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Research Proposal: Real-time Anxiety Prediction in Virtual Reality Therapy

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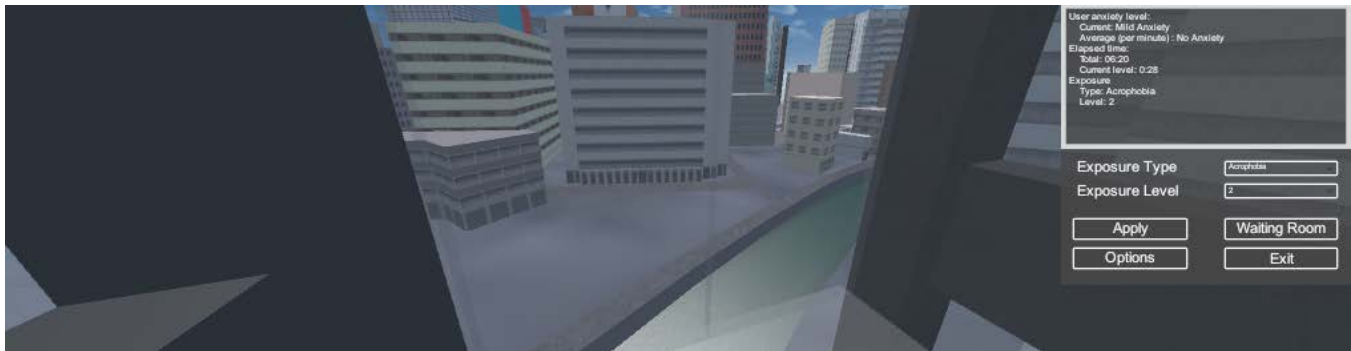


Figure 1: The Virtual Reality acrophobia environment

ABSTRACT

This paper contains the research proposal of Deniz Mevlevioglu that was presented at the MMSys 2022 doctoral symposium. The benefits of real-time anxiety prediction in Virtual Reality are vast, including uses from therapy to entertainment. These anxiety predictions can be made using biosensors by tracking physiological measurements such as heart rate, electrical brain activity and skin conductivity. However, there are multiple challenges when trying to achieve accurate predictions. First of all, defining anxiety in a useful context and getting objective measurements to predict it can be difficult due to different interpretations of the word. Secondly, personal differences can make it difficult to fit everyone into a generalisable model. Lastly, Virtual Reality strives for immersion, and many systems that use objective measures such as on-body sensors to detect anxiety can make it hard for the user to immerse themselves into the virtual world. Our research aims to come up with a system that will address these problems and manage to get accurate and objective predictions of anxiety in real-time while still allowing the users to be immersed in the experience. To this end, we aim to use fast-performing classification models with multi-modal on-body sensor data to maximise comfort and minimise noise and inaccuracies.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; **Virtual reality**; • **Computing methodologies** → **Machine learning**.

KEYWORDS

VRET, biosensors, anxiety, machine learning, GSR, EEG, PPG

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1 INTRODUCTION

Virtual Reality (VR) has been getting more and more popular in the last few years, with its area of use expanding rapidly. With growing evidence for the usefulness of VR therapy for medicinal uses, the research in this area is becoming more and more important [6, 11]. Virtual Reality Exposure Therapy (VRET) aims to treat specific phobias and some other mental conditions by coupling relaxing exercises with gradual virtual exposure to feared stimuli. VRET has become established as an alternative and cheaper therapy method to in-vivo exposure therapy [11]. We predict that anxiety detection can enhance VRET by giving information about the user's condition and their response to the therapy provided. Objective measures for anxiety are more suitable for VR because self-measurement can break the immersion and is harder to interpret due to personal differences. It is important for this feedback to be timely and accurate for it to be useful during therapy. Neither emotion detection using



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sensors nor using sensors within VR are new concepts [2]. However, there are a number of challenges when it comes to predicting anxiety in real-time and in VR.

Most current systems that use sensors to detect anxiety rely on the user being still and not moving [2]. This is important for having high-quality, noise-free signals from the sensors. However, VR therapy is not meant for having the user stay still. Interacting with the environment and acting as if you would in real-life is an important feature of VR for immersion. The therapy element relies on the user's feeling of presence in the VR environment [5]. Allowing the user free movement introduces noise into the data, compromising accuracy. There are on-body sensors that work fairly well with movement, however, they are not reliable to have constant real-time readings. This is where multi-modal systems, using multiple types of data and signals become important. In the case where one type of data becomes noisy and unusable, the other types can increase the accuracy, making the system more reliable.

Machine learning classification models are generally used to deal with increasingly complex data coming from multiple types of signals. There has been some research in this area, however, a comprehensive and generalisable system is yet to be developed.

In our research, we aim to make a reliable and generalisable real-time anxiety prediction framework for decision support in VRET. To this end, we integrate heart rate (HR), heart rate variability (HRV), electrical brain activity and electrodermal activity (EDA) into our VR experience and use these measures to get accurate predictions on the current anxiety level of the user. These readings are then used to adjust the therapy to their personal needs. For example, if the user is feeling no anxiety, the exposure level can be increased and vice-versa. For this system to be useful it needs to be accurate as well as comfortable for the user. So our goal is to make the system as light and usable as possible while maintaining high accuracy.

2 RELATED WORK

By now, VRET is an established therapy method with many examples and a large body of research [11, 12, 15]. There are also many applications that use machine learning classification to measure anxiety from physiological and behavioural measures [2, 7, 18]. These applications have varied results, however, it is hard to compare them quantitatively due to the differences in methods such as how they define anxiety, how many levels of anxiety they are predicting and how they define the base level of anxiety. The most common measures used as features are HR, HRV, EDA, electrical brain activity, blood volume pressure (BVP), skin temperature (SKT), head movement, respiratory rate (RESP) and eye movement. There are many successful applications, however, it should be noted that a lot of these systems are not applicable to Virtual Reality due to the restriction of movement and computational complexity.

There are some applications that bring anxiety prediction into VR with varying measurements, classification models and environments [10, 14]. Models used, features, measures and accuracies of some of these systems can be viewed in table 1. It can be seen that there are very different approaches to how anxiety is defined and measured. Some of these studies also integrate anxiety prediction into VRET [13, 14]. Our system aims to be transferrable by using well-established methods to define anxiety and light-weight

by using the most comfortable sensors and fastest classification models.

Reference	Features	Measure	Model	Output levels	Accuracy
Kaminska et al., 2021 [4]	EEG, EMDR	SCWT	MLP	2	96.42%
Salkevicius et al., 2019 [14]	BVP, EDA, SKT	VR Content, SUDS	SVM	4	86.3%
Tartarisco et al., 2015 [13]	ECG, RESP	STAI-Y1	Neuro-fuzzy	4	83%
Wu et al., 2010 [17]	EDA, RESP, ECG, EEG	SCWT	SVM	3	84%

Table 1: Previous research on real-time anxiety prediction in Virtual Reality

Note: EEG: Electroencephalogram, EMDR: Eye Movement Desensitization and Reprocessing, EMG: Electromyogram, PPG: Photoplethysmogram, SCWT: Stroop Colour-Word Task, SUDS: Subjective Units of Distress Scale, STAI: State Trait Anxiety Inventory, MLP: Multi-layer Perceptron, SVM: Support Vector Machine

3 AIMS & OBJECTIVES

This study aims to make a system that will be able to reliably, accurately and objectively predict the user's current anxiety in real-time in a VR environment. To accomplish this, the following steps will be followed:

- Find a generalisable way to detect and measure anxiety that will be useful in the context of VR therapy
- Decide on on-body sensors with the highest accuracy and lowest interference in the experience
- Make sure that this model can do these predictions efficiently, as the VR application itself will be costly
- Develop a framework that will allow this system to be embedded into different types of VR therapy experiences

4 CURRENT WORK

For the first two years of our research, the focus has been on background research and development of the VR applications. This includes literature review, framework prototyping and developing the environment for anxiety measurement experiments.

4.1 Literature Review

To have a better understanding of the area, the state of the art in sensor technology and VRET, and the current problems and deficiencies in the topic, a comprehensive literature review has been conducted on the topic of anxiety classification in virtual reality

therapy using biosensors. This systematic review let me identify and better focus my research by showing me the strengths and weaknesses of the prior research in the area. There are a good number of studies, however, there is a lack of unity when it comes to generalisation, personalisation and finding a common definition of anxiety. It is hard to compare research in the area to each other because there is a lack of gold standards and useful benchmarks. Given that it is still the early days of emotion detection within VR, it is important to contribute high-quality studies into the area to make it easier for future research and understanding. This systematic review also allowed us to better design our applications and experiments by being able to see common practices and/or mistakes [8].

4.2 Anxiety Measurement

From the background research, it became clear that how anxiety is defined is very important for personalisation and generalisation. Without the anxiety levels being defined well, the predictions are meaningless regardless of the accuracy. This is because what they are predicting is unclear, which renders them useless. To solve this important problem, a VR environment was developed. This system is currently going through pilot experiments.

The VR system that we developed aims to induce and measure anxiety classification levels from the users by using biosensors. To be able to generalise and extend beyond the use of one specific experience, a well established cognitive test called Stroop Colour-Word Task (SCWT) was used [3, 8]. In this task, the user is shown some text with coloured ink. In the traditional test, there are two levels [3]. The first one is called congruent, the text of the word matches the colour ("red" written in red ink). The second is called interference or incongruent, the text does not match the colour ("red" written in blue ink). This task was initially used to measure how well people perform when extra information interferes with the task, however, it was quickly discovered that is also useful for measuring stress or anxiety. The emotional version of this task [16], adds a third stage where negatively associated words (ANEW) [1] are used to increase anxiety levels. Our application brings this emotional version of the SCWT into VR (Fig 2). By doing so, we are able to differentiate between three levels of anxiety; no anxiety, mild anxiety and severe anxiety.

A shimmer device is used to record electro-dermal activity (EDA) and heart rate from the user. A MyndPlay BrainBand device is used to measure electrical brain activity. This information, along with self-reported measures of anxiety using subjective units of distress scale (SUDS), reaction time and the accuracy of the answers and time is logged in an external .csv file to validate the results. If the results show that the system is effective at distinguishing the anxiety levels, the information from these files will be used to train the anxiety classification machine learning models.

4.3 VRET framework

Another important aspect of this research is to make the anxiety prediction transferable and generalisable. To this end, a prototype VR application has been designed and prototyped. The anxiety prediction and therapy parts of this framework are separate to



Figure 2: The Virtual Reality waiting room environment

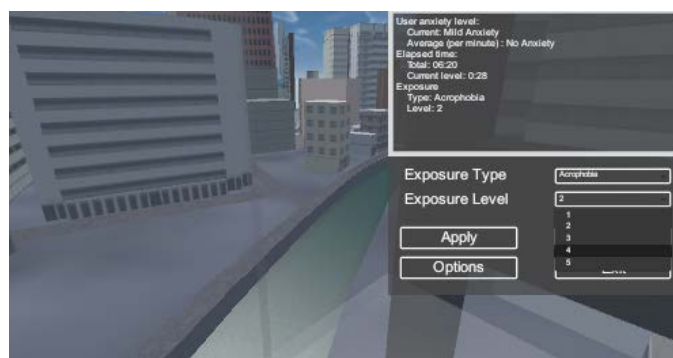


Figure 3: Graphical User Interface that is visible to the therapist and provides user information.

make it possible for the insertion of different therapy methods and environments under it.

The framework involves two components, the first is the system that predicts anxiety and the other one is the exposure component. The therapy relies on the experience giving a similar feeling of encountering this stimulus in real life, which is increased anxiety. This system is built to work with different phobias and therapy applications. In this prototype, for testing purposes we use acrophobia (fear of heights) [9].

The first environment user is greeted within the application is called the waiting room. This room is modelled after a familiar setting of a clinic waiting room, and its purpose is to get the user accustomed to the virtual space. Additionally, in this scene, the user goes through the non-interference stage of SCWT to get their baseline levels of pulse rate, brain activity and electrodermal activity. This baseline detection allows for readings and predictions to be personalised, as the readings can differ wildly from person to person. When the baseline recording is complete, the therapist can move them into the exposure scene and set the level of exposure. Through the graphical user interface (figure 3) that is only visible to the therapist, it is possible to monitor the current anxiety level and other statistics such as the level of exposure and time spent in this exposure level.

From the user interface, the therapist is able to pick an exposure type and exposure level. This works with multiple environments and has been tested using scenes for acrophobia and claustrophobia (fear of enclosed spaces). A C# interface is used to make an IExposure class that will have a method for setting the exposure level. When the therapist clicks to change the exposure level, the system looks for the interface IExposure and calls the method ChangeExposure() with the specified parameter. As long as the scene that is being loaded has this interface, it can be used with the framework.

5 FUTURE WORK

If the EVRST is validated through the pilot experiments, the datasets will be used to train classification models. Once a satisfactory accuracy level is achieved from the models, the classification will be integrated within the VRET framework. We aim for the VRET framework to be fully functional before the third year of the PhD. This will include two different exposure environments (acrophobia and possibly claustrophobia). Each exposure environment will have five exposure levels, changing based on the stimulus. The interface should work and be self-explanatory for therapist use. When the system is completed, we will run experiments to assess the usability of the system.

5.1 Anxiety Classification

Based on prior research and pilot tests, few suitable models were identified. A summary of the structure can be observed in figure 4. Supervised learning will be used to classify anxiety on three levels based on EVRST stages. Stage 1 will correspond to no anxiety or baseline, stage 2 will correspond to mild anxiety and stage 3 will correspond to severe anxiety. Features for the classification will be heart rate (HR) measured in beats per minute, heart rate variability (HRV), skin conductivity level (SCL) measured in microsiemens (μS), brain waves such as high alpha, low alpha, high beta, low beta, theta, low gamma, high gamma, alpha/beta ratio and frontal alpha asymmetry (FAA). For each user, the baseline will be detected and the rest of the values will be transformed into ratios of this baseline.

Multiple classifiers including random decision forest (RDF), support vector machine (SVM), K-nearest neighbour (KNN) and artificial neural network (ANN) will be compared in terms of performance and accuracy to choose the best option. When comparing results and performance, accuracy will be given the highest priority. When the accuracy is similar, the fastest algorithm will be picked.

5.2 Framework Validation

Once the framework is completed, the experimentation for usability will begin. We hope to conduct these experiments in the third year. As the anxiety classification will have been validated before the completion of the framework, this experiment will focus on user experience. The research questions we aim to address with this experiment are as follows:

- (1) Is the system intuitive and easy to use as a decision support system?
- (2) Is the real-time anxiety detection system reliable?
- (3) Is the system useful and does it motivate the user to keep using it?

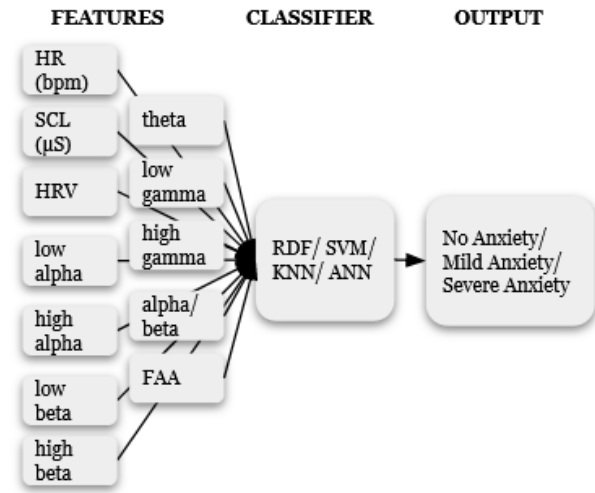


Figure 4: Structure for anxiety classification

HR: Heart rate, **bpm:** beats per minute, **SCL:** Skin conductivity level, μS : microSiemens, **HRV:** Heart rate variability, **FAA:** Frontal Alpha Asymmetry, **RDF:** Random decision forest, **SVM:** Support vector machine, **KNN:** K-nearest neighbour, **ANN:** Artificial Neural Network

This PhD focuses on the technical possibility of anxiety classification in real-time, and a framework that allows this prediction to assist therapists in decision-making. However, the scope of this research does not include the clinical validation of results. No conclusions will be drawn regarding the efficacy of this framework in the long-term improvement of anxiety disorder symptoms.

6 CONCLUSION

The current state of the art fails to find a reliable, generalisable and transferrable way to predict anxiety in real-time. The main challenges for this lie in the differences between defining anxiety and the lack of a gold standard in terms of baseline detection. The purpose of this research is to come up with a reliable and transferable framework that can be used with a variety of applications and work in various scenarios.

This research will contribute to the state of the art by making this system generalisable and transferable for different environments. It tackles the problem of defining anxiety and detecting baseline by using a well-established and validated cognitive task of EVRST, which will allow it to be used in multiple contexts. The system also contributes to the literature by developing a framework compatible with different phobias or conditions.

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