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Using physiological measures for emotional assessment: A computer-aided tool for cognitive and behavioral therapy

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Abstract: In the context of cognitive and behavioral therapies, the use of immersion technologies to replace classical exposure often improves the therapeutic process. As validating the efficiency of such a technique is necessary, both therapists and VR specialists need tools to monitor the impact of virtual reality exposure on patients. The present study investigates two possible solutions to assess affective states from physiological measurements—automatic evaluation of the arousal and valence components of affective reactions and classification into classes of emotions. The results show that these dimensional reductions of physiological data could not lead statistically to a fine identification of affective states statistically speaking, but the correlations we found could be used in a biofeedback loop with the virtual environment or in combination with other cognitive and behavioral assessments tools.

Keywords: Cognitive and behavioral therapy, arousal, valence, physiological measures, emotions, presence

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INTRODUCTION

Cognitive and Behavioral Therapies (CBT) tend to help patients 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 1980s. More recently, with the development of immersion technologies, a variant of exposure has been developed—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 classic 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 to compare the results with the classic techniques; this comparison 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 favor of VRE. The key factor is certainly the Sense of Presence (SoP). If we were to have 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 SoP is finding 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 behavior, and emotional states. This is what psychologists do when they evaluate their patients all along the therapeutic process. Actually, the need is not to replace them but rather 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. This model covers a large spectrum of emotions, is widely used in psychology, and has already been related to the SoP.

Our working hypothesis for studying the efficiency of VRE is the following: the observation of the patient's reactions with Arousal and Valence indices can provide only 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. To build this tool, we have to deal with several constraints: dependency on an individual, difficulty to induce emotions, the choice of physiological signals, the selection of computational models, and the evaluation of the reliability, to name a few.

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 was performed to correlate the data with the emotional classes, the cognitive evaluation of Arousal and Valence, and their expected values.

OVERVIEW AND OVERLAYS OF CBT AND VR

Sense of presence in Virtual Reality Exposure

Just like Human-Computer Interaction, VR is a domain of computer science that is highly dependant on the understanding of human behaviors. The SoP during an immersion experience is commonly defined as the sense of 'being there' (1) or as the 'illusion of non-mediation' (2). Regardless of its definition, Presence is generally evaluated with questionnaires. However, Usoh et al (3) 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 (4) 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. Likewise, Baños et al (5) present a study whose results suggest that both immersion and affective content have an impact on presence, and that immersion is more relevant for non-emotional environments than for emotional ones. 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 behaviors, 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 like navigation and orientation in space as in (6). However, this approach 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 at least have the advantage of being universal and objective. Dillon et al (7) already proposed using the physiological measurement of Arousal to indicate the presence during immersion. Wiederhold et al (8) also concluded that the "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 link physiological measures directly to the SoP, but these arguments encouraged our investigations about the evaluation of low-level human reactions.

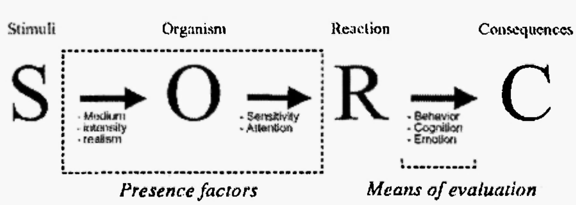


Fig. 1: The S-O-R chain of human behavior

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 (9), 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 Social Anxiety Scale—a self-assessment questionnaire to appreciate the degree of anxiety of the subject in many usual social situations created by Liebowitz (10). Afterward, we studied in more detail the interconnections between the stress generated and the SoP during this immersion (11). According to the S-O-R model of human behavior (Figure 1) commonly accepted by the psychiatric community, we started to emphasize 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.
- Provide VR specialists with a way to compare the efficiency of various immersion protocols: thanks to emotional assessment, the SoP could be confirmed or denied objectively.

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' behaviors. 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 analyze more precisely the patients' reactions. This led us to study the possibilities offered by affective computing systems.

Affective computing

Picard (12) 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 (13) 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 (14)

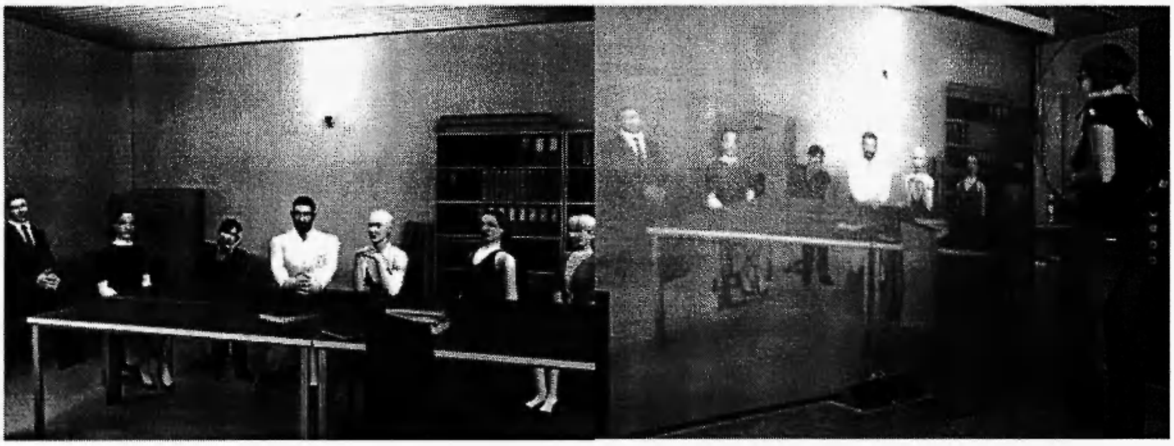


Fig 2: Social Anxiety exposure environment for public speaking training: the virtual environment (left) and the wide-screen immersion (right)

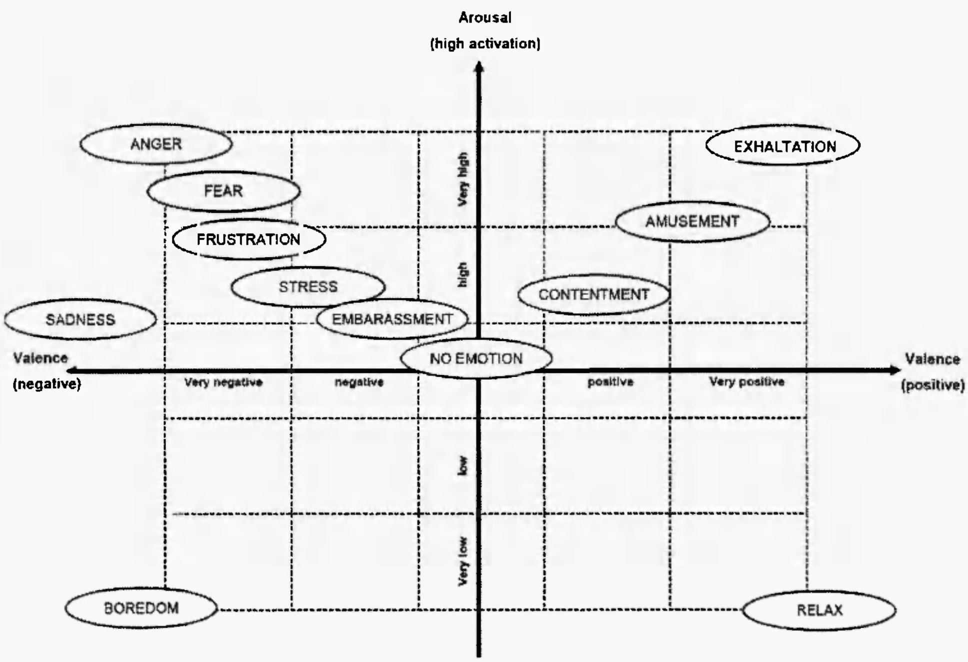


Fig. 3: *The affective state in the 2D space Arousal/Valence*

correlate the galvanic skin response to the intensity of the emotion and Hazlett (15) demonstrates that positive valence can be measured with physiological measures (EMG, electromyography). 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 (7).

The simplicity if this model is indeed very attractive. As shown in Figure 3, a large scope of emotions can be labeled 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 (16-18) designed protocols to learn and optimize the correlations between physiological data and affective states. Whatever the algorithm used (statistical or fuzzy, respectively), the principle of experimental affective computing remains the same: record various physiological signals, compute several parameters, and operate a classification/recognition.

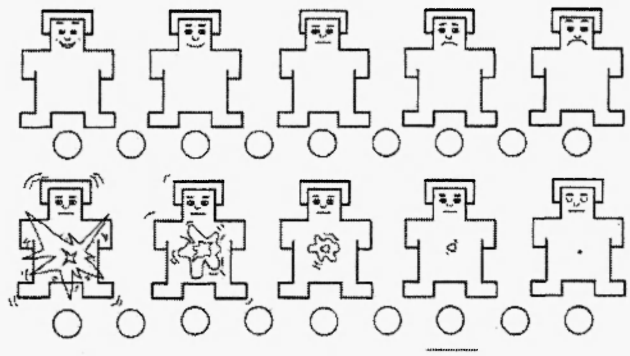


Fig. 4: Iconographic SAM rating: Valence (top) and Arousal (bottom) (22)

METHODOLOGY AND EXPERIMENTS

Principle

If isolated from the CBT-VRE context, the experiments we conducted simply consisted of 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 to provide a reference point. We then tried to find the best correlations between several features derived from the physiological measurements and the theoretical or estimated arousal and valence.

Protocol

No ideal way exists to induce specific emotions and to ensure the person has actually felt the expected emotion. However, the Velten (19) Mood Induction Procedure is still widely used to induce different moods experimentally. The subject is simply instructed to try to feel the mood expressed on a card, and the experiment relies on his capability to reproduce it with memories. To take advantage of the ability of professional actors to feel deep emotions when playing a role, Healey and Picard (16) chose an actress for her experiments with emotions. We therefore similarly asked a professional actor to perform our experiments. Moreover, by referring to a single person, we "maximize the chances of getting a consistent interpretation for each emotion" (20).

During several self-induction sessions, the actor was asked to concentrate sequentially on five distinctive affective states, labeled according to basic emotions: "neutral/no emotion" (low arousal, neutral valence), "fear/panic" (high negative), "boredom" (low negative), "joy/meditation" (low positive), "exaltation" (high positive). Simultaneously, a Physio-Recorder from the Vienna Test System Corporation was used to measure six physiological signals:

- SCL: skin conductance level (electro-dermal activity, in micro-Siemens, µS),
- HR and PVA: heart rate and pulse volume amplitude (measured with a photoplethysmo sensor strapped to a finger, respectively expressed in beats-per-minute and in percents of volume change),
- EMG: frontal electromyography (venter frontalis EMG, in micro-Volts, µV),
- BF: breathing frequency (abdominal and thoracic respiration together, in resp-per-minute),
- ST: skin surface temperature (on non-dominant hand finger, in Celsius degrees).

Each session started with a relaxation phase requested by the actor and for sensors to reach stable assessment values (e.g. 10 minutes for skin temperature). Then, lying down, the actor started the induction procedure by acting on a guiding software. This application displayed the current emotion to be induced and timed 2 minutes before beeping. Then, a subjective arousal and valence evaluation screen proposed to select values on a 1-9 scale associated with the Self Assessment Manikin from Bradley & Lang (21); Morris (22) (Figure 4). For each emotion, the timing and the subjective arousal and valence were stored.

Data collection and features extraction

During the 4 months of experiments, we regularly made recording sessions of approximately 30 minutes (including the relaxation phase). Due to sensor failures, the first recordings were considered a training period for the actor, and we finally obtained ten full sessions.

The physiological signals contained in the database were split according to the time sheet and regrouped by emotions (ten times five records of 2 minutes each). For each record X, we computed the six parameters proposed by Picard (20) on the N = 1200 values (120 seconds at 10Hz): 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).

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

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

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

$$\tilde{d}_x = \frac{1}{(N-1)}\sum_{n=1}^{N-1}|\tilde{X}_{n+1} - \tilde{X}_n| = \frac{d_x}{s_x} \tag{4}$$

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

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

Table 1. Features selected for their best Pearson correlation with arousal and valence.

Valence	*Arousal*	Parameter
d_{HR} r=.225, P<.1	s_{HR} r=.424, P<.005	Heart Rate
e_{PVA} r=-.263, P<.05	d_{PVA} r=.371, P<.01	Pulse Volume Amplitude
-	$\tilde{d}_{SLC}$ r=.491, P<.001	Skin Conductance Level
-	$\tilde{d}_{EMG}$ r=.421, P<.005	Electromyography
-	m_{ST} r=.389, P<.01	Skin Temperature
e_{BF} r=.242, P<.1	-	Breathing Frequency

RESULTS

Among the 36 features collected (6 for each signal) over 50 records (10 sessions of 5 emotions), we had to extract the most representative and a way to exploit them. We conducted two approaches in parallel.

Best feature selection for arousal and valence

The first approach consisted in determining if numerical features could be correlated to arousal and valence as suggested in the literature. A simple Pearson correlation was computed between every feature and self-estimated arousal/valence in order to identify the most representative. Table 1 shows the ordered list of signals for which the computed features were correlated at best.

Our results are compliant with numerous studies that suggest that pulse (HR and PVA) and SCL signals are the most involved in the recognition of affective states. To be more precise, we first found that the standard deviation of HR is significant for the evaluation of arousal. In other words, the heart rate is regular when little aroused and is irregular when the affect is intense. As a side effect, the arousal of the affective state is also correlated with m_{ST} and inversely correlated with d_{PVA}, which represents an average variation of blood volume between two successive measures. But the best correlation for arousal was found with the SCL signal: the feature $\tilde{d}_{SCL}$ is high when the skin conductance varies in large steps (d_{SCL}) and regularly ($1/s_{SCL}$). A strong negative correlation with arousal suggests that intense emotions can be observed by irregular small variations of the skin conductance. Similar conclusions can be made from the positive correlation with $\tilde{d}_{EMG}$; high arousal can be observed by regular high variations of the frontal EMG.

On the other hand, the correlations between physiological parameters and the valence of affective states are very low. This result confirms the lack of publications proposing such evaluation. Once again, pulse is a good indicator but with different features than for arousal. Positive emotions (joy and exaltation) seem to provoke lower variation amplitudes in heart rate (low d_{HR}) than do negative ones (boredom and fear). Although quite low, this correlation is coherent with what Simons et al (23, 622) suggested: "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." The e_{PVA} feature is harder to interpret; it is high when pulse volume varies in very large steps (e_{PVA}) and regularly ($1/s_{\mathrm{PVA}}$). The negative correlation with valence suggests that negative states could be identified by irregular small variations of blood volume. We also found that breathing frequency was correlated more to valence than to arousal for every feature, with the highest score for e_{BF}; the respiration frequency varies probably more with negative emotions than with positive ones.

To sum up, physiological signals indicate quite well the level of arousal but rather badly the valence of affective states. However, this lack of direct correlation could be overcome by a more complex combination of features.

Classification into affective states

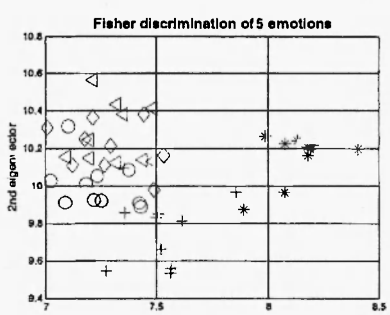
The second approach consisted in computing the discriminant function analysis of physiological signals similarly to Nasoz et al (24) and Vyzas (25). As we wanted to isolate the two functions that best fit to arousal and valence, we chose the two-group analysis called Fisher linear discriminant analysis. This method allows dimensionality reduction 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; the matrix is rank deficient), we had to apply a variation of the traditional Fisher projection algorithm by first projecting the data matrix into an orthonormal basis [N × 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 labels: five classes of emotions, three classes for arousal (low, middle and high values) and three classes for valence (negative, neutral and positive). 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 the K-nearest-neighbors classification algorithm, and the leave-one-out method was chosen for cross validation. Here is the simplified procedure applied to each data point:

- the data point to be classified is excluded from the original data set and the remaining data considered as the training set,
- 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,
- the data point is then classified according to the KNN principle based on the Euclidean common measure distance,

and finally, confusion matrices are calculated for the various classifications considered.

The 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' identification is similar to a random guess.

When considering valence as three modal classes, we obtained better results than for the five emotion classes. Figure 7 shows the results of Fisher discrimination of arousal and valence and allows to compare between theoretical (top) and self-reported classes (bottom) of arousal (left) and valence (right). With an acceptable classification rate of 45%, the three classes of negative/neutral and positive affective states appear as coherent, well distributed areas on the 2D Fisher plot. However, the classification with self reported arousal is too unbalanced for a meaningful interpretation. In fact, we obtained almost one unique class in which 85% of the data is classified because the self reported arousal was always highly scored by the actor. This is in contradiction with the expected theoretical arousal values that should be, according to the repartition of the five emotions, equally split into low, middle and high arousal. This bias is verified by the very



		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%

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

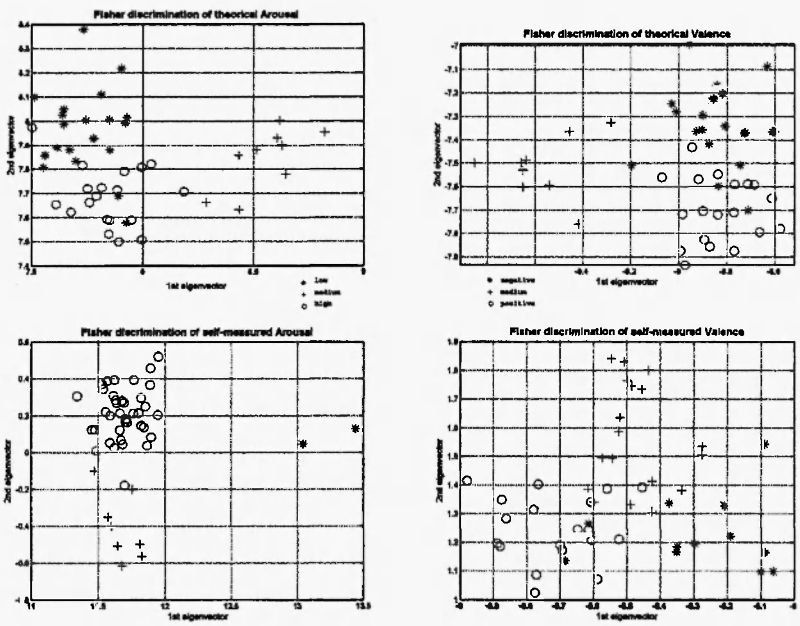


Fig. 7: Fisher's discrimination of arousal and valence: comparison between theoretical and self-reported classes of arousal and valence

low correlation between the theoretical and evaluated arousal (r = 0.19). On the other hand, we can notice a very high correlation between theoretical and evaluated valence (r = 0.96), which validates our previous conclusions regarding the validity of the classification of the valence component and which confirms its correct cognitive assessment.

CONCLUSION

We have been experimenting with biofeedback devices to develop computerized interpretation of physiological signals into arousal, valence, and classes of affective states. Following a long-term study on one person, we have been able to establish numerical features providing a good estimation of the arousal. However, our procedure did not lead to statistically generalizable computation of valence or classification into affective classes. If our objectives had been to investigate the medical aspect, we could have pushed our investigations, which already offered promising perspectives. For instance, the Fisher linear discriminant analysis on the 36 features could certainly be optimized to guarantee higher classification rates for the three classes of valence. Additional parameters and signals, such as heart rate variability (26) and electroencephalogram, could also be considered to improve these results, but our goal was to design an on-line physiological assessment tool that could easily be integrated in an exposure session. As such, the features selected as best correlated to arousal give an objective numerical evaluation of the intensity of affective states. We did not manage to establish meaningful linear correlations of valence but rather only a correct classification into three ranges. This result would not help therapists much, who can obtain such non-quantitative information easily with cognitive assessment.

However, this experimentation allowed us to establish better the limitations of affective computing. We have been able to confront the theory of affective computing presented in the literature with our criteria of efficient assessment for psychotherapy (i.e. how complex the interpretation of signals is and which precisions we can realistically expect in 'normal' conditions—not in the specific medical experimental framework of the publications).

First, to ensure a good quality of recognition, the data set has to be trustworthy. If with our 10 sessions the learning set was too small to establish statistical validity, applying this procedure in therapy would require even more time. As such, we would encourage the use of physiological assessment in specific cases only, for example, when the therapist cannot establish a simple diagnostic and foresees a long therapeutic work.

Second, our results would not have been conclusive if the method was used to identify emotions in an unknown context, but the system we built was sufficient to correlate reactions of the patient with a known stimulus. It could very well be used to assess the patient's response to visual or auditory events during VRE, and be eventually completed with behavioral observations. A biofeedback loop could then be established between the patient and the virtual content. In the context of social phobia therapy, we plan to use the evaluated/recognized intensity of the emotion as a motivating factor for the behavior of the virtual humans; the attitude of the assembly could for example be adapted to lower or increase the stress of the subject.

Finally, we think that physiological measurements have to be combined with cognitive and behavioral evaluations of subjects' reactions. As our approach is driven by close collaboration with therapists, we try to create the tools they imagine and which could be useful for their work. This physiological Arousal/Valence assessment tool is an example. We also successfully experimented with eye tracking systems to trace off the patients' gaze-avoidance behavior (27) or with an interactive storytelling system to author and control VRE (28). All together, these tools provide therapists with the ability to monitor their patients from multiple points of view: emotional, but also cognitive and behavioral.

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