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A Decision Support System for Real-Time Stress Detection During Virtual Reality Exposure

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Abstract. Virtual Reality (VR) is increasingly being used in combination with psycho-physiological measures to improve assessment of distress in mental health research and therapy. However, the analysis and interpretation of multiple physiological measures is time consuming and requires specific skills, which are not available to most clinicians. To address this issue, we designed and developed a Decision Support System (DSS) for automatic classification of stress levels during exposure to VR environments. The DSS integrates different biosensor data (ECG, breathing rate, EEG) and behavioral data (body gestures correlated with stress), following a training process in which self-rated and clinical-rated stress levels are used as ground truth. Detected stress events for each VR session are reported to the therapist as an aggregated value (ranging from 0 to 1) and graphically displayed on a diagram accessible by the therapist through a web-based interface.

Keywords. Psychological Stress, Psychophysiology, Virtual Reality, Decision Support System, Biosensors.

Introduction

In recent years, there has been growing interest towards the use of Virtual Reality (VR) in mental health research and practice. In particular, an emerging application of this approach concerns the assessment and management of psychological stress. At this purpose, one of the most investigated cognitive-behavioral techniques is the Stress Inoculation Training (SIT; [1]). SIT is implemented through gradual and repeated exposure to events, which have been previously identified as potential stressors. The key idea underlying this technique is that "inoculating" the stressor in combination with the acquisition of effective coping skills can prepare the patient to face similar situations in daily life. VR is thought to further enhance the efficacy this process by exposing the patient to realistic simulations of typical stressful situations [2].

A key issue in the application of VR in the SIT approach is how to accurately evaluate the stress response during the exposure to the simulated stressor. The use of biosensors for monitoring physiological and behavioral correlates of stress has been proposed as a potential solution to this need [3; 4]. However, the analysis and interpretation of multiple psychophysiological measures is time-consuming and requires specific technical skills, which are often not often available to clinicians. In the following, we present a Decision Support System (DSS) that has been designed to assist the therapist/researcher in the assessment of stress levels during virtual exposure. The specific goal of the DSS is to evaluate the psychological state of each patient by analyzing previously acquired knowledge, such as patient's physiological and behavioral profile, and current sensory data. For each user, the DSS implements a personal classifier that uses machine-learning techniques. Once trained, the DSS analyzes the new incoming multi-sensors data acquired from the user and infers his/her stress levels.

1. System Architecture

The system's architecture consists of three main components: a) VR platform; b) biosensors module; c) analysis and decision module.

1.1. VR Platform and Virtual Environments

The VR platform integrating the decision support system is NeuroVR-2 [5] (http://www.neurovr2.org). A set of virtual environments for stress inoculation was developed for this VR platform, targeting two highly-stressed professionals: teachers and nurses. Virtual stressful situations were developed following design guidelines collected in focus groups and in-depth interviews, which involved representative samples of these professionals.

1.2. Biosensors Module

As concerns the biosensors module, the system currently supports the following physiological and behavioral data acquisition platforms:

- ECG and breathing (through a custom-designed Personal Biomonitoring System described elsewhere [6])
- EEG, through the platform "Enobio"[8]
- Gesture-recognition system based on Microsoft Kinect, which is able to automatically detect stress-related gestures (through the platform "CBAR" [9]).

These platforms feature minimally invasive equipment and support wireless connectivity: two essential requirements for ensuring patient's comfort during VR exposure.

1.2.1. Personal Biomonitoring System (PBS)

The PBS uses wireless sensors for ECG, activity monitoring (including posture) and breathing rate [6]. The system consists of a chest band in which sensor modules and electrodes are integrated; these components have been designed to ensure minimal discomfort of the user. Acquired data are pre-processed on a wearable platform with the purpose of extracting features to be transmitted to the central database; this approach avoids using large sets of raw data and allows increasing battery life of the wearable platform, as effect of reduced synchronization and processing times. For the breathing rate, the sensors – integrated in a flexible band - were selected for accuracy in chest movement and reduced sensitivity to artifacts. A piezoelectric PVDF transducer was used to measure mechanical forces associated with chest movements [7].

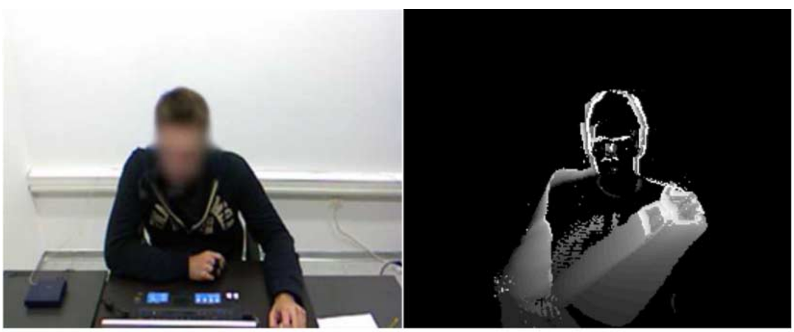
1.2.2. Electroencephalogram System "Enobio"

Enobio is a wearable, modular and wireless electrophysiology sensor system for monitoring brain activity (EEG) [8]. In the Enobio platform (Fig. 1), a feature extractor computes the Fourier Transform and extracts the frequency power of several bands in real time. In order to identify relevant EEG features for detecting stress in VR, a study was undertaken [9]. The experimental setup consisted having the subject performing different tasks designed to induce psychological stress (i.e. exposing the participant to a fake blood sample). During the execution of these tasks, EEG was recorded with Biosemi 32 channel. For every single pair of symmetrical EEG channels, alpha asymmetry and the alpha/beta ratio (for each channel in this case) were extracted. Alpha asymmetry is related with the valence dimension of emotions [10] while the beta/alpha ratio is related with the arousal dimension of emotions [11]. Statistical analysis of data collected from 12 participants showed that both beta-alpha ratio and alpha asymmetry were correlated to stress levels on each task [9]. An interesting feature of the Enobio system is its real-time capability. Not only all data processing steps, but also the fusion stages can be performed in real time, allowing continuous monitoring of stress levels during VR exposure.

Figure 1. The wireless EEG system "Enobio"

1.2.3. Gesture Recognition System "CBAR"

A further module integrated in the VR platform is the "Camera and accelerometer – based Activity Recognition" (CBAR) system. Its purpose is to monitor in real-time the subject's activities through a video and an accelerometer modality, extracting behavioral features that correlate with stress. The CBAR video modality is based on a low-cost camera (Kinect), monitoring the subject as shown in Fig. 2(a). From the video images sequence, Motion History Images (MHIs) [12] are extracted (Fig. 2(b)), allowing the calculation of parameters related to upper-body activity. The accelerometer modality is based on two tri-axial accelerometers placed at the subject's knees, for monitoring lower body activity. Implementation details of both modalities can be found in [13]. In the clinical setting, the CBAR extracts in real-time a set of behavioral features from both modalities and provides them to the VR platform. These features express qualitative aspects of the subject's movement, such as the average upper body activity level and its deviation calculated through the non-black portion either of all MHIs or only of MHIs that signify "increased activity", the frequency of occurrence of specific gestures (e.g. hand on head) and foot trembling. These features showed significant correlates to psychological stress in the experimental evaluation of [13], being capable to enhance automatic stress detection that is more typically based on biosignals monitoring. Therefore, within the Interstress VR platform, the behavioral features extracted from the CBAR augment the automatic stress monitoring process so as to increase its effectiveness, whereas, in a more general view, they augment the platform and the clinician with objective information regarding the patient's behavioural correlates of stress.



(a) (b)

Figure 2. The Camera and accelerometer –based Activity Recognition CBAR

1.3. Central Database and Decision Module

Biosensor and activity data collected during VR sessions are filtered, pre-processed in order to extract specific stress-related features and sent to a central database, where they are linked by means of the timestamp information. The extracted features are handled by the analysis and decision module (DSS), which allows classifying the current stress level, after previous knowledge acquired during a training phase. The DSS application (installed and running on a remote machine in respect to the database), works at regular intervals, to query the remote database and to download data related to all users and their VR sessions. In order to enforce the data security, the database is indirectly accessed by the DSS using the WSDL layer interface exposed by the INTERSTRESS architecture. The DSS is realized on a knowledge basis, using Fuzzy Logic (FL), artificial neural network (ANN) and pattern classification algorithms. The FL rule-based algorithm consists of three steps: fuzzification, inference and defuzzification (Fig.3). The fuzzification converts the input from continuous values to linguistic variables through the definition of membership functions. The inference engine applies a set of fuzzy rules to generate linguistic values as output. In the final, defuzzification step, the linguistic variables are converted to continuous values (real outputs of the system) [14]. We developed membership functions and fuzzy rules for each parameter considered. The fuzzified features extracted from bio- and activity sensors are used as input by the classifier, a Kohonen's self-organizing ANN based on unsupervised learning [15].

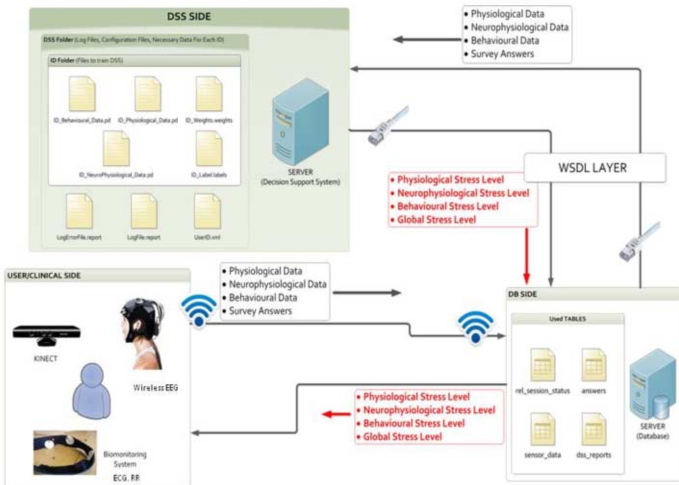


Figure 3. Architecture of the Decision Support System.

As shown in Fig. 4, data processing in the decision module consists of a training phase and a test phase. In the training phase, the self-organizing map is trained to adapt itself to classify the given inputs. The loaded features, along with self- and clinical-reported stress levels, form the training set. For this purpose, the following psychological questionnaires are used immediately after virtual exposure: i) Visual Analogue Scale for Anxiety (VAS-A, self-rated by the patient); ii) State Anxiety Inventory Y1 (STAI-Y1, self-rated); iii) Cognitive Behavioral Checklist (clinical-rated). In this way, synaptic weights of networks internal connections are modified, with the help of a learning algorithm, in order to force the output to minimize the error with the presented example (the stress score obtained from these surveys). In the test phase, the fuzzified features are given as an input to the network. The ANN, adequately trained, is able to classify the given input in order to present a consequent output value. The value obtained (output of ANN), is the inferred stress level. When the decision module infers a new stress level value, this is uploaded again to the remote database (Fig. 2). Patient's stress levels based on DSS reports values are then graphically displayed on a diagram, which is accessible by the therapist through a Web-based interface.

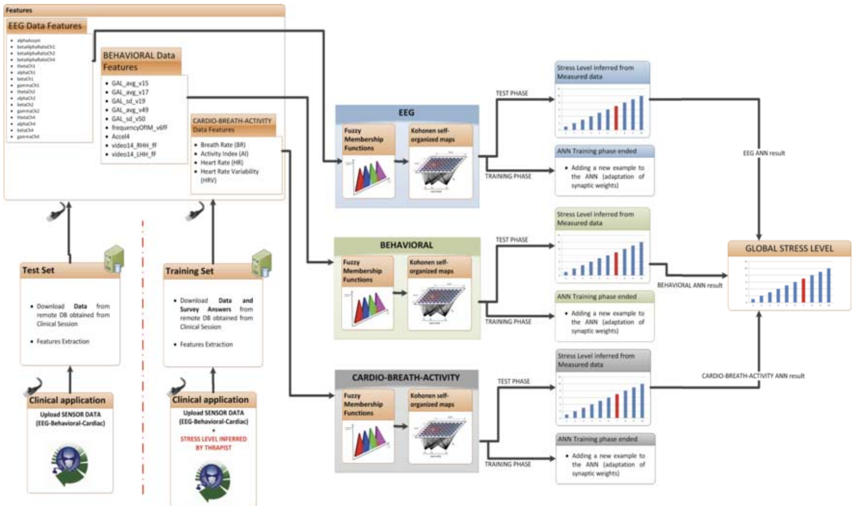


Figure 4. The Decision Support System process, from data acquisition to classification of global stress level.

2. Conclusions and Discussion

Here, we have described a decision support system that assists the therapist in analyzing and interpreting patient's stress levels during VR exposure. The DSS is based on multi-parametric measures physiological and behavioral measures collected from different wireless biosensor modules. This strategy allows a closed-loop approach actually missing in current strategies to the evaluation and treatment of psychological stress [16]: a) the assessment is conducted continuously throughout the virtual experiences: it enables tracking of the individual's psycho-physiological status over time in the context of a realistic stressful situation; b) the information provided by the DSS is constantly used by the therapist to improve both the appraisal and the coping skills of the patient. To test and validate the system, we have recently started a controlled clinical trial, approved by the US ClinicalTrial.gov database (Management and Treatment of Stress-related Disorders - INTERSTRESS NCT01683617).

3. Acknowledgments

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