An Overview of the Feasibility of Permanent, Real-Time, Unobtrusive Stress Measurement with Current Wearables

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ABSTRACT

Negative consequences of stress are a pervasive problem in our modern society. Recent developments in wearable lifestyle hardware have led to unobtrusive, sensor-packed, always-on devices that might finally be able to continuously monitor biosignals to detect, determine or even prevent stress or some of its negative outcomes. In this work, we give a concise overview of a majority of biosignals that are in some way relevant for stress classification and outline state-of-the-art machine learning algorithms for this task. Additionally, we provide a list of all recent wearables including an evaluation of their feasibility to implement such algorithms as well as directions to look for an assessment of the accuracy and validity of their recorded data with respect to stress tracking.

CCS CONCEPTS

• **Applied computing → Consumer health**; *Health informatics*; • **General and reference** → Surveys and overviews.

KEYWORDS

Stress, Wearables, Algorithms, Review, Overview

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1 INTRODUCTION

Hans Selye coined the term *stress* as the "non-specific response of the body to any demand for change" [66]. Experiencing permanent stress factors like high workload, time pressure or family responsibilities can negatively influence peoples' health. Besides effects on the human brain (e.g. depression or burnout) long-term prolonged stress can also lead to chronic conditions like obesity, hypertension or Type II diabetes [17]. In Europe, stress is the second most frequent work-related health problem [78]. Even though the awareness of stress as a serious health risk rises, an increase of stress-based widespread diseases can be observed [89].

When reacting to stress, the body shows symptoms similar to anger and fear which is reflected in an increased electrodermal activity or elevated heart rate. To detect stress based on such biosignals, several methods have been evaluated in previous research work [84]. Applying these procedures in daily life requires consideration of different aspects. First, the level of data quality builds the ground truth for further computation and deriving valuable information for the user. Second, since high quality data mostly requires elaborated procedures and clinical-grade devices for data acquisition, accessibility and usability for the user also play a key role for regular stress measurement. Therefore, detecting stress should not feel like an intervention, but ideally take place in an unobtrusive and implicit way. This is not only relevant for healthy subjects interested in quantifying their own stress responses, but could also increase motivation for long-term observation within risk groups.

Within this work, we examine the feasibility of current state of the art wearable technology to facilitate reliable and unobtrusive long-term stress measurements. For that reason, the biosignals to be used are identified and evaluated regarding their applicability for stress detection. Further, established computation approaches are compared based on a performance matrix (i.e. applied features and achieved accuracy). Finally, the identified advantages and limitations of current state of the art wearable technology for stress detection will be discussed based on a concise overview of the most recent wearable devices available for consumers.

2 BIOSIGNALS TO MEASURE STRESS

Stress is a complex response mechanism of the human body to internal or external stimuli. It is promoted by the Sympathetic Nervous System (SNS) and the Hypothalamus-Pituitary-Adrenal (HPA) axis, and ultimately by noradrenergic innervation of target tissues as well as the release of stress hormones such as adrenaline, noradrenaline, and cortisol [4, 43]. This in turn leads to changes in physiology and conscious or unconscious behavior [26]. These changes can be measured and ideally allow determining the current stress level of a human.

Since concentration changes of hormones define the stress response directly, tracking those over time is used as the gold-standard to determine the current stress state. They can be measured in blood, urine, or saliva [4]. For instance, cortisol or α-amylase can be measured in saliva and allow a direct quantization of stress [43, 64]. Cortisol fluctuations over the course of a day are very specific markers of ongoing stress, since the concentration progress is very specific in healthy, unstressed adults, being highest in the morning and lowest during the night [4].

Even though those biomarkers provide a ground-truth observation about the stress level, their measurement can be considered quite obtrusive and a continuous, real-time sampling is not feasible with current technology. Therefore, another approach is to look at indirect markers of stress found in biosignals which reflect the physiological or behavioral changes induced by the stress hormones. It has been shown that a large array of more or less unobtrusively recordable biosignals show changes in patterns that can be detected during periods of stress. Most of them have been discussed in previous literature extensively [72, 80]. Therefore, this work only provides a list including a brief description and references to look up for more details.

We distinguish between *directly* and *indirectly* measurable biosignals. The first are signals that measure a physical quantity or a derivative thereof, like for example electrical changes on the human skin surface or frequency of occurrence. The second are signals that quantify changes in small-/large-scale and conscious/unconscious behavioral patterns which cannot be measured as a physical quantity directly. Their extraction usually requires much more complex signal processing and classification methods [19].

2.1 Directly Measurable Biosignals

Arguably the most prominent biosignal of the human body is the **electrocardiogram (ECG)**. It measures changes in the electrical field of the human heart's electric activation system, projected on the body surface [31]. A multitude of parameters or features can be derived from it that reflect sympathetic activation. This includes **heart rate (HR)**, **heart rate variability (HRV)**, heart rate recovery, **respiratory sinus arrhythmia (RSA)**, or even changes in the duration of different activation phases, like changes in the ST-segment or T-wave amplitude [10, 12, 32].

Another measure of heart activity is the **blood volume pulse (BVP)**, which can be measured using the **photoplethysmogram (PPG)** [6]. Furthermore, **blood pressure (BP)** is also linked to the functioning of the heart and is widely known for its prominent correlation to stress in public media. Blood pressure changes by themselves can be used as a determinant for stress, as well as derived measures like baroreflex function [12, 80].

The **respiration** or **breathing rate (Resp)** can be measured using chest straps, depth imaging [42], thoracic electrical bioimpedance [68], or the RSA [12, 80]. Several breathing characteristics, such as respiration variability, respiratory rate, tidal volume and in-/expiratory duration change with stress experience as well as the gas composition of the exhaled breath [49, 84]. Depending on on the respiration rate and other influence factors, the **peripheral blood oxygen saturation (SpO2)** can also provide insights in the stress state [2].

Temperature changes on the skin surface, **skin/surface temperature (ST)**, in various areas or the core body temperature have been shown to change with stress [80, 86]. They are usually measured using thermometers or thermal imaging [4].

Perspiration can be an indicator of experienced stress and can be measured directly in different ways [93]. Another, more sophisticated, approach of perspiration measurement is the assessment of the **electrodermal activity (EDA)**, which measures changes in skin conductance. This is, next to the ECG, the most prominent unobtrusively recordable signal for the determination of sympathetic activation and thus stress [18].

Besides ECG and EDA, stress-related studies also often include measuring the **electromyogram (EMG)**. It has been shown that in particular the upper trapezius muscle and the masseter muscle show specific, unconsciously performed activation patterns during episodes of stress [4, 36, 50, 88].

The **electroencephalogram (EEG)** measures the electrical brain activity through surface electrodes and is a standard, non-invasive method for monitoring and analyzing the state of the brain [63]. Through changes in certain frequency bands of the EEG signal, in particular in the Alpha and Beta band, the experienced mental stress can be assessed [4]. Additionally, **near-infrared spectroscopy (NIRS)** is also capable of measuring human brain activity using optical determination of the (de)oxyhemoglobin concentration in the brain [81].

EEG recordings can also be used to derive the **electrooculogram (EOG)**, which allows measuring parameters such as **blink rate** and eye movement. Other parameters, such as **pupil diameter (PD)** or gaze characteristics can be measured using eye-tracker systems and show changes during the experience of acute stress [4, 85]. Gaze properties can be categorized both as *direct* and as *indirect* biosignals. There are directly quantifiable parameters, e.g. duration, speed and occurrence of saccades, but also general changes in characteristics of gaze and object focus, e.g. attentional selectivity, that fall into the category of indirectly measurable biosignals [85].

2.2 Indirectly Measurable Biosignals

Not only changes in subconscious behavioral aspects of the eye can provide stress-related information, also the **facial expression** itself as well as the **head movement patterns** for specific tasks or in general [4]. Beyond that, the usage of every-day items like the **keyboard or mouse dynamics, mobile phone usage, calendar events** (e.g. meeting behaviors or avoidance) and location change patterns are different under stress [4]. Additionally, other movement patterns such as **body posture** [4], recorded for example by

Classifier	Accuracy	Signals	References
Decision Tree	88.02%	EDA, HR, PD, HRV	[91]
	80.9 %	EDA, HRV, IMU	[79]
	75.2 %	EDA, Resp, HRV	[40]
Naive Bayesian Network	88.71 %	PD	[62]
	78.65 %	EDA, HR, PD, HRV	[91]
	70.81 %	EDA, Resp, HRV	[40]
LDA	90.00 %	HRV	[53]
	81.82%	EDA	[48]
SVM	98.00 %	Thermal Images, EEG	[24]
	92.60 %	Speech	[45]
	90.10 %	EDA, HR, PD, ST	[91]
kNN	93.8 %	HRV, EDA, ST	[41]
	80.9 %	HRV	[92]
HMM	96.40 %	HRV	[46]
	87.00 %	EDA, PPG, HRV	[55]
ANN	99.00 %	EDA, ECG, Resp	[5]
	89.23%	EDA, PPG	[70]
	84.59 %	Breath	[16]

Table 1: Summary of the most common classifiers Decision tree, Naive Bayesian Network, Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), k-Nearest Neighbours (kNN), Hidden Markov Model (HMM) and Artificial Neural Networks (ANN) for stress recognition including their used signals and achieved accuracy.

inertial measurement units (IMUs) that measure acceleration and angular velocity, and potentially gait characteristics change as well. Furthermore, **speech characteristics** have been shown to change while in stressful situations [4, 68].

2.3 Further Biosignals Relevant for Stress Classification

Although not directly linked to stress, other signals can be helpful to be recorded in order to improve stress detection in the directly and indirectly measurable signals. Since the emergence of autonomic response classification, it has been acknowledged that stress quantification yields most accurate results if it is generated from the profiling of direct and indirect biosignals across multiple response domains and across time [12]. For example, lactate or Ammonium concentrations in sweat might allow to discard phases of high intense physical activity [94], which cannot be distinguished from pure mental stress in other biosignals, while, at the same time, analyzing HRV, EDA, respiration and head movement patterns. Similarly, analysis of sleep patterns can be used to determine phases of bad sleep which result in a worse stress reaction or limited ability of the body to cope with it [52].

3 SYSTEMATIC COMPUTATION

Developing wearable devices that generate trustworthy stress measurements encompasses different challenges that need to be tackled. Besides acquiring valuable data and gaining user trust, a major aspect is the performance (e.g. accuracy) of the embedded signal processing algorithms. With constantly increasing computational power, it is possible to not only apply classifiers that show a shallow architecture like for example Naive Bayes or Decision Trees, but also complex models like Artificial Neural Networks (ANN).

Therefore, in this section we compare current state of the art algorithms for stress measurement. For this purpose, we use a taxonomy consisting of the selected signals and classification accuracy and compiled them in Table 1. The overview is based on the structure of previous review research work [4, 21, 69] and updated with state of the art research insights.

4 WEARABLES

In the last years, a lot of wearable lifestyle devices were introduced in a commercial setting. These wearables often contain biosignal sensors that measure one or several of the above mentioned direct or indirect signals. On the one hand, these wearables provide the merit that their users are usually very engaged in using and recording data with them. On the other hand, the quality and accuracy of the measured biosignals is rarely thoroughly scientifically validated.

In Table 2, we give an overview of the most recent wearables and possible validation studies either originating from the manufacturer or from independent researchers. Due to the fast development pace of new wearables and the dilemma that listing the newest devices also means chances are very low to find scientific studies using those, we also include references of validation studies for previous hardware models, where we assume that the actual sensing technology has not changed much and the study still seems applicable for the current version.

In order to identify the included wearables we searched for reviews from 2018 and 2019 found in the literature databases *Scopus*, *Google Scholar* and *IEEE Xplore* that contained the terms 'wearable', 'review' or 'validity'. We identified and used four recent review articles [13, 33, 59, 65].

Additionally, we used the Google search with the term 'fitness health wearables' and 'stress tracking wearables', restricted results

Device name	HR	ECG	BP	Resp	ST	SpO2	EDA	EMG	EEG	GPS	Mic	IMU	SMP	References
	Available sensors													
Apple Watch Series 4	x	x		x						x	x	x	4	[8, 34]
Artinis PortaLite/OctaMon									x				4	[9, 77]
Biostrap/Wavelet Wristband	x	x		x		x						x	6	[14, 20, 39, 75]
Casio Pro Trek Smart WSD F30										x	x	x	1	[15]
Empatica E4/Embrace2	x						x					x	6	[22, 27, 44, 51, 61]
Fitbit Charge 3/Versa/Ionic	x					x						x	2	[25, 30, 38]
Garmin Vivosmart 4/Fenix 5 Plus/Instinct	x					x						x	2	[28, 73]
Hexoskin	x	x		x								x	5	[1, 3, 35]
Lief	x	x		x								x	5	[47]
Lowdown Focus									x				4	[74]
Misfit Vapor 2	x									x	x	x	0	[54]
Muse 2 Headband	x			x		x			x			x	5	[7, 11, 56, 63]
Omron HeartGuide*	x		x										2	[57]
Oura Smart Ring	x				x							x	0	[29, 58]
Polar Vantage V	x									x		x	0	[23, 60]
Samsung Galaxy Watch/Active*	x		x*							x	x	x	1	[38]
Sentio Feel	x				x		x						6	[67]
Skagen Falster 2	x									x	x	x	0	[71]
Spire Health Tag/Stone	x			x								x	1	[37, 76]
TicWatch (Pro/S2/...)	x									x		x	0	[83]
VivaLNK Vital Scout	x	x		x								x	5	[87]
WellBe Bracelet	x											x	0	[82]
Withings Move ECG*/Steel HR Sport	x	x		x						x		x	4	[90]

Table 2: Overview of most recent wearables from various manufacturers that have the potential to track stress continuously. For each wearable the available hardware sensors and/or possibility to measure a specific biosignal are given, the resulting potential to measure stress (SMP) based on the amount of algorithms in Table 1 that could be computed on the available signals, and references to the manufacturer's product page and references to independent scientific papers that assessed some aspects of their accuracy. A star (*) at a product or feature indicates that this has not been released yet at the time of writing.

to pages not older than one year and gathered device names from the first five websites reviewing or comparing wearables in articles that were posted within the last three months (December 2018 to February 2019). The wearables found were merged with those from the review articles. The most recent one for each manufacturer were included into our list. Wearables which are no longer produced, had a clear successor, or tracked IMU signals only, were excluded, e.g. the Myo armband from Thalmic Labs (retired) or the Bellabeat Leaf/Time (only IMU). We then searched for articles trying to validate any aspect of those wearables. For this we used the search terms 'validity', 'accuracy' and 'study' in combinations with the respective wearable name or manufacturer name in addition to the combination of recent model names. We also looked at the product pages of the wearables for any validation research papers.

Finally, we provide a score of how many of the algorithms presented in the previous section could be implemented using those devices. This can be seen as a very coarse assessment metric of their current or future use for the detection and/or continuous recording of stress and provides a better approach to using Table 2 as an overview.

5 DISCUSSION

With the trend of increasing computational power and the possibility to unobtrusively integrate sophisticated sensors, e.g. an one channel ECG into the Apple Watch Series 4, the approach of enabling real-time, user-friendly stress monitoring in daily life becomes more and more feasible. Beyond this, the potential of deep architecture algorithms (e.g. deep learning) also seems to be very promising when it comes to classification accuracy.

Nevertheless, current technology still needs further innovation, since only few devices (e.g. Omron HeartGuide or Apple Watch) are able to provide reliable measures for stress analysis (e.g. BP or ECG). We listed validation study references for most of the wearables. However, we do not provide a scientifically critical discussion for each of these papers. To give one example, the Biostrap/Wavelet device uses the PPG signal to calculate the HRV. In a validation paper, the HRV measure was evaluated using two other PPG-based devices [39]. Scientifically, such an approach is not without questions, as one would expect that in order to validate the HRV, a clinically validated ECG system needs to be used as reference. Furthermore, the HRV does not allow a strong real-time stress feedback, as it requires computations over a window of several seconds. It also doesn't make much sense to feed back stress information to the user in strong real-time, since it usually is a somewhat slowly increasing and long-lasting state of the body. It could be argued, that real-time stress tracking could already mean to inform the user within minutes when high stress levels are detected and give options on how to reduce the stress (e.g. guided breathing, already available in many smartwatches and smartphone health apps).

6 CONCLUSION AND OUTLOOK

From a technical point of view, current wearable technology is ready to provide good and continuous insights into stress-related parameters. However, few devices particularly focus on this topic and instead try to address all possible customer needs. To reach a broad view on stress across the population, it is in general necessary for prominent manufacturers like Apple or Samsung to integrate EDA and reliable HRV measurement capabilities into their mass production devices. EDA and ECG can be measured from the wrist in an acceptable quality [8, 18, 22, 67], and it would be the logical next step to include it into the standard array of sensors for wrist wearable devices as has happened with the PPG sensor.

Another possibility would be to use interactions with the user to allow a determination of stress variables, for example, asking about subjective measures of stress, based on traditional stress questionnaire items, as unobtrusively as possible.

The next steps in this line of work would be trying to assess all state-of-the-art algorithms for stress detection and assign profiling information for each wearable. However, due to the fast paced nature of new wearable releases, this will remain a continuously ongoing process in research.

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