Stress Detection by means of Stress Physiological Template

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***Abstract*—This paper describes a stress detection system based on fuzzy logic and two physiological signals: Galvanic Skin Response and Heart Rate. Instead of providing a global stress classification, this approach creates an individual stress templates, gathering the behaviour of individuals under situations with different degrees of stress. The proposed method is able to detect stress properly with a rate of 99.5%, being evaluated with a database of 80 individuals. This result improves former approaches in the literature and well-known machine learning techniques like SVM, k-NN, GMM and Linear Discriminant Analysis. Finally, the proposed method is highly suitable for real-time applications.**

***Keywords*-Stress Detection, Physiological Signals, SVM, k-NN, Fuzzy Logic, Galvanic Skin Response, Heart Rate.**

I. Introduction

Modern society is demanding an increase in security in contemporary scenarios and applications such as bank account access, electronic voting, commerce or border crossing frontiers in airports.

One of the most upward trending in providing solutions for previous demands is biometrics, which 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.

However, biometrics are sensitive to scenarios where individuals are forced to provide the biometric data to the corresponding sensor. 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.

The proposed scheme only considers two phsyiological signals, 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.

The main contribution of this paper is the use of a stress template, whose aim 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 assumption 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.

In addition, this paper compares the proposed method to other approaches presented in the literature together with competitive machine learning techniques like Support Vector Machines (SVM), k-nearest neighbor (k-NN), Fisher Linear Discriminant and Gaussian Mixture Model (GMM), using a database of 80 individuals.

Finally, the layout of the paper remains as follows: Section II presents the literature review. Section III covers the description of the stress detection method and the creation of the stress template together with the database involved for evaluation purposes. Finally, results are presented in Section IV, ending the paper with conclusions and future work in Section V.

II. State of the Art

The problem of stress detection has been tackled with different approaches. However, former works can be divided

Physiological Signals	References
BVP (Blood Volume Pressure)	[10], [11]
	[6], [12]
GSR (Galvanic Skin Response)	[10], [11]
	[6], [13], [12]
PD (Pupil Dilation)	[11], [6], [12]
ST (Skin Temperature)	[11], [14]
ECG, EKG (Electrocardiogram)	[10]
Breath (RR)	[10]
EMG (Electromyogram)	[10]
EEG (Electroencephalogram)	[10]

Table I
LITERATURE REVIEW ON PHYSIOLOGICAL SIGNALS INVOLVED IN STRESS DETECTION.

Algorithms	References
SVM (Support Vector Machines)	[11], [6]
ANOVA Analysis	[12]
Bayes classifier	[14]
Fisher Analysis	[10], [17]
k-NN	[17]
Fuzzy Logic	[1], [18], [8], [16]

Table II
LITERATURE REVIEW ON ALGORITHMS APPLIED TO STRESS DETECTION.

into two different groups, depending on the use of physiological signals or other behavioural characteristics. The presented state of the art is focused on stress detection based on physiological signals.

In this sense, the essay presented by [1] presents a study of stress detection only based on Finger Temperature (FT), together with Fuzzy Logic [2], and Case-Based Reasoning [3].

In addition, 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: [4] 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.

On the other hand, the research provided in [5], [6] 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, the fact that 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 under stress, PD is wider and the eye movement is faster. The article presented in [7], 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) [8], [9].

In summary, stress can be detected through many different manners, as stated in [8], where a wide study is carried out regarding previous physiological signals.

Table I 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 [8] proposes fuzzy logic (as M. Jiang and Z. Wang [15]) to elucidate to what extent a user is under stress. On the other hand, the research presented by A. de Santos et al. [16] 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. Table II contains a summary of previous approaches within literature.

III. METHODOLOGY

This section covers three different aspects. First of all, the physiological signals involved in the paper are described and justified. Afterwards, the database collected to validate the algorithms is presented, providing a complete description on the stress template extraction, which is the main contribution of this paper.

A. Physiological Signals

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 [7], [19], [11].

First of all, Galvanic Skin Response (GSR), known also as electrodermal activity (EDA), is an indicator of skin conductance [20], [11]. More in detail, glands in the skin produce ionic sweat, provoking alterations on electric conductivity.

No general features on GSR like basis threshold, peaks or frequency variation can be extracted for a global decision, since parameters extracted from GSR signals are strongly related to each individual.

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 [4], [21].

HR describes the heart activity when the Autonomic Nervous System (ANS) attempts to tackle with the human body demands depending on the stimuli received [10]. 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.

Summarizing, both HR and GSR behave differently for each individual, and therefore posterior stress template must gather properly this unique response in order to obtain an accurate result in stress detection.

B. Database Acquisition

The database was collected based on experiments consisting of extracting GSR and HR signal from 80 female individuals, with ages from 19 to 32 years with an average of 21.8 years old and a deviation of 2.15 years. Individuals were attached sensors to their fingers, wrist and ankle, acquiring at the same time HR and GSR signals by means of a recording device I-330-C2 Physiolab (J & J Engineering). Furthermore, a sample per second was taken for each previous signals.

These experiments will focus on two main stressing tasks, namely Hyperventilation (HV) and Talk Preparation (TP). These tasks have been extensively in depth studied [22], [23] yielding to the conclusion that both provoke positive stress stimuli on individuals.Each experiment was divided into four steps, which are described in subsequent subsections:

1) Base Line 1, BL1: First step consisted of attaching sensors to individuals, and after a variable period of time where the subject is asked to relax, an acquisition of HR and GSR was performed during 120 seconds. This 120 samples of HR and GSR are supposed to describe the behaviour of the individual during non-stressing situation.

2) Hyperventilation, HV: Afterwards, the individual is required to breath deeply and fast each 2-3 seconds, indicated by the experimenter. This task is performed until the subjects clearly perceives changes in his/her corporal sensations. It is in this moment precisely when HR and GSR are sampled during 90 seconds, representing an obvious behaviour of both physiological signals under a stressing situation.

3) Talk Preparation, TP: Once HV has been performed, and after a period of time, the individual is said to prepare a talk about a certain topic in order to give a speech in front of a recording camera. The subject is given one or two minutes to prepare it, and before starting the recording, both HR and GSR signals are sampled again during 90 seconds, represanting a stressing situation.

4) Base Line 2, BL2: Finally, the experiment comes to an end, being in this moment when HR and GSR from the participant are acquired again during 120 seconds. However, this task is quite difficult to be classified as stressing/non-stressing [22], [23], and therefore will not be considered within the scheme validation. It is importante to state that for the sake of independence in the order of the tasks, the population was divided into two groups: Group 1 and Group 2. The former group performs HV before TP, and Group 2 makes first TP and aftewrds HV.

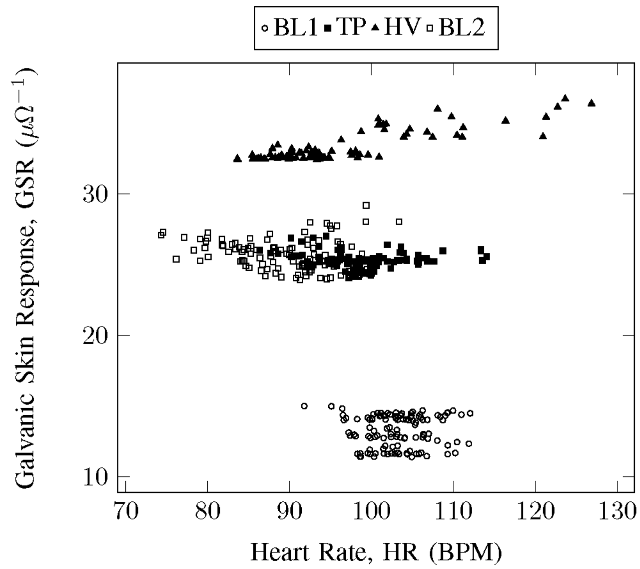

Figure 1. Graphic representation of γ. Notice how the relation between HR and GSR varies depending on the stressing stimuli (BL1, TP, HV and BL2).

C. Template Extraction

Mathematically, both HR and GSR are considered as stochastic signals. Thus, $\mathcal{H}$ represents the space of HR possible signals and $\mathcal{G}$ represents the space of GSR possible signals.

Each stage (BL1,HV,TP,BL2) 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, requiring no previous data normalization.

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 1 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 1, ∘), and on the contrary, the evidence of an arousal when undergoing on stressing tasks like Talk Preparation (Figure 1, ▪) and Hyperventilation (Figure 1, ▴).

This approach will facilitate a system access implementation based on fuzzy logic, able to provide a more accurate decision on the degree of stress of a certain individual, describing 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}.

IV. Results

This section aims at comparing the results provided by former approaches: GMM, k-NN, Fisher Discriminant Analysis, SVM and the proposed method based on Fuzzy Logic, concerning the capability to detect stress and non-stress situations properly. This parameters are defined in the following section.

A. 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. 1:

$$\mathrm{TSD} = \frac{\#\text{True Positives}}{\#\text{True Positives} + \#\text{False Negatives}} \quad (1)$$

  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. 2:

$$\mathrm{TNSD} = \frac{\#\text{True Negatives}}{\#\text{True Negatives} + \#\text{False Positives}} \quad (2)$$

  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.

Reader may notice that a compromise must be achieved between TSD and TNSD.

B. Temporal Parameters

The performance of the system (TSD and TNSD) depends on two temporal parameters: Template time (t_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_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_T, t_{acq}, TSD and TNSD must be achieved.

The best values combination in terms of performance is represented in Table III.

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 existing approaches in literature, showed in Table IV, 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 involved.

V. Conclusions

This paper has proposed a stress detection system based on fuzzy logic, by using two physiological signals Skin Conductivity, GSR, and Heart Rate, HR.

On the one hand, fuzzy logic allows to describe the behaviour of an individual under stressing and non-stressing situations. On the other hand, both former signals provides the stress detection system with precise and real-time information on the state of mind of a given individual.

In addition, one of the main contribution of this work consists of the proposal of a stress template able to describe the behaviour of previous signals, given different situations in terms of stress degree. The stress detection system benefits from this template in the sense that physiological signals of a given individual are compared to those same signals behaviour of the same user, avoiding to provide a global stress detection system, which usually leads to unaccurate classification.

Due to the stress template, the system is able to detect stress in real-time, requiring only 10 seconds to achieve a True Stress Detection rate (i.e., detect stress properly) of 99.5%, which improves not only competitive machine learning techniques applied to the same data, but also the existing approaches in literature. In fact, the database of 80 individuals provides a distinctive amount of data in comparison to previous experiments in the literature, ensuring the viability of the obtained result.

Moreover, their characteristics in terms of computational cost and hardware requirements make of this stress detection algorithm a suitable system to be embedded in current biometric systems in order to increase the overall security.

Concerning future work, an implementation of the proposed system on hardware devices and the application of this system in mobile devices are the main issues for future considerations.

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	GMM ($t_T = 5$, $t_{acq} = 10$)	k-NN ($t_T = 5$, $t_{acq} = 5$)	Disc. Anal. ($t_T = 7$, $t_{acq} = 10$)	SVM ($t_T = 5$, $t_{acq} = 10$)	Fuzzy Logic ($t_T = 7$, $t_{acq} = 10$)
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 III
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
[19]	97.4%	ECG, EMG, RR, GSR	Not provided
[25]	79.5-96.6%	ECG, EMG, RR, GSR	1 subject
[26]	85-96%	BVP, ST, RR, GSR	Not provided
[27]	75-85%	ECG, EMG, RR, GSR	1 subject
[28]	76%	ECG, EMG, GSR	8 subjects
[29]	60-78%	ST, GSR	35 subjects
Best of our proposed methods	99.5%	HR, GSR	80 subjects

Table IV
A COMPARISON BETWEEN APPROACHES COMPARING STRESS DETECTION RATES, PHYSIOLOGICAL SIGNALS AND POPULATION INVOLVED. THE INITIALS ST STAND FOR SKIN TEMPERATURE.

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