Secure access control by means of human stress detection

Alberto de Santos

Group of Biometrics, Biosignals and
Security, GB2S
Universidad Politécnica de Madrid
Campus de Montegancedo
Pozuelo de Alarcón, 28223, Madrid
Email: alberto@cedint.upm.es

Carmen Sánchez Ávila

Group of Biometrics, Biosignals and
Security, GB2S
Universidad Politécnica de Madrid
Campus de Montegancedo
Pozuelo de Alarcón, 28223, Madrid
Email: csa@cedint.upm.es

Gonzalo Bailador

and Javier Guerra
Group of Biometrics, Biosignals and
Security, GB2S
Universidad Politécnica de Madrid
Campus de Montegancedo
Pozuelo de Alarcón, 28223, Madrid
Email: {gbailador,jguerra}@cedint.upm.es

Abstract—This paper proposes a stress detection system based on fuzzy logic and the physiological signals heart rate and galvanic skin response. The main contribution of this method relies on the creation of a stress template, collecting the behaviour of previous signals under situations with a different level of stress in each individual. The creation of this template provides an accuracy of 99.5% in stress detection, improving the results obtained by current pattern recognition techniques like GMM, k -NN, SVM or Fisher Linear Discriminant.

In addition, this system can be embedded in security systems to detect critical situations in accesses as cross-border control. Furthermore, its applications can be extended to other fields as vehicle driver state-of-mind management, medicine or sport training.

I. INTRODUCTION

Most of the attacks in accesses to airports or secure environments involve a high and positive response in the physiological stress of individuals who attempt to carry out previous attacks. Therefore, a stress detection could avoid these previous scenarios, by measuring the degree of stress of individuals registered within the system.

In addition, the proposed problem is solved by means of biometrics. However, this situation does not avoid external users to employ registered users as keys to access the system. In this case, the stress detection system is able to evaluate to what extent that individual is under an abnormal situation, carrying out pertinent actions according to defined policies, which are out of the scope of this document.

The stress detection system is based on the physiological response of the automatic neurosystem, which prepares humans to face properly the demands appearing in their surroundings (attacks, abnormal events and the like).

This response can be measured by means of two physiological signals: Heart Rate and Galvanic Skin Response, able to provide an accurate and precise result in stress detection. In fact, these signals provide real-time response so that stress can be fast and accurately detected with only few seconds (up to 10 seconds). On the other hand, the proposed stress detection system is based on the creation of a stress template, gathering the behaviour of individuals under two situations: a stressing and a non-stressing stage. After this

stress template is created, the system compares subsequent physiological acquisitions to previous stress template, so that a decision can be carried out based on the individual behaviour of human subjects.

The stress template is created based on fuzzy logic, providing therefore a bounded output indicating the degree of stress of individuals. This output implies that the system is not only able to detect stress properly but to indicate to what extent an individual is under stressing conditions.

The evaluation of the proposed method has been carried out by using a database of 80 individuals, achieving a stress detection rate of 99.5%. A considerable rate when compared to both other pattern recognition techniques like GMM, k -NN, SVM or Fisher Linear Discriminant and previous approaches in literature.

The results provided by this work can improve the overall security of accesses control, since threats could be detected by inferring the intentions of individuals. These intentions are strongly related to the state of mind of humans, and therefore to the stress level.

In other words, the proposed stress detection system is able to detect future attacks or abnormal situations in accesses and boundaries control, increasing the whole system security.

The layout of this paper remains as follows. First of all, a literature review is presented in Section II; the description of the method is provided in Section III together with the database acquisition in Section IV. Finally, evaluation and results are contained within Section V, presenting the conclusions and future work in Section VI.

II. 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, like keystroke dynamics [1] or face recognition [2].

On the other hand, there exist many previous works related to stress detection based on physiological signals. The essay presented by [3] presents a study of stress detection only based

Physiological Signals	References
BVP (Blood Volume Pressure)	[10], [16] [17], [18]
GSR (Galvanic Skin Response)	[10], [16] [17], [19], [18]
PD (Pupil Dilation)	[16], [17], [18]
ST (Skin Temperature)	[16], [20]
ECG, EKG (Electrocardiogram)	[10]
Breath (RR)	[10]
EMG (Electromyogram)	[10]
EEG (Electroencephalogram)	[10]

TABLE I

LITERATURE REVIEW ON PHYSIOLOGICAL SIGNALS INVOLVED IN STRESS DETECTION.

on Finger Temperature (FT), together with Fuzzy Logic [4], and Case-Based Reasoning [1].

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: [5] 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.

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 [6], not only consider PD and ET, but also Galvanic Skin Response (GSR), Blood Volume Pulse (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) [7], [8].

In summary, stress can be detected through many different manners, as stated in [7], where a wide study is carried out regarding previous physiological signals together with others related to stress (Positron Emission Technology (PET) [7], [9], Functional Magnetic Resonance Imaging (fMRI) [10], [11], Electroencephalography (EEG) [7], [12], likewise Electromyograms (EMG) [13], [12], [14] or Respiratory Rate (RR) [15]). Nonetheless, these other signals lack of future integrity because they involve more invasive acquisition procedures.

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

Algorithms	References
SVM (Support Vector Machines)	[16], [17]
ANOVA Analysis	[18]
Bayes classifier	[20]
Fisher Analysis	[10], [23]
k -NN	[23]
Fuzzy Logic	[3], [11] [7], [22]

TABLE II

LITERATURE REVIEW ON ALGORITHMS APPLIED TO STRESS DETECTION.

Experiments	References
Stroop Test	[16], [17] [20]
Videogames	[18]
Driver and Pilot Simulation	[10]
Hyperventilation and Talk Preparation	[22], [23]

TABLE III

LITERATURE REVIEW ON EXPERIMENT LAYOUTS ORIENTED TO PROVOKE STRESS.

presented by [7] proposes fuzzy logic (as [21]) to elucidate to what extent a user is under stress. On the other hand, the research presented by [22] 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 or Bayes classifier. In order to not extend excessively the document, Table II 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 III and Table IV briefly show which experiments have been involved for provoking stress and which populations were required in order to validate stress detection algorithms. More extensively, the research by [24] 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 [9], since they are considered pioneers on stress detection field.

Populations	References
6 male individuals	[17]
42 adults with ALS ¹	[19]
14 males and 4 females	[18]
32 individuals	[16], [20]
3 experienced drivers	[9]
10 pilots (with and without experience)	[9]

TABLE IV

LITERATURE REVIEW ON POPULATIONS INVOLVED IN STRESS DETECTION EVALUATION.

III. STRESS DETECTION SYSTEM

The main contribution of the proposed stress detection system is the creation of a stress template, describing the behaviour of a specific individual in different stressing and non-stressing situations. In other words, this template collects the physiological reaction (in terms of GSR and HR) of an individual under different scenarios.

Therefore, after template is created, subsequent acquisitions of GSR and HR signals are compared to that template, indicating to some extent the state-of-mind of an individual, deciding whether the user is stressed.

The template is unique for each individual, since the behaviour and physiological response vary between different individuals. However, this uniqueness is not enough to consider this stress template so distinctive as for biometric applications [22].

Subsequent sections will describe the template extraction and the proposed update mechanism.

A. Template Extraction

The template must collect the behaviour of individuals under at least two situations: a stressing and a non-stressing scenario [23], [22].

Mathematically, HR and GSR signals can be considered as one-dimensional signals. Let h_{BL1} and g_{BL1} represent signals HR and GSR respectively acquired during the first task, BL1. Similarly, let h_{HV} and g_{HV} represent signals HR and GSR respectively acquired during the second task, HV.

From these signals, the method extracts the average and standard deviation value, as a simple descriptor of the information contained in each signal. For instance, μ_{BL1}^h makes reference to the mean value of the signal h_{BL1} . Although, the average value can be calculated based on the whole signal, a temporal parameter is defined to introduce a constraint on this aspect. In other words, this temporal parameter, namely t_T , indicates the number of samples (seconds) needed to create a correct stress template $\mathcal{T}$.

The definition of the template as $\mathcal{T} = \{\mu_{task}^s, \sigma_{task}^s\}$ where $task = \{BL1, HV\}$ and $s = \{h, g\}$ allows the description of the individual behaviour by means of Gaussian distributions centered in $(\mu_{BL1}^s, \mu_{HV}^s)$ and with standard deviation of $(\sigma_{BL1}^s, \sigma_{HV}^s)$, considering $s = \{h, g\}$. This approach will facilitate the implementation of fuzzy antecedent membership functions by Gaussian distributions in a posterior fuzzy decision algorithm.

In addition, the proposed template $\mathcal{T}$ considers no normalization for signals h and g , in contrast to previous approaches [16], [24], [10]. The decision to avoid normalization was done based on the experience, since data without normalization provided more accurate results in terms of stress detection.

B. Template Update Mechanism

The extracted template and the response to stressing situations may vary over time. Hence, the template must consider this changes to adapt the pattern to the daily behaviour of the individual.

This adapting period is essential, since by this updating mechanism the algorithm can learn and predict more precisely the behaviour of the individual. A detailed description of this mechanism can be found in [22], [25].

C. Stress Detection Description

The stress detection implementation is based on a Mamdani fuzzy system since it has been widely used in expert decision systems due to their comprehensible rules [26], [27]. This implementation provides a fuzzy output on the interval $[0, 1]$ based on template $\mathcal{T}$.

This fuzzy system is described by Gaussian-based antecedent functions whose parameters coincide with centroids $(\mu_{BL1}^s, \mu_{HV}^s)$ and with standard deviation of $(\sigma_{BL1}^s, \sigma_{HV}^s)$. Gaussian functions selection is justified, since they are very suitable for data provided by HR and GSR signals.

Furthermore, two triangular functions describing each output possibility (stress or non-stress) characterize the consequent membership functions. Triangular functions were selected according to their adequate properties to provide an accurate output [27].

The proposed set of rules considers two intuitive rules, one for each stressing/non-stressing situation (BL1 and HV).

Mathematically, let h_i^k and g_i^k be the physiological signals HR and GSR respectively for a given k subject ($k \in \{1, \dots, 80\}$) in the state i , $i \in \{BL1, HV\}$. This state i represents the two situations corresponding to the experiments to induce stress: BL1 and HV. Let s_m^k be the output of the system, given a k subject and m representing the two possible aforementioned situations: stress ($m = S$) or non-stress ($m = NS$). Therefore, the rules are mathematically described as follows:

$$\begin{aligned} h_1^k \cap g_1^k &\rightarrow s_{m=NS}^k \\ h_2^k \cap g_2^k &\rightarrow s_{m=S}^k \end{aligned} \quad (1)$$

Finally, defuzzification method was carried out by a centroid method [4].

IV. DATA ACQUISITION

In order to evaluate the proposed method, physiological data from galvanic skin response (GSR) and heart rate (HR) must be collected under different situations in terms of stress level. The aim of these data is to evaluate to what extent the proposed algorithm is able to correctly classify samples collected under stressing condition as stress and vice versa.

The database was obtained with 80 individuals in a single session, with ages between 19 and 32 years old.

The selected device for data acquisition is I-330-C2 PHYS-IOLAB (J & J Engineering), able to process and store 6 channels including EMG (Electromyography), ECG (Electrocardiogram), RR (Respiration Rate), HR and GSR.

In addition, sensors were attached to hand right fingers [28], 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.

- First Task, Relaxation. First of all, the individual get relaxed for a period of time of several minutes in a comfortable seat. Afterwards, both physiological signals are measured during 120 seconds. This period corresponds to a non-stressing situation.
- Second Task, Hyperventilation. Secondly, the individual is forced to breath deeply, fast and iteratively in a short period of time. Once the individual start feeling uncomfortable and dizzy, he/she is allowed to breathe normally, recording at this precise moment both physiological signals, during 90 seconds. Hyperventilation provokes similar response in GSR and HR to stressing situations [29], and therefore this task is regarded as a stressing task.
- Third Task, Talk Preparation. After hyperventilation, the individual is given time to recover from previous task until he/she can breathe normally. Then, the individual is required to prepare a short speech of a given topic, pointing out that he/she will be recorded with a camera. Before starting the recording, the physiological signals are collected for a period of 90 seconds. This task is also considered as a stressing stage [29].
- Fourth Task, Relaxation. Finally, the individual is required to relax, concluding the experiments. Again, the physiological signals are extracted for 120 seconds. This period of time corresponds neither to stress nor to non-stress, since the most suitable classifications is post-stress, a difficult state to classify according to experienced psychologists [29], [30].

Aiming independence on the task order, tasks second and three were carried out in the opposite order for half of the population. In addition, tasks are renamed as follows: First task is a Base Line 1 (BL1), Second Task, Hyperventilation is represented by HV; Third Task, Talk Preparation, (TP); and final task is a Base Line 2 (BL2).

Reader may notice that stressing situations are associated to HV and TP, and non-stressing situations are related to BL1. Finally, sample acquisition rate is one sample per second for both HR and GSR.

Finally, a visual example of GSR and HR respectively is provided in Figures 1 and 2 where both physiological signals from an individual are presented along the four different sessions BL1, HV, TP and BL2.

V. EVALUATION

This section aims at comparing the results provided by approaches presented in literature for stress detection: GMM [31], k -NN [32], Fisher Discriminant Analysis [33], SVM [34] and the proposed method based on Fuzzy Logic [4].

A. Acquisition Time

Before presenting the results, it is important to define a temporal parameter able to measure the number of samples to detect stress properly given a template $\mathcal{T}$. In other words, this

temporal parameter indicates how much time the system requires to collect physiological data from individual to provide an accurate result in stress detection.

This temporal parameter is defined as t_{acq} , in reference to the acquisition time required to collect enough data to detect stress properly.

B. Comparative Evaluation

In order to evaluate the performance of the proposed approaches, the procedure presented previously was carried out for every system. Table V is presented to compare the stress detection accuracy of previous methods.

Best result is achieved with fuzzy logic, although the rest of the results are competitive when compared to those obtained within literature. The increase in accuracy for the rest of methods (GMM, k -NN, Fisher and SVM) is due to the creation of the stress template, which provide individual stress detection, in contrast to most approaches in literature, which proposed a unique and global stress detection system for all individuals in population.

In addition, these results highlight the improvement achieved in comparison to other approaches, showed in Table VI, 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.

C. Evaluation Criteria: True Stress Detection and True Non-Stress Detection

A stress detection system must reach a compromise between detecting properly which individuals are under stress situations, and which individuals are in a relaxed 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. 2:

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

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. 3:

$$TNSD = \frac{\#True\ Negatives}{\#True\ Negatives + \#False\ Positives} \quad (3)$$

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

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).

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).

	GMM ($t_{\mathcal{T}} = 5$, $t_{acq} = 10$)	k -NN ($t_{\mathcal{T}} = 5$, $t_{acq} = 5$)	Disc. Anal. ($t_{\mathcal{T}} = 7$, $t_{acq} = 10$)	SVM ($t_{\mathcal{T}} = 5$, $t_{acq} = 10$)	Proposed ($t_{\mathcal{T}} = 7$, $t_{acq} = 10$)
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 V

COMPARATIVE STRESS DETECTION PERFORMANCES. TEMPORAL PARAMETERS ARE PROVIDED IN SECONDS AND RATES IN PERCENTAGE (%).

means classifying as stressed an individual which is calm and relaxed.

Reader may notice that there must exist a trade-off between TSD and TNSD so that the system could avoid false positives (detect non-stress when the individual is under stress) and false negatives (detect non-stress when the individual is stressed).

D. Stress detection in a real scenario

Once the system is implemented and evaluated, another evaluation scenario is presented. This scenario is based on stressing tasks like playing games or listening to classical music.

More in detail, the procedure of this evaluation is as follows:

- Relaxation. This period consists of relaxing the individual as in the database, using the physiological data acquired in this period as training data for non-stressing situations.
- Stress. This stressing period is achieved by hyperventilation, where the individual carries out the process of

breathing as described in Section IV. The data collected in this session is considered as stressing, for the creation of the template.

- Non-Stressing task. After this period of enrollment, the user listens to classical music for a period of time, aiming to relax the individual. The data collected in this session must be classified as non-stressing.
- Stressing-task. Afterwards, the individual is required to play a battle video game with very loud stressing music. The videogame provides some frustration because the player needs to focus on the game, but the music avoid this concentration. The arousal of physiological signals in this task must be associated to stress.

The system can provide both a binary or a continuous output. The results presented in this section employs the system in a continuous configuration, so that the arousal effect of previous different tasks is appreciated.

Figure 3 provides a visual example of a session of this

Reference	Stress Detection Rate (%)	Physiological Signals	Population
[9]	97.4%	ECG, EMG, RR, GSR	Not provided
[35]	79.5-96.6%	ECG, EMG, RR, GSR	1 subject
[28]	85-96%	BVP, ST, RR, GSR	Not provided
[36]	75-85%	ECG, EMG, RR, GSR	1 subject
[37]	76%	ECG, EMG, GSR	8 subjects
[38]	60-78%	ST, GSR	35 subjects
Best of our proposed methods	99.5%	HR, GSR	80 subjects

TABLE VI

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

Fig. 3. Samples of GSR, HR and the Stress detection output for a real scenario with a BL1, Task1 (Relax); HV and Task2 (stress). Reader may notice that Task2 (battle video game) provokes an arousal in stress comparable to hyperventilation.

experimental layout. A total of 6 individuals carried out the experiments with similar results. BL1 and HV stand for Base Line 1 and Hyperventilation as stated previously; Task 1 and Task 2 are the non-stressing and stressing tasks respectively. From Figure 3 some conclusions can be extracted. First of all, the system distinguishes properly between stressing and non-stressing tasks, providing lower and higher values respectively. In addition, the Task 2 with loud music and the video game stresses the individual even more than hyperventilation. In other words, this task can be used as an enrollment stage instead of hyperventilation, as suggested in literature [9], [10], [17].

VI. CONCLUSION AND FUTURE WORK

A stress detection system based on physiological signals has been described, implemented and evaluated. The system is able to detect stress properly with a True Stress Detection rate of 99.5% by means of two physiological signals, namely Heart Rate and Galvanic Skin Response, being both signals easy-to-acquire, providing a suitable solution for embedded biometric systems in a near future.

The main contribution of this stress detection system in comparison to previous approaches in literature consists of the creation of a stress template for each individual, describing the behaviour of previous physiological signals along two different situations: a stressing and a non-stressing scenario.

The creation of this template contains information of the behaviour of the proposed physiological signals, being gathered in gaussian distributions based on fuzzy logic, provided their average and standard deviation values for each situation. This template must be updated so that changes in the behaviour of the individual can be considered and included within the template over time.

Main characteristics of this system regard non-invasiveness, fast-oriented implementation and an competitive accuracy in detecting stress when compared to previous approaches.

The system is evaluated with an own private database of 80 individuals. In addition, the evaluation has considered also the comparison of the performance of the proposed method with other existing approaches in literature and competitive machine learning techniques like GMM, SVM, k -NN and Fisher Lineal Discriminant.

In addition, this paper presents a real scenario to apply the proposed system based on two different task: a relaxing/non-stressing situation where the individual must listen to classical music, and a stressing situation where the user must play a battle video game while listening to loud stressing music. The results of this evaluation show that the system is able to detect the arousal of the stress human activity.

As future work, a combination of the schemes presented in this paper will be considered to increase the performance of the whole system, together with the research of a more comfortable enrollment phase avoiding hyperventilation and using only data from the Base Line 1.

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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REFERENCES

- [1] J. Andren and P. Funk, "A case-based approach using behavioural biometrics to determine a user's stress level," in *ICCBR Workshops*, 2005, pp. 9–17.
- [2] D. F. Dinges, S. Venkataraman, E. L. McGlinchey, and D. N. Metaxas, "Monitoring of facial stress during space flight: Optical computer recognition combining discriminative and generative methods," *Acta Astronautica*, vol. 60, no. 4-7, pp. 341 – 350, 2007, benefits of human presence in space - historical, scientific, medical, cultural and political aspects. A selection of papers presented at the 15th IAA Humans in Space Symposium, Graz, Austria, 2005.
- [3] S. Begum, M. U. Ahmed, P. Funk, N. Xiong, and B. von Schele, "Using calibration and fuzzification of cases for improved diagnosis and treatment of stress," in *8th European Conference on Case-based Reasoning workshop proceedings*, M. Minor, Ed., September 2006, pp. 113–122.
- [4] L. A. Zadeh, "Fuzzy logic = computing with words," *IEEE Transactions on Fuzzy Systems*, vol. 4, no. 2, pp. 103–111, May 1996.
- [5] E. Jovanov, A. O'Donnell Lords, D. Raskovic, P. G. Cox, R. Adhami, and F. Andrasik, "Stress monitoring using a distributed wireless intelligent sensor system," *Engineering in Medicine and Biology Magazine, IEEE*, vol. 22, no. 3, pp. 49–55, 2003.
- [6] H. Prendinger and M. Ishizuka, "Symmetric multimodality revisited: Unveiling users' physiological activity," *IEEE Transactions on Industrial Electronics*, vol. 54, no. 2, pp. 692–698, Apr. 2007.
- [7] N. Sarkar, "A novel interface system for seamlessly integrating human-robot cooperative activities in space," NASA Institute for Advanced Concepts, Tech. Rep., 2002.
- [8] J. Kim and E. Ande, "Emotion recognition based on physiological changes in music listening," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 12, pp. 2067–2083, Dec. 2008.
- [9] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, no. 2, pp. 156–166, Jun. 2005.
- [10] W. Picard and J. A. Healey, "Wearable and automotive systems for affect recognition from physiology," MIT, Tech. Rep., 2000.
- [11] N. Sarkar, "Psychophysiological control architecture for human-robot coordination-concepts and initial experiments," in *IEEE International Conference on Robotics and Automation, 2002. Proceedings. ICRA'02.*, vol. 4, 2002, pp. 3719–3724.
- [12] L. Li and J. hua Chen, "Emotion recognition using physiological signals," in *Advances in Artificial Reality and Tele-Existence*, ser. Lecture Notes in Computer Science, vol. 4282. Springer Berlin / Heidelberg, 2006, pp. 437–446.
- [13] C. Chin and A. Barreto, "Electromyograms as physiological inputs that provide efficient computer cursor control," in *Proceedings of the 2006 WSEAS International Conference on Mathematical Biology and Ecology (MABE'06)*, 2006, pp. 221–226.
- [14] J. Shin, H. Seongo, D. Cha, Y. Yoon, and H. Yoon, "Estimation of stress status using biosignal and fuzzy theory," in *Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE*, vol. 3, Oct-1 Nov 1998, pp. 1393–1394.
- [15] J. W. Shin, J. S. Lee, A. R. Sul, C. G. Lee, Y. R. Yoon, H. Takeuchi, and H. Minamitani, "Chronic stress evaluation using neuro-fuzzy," in *26th Annual International Conference of the IEEE on Engineering in Medicine and Biology Society, 2004. IEMBS'04*, vol. 1, San Francisco, CA, Sep. 2004, pp. 373–374.

- [16] A. Barreto and J. Zhai, "Stress detection in computer users based on digital signal processing of noninvasive physiological variables," in *28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. EMBS '06.*, August 2006, pp. 1355–1358.
- [17] J. Zhai, A. Barreto, C. Chin, and C. Li, "Realization of stress detection using psychophysiological signals for improvement of human-computer interactions," in *SoutheastCon, 2005. Proceedings.*, April 2005, pp. 415–420.
- [18] T. Lin, M. Omata, W. Hu, and A. Imamiya, "Do physiological data relate to traditional usability indexes?" in *OZCHI'05: Proceedings of the 17th Australia conference on Computer-Human Interaction*. Narrabundah, Australia, Australia: Computer-Human Interaction Special Interest Group (CHISIG) of Australia, 2005, pp. 1–10.
- [19] M. M. Moore and U. Dua, "A galvanic skin response interface for people with severe motor disabilities," *Proceedings of the ACM SIGACCESS Conference on Computers and Accessibility, ASSETS 2004*, pp. 48–54, 2004.
- [20] J. Zhai and A. Barreto, "Stress detection in computer users through non-invasive monitoring of physiological signals," *Biomedical Science Instrumentation*, vol. 42, pp. 495–500, 2006.
- [21] M. Jiang and Z. Wang, "A method for stress detection based on FCM algorithm," in *CISP'09. 2nd International Congress on Image and Signal Processing, 2009.*, Tianjin, oct 2009, pp. 1–5.
- [22] A. de Santos Sierra, C. Sanchez Avila, G. Bailador del Pozo, and J. Guerra Casanova, "A stress detection system based on physiological signals and fuzzy logic," *Industrial Electronics, IEEE Transactions on*, vol. PP, no. 99, 2011.
- [23] A. de Santos Sierra, C. Sanchez-Avila, J. Guerra Casanova, G. Bailador del Pozo, and V. Jara Vera, "Two stress detection schemes based on physiological signals for real-time applications," in *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2010 Sixth International Conference on*, 2010, pp. 364–367.
- [24] C. L. Lisetti and F. Nasoz, "Using noninvasivewearable computers to recognize human emotions from physiological signals," *EURASIP Journal on Applied Signal Processing*, vol. 11, p. 16721687, 2004.
- [25]
- [26] K. Guney and N. Sarikaya, "Comparison of mamdani and sugeno fuzzy inference system models for resonant frequency calculation of rectangular microstrip antennas," *Progress In Electromagnetics Research B*, vol. 12, pp. 81–104, 2009.
- [27] G. Bailador and G. Triviño, "Pattern recognition using temporal fuzzy automata," *Fuzzy Sets and Systems*, vol. 161, no. 1, 2009.
- [28] H. Cai and Y. Lin, in *An experiment to non-intrusively collect physiological parameters towards driver state detection*. Academic Press, 2007.
- [29] A. Cano-Vindel, J. J. Miguel-Tobal, H. Gonzalez-Ordi, and I. Iruarizaga-Diez, "Hyperventilation and anxiety experience," *Anxiety and stress*, vol. 13, no. 2–3, pp. 291–302, 2007.
- [30] M. J. Zvolensky and G. H. Eifert, "A review of psychological factors/processes affecting anxious responding during voluntary hyperventilation and inhalations of carbon dioxide-enriched," *Clinical Psychological Review*, vol. 21, pp. 375–400, 2001.
- [31] G. J. McLachlan and K. E. Basford, *Mixture models. Inference and applications to clustering*. Statistics: Textbooks and Monographs, New York: Dekker, 1988.
- [32] N. J. Nilsson, *Introduction to Machine Learning*, 1996.
- [33] D. Michie, D. J. Spiegelhalter, C. C. Taylor, and J. Campbell, Eds., *Machine learning, neural and statistical classification*. Upper Saddle River, NJ, USA: Ellis Horwood, 1994.
- [34] L. Wang, *Data Mining with Computational Intelligence*. Berlin, Heidelberg: Springer-Verlag, 2009.
- [35] J. Wagner, N. J. Kim, and E. Andre, "From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification," *IEEE Computer Society*, pp. 940–943, 2005.
- [36] L. Guang-yuan and H. Min, "Emotion recognition of physiological signals based on adaptive hierarchical genetic algorithm," *World Congress on Computer Science and Information Engineering*, vol. 4, pp. 670–674, 2009.
- [37] D. Kulic and E. Croft, "Anxiety detection during human-robot interaction," in *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005. (IROS 2005).*, Aug. 2005, pp. 616–621.
- [38] M. S. Sharawi, M. Shibli, and M. I. Sharawi, "Design and implementation of a human stress detection system: A biomechanics approach," in *5th International Symposium on Mechatronics and Its Applications, 2008. ISMA 2008.*, Amman, May 2008, pp. 1–5.