Biomedical Signal Processing and Control 6 (2011) 261–268

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

An integrated system based on physiological signals for the assessment of affective states in patients with anxiety disorders

Christos D. Katsis, Nikolaos S. Katertsidis, Dimitrios I. Fotiadis*

Unit of Medical Technology and Intelligent Information Systems, Department of Materials Science and Engineering, University of Ioannina, GR45110 Ioannina, Greece

ARTICLE INFO

Article history:
Received 29 April 2010
Received in revised form
14 September 2010
Accepted 6 December 2010
Available online 28 December 2010

Keywords:
Anxiety disorders
Biosignal processing
Wearable devices

ABSTRACT

Anxiety disorders are psychiatric disorders characterized by a constant and abnormal anxiety that interferes with daily-life activities. Their high prevalence in the general population and the severe limitations they cause have drawn attention to the development of new and efficient strategies for their treatment. In this work we describe the INTREPID system which provides an innovative and intelligent solution for the monitoring of patients with anxiety disorders during therapeutic sessions. It recognizes an individual's affective state based on 5 pre-defined classes (relaxed, neutral, startled, apprehensive and very apprehensive), from physiological data collected via non-invasive technologies (blood volume pulse, heart rate, galvanic skin response and respiration). The system is validated using data obtained through an emotion elicitation experiment based on the International Affective Picture System. Four different classification algorithms are implemented (Artificial Neural Networks, Support Vector Machines, Random Forests and a Neuro-Fuzzy System). The overall classification accuracy achieved is 84.3%.

1. Introduction

Emotion is a broad term, and includes several modalities which make a unique, exact definition unfeasible. After over a century of research, emotion experts still do debate upon what emotions are, and how they are communicated. The physiological muscle movements, comprising what looks to an outsider to be a facial expression, may not always correspond to a real underlying emotional state. Hence, emotions are characterized by the awareness of a given situation, overt expressions and behaviors, readiness to act, and physiological changes supplemented with subjective feelings [1,2]. Emotions influence our decisions and actions, the same as reason [3]. They affect different aspects of cognition such as: goal generation, decision-making and priority setting [4]; focus and attention [5]; perception and understanding [6]; categorization and preference [7]; motivation and performance [8]; intention [9]; and learning [3]. The increasing interaction of machines and people has created a strong motivation for systems able to recognize, interpret, and process human emotions. However, the simulation of empathy is still one of the least explored frontiers in human–computer interaction.

The usual way to assess human affective state is by employing advanced image-video processing techniques in order to extract the facial characteristics. Most works in automatic understanding of affective condition focus on the classification of the universal expressions defined by Ekman and Friesen [10]. Thus, the implemented algorithms were tailored toward developing models to recognize the universal expressions from static images or video sequences [11–17]. It must be noticed, that although the aforementioned methodologies report high classification results, the physiological muscle movements, comprising what looks to an outsider to be a facial expression, may not always correspond to a real underlying emotional state. To overcome this issue a biosignal based approach is proposed.

In recent years, the acceptance that explicit physical manifestations of many types accompany emotional states has encouraged researchers to propose different methods for recognizing and measuring emotions, as they are experienced [18]. Ekman et al. [19] and Winton et al. [20] provided some of the first findings showing significant differences in autonomic nervous system signals in relation to a small number of emotional categories. However, there was no exploration of automated classification. Flidlund and Izard [21] appear to be the first who applied pattern recognition on the classification of four different emotions (happiness, sadness, anger, and fear) from physiological signals, attaining 38–51% accuracy. Subsequently, Picard et al. [22] accomplished 81% accuracy for the detection of anger, hate, grief, platonic love, romantic love, joy, reverence and the neutral state, based on the utilization of statistical methods and features calculated from the respiration, skin conductance, blood volume pulse, and electromyogram of a single individual. Indeed, there is a growing evidence that affective states have their corresponding physiological signals that can be mapped

* Corresponding author. Tel.: +30 2651 098803; fax: +30 2651 097092.
E-mail address: fotiadis@cs.uoi.gr (D.I. Fotiadis).

1746-8094/$ – see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.bspc.2010.12.001

respectively; thus emotion recognition methodologies based on the classification of extracted series of features from these biosignals are continuously gaining popularity [23–27].

An automated and on-line approach in affective assessment, based on specific biological signals, is presented in this paper. Our methodology has been integrated into an advanced tracking system, named INTREPID, which is able to estimate the anxiety state of individuals by classifying features extracted from blood volume pulse (BVP), heart rate (HR), galvanic skin response (GSR) and respiration (RSP). It consists of the following modules: (a) the Multi-Sensor System used to collect the biosignals, (b) the Sensor Management Module which manages and coordinates the Multi-Sensor System, and (c) the Data Fusion Module which is responsible for the system's perception of anxiety states. The INTREPID system contributes to the treatment of anxiety disorders in an unobtrusive, personalized and intelligent manner. By providing a powerful and innovative human–computer interaction environment, it allows psychologists to effectively design the next steps of a patient's therapy, taking into account his individualized physiological and emotional condition.

In the following sections, first, we provide information on the selected biosignals and the extracted features and then, we describe the system's modules and their functionalities. Then, the initial evaluation of the system using data obtained through an emotion elicitation experiment, based on the International Affective Picture System, is presented. Finally, the limitations and applications of the proposed approach are discussed.

2. Materials and methods

2.1. Biosignals

During stress, the brain focuses on the perceived threat and stimulates behaviors that propel the organism to act accordingly [28]. Blood flow is redirected to provide the highest perfusion to the brain and the musculoskeletal system, while cardiac output and respiration are enhanced. These bodily changes are mediated by the autonomic nervous system (ANS), which responds rapidly to stressors and controls a wide range of systemic functions. The cardiovascular, respiratory, renal, endocrine and other systems, such as the gastrointestinal system, are regulated by either the sympathetic division or the parasympathetic division of the ANS, or both [29]. Reduction of the parasympathetic nervous system activity results in removal of inhibition of the sympathetic nervous system (SNS), thus increasing sympathetic functions, while increased activity antagonizes the SNS. The balance of activities aids in the maintenance of an internal stable environment in the face of changing external conditions [30]. Different anxiety levels can affect this balance resulting in a wide variety of bodily reactions, which can be monitored and measured. Through these, the affective state of a subject may be deduced. An important aspect of this procedure is the selection of the appropriate biosignals (in terms of effectiveness and comfortableness) for monitoring and analysis. After a thorough research of many physiological parameters related to cardiovascular, brain, electrodermal, respiratory, and somatomotor activity, the following non-invasive biosignals were selected:

Blood volume pulse (BVP)/heart rate (HR): The cardiovascular system is a rich and intricate physiological system with multiple regulatory subsystems that are subject to central and peripheral autonomic controls and humoral influences. Consequently, it is highly sensitive to neurobehavioral processes [18]. An example of a BVP signal is shown in Fig. 1. The pulse train indicates the heart beats, and the shape of the envelope indicates the relative constriction of the blood vessel. The vasoconstriction is controlled by the sympathetic division of the ANS, and is a defensive reaction [31]. It increases in response to pain, hunger, fear and rage, and decreases in response to quiet relaxation [9]. HR refers to the frequency of the contractions of the heart muscle or myocardium. Lower heart rate is generally associated with a relaxed state or a state of experiencing pleasant stimuli, while HR accelerations occur in response to exercise, emotional states, loud noises, sexual arousal and mental effort [32].

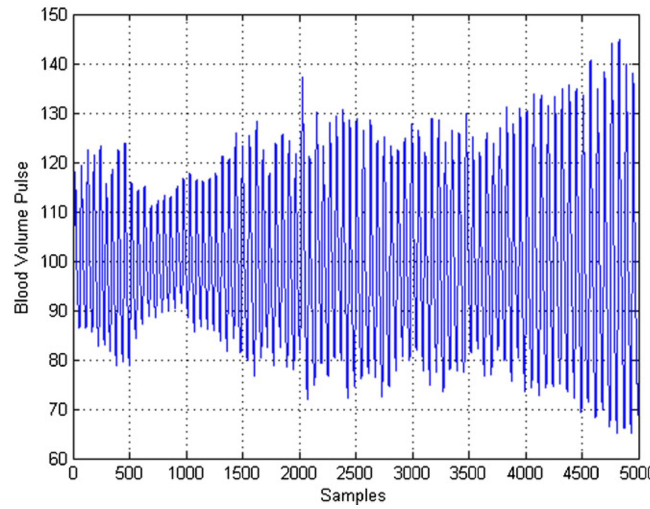

Fig. 1. Example of a BVP signal with decreasing vasoconstriction.

Galvanic skin response (GSR): It is one of the most widely used response systems in the history of psychophysiology. GSR (also referred as electrodermal activity) has been applied to a wide variety of questions ranging from basic research examining attention, information processing, and emotion, to more applied clinical research examining predictors and/or correlates of normal and abnormal behavior. It is a sensitive peripheral index of the sympathetic division of the ANS, and measures alterations in skin conductivity, due to psychologically induced sweat gland activity [18]. As a person becomes more or less stressed, his skin conductance increases or decreases proportionally. Fig. 2 illustrates an example of a GSR signal. This is typically characterized by two components: a tonic baseline level (skin conductance level, SCL) and short-term phasic responses (skin conductance responses, SCRs) superimposed on the tonic baseline level. Phasic responses (momentary increases in skin conductance) determine the event-

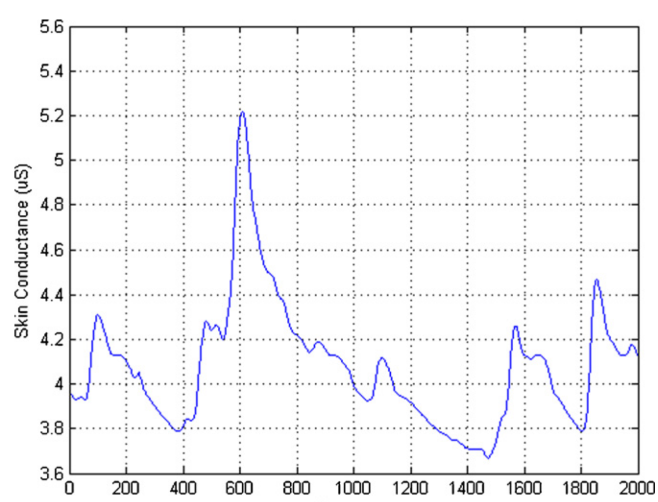

Fig. 2. Example of a GSR signal.

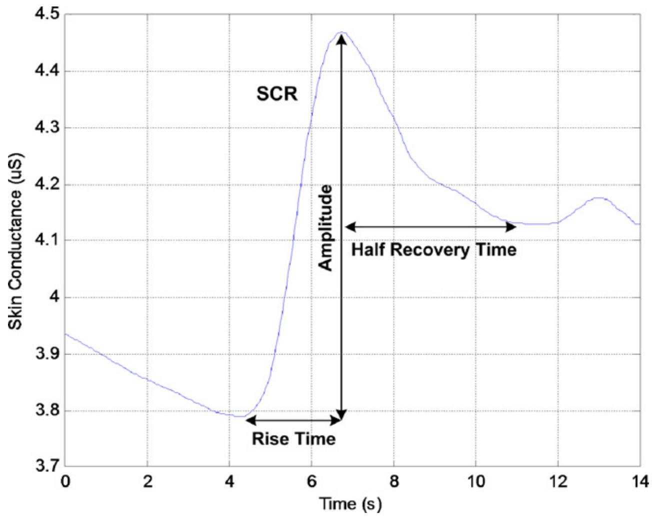

Fig. 3. Characteristics of the skin conductance response (SCR).

related responses that occur in an individual, due to environmental stimuli. A stimulus may vary from a deep breath to a thought burst. The characteristics of a typical skin conductance response (SCR) resemble a peak, and are depicted in Fig. 3. The amplitude of the response is the difference between the peak of the response and the baseline. The size of an elicited SCR typically ranges from 0.1 to 1.0 μS. The duration of the response is the difference between the time of the response onset and the time of the peak. The half recovery time is the difference between the time of the peak and the time at which the response decays to one half of the magnitude of the peak [33].

Respiration (RSP): Respiration is an indicator of how deep and fast a person is breathing. The respiratory system is remarkably complicated and sensitive to a variety of psychological variables, including emotions. An example of steady breathing is depicted in Fig. 4. Physical activity and emotional arousal are reported to cause faster and deeper respiration, while peaceful rest and relaxation are reported to lead to slower and shallower respiration [22]. A state of stress would therefore be indicated by frequent respiration. However, sudden stressors such as a startle tend to cause momentary cession of respiration [34].

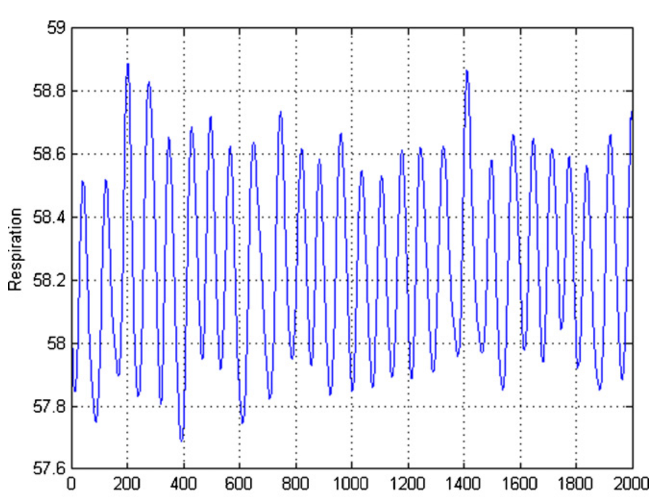

Fig. 4. Example of a respiration signal (steadily breathing).

Table 1
Extracted features from the selected biosignals.

HR	BVP	GSR	RSP
Mean value	Relative Std of amplitude	Mean amp of skin conductance responses	Mean amp of breaths
–	–	Rate of skin conductance responses	Respiration rate
–	–	Mean absolute first difference	Mean absolute first difference

2.2. Biosignal processing

The raw biosignals are processed in order to construct vectors of features, which are subsequently utilized for the emotional assessment of a subject a filtering stage is initially employed, consisting of moving average filters. A moving average filter smoothes data by replacing each data point in a series with the average of the neighboring data points, defined within a span. This process is equivalent to low-pass filtering with the response of the smoothing given by the difference equation:

$$y_s(i) = \frac{1}{2N+1}(y(i+N) + y(i+N-1) + \cdots + y(1-N)) \qquad (1)$$

where $y_s(i)$ is the smoothed value for the ith data point, N is the number of neighboring data points on either side of $y_s(i)$, and $2N+1$ is the span. N is set empirically to 5, 13 and 19 for the BVP, GSR and RSP biosignals respectively, to compensate for the different needs (i.e. sampling rate, introduced outliers or generated movement artefacts).

A selected set of features is constructed, providing a combination of simple statistics and complex characteristics which are physically motivated, and aimed at capturing the underlying nature of the physiological signals. These features are empirically selected after contacting a series of experiments. They are also characterized by their real-time nature and low computational load, allowing even their utilization in a mobile or PDA device. Table 1 presents the extracted features for the four selected biosignals.

These features are analyzed below:

Mean value: It is the mean value for a 10 s window of a signal.

Relative Std (RSD): It is the relative standard deviation of a BVP-amplitudes array X, and is given as:

$$RSD = \frac{(\text{standard deviation of array } X) * 100}{\text{mean of array } X} \qquad (2)$$

Mean absolute first difference (MAFD): For a signal $X_N = (x_1, x_2, \ldots, x_N)$ it is defined as:

$$MAFD = \frac{1}{N-1}\sum_{i=1}^{N-1} |x_{i+1} - x_i|, \qquad (3)$$

where N is the number of samples contained in a 10 s window. This feature approximates the gradient.

Mean Amp: For the GSR signal, it is the mean value of the increases in skin conductance between SCR initiations and SCR peaks, which occurred in a 10 s time window. For the respiration signal, it is the mean value of the chest cavity expansions occurred in a time window of 10 s.

Rate: It is the respiration rate and the number of SCRs per minute, which are calculated every 10 s.

2.3. INTREPID architecture

The INTREPID system (Fig. 5) consists of one hardware component, the Multi-Sensor System, and two software ones, the Sensor Management Module and the Data Fusion Module, running on a control PC having Bluetooth connectivity:

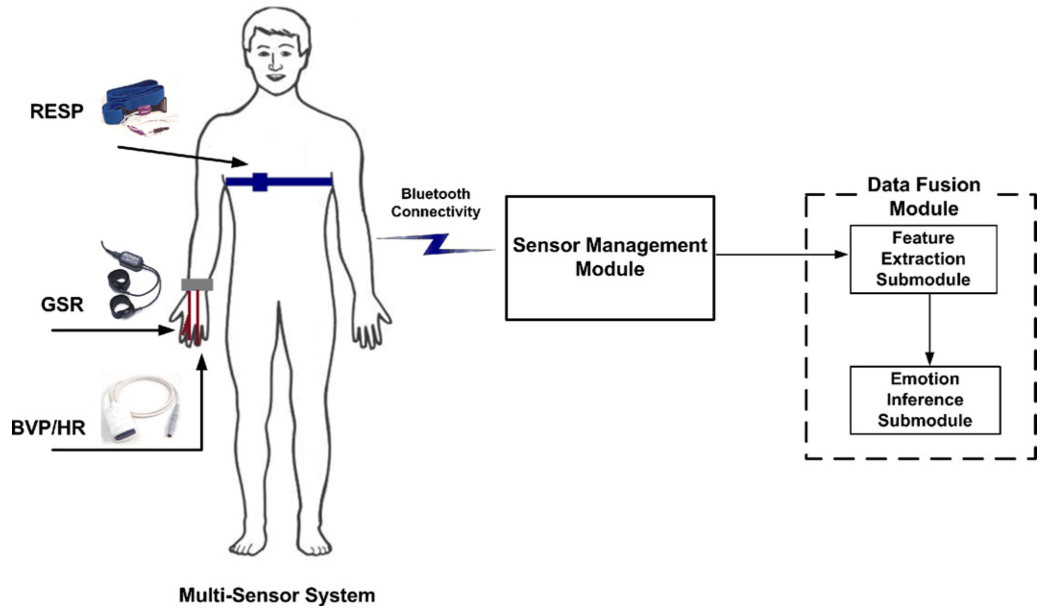

Fig. 5. The INTREPID system architecture.

The multi-sensor system: It is a set of wireless and wearable biometric, proprietary submodules that simultaneously monitor and transmit the above-mentioned biosignals (GSR, BVP, HR and RSP) related to the underlying affective state of a subject (Fig. 6). The sensing submodules are composed of: (a) a skin conductance sensor measuring electrodermal activity, (b) a photoplethysmographic sensor measuring blood volume pulse and heart rate, and (c) a piezoelectric respiration sensor. The obtained data, transmitted through Bluetooth communication (Bluetooth version 2.0, class 1, compliant with the Serial Port Profile), are presented in Table 2.

The Sensor Management Module: It calibrates and manages the Multi-Sensor System, which acts in a dynamic and uncertain environment such as a subject's body, in order to improve the performance of the INTREPID system's perception of anxiety states. The Sensor Management Module is a multi-threaded .NET application, especially designed to provide a friendly User Interface and enhanced functionalities (Fig. 7).

The Data Fusion Module: It successfully assesses, in real time, the emotional state of a subject through association of the information coming from the biometric sensors. The Data Fusion Module is divided in two major components, namely the Feature Extraction and the Emotion Inference submodules. The former converts the input signals into extracted features that can be used by the latter in order to determine a subject's emotional state.

The Feature Extraction submodule receives data from the sensors through the Sensor Management Module. It provides a vector of the desired features which is fed to the Emotion Inference submodule for the decision making process. The Emotion Inference submodule performs a classification of the patient's emotional state based on 5 pre-defined emotional classes (relaxed, neutral, startled, apprehensive and very apprehensive). Four classification schemes were investigated, namely Artificial Neural Networks (ANN) [35], Support Vector Machines (SVM) [36], Random Forests (RF) [37] and a Neuro-Fuzzy System (NFS) [38].

The ANN employed is a feed-forward multilayer perceptron with an input layer consisting of 8 neurons (equal to the number of the extracted features). The number of hidden layers is set to 2, the learning rate to 0.1, the momentum to 0.2, and the number of epochs to 500. The SVM implementation is based on the LIBSVM library [39], using an RBF kernel. The kernel parameters C and γ are set to 10 and 0.01, respectively. Random Forests is an ensemble classifier that consists of many decision trees, and outputs the class

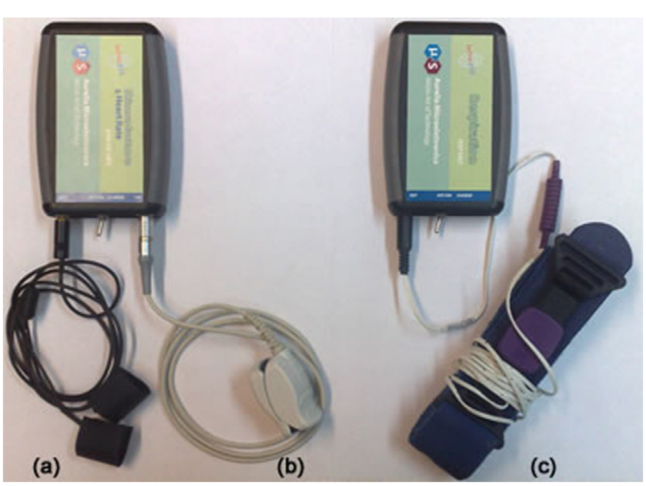

Fig. 6. The INTREPID system sensing submodules: (a) GSR submodule, (b) BVP/HR submodule and (c) RSP submodule.

Table 2
Data specifications of the INTREPID multi-sensor system.

Sensor module	Sampling rate (samples per second)	Data resolution (bit)	Description of transmitted data
BVP/HR	75 (BVP)/3 (HR)	8 (BVP)/9 (HR)	Digital samples of the blood volume pulse and the determined heart rate
GSR	64	12	Digital samples of the voltage related to the electrodermal activity
RSP	64	12	Digital samples derived from the amplified and filtered raw analogue signal

Fig. 7. User interface of the Sensor Management and Data Fusion Modules.

that was voted by the majority of the individual trees. The number of trees to be generated is set to 20.All the above-mentioned parameters are selected heuristically, after a series of experiments. The NFS is based on the Takagi–Sugeno–Kang (TSK) fuzzy logic method [40] with Sigmoid and Gaussian-bell input membership functions. If $X_p = (x_1, x_2, \ldots, x_p)$ is an input feature set, a typical TSK fuzzy inference system consists of IF–THEN rules with consequent parts that are constant (zeroth-order) or linear function (first-order) of the inputs:

$$\begin{aligned} R^k : &\text{ if } x_1 \text{ is } F_{1k}(x_1) \text{ and } \ldots, x_p \text{ is } F_{pk}(x_p) \\ &\text{ then } y_k = a_{i1}x_1 + \cdots + a_{ip}x_p + a_{i(p+1)}, \text{ with } k = 1, \ldots, N \end{aligned} \tag{4}$$

where N is the number of rules, y_k is the output of the kth rule, and $F_{1k}, \ldots, F_{pk}$ are the input membership functions. The output of each rule is weighted by its firing strength:

$$w_k = \prod_{i=1}^{p} F_{ik}(x_i) \tag{5}$$

The final output of the system is the weighted average of all rule outputs, computed as:

$$y = \frac{\sum_{k=1}^{N} w_k y_k}{\sum_{k=1}^{N} w_k}. \tag{6}$$

After an initial structure is set, the system is trained using an Adaptive-Network-Based Fuzzy Inference System (ANFIS) method [41]. The hybrid learning algorithm of the MATLAB ANFIS Tool [42] is used.

3. Results

The INTREPID system is validated with an emotion elicitation experiment, employing visual stimulation through still images for effective emotion induction. This is based on the International Affective Picture System (IAPS) [38], which consists of over 800 photographs classified by a large number of participants in terms of arousal and valence. The former refers to how strong a picture content is, whereas the latter to how positive or negative the content is considered to be. Five healthy subjects (2 men and 3 women) are employed. During data collection, the GSR sensing submodule is placed on the middle phalanges of the index and middle fingers of the right hand, the BVP/HR sensing submodule on the tip of the ring finger of the right hand, and the RSP sensing submodule around the diaphragm. In addition, the subjects are seated and relatively motionless. An elicitation procedure is adopted whereby the subjects relax for 10 min at the beginning of the experiment. After that, they are presented with a set of 5 low arousal and neutral valence photographs (each for 10 s), followed by sets of increasing arousal and negative valence. In between the last three sets, the subjects are shown again a set of low arousal and neutral valence photographs in order to normalize their mood. A progressive increase in arousal level is adopted in order to minimize the effect, which the content of any one photograph might have on subsequent photographs.

The obtained raw signals are initially segmented in windows of 10 s. Then, for each window, the selected features are extracted. As a result, a dataset of 600 instances for training and testing the classifiers is collected for 5 emotional states (relaxed, neutral, startled, apprehensive and very apprehensive). The annotation of these instances was performed by an experienced clinical psychologist using the acknowledge technique SAM (Self Assessment Manikin) [43]. According to SAM, each one of the five emotional states corresponds to a representative icon stating the arousal level.

The overall classification accuracy achieved for the ANN, SVM, RF and NFS classifiers is 77.33%, 78.50%, 80.83% and 84.3%, respectively. Because of the relative small amount of data available, a leave-one-out cross validation is used in all cases. Furthermore, in Tables 3–6, the confusion matrices for ANN, SVM, RF and NFS are presented. In general, it can be noticed that the NFS classifier provides a significant improvement over the other three classification schemes. In addition, some emotions (e.g. startled) are not recognized as well as others, because they seem to provide lower differential effects on physiology. The classification rate achieved with the NFS for each of the 5 emotional classes is analytically provided in Table 7.

4. Discussion

Anxiety disorders are psychiatric disorders characterized by an excessive, uncontrollable and often irrational worry about every-

Table 3
Confusion matrix for the ANN classifier.

	Relaxed	Neutral	Startled	Apprehensive	Very Apprehensive
Classified as relaxed	115	4	1	0	0
Classified as neutral	22	67	30	1	0
Classified as startled	1	17	86	16	0
Classified as apprehensive	0	1	21	84	14
Classified as very apprehensive	0	1	0	7	112

Table 4
Confusion matrix for the SVM classifier.

	Relaxed	Neutral	Startled	Apprehensive	Very apprehensive
Classified as relaxed	106	14	0	0	0
Classified as neutral	6	86	27	1	0
Classified as startled	1	16	81	22	0
Classified as apprehensive	0	1	21	87	11
Classified as very apprehensive	0	1	1	7	111

Table 5
Confusion matrix for the RF classifier.

	Relaxed	Neutral	Startled	Apprehensive	Very apprehensive
Classified as relaxed	112	6	2	0	0
Classified as neutral	7	92	19	2	0
Classified as startled	1	20	79	20	0
Classified as apprehensive	0	2	20	88	10
Classified as very apprehensive	0	0	0	6	114

Table 6
Confusion matrix for the NFS classifier.

	Relaxed	Neutral	Startled	Apprehensive	Very apprehensive
Classified as relaxed	109	8	3	0	0
Classified as neutral	5	101	10	4	0
Classified as startled	1	12	94	13	0
Classified as apprehensive	0	0	14	102	4
Classified as very apprehensive	0	2	3	15	100

day things. Their high prevalence in the general population and the severe limitations they cause, have drawn attention to the development of new and efficient strategies for their treatment. Traditional treatments of anxiety disorders have focused on counseling (cognitive behavioral therapy), and on exposure strategies that allow patients to gradually confront their anxieties and feel more comfortable in anxiety-provoking situations. The aim is to identify the negative thought-patterns that lead to the patient's anxiety, and replace them with positive, more realistic ones. However, this approach is, in many cases, anti-intuitive. Cognitive behavioral therapy usually helps one-third of the patients substantially, while another third does not respond at all to treatment. The INTREPID system contributes to the treatment of anxiety disorders in an unobtrusive and personalized manner, by providing an innovative and intelligent solution for the monitoring of patients during therapeutic sessions. It effectively exploits the synergy in the information acquired from miniaturized wearable biosensors, and efficiently monitors the symptoms of anxiety disorders by distinguishing between various levels of apprehension. Thus, the INTREPID system provides valuable information to therapists in order to help them during a therapeutic session, as well as in planning new research and treatment protocols for anxiety disorders.

Table 7
Achieved classification rate for each class using the NFS classifier.

Emotional class	Classification rate (%)
Relaxed state	90.83
Neutral state	84.17
Startled state	78.33
Apprehensive state	85.00
Very apprehensive state	83.33

The definition between various levels of apprehension is not a trivial procedure. Because the transition from one apprehension level to another is a gradual one, the affective states of a subject may not always have distinct boundaries. In addition, the mapping of various physiological parameters to different levels of apprehension is not sharply defined. Though research in psychophysiology provides a good understanding of physiological variation according to emotional states [18], person stereotype and day-to-day deviations prevent the formation of an accurate mapping from the physiology domain to a range of affective states. Also, as the number of physiological parameters increase, the task of designing a system capable of fusing all the parameters to obtain a single output representing apprehension becomes increasingly complex.

Given a specific application, biosensor suite, and inference requirements to be achieved, there is generally a number of competing algorithms which may be utilized for the fusion of data. However, there is no a perfect algorithm that is optimal under all conditions. The ANN, SVM, RF and NFS classifiers were utilized due to their well-known capabilities, which are applicable to a variety of different pattern-recognition tasks. In our approach, the use of the NFS is advantageous, since it improves the efficiency of the proposed system. The fuzzy inference system trained with the ANFIS method accomplished an overall classification ratio of 84.3%for 5 emotional states and a time window of 10 s. This time window is a significant factor for an online approach, since it determines how often the INTREPID system provides updates about the emotional state of a subject. The objective of a real time or near real

Table 8
Performance of biosignal-based emotion recognition methods reported in the literature.

Work	Classification method	Emotional classes	Data type	Classification accuracy (%)
Picard et al. [22]	Fisher Projection	Neutral, anger, hatred, grief, platonic love, romantic love, joy, and reverence	1 facial EMG, BVP, HR, GSR, RSP	81.0
Lisetti and Nasoz [24]	ANN	Sadness, amusement, anger, fear, and surprise	HR, GSR, skin temperature	84.1
Haag et al. [23]	ANN	Valence/arousal	EMG, BVP, ECG, GSR, skin temperature, RSP	96.0/89.9
Kim et al. [25]	SVM	Sadness, anger, stress, and surprise	ECG, GSR, skin temperature	61.8
Li and Chen [26]	Canonical Correlation Analysis	Fear, joy, and neutral	ECG, GSR, skin temperature, RSP	85.3
Katsis et al. [27]	SVM	High stress, low stress, disappointment, and euphoria	4 facial EMGs, ECG, GSR, RSP	79.3
This work	NFS	Relaxed, neutral, startled, apprehensive, and very apprehensive	BVP, HR, GSR, RSP	84.3

time emotion classifier is to first recognize as correctly as possible the emotional state of a user (high classification rate), and second to recognize it as soon as possible (high sensitivity). The former suggests a large window size, to minimize variance in the features within a class, while the latter suggests a small window size. The 10 s window has been identified as a suitable compromise between these two arguments, based on the acknowledgment that there is a time delay between the experience of an emotion, and its corresponding manifestation in physiology [18]. Regarding computational efficiency, the system is able to provide classification output within a few milliseconds, using a computer with a Core 2 Duo CPU (2.5 GHz) and 4 GB of RAM.

The achieved performance in terms of classification accuracy is comparable or even better to other biosignal-based emotion recognition approaches reported in the literature (Table 8). However, it must be emphasized that since the other methodologies have been applied in different datasets, containing different types of biosignals and involving dissimilar emotional classes, a direct comparison is not feasible. For example, Haag et al. [23] and Li et al. [26] reported higher accuracies in classification problems with fewer and more diversified emotional classes. In addition, their methodologies are not real-time, but rather depend on session-long summarizing of data. On the other hand, due to the fact that emotions may vary from person to person and within different situations, the INTREPID system has to be further validated using a variety of patients in real clinical conditions.

5. Conclusions

In this work, an advanced monitoring system which optimally classifies subjects'levels of apprehension is presented. The proposed system estimates, in real time, the affective condition of individuals by classifying features extracted from BVP, HR, GSR and RSP biosignals. The system is validated using data obtained through an emotion elicitation experiment based on the International Affective Picture System. As a future work, the INTREPID system is planned to be clinically tested with real patients in selected pilot trials. Moreover, the INTREPID system could be further extended by incorporating additional biosignals (e.g. Electroencephalogram and Electromyogram). On the other hand, special attention will be given to provide a well balanced system, characterized by subject comfortability and performance efficiency. In addition, a biofeedback adaptation will be investigated, allowing patients to gradually confront their anxieties and feel more comfortable in anxiety provoking situations, as well as to practice the skills they have learned during therapy.

Acknowledgments

This work is part funded by the European Commission (INTREPID: IST-2002-507464).

References

[1] R. Plutchik, The Psychology and Biology of Emotion, HarperCollins College Publishers, New York, 1994.
[2] N.R. Carlson, Physiology of Behaviour, Allyn and Bacon, Needham Heights, MA, 1998.
[3] D. Goleman, Emotional Intelligence: Why It Can Matter More Than IQ, Bantam Books, New York, 1995.
[4] A. Damasio, Descartes' Error, Avon Books, NY, 1994.
[5] D. Derryberry, D. Tucker, Neural mechanisms of emotion, J. Consult. Clin. Psychol. 60 (3) (1992) 329–337.
[6] G. Bower, Mood memory, Am. Psychol. 36 (2) (1981) 129–148.
[7] R. Zajonc, On the primacy of affect, Am. Psychol. 39 (2) (1984) 117–124.
[8] S. Bull, See yourself write: a simple student model to make students think, in: A. Jameson, C. Paris, C. Tasso (Eds.), User Modeling: Proceedings of the Sixth International Conference, Springer, New York, 1997, pp. 315–326.
[9] N.H. Frijda, The Emotions, Cambridge University Press, 1986.
[10] P. Ekman, W. Friesen, Unmasking the Face, Prentice-Hall, Englewood Cliffs, NJ, 1975.
[11] Essa, A. Pentland, A vision system for observing and extracting facial action parameters, in: Proceedings of the CVPR, 1994, pp. 76–83.
[12] I. Essa, A. Gardner, Prosody analysis for speaker affect determination, in: Proceedings of the Workshop Perceptual User Interfaces, 1997, pp. 45–46.
[13] K. Anderson, P.W. McOwan, A real-time automated system for the recognition of human facial expressions, IEEE Trans. Syst., Man, Cybern. B, Cybern. 36 (February (1)) (2006) 96–105.
[14] M.J. Black, Y. Yacoob, Tracking and recognizing rigid and non-rigid facial motions using local parametric models of image motion, in: Proceedings of the International Conference on Computational Vision, 1995, pp. 374–381.
[15] M. Black, Y. Yaccob, Recognizing facial expressions in image sequences using local parameterized models of image motion, Int. J. Comput. Vis. 25 (1) (1997) 23–48, Oct.
[16] G. Donato, M.S. Barlet, J.C. Hager, P. Ekman, T.J. Sejnowski, Classifying facial actions, IEEE Trans. Pattern Anal. Mach. Intell. 21 (October (10)) (1999) 974–989.
[17] M.S. Bartlett, J.C. Hager, P. Ekman, T.J. Sejnowski, Measuring facial expressions by computer image analysis, Psychophysiology 36 (March (2)) (1996) 253–263.
[18] J.T. Cacioppo, L.G. Tassinary, G.G. Berntson (Eds.), Handbook of Psychophysiology, 3rd ed., Cambridge University Press, 2007.
[19] P. Ekman, R.W. Levenson, W.V. Friesen, Autonomic nervous system activity distinguishes among emotions, Science 221 (1983) 1208–1210.
[20] W.M. Winton, L. Putnam, R. Krauss, Facial and autonomic manifestations of the dimensional structure of emotion, J. Exp. Soc. Psychol. 20 (1984) 195–216.
[21] A.J. Fidlund, E.Z. Izard, Electromyographic studies of facial expressions of emotions and patterns of emotions, in: J.T. Cacioppo, R.E. Petty (Eds.), Social Psychophysiology: A Sourcebook, The Guilford Press, NY, 1983, pp. 243–286.
[22] R.W. Picard, E. Vyzas, J. Healy, Toward machine emotional intelligence: analysis of affective physiological state, IEEE Trans. Pattern. Anal. Mach. Intell. 23 (10) (2001) 1175–1191.
[23] A. Haag, S. Goronzy, P. Schaich, J. Williams, Emotion recognition using biosensors: first steps towards an automatic system, in: E. André, L. Dybkjaer, W. Minker, P. Heisterkamp (Eds.), Affective Dialogue Systems, Springer, 2004, pp. 36–48.

[24] C.L. Lisetti, F. Nasoz, Using noninvasive wearable computers to recognize human emotions from physiological signals, EURASIP J. Appl. Signal Process. 11 (2004) 1672–1687.
[25] K.H. Kim, S.W. Bang, S.R. Kim, Emotion recognition system using short-term monitoring of physiological signals, Med. Biol. Eng. Comput. 42 (3) (2004) 419–427.
[26] L. Li, J. Chen, Emotion recognition using physiological signals, in: R. Liang, Z. Pan, A. Cheok, M. Haller, R.W.H. Lau, H. Saito (Eds.), Advances in Artificial Reality and Tele-Existence, Springer, 2006, pp. 437–446.
[27] C.D. Katsis, N. Katertsidis, G. Ganiatsas, D.I. Fotiadis, Towards emotion recognition in car racing drivers: a biosignal processing approach, IEEE Trans. Syst. Man. Cybern. Syst. Hum. 38 (3) (2008) 502–512.
[28] K.E. Habib, K.P. Weld, K.C. Rice, J. Pushkas, M. Champoux, S. Listwak, E.L. Webster, A.J. Atkinson, J. Schulkin, C. Contoreggi, G.P. Chrousos, S.M. McCann, S.J. Suomi, J.D. Higley, P.W. Gold, Oral administration of a corticotrophin releasing hormone receptor antagonist significantly attenuates behavioral, neuroendocrine, and autonomic responses to stress in primates, Proc. Natl. Acad. Sci. 97 (11) (2000) 6079–6084.
[29] K.E. Habib, P.W. Gold, G.P. Chrousos, Neuroendocrinology of stress, Endocrinol. Metab. Clin. North Am. 30 (3) (2001) 695–728.
[30] P.J. Lang, M.M. Bradley, B.N. Cuthbert, International Affective Picture System (IAPS): Instruction Manual and Affective Ratings, Technical Report A-5, The Center for Research in Psychophysiology, University of Florida, 2001.
[31] D. Kahneman, Attention and Effort, Prentice-Hall, Englewood Cliffs, NJ, 1973.
[32] F.J. McGuigan, Cognitive Psychophysiology: Principles of Covert Behaviour, Prentice-Hall, Englewood Cliffs, NJ, 1978.
[33] W. Boucsein, Electrodermal Activity, Plenum Press, New York, 1992.
[34] J.M. Gorman, J.D. Martinez, J.D. Coplan, J. Kent, M. Kleber, The effect of successful treatment on the emotional and physiological response to carbon dioxide inhalation in patients with panic disorder, Biol. Psychiatry 56 (11) (2004) 862–867.
[35] S. Haykin, Neural Networks and Learning Machines, 3rd ed., Prentice Hall, 2008.
[36] C.J.C. Burges, A tutorial on support vector machines for pattern recognition, Data Min. Knowl. Discov. 2 (3) (1998) 121–167.
[37] L. Breiman, Random forests, Machine Learning 45 (1) (2001) 5–32.
[38] L. Rutkowski, Flexible Neuro-Fuzzy Systems: Structures, Learning and Performance Evaluation, Springer, 2004.
[39] C.C. Chang, C.J. Lin, LIBSVM: A Library for Support Vector Machines, 2010 (accessed at 13/09/2010) http://www.csie.ntu.edu.tw/∼cjlin/libsvm.
[40] M. Sugeno, Industrial Applications of Fuzzy Control, Elsevier Science Publishing Co., 1985.
[41] J.S.R. Jang, ANFIS: adaptive-network-based fuzzy inference systems, IEEE Trans. Syst. Man. Cybern. 23 (3) (1993) 665–685.
[42] MathWorks, MATLAB Fuzzy Logic Toolbox 2: User's Guide, The MathWorks Inc., Natick, MA, 2009.
[43] M.K. Greenwald, M.M. Bradley, A.O. Hamm, P.J. Lang, Looking at pictures: evaluative, facial, visceral and behavioral responses, Psychophysiology 30 (3) (1993) 261–731.