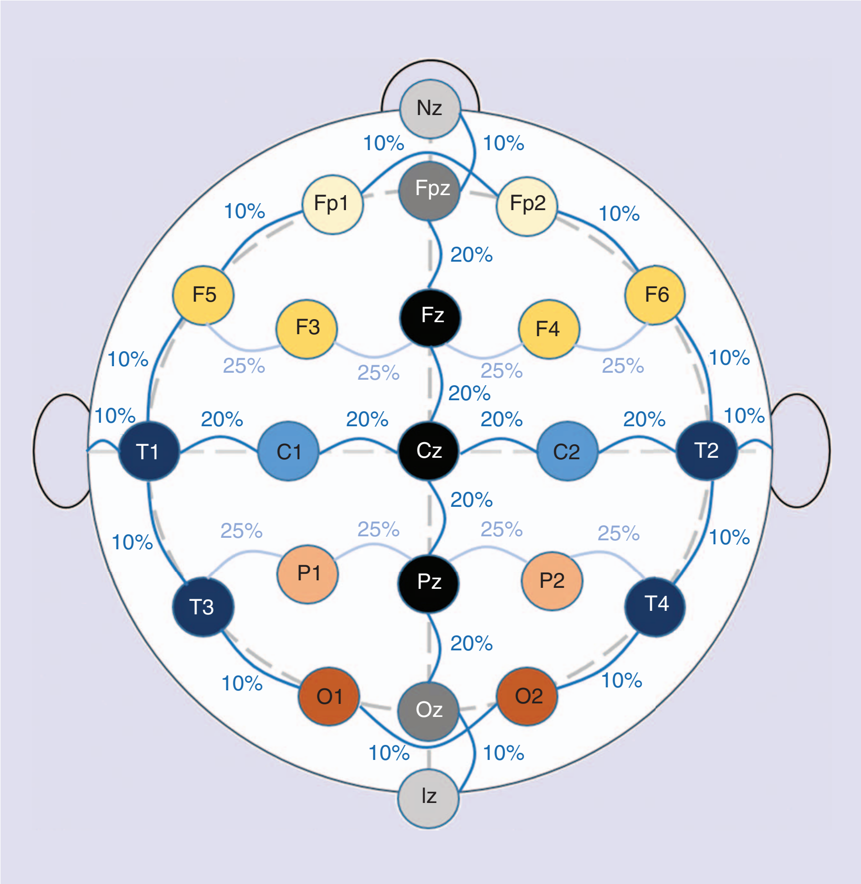

FIGURE 2. The top view of the 10/20 system EEG electrode placement. Electrode lobe mapping: F, frontal (Fp is used to identify forehead placements and should not be confused with frontal-parietal lobe, which does not exist.); T, temporal; C, central (central lobe is used for identification purposes only [51]); P, parietal; and O, occipital. Boundary references include the nasion (N) and inion (I). Odd numbers correspond to the left hemisphere, and even numbers to the right hemisphere. (z) Zero reference points. The lighter-colored arcs between electrodes represent additional placements that are typically added to the standard 19-electrode system.

Table 2. A comparison of EEG systems.

EEG System	Software	Real Time	Electrodes/Channels	Connectivity	Portable	Additional Features
BioSemi ActiveTwo[a] [49]	ActiView	Yes	Up to 256 electrodes/ seven channels	Wired	No	• 24-bit ADC per channel • Very high S/N ratio • Very low drift error in timing
ABM B-Alert X10 [48]	• B-Alert Live • B-Alert Lab • B-Alert Fuse • AMP	Yes	Nine electrodes/ channels + one optional	Wireless (Bluetooth)	Yes	• Very low drift error in timing • SDK compatible with MATLAB • Full integration with AcqKnowledge (Biopac) • Optional channel for ECG, EMG, or EOG
Emotiv EPOC+ [47]	• Emotiv (Xavier) control panel • Emotiv brain visualizer • Emotiv Insight app	Yes	14 Electrodes/ channels + two reference	Wireless	Yes	• Real-time 3-D rendering • Light weight • Dense array spatial resolution • SW compatible with/Windows, OSX, Linux, Android, and iOS

[a]BioSemi ActiveTwo is considered to be the EEG gold standard.
ABM: Advanced Brain Monitoring, AMP: Alterness and Memory Profiler, S/N: signal to noise.

Table 3. A comparison of GSR systems.

GSR System	Software	Real Time	Channels	Connectivity	Portable	Additional Features
ProComp Infiniti[a] [61]	BioGraph Infiniti (Suites) ● EEG ● Physiology ● Rehab ● DynaMap	Yes	8	Wired	No	● Integrates with various sensor types (EEG, ECG, EMG, GSR, HR, BVP, respiration, force)
Biopac MP150 + Bionomadix PPGED-R TX/RX pair [44]	AcqKnowledge	Yes	1 (GSR) + 1 (PPG)	Wireless (2.4 GHz bi-directional digital RF)	No	● Additional PPG sensing ● Can be used simultaneously with other Biopac modules
Shimmer3 GSR+ [62]	Consensys	Yes	2 (GSR) + 1 (PPG)	Wireless (Bluetooth)	No	● Additional PPG sensing ● Multiconfiguration PPG (finger or earlobe) ● 9 DoF sensor ● Lightweight ● Onboard 8-Gb memory

[a]The ProComp Infiniti is considered to be the GSR gold standard.
BVP: blood volume pressure, HR: heart rate, PPG: photoplethsymography, RF: radio frequency.

necessary, especially if the subject wearing the electrodes has moist skin. Dry GSR electrodes can be placed directly on skin and measure EDA [56]. These conveniences have made wearable GSR sensors, such as the Shimmer3 GSR unit and the Empatica E3 wristband, possible.

Similar to the ECG and EEG units available as modules to the Biopac MP150 system, Biopac also offers a GSR unit (GSR100C) that allows for the measurement of EDA. This unit uses the same AcqKnowledge software suite as all of the other amplifier modules for the MP150 system. As an alternative to the normal wired interface, Biopac also offers a wireless version included in its Bionomadix PPGED-R module that allows for tether-free transmission of measured data to the MP150 acquisition unit. The Bionomadix PPGED-R module offers both PPG and GSR sensing capability.

Thought Technology, Inc., like Biopac, offers an array of modules and sensors that can be used for affective computing. Specific to their GSR capabilities, Thought Technology offers a skin conductance sensor (SA9309M) that interfaces with either of its ProComp or FlexComp data acquisition systems. These systems are (optical) wire-based systems that have been used in several studies for GSR measurement [57], [58]. Each acquisition system comes with the Biograph Inifiti software suite that allows real-time display of raw data.

Shimmer Sensing offers a GSR unit that has many of the same benefits as its ECG unit; the form factor is small, wireless, and simplistic. Like the ECG module, it too contains 9 DoF sensing. Additionally, the GSR module has an expansion port for PPG sensing. This module is used with the same Consensys base and software suite as the ECG module, which allows for real-time acquisition and analysis.

Empatica Inc. is a company that rose out of MIT research, focusing on effective affective computing systems for research. Empatica's flagship device is the E4 wristband, which houses PPG, EDA, and temperature sensors, along with a three-axis accelerometer within a compact wristband. Data collected is logged in real time, whether natively in the onboard flash or streamed wirelessly to its RealTime app. A study comparing Empatica's GSR measurements to those of Thought Technology's ProComp Infiniti system [60] revealed a 93% correlation in data. See Table 3 for a comparison of GSR systems. The E4 wristband is revisited in the following section.

BLOOD ACTIVITY AND PPG

BLOOD ACTIVITY

Inherent in the change of HR and HRV is a change in blood volume and blood pressure. Blood volume pulse (BVP) is the phasic change in blood volume that corresponds to each heartbeat interval [23]. Furthermore, BVP is also used to determine changes in blood pressure in correspondence with blood volume. Variability in blood pressure is due to vasodialation and vasoconstriction of arteries, capillaries, and other vasculature, which can be discerned by BVP measurements [23]. These fluctuations of blood pressure and blood volume are direct products of heart activity. Therefore, another means of stress measurement is made available by way of BVP.

PPG

PPG is a low-cost, noninvasive optical technique that is commonly used to detect blood volume changes in microvasculature [65]. A PPG sensor simply uses an optical pulse generated by a red or near-infrared (NIR) light source (typically a light-emitting diode), with a closely placed photodetector acting as the receiver of reflected light. The amount of light received back at the photodetector provides insight into the amount of blood volume in the area illuminated. Less light received by

Table 4. A comparison of PPG systems.

PPG System	Software	Real Time	Connectivity	Portable	Additional Features
UFI model 1020[a] + simple recorder [71]	Simple software (UFI)	Yes	Wired	No	• Multiple configurations (finger strap, finger clip, ear clip, and adhesive pad)
Empatica E4 [72]	• Empatica manager • RealTime app • Empatica Connect • Mobile API (iOS/Android)	Yes	Wireless (Bluetooth low energy)	Yes	• GSR sensing • Three-axis accelerometer • Temperature sensor • 60+ h of flash storage • Splash resistant • Watch-like wearable

Angel Sensor [73]	• Seraphim API
	• Mobile API (iOS/Android)
		Yes	Wireless (Bluetooth low energy and proprietary Seraphim sense)	Yes	• Full access SDK/API available for iOS, Android, and Lua engine
					• Three-axis accelerometer
					• 3-D Orientation (gyroscope)
					• Temperature sensor
					• Vibrating motor
					• RFID/NFC tag with writable memory
					• Splash resistant
					• Watch-like wearable
					• Fitness features
					  • Blood oxygen monitoring
					  • Step and calorie count
					  • Sleep quality
					  • Health journal (up to 7 d)

[a]The UFI 1020 is considered to be the PPG gold standard.
NFC: near field communication, RFID: radio frequency identification, 3-D: three dimensional.

the photodetector means that more light was absorbed at the site of illumination, which directly corresponds to higher blood volume [65]. When pulsed at a rate high enough, BVP can be determined with this optical approach. From this, HR and HRV can be deduced [66]. Hence, PPG provides a cheaper alternative to ECG measurements. Several studies have been conducted to test the validity of PPG sensor data compared to the ECG standard and have shown that PPG sensors provide comparable results [63], [67]–[69].

The more popular and validated PPG systems include Empatica's E3 and E4 wristbands, UFI's model 1020 Pulse plethysmograph, and Biopac's Bionomadix PPGED-R add-on to its MP150 system. As mentioned in the GSR section, the E4 wristband contains multiple sensors that allow for convenient and comfortable sensing on the wrist. The E4 wristband is based on the E3 band, which has been measured up to the ECG gold standard (Biopac's MP150 system equipped with an ECG100C module). One particular study showed a high correlation in both frequency and time domains, also revealing only 2.14% error among a total of 9,287 ECG peaks [63]. Another study claimed that the onboard accelerometer, along with a secondary light source, is used to remove artifacts that often plague PPG readings due to movement [64]. The UFI model 1020 has been used in a number of studies to reliably measure BVP and estimate HRV [36], [70].

In addition to the aforementioned systems, and as included in the GSR discussion, Shimmer Sensing offers a PPG extension in its GSR+ kit as well. A developing company by the name of Seraphim Sense has launched its Angel Sensor smart health bracelet after a successful Kickstarter campaign in 2013. To the best of our knowledge, the Angel Sensor bracelet is the first of its kind to offer an open platform for developers to access the plethora of sensing capabilities housed on the device. See its features compared against the validated PPG systems in Table 4.

OTHER PHYSIOLOGICAL MEASURES OF STRESS

MUSCLE ACTIVITY AND EMG

Neural activity leading to involuntary muscle control is another by-product of SNS activation. Muscle action potentials have been used in studies to identify stress response. A study conducted in 1994 by Lundberg et al. shows that trapezoid muscle action potentials highly correlate with perceived stress scores and blood pressure response to stress [30]. EMG sensor usage in affective computing seems to have declined in recent years due to the more popular sensors (i.e., PPG, EDA). Many companies offer reliable EMG sensors for sensor fusion (simultaneous sensing) as well as with more commonly used sensors. The technology involved in EMG sensing is similar to ECG and EEG in the fact that it uses electrodes to detect potential spikes. However, the source of the targeted potential is from skeletal muscles that produce a range of less than 50 μV up to 30 mV [31]. But an issue associated with this is that recordings are extremely localized and quality is dependent on the muscle tone of the individual tested. Lipid layers covering muscle greatly impede measurement of EMG signals.

Eye activity, specifically pupil dilation and blink rate, has been used in some stress studies to correlate with physiological measures of individuals experiencing stress.

RESPIRATORY RESPONSE, PIEZOELECTRICITY, AND ELECTROMAGNETIC GENERATION

Respiratory activity is another physiological feature that has been used to indicate stress. Ventilation has proven to be a result of the ANS in response to mental and physical stress [32]. Hyperventilation, in particular, has been associated with stress. In the process of hyperventilation, more CO_2 leaves the body than can be produced by metabolic processes, which may result in a host of physiological consequences including reductions in cerebral and myocardial perfusion and O_2 delivery, ECG and EEG changes, withdrawal of cardiac vagal tone, muscle spasms, and tetanus [32], [33]. Because changes that occur due to respiratory alterations can be sensed from ECG and EEG directly, these sources are more likely to be used.

A study by Jennifer Healey and Rosalind Picard shows that heart activity and skin conductance show greater correlation to stress than both respiration and EMG [39]. However, the technology involved is usually in the form of a piezoelectric transducer that changes linearly in response to longitudinal pull. Piezoelectric transducers are composed of ceramic material that provides an electrical response to physical changes. These transducers are often placed on a belt and clipped on an individual around his or her chest, so that the transducers provide respective output as the chest expands and contracts. Alternatively, electromagnetics can be used in place of the piezo material. A study by Bryson Padasdao and Olga Boric-Lubecke exhibits the way in which to use a servomotor in place of the piezo transducer [34].

PHYSICAL STRESS–BASED AFFECTIVE COMPUTING

Here, we will discuss the physical manifestations of stress, which include facial-related features and behavioral traits of individuals experiencing stress. These modes of measurement use AFEA software and body tracking to identify affective states.

FACIAL FEATURES AND BEHAVIOR

FACIAL EXPRESSION RECOGNITION

Documentation dating back to the late 1800s, such as Charles Darwin's book *The Expression of the Emotions in Man and Animals*, correlates facial expression to emotional state. Studies in the late 1900s and early 2000s confirmed this connection of facial expression to specific emotional states via the study of the HPA axis and cardiovascular responses to stress [35]. A more recent study conducted by J.S. Lerner et al. has identified the positive association of fear with cardiovascular and cortisol stress response, whereas a negative association of these responses was identified for indignation (anger and disgust) [35]. This same study also showed that facial expression analysis correlated with biological markers of stress are better than self-reported emotional states.

A rising mode of affective computing is the advancement of AFEA algorithms. Many investigators have used facial expression analysis organically to detect sadness, anger, happiness, and deceit [77]. Many facial expression recognition systems are based on a protocol called the Facial Action Code System (FACS), which was published by Paul Ekman and Wallace Friesen in 1978 and later updated in 1992 and again in 2002 [76], [78]. This system objectively measures the frequency and intensity of facial expressions and deduces what is referred to as an action unit (AU). AUs are the smallest discriminable movements detectable in a facial expression [76]. FACS is separate from emotion in nature, yet its AUs are significantly appreciated in detecting emotional state based on facial expression. AUs dealing with eye constriction and lip, cheek, and brow arrangement are essential for computing affective state by the use of facial expression recognition software.

This rule-based coding approach of FACS is used as a part of the analytical class of automated face recognition. There are two major classes of automated face recognition: analytical and holistic. The difference between the two classes is in the template references. The analytical class focuses on geometrical feature extraction, whereas the holistic class focuses on usage of a feature vector to represent an entire facial template [74]. Facial expression recognition systems such as FACS have enabled the possibility for AFEA. Lien et al. demonstrated an AFEA system based on FACS with up to 93% accuracy [79]. Other commonly used methods for facial expression recognition include hidden Markov models (HMMs), contour models, principle component analysis (PCA), and artificial neural networks (ANNs) [74], [75], [79].

Leaders in affective computing include Affectiva, Inc. and Emotient, Inc. Affectiva, like Empatica, was formed out of MIT's Media Lab and cofounded by the founder/director of the Affective Computing Research Group, Rosalind Picard [80]. Affectiva produces a FACS-based AFEA called Affdex that uses advanced computer vision and machine learning within a scalable cloud-based structure to perform facial analysis using any standard webcam [82]. The system intends to extend beyond the basic emotions (anger, joy, surprise, disgust, sadness, and fear) to provide better real-world assessment of multimedia [82]. Although the foremost goal of Affdex software is to assess user response to commercial content, the core of the system assesses user emotion and has great potential for other applications such as assessing pain and depression and helping individuals with autism [81].

Emotient is an AFEA company that has produced software for commercial applications, now under the authority of Apple after an early 2016 acquisition. The company started at the University of California, San Diego, where the original platform, Computer Expression Recognition Toolbox (CERT), was created. The group that innovated the FACS-based system later converted the AFEA platform into Emotient in 2012 and commercially offered the software under the name FACial Expression Toolkit (FACET). FACET software has been evaluated in research of a speech-based emotion recognition system for analyzing job interview videos [84]. It has also been assessed for applications of the automated detection of driver fatigue and automated teaching systems [83]. These are only a few of the applications; many more have been considered for use in medical, educational, safety, and security fields.

EYE TRACKING

Eye activity, specifically pupil dilation and blink rate, has been used in some stress studies to correlate with physiological measures of individuals experiencing stress [36], [37]. A study done by Haak et al. shows a strong relationship between eye-blink frequency and emotional stress via correlation with EEG measurements. This study used driving simulations to assess blink rate under stress and nonstress conditions, showing that eye blink frequency tends to increase positively with stress [37]. Pupil dilation has proved to be quite useful in increasing confidence of stress detection. A study conducted by Barreto et al. shows that inclusion of pupil dilation in the analysis of stress increases the accuracy of detection [36]. This assessment of pupil dilation was based on a study by Partala and Surakka in 2002 that revealed a distinct pattern of eye dilation associated with emotional arousal [38].

As an alternative to total face assessment, investigators have also isolated eye activity for evaluation in affective computing [85], [86] (see Table 5). Regarding eye activity alone, a multitude of eye-tracker systems can fit the need of extracting important information regarding eye placement and movement. Two systems, in particular, are the Tobii X120 series and Eye Tribe ET1000 eye trackers. Tobii X120 has been used in affective computing research for assessing emotional state during visual stimuli in a normal population (via video) [86] as well as an autistic population (via a virtual reality [VR] environment) [87]. Both studies show Tobii X120 to be effective in tracking and extracting valuable eye activity. Tobii X120 has since been replaced by Tobii Pro X3-120, which produces the same performance in a smaller form factor. Additionally, Tobii offers a wearable eye tracker, Tobii Pro Glasses 2, that is lightweight and promotes natural viewing behavior. Eye Tribe's ET1000 eye tracker has not been used in much published research; however, it has received a Best of Innovation Award in Accessible Technologies from the Consumer Electronics Showcase (CES) in 2015 and considered for the 2016 Best of Innovation Award in Tech For A Better World. ET1000 has been compared to the performance of Tobii X120, but it holds a smaller form factor and is offered at a lower price. Eye Tribe software offers mobile solutions for tablets, smart phones, and even VR headsets [89].

BEHAVIOR AND GESTURING

Physical and physiological manifestations of stress also include a behavioral component that accompanies symptoms. Such symptoms could be fist or jaw clenching, body stiffness, crossing of the arms, pacing, jittering, and a number of other behaviors [90], [91]. Behavior and gesture analysis has been used for studies regarding those with autism [92]. Visual sensors, such as those used to detect facial features, can be used to discern stress behavior via posture and movement sensing. The study carried out by Piana et al. used an Xbox Kinect to capture gesture features for analysis of emotional state in autistic children [92]. Automated gesture analysis systems use the same visual processing algorithms as used in AFEA and eye-tracker systems (HMM, ANNs, PCA, etc.) [74]. Hence, a similar system could potentially be used for aiding in stress detection of nonautistic individuals.

EVALUATION OF AFFECTIVE COMPUTING FOR STRESS DETECTION

Many of the methods and technologies discussed in this article are reliable in detecting physical and physiological measures of stress. However, due to the complexity of the human makeup, it is not always sufficient to have only one method of measurement to compute affective state. The best systems for affective computing integrate multiple sensor sources to most accurately detect affect. Similar logic applies to stress detection. Due to the relationship between affective state and stress, and the corresponding physiological changes in BVP,

Table 5. A comparison of eye-tracker systems.

Eye Tracker	Software	Gaze Accuracy	Additional Features
Tobii Pro X3-120 [88]	• Tobii Studio • Tobii Analytics SDK	0.4° (binocular) 0.5° (monocular)	• API hooks for C#, Python 2.7, C++, and MATLAB • Supported across Windows (all), Ubuntu (Py & C++), and Mac OSX 10.7 (all except C#)
Eye Tribe ET1000 [89]	• Eye Tribe Tracker • Eye Tribe SDK	0.5°	• SDK is available for C#, C++, and Java • Offers active tracking for enabling device control • Compatible with VR headsets (Oculus Rift DK 2, HTC Vive, and Gear VR)

VR: virtual reality.

Table 6. A technology comparison convenience chart.

Sensor Technology for Stress Detection					
	EEG	ECG	PPG	GSR	AFEA
Highly wearable			✓	✓	✓
Highly accurate	✓	✓	✓	✓	✓
Low cost			✓	✓	
Low maintenance			✓		✓
Highly unobtrusive			✓	✓	✓

AFEA includes eye tracking
AFEA: automated facial expression analysis.

skin conductance, and HR, a combination of these sensor sources would likely be best for accurately detecting stress.

Companies such as iMotions, Inc. have developed systems that integrate multiple methods of measurement in a single platform [93]. For example, they have integrated physiological sensors with AFEA and eye-tracking software to better assess affective states. The central benefit of such a platform is that it allows researchers to perform full experiments within a single environment. Stimuli can be generated and integrated into a test just as well as the response is recorded. This allows investigators to make stronger correlations of facial expression recognition and eye activity with proven biological metrics.

iMotions' biometric research platform integrates some of the most popular and highly validated measurement systems offered by Biopac Systems, Empatica, Shimmer Sensors, Emotient, Affectiva, Emotiv, Tobii, and ABM. Such a system allows for full integration of GSR, EEG, EMG, ECG, BVP, eye tracking, and facial expression recognition all in a single platform for analysis. Table 6 shows the technology available for affective computing and stress detection.

FINAL ASSESSMENT AND AREAS FOR FUTURE RESEARCH

Affective computing is a growing field. As it grows, so will the robustness of stress-detection systems. Much of the technology used within affective computing can be directly applied to stress detection, especially more contemporary noninvasive technologies, such as facial expression, gesture recognition, and eye tracking. These modes of affective computing, coupled with VR technology, could be revolutionary in the assessment and intervention of stress.

Many commercially and readily available devices come equipped with much of the sensing capabilities used for stress detection and affective computing as a whole. Popular products ranging from fitness bands (e.g., BASIS Peak, Microsoft Band) that contain GSR, PPG, and temperature sensors to smartphones with a PPG sensor and camera (e.g., Samsung Galaxy S6) can be used in detecting stress. Given this proposal for use, corresponding research must evaluate the apps that accompany these smart bands and smart watches [94]–[96]. Comparing commercially available products such as BASIS Peak [94] and Samsung Galaxy S Health [97] apps against gold standards in ECG, GSR, etc. may reveal corresponding results. Consumers aware of such rankings can be better aided in the decision-making process when choosing a product.

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