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Real-Time Stress Detection by Means of Physiological Signals

Alberto de Santos Sierra, Carmen Sánchez Ávila, Javier Guerra Casanova and Gonzalo Bailador del Pozo
Group of Biometrics, Biosignals and Security
Universidad Politécnica de Madrid
Spain

1. Introduction

The incessant demand of security in modern society is requiring a certain effort on providing protected and reliable frames for contemporary scenarios and applications such as bank account access, electronic voting, commerce or border crossing frontiers in airports.
Biometrics is of essential importance due to their capability to identify individuals univocally with low rates in false alarms, aiming to avoid the use of passwords, pin-codes or different tokens for personal identification. Instead, biometrics claim to extract precise and unique information from inidividuals based on whether behavioural or physical characteristics. In fact, there are a wide range of possible techniques for biometric identification, whose enumeration is far beyond the scope of this topic.
However, despite of avoiding the use of pin-codes, biometrics do not consider the case of individuals being forced to provide the biometric data to the corresponding sensor, allowing non-desired accesses. In other words, given a cash withdraw machine in a bank provided with the most sofisticated biometric system able to detect even fake or non-living samples, if a person is forced to present the required biometric data (iris, fingerprint, hand, . . .), the system would let enter that person, as long as the biometric template coincides with the acquired data. Thus, individuals registered or enrolled within the systems could be used as keys to access a complex door.
The presented approach proposes a stress detection system able to cope with this lack of security, based on the fact that former situations take place provoking a huge response in the human stress mechanism. Such response is impossible to disguise, providing a suitable method to detect anomalous situations in where the whole security could be compromised.
This stress detection must provide precise and real-time information on the state-of-mind of the individual, requiring a low number of physiological parameters to keep the acquisition system as less invasive and intrusive as possible. Notice that this fact is an essential concern due to the current misgivings on hygienic considerations.
Therefore, only two phsyiological signals are required, namely Galvanic Skin Response (Skin Conductivity) and Heart Rate, since both provide accurate and precise information on the physiological situation of individuals. The inclusion of adequate sensors for both signals acquisitions require little hardware, being straightforward to include former sensors in current biometric systems.

Besides, this chapter proposes a wide variety of methods for stress detection, in order to elucidate which method is more suitable for implementation and integration in future biometric devices. In addition, methods are oriented for real-time applications, which in most cases provoke a reduction in stress detection accuracy.
Finally, the study comes up with the conclusion that best approach combining accuracy and real-time application is based on fuzzy logic, modelling the behaviour of individuals under different stressing and non-stressing situations, creating a stress template gathering previous physiological information.
The use of the proposed stress template is twofold: On the one hand, to collect and gather the different behaviour of each individual under a variety of situations in order to compare posterior physiological acquisitions. On the other hand, the idea of template implies modelling each individual separately, providing a frame to distinguish to what extent individuals react against stressing situations. This template is based on the idea that human individuals react differently to a same event, and therefore, a stress detection system cannot provide a result based on general parameters but concrete, personal and individualize features.

2. Literature review

The problem of stress detection has been tackled with different approaches. However, former works can be divided into two different groups, depending on the use of physiological signals or other behavioural characteristics.
For example, the work presented by Andren & Funk (2005) provides a system able to compute the stress level of an individual by the manner and rhythm in which a person types characters on a keyboard or keypad. In addition, Dinges et al. (2007) provides a study of stress detection based on facial recognition. Both approaches are related to behavioural human characteristics.
On the other hand, there exist many previous works related to stress detection based on physiological signals. The essay presented by Begum et al. (2006) presents a study of stress detection only based on Finger Temperature (FT), together with Fuzzy Logic Zadeh (1996), and Case-Based Reasoning Andren & Funk (2005).
Focusing on stress detection by means of physiological signals, it is necessary to describe which possible signals can be related to stress and their extent.
It is not common to focus only on one certain physiological feature, but on many of them, in order to obtain further and more precise information about the state of mind. Considering this multimodal approach, there are several articles which study a variety of parameters and signals, as well as the combination among them.
Heart Rate variability (HR) has been considered as an earlier stress marker in human body, being widely studied and analyzed. Several authors consider this signal in their reports: Jovanov et al. (2003) presented a stress monitoring system based on a distributed wireless architecture implemented on intelligent sensors, recording HR along different positions in individual body by means of sensors located beneath clothes.
In additoin, the research provided in Angus et al. (2005); Zhai et al. (2005) proposes a system considering Finger Temperature (FT), Galvanic Skin Response (GSR) and Blood Volume Pulse (BVP). The main characteristic of this system lies on the fact that signals are acquired in a non-intrusive manner and furthermore, these previous physiological signals provide a predictable relation with stress variation.
There exist physiological signals of different nature like Pupil Dilation (PD) and Eyetracking (ET) providing very precise information about frame stress. When an individual is

Physiological Signals	References
BVP (Blood Volume Pressure)	Barreto & Zhai (2006); Picard & Healey (2000) Lin et al. (2005); Zhai et al. (2005)
GSR (Galvanic Skin Response)	Barreto & Zhai (2006); Picard & Healey (2000) Lin et al. (2005); Moore & Dua (2004); Zhai et al. (2005)
PD (Pupil Dilation)	Barreto & Zhai (2006); Lin et al. (2005); Zhai et al. (2005)
ST (Skin Temperature)	Barreto & Zhai (2006); Zhai & Barreto (2006)
ECG, EKG (Electrocardiogram)	Picard & Healey (2000)
Breath (RR)	Picard & Healey (2000)
EMG (Electromyogram)	Picard & Healey (2000)
EEG (Electroencephalogram)	Picard & Healey (2000)

Table 1. Literature Review on physiological signals involved in stress detection.

under stress, PD is wider and the eye movement is faster. The article presented in Prendinger & Ishizuka (2007), not only consider PD and ET, but also GSR, BVP and FT. The main purpose of this approach is to recognize emotions, interest and attention from emotion recognition, a very remarkable conclusion for future computer applications and for the improvement of Human Computer Interaction (HCI) Kim & Ande (2008); Sarkar (2002a).
In summary, stress can be detected through many different manners, as stated in Sarkar (2002a), where a wide study is carried out regarding previous physiological signals together with others related to stress (Positron Emission Technology (PET) Healey & Picard (2005); Sarkar (2002a), Functional Magnetic Resonance Imaging (fMRI) Picard & Healey (2000); Sarkar (2002b), Electroencephalography (EEG) Li & hua Chen (2006); Sarkar (2002a), likewise Electromyograms (EMG) Chin & Barreto (2006a); Li & hua Chen (2006); Shin et al. (1998) or Respiratory Rate (RR) Shin et al. (2004)). Nonetheless, these other signals lack of future integrity because they involve more invasive acquisition procedures.
Table 1 gathers a summary on the signals involved in stress detection within literature.
Together with signal processing and feature extraction, the comparison algorithms to elucidate the stress level of an individual are of great importance. There are some previous work considering several approaches for stress detection. The work presented by N. Sarkar Sarkar (2002a) proposes fuzzy logic (as M. Jiang and Z. Wang Jiang & Wang (2009)) to elucidate to what extent a user is under stress. On the other hand, the research presented by A. de Santos et al. de Santos Sierra et al. (2011) proposes the creation of a fuzzy stress template to which subsequent physiological acquisitions could be compared and contrasted. Other approaches have been proposed, based on different techniques like, SVM, *k*-NN, Bayes classifier. In order to extend excesively the document, Table 2 contains a summary of previous approaches within literature.
Finally, a matter of importance are both how stress is induced in individuals and the number of samples to evaluate former approaches. Table 3 and Table 4 briefly show which experiments have been involved for provoking stress and which populations were required in order to validate stress detection algorithms. More extensiveley, the research by Lisetti & Nasoz (2004) provides a complete study on emotion recognition including a deep literature review on the experiments carried out to provoke emotions considering populations, algorithms, approaches and so forth.
Moreover, special mention deserves the work presented by Healey & Picard (2005), since they are considered pioneers on stress detection field.

Algorithms	References
SVM (Support Vector Machines)	Barreto & Zhai (2006); Zhai et al. (2005)
ANOVA Analysis	Lin et al. (2005)
Bayes classifier	Zhai & Barreto (2006)
Fisher Analysis	de Santos Sierra et al. (2010); Picard & Healey (2000)
k-NN	de Santos Sierra et al. (2010)
Fuzzy Logic	Begum et al. (2006); Sarkar (2002b)
	de Santos Sierra et al. (2011); Sarkar (2002a)

Table 2. Literature Review on algorithms applied to stress detection.

Experiments	References
Stroop Test	Barreto & Zhai (2006); Zhai et al. (2005)
	Zhai & Barreto (2006)
Videogames	Lin et al. (2005)
Driver and Pilot Simulation	Picard & Healey (2000)
Hyperventilation and Talk Preparation	de Santos Sierra et al. (2011; 2010)

Table 3. Literature Review on experiment layouts oriented to provoke stress.

Populations	References
6 male individuals	Zhai et al. (2005)
42 adults with ALS[1]	Moore & Dua (2004)
14 males and 4 females	Lin et al. (2005)
32 individuals	Barreto & Zhai (2006); Zhai & Barreto (2006)
3 experienced drivers	Healey & Picard (2005)
10 pilots (with and without experience)	Healey & Picard (2005)

Table 4. Literature Review on populations involved in stress detection evaluation.

3. Physiological signals

Although several possible signals have been considered within the literature to detect stress (Section 2), this paper proposes the use of two signals: Galvanic Skin Response (GSR), also known as Skin Conductance (SC), and Heart Rate (HR). These two signals were selected based on their properties regarding non-invasivity when being acquired and because their variation is strongly related to stress stimuli Barreto & Zhai (2006); Healey & Picard (2005); Prendinger & Ishizuka (2007).

Galvanic Skin Response (GSR), known also as electrodermal activity (EDA), is an indicator of skin conductance Barreto & Zhai (2006); Shi et al. (2007). More in detail, glands in the skin produce ionic sweat, provoking alterations on electric conductivity. First experiment dates back to 1907, when Carl Jung first described some relation between emotions and the response of this parameter Angus et al. (2005); Zhai et al. (2005).

GSR can be obtained by different methods, but the device proposed to acquire signals (Section 4.1) is based on an exosomatic acquisition. In other words, extracting skin conductivity requires a small current passing through the skin. GSR is typically acquired in hand fingers and its measure units are μSiemens ($\mu\Omega^{-1}$) Angus et al. (2005).

Main parameters of GSR like basis threshold, peaks or frequency variation vary enormously among different individuals and thus, no general features can be extracted from GSR signals

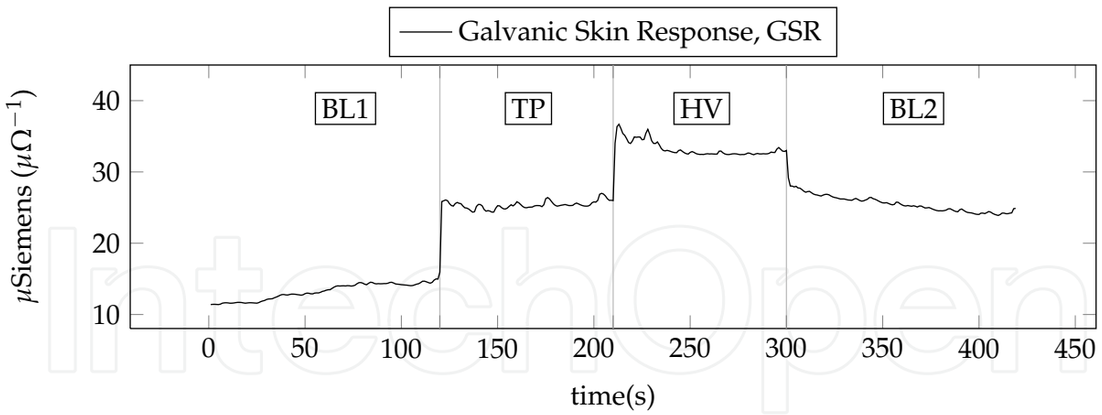


Fig. 1. A GSR (Galvanic Skin Response signal) sample during the four stages: First Base Line (BL1), Talk Preparation (TP), Hyperventilation (HV) and Second Base Line (BL2). Notice how GSR arousal responds positively to stressing stimuli (HV and TP).

for a global stress detection purpose, since parameters extracted from GSR signals are strongly related to each individual.
Figure 1 shows an original GSR signal, measured during the experiments. Reader may notice the different arousal of this signal, depending on the stressing stimulus. Initials in Figure 1 stands for BL1 (Base Line 1), TP (Talk Preparation), HV (Hyperventilation) and BL2 (Base Line 2) whose meanings are extensively explained in Section 4.5.
On the other hand, Heart Rate (HR) measures the number of heartbeats per unit of time. HR can be obtained at any place on the human body, being an accessible parameter to be easily acquired Choi & Gutierrez-Osuna (2009); Jovanov et al. (2003).
HR describes the heart activity when the Autonomic Nervous System (ANS) attempts to tackle with the human body demands depending on the stimuli received Picard & Healey (2000). Concretely, ANS react against a stressing stimulus provoking an increase in blood volume within the veins, so rest of the body can react properly, increasing the number of heartbeats.
Most common methods for HR extraction consider to measure the frequency of the well-known QRS complex in a electrocardiogram signal Bar-Or et al. (2004); Sharawi et al. (2008). In contrast to ECG biometric properties Israel et al. (2005), HR is not distinctive enough to identify an individual.
Summarizing, both HR and GSR behave differently for each individual, and therefore posterior stress template must gathered properly this unique response in order to obtain an accurate result in stress detection. Figure 2 shows an original HR signal (measured in Beats per Minute, BPM), measured during the experiments. Reader may notice the different arousal of this signal, depending on the stress stimuli. Initials in Figure 2 stands for BL1 (Base Line 1), TP (Talk Preparation), HV (Hyperventilation) and BL2 (Base Line 2) whose meanings are extensively explained in Section 4.5.1.

4. Database acquisition

This section provides an overview of how the dataset was built considering the experimental setup and the characteristics of the database and which psychological tests were carried out to assess in which manner an individual is likely to react against stress situations Yanushkevich et al. (2007).

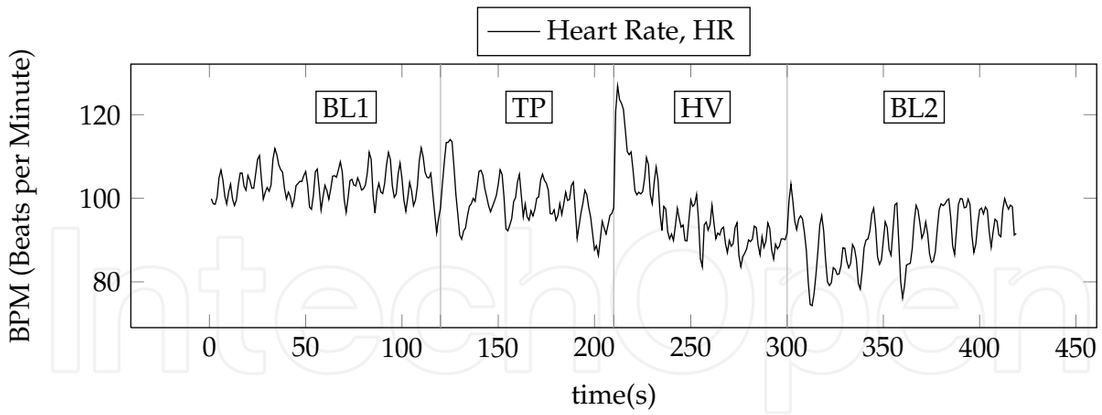


Fig. 2. A HR (Heart Rate signal) sample during the four stages: First Base Line (BL1), Talk Preparation (TP), Hyperventilation (HV) and Second Base Line (BL2).

4.1 Overview

The experiments were carried out in a Faraday room in the Human Psychology Laboratory from Psychology Faculty of Complutense University of Madrid (UCM), endowed with electromagnetic, thermal and acoustic insulation, with the aim of collecting HR and GSR signals from each participant.

The device proposed to carry out these experiments is I-330-C2 PHYSIOLAB (J &J Engineering) able to process and store 6 channels including EMG (Electromyography), ECG (Electrocardiogram), RR (Respiration Rate), HR and GSR. Sensors were attached to hand right (or left, but not both) fingers Cai & Lin (2007), wrist and ankle, in order to acquire both HR and GSR, avoiding sensors detachments, unplugged connectors to analog-to-digital converter and/or software acquisition errors. Moreover, sample acquisition rate is one sample per second for both HR and GSR.

4.2 Participants

The participants were students from Psychology Faculty (UCM) and Social Work (UCM), being a total of 80 female individuals, with ages from 19 to 32 years old, with an average of 21.8 years old and a standard deviation of 2.15. The lack of male individuals is due to the Faculty where the experiment took place, given the fact that the percentage of male students is almost negligible in comparison to the amount of females.

4.3 Task justification

Provoking stress on an individual requires a specific experimental design in order to obtain an adequate arousal to the proposed physiological signal Dinges et al. (2007); Healey & Picard (2005). Concretely, this paper proposes to induce stress by using Hyperventilation and Talk Preparation Cano-Vindel et al. (2007).

Hyperventilation (HV) is defined as a certain kind of breath, which exceeds standard metabolic demands, as a result of excess in respiratory rhythm.

As a consequence, several physiological changes emerge: arterial pressure diminution in blood until a certain level so-called hypocapnea Cano-Vindel et al. (2007); Zvolensky & Eifert (2001), and blood pH increment, known as alkalosis.

However, voluntary hyperventilation does not produce always an actual anxiety reaction Cano-Vindel et al. (2007), and therefore, an additional anxiogenic task is required to ensure

that a positive valence in terms of stress response is provoked. Such a task is Talk Preparation (TP).
Results provided by Cano-Vindel et al. (2007); Zvolensky & Eifert (2001) highlight the fact that hyperventilation produces a physiological reaction similar to that reaction induced by a threatening task of preparing a talk.
As a conclusion, talk preparation and hyperventilation provoke both an alteration in physiological parameters together with different emotional experiences. These previous tasks have been widely studied and evaluated with positive results, and they are very suitable to induce stressing stimuli on individuals.

4.4 Tests

When performing psychological experiments, an important tool to validate results requires the utilization of tests to extract subjective information from the individual.
There exist several tests able to provide information about the predisposition of a certain individual to be affected by anxiety and stress: ISRA test (Inventory of Situations and Responses of Anxiety Miguel-Tobal & Cano-Vindel (2002)), IACTA test (Cognitive Activity Inventory on Anxiety Disorders Cano-Vindel & Miguel-Tobal (2001)) and ASI (Anxiety Sensitivity Index Peterson & Reiss (1992)).
The two former tests were developed by Cano-Vindel (Professor of Faculty of Psychology, Complutense University of Madrid) together with his research group, and have been widely used and accepted by scientific community Cano-Vindel & Miguel-Tobal (2001); Cano-Vindel et al. (2007).
The tests used to detect predisposition to anxiety are described as follows:

- ISRA: Inventory designed according to the model of three response systems which evaluates signs of anxiety in a Cognitive level (C), Physiological level (P), and Motor (M). Furthermore, the addition of this three values provides a general measure of anxiety level, denoted by Total (T). ISRA test also includes to assess tendency to show anxiety in four areas, namely Assessment situations (F1), Interpersonal situations (F2), Phobics situations (F3) and Daily life situations (F4).

  This test provides good psychometrics properties, excellent internal consistency (Cronbach's alpha .99), good test-reset reliability (.81 for T) and good capability in discriminating different samples.
- IACTA: This test is able to measure sub-scales of social phobia, panic attacks and agoraphobia.
- ASI: This index provides information about the fear to anxiety symptom. Three different factors are measured: Physical worries, social worries and thoughts related to mental handicap. Subjects with a high total score in ASI show more elevated levels of anxiety after hyperventilation task compared to subjects with a low score. However, physical worries is the main factor to predict the anxiety level after hyperventilation in both no-clinic subjects and panic disorders patients Cano-Vindel et al. (2007); Zvolensky & Eifert (2001).

4.5 Procedure

The experiments were split into two sessions:

- First session regards a subject selection, applying ISRA, IACTA and ASI test.
- Second session consisted of the HR and GSR sample acquisition under hyperventilation and talk preparation.

4.5.1 First session

Several collective assessments were carried out applying ISRA, IACTA and ASI test. Participants were to fulfill previous tests in the same order as described previously. The average length of this step was deemed to be about 50 minutes.

Finally, two groups (namely Group 1 and Group 2) were created ensuring that the distribution of their respective anxiety levels, measured by psychological tests Cano-Vindel & Miguel-Tobal (2001); Miguel-Tobal & Cano-Vindel (2002), were similar. In other words, this selection seeks to avoid one group containing people which barely react against stress, and other group with people which overreact under stressing conditions. Therefore, both groups must be well-balanced in terms of anxiety levels in order to validate the experiments.

Participants from Group 1 underwent an experimental session using physiological and subjective signals under following conditions: calm state (base line, namely BL1), stimulating task (hyperventilation, HV), threatening task (talk preparation, TP) and base line post-stress (BL2). On the other hand, the order of tasks was swapped for participants from Group 2: calm state (base line), threatening task (talk preparation), stimulating task (hyperventilation) and base line post-stress. Main reason to alter the order consists of making independent the task order from the results obtained Cano-Vindel et al. (2007); Miguel-Tobal & Cano-Vindel (2002). The emotional experience was assessed after each situation (Base line (BL1), threatening (TP) and stimulating task (HV) and base line post-stress (BL2)), using a Likert scale (0-100) Cano-Vindel et al. (2007).

Specifically, individuals were asked to evaluate the following emotional parameters: displeasure, anxiety level, corporal sensations and thoughts lack of control. In fact, control dimension was divided into two variables to explore possible differences among previous facets. Lack of control on observable behavior was not assessed, since the subjects were strongly indicated not to move during the experiment procedure, in order to avoid noise in physiological signal acquisition (Section 4.1).

Furthermore, a precise order was given to avoid ambiguities regarding emotions: 'Assess anxiety level/intensity experimented at this very precise moment'. Usually, participants did not understand the meaning of evaluating their emotions (which emotion?).

After this four parameters evaluation (i.e., displeasure, anxiety level, corporal sensations and thoughts lack of control), next step was carried out, consisting of recording Heart Rate (HR) and Galvanic Skin Response (GSR), together with new evaluations of previous four parameters (displeasure, anxiety level, corporal sensations and thoughts lack of control) regarding emotional experience.

The experimental session consisted of the following steps for participants from Group 1:

- Sensors location and adaptation time. After this adaptation time (variable time), base line of physiological signals (heart rate and skin conductivity) were taken under rest situation, during 2 minutes. Once the signals were recorded, a new assessment of emotional parameters was carried out. Besides, this step is so-called BL1.
- Hyperventilation task (HV), consisting of deep and fast breathes each 3 seconds, conducted by a sound produced by the experimenter. This task was performed till the individual realized clearly of changes in his or her corporal sensations. The participant let the experimenter know that moment, by the use of a simple word. The experimenter made the participant to breath deeply three times more, recording after that moment physiological signals (90 seconds), followed by a new evaluation of the emotional parameters.

- Talk preparation task facing an audience (TP). The experimenter asked the individual to prepare mentally a talk of few minutes on a certain topic explained during the lectures that these students attended, in order to be recorded by a video-camera. After three minutes, new appraisal of emotional parameters were inquired, recording again HR and GSR (90 seconds), informing the participant that the talk was not necessary anymore.
- Rest period (BL2). The experiment comes to an end, and post-stress base line is recorded during 2 minutes, acquiring HR and GSR signals, together with a new subjective evaluation of the emotional parameters.

Obviously, BL1 implies no stressing stimuli on the individual in contrast to HV and TP. However, nothing can be assured in relation to BL2, since it cannot be considered neither as a stressing nor as a relaxing state Cano-Vindel & Miguel-Tobal (2001); Cano-Vindel et al. (2007); Miguel-Tobal & Cano-Vindel (2002).
Individuals from Group 1 carried out the talk preparation task (TP), after base line state (BL1), followed by the hyperventilation task (HV), ending with post-stress base line (BL2). On the other hand, individuals from Group 2 performed the experiment in the following order: BL1, TP, HV and BL2.

4.6 Database discussion

A biometric database based on a certain physical characteristic, e. g. Iris, consists of different samples taken from a wide range of users during different sessions separated by a lapse of time of days, weeks or even months. On the contrary, the database gathered in these experiments does not verify any of the previous points described above.
This stress database consists of a unique sample of a very specific set of individuals, namely female students with ages on the interval 19 to 32 years old, with an average of 21.8 years old and a standard deviation of 2.15 (Section 4.2).
However, there exists justification for this drawback. A psychological experiment is far from being repeatable, since the specific tasks previously described (Section 4.3) require a component of surprise and unexpectedness. In other words, if an individual carries out again the same tasks, even after an undefined period of time, such person would be prepared to come through the task, and what is more, the response of her or his physiological signals will not be certainly the same Cano-Vindel et al. (2007).
Obviously, a third session similar to second one (first session consisted of answering tests ISRA, IACTA and ASI, second session attempted to register the physiological signals) could have taken place with different tasks. Though, this option was rejected, since different tasks provoke different stress responses Chin & Barreto (2006b); Fairclough (2009); Kim & Ande (2008); L. et al. (2007), and therefore, the signals registered in both sessions would not correspond to same degrees of stress.
The physiological response to a stressing agent is strongly related to each individual and such a response is similar, independently of the time during the stressing stimulus provoked the response Yerkes & Dodson (1908). As an overview, the stress mechanism could be considered as a linear temporal invariant system, which provides certain outputs depending on the inputs. Therefore, same inputs produce same outputs. Moreover, stress mechanism extracts some information from the stimuli, so that if such stressing agent appears again, the human body is able to react faster and better, compared to first time Lin et al. (2005); Rosch (1996). This characteristic makes useless to repeat same tasks after a certain period of time, and furthermore makes unnecessary a third session with different tasks, since the response will not be the same, as the stimuli provided by different task, provoke different responses. Then,

this implies that these experiments assure that a final stress detection system is able to detect stress in real applications, despite of being train with the presented database.
Finally, it is difficult, even for expert psychologists, to state whether the response among female and male individuals differs as much as previous response varies within female individuals Sapolsky (1988). Several researchers support the idea that male and female individuals suffer different responses when stress agent endures through time, (e.g., a great amount of work at job, a bad economical situation, and so forth), but they have similar responses when stress stimuli consist of specific actions in a very short period of time, e.g. an accident, an armed robbery and the like Lin et al. (2005).
Thereby, it is justified to extend the results obtained with this database to a wider population, even containing males and females. Nonetheless, the algorithm responsible for detecting stress has been implemented independently of this likely drawback, since it considers how an individual behaves under both stress and relax situation. This procedure provides in theory more independence from database population.

5. Template extraction

Before describing the different approaches compared within this paper, how the template is created is explained, combining both the physiological signals and the different stressing and non-stressing tasks.
In other words, the template extraction is required so that the system could create a profile in order to contrast, whether a user is actually under stress. This template is based on specific characteristics extracted from individual concerning parameters from the physiological signals HR and GSR.
On the other hand, once the user is associated to a template, the individual is able to access the system, and therefore a template comparison is required. Both steps are described in following sections.
First step consists of extracting a stress template from the user. Such a template describes the behavior of HR and GSR signals in both situations calm state (relax) and excited state (stress). As stated in Section 4.1, HR and GSR signals are recorded by I-330-C2 PHYSIOLAB (J &J Engineering) able to process and store 6 channels including EMG, ECG, RR, HR and GSR.
The main aim of a stress detection system consists of elucidating calm state (relax) or excited state (stress). Therefore, the system must know how both signals (HR and GSR) behave in both situations. Since these states cannot be controlled easily by an individual, calm state and excited state must be induced while HR and GSR are recorded.
Each user must undergo the experiments described previously (Section 4.5). Briefly, as an overview, there exist four stages in the experiments:

- First stage (BL1): Elicit a relax state by suggesting the individual to sit comfortably.
- Second stage (HV): Hyperventilation, i.e., deep and fast respirations.
- Third stage (TP): Speech/talk preparation.
- Forth stage (BL2): Relax state.

Three states emerge from previous stages (Section 4.5): Calm state (First stage, BL1), Excited state (Second and Third stage, HV and TP) and post-excited state (Forth stage, BL2). This latter state regards the fact that after a stress short period of time, HV and GSR require more time to achieve a calm state. Thereby, forth stage and first stage diverge in terms of HR and GSR despite of corresponding to the same instructions in the experiment.

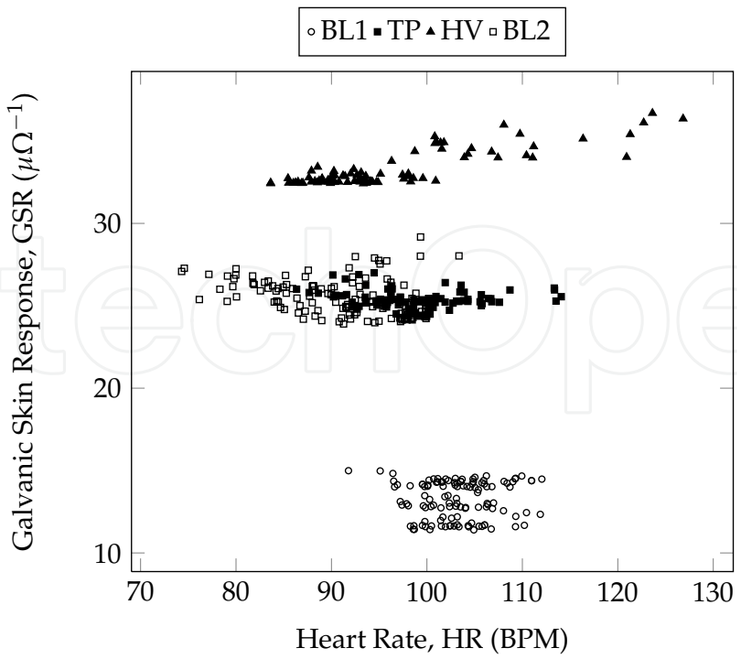


Fig. 3. Graphic representation of γ. Notice how the relation between HR and GSR varies depending on the stressing stimuli (BL1, TP, HV and BL2).

The experiments involve Hyperventilation (HV) and Talk Preparation (TP), as presented in Section 4.3. However, any task involving a considerable cognitive load (such mathematical operations, color distinction, Stroop test and so forth) may come in useful for inducing stress in a similar manner as previous task met such a required goal Cano-Vindel et al. (2007); Conway et al. (2000); Healey & Picard (2005); Kim & Ande (2008).
Mathematically, both HR and GSR are considered as stochastic signals. Therefore, $\mathcal{H}$ represents the space of HR possible signals and $\mathcal{G}$ represents the space of GSR possible signals. Each stage will come up with a pair of signals $h \in \mathcal{H}$ and $g \in \mathcal{G}$ according to the experimental task conducted in each situation. Thus, a template extraction requires four pair of signals, namely $\gamma = [(h_1, g_1), (h_2, g_2), (h_3, g_3), (h_4, g_4)] \in \mathcal{H} \times \mathcal{G}$ corresponding to how the individual behaves under different states. Notice that signals h_i and g_i are not normalized, in contrast to previous approaches Angus et al. (2005); Healey & Picard (2005) . The decision to avoid normalization was done based on the experience, since data without normalization provided more accurate results in terms of stress detection.
Once γ is obtained, for each pair of signals, (h_i, g_i), $i = \{1, 2, 3, 4\}$, a mean vector is obtained together with the deviation for each pair. In other words, four parameters are obtained: $\zeta_{h_i} = \bar{h}_i$ and $\zeta_{g_i} = \bar{g}_i$, which represent the mean of signals h_i and g_i in addition to σ_{h_i} and σ_{g_i} related to the dispersion for each pair. Finally, stress template, namely $\mathcal{T}$ is described by $\mathcal{T} = (\zeta_{h_i}, \zeta_{g_i}, \sigma_{h_i}, \sigma_{g_i})$, $i = \{1, 2, 3, 4\}$.
Figure 3 provides a visual example of a scattering representation of each pair of signals γ. Notice how non-stressing stimuli provokes a low excitation in GSR (Figure 3, ◦), and on the contrary, the evidence of an arousal when undergoing on stressing tasks like Talk Preparation (Figure 3, ▪) and Hyperventilation (Figure 3, ▲).
The aim of this action is to described the information in HR and GSR by four Gaussian distributions, centered in $(\zeta_{h_i}, \zeta_{g_i})$ and with standard deviation σ_{h_i} and σ_{g_i}. This approach

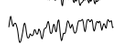
Task	HR	GSR	ζ_h	ζ_g	σ_h	σ_g
BL1			103.2	13.22	3.84	1.13
TP			98.9	25.28	5.74	1.13
HV			96.14	33.18	9.5	1.31
BL2			90.67	25.60	6.69	1.32

Table 5. Parameters extracted from GSR and HR signals in relation to experimental task (BL1, TP, HV and BL2). Those pieces of signals (columns HR and GSR) have been extracted from Figure 2 and Figure 1 respectively.

will facilitate the implementation of fuzzy antecedent membership functions by Gaussian distributions in a posterior fuzzy decision algorithm. This approach will facilitate a system access (section 6) implementation based on fuzzy logic, able to provide a more accurate decision on the degree of stress of a certain individual.
Furthermore, Table 5 provides a visual example of how previous parameters ζ_{h_i}, ζ_{g_i}, σ_{h_i} and σ_{g_i}, $i = \{1, 2, 3, 4\}$ are extracted from signals HR and GSR (Figure 1 and Figure 2) depending on the experimental task (BL1, TP, HV and BL2).
Let $t_{\mathcal{T}}$ be the time used to acquire both signals in order to extract the stress template. Evidently, the performance of the system depends on this parameter, since the longer $t_{\mathcal{T}}$, the more information the system obtains, and therefore, the stress template may be more accurate. A study regarding this relation between $t_{\mathcal{T}}$ and system performance is presented in Section 7.3.
Finally, after template extraction, the template must be stored. The template $\mathcal{T}$ requires 16×32 bits, since each template element (whatever ζ_{h_i}, ζ_{g_i}, σ_{h_i} or σ_{g_i}), is represented by a float element. In other words, 512 bits, i.e. 64 Bytes.

6. Stress detection

After a stress template extraction, $\mathcal{T}$ describes how an individual behaves under stressing and non-stressing situations. This section describes how the stress detection procedure is performed in addition to an overview on the algorithm involved to elucidate on the degree of stress. Once the user is enrolled, and a template is created, describing how such a user behaves under different stressing situations, the subject is able to access the system. In other words, the system is able to decide whether a certain registered user is under stressing stimuli. First requirement for a stress detection system access regards user identification and verification. The individual attempting to access the system, must be firstly identified so that the system can load his/her template, $\mathcal{P}$. This step is indispensable, otherwise, the system could not contrast the information (resulting from a HR and GSR acquisition) presented by the user.
Firstly, the signals GSR and HR must be measured from the individual. This acquisition process lasts a variable time, t_{acq} (acquisition time), responsible for the performance of the overall system, in addition to $t_{\mathcal{T}}$. In fact, the main difference between t_{acq} and $t_{\mathcal{T}}$ relies on the fact that $t_{\mathcal{T}}$ is related to the required time to obtain template $\mathcal{T}$ and t_{acq} regards the time needed to decide to what extent an individual is under stress. Both are measured in seconds, and main aim of posterior expert system consists of obtaining highest accuracy in detecting stress by requiring shortest time of t_{acq} and $t_{\mathcal{T}}$.
This compromise will be discussed in Section 7.3.

This document proposes five different approaches to solve stress detection, given a template and two physiological signals: GMM McLachlan & Basford (1988), k-Nearest Neighbour (k-NN) Nilsson (1996), Fisher's linear discriminant analysis Michie et al. (1994), Support vector machines (SVMs) Wang (2009) and Fuzzy Logic Zadeh (1996).

6.1 Gaussian mixture model

Let $\mathbf{x}$ be a two-dimensional observation describing a sample of both GSR and HR. The probability density function of $\mathbf{x}$ in the finite mixture form is expressed in Eq. 1 and Eq. 2,

$$p(\mathbf{x};\phi_c) = \sum_{i=1}^{K} \pi_i g(\mathbf{x};\boldsymbol{\mu}_i,\boldsymbol{\Sigma}_i) \tag{1}$$

$$g(\mathbf{x};\boldsymbol{\mu}_i,\boldsymbol{\Sigma}_i) = \frac{1}{2\pi|\boldsymbol{\Sigma}_i|^{\frac{1}{2}}} e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_i)^T\boldsymbol{\Sigma}_i^{-1}(\mathbf{x}-\boldsymbol{\mu}_i)} \tag{2}$$

where K is the number of mixtures, the parameter $\phi_c = \{\pi_i,\boldsymbol{\mu}_i,\boldsymbol{\Sigma}_i\}_{i=1}^{K}$ consists of the mixture weight π_i ($\Sigma\pi_i = 1$), the mean vector $\boldsymbol{\mu}_i$ and the covariance matrix $\boldsymbol{\Sigma}_i$ of the ith Gaussian component $\forall i = 1,2,\ldots,K$, in the c class. In fact, Eq. 2 is a specific case with $d = 2$ McLachlan & Basford (1988); Wolfe (1970), since there are only two physiological signals, HR and GSR.

The parameters represented by ϕ_c are estimated by applying the Expectation Maximization (EM) algorithm Wolfe (1970). Let $\{\mathbf{x}^t\}_{t=1}^{N}$ be the training samples, then EM algorithm finds

$$\phi_c^* = \text{argmax}\,\Pi_{t=1}^{N} P(\mathbf{x}^t|\phi_c) \tag{3}$$

6.2 k-Nearest neighbour

The k-Nearest Neighbour (k-NN) is a simple method used for density estimation. The probability of a point x' falling within a volum V centred at a pont x is given by the followinf relation (Equation 4):

$$\theta = \int_{V(x)} p(x)dx \tag{4}$$

where the integral is carried out over the volume V. This integral can be approximated by the relation $\theta \sim p(x)V$ when V is small.

In fact, the probability θ may be approximated by the proportion of samples falling within V, so that $\theta \sim \frac{k}{n}$.

The distance metric used in k-NN methods can be described by a simple Euclidean distance. In other words, given two patterns $(x_1,x_2,\ldots,x_n)$ and $(y_1,y_2,\ldots,y_n)$, then the distance is given by $\sqrt{\sum_{j=1}^{n}(x_j-y_j)^2}$.

A deeper understanding of k-NN is provided in Nilsson (1996).

6.3 Fisher linear discriminant analysis

Fisher's linear discriminant analysis is an empirical method for classification based purely on attribute vectors Michie et al. (1994). A hyperplane in th p-dimensional attribute space is chosen to separate the known classes as accurate as possible. Points are then classifed according to the side of the hyperplane that they fall on.

More precisely, in the case of two classes, let $\bar{x}, \bar{x}_1, \bar{x}_2$ be respectively the means of the attribute vectors overall and for the two classes. Suppose that a coefficient set $a_1, \ldots, a_p$ is given, obtaining the particular linear combination attributes $g(x) = \sum a_j x_j$, which is called the discriminant between the classes.
The criterion proposed by Fisher is the ratio of between-class to within-class variances. Formally, we seek a direction w such that:

$$J_F = \frac{|w^T(m_1 - m_2)|^2}{w^T S_W w}$$

is maximum, where m_1 and m_2 are the group means and S_W is the pooled within-class sample covariance matrix, in its bias-corrected form given by $\frac{1}{n-2}\left(n_1\hat{\Sigma}_1 - n_2\hat{\Sigma}_2\right)$
where $\hat{\Sigma}_1$ and $\hat{\Sigma}_2$ are the maximum likelihood estimates of the covariance matrices of classes ω_1 and ω_2 respectively, with n_i samples in class ω_i.

6.4 Support vector machines

Support vector machines (SVMs) have been widely applied to pattern classification problems and non-linear regressions Wang (2009).
After SVM classifiers are trained, they can be used to predict future trends.
In this case, the supervised classification that involves two steps: firstly, an SVM is trained as a classifier with a part of the data in a specific data set. In the second step (i.e., prediction), we use the classifier trained in the first step to classify the rest of the data in the data set.
The SVM is a statistical learning algorithm pioneered by Vapnik Vapnik (1995). The basic idea of the SVM algorithm is to find an optimal hyper-plane that can maximize the margin (a precise definition of margin will be given later) between two groups of samples. The vectors nearest to the optimal hyper-plane are called support vectors.
In comparison with other algorithms, SVMs have shown outstanding capabilities in dealing with classification problems.

6.5 Fuzzy logic

An automatic decision algorithm must elucidate a certain output accordingly to specific inputs. There exist several kinds of decision strategies in relation to the concrete task to solve Andren & Funk (2005); Jiang & Wang (2009); Liao et al. (2005).
The decision algorithm proposed in this article is based on fuzzy logic Zadeh (1996), since it is a very suitable strategy considering the data involved. In other words, a fuzzy decision algorithm provides an indefinite output allowing, however, to achieve a more precise decision than by using crisp decision algorithms Begum et al. (2006); Picard & Healey (2000); Sarkar (2002a;b).
As a main description, a stress fuzzy decision algorithm attempts to elucidate to what extent a certain individual is under stressing stimuli, by capturing his or her physiological HR and GSR signals during t_{acq} seconds, and comparing his or her response with a previous stored template $\mathcal{T}$, obtained by a prior acquisition carried out during $t_{\mathcal{T}}$ seconds. It is on that template comparison where this decision algorithm focuses on.
Any fuzzy decider requires different elements, which are described in subsequent points:

- **Antecedent membership functions**. The antecedent membership functions attempt to represent the information extracted from input, and they constitute in fact the template $\mathcal{T}$ itself.

Two different groups of antecedent membership functions are required by this system. Both groups of functions describes how HR and GSR behave under previous four situations (BL1, TP, HV, BL2).

- **Consequent membership functions**. The aim of these membership functions consists of describing the output of the system. This paper proposes an output on the interval $[0, 1]$, where 0 represents relax state and 1, stress state.
- **Rule description**. The rules describing how to transform the information provided in antecedent membership functions into consequent functions is maybe the most important part of a fuzzy decision system Pedrycz (1994). Rules provide a method to combine properly the information supplied by previous membership functions in order to produce an output stating to what extent an individual is under stress.

7. Results

This section aims at comparing the results provided by former approaches: GMM, k-NN, Fisher Discriminant Analysis, SVM and Fuzzy Logic, considering previous parameters: threshold ρ_{th} and temporal parameters ($t_{\mathcal{T}}$ and t_{acq}).

7.1 Database: Training, validation and testing data

In order to obtain valid results, the database must be divided into three groups:

- Training data: Used to extract the template, i.e., $\mathcal{T} = (\zeta_{h_i}, \zeta_{g_i}, \sigma_{h_i}, \sigma_{g_i})$.
- Validation data: Used to fixed threshold ρ_{th} and temporal parameters ($t_{\mathcal{T}}$ and t_{acq}) in order to maximize the performance of the system.
- Testing data: Used to obtain which implementation and metric is most suitable, and therefore, which is the performance of the whole system.

For each individual, a vector containing $t_{\mathcal{T}}$ seconds of γ (for each task BL1, HV, TP and BL2) was used for training data; a vector of t_{acq} seconds for each task was used to validate the system, and rest of the data was used as testing data. This latter testing data will be split in slots of t_{acq} seconds. Notice that one second corresponds to one sample in HR and GSR one-dimensional signals (Section 4.1). This assignment is done randomly. Notice that this validation scheme is similar to a K-fold cross-validation.
The justification for this division is based on the research carried out by Picard & Healey (2000), where several physiological signals (not only HR and GSR) were recorded during a period of time of thirty-two days in a same person. Eight emotions were provoked during thirty minutes per day, and no substantial changes were appreciated during that period in each emotions. In other words, physiological signals behave similarly in each task through time, and therefore h and g signals can be divided into smaller parts, considering each segment as an independent acquisition.

7.2 Stress evaluation parameters

A stress detection system must reach a compromise between detecting properly which individuals are under stress situations, and which individuals are in a relax state.
Thereby, two assessment parameters are defined:

- True Stress Detection rate (TSD): When the system properly detects stress when an individual is under stress stimuli. This TSD factor corresponds to the sensitivity statistical measure, since TSD can be described as follows in Eq. 5:

$$\text{TSD} = \frac{\#\text{True Positives}}{\#\text{True Positives} + \#\text{False Negatives}} \tag{5}$$

  where a True Positive means classifying as stressed an individual which is indeed under stress, and False Negative means classifying as relaxed an individual which is under stressing situations.

- True Non-Stress Detection rate (TNSD): When the system correctly detects no stress in an individual and the subject is indeed not under stressing situations. This TNSD factor corresponds to the specificity statistical measure, since TNSD can be described by Eq. 6:

$$\text{TNSD} = \frac{\#\text{True Negatives}}{\#\text{True Negatives} + \#\text{False Positives}} \tag{6}$$

  where a True Negative means classifying as non-stressed an individual which is not under stress, and False Positive means classifying as stressed an individual which is calm and relaxed.

Obviously, TSD and TNSD depend strongly on threshold ρ_{th}. If $\rho_{th} \rightarrow 0$ then the system considers every output as a stress stimuli (TSD decreases, TNSD increases) and vice versa.
Therefore, a compromise must be achieved by finding a threshold ρ_{th} where TSD equals TNSD. This threshold is defined as True Equal Stress Detection rate (TESD).
Notice that the higher TESD, the more accurate the performance of the system.
At this point, one question arises: Which is the best indicator (TESD,TSD or TNSD) to provide an evaluation on the performance of a stress detection system? TESD is obtained with validation data, and therefore threshold ρ_{th} and temporal parameters $t_{\mathcal{T}}$ and t_{acq} are fixed to maximized TESD. These parameters are set *a posteriori* Yanushkevich et al. (2007). On the other hand, TSD and TNSD are obtained with testing data, i.e. TSD and TNSD give an understanding on how the system behaves with real data. Notice that previous parameters (ρ_{th}, $t_{\mathcal{T}}$ and t_{acq}) have been already fixed and adapted with validation data, and therefore the performance of the system might be barely unbalanced. In other words, TSD and TNSD will not be equal at TESD, but TSD could increase in expense of TNSD or vice versa.
This suggests that TESD is a fine system performance indicator, since it provides an approximation based on validation data. However, TSD and TNSD provides a real rate of the performance. Obviously, TESD cannot be always calculated in previous schemes (Section **??**), as TESD requires both stressing and non-stressing data during the training and the validation data.

7.3 Temporal parameters

The performance of the system (TSD and TNSD) not only depends on previous threshold ρ_{th} but also on two temporal parameters: Template time $(t_{\mathcal{T}})$ and Acquisition time (t_{acq}). The former time regards the required time to obtain the template, and the latter is related to the time demanded to acquire stress information from an individual.

Evidently, the longer $t_{\mathcal{T}}$ and t_{acq}, the more accurate the system is. However, in real applications, time is the most valued asset, and therefore, a balance among $t_{\mathcal{T}}$, t_{acq}, TSD and TNSD must be achieved.
These temporal parameters are fixed during the validation step, and remain constant during the testing stage.
Figure 4 provides information about how TSD varies in relation to different values of $t_{\mathcal{T}}$ and t_{acq}.

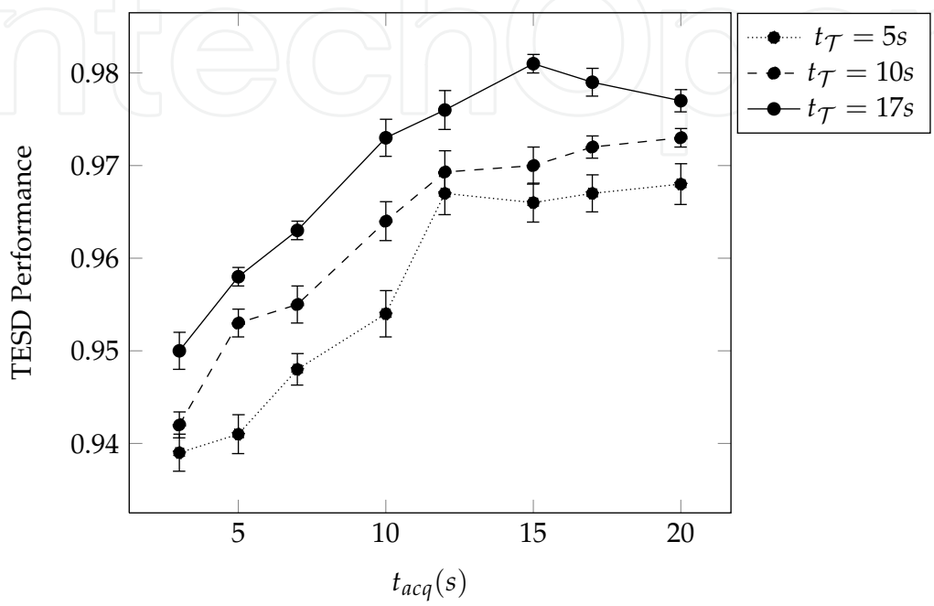


Fig. 4. Relation between TESD Performance and time to obtain template $(t_{\mathcal{T}})$ and acquisition time (t_{acq}). These values were obtained with $\rho_{th} = 0.27$.

Reader can notice how the performance in detecting stress (TSD) increases as $t_{\mathcal{T}}$ and t_{acq} do so. In fact, a TESD= 99.16% (Figure 4, —●—) is obtained with $t_{\mathcal{T}} = 17s$ and $t_{acq} = 17s$, which means that physiological signals GSR and HR from an individual are measured during $t_{\mathcal{T}} = 17s$, and furthermore, that in subsequent accesses, such an individual must present their physiological signals during $t_{acq} = 17s$, so the system can decide to what extent is under stress.
As before, the results obtained in this section are achieved for a given scheme, concretely Fuzzy Logic. In order to obtain the best combination of parameters, this procedure must be repeated for each scheme and implementation.

7.4 Evaluation performance

In order to evaluate the performance of the proposed approaches, the procedure presented previously was carried out for every system. A detailed description of these results is far beyond the scope of this section and therefore, Table 6 is presented to compared former methods when detecting stress. Reader may notice that the performance of the proposed methods depends on the temporal parameters $t_{\mathcal{T}}$ and t_{acq}, all of them measured in seconds.
The best result in every scheme is achieved with scheme BL1+HV which means that for an accurate stress detection, only two tasks are required: a relaxing situation and a stressing

	GMM ($t_{\mathcal{T}} = 5$, $t_{\text{acq}} = 10$)	k-NN ($t_{\mathcal{T}} = 5$, $t_{\text{acq}} = 5$)	Disc. Anal. ($t_{\mathcal{T}} = 7$, $t_{\text{acq}} = 10$)	SVM ($t_{\mathcal{T}} = 5$, $t_{\text{acq}} = 10$)	Fuzzy Logic ($t_{\mathcal{T}} = 7$, $t_{\text{acq}} = 10$)
TSD	95.1 ± 0.2	92.8 ± 0.4	95.6 ± 0.3	95.6 ± 0.4	99.5 ± 0.3
TNSD	86.3 ± 0.4	97.3 ± 1.3	96.7 ± 0.4	96.7 ± 0.3	97.4 ± 0.2

Table 6. Comparative stress detection performances. Best result is achieved with fuzzy logic, although the rest of the results are competitive when compared to those obtained within literature. Temporal parameters are provided in seconds and rates in percentage (%).

Reference	Stress Detection Rate (%)	Physiological Signals	Population
Healey & Picard (2005)	97.4%	ECG, EMG, RR, GSR	Not provided
Wagner et al. (2005)	79.5-96.6%	ECG, EMG, RR, GSR	1 subject
Cai & Lin (2007)	85-96%	BVP, ST, RR, GSR	Not provided
Guang-yuan & Min (2009)	75-85%	ECG, EMG, RR, GSR	1 subject
Kulic & Croft (2005)	76%	ECG, EMG, GSR	8 subjects
Sharawi et al. (2008)	60-78%	ST, GSR	35 subjects
Best of our proposed methods	99.5%	HR, GSR	80 subjects

Table 7. A comparison between approaches comparing stress detection rates, physiological signals and population involved. The initials ST stand for Skin Temperature.

situation. An outstanding result, since it allows to decrease (in terms of time) the template extraction step, among other aspects discussed in posterior Section 8.
The conclusion is that stress can be detected by means of fuzzy logic with an accuracy of 99.5% recording the signal of the user during 10 seconds to create the template and 7 seconds for stress detection. These results highlight the improvement achieved in comparison to other approaches, showed in Table 7, providing the following parameters to be compared: Stress Detection rate (TSD), the physiological signals involved and the population used to evaluate the proposed approach. This improvement is achieved not only in terms of accuracy in stress detection, but also in relation to the number of physiological signals (only HR and GSR) and the population.

8. Conclusions and future work

The proposed stress detection systems are able to detect stress by using only two physiological signals (HR and GSR) providing a precise output indicating to what extent a user is under a stressing stimulus.
In addition, HR and GSR allows a plausible future integration of former proposed systems on current biometric systems, achieving and increase in the overall security.
Main characteristics of the proposed systems regard non-invasiveness, fast-oriented implementation and an outstanding accuracy in detecting stress when compared to previous approaches in literature.
In other words, the system can detect stress almost instantly, allowing a possible integration in real-time systems. Notice that only two physiological signals are involved in contrast to the amount of features required to elucidate on the stress degree provided by previous approaches.

An individualization of not only the template $\mathcal{T}$, but also ρ_{th}, $t_{\mathcal{T}}$ and t_{acq} must be adapted for each individual, so that the overall performance can be increased.
These parameters (ρ_{th}, $t_{\mathcal{T}}$ and t_{acq}) have been fixed for the whole database within this work, and therefore, if a different version of these parameters is considered for each individual, then the accuracy of the system could be increased. This implementation remains as future work.
The database acquisition was based on psychological experiments carried out by expert psychologists. These experiments ensure that stressing situations are provoked on an individual, validating posterior HR and GSR acquisitions.
This paper provides a decision system able to detect stress with an accuracy of 99.5% using fuzzy logic and 10 seconds to extract the stress template and 7 seconds to detect stress on an individual using two physiological signals HR and GSR measured only during two tasks: a stressing task and a relaxing stage.
The rest of the approaches are also competitives in terms of computational cost and performance. This results are achieved due to the fact that the stress template provides precise information on the state of mind of individuals, coming up with an innovative concept in stress detection. A combination of approaches is regarded as future work.
Finally, these systems may be applicable in scenarios related to aliveness detection (e.g., detecting if an individual is accessing a biometric system with an amputated finger), civil applications (e.g., driver control), withdrawing money from a cash dispenser, electronic voting (e.g., someone is forced to emit a certain vote) and so forth. Moreover, future research entails an integration in mobile devices.

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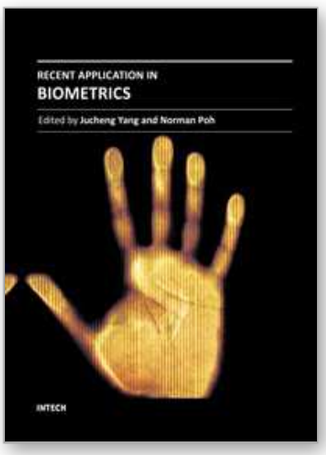
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In the recent years, a number of recognition and authentication systems based on biometric measurements have been proposed. Algorithms and sensors have been developed to acquire and process many different biometric traits. Moreover, the biometric technology is being used in novel ways, with potential commercial and practical implications to our daily activities. The key objective of the book is to provide a collection of comprehensive references on some recent theoretical development as well as novel applications in biometrics. The topics covered in this book reflect well both aspects of development. They include biometric sample quality, privacy preserving and cancellable biometrics, contactless biometrics, novel and unconventional biometrics, and the technical challenges in implementing the technology in portable devices. The book consists of 15 chapters. It is divided into four sections, namely, biometric applications on mobile platforms, cancelable biometrics, biometric encryption, and other applications. The book was reviewed by editors Dr. Jucheng Yang and Dr. Norman Poh. We deeply appreciate the efforts of our guest editors: Dr. Girija Chetty, Dr. Loris Nanni, Dr. Jianjiang Feng, Dr. Dongsun Park and Dr. Sook Yoon, as well as a number of anonymous reviewers.

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InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
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