AMSE JOURNALS-AMSE IFRATH Publication –2014-Series: Modelling C; Vol. 75
Special Handicap; pp 131-141
Submitted Sept. 2014; Accepted Oct. 31, 2014

Anxiety recognition using relevant features from BVP signal: Application on phobic individuals

*Wahida Handouzi, *Choubeila Maaoui, *Alain Pruski, *Abdelhak Moussaoui
*Laboratory « Conception, Optimisation et Modélisation des Systèmes » (LCOMS), Lorraine University, Metz, France (name.surname@univ-lorraine.fr)

Abstract: Today, it is possible to detect and measure the various events held emotion nature. This detection is imperfect, because on the one hand, the data complexity and on the other hand, the variability between individuals. In this paper, we present a technique for anxiety data validation. These data are obtained by exposing the subjects to anxiogenic virtual environments. The purpose of this study is the anxiety recognition through a single physiological signal (volume blood pressure). Support vector machine classifiers were used for model construction. For validation, we used the relevant features chosen. The result is a reliable anxiety data for future use in the treatment of social phobia in cognitive behavioral therapy in virtuo.

Keywords: Anxiety recognition, blood volume pulse signal (BVP), exposure virtual reality (EVR), features selection, support vector machine (SVM), objective validation.

1. Introduction

Disability caused by social anxiety has attracted the attention of scientists leading to the development of effective strategies to reduce and / or treating it. Efficiency of cognitive behavioral therapy (CBT) in virtuo for treating this disease has been proved by several studies [1] [2]. This technique is to perform a cognitive reconstruction by exposing the patient to anxiogenic situations and patients led them to a gradual acceptance. Controlling these therapies in a progressive manner using automatic anxiety recognition has many advantages. It helps in preserving the privacy and safety of the patient.

Anxiety is a psychological and physiological state characterized by cognitive and behavioral somatic, emotional components. It is a fear considered a normal reaction to a stressful situation, but becomes pathological when there is no real danger. [3]

The autonomic nervous system (ANS) is responsible for sensing what happens in the body and regulating involuntary responses including those of the heart and smooth muscles (muscles that control such things as constriction of bloods vessels, the respiratory tract, and the gastrointestinal tract) [4]. There are two components of the ANS, the parasympathetic and the sympathetic. The parasympathetic component is responsible for slowing the heart rate and relaxing the smooth muscles. The sympathetic component of the ANS is responsible for the opposite, i.e. raising the heart rate and constricting the blood vessels which cause, among other effects, an increase in blood pressure. The sympathetic response is slower and longer lasting than the parasympathetic response and is associated with the so-called flight or fight reaction [4] [5].

In this paper, our challenge is to assess the users emotional state by using the features selected. We will show the different development stages of a short term anxiety recognition system based only on the volume blood pulse signal (BVP). The advantage of using a single sensor is the contribution to reducing the time required for data processing and minimizing the discomfort of the subject.

In the following sections we will present first, previous work on emotion recognition using physiological signals. Second, the followed methodology for the development of the recognition system and the most important steps for data processing are described. Third, the results will be shown. Finally, we discuss the limitations and future applications of the proposed approach.

2. State of the art

Almost all methods of emotion recognition are based on methodologies based on classification techniques. They also combine multiple physiological signals to increase the recognition rate.

In 2005, a novel system have been designed and built to detecting stress during real-world driving tasks using physiological sensors (Electromyography, electrocardiogram, electrodermal activity, respiration and video). The result was 97% from statistical and spectral analyzes [6].

Kim used the music to stimulate subjects. It has measured four physiological signals (Electromyography, electrocardiogram, skin conductance and respiration) to differentiate between the valence and arousal. The result was 95% accuracy. Self-evaluation of subjects allowed the validation of the results [7]. In 2010, Maaoui used the international system of emotional picture (IAPS) to induce different levels of apprehension. The results of the statistical analysis on the temperature, blood volume pulse, electromyography, skin conductance and finally respiration was 84.3% [8]. Analysis of four physiological signals (photoplethysmography (PPG), skin temperature (SKT), electrodermal activity (EDA) and electrocardiogram (ECG)) to recognize seven emotional states (happiness, sadness, anger, fear, disgust, surprise and stress) was 70%. The system of self-assessment was used for validation. The used stimulation method was the exhibition of audio-visual clips captured in films, documentaries and television [9].

3. Methodology

3. 1. Selection of subjects

Seven subjects suffering by social anxiety disorder were selected by a psychotherapist. The diagnosis was based on the results of different questionnaires: Liebowitz Social Anxiety Scale (LSAS) [10], questionnaires fears ... etc.

3. 2. The anxiety induction

Define a methodology for the development of a recognition system to translate the signal into a specific emotion is necessary. A number of questions arise in such a situation, before being able to train the system, it is first necessary to elicit this emotion in valid and reliable way so much that possible then record the signal that accompanies it and finally ensure valid and reliable interpretation of it. A detailed of experiment course protocol must be designed. These different steps are explained in more detail in the following.

For this, we have developed six stressful virtual environments inspired by Liebowitz Social Anxiety scale (LSAS): call in public, entering a room where people are already seated, be the center of attention, talk to a person who has authority, go to a party, talking to an unknown person (Fig. 1).

(a) (b) (c)

(d) (e) (f)

Fig. 1. The six stressful virtual environments used: (a) Call in public, (b) Entering a room where people are already seated, (c) Be the center of attention, (d) Talking to an unknown person, (e) Go to a party, (f) Talk to a person who has authority.

We opted for static scenes without direct interaction with subjects. We used the following equipment: a screen 24 inches and a mouse.

3. 3. The acquisition protocol

For BVP signal acquisition, we used the Procomp Infiniti encoder. It is an eight (8) channel, multi-modality device for real-time computerized psychophysiology, biofeedback and data acquisition [12].

The BVP sensor (BVP-Flex/Pro) is held pressed against the palmar surface of a fingertip with an elastic strap (supplied with the sensor) or a small length of adhesive tape

Fig. 2. The Procomp infinity encoder and the blood volume pulse sensor.

During the experiment subjects were required to sit in a chair then the BVP sensor was placed on the left hand. The instructions are to keep still this hand because the sensor is sensitive to movements while the right hand can be used to navigate through the environment. The following figure illustrates the used equipment and the working environment, knowing that the artificial light is off during experience.

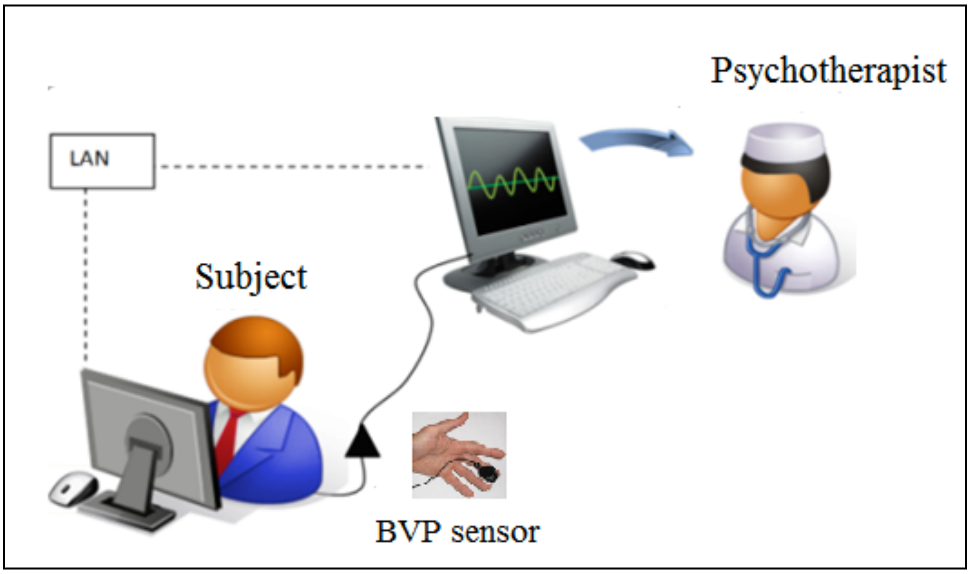

Fig. 3. Experiment environment and used materials.

The clinical protocol and associated experience has been made in collaboration with a psychiatric clinic specializing in TCC.

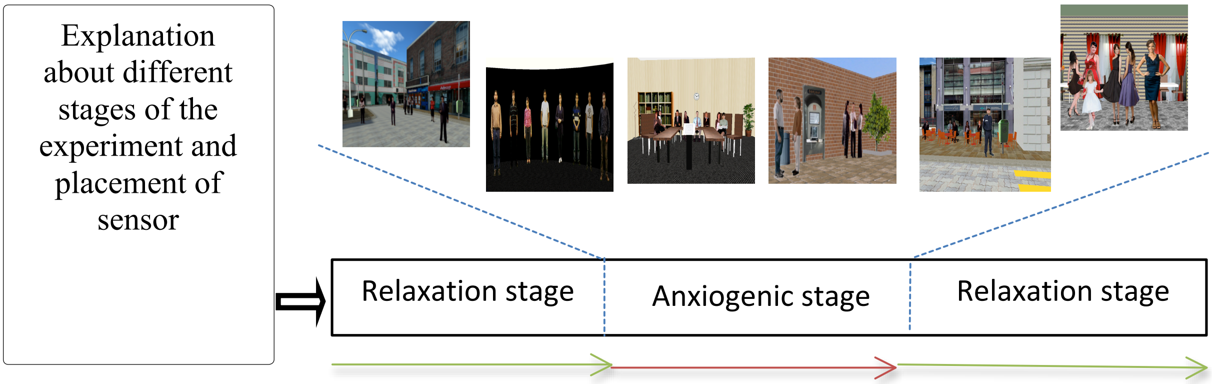

Fig. 4. The illustration of the experience protocol.

3. 4. Procedure

It is necessary to treat the BVP signal in a manner to keep the relevant information and to ensure valid and reliable data interpretation. The details of the signal processing and the selected parameters are explained in detail below.

A. Pretreatment

The BVP signal was acquired using the Procomp Infiniti. The sampling rate was 256 samples / second. In an effort to simplify the calculations, we performed a sub-sampling of the signal at 128 samples / second, and then we applied a low-pass filter 3rd order with a cutoff frequency equal to 2 Hz.

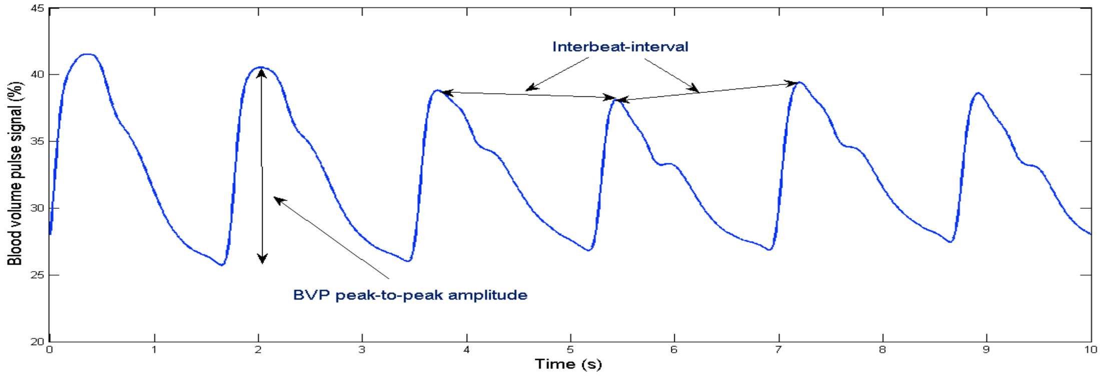

Fig. 5. Example of BVP signal.

After that, we normalized the signal using Equation 1, which put the signal between an interval [a, b] in our case, we chose the interval [0, 10].

$$Signal = \frac{(signal - min\_signal\ ).*(b-a)}{max\_signal - min\_signal} + a \quad (1)$$

B. Features selection

The most important step in this paper is the features selection for the anxiety recognition.

Several features can be calculated from the BVP signal in various areas of analysis: time, frequency and geometric. Some of them may vary depending on the emotional state.

Features	Interpretations
Time average (average amplitude)	Provides information on the activation of the sympathetic system [4] [6] [8].
Standard deviation	[6] [8]
First derivative	[6] [8]
First normalized derivative	[6] [8].
Second derivative	[6] [8].
Second normalized derivative	[6] [8].
Interbeat intervalle (IBI)	*IBI (i) = (max (i + 1) -max (i)) (i = 1: n)* Reflects the variability cardiac, this variability decreases during stress [14] [15].
BVP peak-to-peak amplitude variation (BAV)	*Variation amplitude peak to peak of BVP=(Max(i) – Min(i))* Provides information on the activation of the sympathetic system. If the amplitude decreases it means that the body is in a state of alert where activation of the sympathetic system [5] [14].
Power spectral density of very low frequencies (VLF)	*VLF of HR [0.03 Hz, 0.04 Hz];* They are supposed to reflect the activity of the sympathetic nervous system in particular, but also vascular tone loop baroreflex system, thermal regulation and activity of the renin-angiotensin system, thus

	increasing VLF is interpreted in this case as the increased activity of the sympathetic system. [4] [15].
Power spectral density of low frequencies (LF, Mayer waves)	*LF of HR [0.05 Hz, 0.15 Hz]* The lower frequency changes are not influenced by the RSA and can reveal the activity of baroreflex function (sympathetic and parasympathetic) [4] [16].
Power spectral density of high frequencies (HF, Traube-Hering waves)	*HF of RC [0.15 Hz, 0.4 Hz];* High frequencies reflect respiratory sinus arrhythmia (RSA) and the activity of the parasympathetic system [17].

Table. 1. Some Emotion-Relevant Features Extracted from BVP signal

Among these parameters we will take those who satisfy the following conditions:

- Satisfy the constraint of 4 seconds for recognition in the short term.
- Relevant to the recognition of anxiety.
- Their dynamic reflecting the influence of stress.
- Reducing the time required to process

C. Classification and validation

After the features selection, we have trained the statistical classifier SVM with the goal of learning the corresponding emotion. SVM is the most known form among kernel methods, inspired by statistical learning theory of Vladimir Vapnik [18]. This method has the following advantages:

- A low parameter number to set;
- A low samples number is sufficient for support vectors determination allowing discrimination between classes;
- Treatment of linear or nonlinear problems according to the kernel function.

The detection and measuring different emotional manifestations is imperfect, because on the one hand, the complexity of the data and on the other hand, the variability between individuals. To asses data we use the dynamics of selected parameters to filter the database and get a reliable model. The recognition process of anxiety is described below.

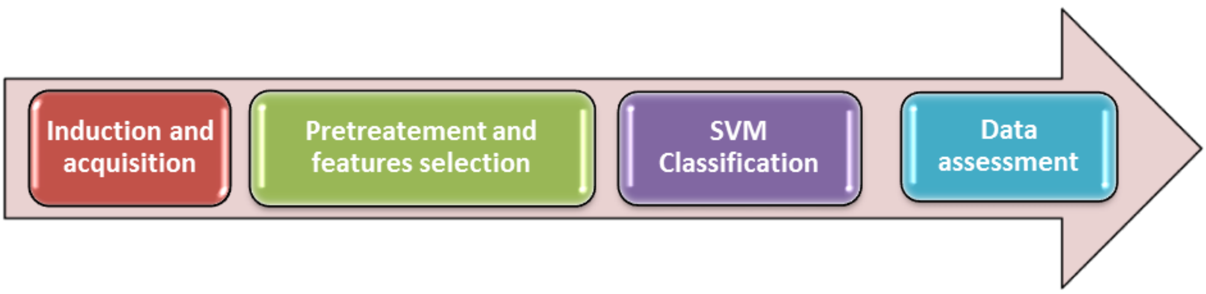

Fig. 6. The recognition process.

4. Results and Discussion

To build the model, we took the last twenty seconds of the relaxation stage for the rest class. For the anxiety class, we also took 20 seconds of the signal from the anxiety stage.

Then we calculated the three features listed below every four seconds. We assumed that they are important to recognize anxiety and sensitive to help us in the assessment of the database using their interpretations and dynamic (Table I) avoiding duplication of information:

- Feature 1: Moving average of IBI (MIBI) reflects the cardiac variability, this variability decreases during stress.
- Feature 2: Moving average of BVP peak-to-peak Amplitude Variation (MBAV) provides information on the activation of the sympathetic system and indicates the relative constriction of the blood vessel. If the amplitude decreases it means that the body is in a state of alert where activation of the sympathetic system.
- Feature 3: Power Spectral Density (PSD) estimation of [0.25Hz, 0.4Hz] reflects a portion of Respiratory Sinus Arrhythmia (RSA) and the activity of the parasympathetic system. This system decreases during stress.

Then, we form two independent bases, learning base (consisting of 4 subjects) and test database (other 3 subjects). We achieve an overall rate of 76% for both states.

The confusion matrix of these data shows that we have much more confusion in the rest class then in the anxiety class.

All subjects	Rest	Anxiety
Rest	85.71%	14.29%
Anxiety	5.72%	94.28%

Table. 2. Confusion matrix.

This begs a question: Are the subjects really quiet in the relaxation stage and anxious in the anxiogenic stage?

To answer this question, we examined the features dynamics for each model class by following steps.

This examination is done by the same steps for the confusion matrix i.e. the global base is the training set, from the latter, we group two sets: calm set and anxious set; each group is tested in the training set; such, misclassified samples are removed or placed in the other group, after checking membership in a given interval. This interval is determined by centering all the values of feature of each emotion on its maximum and minimum; we do the same for the two other features.

The result of this technique is based on the classifier and also on changing settings. Namely, when a sample is misclassified, we look at the evolution of the three parameters, and we decided to change her class or simply remove it from the set and put another sample of the signal.

This technique is based on the classifier, and also in features signification i.e. that when a sample is misclassified, we look at the evolution of the three parameters, so we decide to change class or simply removed it from the set and put another sample from the signal. We conclude that we are able to validate the model and make it more reliable for future applications

All subjects	Rest	Anxiety
Rest	100%	0%
Anxiety	0%	100%

Table. 3. New confusion matrix.

In this study, we were able to get 76% recognition rate of anxiety for independent databases (Rest and anxiety). This is achieved using a single physiological signal "Blood volume pulse, BVP". We were able to evaluate the model and improve the data obtained using a new technique based on the relevant features dynamics (Moving average IBI (MIBI), moving average of BVP peak-to-peak Amplitude Variation (MBAV), Power Spectral Density (PSD) estimation of [0.25Hz, 0.4Hz]).

These features are easy to calculate (the objective was to take the minimum number of features and have the maximum accuracy), and also satisfy the constraint of the short term recognition in (4s).

The performance in terms of classification accuracy is encouraging compared with other results in the approaches reported below (Table IV). Although, it is difficult to compare this work in terms of datasets, physiological signals used and involving different emotional classes. A direct comparison is not possible. Moreover, due to the fact that emotions can vary from person to person following situations and stimuli used.

Authors	Stimuli	Evaluation	Sensors	Emotions	Rate
Healey, Picard et al (2005) [6]	Rest, city driving in highway + video	Self-assessment	4 physiological signals and video	Three levels of stress	97%
Kim et al (2008) [7]	Music	Self-assessment	4 physiological signals	Different combinations of arousal and valence.	95%
Christos D. Katis et al (2010) [5]	International affective picture system (IAPS)	Self-assessment	4 physiological signals	Levels of apprehension	84.3%
This paper	Exposure to virtual reality	Dynamic features chosen	One physiological signal	Rest and anxiety	76%

Table. 4. Performance of emotion recognition methods reported about in the literature.

Conclusion and outlook

In this article, we discussed all the essential steps for the development of automatic anxiety recognition using a single physiological signal "blood volume pulse" to reduce discomfort caused by wearing multiple physiological sensors. We achieved 76% accuracy for subjects suffering by social anxiety disorder. The anxiety model is obtained through an emotion elicitation experiment based on the exposure to virtual reality. The features were chosen based on their relevance and ease of calculation and essentially their dynamics under stress. These dynamics help for data validation and made it more reliable.

Finally, we have developed an approach based on the use of virtual reality and a reliable model that could be a complement to the diagnosis and treatment of social phobia by cognitive behavioral therapy approach.

References

[1] H. Grillon, F. Riquier, B. Herbelin, and D. Thalmann, “Virtual Reality as Therapeutic Tool in the Confines of Social Anxiety Disorder Treatment,” *Int. J. Disabil. Hum. Dev.*, vol. 5, no. 3, pp. 243–250, 2006.

[2] M. M. North, S. M. North, and J. R. Coble, “Virtual Reality Therapy : An effective Treatment for the Fear of Public Speaking,” *Int. J. VIRTUAL Real.*, vol. 3, no. 2, pp. 1–7, 1998.

[3] A. P. Association, *Diagnostic and Statistical Manual of Mental Disorders DSM-V- Five Edition*, American Psychiatric Publishing., vol. 5. American Psychiatric Association, 2013.

[4] P. Petta, C. Pelachaud, and R. Cowie, *Emotion-Oriented Systems*, Springer Heidelberg Dordrecht London New York. 2011.

[5] C. D. Katsis, N. S. Katertsidis, and D. I. Fotiadis, “An integrated system based on physiological signals for the assessment of affective states in patients with anxiety disorders,” *Biomed. Signal Process. Control*, vol. 6, no. 3, pp. 261–268, juillet 2011.

[6] J. A. Healey and R. W. Picard, “Detecting Stress During Real-World Driving Tasks using Physiological Sensors,” *IEEE Trans. Intell. Transp. Syst.*, vol. 6, no. 2, pp. 156–166, Jun. 2005.

[7] J. Kim and E. Andre, “Emotion recognition based on physiological changes in music listening,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 12, pp. 2067–2083, 2008.

[8] C. Maaoui and A. Pruski, “Emotion Recognition through Physiological Signals for Human-Machine Communication,” in *Cutting Edge Robotics 2010*, Vedran Kordic, 2010, pp. 317–332.

[9] Byoung-Jun Park, Eun-Hye Jang, Myung-Ae Chung, and Sang-Hyeob Kim, “Design of prototype-based emotion recognizer using physiological signals,” *ETRI J.*, vol. 35, no. 5, pp. 869–879, Oct. 2013.

[10] R. G. Heimberg, K. J. Horner, H. R. Juster, S. A. Safren, E. J. Brown, F. R. Schneier, and M. R. Liebowitz, “Psychometric properties of the Liebowitz Social Anxiety Scale,” *Psychol. Med.*, vol. 29, no. 1, pp. 199–212, Jan. 1999.

[11] J. A. Coan and J. B, *Handbook of emotion elicitation and assessment*, vol. viii. New York, NY, US: Oxford University Press, 2007.

[12] Thought Technology Ltd, “ProComp Infiniti Hardware Manual,” Canada, Manual, 2011 2003.

[13] F. Abdat, “Reconnaissance automatique des émotions par données multimodales : expressions faciales et signaux physiologiques,” Université de Metz, France, 2010.

[14] E. Peper, R. Harvey, I.-M. Lin, H. Tylova, and D. Moss, “Is there more to blood volume pulse than heart rate variability respiratory sinus arrhythmia, and cardiorespiratory synchrony?,” *Biofeedback*, vol. 35, no. 2, pp. 54–61, 2007.

[15] L. IzsÓ and E. Láng, “Heart period variability as mental effort monitor in Human Computer Interaction,” *Behav. Inf. Technol.*, vol. 19, no. 4, pp. 297–306, 2000.

[16] K. H. Kim, S. W. Bang, and S. R. Kim, “Emotion recognition system using short-term monitoring of physiological signals,” *Med. Biol. Eng. Comput.*, vol. 42, no. 3, pp. 419–427, May 2004.

[17] M. Brennan, M. Palaniswami, and P. Kamen, “Poincaré plot interpretation using a physiological model of HRV based on a network of oscillators,” *Am. J. Physiol. Heart Circ. Physiol.*, vol. 283, no. 5, pp. H1873–1886, Nov. 2002.

[18] V. N. Vapnik, “An overview of statistical learning theory,” *IEEE Trans. Neural Netw.*, vol. 10, no. 5, pp. 988–999, 1999.