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Katerina Giannakaki, Alexandros Roniotis, Olympia Simantiraki, Giorgos Giannakakis

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Giorgos Giannakakis, *Member, IEEE*, Dimitris Grigoriadis, Katerina Giannakaki, Olympia Simantiraki, Alexandros Roniotis and Manolis Tsiknakis, *Member, IEEE*

Abstract— This review investigates the effects of psychological stress on the human body measured through biosignals. When a potentially threatening stimulus is perceived, a cascade of physiological processes occurs mobilizing the body and nervous system to confront the imminent threat and ensure effective adaptation. Biosignals that can be measured reliably in relation to such stressors include physiological (EEG, ECG, EDA, EMG) and physical measures (respiratory rate, speech, skin temperature, pupil size, eye activity). A fundamental objective in this area of psychophysiological research is to establish reliable biosignal indices that reveal the underlying physiological mechanisms of the stress response. Motivated by the lack of comprehensive guidelines on the relationship between the multitude of biosignal features used in the literature and their corresponding behaviour during stress, in this paper, the impact of stress to multiple bodily responses is surveyed. Emphasis is put on the efficiency, robustness and consistency of biosignal data features across the current state of knowledge in stress detection. It is also explored multimodal biosignal analysis and modelling methods for deriving accurate stress correlates. This paper aims to provide a comprehensive review on biosignal patterns caused during stress conditions and reliable practical guidelines towards more efficient detection of stress.

Index Terms—stress, biosignals, physiological measures, EEG, ECG, EDA, HRV, stress response

1 Introduction

STRESS is a fundamental concept with an increasingly active research interest within the fields of psychology, neuroscience, medicine, and associated fields such as affective computing. The term may be used in reference to external (way of living, relationship problems, financial problems) or internal (personality structure, way of thinking) affairs triggering negative emotions (worry, fear) and associated physiological (i.e., bodily) changes. Common notion testifies that the experience of stress relates both to the perception and subjective evaluation of an event, as well as to the perception of the bodily changes triggered by it.

A physiological *stress response* refers to the bodily changes elicited by environmental events or conditions, known as *stressors*. This response comprises physiological processes responsible for: (i) processing the potential stressor and organizing an adaptive response, (ii) mobilizing the myoskeletal system in order to prepare and execute motor actions, and (iii) preparing the body to withstand injuries and increased metabolic demands.

- G. Giannakakis is with the Institute of Computer Science, Foundation for Research and Technology Hellas, Greece, email: ggian@ics.forth.gr
- D. Grigoriadis is with the Department of Computer Science and Biomedical Informatics, University of Thessaly, Greece.
- K. Giannakaki is with the School of Medicine, University of Crete, Greece.
- O. Simantiraki is with the University del País Vasco, Vitoria, Spain.
- A. Roniotis is with the Department of Electrical and Computer Engineering, Hellenic Mediterranean University, Heraklion, Greece.
- M. Tsiknakis is with the Foundation for Research and Technology Hellas and the Department of Electrical and Computer Engineering, School of Engineering, Hellenic Mediterranean University, Heraklion, Greece.

The multidimensional nature of stress can be decomposed into three main components: the *psychological*, the *behavioural* and the *physiological*. Available methods for assessing the subjective experience of stress are by definition influenced by a multitude of systematic measurement errors, such as the response bias (e.g., the tendency to respond in a manner considered as desirable to the experimenter. Besides, even though some *behavioural* bodily patterns (such as facial expressions and body gestures) are manifested in response to stress, they may also be subject to intentional or even partially conscious control. Consequently, related recordings may also contain systematic errors when used to estimate the magnitude of the stress response.

The above limitations in combination with the increasingly available top-quality and off-the-shelf sensor technology enhance the need for relevant and appropriate physiological stress detectors that would not be able to be manipulated or hidden. Biosignal features of stress-related processes can be largely involuntary (i.e., mainly mediated by the autonomic nervous system (ANS)). Such measures can be sought through electrocardiography (ECG), blood volume pressure (BVP), electromyography (EMG), electrodermal activity (EDA), respiratory (RSP), skin temperature (SKT), pupil diameter (PD), eye activity and speech recordings. In addition, brain activity recorded through electroencephalographic (EEG) signals has been investigated for neurophysiological activity directly associated with the neural processes involved in the generation of the stress response, and secondary effects of the stressor and/or the stress experience on ongoing neurophysiological activity.

Various studies focus on the recognition of stress through physiological measures that this paper investigates in detail. However, the existing few related reviews provide limited information without offering systematic and comprehensive guidelines on the effect of stress on biosignal response. Moreover, to our knowledge, no other review investigates the patterns of individual biosignals features during stress but they are confined to providing single- or multi-modal classification efficacy. Most importantly, there is no other study that solicits collective evidence from the surveyed papers to derive conclusions about the effectiveness and reproducibility of each physiological feature with regards to stress detection.

This paper investigates systematic and consistent biosignals patterns during stress conditions. Towards this objective, an extensive investigation of published studies based on biosignals was performed focusing on acute psychological, social and mental aspects of stress detection. In particular, it is stated precisely for each biosignal feature the studies that report significant changes (increase/decrease), or no difference between the neutral and stressful emotional states. This information is summarized in tables 2,3,4,5,6 which to our knowledge is not provided to any other publication. In addition, stress-relevant biosignals features are investigated in terms of their degree of (i) *consistency* (i.e. reproducibility, validity) across different conditions/studies, and (ii) *efficiency* for automatic stress assessment. A structured overview of available techniques that induce stress in laboratory conditions is provided along with attempts for the formulation of stress ground truth and methodological limitations. In conclusion, the aim of the present work is to provide a complete and comprehensive information about reliable and effective biosignal indices with consistent pattern during stress conditions.

1.1 Theories of stress

In the scientific literature, stress was introduced as the prototypical response of the organism to threat or attack described by Canon as the Fight or Flight response [1]. The physiological components of stress were more formally described by Selye who proposed the General Adaptation Syndrome (GAS) [2], a general physiological reaction to a wide range of stressors comprising of alarm, resistance and exhaustion stages. More recently, a cognitive-evaluative component was introduced into the stress mechanism to account for both intra- and inter-individual variability in the association between environmental events and induced stress levels [3]. Under this notion, the mapping between stressor and stress response is neither universal (i.e., the same across individuals) nor constant (i.e., the same at different instances for a given person), as it is regulated by cognitive processes of evaluation.

Lazarus considered stress as a transactional model between a person and its environment [3]. The intensity and the significance of this transaction is appraised personally providing corresponding coping resources. There are two types of appraisal, the *primary appraisal* that relates to the personal commitment for goals accomplishment and the *secondary appraisal* that relates to the personal responsibility and the availability of coping resources. Holmes and

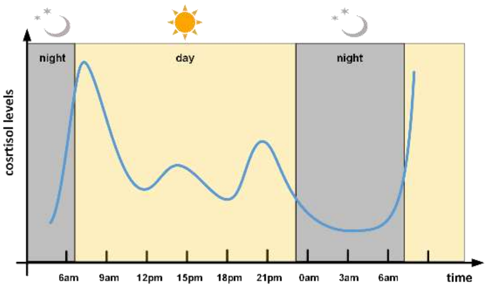

Fig. 1. Schematic illustration of the typical circadian pattern of blood cortisol levels, which follow the sleep-wake cycle. The primary peak is observed around awakening (cortisol awakening response). Smaller peaks are noted after each meal.

Rahe [4] report that the occurrence of critical life events, regardless of their positivity or negativity, cause changes in the organism that may lead to the genesis of stress syndromes. Other studies indicate gender differences in stress adaptation and the existence of specific personality types as well as traits such as social presence, empathy, independence, intellectual efficiency, work orientation, etc which are considered to be more prone to stress [5]. According to the personality theory of Type A and B, personalities of Type A decide to be in more demanding conditions having the tendency to overreact on them, hence being more vulnerable to stress [6].

1.2 The stress response: physiology of stress

When a person perceives an upcoming threat, a cascade of physiological processes occurs which are subsumed under the term "*stress response*". The physiological endpoints of these processes help the body to adapt to the stressor [7]. From an evolutionary perspective, the stress response eventually serves homeostasis by regulating body functions such as temperature, heart activity, blood pressure, respiration, and glucose levels, essential for survival through a range of environmental conditions.

The stress mechanism begins in the brain and, although stress has widespread effects throughout the brain, three main brain regions, the hippocampus [8], the amygdala and the prefrontal cortex seem to have a critical involvement [9]. Stressful audio-visual stimuli are firstly processed at the thalamus and then the information is relayed through two pathways. The fast pathway leads directly to the amygdala where the low level analysis of the stimulus is performed without the contribution of consciousness/higher cognitive functions, thus representing an evolutionarily primitive pathway. The slow pathway moves the information to the prefrontal cortex where cognitive analysis/appraisal is performed and from there to amygdala providing higher level processing [10]. However, the effects of acute stress on the neural activity or brain regions activation are not yet consistent. A review of brain imaging studies presented that brain activity region is related each time to the stressor presented [11].

The experience of stress is paralleled by the activity in two principal pathways, one involving the Hypothalamus, Pituitary gland, and Adrenal cortex (known as the *Hypothalamus-Pituitary-Adrenal (HPA)* axis) and the second

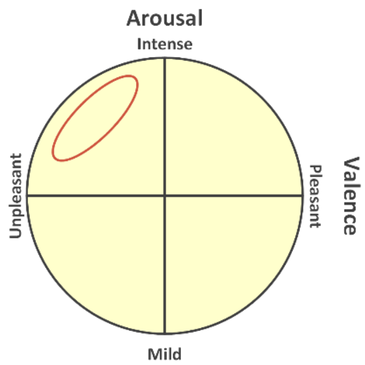

Fig. 2. Mapping of stress state in the circumplex model of affect.

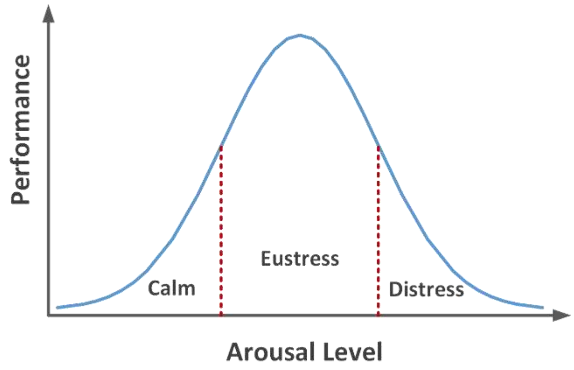

Fig. 3. Schematic illustration of the association between arousal levels and human performance

the sympathetic component of the autonomic nervous system and the adrenal medulla (known as the *Sympathetic–Adrenal Medullary (SAM) system).*

The HPA axis is firstly activated in the hypothalamus, either directly or through neurotransmitters sent by the amygdala. In turn, the hypothalamus assessing the severity of stimulus releases corticotropin hormone (CRH) into the anterior lobe of the pituitary gland, which triggers the release of adrenocorticotropin (ACTH) into the blood stream. Afterwards, ACTH stimulates the synthesis and secretion of the epinephrine (known also as adrenaline), norepinephrine and cortisol hormones in the adrenal cortex (a gland located at the top of each kidney). These three primary stress hormones increase glucose levels providing an immediate energy resource for muscles and nerve cells in order to serve adaptation to stressors.

Cortisol's physiological secretion takes place over a regular 24-hour (circadian) pattern illustrated schematically in Fig. 1. The characteristic early morning peak is internally driven occurring prior to awakening with a further increase triggered by exposure to psychological stress in response to awakening [12]. In the presence of acute stressors, there is a rapid increase in HPA activity resulting in a sharp rise in cortisol levels [13]. This effect is, normally, regulated through a feedback loop (circulating cortisol in the pituitary and hypothalamus inhibit secretion of ACTH).

Increased arousal and body mobilization in response to a stressor takes place, in parallel, via activation of the SAM pathway. Briefly, the core process in this pathway involves phasic secretion of the hormones epinephrine and norepinephrine (also known as adrenaline and noradrenaline, respectively) from the adrenal medulla. Binding of these hormones in specialized receptors throughout the body and brain triggers the rapid mobilization of cardiovascular, musculoskeletal, gastrointestinal, nervous and endocrine systems comprising the "fight-or-flight" response. The main physiological effects of SAM activation involve increased heart rate, respiratory rate, blood pressure, muscle tension, diversion of blood flow from the internal organs to the brain and muscles, perspiration, and pupil dilation [14].

1.3 Stress and human emotions

The term "stress" was introduced by Selye in 1926, but till today its definition remains elusive and subjective. Cohen formulated it later as "a process in which environmental demands tax or exceed the adaptive capacity of an organism, resulting in psychological and biological changes" [15]. In practice, it is a general term in psychology referring to a wide range of negatively loaded emotional states such as agitation, irritability, anxiety, anger, overstimulation, frustration and unhappiness. However, there are also studies supporting the view that under certain circumstances, stress can have positive effects on the immune response [16] and that the impact of stress on one's health and performance can vary depending on the person's mindset regarding stress [17]. Thus, it should not be treated as a unitary concept but as a term with many psychological manifestations. In general, despite the problem of delineation, stress is a state of negative valence and positive arousal. According to the circumplex model of affect [18], stress would be mapped in the upper left quadrant of the emotional space as shown in Fig. 2.

Regarding personal perception, stress is divided into two main categories, the eustress (greek prefix eu- means "good" - positive stress) and distress (negative stress). It is believed that the effect of stress arousal level on personal performance generally follows the pattern of Hebb's curve, an inverted U-shaped curve [19] as presented in Fig. 3.

In this formulation, very high stress levels (distress) or very low stress levels (calm) are typically associated with reduced performance. Optimal performance is more often associated with moderate stress levels (hence termed eustress - positive stress). Finally, the valence of affective states associated with the presence of stressors is highly time-dependent: during stressor anticipation and shortly after the appearance of the stressor negative emotions are likely to be triggered which, however, may be rapidly followed by positive emotions on stressor withdrawal.

1.4 Stress and anxiety

Concepts of stress and anxiety have a significant overlap [20] and are closely related [13]. Hence they are often used interchangeably in the literature as there is not a clear consensus among researchers on their meaning [21]. However, there is the notion that anxiety may be regarded as one of the emotional effects and manifestations of stress [13, 22] which can be observed even after an acute stressor

TABLE 1: TYPES OF STRESSORS USED IN PSYCHOPHYSIOLOGY RESEARCH

Stressor type	Description and examples
Physical	Strenuous physical activity, sleep deprivation, tiredness, painful stimuli, acute injury or medical emergency
Environmental	Extreme temperature conditions, high levels of humidity, low oxygen/high carbon dioxide (or other noxious gas) levels, high levels of noise, earthquake in the surrounding area
Mental/task related	Task demands and conditions taxing the person's cognitive capacities, inconsistent reward/reinforcement schedule, rapidly changing or conflicting task instructions
Social	Disturbances in social interactions, undesirable social roles, criticism, self-criticism, unfair treatment
Psychological/emotional	Disturbances in personal life (e.g. break up/divorce, death of important person, job loss), intense emotional states, mental disorder affecting daily function
Chronic	Severe financial difficulties, poor living conditions, job insecurity, chronic disease or disability in self or family, marriage difficulties
Traumatic	Memory of past traumatic experience that intrudes into consciousness and still affects the psycho-emotional state of a person

[23]. Some studies report that the feeling of sustained anxiety is part of stress definition [22] and that stress and anxiety share similar symptoms. The term anxiety gained ground when used as a central notion in Freud's formulation of psychoanalytic concepts, yet the conceptualization of conflict-induced anxiety serving as a cue of danger and triggering defense mechanisms, is closely related to the concept of stress [20]. It should also be noted that continued exposure to stress may lead to psychiatric disorders such as generalized anxiety disorders and depression [13].

1.5 Stressors

Stressors are exogenous or endogenous stimuli, events or conditions that are able to elicit the stress response. Literature reveals diverse stressors which vary along different dimensions with no strict taxonomy that considers adequately all these dimensions [24]. A tentative categorization of stressors used in psychophysiology research in terms of their nature is listed in Table 1.

Besides, depending on time course/duration of the stressor and the persons' adaptive psychological and behavioural coping strategies, the stress response can be characterized as acute or chronic. *Chronic stress* refers to an established type of stress that impacts people daily independently of the presence of significant stressors and can last for years. On the other hand, *acute stress* responses have a time-limited course as determined by (i) the duration of the eliciting environmental event or condition, (ii) self-regulatory physiological (e.g., parasympathetic system activation), behavioural (e.g., an active coping strategy causing attention refocusing), or psychological processes (such as evaluation-appraisal of the stressor or active suppression of the stress experience). Notably, chronic stress can be viewed as the result of a series of repeated acute stressors taking place over a long period of time. Stressors have a multidimensional impact affecting various levels of human activity, not always being able to estimate the primary affect or the affect intensity.

This study focuses on acute, task-related, psychological/emotional stress and its psychological impact.

2 BIOSIGNALS RELATED TO STRESS

Biosignals are time-varying measures of human's body processes [25] that can be divided into two main categories

- Physical signals
- Physiological signals

Physical biosignals are measures of body deformation as the *result of muscle activity* and include pupil size, eye movements, blinks, head, body and extremity semivoluntary position/movements, respiration, facial expressions and voice. Physiological signals are more directly related with body vital functions, such as cardiac activity (Electrocardiogram [ECG], Blood Volume Pulse [BVP]), brain function (EEG), exocrine activity (sweating assessed through electrodermal activity [EDA]), and muscle excitability assessed through electromyography (EMG). The distribution of associated measures on the body is shown in Fig. 4.

In subsequent sections, biosignals are categorized according to their source on the body into those recorded from the head, the heart, and the remaining body parts.

2.1 Head

2.1.1 Electroencephalogram (EEG)

Electroencephalogram (EEG) is a widely used technique to estimate changes in neurophysiological activity associated with external stimuli and/or with the performance of specific tasks. The value of EEG in psychophysiological research relates to its purported sensitivity to localized brain

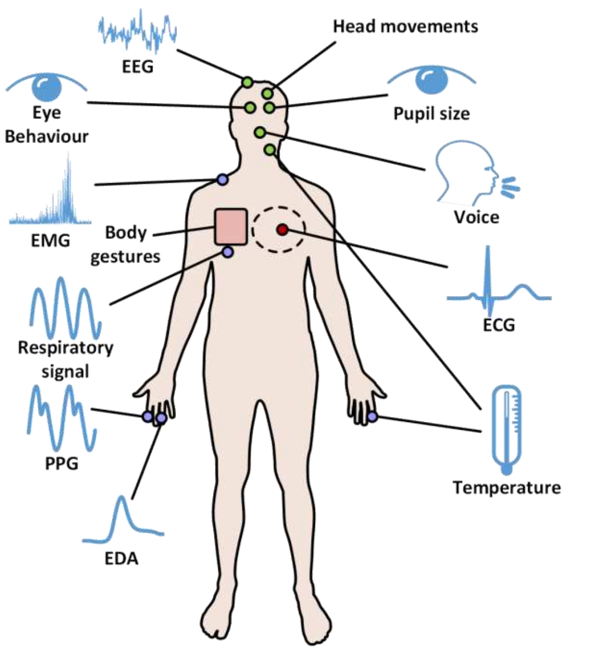

Fig. 4. Common physiological and physical measures related to stress investigated in this study.

activity in regions involved in the generation of the stress response, or activity associated with increased arousal or specific psycho-emotional states [26]. The left anterior region of the brain appears to be related to approach-type emotions (e.g. happiness, anger), while the right anterior region to avoidance-type emotions (e.g. sadness, fear) [27].

EEG asymmetry index is a robust stress feature revealing emotional arousal [28] implicated in many studies to differentially dissociate psychological states [29]. The EEG asymmetry index is the subtraction of the alpha's power natural logarithm of the right hemisphere from that of the left hemisphere, as provided by the equation

$$Asymmetry\ index = \ln(a)\Big|_{L_{channel}} - \ln(a)\Big|_{R_{channel}}$$

The most common positions used in the estimation of alpha asymmetry are channels F3-F4 as they are located above the dorsolateral prefrontal cortex [30, 31], a region directly affected by stressful conditions [32]. However, there are stress studies employing lateral (e.g. F7-F8 [33]), anterior (e.g. Fp1-Fp2 [34, 35]), and posterior pairs (e.g. C3-C4, O1-O2 [29], T5-T6 [35]) as shown in Fig. 5.

The majority of studies support the notion that in stress state there is generally greater frontal right alpha activity in relation to the left alpha activity [26]. This phenomenon occurs during stressful periods (e.g. students during exams period) [31] when exposed to stressful stimuli such as sad/happy films [33], fearful films [36], or in the case of chronic stress [34]. Conversely, situations associated with affective states of positive valence have been shown to elicit greater relative left frontal power [33, 37]. Notably, asymmetries direction/magnitude and their association with physiological measures (e.g. heart rate) may vary across recording sites and spectral bands [35].

Power spectrum or relative power indices have been widely explored for revealing intra-individual changes associated with the intensity of the stress response [38-42]. EEG spectrum can be divided into frequency intervals, also referred as rhythms, namely delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (30-70 Hz). The predominance of the alpha rhythm is observed during relaxation or conditions with minimal cognitive demands or emotional strain. Conversely, conditions with significant processing demands or high alertness levels are associated with higher frequency rhythmic activity such as relative beta power [43].

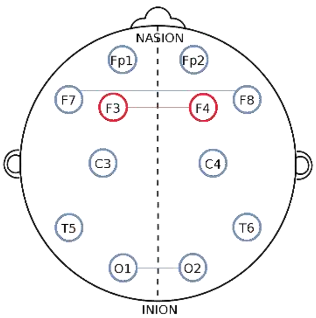

Fig. 5. Common position of electrode pairs for EEG asymmetry estimation according to the 10/20 system. The most commonly used electrode pair is the F3-F4 (red colour sites), while blue coloured sites are electrode pairs that also used in psychophysiological studies.

TABLE 2: EEG FEATURES USED IN STRESS DETECTION STUDIES AND SIGNIFICANT CHANGES DURING STRESS CONDITIONS

Feature	Studies	↑	↓	=
δ activity	3 [29, 45, 53]	2	2	0
θ activity	6 [29, 35, 44, 45, 53, 54]	3	3	0
α activity	9 [29, 35, 44-48, 53]	2	7	0
β activity	7 [29, 35, 43, 44, 46, 47, 53]	5	2	0
γ activity	1 [35]	1	0	0
β/α ratio	1 [30]	1	0	0
Asymmetry index	11 [29-31, 33-35, 44, 53, 55, 56]	1	9	1
Coherence	3 [29, 53]	1	2	0
β Coherence	1 [44]	1	0	0
α Coherence	1 [44]	0	1	0
Brain Load Index	1 [55]	1	0	0
ApEn	1 [44]	0	1	0
Linear CMIF	1 [44]	0	1	0
Non-linear CMIF	1 [44]	1	0	0

↑: significant increase ($p<0.05$) during stress, ↓: significant decrease ($p<0.05$) during stress, =: no significant difference. Note that in studies where a feature is significantly increased in one channel and significantly decreased in another is counted in both ↑ and ↓ columns (e.g. δ activity 3,2,2,0). This formulation is followed to the rest of the manuscript.

Although there are some conflicting results in spectral features, stress conditions are considered to decrease the alpha activity [29, 35, 44-49] and increase the beta activity waves [47, 50]. More recent studies suggest that these effects may display even greater frequency-specificity. For instance, certain conditions such as sleep deprivation and performance of a cognitive task (Stroop Colour-Word Test (SCWT)) may only affect the lower alpha power (7.5-10.5 Hz) whereas the higher alpha power (11-12 Hz) may actually be reduced in both conditions [44]. Minguillon et al. reports increased power during stress which is reflected to most of the subbands [35]. Besides, a specific frequency beta subband (18–22 Hz) is considered to be correlated with emotional "intensity" which may be considered as equivalent to anxiety [51]. In [43] beta activity in frontal and temporal locations was increased in the non-stress versus the stress group. An index that integrates the variations of both alpha and beta rhythms is reflected in the beta to alpha power ratio (b/a ratio) being a measure of cognitive load associated with the arousal dimension [52]. Increased beta/alpha relative power ratio is commonly expected in stress groups [30].

Stress is positively correlated with beta power at anterior temporal lobe [49] or high-beta waves in temporal lobe [44, 57]. Power of higher frequency rhythms (such as gamma band) may provide a sensitive index of stress response magnitude (relative power in the gamma band recorded from prefrontal electrodes [35]), although caution is advised when interpreting results in this frequency range due to the potential of contamination by myogenic activity. This is important as the gamma band has higher temporal resolution compared with established markers such as the HR or the cortisol.

Fig. 6. Normal (left) and dilated (right) human pupil.

Coherence is another feature of spectral correlation between brain regions which varies with respect to stress states [39, 58]. Stressors increase theta and high beta (23-36Hz) coherence, while decrease alpha coherence in anterior sites [44]. During sleep deprivation, the nonlinear cross mutual information function (CMIF) increases mainly at the anterior, central and temporal regions, in a clear contrast to the decrease and the spreading of its linear counterpart [44]. Approximate Entropy (ApEn), a nonlinear measure that indicates time series irregularity or complexity, presents significant decrease during stressful situations, mainly in anterior sites [44].

Inspecting Table 2, it can be concluded that although there are conflicting results regarding some EEG features, still the decrease of alpha asymmetry index is a consistent EEG feature across stress studies. Potentially, the decrease of alpha and the increase of beta activity may also provide reliable estimators of stress.

2.1.2 Pupil diameter (PD)

Pupil size is controlled by two sets of muscles, the constrictor and dilator pupillae, which are governed by the sympathetic (SNS) and parasympathetic (PNS) divisions of the ANS [59]. Thus, it reflects autonomic involuntary activity and it is associated with emotional, cognitive or sexual arousal.

There is research interest in exploring the relationship between pupil size variation and affective state [60-65]. It has been employed as an index of stress and anxiety levels [66-69]. Pupil diameter is increased during stress elicited by stressful stimuli in laboratory environment [64, 65, 70].

Pupillary response to images inducing negative valence also tends to be higher among persons reporting higher overall levels of stress [71]. Besides, pupil size may increase in response to positive, and negative arousing sounds, as compared to emotionally neutral ones [61]. It has been found that there is a significant effect on pupil size as a result of audience anxiety [67]. The higher the anxiety level, the bigger the pupil becomes, presenting significant differences in expressions of contemning and surprise [72]. Other studies refer that under stress conditions pupil dilates more often [73]. An interesting approach, is that the pupil dilation among a cocaine-induced paranoia (CIP) group was significantly greater in response to a video image of crack cocaine than a non-CIP group [74] which can be attributed either to the recall of an event of cocaine intake or to the trait anxiety it is caused by it.

When investigating pupil size, some limitations have to be taken into consideration. Pupil size variation is affected by age as various studies refer a marked reduction of pupil size with the ageing [75]. The effect of gender in pupil size is ambiguous, as there are studies showing no interaction [75], while others studies gender seems to affect pupil in painful [76] or auditory stimuli [61]. Besides, illumination affects pupil size [65, 77] causing the so-called light reflex, leading to the constriction of the pupil when the amount of light increases. Thus, the usage of pupil changes in research studies should be performed with caution and in relation to well-established reference points such as pupil size in the normal state.

2.1.3 Speech

Stress conditions may cause variations to speech compared to speech in neutral conditions [78]. A scientific area called Voice Stress Analysis (VSA) has been established to estimate stress in the voice, dealing with the vocal characteristics influenced from the stress, in order to discriminate stressed and neutral speech [79].

The mechanism of human speech production is described in [80] and is shown in Fig. 7. The vocal characteristics can be categorized into three components, namely *speech excitation (source)*, *vocal tract (filter-system)* and *speech signal (output)*.

During stress conditions, the first component is affected by the increased tension of the muscle of the vocal folds [81], the second component is affected by the change in the position of the vocal tract's articulators and the third component is due to its linkage with the other two components. Table 3 summarizes the speech features and their significant changes during stress conditions.

Speaker's pitch (f_0) is one of the most studied indicators of emotional stress being typically increased during stress conditions [82-92]. Stressed speakers tend to differentiate their speech by emphasizing ports rich in information [93] and therefore specific frequency bands and intensity seem to be more sensitive to stressed or neutral speech. Besides mean pitch (f_0), also the first two formants (F_1, F_2) [84, 88, 91, 92] and energy are studied. In [94], articulatory, excitation (pitch, duration, intensity) and cepstral based features were extracted from the SUSAS database achieving a classification accuracy rate of 91%. The work of [84] distinguished between neutral, loud, angry, Lombard effect, and clear speech by extracting production features, such as f_0, intensity, spectral tilt and the distribution of spectral energy. Dialogs classified for stress using acoustic information derived by a combination of spectral and temporal

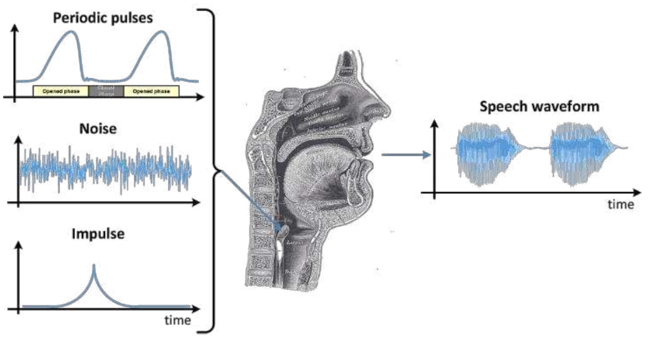

Fig. 7. Representation of the human speech production mechanism. It can be considered as a system with 3 possible inputs (periodic pulses or noise or impulse). These are modulated in the vocal tract by the articulators (system) producing the output speech waveform.

TABLE 3: SPEECH FEATURES USED IN STRESS DETECTION AND SIGNIFICANT CHANGES DURING STRESS CONDITIONS

Feature	Studies	↑	↓	=
Pitch (f_0)	11 [82-92]	11	0	0
Formant 1 (F_1)	4 [84, 88, 91, 92]	3	1	0
Formant 2 (F_2)	4 [84, 88, 91, 92]	2	2	0
Spectral slope	2 [87, 98]	2	0	0
Utterance duration	2 [86, 96]	1	1	0
Glottal pulse	1 [84]	0	1	0
Duration of Words	3 [83, 84, 87]	3	0	0
Duration of vowel	4 [83, 84, 87]	3	1	0
Duration of Diphthong	4 [83, 84, 87]	3	1	0
Intensity	4 [83-85, 103]	4	0	0
Jitter	2 [89, 91]	1	1	0

↑: significant increase ($p<0.05$) during stress
↓: significant decrease ($p<0.05$) during stress
=: no significant difference

features (e.g. loudness, jitter, shimmer, etc) [95], or prosodic, lexical and dialog acts [96]. Loud, angry and Lombard frequency were all significantly different from neutral states [82, 97]. In [98], features based on the spectral tilt of the glottal source and of the speech signal itself presented less negative spectral tilt during stress using the SUSAS dataset. In [99], 12 log-Gabor filters and ERB frequency bands average energy from spectrogram features achieved stress recognition accuracy of 79%.

Non-linear speech features have also been employed for stress detection. The Teager Energy Operator (TEO) has been proposed to be robust to noisy environments and useful in stress classification [81, 100]. Another interesting approach of stress speech analysis is the subband analysis using multiresolution wavelet analysis (MWA) [101] or the combination of MWA and TEO [102] modelling categories of drivers' stress. Additionally, features based on TEO and Hidden Markov Model (HMM) were used in order to classify stressed speech [92].

Yao et al. [104] proposed an approach investigating the physical characteristics of the vocal folds, i.e. the Muscle Tension Ratio (MTR) to identify speech under stress. The experiments indicated that the MTR outperforms the conversational methods of stress measurement. Other studies propose micro tremors (MT involuntary vibrations at 8-12 Hz) as indicators to reveal stress. It is considered that voice microtremors are induced by CNS, being able to reveal stress existence [105]. These tremors were found to be correlated with EMG, as EMG tremor leads voice tremor at the same amount of time mainly in vowels [105].

Due to the intrusive role of stress in speech, the reliable stress identification could improve the performance of Automatic Speech Recognition (ASR) when the speaker is under stress [106], could prioritize emergency calls accurately [107] and be used as an alibi for innocent people [91].

2.1.4 Eye activity (EA)

Stress is considered to affect eye function and behaviour. Eye blinks frequency is increased during stress states [108, 109]. This can be partially attributed to the redirection of blood periorbital eye musculature facilitating rapid eye movements [110]. However, tasks that demand to pay more attention (e.g. reading a difficult text) eye blinks are decreased [109]. Gaze distribution is also considered to be affected by stress [73, 111]. Gaze features such as gaze direction, gaze congruence and the size of the gaze-cuing effect have been employed in stress detection studies [112, 113]. Higher trait anxiety leads to significant fixation instability in both volitional and stimulus driven conditions, but it is more pronounced in the presence of threat [111]. People with increased trait anxiety tend to have the initial fixation on the emotional picture, contrary to the neutral one. However, in order to regulate emotion, they try to avoid attention (lower frequency of fixation) in harm stimuli in a later phase [114]. Specific inhibitory deficits related to anxiety can be revealed through the antisaccade task, where saccadic control is disrupted [115].

TABLE 4: TEMPERATURE FEATURES FROM DIFFERENT BODY ROI USED IN AUTOMATIC STRESS DETECTION AND SIGNIFICANT CHANGES DURING STRESS CONDITIONS

Feature	Studies	↑	↓	=
Body	1 [129]	1	0	0
Finger	5 [127, 130-133]	0	4	1
Whole Facial	5 [130, 131, 134-136]	4	1	0
Temp variability	1 [133]	0	1	0
Forehead	5 [131, 137-139]	3	0	2
Periorbital	2 [110, 131]	1	0	1
Nose	3 [131, 132, 140]	0	3	0
Maxillary	2 [135, 139]	0	2	0

↑: significant increase ($p<0.05$) during stress
↓: significant decrease ($p<0.05$) during stress
=: no difference

2.2 Body and extremities

2.2.1 Body posture/movements (BM)

Body posture can also give insights about stress levels [116, 117]. It is considered that the higher the stress the lower the amount of upper body movements [118]. In [117] a combined analysis of facial cues and upper body gestures was performed in recognizing various emotional states including anxiety. Head mobility features have also been used in order to anticipate the existence of stress [109, 119]. It has been reported that head movements during stressful conditions are more frequent [73], more rapid [120, 121] and there is greater overall head motion [122, 123]. In [124] head nods and shakes were employed among other features in order to discriminate complex emotional situations.

2.2.2 Skin Temperature (SKT)

Variations in skin temperature (SKT) are associated with stress conditions and anxiety [125]. In pathological situations, one meets the psychogenic fever, a stress related disease with either high body temperature or persistent low-grade during situations of chronic stress [126]. In psychophysiological research, acute changes in SKT can be monitored via sensors placed on the surface of the skin (e.g. a finger) [127], or through thermal imaging [128].

Skin temperature is measured at different body parts (finger, upper arm, face, mouth, armpit) presenting, however, contradicting reports under stress; temperature increases in some parts and decreases in others. Their behaviour is presented in Table 4. Body temperature using an axillary thermometer is considered to increase as a matter of psychological stress [129]. Other studies claim that finger surface temperature decreases during stress conditions [127, 130-133]. In some cases, in order to reveal transient temperature changes, the slope of the temperature variation is used instead of the temperature's mean value [141]. In [130], it is indicated that different temperature patterns appear in different body parts. Specifically, during personal questions, there was a significant temperature decrease at the hand sites, contrary to significant warming of the facial region (eyes and cheek). Besides, a different temperature behaviour between right and left facial areas is presented. The study of [132] reports that during TSST stress test, the temperature of the fingertip, finger base and hand palm decrease significantly, whereas the temperature of upper arm shows significant increase.

2.2.3 Thermal Infrared Imaging (TII)

Thermal infrared imaging (TII) is a contactless technique measuring, among other parameters, skin temperature. An infrared thermal camera records tissue oxygen saturation (StO_2) which is not affected by the user's skin colour or lighting conditions.

During states of increased arousal, the blood flow of vessels increases, raising adjacent region's temperature. Recent studies have used thermal infrared imaging in order to recognize affective states [134] including extreme fear [142], arousal [143] or situations of stress [144]. In most affect studies using TII, facial skin temperature is used to extract meaningful information [134, 135]. Facial areas whose temperature are considered to be mostly affected by stressors are corrugator, nose, perioral and chin [139].

It seems that there is no consistent way of how stress modulates temperature in the facial area. It has been observed that the forehead temperature increases during stress [137, 138] (in [138] all participants presented typical temperature increase). The temperature in periorbital areas also increases [110, 136] which may be attributed to the increased blood flow circulation around the eyes that has been associated with anxious states. In [135], it is also reported that temperature increases in supraorbital and periorbital areas during stress conditions as a result of increased blood flow. Hong et al. [139] proposed a differential measure between forehead and maxillary area that has a significant correlation with established stress marker such as HR. Table 4 summarizes the behaviour of temperature features from different facial and finger sites.

In [131, 132, 140] nose temperature was investigated through infrared camera and found reduced when a novel (unknown) task was presented to participants, which it was considered to be related to the task difficulty. In [132] the nasal temperature decrease occurs only for females and not for males. Decrease in nasal temperature is observed also in monkeys when facing negative emotions [145]. Perinasal area temperature is also decreased [146, 147] during stress which is associated with the presence of perspiration

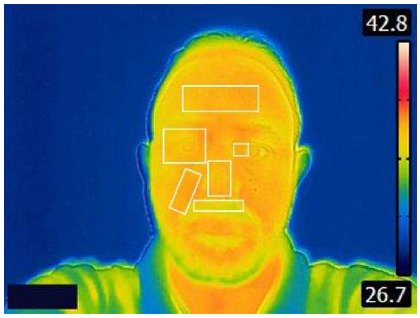

Fig. 8. Facial ROI (forehead, periorbital region, eye, nose, cheek, maxillary (perinasal)) that usually used in order to extract affective information from thermal imaging images.

in the area. Extending this, the maxillary area was considered the palm signal equivalent being validated with EDA signals [135].

2.2.4 Electromyogram (EMG)

Electromyogram (EMG) is a technique evaluating muscles functioning and tension through recordings of muscle's action potentials [148] carried from motor neurons to the muscles. Ongoing activity in large bundles of muscle fibers can be sampled reliably through surface electrodes (sEMG) attached to the skin above the muscle. The activation of the SNS due to stress conditions provokes elevation of muscles tone [149] in both tonic and phasic changes in EMG power.

A bipolar montage is typically employed with electrodes placed on the trapezius muscle (occipital bone of the upper thoracic vertebrae) [150, 151] and forehead muscles [152]. EMG activity of trapezius muscle is increased in response to stress during mental arithmetic CPT and SCWT stress tests [151, 153-155]. In [153], it is reported increased amplitude of the EMG signal when trapezius muscle activity rises and also decreased total gaps in muscle activity. It should be noted that EMG activity is increased in a more apparent way during CPT test in relation to the SCWT test [154]. Also, significant positive correlation between negative stress ratings and EMG activity during work has been reported [156] without respective correlation on positive responses. This indicates a specificity of muscle activity on negative stress which should be investigated.

Also, EMG of trapezius muscle activity is reported to be greater under high or low mental workload, during computer data entry work [157] or computer work in time-pressed situation [158]. Besides, it is reported an association of high emotional stress with greater muscle activity in long-term Visual Display Unit work [159]. Muscle activity was also measured for the same computer task with and without memory demands, resulting in higher muscle activity while performing the memory demanding condition [160]. In [161], EMG of the trapezius muscles was measured during unexpected and varying intensity electrical pulses stimuli. In the pre-stimulus phase, they report higher mean EMG activity and an immediate EMG response when the stimulus was delivered. Another study examined the shoulder muscle forces in an EMG- and a stress-based method [162].

Muscle tremor is also considered an indicator that may reveal stress. The normal physiological tremor's frequency band is 6.5-11Hz. Stress or anxiety states cause tremor in the highest limit of the frequency band (near 11Hz) [163]. The amplitude of tremor is increased by factors such as anxiety or/and arousal [163].

2.2.5 Respiration and Breath Rate (BR)

Respiration can be measured as the rate or volume at which mammals exchange air in their lungs. Breath rate and breath depth (amplitude) are the most common measures of respiration [164]. Under stress conditions, breath rate generally increases [132, 165, 166] with emotional arousal and decreases with relaxation, while tense situations may cause momentary interruption in breath. The breath rate (BR) significant changes during stress is presented in Table 6. Besides, negative emotions such as stress are linked to irregularities in the respiration pattern [167], increase of the minute volume, the shift from abdominal to thoracic breathing [168] and faster and shallower breathing [169].

Respiration function is measured most accurately by breath sensors which estimate the amount of air exchange in the lungs, which should be performed without talking or moving. Chest cavity expansion can also be used for breathing activity using either a Hall Effect sensor, strain gauge or stretch sensor [170]. For non-intrusive stress detection, basically two different techniques have been used for acquiring the RR signal; either from an elastic Hall Effect sensor strapped around the subject's diaphragm [150] or by installing a thermistor based sensor in the nasal passage [171]. Monitoring of breath regulation has also been proposed as a way to minify the oscillations in HRV due to respiration [172]. Most studies use respiratory rate as a feature, combine it with additional biosignals for calculating the stress level of the subjects [173]. Other used BR signals features may be mean, variance, standard deviation, kurtosis, skewness, maximum minus minimum value, mean of derivative and the power 5 frequency band of 0.25 to 2.75Hz [174]. From the respiration process, the Oxygen consumption rate (VO_2) can be extracted as an index of energy expenditure, been a reliable estimator due to the fact that oxygen needs are increased in stress conditions [175].

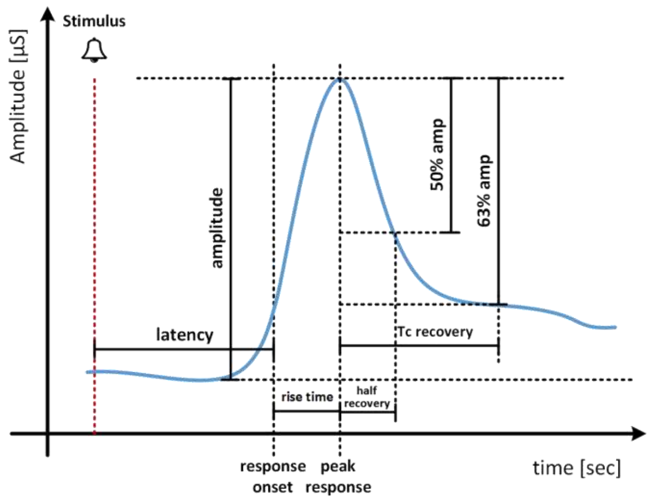

Fig. 9. A typical skin conductance response variation and common extracted features

TABLE 5: EDA FEATURES USED IN AUTOMATIC STRESS DETECTION AND SIGNIFICANT CHANGES DURING STRESS CONDITIONS

Feature	Studies	↑	↓	=
SCR	9 [7, 64, 127, 180, 183-187]	7	0	2
SCL	5 [116, 180-183]	5	0	0
Ns-SCR	1 [180]	1	0	0
SCR frequency	0	0	0	0
SCR amplitude	2 [7, 116, 187]	1	0	1
SCR latency	0	0	0	0
SCR rise time	1 [187]	1	0	0
SCR 50% recovery time	2 [187]	1	0	1

↑: significant increase (p<0.05) during stress
↓: significant decrease (p<0.05) during stress
=: no difference

2.2.6 Electrodermal activity (EDA)

Electrodermal activity (EDA) is a physiological measurement of electricity flow through the skin. Even moderate amounts of sweating that are not observable at the skin surface can alter skin electrical conductivity.

EDA recordings can be obtained using a bipolar montage from the hand's palmar sites (such as two fingers) or the feet where the highest density of sweat glands (>2000/cm^2) is observed [7]. EDA can be distinguished to

- **Skin Conductance Level (SCL)**: the slowing changing background (tonic part) of the EDA
- **Skin Conductance Response (SCR)**: time-varying peaks (phasic part) as a response to a stimulus
- **Non-specific Skin Conductance Response (NS.SCR):** it occurs without the presence of an external stimulus

There are also other features derived from these three parameters and the most common, in psychophysiological studies, are listed in Table 5.

Sweat gland activity is mainly controlled by the SNS leading to the SCR increase during emotional arousal [176]. The NS.SCR is related to cognitive processes, and psychophysiological states [177]. It is a measure directly related to the arousal [178] as well as the fact that is influenced exclusively by the sympathetic and not by the parasympathetic nervous system as other physiological measures which lead to the usage of SCR as a reliable indicator of stress [7, 179].

When a person is under stress, both tonic part SCL [116, 180-183] and phasic part SCR [7, 64, 127, 180, 183-185] increases due to skin moisture increase. The peaks of SCR usually appear between 1.5 and 6.5 sec after the onset of stressor stimuli. According to [150], SCL was considered the most effective stress correlate among features from HRV, RSP and EMG.

Other common EDA features that are used in stress studies are the SCR frequency, SCR amplitude, SCR latency, SCR rise time, SCR half recovery (time of 50% peak response amplitude), SCR response onset, as presented in Fig. 9 and Table 5. The SCR amplitude increases or having no change [187], the SCR duration [183] or SCR latency. An interesting aspect is that even the expectation of a painful or stressful event can elicit increases in the EDA. In [184] the expectation of an aversive event could elicit an increase in SCR similar as the event would have been performed.

The SCR on both anticipation and application of electric shock increases depending on the shock intensity [185]. It is notable that skin conductance is significantly correlated with heart rate [127], both of them being indices of arousal.

Summarizing, it is evident that SCR and SCL are two EDA features which present consistently increased variation during stress. Its characteristic that is influenced exclusively by the SNS making the EDA activity a significant factor in the stress recognition process.

2.3 Heart Activity

Heart activity is modulated by two neuromodulatory receptors types (acetylcholine and norepinephrine) of heart cells corresponding to the Parasympathetic (PNS) and Sympathetic (SNS) nervous system respectively. Stress leads to the activation of the SNS, resulting in the increase of heart rate and its force of contraction. As a result, the amount of blood circulates faster through the body in order to deliver immediate more oxygen to the organs and skeletal muscles as an attempt to eliminate the stressor.

2.3.1 Electrocardiogram (ECG)

Electrocardiogram (ECG) is the signal of the electrical activity of the heart manifesting its contractile activity. The characteristic peaks of the ECG are denoted with the letters P, Q, R, S and T as shown in Fig. 10.

The R-peak is the most prominent and most of the analyses exploit the distribution of this peak through successive R peaks intervals, or RR intervals (RRI).

2.3.2 Heart Rate (HR)

Heart Rate is the most widely adopted and straightforward measure to estimate levels of stress. It is the number of heart beats per minute (measured in bpm). Alternatively, the mean RR interval, which is the interval between consecutive heartbeats can be used, having an inverse relationship with heart rate. In literature, there are many studies reporting that heart rate increases significantly during states of stress [109, 131, 132, 151, 154, 160, 182, 187-196], whereas there are few others claiming that there is no significant change. This measure is the most straightforward and the most used with the vast majority being a reliable measure for the arousal part of stress.

2.3.3 Heart Rate Variability (HRV)

Heart Rate Variability (HRV) is the distribution of RR intervals [RR_i, RR_{i+1},…] over a time interval as shown in Fig. 10. It is considered that it reflects the activity of the sympathetic and vagal components of the ANS. The HRV parameters are a set of statistical metrics providing information of the heart activity in time, frequency and nonlinear domain.

Fig. 10. Typical ECG signal with characteristics peaks P, Q, R, S, T and RR intervals

Normally, HRV parameters need at least 5 minutes of recording in order to have enough samples [215], however, there are some studies claiming that even with a shorter time period, can provide reliable estimators of mental stress [210, 216]. In spectral analysis, high frequency band of HRV reflects vagal modulation [215], while low frequency bands may include both sympathetic and vagal modulation [217]. The HRV has a chaotic (disordered) behaviour in states of anger, anxiety or sadness [218] whose rhythmicity can be described by a measure known as cardiac coherence [219]. Table 6 summarizes HRV related features employed in stress studies and their changes during stress conditions.

In time domain, HRV are parameters derived from the

TABLE 6: HEART ACTIVITY, RESPIRATORY AND BVP FEATURES USED IN AUTOMATIC STRESS DETECTION AND SIGNIFICANT CHANGES DURING STRESS CONDITIONS

Feature	Studies	↑	↓	=
HR	23 [109, 131, 132, 151, 154, 160, 165, 180, 182, 187-200]	18	0	5
STD HR	1 [198]	0	0	1
RR	8 [180, 198, 200-205]	0	6	2
SDNN	12 [180, 187, 193, 194, 197, 198, 200, 201, 203-206]	1	7	4
RMSSD	6 [187, 190, 197, 198, 203, 204]	0	5	1
NN50	2 [187, 200]	0	2	0
pNN50	6 [116, 194, 198, 200, 203, 207]	0	6	0
HRV triangular	2 [198, 200]	0	1	1
Total power	4 [133, 197, 204, 206]	0	4	0
VLF	3 [187, 204]	0	0	3
LF	12 [180, 187, 192-195, 197, 199, 203-205, 208]	5	3	4
HF	14 [180, 187, 192-194, 197, 199, 201, 203-205, 208-210]	1	6	7
LF/HF	17 [165, 180, 187, 188, 192-194, 198-200, 202-204, 207-210]	10	0	7
VLF relative	2 [187, 188]	2	0	0
LF relative	8 [187, 188, 200-202, 204, 208]	4	1	3
HF relative	7 [187, 200-202, 204, 208]	0	4	3
SD1	1 [211]	0	0	1
SD2	1 [211]	0	1	0
D2	2 [211]	0	2	0
BR	5 [165, 180, 193, 199, 204]	2	0	3
SBP	15 [129, 132, 151, 154, 160, 188-191, 195, 201, 206, 212-214]	15	0	0
DBP	15 [129, 132, 151, 154, 160, 188-191, 195, 201, 209, 212-214]	15	0	0
BP HF	1 [206]	1	0	0
ApEn	1 [211]	0	1	0
SampEn	1 [192]	0	0	1

↑: significant increase (p<0.05) during stress
↓: significant decrease (p<0.05) during stress
=: no difference

variability of RR intervals. SDNN is reduced during stress conditions [180, 187, 193, 194, 197, 198, 201, 203-206]. RMSSD is considered a measure mediated by the vagal tone which generally decreases during stress conditions [187, 190, 197, 198, 203, 204]. In [220], one time-domain HRV measure (RMSSD) and one spectral domain HRV measure (HF) were found to be reduced in stress conditions presenting also ethnic and sex differentiations (females showed significantly larger decreases of both RMSSD and HF as a response to stress than males).

In frequency domain, the LF band is modulated by both sympathetic and parasympathetic activity, while the HF band corresponds only to parasympathetic activity. Thus, the ratio LF/HF is considered a distinctive approach for the sympathetic modulation [210]. Indeed, the LF/HF ratio is the more prominent feature in frequency domain increasing during stress condition [165, 180, 187, 188, 192-194, 198, 199, 202-204, 207-210]. In fact, its robustness may be attributed to the combined information of LF (and LF relative) increase [193, 195, 199, 201, 202, 205, 208] and HF (and HF relative) decrease [199, 201, 202, 209, 210] response to stressors. In [221], negative images were presented as laboratory stressor but also first time airplane skydive as a real acute stressor. Some studies report VLF band increase during stress condition [187, 188] but there is not a typical pattern. Acute stress, when it is elicited in the immediate pre-sleep period, can also affect HRV during sleep and it is associated decreases in parasympathetic modulation (HF) during NREM and REM sleep and increases in sympathovagal balance (LF/HF) during NREM sleep [210]. It is worth noted that, NREM and REM sleep stages are also significantly different between control and stress groups.

Nonlinear HRV measures are not so popular in stress studies. In [193, 211], the correlation dimension D2 was found to be reduced (less complexity in RR time series) as a result of stress presence. Besides, in [192], the sample entropy (SampEn) was investigated without yielding a specific assumption. In [193], a comparison between short-term and chronic stress based on HRV parameters was performed. In [218] HRV variability is investigated on different stress factors, i.e. stressed, tensed, concentrated and stimulated. Heart period and end-tidal CO2 were lower, whereas self-reported mood states were higher during high mental workload [157].

Morphological features of ECG can also contain stress evidence as reported in recent studies. The T-wave amplitude (TWA), has also been linked to mental stress as increased SNS activity shortens the interbeat interval (IBI), which in turn decreases the TWA. In [196], the TWA_Zero and the TWA_Toffset were both found significantly reduced during a stress task. In [222] a QT prolongation was observed as typical of stress state without significant RRI changes [151].

Concluding, the relationship between stress and ANS response reflected in the HRV parameters is not straightforward, however, there are HRV parameters presenting consistent patterns during stress. Inspecting Table 6, the features HR, RMSSD, SDNN and LF/HF ratio provided the strongest covariation with acute stress followed by other spectral measures (LF, LF norm, HF, HF norm, heart rate) which all correlated with acute stress.

2.3.4 Blood volume pressure (BVP)

Blood pressure (BP) is the pressure that is applied on vessels walls due to circulatory blood. It is described by various measures, the most common of which are systolic blood pressure (SBP), diastolic blood pressure (DBP), mean arterial pressure (MAP), stroke volume (SV), cardiac output (CO) and total peripheral resistance (TPR). BP increases with age because of the arterial walls' rigidity. During stress conditions, sympathetic activation leads to vasoconstriction and high cardiac output, so high blood pressure is observed also called hypertension.

A 3-year study [212] of 24-hour ambulatory blood pressure (ABP) revealed that people with increased job strain present increased SBP, DBP when they are at work or home and increased SBP during sleep. In [190] MAP, SBP and DBP were significantly higher during a mental arithmetic stress task. An interesting point was also the recovery phase where MAP was higher during early recovery (just after the task) in relation to late recovery. In [151, 213, 214] SBP and DBP are increased during mental arithmetic tasks (PASAT) and SCWT tests. However, Hjortskov claimed that BVP measures are not so sensitive to mental stress levels [209] compared to HRV parameters that are more prominent in such studies. In [160], SBP was reported significantly higher during memory demanding task, while performing a computer work in relation to baseline or to the no memory demanding task.

Inspecting Table 6, it is clear that SBP and DBP increase during stress in all studies investigated [129, 132, 151, 154, 160, 188-191, 195, 201, 209, 212-214], thus being consistent stress measures.

2.3.5 Photoplethysmography (PPG)

Photoplethysmography (PPG) is an optical non-invasive method measuring variations of skin hue associated with concurrent changes in blood volume in subcutaneous blood vessels during the cardiac cycle. PPG sensors use optical pulses generated by a red or near-infrared light source (light-emitting diode) and receive the reflected light with a photodetector. A typical PPG signal and its corresponding ECG is presented in Fig. 11.

From the PPG signals the pulse rate (PR), pulse rate variability (PRV), BVP blood oxygen saturation level (SpO2),

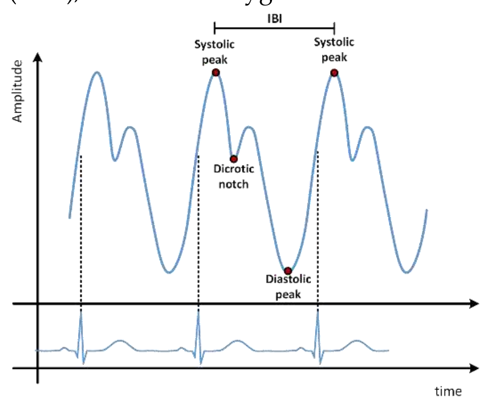

Fig. 11. A schematic representation of a PPG signal and its corresponding ECG

and BP can be extracted. Besides, PPG has been used for HRV parameters estimation as it presents high temporal peak agreement in relation to ECG. However, although HRV and PRV are highly correlated, they could not be considered identical [223]. In [224] the stress-induced vascular response index (sVRI), a PPG-based measure is proposed to assess stress levels. Stress can also be reflected in peripheral vasoconstriction, being related to decreased pulse wave amplitude (PWA) in PPG signals [225]. The PWA appears to have a consistent significant decrease during memory demanding tasks compared to the rest period [226] and during a simulated flight task [227]. In other studies, wavelet analysis of the PPG signal took place defining stress parameters comparing scales of CWT between stress and rest condition [228].

As PPG is based on variations of the reflected light, it also allows camera-based approaches [229] (known as remote photoplethysmography (rPPG)). rPPG has also been used effectively in stress estimation [165, 199] and it can be obtained reliably even using low cost web cameras [229].

3 Combined Multimodal Biosignal Analysis

Recent stress recognition studies base their analysis on multimodal biosignal analysis in order to acquire a more complete picture of emotional states. Then, the most robust biosignals features are selected and usually feed classification schemes which rule the existence or absence of stress. In particular, data analysis include methods of cleaning, transforming, modelling data, extracting specific/relevant information in pursuit of discriminating different conditions/states and supporting decision-making. These methods include classifiers such as SVM, Deep Learning, Logistic regression, Naïve Bayes, decision trees, random forest, K-nn and Neural Networks. In order to assess each method's efficacy, performance measures have been established based on the True Positive (*TP*), False Positive (*FP*), True Negative (*TN*), and False Negative (*FN*) values. Then sensitivity (*TP*/(*TP*+*FN*)), specificity (*TN*/(*TN*+*FP*)) and accuracy ((*TP*+*TN*)/(*TP*+*TN*+*FP*+*FN*)) measures can be calculated which are indicative of the system's performance. The accuracy is considered a more complete measure, thus it is used widely in research studies. An overview of multimodal analysis studies, along with study population, stimuli used, biosignals recorded, classification scheme and best accuracy received is summarized in Table 7. In this table, studies with a population of under 8 subjects were excluded.

Table 7: Overview of stress detection studies in chronological order, their details and best accuracy achieved

Study	Population (subjects)	Women/ Men	Age	Stimuli	Biosignals used	Classification system	Best Accuracy achieved
Womack and Hansen (1996) [230]	11 subjects	men	22-76	simulated/actual stress speech	Speech (MFCC, formants, etc)	HMM	91.00%
Zhou et al (2001) [81]	16 subjects	3/13	22-76	simulated/actual stress speech	Speech (TEO-CB-Auto-Env)	HMM	92.90%
Kim et al. (2004) [231]	50 subjects		7-8	Videos, images, sounds	EDA, SKT, ECG	SVM	78.40%
Lee et al. (2004) [127]	80 subjects			Stroop Color-Naming Task	EDA, SKT, HRV	MLP, GRNN, ANFIS	96.67%
Healey et al. (2005) [150]	24 subjects			Driving Task	ECG, EMG, EDA, RSP	LDA	97.30%
Zhai et al. (2006) [69]	32 subjects		21-42	Paced Stroop Test	EDA, BVP, PD, SKT	SVM	90.10%
Patro et al (2007) [232]	30 subjects	men		SUSE	Speech (SFF,SAF,MFCC)	VQ	84.68%
Katsis et al. (2008) [233]	10 subjects	men	22-35	Driving Task	4 facial EMGs, ECG, EDA, RSP	SVM, ANFIS	79.30%
Khalilzadeh et al.(2010) [174]	9 subjects	men	21-28	IAPS pictures	BVP, RR, EEG, GSR, PPG	Elman neural network	82.60%
Nhan et al. (2010) [134]	12 subjects	9/3	24.0±2.9	IAPS pictures	Thermal imaging, BVP, RR	LDA, GA	81.40%
Setz et al. (2010) [7]	33 subjects	men	24.06	MIST	EDA, ECG, RSP	LDA, SVM	82.80%
Hosseini et al. (2011) [173]	15 subjects	men	20-24	IAPS pictures	EEG, BVP, EDA, HRV, RR	SVM, ENN	84.60%
Melillo et al. (2011) [211]	42 subjects			Ongoing university examination	non linear HRV	LDA	90.00%
Sumitra et al (2011) [234]	15 subjects			contextual thinking, Lombard speech	Speech	HMM	59.53%
Wijsman et al. (2011) [235]	30 subjects	5/25	33.1±7.87	Norinder, Logical Puzzle, Memory Tasks	HR, HRV, EDA, RSP, EMG	Fischer's LS	79.26%
Giakoumis et al. (2012) [116]	21 subjects	4/17	30.4±3.7	custom Stroop CWT	EDA, ECG, Body activity	LDA	96.60%

Karthikeyan et al. (2012) [133]	60 subjects	30/30	22.5±2.5	Stroop CWT	ST	PNN	88.75%
Karthikeyan et al. (2012) [236]	10 subjects	women		Stroop CWT	EMG	K-nn	90.70%
Kurniawan et al. (2013) [90]	10 subjects			Stroop CWT, TSST, TMCT	Speech, EDA	K-means, GMM, SVM, Dtree	92.60%
Ren et al. (2013) [64]	30 subjects	16/14	26.8±2.56	Stroop CWT	Pupil, EDA	Naïve Bayes, Random Forest	85.53%
Wijsman et al. (2013) [237]	30 subjects	7/16	33.1±7.9	Mental tasks	ECG, EDA, RSP, EMG	GEE	74.50%
McDuff (2014) [165]	10 subjects	7/3	18-30	Mental Arithmetic Task (MAT)	PPG (HRV), BR	SVM	85.00%
Pedrotti et al. (2014) [65]	33 subjects	17/16	41.0±11.3	Lane Change Test	Pupil, EDA	NN	79.20%
Sharma et al. (2014) [40]	13 subjects	8/5	16-25		EEG, EDA, SKT, Facial cues	GA, SVM, ANN	99.00%
Hou et al. (2015) [238]	9 subjects	men	21-28	Stroop CWT	EEG	SVM, k-NN	85.17%
Al-shargie et al. (2015) [46]	12 subjects	men	20-24	MIST	EEG	SVM	94.00%
Al-shargie et al. (2016) [47]	22 subjects	men	26±4	MIST	EEG, fNIRS	SVM	95.10%
Baltaci et al. (2016) [68]	11 subjects	2/9	33±3.46	IAPS pictures	Pupil, facial TI	Decision Tree, Adaboost RF	83.80%
Maaoui et al. (2016) [239]	12 subjects		22-27	Stroop CWT	PPG (HRV)	SVM RBF	94.40%
McDuff et al. (2016) [199]	10 subjects	5/5	18-28	Berg Card Sorting Task (BCST)	PPG (HR, HRV, BR)	Naïve Bayes	86.00%
Simantiraki et al (2016) [98]	9 subjects	men	22-76	SUSAS (simulated stress speech)	Spectral Slope	Random Forest	92.06%
Giannakakis et al. (2017) [109]	23 subjects	7/16	45.1±10.6	Emotion recall, IAPS, Stroop CWT, videos	Facial rPPG, Facial Videos	K-nn, GLR, NVB, SVM	91.68%
Minguillon et al. (2018) [240]	10 subjects	5/5	20±2	MVC/MIST	EEG, ECG, EMG, EDA	LDA	86%
Anusha et al. (2018) [241]	34 subjects	14/20	21.4±1.7	Stroop CWT,MAT,TSST	EDA, ECG, SKT	QDA, K-nn	95.86%
Khosrowabadi (2018) [242]	26 subjects	6/20	18-30	AV emotional stimuli	EEG	K-nn, SVM	90.9%
Huysmans et al., (2018) [243]	12 subjects	7/5	37.3 ±8.8	Stroop CWT, Mental task, Stress event recall	ECG, EDA, BVP	SOM, ANN	79%
Xia et al. (2018) [244]	22 subjects	0/22	22.5±1.53	Mental Arithmetic Task	EEG, ECG	PCA, SVM	79.54%
Villa et al. (2018) [245]	20 subjects		20-30	TSST, MST	ECG, EDA	FDA	87.5%
Airij (2018) [246]	35 subjects	16/19		Mental Arithmetic Task	HR, EDA, SKT	Fuzzy Logic, K-nn	96.19%
Asif et al. (2019) [247]	27 subjects	13/14	20-35	Music Tracks	EEG	SMO, LR	98.76%
Cheema et al. (2019) [248]	30 subjects	0/30	20.1±2.3	Institute examination	PCG, ECG	LS-SVM	96.67%

Note: Stroop CWT: Stroop Colour-Word Test, TSST: Trier Social Stress Test, SUSE: Speech Under Simulated Emotion, MIST: Montreal Imaging Stress Task, TMCT: Trier Mental Challenge Test, LCT: Lane Change Test, HMM: Hidden Markov Models, SVM: Support Vector Machines, NVB: Naïve Bayes, GA: Genetic Algorithms

4 Stress Inducing Methods

Although stress occurs in many aspects of real life, in the majority of the reported studies in the literature, stress is induced to the participants in controlled environments. In this section, laboratory stressors used in research and clinical practice are described.

There are many studies of affect that use pictures from the International Affective Picture System (IAPS) [249]. The IAPS is a set of emotionally bearing pictures that have been evaluated on a 9-scale rating of arousal and valence dimensions. The IAPS collection is considered a quite reliable tool and it has been used in [68, 73, 109, 134, 174] for stress recognition.

The Stroop Colour-Word Test (SCWT) [250] date back to 1883 and it is a task asking to name a series of words with colour names written in congruent and incongruent colours. It has been validated in terms of reaction in physiological measures [251] and it is considered a reliable stressor. Various studies have used this method to induce stress [44, 64, 90, 109, 116, 133, 151, 154, 186, 187, 189, 192, 205, 209, 216, 238]. Variations of SCWT are the Stroop Colour-Naming Task consisting of visual stimuli using high chromatic yellow illumination and auditory stimuli [127] and the Paced Stroop Test [69]. Stroop test may be dimmed when the user has increased reactivity, intelligence or experience of similar tests.

Mental Arithmetic (MA) tests have been considered to induce stress and they have been used in stress studies

[151, 165, 190, 195, 201, 213, 252]. The Paced Auditory Serial Addition Test (PASAT) [253] is a neuropsychological test for assessing attentional processing that has also been used towards this direction. The Montreal Imaging Stress Task (MIST) [254] is a computer-based stress induction protocol consisting mainly of mental arithmetic problems and it was used in [7, 35, 46, 47]. The Berg Card Sorting Task (BCST) [255] is a card sorting problem where participants are required to sort cards into piles according to a not pre revealed rule [199]. There are also some no standardized tasks such as the mirror tracing task (tracing of a star that can only be seen in mirror image) [189]. Time pressure and distractor existence during stressors of mental tasks are additional stress effective factors besides mental tasks (such as the Norinder test) [153].

In addition, attention tasks regarding car behaviour have also been used in stress induction using driving simulation environment with straight/curved race track or with/without billboards [108], and driving tasks [256] such as simulated Lane Change Test (LCT) [65]. A combination of mental tasks can be used when research focuses on different stressors as in [187] where five different mental tasks were used, the digit span test, the SCWT, the corsi reverse, the kohs block test and the towers of Hanoi.

Kirschbaum et al. created the Trier Social Stress Test (TSST), a protocol for the induction of stress in laboratory setting [257] which has been used in [90, 131, 132, 258]. The cold pressor test (CPT) [259] is a process of inducing stress involving immersion of participant's hand in ice water. Its psychological effects were evaluated in [260] while other studies used this process in a stress survey [131]. Speech task [191, 193] is a type of social stressor where subjects are asked to prepare a speech to be videotaped and rated by experts on poise and articulation. In [210], participants were asked to give a 15-minute speech on awakening with only 2 minutes of preparation, which would be evaluated for content and quality. Another interesting approach of social pressure is that participants' performance in mental tasks will be published in colleagues [237].

There are also some controversial stressors regarding the applicability and ethics arise that have been used in the literature. There are studies employing verbal threats of electrical shock [111, 180] in order to induce stress to participants. Despite its controversiality, this technique was able to cause arousal and alertness needed for the experiment. In [221] a first time skydive from airplane was used as stressor measuring HRV the time interval 120 min before and 60 min after the skydive. Another stressor is the sleep lack that is related to physical stress. In [44] participants left with 30 hours of sleep deprivation for the experiment. In addition to the aforementioned methods, among stress induction methods have been proposed the Maastricht Acute Stress Test, the CO2 challenge test and the Mannheim Multicomponent Stress Test [261].

5 Ground Truth of Stress

Stress is a multifaceted experience with many different types being subjective in terms of the way it is perceived. In some cases, the stress state is a subconscious procedure in which even the self may not assess his/her own stress levels and their intensity. In addition, there are not direct measures to evaluate the behavioural and affective component of stress. These parameters make the determination of a ground truth a difficult process.

Some studies establish stress ground truth using the person's perceived stress as expressed in self-report ratings (e.g. 1–10) or scores from questionnaires. Then, the association of these scores/ratings with stress levels [56, 156] is investigated either within a session or between sessions (the first session served as a baseline) [56]. Ground truth may be formed as a combination of questionnaires and clinical interviews [33] or a combination of questionnaires and scores from stress indicators of driving behaviour (stops, turns, gaze changes, etc.) [150].

In other studies, stress ground truth is determined as a neutral or reference period and the stress state is determined by the presentation of stressors [7, 132, 151, 153, 190, 192, 198, 210] or the exposure to stressful situations [180]. The baseline can be formulated as the presentation of neutral images from IAPS [68], as the congruent segment of the SCWT [262], as different simulated driving conditions [65] or workload demands in an office environment [73]. In other studies, the baseline is considered the person's relaxed state achieved through relaxation videos [239] or following relaxation instructions of a psychologist [35]. Following examination stress protocols, the baseline was considered as the summer period [31] or two weeks after the examination procedure [39]. Sharma used a meditation script role play and a questionnaire to evaluate stress levels of the meditation observer [40].

Ground truth of stress can be established from biosignals or biomarkers that are considered reliable for stress level identification. In some studies, the salivary cortisol levels and the SDNN cardiovascular measure were employed to define stress groups [49] or stressors [198]. In this case, baseline normal values (e.g. pain threshold [161], baseline salivary cortisol level [198]) considering the stress level's intensity as the deviation from the baseline.

In general, stress ground truth determination is not a straightforward procedure mainly in real world conditions. The assessment through the use of self reports or ratings may have wide inconsistencies [73] and involve subjective bias. In addition, stress self-assessment may not illustrate unconscious or subconscious psychological processes. Measurement of stress responses in different people requires the formulation of an objective measure framework. In [109], this issue is addressed normalizing all features data according to a relaxed state (baseline) and using pairwise preference transformation allowing a fair assessment between rankings of different subjects. In [263], the normalization factor "stress response factor" is employed to estimate each subject's stress profile and in [264] authors propose the model cStress as an attempt to provide a stress golden standard. A recent study [265] provides a framework for a reliable emotion evaluation addressing issues such as subjective participants' statements through questionnaires or scales. In any case, the ground truth using established stimuli in laboratory settings are far from stress in real life situations (e.g. unemployment, death or divorce).

An objective baseline formulation might be a psychophysiological pattern combining involuntary and specific physiological measures and clinician diagnosis expertise.

6 Limitations

Most of the studies discussed in this paper have been performed in laboratory or well-controlled environments. The induced stressors were usually intense in order to achieve a prominent and measurable amount of acute stress. However, in real life conditions, stressors are usually complex procedures that involve many aspects of human personality or multiple stressors occur due to the complexity of the way of living. Different sessions of an experiment would be employed to cover different stressors but their simultaneous application is not always possible.

As referred in the previous section, the proper characterization of physiological signals used in stress studies face the difficulty of establishing the ground truth. It is admitted by most researchers that it doesn't exist a generally adopted and commonly used experimental protocol and the estimation of ground truth underlie subjectivity. Besides, most of biosignals discussed related to stress provide a personalized imprint of the organism. Therefore, a baseline measurement is needed for protocol calibration and the determination of normal conditions.

Another issue is that most biosignals are susceptible to noise or artifacts due to individual's body parts movements or activities. Biosignals that are affected mostly by this kind of artifacts are EEG, EMG, ECG, PPG, RSP. Signals denoising includes techniques such as low-, band- and high-pass filtering, notch filtering, the Least Mean Squares (LSM) or Recursive LSM, wavelet denoising, as well as Blind Source Separation (BSS) techniques like Principal Component Analysis (PCA), Independent Component Analysis (ICA), and their variations. Although these techniques may sometimes remove undesired peaks and artifacts efficiently, the remaining noise may distort signal's information. Environmental conditions (e.g., temperature, humidity, lightning, etc.) are known to affect various biosignals and body vital functions. Examples, among others, are the PD which varies in response to light stimulation (pupil light reflex), or the SKT measures which are affected by temperature, physical activity. Thus, the experimental environmental conditions should be kept constant with low intensity lightning or constant temperature during experiments.

The effectiveness of stress inducing tasks is also a question under investigation. Their effectivenesses are subject to originality and habituation. Other important dimensions are its duration and associated involved processes (e.g., habituation during continuous/repeated exposure, competition with opposing external stimuli and self-regulation). Our experience indicates that the most effective stressful effects are observed at the beginning of the experimental procedure. The engagement of the participant wanes as the experiment progresses, and its maintenance can be partially achieved with relaxation intervals between tasks.

Most research groups use their own data or their problem position is different, therefore the direct comparative evaluation of the used algorithms and methods is not possible. In the area of speech emotion recognition, some first attempts of establishing and using a general protocol test procedure were introduced [266].

7 Discussion

Stress detection, assessment and analysis in humans are significant processes in order to confront this phenomenon. Despite the subjective dimension of stress, research pursuits on finding reliable, objective measures to effectively represent stress and measures that would not be able to be controlled or manipulated. Most of the physiological measures (guided by the ANS) are involuntary, thus there is the notion that can represent stress levels in a more reliable way. Although there are some surveys on this area [179, 267, 268], there is lack of a comprehensive guidelines on the relationship between the multitude of biosignal features used in the literature and their corresponding capacity to predict stress. Moreover, there is not collective information on significant differentiations of each biosignal's features during stress conditions. This survey performs an extensive review on biosignals features behaviour during stress response.

According to the analysis performed in section 2 and the corresponding tables with significant changes, there are specific biosignals that present consistent pattern so as to be efficient and specific in discriminating stress conditions. Heart rate (HR) is the most prominent feature which increases significantly during stress, however, this can be attributed only to the arousal dimension. Skin Conductance Response (SCR) and Level (SCL) appear also to be consistent measures being typically increased during stress. They are both influenced exclusively by SNS and not by the PNS which is a very significant factor for assessing stress. Regarding brain activity, the most consistent measure is the EEG alpha asymmetry index which appears to be reduced during stress conditions. Corresponding consistent variations across studies during stress conditions are the increase of LF/HF ratio, the decrease of SDNN, the increase of systolic (SBP) and diastolic blood pressure (DBP), the increase of respiration rate (RSP) and the increase of voice pitch (f_0). However, as univariate analysis may not incorporate all the information needed, the crucial part in stress studies is the identification of the most appropriate fusion of features for the investigated each time stress type.

Another important issue to concern is the substantial intra- and inter-individual variability of the stress response. For a given person, the same stimulus or condition may elicit a strong or weaker stress response depending on varying social (e.g., high vs. low peer pressure), contextual (e.g., high reward vs. low reward), and cognitive-emotional parameters (e.g., instruction to engage in cognitive appraisal of the situation). Different persons may develop very disparate stress responses to the same stressor. Moreover, different stressor types may be more appropriate and specific to particular types of stress. According to section

4, the Stroop Colour Word Test (SCWT) and mental arithmetic tasks appear to be the most used stressors in eliciting task related stress entailing their efficacy. For social stress, studies prefer to use stressors dealing with social exposure, such as interviews or implication that the participants would be judged or rated for their performance. Psychological stress is elicited more effectively using negatively charged content either by using images (e.g. IAPS database) and videos or by provoking memories of past traumatic events.

Besides, in stress studies, there is a difficulty in establishing the ground truth of determining stress and calm conditions as they are considered multifaceted states. Biosignals that appear consistent behaviour as described in this paper could be a good basis in providing ground truth for primary states such as arousal and under appropriate modelling to more complex emotional states such as stress.

This review aims not only to contribute to the effective automatic stress recognition but also to give insights in understanding the underlying mechanisms of stress and its types as they are manifested in physiological biosignals.

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Giorgos Giannakakis received his Dipl. Ing. in Electrical and Computer Engineering from the National Technical University of Athens (NTUA) in 2003, his M.Sc. and Ph.D. in Biomedical Engineering from the School of Medicine of the University of Patras – School of Electrical and Computer Engineering, NTUA in 2005 and 2009 respectively. From 2005 to 2009, he has worked as scientific associate at the Institute of Communications and Computer Systems (ICCS) in Athens. Since November 2012, he is research associate at the Institute of Computer Science of the Foundation for Research and Technology - Hellas (FORTH). He has been awarded the honorary praise of the best interdisciplinary diploma thesis in NTUA (2003) and the Greek state post-doctoral scholarship (2017). His research interests include the areas of biosignal processing and analysis, computer vision, affective computing and computational neuroscience.

Dimitris Grigoriadis received his B.Sc. in Informatics Engineering from the Technological Educational Institute of Crete in 2016 and he holds a M.Sc. in Information Technologies in Medicine and Biology of the National and Kapodistrian University of Athens. He is currently a Phd candidate at the University of Thessaly. From 2015 to 2016, he got an internship in Biomedical Informatics & eHealth Laboratory of the Technological Educational Institute of Crete. His research interests include the areas of biosignal processing and analysis, affective computing and bioinformatics.

Katerina Giannakaki received her Dipl. Ing. in Electrical and Computer Engineering from the University of Patras, Greece, in 2009, and the M.Sc. in the Brain and Mind sciences of the School of Medicine, University of Crete and Foundation for Research and Technology - Hellas (FORTH). During her graduate studies, she got an internship in the laboratories of Visual Cognition (School of Medicine, University of Crete), the Bioinformatics in Structural Biology and Computational BioMedicine (FORTH). Her research interests focus on the fields of human-computer interaction and affective computing, biosignal analysis, machine learning, and computational neuroscience.

Olympia Simantiraki received her B.Sc. in 2012 and M.Sc. in 2014 from the Computer Science Department of the University of Crete. She is currently a Ph.D. student at the University of the Basque Country. From 2011-2014, she had also been a research assistant at the Signal Processing Laboratory, Institute of Computer Science, FORTH. In 2014, she was an intern at TOSHIBA, Cambridge Research Laboratory, Speech Technology Group. From 2015 until 2016, she had been an R&D engineer at the Computational BioMedicine Lab (FORTH).

Alexandros Roniotis holds a Ph.D. in Electronics and Computer Engineering from the Technical University of Crete, Greece. In 2006, he completed his B.Sc. in Informatics and Telecommunications from the University of Athens, Greece and in 2007 his M.Sc. in Signal Processing and Communications in the Department of Electrical and Electronic Engineering, Imperial College London, UK. His PostDoc research in the Institute of Computer Science, FORTH and in the Technological Institute of Crete, Greece, includes modeling of biological processes, affective computing and signal processing for biomedical applications.

Manolis Tsiknakis received the B.Eng. degree in Electric and Electronic Engineering, in 1983, the M.Sc. degree in Microprocessor Engineering, in 1985, and the Ph.D. degree in Systems Engineering from the University of Bradford, Bradford, U.K., in 1989. From February 1992 until January 2012 he has been with the Institute of Computer Science, Foundation for Research and Technology-Hellas, Greece, as a Principal Researcher and Head of the Center of eHealth Technologies. He is currently a Professor of Biomedical Informatics at the Department of Informatics Engineering, Technological Educational Institute of Crete and a visiting researcher at FORTH. Prof Tsiknakis led the effort for the design and implementation of HYGEIAnet, the regional health informatics network of Crete, an eEurope award winner in 2002 and was FORTH's best-applied research award winner in 2003. He is an associate editor in the IEEE Journal of Biomedical and Health Informatics. He has published extensively – over 200 papers - in refereed scientific journals and conferences on issues related to the application of innovative ICT in the domain of clinical and translational research, care and wellness management. His current research interests include biomedical informatics and engineering, approaches for semantic health data integration, cloud computing and their application in biomedicine; affective computing, behavioral modeling and human activity recognition using wearable sensors, smart eHealth and mHealth service platforms.