Using physiological measures for emotional assessment: a computer-aided tool for cognitive and behavioural therapy

B Herbelin[1], P Benzaki[2], F Riquier[3], O Renault[4] and D Thalmann[5]

[1,2,4,5] VRLab, Swiss Federal Institute of Technology (EPFL),
1015 Lausanne, SWITZERLAND

[3]STAH, Adult Psychiatry University Department (DUPA),
1008 Prilly, SWITZERLAND

[1]bruno.herbelin@epfl.ch, [2]patrick.benzaki@wanadoo.fr, [3]francoise.riquier@inst.hospvd.ch,
[4]olivier.renault@epfl.ch, [5]daniel.thalmann@epfl.ch

[1,2,4,5] vrlab.epfl.ch, [3]www.chuv.ch/psy/dupa.htm

ABSTRACT

In the context of Cognitive and Behavioural Therapies, the use of immersion technologies to replace classical exposure could improve the therapeutic process. As it is necessary to validate the efficiency of such a technique, both therapists and VR specialists need tools to monitor the impact of Virtual Reality Exposure on the patients. According to previous observations and experiments, it appears that an automatic evaluation of the Arousal and Valence components of affective reactions can provide significant information. The present study investigates a possible solution of Arousal and Valence computation from physiological measurements. Results show that the dimensional reduction is not statistically meaningful, but the correlations found encourage the investigation of this approach as a complement to cognitive and behavioural study of the patient.

1. INTRODUCTION

Cognitive and Behavioural Therapies (CBT) tend to help patients to cope with their anxiety (or phobias) by successive imaginary, mediated, or in-vivo exposures. The efficiency of this form of psychotherapy has been recognized since the early eighties. More recently, with the development of the immersion technologies, a variant of exposure has been developed; the Virtual Reality Exposure (VRE). Because this technique presents several advantages (flexibility, cost), researchers aim to determine if this kind of artificially mediated stimulation has the same impact on the patient as the classical in-vivo or imaginary exposures.

One approach to determine the efficiency of VRE is to develop these experiments on large cohorts and on different phobias in order to compare the results with the classical techniques; this would be a long process. However, by taking into account the actual knowledge in Virtual Reality and Affective Computing, we can already provide some strong theoretical arguments in favour VRE. The key factor is certainly the Sense of Presence (SoP); if we had means of proving that the SoP during a VRE is comparable with the one during an in-vivo exposure, then the efficiency of both methods would be comparable as well.

The problem when studying the Sense of Presence is to find a valuable means of evaluation. In effect, trying to give a single value to the SoP may even be a non-sense. What is concretely done is the analysis of quantitative and qualitative indices of the subject’s reactions during an immersion experience: cognitive response, overt behaviour and emotional states. This is also what psychologists do when they evaluate their patients all along the therapeutic process. Actually, the need is not to replace them, but to provide them with an automatic ‘sensor’ of the patient’s state. Toward that end, studies on Affective Computing propose several means and techniques to perform a transformation of human factors into computable data. Among them, the Arousal/Valence model retained our attention: it covers a large spectrum of emotions, it is widely used in psychology, and it has already been related to the Sense of Presence.

Our working hypothesis for studying the efficiency of VRE is the following; the observation of the patient’s reactions with Arousal and Valence indices only can provide enough information on his sensitivity to the virtual content. Aside from the possible discussions on this hypothesis, the objective of this paper is to show that we can obtain a correct evaluation of Arousal and Valence with physiological measures exclusively. In order to build this tool, we have to deal with several constraints: dependency on an individual, difficulty to induce emotions, choice of physiological signals, selection of computational models, evaluation of the reliability, etc. As a first approach, we designed an emotion induction protocol involving one actor over several sessions during which we measured five different physiological signals. Statistical analysis has then been performed to correlate these data with the emotional classes, the cognitive evaluation of Arousal and Valence, and their expected values.

2. OVERVIEW AND OVERLAYS OF CBT AND VR

2.1 Sense of Presence in Virtual Reality Exposure

Just as Human-Computer Interaction, VR is a domain of computer science which is highly dependant on the understanding of human behaviours. The Sense of Presence during an immersion experience is commonly defined as the sense of 'being there' (Slater 1994) or as the 'illusion of non-mediation' (Lombard and Ditton 1997). Regardless of its definition, Presence is generally evaluated with questionnaires. However, Usoh et al (2000) have shown that there is no significant difference between the answers to Presence questionnaires of subjects having a real experience and those having a virtual one. Moreover, in the context of a therapy using VRE, the answers to a questionnaire cannot distinguish the part related to the patient's troubles to the one related to his presence in the virtual environment. For instance, the experiments conducted by Pertaub et al (2002) have shown that, for social phobic subjects, the feeling of being present in front of a virtual assembly was highly influenced by the attitude of the virtual actors. As a result, the comparison between the SoP during in-vivo and virtual exposures cannot be done in this classical way.

On the other hand, observations of the subject's overt behaviours, although very useful for therapists, are hard to conduct and to quantify. In practice, only monitoring the performance in the achievement of a task can provide numerical estimations (e.g. navigation and orientation in space as in (Prothero et al, 1995)). But this will not exactly indicate how much the subject was impressed by his Presence in the virtual environment.

Finally, despite the difficulty to interpret the data, physiological measurements have at least the advantage of being universal and objective. Dillon et al (2000) already proposed to use the physiological measurement of Arousal to indicate the presence during immersion. Wiederhold et al (2003) also concluded that "percentage change in heart rate and skin resistance had a high level of correlation with Presence, degree of realism, and immersiveness". The present study does not pretend to directly link physiological measures to the Sense of Presence, but these arguments encouraged our investigations about the evaluation of low-level human reactions.

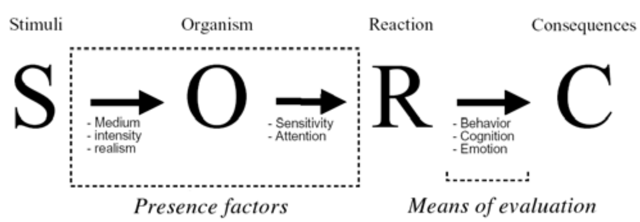


Figure 1. *The S-O-R chain of human behaviour*

2.2 Previous Experiments in VRE

Our collaboration between therapists and computer scientists started some years ago with the ambition of developing an immersive platform for the treatment of Social Anxiety Disorder. In a preliminary study (Herbelin, Riquier et al, 2002), we started to evaluate the stress generated by the exposure to a virtual assembly made of eyes looking at the subject. The subjective stress evaluation (cognitive) and the physiological measures (pulse and Electro-Dermal Activity) appeared to be in strong correlation with the expected reaction previously computed on the Liebowitz scale (a self-assessment questionnaire to appreciate the degree of anxiety of the subject in many usual social situations). Afterwards, we studied in more details the interconnections between the stress generated and the Sense of Presence during this immersion (Herbelin et al, 2002). According to the S-O-R model of human behaviour (figure 1) commonly accepted by the psychiatric community, we started to emphasise the importance of the observation of the subjects' reactions for both domains and pointed out the advantages of developing emotional assessment tools:

- Provide therapists with an easy-to-use computer-aided tool: following the patients' emotional reactions during the exposure sessions can improve the management of the therapy efficiency.

- Give to VR specialists a way to compare the efficiency of various immersion protocols: thanks to emotional assessment, the SoP could be confirmed or denied objectively.

Figure 2. *Social Anxiety exposure environment for public speaking training: the virtual environment (left) and the wide-screen immersion (right).*

We recently developed a realistic simulation to train social phobic students to present their oral exams: a virtual assembly with typical listeners' attitudes was shown on a wide screen (figure 2) or into a head-mounted display. During the therapy of two students, we focused on the patients' behaviours. Special attention was paid to the gaze of the subjects who were trained to observe the audience and to hold the gaze of the virtual humans. The support of VRE was globally considered as beneficial to the therapy (i.e. one passed his exams), though from a scientific point of view, we didn't obtain enough valuable elements to comfort this conclusion and to analyse more precisely the patients' reactions. This lead us to study the possibilities offered by affective computing systems.

2.3 Affective Computing

Picard (1997) has defined affective computing as "computing that relates to, arises from, or deliberately influence emotions". This covers the examination of media content – the stimuli – as well as the analysis of affective states – the reaction. The fully computational extraction of affective content of videos made by Hanjalic and Xu (2001) illustrates perfectly the first case. In the second case, the use of physiological measurements is often chosen to represent internal affective states. For instance, Wang et al (2004) correlate the galvanic skin response to the intensity of the emotion. Moreover, the difference in the objective notwithstanding, affective states could be represented on an Arousal/Valence graph in both cases.

The simplicity if this model is indeed very attractive. As shown in figure 3, a large scope of emotions can be labelled with only a Valence (unpleasant or "negative" to pleasant or "positive") and an Arousal (drowsy or peaceful to exited or alert). However, this apparent simplicity is extremely subjective to human beings, and the computation of those indices hides a great complexity that Hanjalic and Wang overcome by selecting 'arbitrary' digital features. To avoid this, other researchers (Healey and Picard 1998; Rani et al 2003) designed protocols to learn and optimise the correlations between physiological data and affective states. Whatever the algorithm (statistical or fuzzy respectively), the principle is the same: record various physiological signals, compute several parameters, and operate the classification.

3. METHODOLOGY AND EXPERIMENTS

3.1 Principle

If isolated from the CBT-VRE context, the experiments we conducted simply consisted in recording the physiological signals on a person trying to self-induce five classes of emotions situated at the extremes of the theoretical Arousal-Valence model. In addition, the subject estimated his subjective Arousal and Valence each time. We then tried to find the best correlations between several features derived from the physiological measurements and the theoretical/estimated Arousal and Valence.

3.2 Protocol

There is no ideal way to induce specific emotions and to ensure the person has felt 'exactly' the expected emotion. Anyway, one of the most widely used methods to induce an experimental mood is the Velten (1968) Mood Induction Procedure (the subject is instructed to try to feel the mood expressed in a card). In a similar way, and in order to gain advantage from the ability of professional actors to deeply feel the emotions they are playing, Healey and Picard (1998) asked an actress to induce an emotion by self motivation only. We did the same and asked a professional actor to perform all the experiments with self induction of emotions.

©2004 ICDVRAT/University of Reading, UK; ISBN 07 049 11 44 2

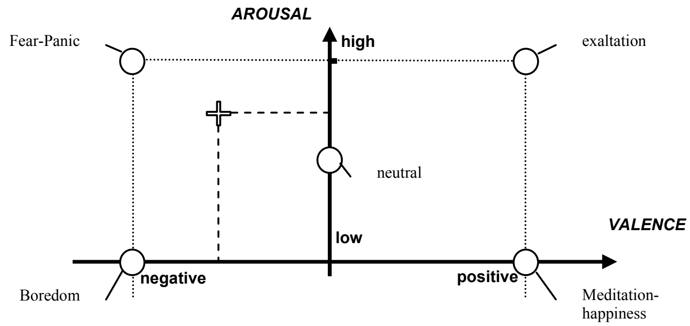


Figure 3. *The affective state in the 2D space Arousal/Valence*

Moreover, by referring to a single person, we "maximize the chances of getting a consistent interpretation for each emotion" (Picard 2001).

We used the Physio-Recorder™ from Vienna Test System Corp. to measure five physiological signals: skin conductivity level (the Electro-Dermal Activity is given in micro-Siemens), frontal *electromyography* (*venter frontalis* EMG, in micro-Volts), skin temperature (Celsius degrees), breathing frequency (abdominal and thoracic amplitude together, in cm), and pulse frequency (Heart Rate, measured with a photoplethysmo sensor strapped to a finger, expressed in beats-per-minute).

Each session starts with a relaxation phase requested by the actor and for sensors to reach stable assessment values (e.g. 10 minutes for surface temperature). Then, still lying down, the actor decides to start the inductions phases by acting on a guiding software: this little application displays the current emotion to induce and times two minutes before beeping. Then, a subjective Arousal and Valence evaluation screen appears and proposes to select values on a 1-9 scale associated with the Self Assessment Manikin from Bradley and Lang (1994) (see figure 4). One session is composed of five major emotions: "NO EMOTION / NEUTRAL", "FEAR / PANIC", "BOREDOM", "HAPPINESS / MEDITATION", and "EXHALTATION". For each of those, the timing and the subjective Arousal and Valence values are stored.

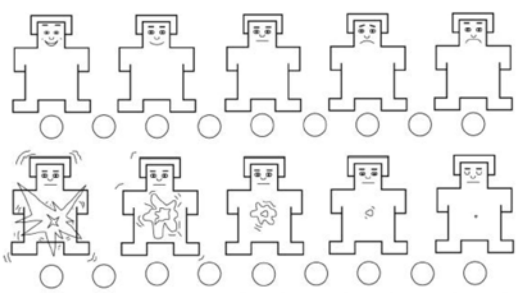


Figure 4. *Iconographic SAM rating: Valence (up) and Arousal (down) (Morris 1995).*

3.3 Data Collection and Features Extraction

During the four months of experiments, we regularly made recording sessions of approximately thirty minutes (including the relaxation phase). Due to sensor failures, the first recordings were considered as a training period for the actor, and we finally obtained ten full sessions.

The database of physiological signals is chopped according to the time sheet and regrouped by emotions (ten times five records of two minutes each). For each record X we compute the six parameters proposed by Picard (2001) on the N values (120 seconds at 10Hz gives N=1200): the mean of the raw signals (Eq.1), the standard deviation of the raw signals (Eq.2), the mean of the absolute values of the first differences of the raw signals (Eq.3), the mean of the absolute values of the first differences of the normalized signals (Eq.4), the mean of the absolute values of the second differences of the raw signals (Eq.5) and the mean of the absolute values of the second differences of the normalized signals (Eq.6).

$$m_X = \frac{1}{N} \sum_{n=1}^{N} X_n \tag{1}$$

$$s_X = \sqrt{\frac{1}{(N-1)} \sum_{n=1}^{N} (X_n - m_X)^2} \tag{2}$$

$$d_X = \frac{1}{(N-1)} \sum_{n=1}^{N-1} |X_{n+1} - X_n| \tag{3}$$

$$\tilde{d}_X = \frac{1}{(N-1)} \sum_{n=1}^{N-1} |\tilde{X}_{n+1} - \tilde{X}_n| = \frac{d_X}{s_X} \tag{4}$$

$$e_X = \frac{1}{(N-2)} \sum_{n=1}^{N-2} |X_{n+2} - X_n| \tag{5}$$

$$\tilde{e}_X = \frac{1}{(N-2)} \sum_{n=1}^{N-2} |\tilde{X}_{n+2} - \tilde{X}_n| = \frac{e_X}{s_X} \tag{6}$$

3.4 Feature selection and evaluation

Among the 30 features collected (6 for 5 signals), we need to extract the most representative. We conducted two approaches in parallel. The first consists in determining if computed features can be correlated to the Arousal and Valence as suggested in literature. A simple Pearson correlation was computed between features and self-measured Arousal/Valence over the 50 records in order to identify the most representatives.

The second approach consists in computing the Discriminant Function Analysis as commonly done when dealing with physiological signals (Nasoz et al, 2003; Christie et al, 2004). Since we want to isolate the two that fit best to the Arousal and Valence, we chose the two-group discriminant analysis, also called *Fisher linear discriminant analysis* (as in Vyzas (1999)). It allows for reducing dimensionality by finding a linear projection of the entry data to a space of fewer dimensions where the classes are hopefully well separated. According to the dimensions of our learning feature matrix (fewer training points per class than the number of total features; matrix is rank deficient), we had to apply a variation of the traditional Fisher projection algorithm by first projecting the data matrix into an ortho-normal basis [N x N] (where N is the number of training points) and produce a matrix of full rank. We then tested this projection considering three kinds of class label: 5-class-emotion, 3-class-arousal and 3-class valence. Then we focused on a resulting discrimination of the physiological features mapped on Arousal and Valence. Evaluation of the discrimination has been carried out with K-nearest-neighbours classification algorithm and the leave-one-out method has been chosen for cross validation. Here is the simplified procedure applied to each data point: (i) the data point to be classified is excluded from the original data set and the remaining data considered as the training set, (ii) the subsequent fisher projection matrix is computed from the training set and both training data and testing point are projected down to the two best eigenvectors of the Fisher projection matrix, (iii) the data point is then classified according to the KNN principle based on the Euclidian common measure distance, (iv) finally confusion matrices are calculated for the various classifications considered.

4. RESULTS

4.1 Combination of best features

The three best correlations between features and both arousal and valence were chosen and combined linearly (to keep the sign of the correlation) to compute potential estimators for Arousal (Eq.7) and Valence (Eq.8).

$$A = \frac{\alpha_A . \widetilde{d}_{SCL} + \beta_A . \widetilde{e}_{SCL} + \chi_A . s_{PULSE}}{\alpha_A + \beta_A + \chi_A} \quad \text{where} \quad \alpha_A < 0, \beta_A < 0, \chi_A > 0 \tag{7}$$

$$V = \frac{\alpha_V . \widetilde{e}_{PUA} + \beta_V . d_{PULSE} + \chi_V . e_{RESP}}{\alpha_V + \beta_V + \chi_V} \quad \text{where} \quad \alpha_V < 0, \beta_V > 0, \chi_V > 0 \tag{8}$$

Concerning the estimation of the intensity of the emotion, our results are compliant with numerous studies that suggest that SCL and ECG signals are the most involved (indeed, correlations are around 50%). We suggest that the standard deviation of the heart rate is significant for the evaluation of the intensity of emotion (i.e. if your heart beat faster than usual, you are in a more intense affect), as are both degrees (n+1 and n+2) of variations of the skin conductivity level (i.e. Arousal is inversely proportional to the decrease of stress). Concerning the estimation of the valence of the emotion, very few papers propose an estimator. Our best correlations were only around 25% but were coherent with what Simons et al (1999) suggest: "The relationship between stimulus valence and heart rate was linear […] with the greatest deceleration associated with negative images and the least with the positive images". We also raised the probable influence of the Valence on the breathing variations. An example of A/V plot is given in figure 5: hopefully, the differences in Arousal are significant and we can distinguish positive and negative emotions. However, we observed various inconsistencies in the other sessions: an emotion is misplaced, the linear order of Valence is not respected, etc. This clearly shows the limitation of this approach and confirms the weakness of the correlations.

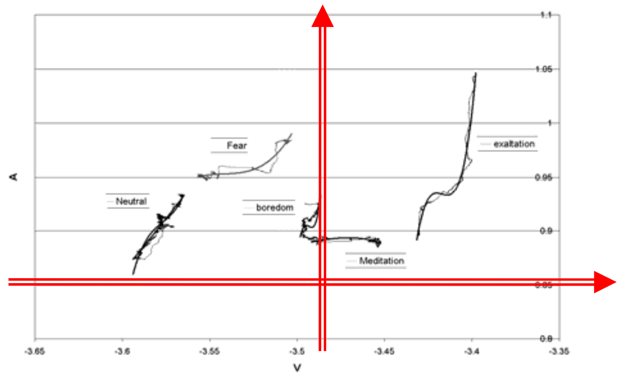
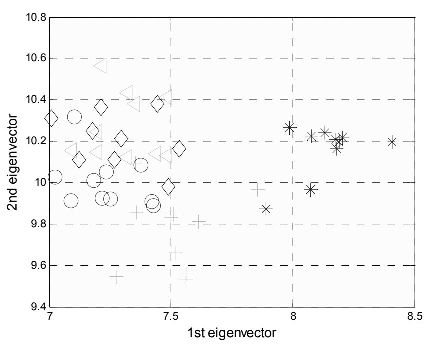


Figure 5. *Affect curves plotted on the V/A space: a possible interpretation of these factors according to the Arousal and Valence theoretical axis (with* $\alpha_A = -2, \beta_A = -2, \chi_A 0.5$, $\alpha_V = -3, \beta_V = 3, \chi_V = 1$).

4.2 Classifications

Results of the various classification protocols have very low classification rates. For example, when considering the five emotional classes (figure 6), only 24% of all the decisions of the algorithm lead to their original label. Neutral and Fear are best identified by our algorithm, although with weak success rates respectively 60% and 30%. Other classes are largely less than a random guess.



		KNN classification					
		Neutral	Fear	Boredom	Meditation	Exhaltation	**Total**
original class	Neutral	**6**	2	0	1	1	**10**
	Fear	1	**3**	1	1	4	**10**
	Boredom	1	2	**2**	1	4	**10**
	Meditation	2	1	5	**1**	1	**10**
	Exhaltation	2	3	1	4	**0**	**10**
	Total	**12**	**11**	**9**	**8**	**10**	**50**

		KNN classification (%)					
		Neutral	Fear	Boredom	Meditation	Exhaltation	**Total**
original class	Neutral	**60%**	20%	0%	10%	10%	**100%**
	Fear	10%	**30%**	10%	10%	40%	**100%**
	Boredom	10%	20%	**20%**	10%	40%	**100%**
	Meditation	20%	10%	50%	**10%**	10%	**100%**
	Exhaltation	20%	30%	10%	40%	**0%**	**100%**

Figure 6. *Fisher discrimination of 5 emotions and the confusion matrix (boredom [circle], meditation[triangle], fear [cross], neutral [star] and exaltation [diamond]).*

We have also compared two different classifications of the learning data: self-measured Arousal and Valence and theoretical Arousal and Valence. It appeared that correlations between self-measured and theoretical Arousal is already very low (-0.1310) and better for the respective Valence correlation (0.8047). We may conclude that it was easier for the actor to assess the hedonic valence component of his emotion.

When considering Arousal and Valence successively as three modal classes (low, medium and high values), we obtained better results, than for the five emotion classes (figure 7). The very low number of data in the ‘very low’ and ‘medium’ categories of self-measured arousal make impossible any kind of interpretation of this part of the confusion matrix. Instead, the relatively high 85% of correct classification of ‘very high’ arousal may results from a subconscious over-evaluation of the real intensity of the felt physiological states. The valence component, as confirmed by the before mentioned correlation coefficients, seems to be better evaluated by the actor (compared to the theoretical model) and this can explains why their respective correct classification rate are very much comparable (39% and 45%).

However, as for the previous numerical approach, the classification could be used as a validation or as a visual monitor of the changes in the affective state.

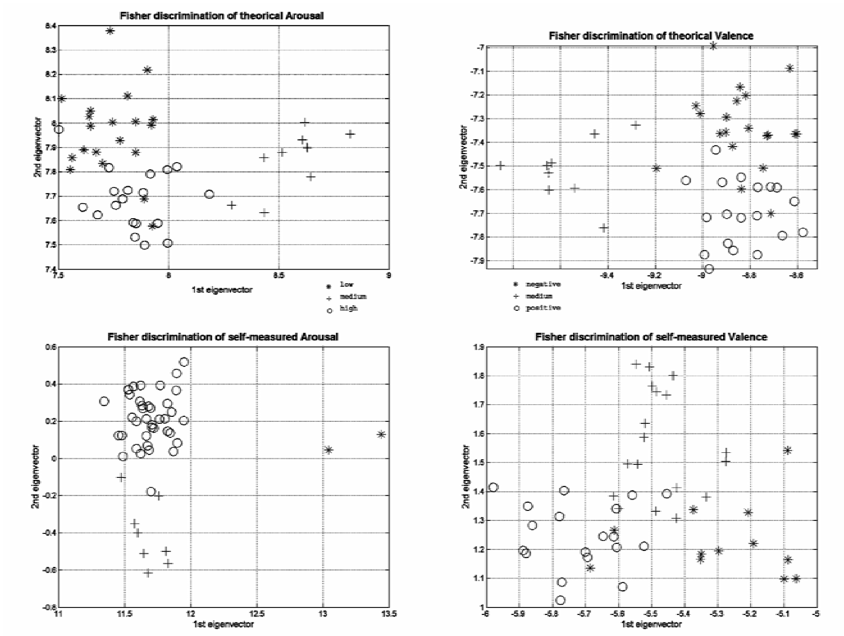


Figure 7. *Fisher's discrimination of Arousal and Valence: comparison between theoretical and self-reported classes of Arousal and Valence.*

5. DISCUSSIONS AND CONCLUSIONS

Using our feature selections and classifications, we didn't manage to extrapolate statistically meaningful Arousal and Valence from our data. First, the learning set was too small: this confirms that, in the context of therapy, patient should be studied for a very long time. Second, the projection of the physiological data into two dimensions seems too 'lossy'. As shown in the results, once the physiological features are projected on the A/V graph, it is not possible to deduce the emotional state. The classification of Arousal and Valence with two eigenvalues each would suggest that the affective state could be better represented in four dimensions.

However, additional parameters could be computed specifically for the most significant physiological signals (like the Heart Rate Variability (McCraty 2002)) and other signals could also be measured (e.g. electroencephalogram). In order to enhance the quality of the recognition, the data set has to be also trustworthy. With self-induction protocol, we can't objectively verify the affective state of the subject. The correlation with the content of media stimulation could help to establish stronger reference points.

Results are non-conclusive if the method is used to identify the emotion in an unknown context. However, the systems we built are sufficient to correlate reactions of the patient with known stimuli. They could be used to assess the patient's response to visual or auditory events during a Virtual Reality Exposure. A biofeedback loop could then be established between the patient and the virtual content. We plan to use the evaluated/recognised intensity of the emotion as a motivating factor for the behaviour of the virtual humans. In the context of social phobia therapy, the attitude of the assembly could, for example, be adapted to the stress of the subject.

Finally, we think that physiological measures have to be combined with cognitive and behavioural evaluations of the subject's reactions. Our approach is driven by the close collaboration with therapists: we try to create what they imagine as interesting tool for their work. This physiological Arousal/Valence assessment tool is an example. Another is the eye tracking system we are currently testing to have a trace of the patients' gaze avoidance behaviour. All together, they could provide therapists with the ability to monitor their patients from multiple points of view: emotional, but also cognitive and behavioural.

Acknowledgements: Authors would like to thank Stéphanie Noverraz for the proof reading of the manuscript.

6. REFERENCES

M M Bradley and P J Lang (1994), Measuring emotions: the Self-Assessment Manikin and the Semantic Differential, J. Behav. Ther. Exp. Psychiatry, **25**:49-59.

C Dillon, E Keogh, J Freeman, and J Davidoff (2000), Aroused and Immersed: The Psychophysiology of Presence, In *Proceedings of Presence 2000 - the 3rd International Workshop on Presence*, 27 March 2000, Technical University of Delft, Netherlands.

A Hanjalic and L Q Xu (2001), User-oriented Affective Video Content Analysis, In *Proceedings of IEEE Workshop on Content-based Access of Image and Video Libraries (CBAIVL'01)*, Kauai, Hawaii, December 2001.

J Healey and R W Picard (1998), Digital Processing of Affective Signals, *Proceeding of the ICASSP'98,* MIT Technical Report N°444.

B Herbelin, F Vexo and D Thalmann (2002), Sense of Presence in Virtual Reality Exposures Therapy, In Proceedings of the 1st International Workshop on Virtual Reality Rehabilitation, *Lausanne, Switzerland, November 2002.*

B Herbelin, F Riquier, F Vexo and D Thalmann (2002), Virtual Reality in Cognitive Behavioral Therapy : a preliminary study on Social Anxiety Disorder, In Proceedings of the 8th International Conference on Virtual Systems and Multimedia*, Gyeongju, Korea, September 2002.*

M Lombard and T Ditton (1997), At the Heart of It All:The Concept of Presence, Journal of Computer-Mediated Communication, **3**(*2*).

R McCraty (2002), Heart Rhythm Coherence-An Emerging Area of Biofeedback, *Biofeedback*, spring 2002,

J D Morris (1995), SAM:The Self-Assessment Manikin, An Efficient Cross-Cultural Measurement of Emotional Response,(Observations), Journal of Advertising Research, November 01, 1995.

F Nasoz, C L Lisetti, K Alvarez, N Finelstein (2003), Emotional Recognition from Physiological Signals for User Modeling of Affect, In *Proceedings of the 3rd Workshop on Affective and Attitude User Modeling,* Pittsburgh, PA, USA, June 2003.

D P Pertaub, M Slater, and C Barker (2002), An experiment on public speaking anxiety in response to three different types of virtual audience, *PRESENCE - Teleoperators and Virtual Environments*, **11**(*1*):68-78.

R W Picard (1997) *Affective Computing* The MIT Press, Cambridge, MA.

R W Picard, E Vyzas and J Healey (2001), Towards Machine Emotional Intelligence: Analysis of Affective Physiological State, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **23**(*10*).

J Prothero, D Parker, T A Furness and M Wells (1995), Towards a Robust, Quantitative Measure of Presence, In *Proceedings of Conference on Experimental Analysis and Measurement of Situational Awareness,* Datona Beach, FL, 359-366.

P Rani, N Sarkar, C Smith (2003), Affect-Sensitive Human-Robot Cooperation, Theory and Experiments, In *Proceedings of the IEEE International Conference on Robotics and Automation*, Taiwan, September 2003, 2382-238.

M Slater and M Usoh (1994), Representation systems, perceptual position, and presence in immersive virtual environments, *PRESENCE: Teleoperators and Virtual Environments*, **2**(*3*):221-233.

M Usoh, E Catena, S Arman, and M Slater, Using Presence Questionnaires in Reality, *PRESENCE: Teleoperators and Virtual Environments,* **9**:497-503.

E Velten (1968), A laboratory task for induction of mood states, *Behavior Research and Therapy,* ***6:***473-482.

E Vyzas (1999), Recognition of Emotional and Cognitive States Using Physiological Data, *Master of Science diploma project,* Department of Mechanical Engineering, MIT.

H Wang, H Prendinger and T Igarashi (2004), Communicating Emotions in Online Chat Using Physiological Sensors and Animated Text, In *Proceedings of the 1st international conference for human-computer interaction*, Vienna, Austria, 1171-1174.

B K Wiederhold, D P Jang, M Kaneda, I Cabral, Y Lurie, T May, I Y Kim, M D Wiederhold and S I Kim (2003), An investigation into physiological responses in virtual environments: an objective measurement of presence, *Towards CyberPsychology: Mind, Cognitions and Society in the Internet Age*, 175-183, Giuseppe Riva & Carlo Galimberti (Eds.), Amsterdam IOS Press.

R F Simons, B H Detenber, T M Roedema and J E Reiss (1999), Emotion-Processing in Three Systems: The Medium and the Message, Psychophysiology, **36**, 619-627.