Between the Buttons: Stress Assessment in Video Games Using Players' Behavioural Data

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Abstract: Flow lies at the heart of the interaction between players and video games. It is usually regarded as the optimal experience blooming in the fragile equilibrium that floats between boredom and anxiety. Under such circumstances, stress assessment can be a crucial experiential marker. In this preliminary study, we propose a computational approach to characterise the stress level of video game players, suitable to be exploited in the development of adaptive video games while enhancing players' experience. To such purpose, a Virtual Reality (VR)-based video game has been created to gather data from participants. The information collected includes both physiological data and motion behavioural data (from game controllers), as well as the subjects' self-reports of perceived stress. Behavioural data are specifically considered in the work presented here. We characterize the stress level evolution in terms of state-space dynamics, which is suitable for either discrete (classification) and continuous stress level assessment. Different experiments have been performed and results so far obtained are encouraging. In particular, along the stress vs. no-stress classification test, an accuracy of up to 84.4% is achieved by using VR-based data.

1 INTRODUCTION

The creation of player-centered technologies, putting players and their objectives at the center of the design and development process, is heavily emphasized in the current video game research realm. Due to their interactive nature, games have a significant potential to elicit in players a variety of cognitive, affective, and behavioral reactions. In such perspective, entertainment and engagement play an essential role and are often related to the Csikszentmihalyi's 'Flow theory' (Csikszentmihalyi and Csikzentmihaly, 1990). Flow is a state of elevated concentration and enjoyment, in which a person is neither anxious nor bored, but completely absorbed in the game.

As such, flow is related to the stress level experienced by the player. Indeed, according to flow theory, a lack of stress can lead to boredom and loss of motivation, while too much stress can cause the player to suffer from anxiety. Both of them can kill the enjoyment of the gaming experience. It is worth noting that video games do not generate stress *per se*; rather, it is the player's own interaction with the game that results in a more or less stressful personal experience, depending on the challenge level of the game, the skill level of the player and game genre preferences (Fullerton, 2014; Schell, 2008).

On the other hand, the expectancy of the players and its fulfillment or failure not only are ingredients triggering a stress response, but also contribute to the players' affective state (Lebois et al., 2016). Players are constantly demanding more immersive experiences, and players' emotional involvement can be seen as a sign of a high level of immersion in the game. Affective-based interaction can increase player engagement, and the emotion-driven game adaptation helps with the personalization of the playing experience, allowing for the fulfillment of each player's unique demands (Yannakakis and Togelius, 2018).

Eventually, stress response and emotional involvement dynamics together contribute in modulating behavioural and physiological response along the gaming session. Yet, there are few examples of how emo-

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tion recognition systems can be used in video games.

The hypothesis that the players' arousal is correlated with the pressure applied to the buttons of the game pad has been investigated by Sykes and Brown (2003). With this aim, they created a video game similar to the classic arcade game *Space Invaders*, with three difficulty levels (easy, medium, hard). The pressure used by players during a game session was recorded and compared across the three levels. According to the study's findings, players push the game pad buttons far harder as the difficulty level rises.

Hiramon (Frommel et al., 2018) is another good example of technique for players' emotional state detection involving their input on game controllers. *Hiramon* is a serious game which aims at teaching players to write Japanese hiragana characters. Players are first shown how characters are written and are required to replicate them (learning period). Then, players are challenged by enemies to write specific characters randomly chosen from those that they have already learned (fight period). During the game, input parameters on a graphic tablet and in-game performance are collected. Self-reports of emotions were also gathered via a questionnaire after each fight of the game, in order to train an ML model to predict levels of valence, arousal, and dominance for a classification problem, with an accuracy of up to 74%.

We aim at overcoming the limitations of the presented works by exploiting new technologies, which provide more opportunities for interaction, and by considering the evolution of the stress level in terms of state-space dynamics.

The main goal of the work presented here is to develop a method for improving the game-play experience by exploiting a computational approach to seamlessly assess players' level of stress while playing, the latter being inferred from motion behavioural data collected from game controllers.

To this purpose, the game used for the experiment has been developed for a Virtual Reality (VR) environment, due to its high level of immersion and realism. Immersive technologies like VR can help to arouse a sense of presence in the game, enhancing players' fun and involvement and eliciting stronger emotional reactions (Pallavicini et al., 2018b; Marín-Morales et al., 2020).

The paper is organized as follows. Section 2 describes the methods with a focus on the design of the game and its elements. Section 3 details the experimental setting used to collect the users' data. Section 4 illustrates the analyses carried out using the collected data, Section 5 focuses on the learning models used to build the stress assessment system. Section 6, presents and discusses the results achieved so far; eventually, in Section 7, some preliminary conclusions are drawn.

2 METHODS

Input data from controllers, coupled with players' self-assessment, are used to infer the stress level. Self-assessment annotations correspond to their perceived stress, used as labels of the generated dataset. For some subjects, self-reported valence and arousal levels were also collected. The survey of Kleinsmith and Bianchi-Berthouze (2012) and of Karg et al. (2013) are significant reviews concerning the affective body expression perception and recognition. They showed that the body is a valid modality for recognizing affect. Body movements were analyzed and used to identify emotion-specific features in order to recognize basic emotions (Ahmed et al., 2019)

The motion behavioural data were taken from the *Oculus Quest 2*[5] devices; jointly, physiological signals were recorded via the *Empatica E4*[6] wristband, to be exploited in future analyses.

2.1 Game Design

The video game[7], developed in *Unity Engine 2020.3.19.f1*, is a first-person horror survival game for a VR environment (Figure 1). The game is set on an abandoned space station and the players' goal is to escape from the station, facing enemies in a hostile environment, surviving with few resources. The horror survival sub-genre was chosen because it has been proven excellent at evoking players' intense emotions, particularly stress (Vachiratamporn et al., 2013).

Some stressors, such as the presence of monstrous enemies, scary sounds and disturbing music, the lack of visibility due to the poor lighting, and the scarcity of resources, were accurately created to enhance a stressful affective state in the players. Lebois et al. (2016) argue that when typical features of stressful situations are present, people categorize events and situations as stressful. Under such circumstances, the most typical features associated with a situation perceived as stressful are: (a) the situation violates personal expectations, there is a discrepancy between the

[5]https://store.facebook.com/it/quest/products/quest-2/

[6]http://www.empatica.com/research/e4/

[7]A demonstration of the recorded gameplay can be found at https://drive.google.com/file/d/1K-DNeWl4NNvwgorEw9AEHh_0EnwJIS50/view?usp=sharing

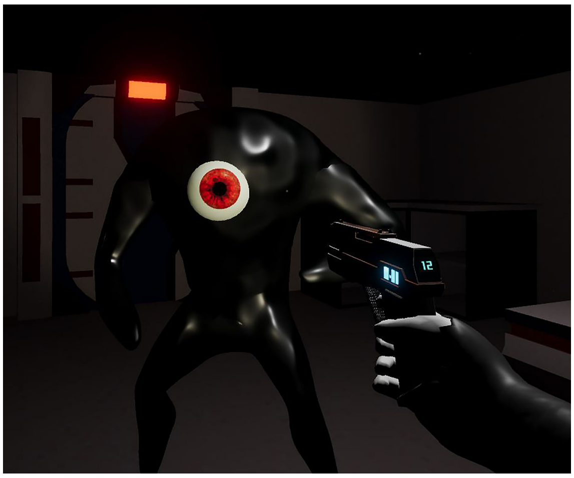


Figure 1: Screen of the video game developed for the experiment.

Table 1: The two types of enemies with their description.

	DESCRIPTION
	Creatures similar to a frog with a big eye at the center of the head. They move quickly and attack jumping towards the player, but they are not really strong.
	Humanoid-shaped creatures with an eye protruding from their torso. They are not very agile and hit the player by waving their arms. If stabbed in the eye, they remain stunned for a few seconds and stop moving.

individual's expectation and the actual situation (Higgins, 1989); (b) the situation or event threatens the well-being of self (Lazarus, 1993); (c) the subject's personal resources available for coping with the situation are not sufficient (Lazarus, 1993). When the core stress conditions are met, they produce different responses of negative emotions and physiological reactions. An individual may experience anxiety, fear, sadness, danger, or even a combination of these categorical emotions during a stressful situation. Subsequently, physiological changes occur in the cardiovascular, endocrine, respiratory, and autonomic systems. Stress perception is thus the result of assigning a situation to the category of a stressful experience.

The two types of enemies designed for the game are described in Table 1. Both of them have a body composed by black slime and a big red eye.

All the designed elements were placed on the game map to create different phases, each one with the aim of inducing a different stressful experience. The structure of the map is linear: six rooms were designed and divided into four stress phases (baseline, low stress, medium stress, and high stress), arranged so that the amount of generated stress gradually increases from the first phase to the last one. The stress phases are organized as follows.

- Baseline phase: a little room with a terminal introducing the players to the game world. The players are asked to put their right hand on a panel and remain still for 15 seconds. This expedient is used to collect baseline data from users.
- Low stress phase: the astronaut's room where the players are safe. The oxygen does not drop and no enemy can be sound. The light allows the players to see quite everything, and some far noises can be heard. All the items necessary to advance in the game (a gun, a knife, and ammunition) can be found here.
- Medium stress phase: composed of two rooms and two corridors, here the enemies are introduced. The light starts to lower, and many scary sounds come from everywhere.
- High stress phase: the last two rooms with a total of five enemies scattered around the areas, in the rooms and corridors that connect them. Approaching the first room, an alarm starts to bother the players. The oxygen runs out, and the character begins to gasp quickly. Here, it is practically impossible to see without using a flashlight. The final room is the one in which there is the greatest concentration of enemies, and it is where the players find the escape pod.

The game session of the test is brief, lasting approximately 5-10 minutes, during which all the game elements and events are presented in the same way to all players, making the experiment more controllable. This also allows a comparison between the data acquired from each different subject.

3 EXPERIMENTAL SETTING

This section covers the experimental process, providing details on the subjects, the data acquisition during the game session, and the self-reports.

Before starting the experiment, a pilot test phase was conducted. This was necessary to understand if there was something to modify in order to accomplish the research goal, to check the validity of the collected data in relation to both the temporal duration of the game session and designed stress phases in the game. It was especially useful to adjust the baseline phase.

The experiment lasted, at most, 30 minutes for the participants who just annotated the stress values: 5-10 minutes for the early questionnaires, 5-10 minutes for the game session, and 5-10 minutes for the labeling phase (see Section 3.3, for details). For the participants who also self-assessed valence and arousal values, the experiment had a total duration of about 50 minutes.

3.1 Participants

A total of 16 volunteer students participated in the experiment. Volunteers did not receive any payment or credit for their collaboration. All of them reported having no anxiety disorders and no neurological alterations. Prior to the study, participants read and signed a consent form because biometric and demographic, personal data were handled. Before starting the game session, participants were required to complete two questionnaires: the Perceived Stress Scale (PSS) questionnaire (Cohen et al., 1983) and a demographic questionnaire.

The first one is a standard psychological instrument for measuring perceived stress and refers to feelings and thoughts during the last month. From the PSS, it resulted that all the participants felt moderately stressed in their life before starting the experiment.

The second questionnaire, which was designed specifically for this work, refers to demographic and static data about the participants. The answers indicate that 15 males and 1 female in the range of 22 and 29 years, with a mean age of 24.68, took part in the experiment. The majority of the subjects claimed to spend, on average, around 11-20 hours per week playing video games; two participants only declared they never play video games. The most popular game genres were action and adventure. Only two participants reported they like horror games. Finally, half of the participants reported that they had never experienced VR environments before the test, whilst, three participants declared they often play VR games.

3.2 Data Acquisition

After completing the two questionnaires, each participant was equipped with the sensors. First, they wore the *E4* on their non-dominant hand, to minimize the movement artifacts. Then, they put on the headset and its controllers, and instructions about the buttons needed to play were given. During the game session, participants were standing and could rotate freely on themselves.

Once this preparation phase was completed, the game, during which all the data were collected, was started. When the participants reached the end of the game, all the devices were removed. A problem that can arise when using VR devices is the motion sickness, which is a feeling of disorientation or nausea. All of them, even the novices, declared that they did not suffer from motion sickness.

3.3 Self-Assessment

In order to validate the experimental protocol and to label the data, self-reports of each participant were collected. Indeed, asking the participants directly about their perceived experience is the most direct way to record their inner state.

Self-reports were collected by exploiting *DANTE*[8] (Dimensional ANnotation Tool for Emotions). *DANTE* is a web-based annotation tool helpful for studying affective responses in presence of a stimulus (Boccignone et al., 2017). It provides an interactive version of the Self-Assessment Manikin (SAM) questionnaire (Bradley and Lang, 1994), and allows for continuous annotation of valence and arousal by moving a slider on a scale with values ranging from -1 to 1 and a step of 0.001.

Specifically for this work, DANTE was extended by adding a stress slider in order to allow participants for the annotation of their own perceived stress level. Such slider represents the continuous extension of a perceived stress Likert scale (visualised in the form of a color bar, cfr. Figure. 2), spanning a range from low (-1) to high (1) stress level.

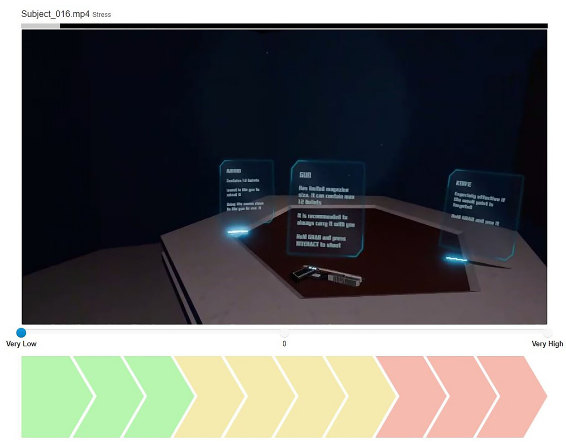


Figure 2: Self-assessment of stress using DANTE.

[8] https://github.com/phuselab/DANTE

The gameplay of each participant was recorded during the game session and the stress label sequence or targets over time $\{l_t\}_{t=1}^{T}$ were collected from all participants, while seeing their own gameplay video.

Seven participants were also asked to evaluate in real-time their subjective emotional experiences in the 2-dimensional affective space, defined by valence and arousal dimensions, In our context, the valence dimension indicates how pleasurable the gaming experience was and (negative to positive), while the arousal dimension denotes how arousing the gaming experience was (low to high).

4 DATA ANALYSIS

The acquired data had to be carefully scrutinized before confronting with the stress level assessment process. Pre-processing, feature extraction, data analysis, and feature selection are the traditional steps considered in the following.

In this paper, we focus on the data related to the *Quest 2* headset and controllers, since, in the pilot test phase, they proved to be particularly significant for the achievement of the initial purpose. The *Quest 2* data concern movement and behavioral information. They represent both the players' action in the video game (which keys are pressed and how hard) as well as the players' movements (basically, their rotation with velocities and accelerations) in the real world. The data were sampled at 64 Hz.

4.1 Preprocessing

The raw data were pre-processed in order to check missing values, noisy data, and other inconsistencies.

The *Quest 2* data and the self-assessed stress labels were first synchronized using the start and end timestamps of the experiment. The timestamps were also saved after each stress phase to make it possible to separate the data related to different stress levels.

Then, the data were standardized using the baseline signal, with the Z-score (or standard score) method, first participant-wise and then using the whole subjects' data. Using the baseline to standardize data provides a common reference for further processing of each feature.

4.2 Feature Extraction

All signals were segmented using a sliding window with a size of 6 seconds and a shift of 1 second. Since the system was designed to be used in real-time during the game session and require a fast response to identify stress, a small window size was chosen.

There is a limited literature on the feature extraction process for the data gathered from *Quest 2*. Thus, we selected the most significant statistical features for all the data obtained from head and left/right hands: mean, standard deviation, minimum and maximum values are used, as well as the average number of times the buttons were pressed within the designated time period. The features extracted for each category of data are shown in Table 2.

Table 2: List of the features extracted from the data collected from *Quest 2*. Abbreviations: h = head, lh = left hand, rh = right hand, vel = velocity, acc = acceleration, ang = angular, press = pressure, pos = position, std = standard deviation, # = number.

Data	Feature	Description
h vel h ang vel h acc h ang acc lh/rh vel lh/rh ang vel lh/rh acc lh/rh ang acc lh/rh grip press lh/rh trigger press lh/rh thumbstick pos x lh/rh thumbstick pos y	μ σ min max	mean std min value max value
lh/rh grip pressed lh/rh trigger pressed	$\mu\#press$	mean of the # of times the button is pressed

After the extraction step, the features were normalized by scaling and translating them in the range between 0 and 1.

4.3 Statistical analysis

A preliminar statistical analysis was conducted on the features that were extracted. This task was completed using *Autorank*[9] (Herbold, 2020). *Autorank* is a Python package used to automatically compare paired populations. The package analyzes the distribution of the data and automatically decides which tests to perform. The first populations compared coincide with the stress phases. The means of all the extracted features from the *Quest 2* data were used. Each subject's data was first analyzed individually, and all the subjects' data were then combined to perform the analysis. This analysis produced no useful

[9] https://github.com/sherbold/autorank

findings. We surmise that this outcome might be due to the fact that the stress experienced during a certain game phase is not continuous throughout it. So, when comparing the complete temporal sequence of one phase with another, no relevant differences are likely to emerge. Then, samples were drawn from subjects with different VR-experience level (experienced and non-experienced). This value was extracted from the demographic questionnaire. To carry out the comparison, an analysis for each stress level was carried out. Even in this case, no statistically significant differences emerged, most likely because of the gap between more experienced and less experienced subjects is not very great.

Subsequently, data were analyzed by comparing their correlations. Pearson correlation was used. Correlation matrices were computed first for every single subject, and then combining the subjects' data together, first dividing the stress phases and then using them together. According to the analyses carried out by differentiating the four designed levels of stress, it appears that, in general, all the features correlate better with the perceived stress level in the baseline phase and the high stress phase. Even using the stress phases together, a good level of correlation emerged with some of the features. In the last study, participants who assessed their emotional state using valence and arousal in addition to stress were used. Their data were separated from those of the other participants to examine the correlation between valence and arousal levels and self-reported stress level. In all cases, the arousal level correlates positively with the stress level. By contrast, the correlation between valence and stress level can be either positive or negative, depending on whether the subject enjoys or not the horror games. A good degree of correlation results between the features and the valence level and, even more markedly, between the features and arousal level, which raises the possibility of further analyses.

4.4 Feature Selection

The final step in processing the extracted features involved selecting the most relevant ones. In this work, a filter approach was used. Since the relationship (i.e. the correlation) between each numerical feature as input and the target label (the stress level) had been calculated, it could be used to select the most informative subset of the original features. Univariate feature selection was performed. The p-values and the F-scores were computed. The features with a p-value less than 0.05 and the higher score were selected. In the Tab.3, all the features selected to be used as the input of the learning models are shown.

5 MODEL-BASED STRESS ASSESSMENT

We assume a State Space Model (SSM) for stress level dynamics. Namely, we use a partially observed Markov model, in which the hidden state s_t is a random variable that evolves over time according to a Markov process and each hidden state generates some behavioural observations, the random vector y_t at each time step (in what follows to avoid cumbersome notation we do not distinguish, unless needed, between a RV X and its realization $X = x$). In brief, a general SSM defines the joint distribution

$$P(y_{1:T}, s_{1:T}) = P(s_1)\prod_{t=1}^{T} P(y_t \mid s_t)P(s_t \mid s_{t_1}), \quad (1)$$

where $P(s_t \mid s_{t_1})$ is the state transition model and $P(y_t \mid s_t)$ is the behavioural observation model.

Here we are interested in exploiting the SSM to perform posterior inference about the hidden states or stress level state estimation. In particular, it can be used either for online inference, by inferring the probability of the hidden state s_t at current time $t < T$ via the filtering posterior distribution $P(s_t|y_{1:t})$, or to estimate s_t, at any time $t \in [1,T]$, given the full sequence of observations, via the smoothing distribution $P(s_t|y_{1:T})$.

Further, the SSM is a suitable approach since it allows characterising stress level s_t either as a discrete RV or a continuous RV. The former can be exploited to segment/classify the behavioural observations into a finite set of stress states; the latter can be used in the service of continuously tracking stress level dynamics over time.

For the simulations reported in the present work we adopted the Hidden Markov Model (HMM, see Bishop, 2006 for a review) and a variant of the Kalman Filter (KF), the Discriminative Kalman Filter (DKF, Burkhart et al., 2020) as implementation models of the discrete and the continuous SSM, respectively.

It is worth noting, that, in principle, more complex implementation models (e.g., resorting to deep neural nets-based models, Girin et al., 2021) could be used, provided that, different from here, a sufficiently large dataset is available.

5.1 Simulation details

5.1.1 Discrete characterization of stress dynamics

HMM is an extensively used technique to model temporal information (Bishop, 2006), in particular for

Table 3: List of the features. The ones selected to be given as input to the learning models are checked with a ✗. Abbreviations: vel = velocity, acc = acceleration, ang = angular, press = pressure, pos = position, # = number.

TYPE	DATA	FEATURE				
		μ	σ	*min*	*max*	$\mu\#press$
head	vel	✗	✗	✗	✗	
	ang vel	✗	✗	✗	✗	
	acc	✗	✗	✗	✗	
	ang acc	✗	✗	✗	✗	
left hand	vel	✗	✗	✗	✗	
	ang vel	✗		✗		
	acc	✗	✗	✗	✗	
	ang acc	✗	✗	✗	✗	
	grip press	✗	✗	✗	✗	
	trigger press	✗	✗		✗	
	thumbstick pos x	✗	✗	✗	✗	
	thumbstick pos y	✗	✗	✗	✗	
	grip pressed					✗
	trigger pressed					✗
right hand	velocity	✗	✗	✗	✗	
	ang vel	✗	✗	✗	✗	
	acc	✗	✗	✗	✗	
	ang acc	✗	✗	✗	✗	
	grip press	✗		✗	✗	
	trigger press	✗	✗	✗	✗	
	thumbstick pos x			✗		
	thumbstick pos y					
	grip pressed					✗
	trigger pressed					✗

speech recognition or facial expressions recognition applications, and it has been used before in video games by Mishra and Ratnaparkhi (2018) for real-time recognition of players' emotions.

Here, we exploited the HMM implementation provided by the *hmmlearn*[10] library; the behavioural observation distribution was assumed to be continuous and Gaussian, $P(y_t \mid s_t = j) = \mathcal{N}(y_t \mid \mu_j, \Sigma_j)$, μ_j, Σ_j being the mean and covariance, respectively, of the observation y_t conditioned on the j-th state.

In the discrete setting, the stress assessment via HMM can be conceived in broad terms as that of solving a classification problem.

To this end, experiments were conducted with different number of discrete states (classes). First, a binary stress vs no-stress classification was performed. Next, three classes, i.e. no-stress vs low stress vs high stress, were used. Finally, a multiclass problem was solved, with the classes identifying the stress phases of the game partition.

In order to employ the HMM for classification purposes, label values where discretized into different levels and a separate model was built for each class and trained on the class samples, separating each subject's sequence of observation to preserve the temporal information.

Leave-One-Out Cross-Validation (LOOCV) was applied. The learning was performed once for each subject, using the selected subject as a test set and all the others as a training set. Then, the estimate of the performance of each model was computed by averaging the scores over all the trials.

The training process was repeated as many times as the number of subjects. Each model was trained using the forward-backward algorithm. The parameters were initialized randomly.

After training, each test sequence was scored in relation to each model. The log-likelihood of the sequence given as input was returned with respect to the model in use. The test set was then classified in the class of the model returning the highest log-likelihood result. The overall accuracy was then calculated by comparing the predicted stress labels to the actual stress labels. This accuracy was given as the average of the accuracy of all the models trained across all LOOCV iterations.

[10] https://github.com/hmmlearn/hmmlearn

5.1.2 Continuous characterization of stress dynamics

The DKF is a novel filtering method that provides a fast, analytic approximation for models with linear, gaussian dynamics but nonlinear, nongaussian observations. For continuous SSMs, the conditional distribution $P(s_t \mid y_{1:t})$ can be expressed recursively using Bayes' rule, $P(s_t \mid y_{1:t}) = \frac{P(y_t|s_t)P(s_t|y_{1:t-1})}{P(y_t|y_{1:t-1})}$, together with the Chapman-Kolmogorov equation, $P(s_t \mid y_{1:t-1}) = \int P(s_t \mid s_{t-1})P(s_{t-1} \mid y_{1:t-1})ds_{t-1}$. The standard KF models the densities $P(s_t \mid s_{t-1})$ and $P(y_t \mid s_t)$ as linear and gaussian so that the posterior $P(s_t \mid y_{1:t})$ is also Gaussian and efficiently computable. The DKF is based on the key approximation for the likelihood

$$P(y_t \mid s_t) = P(y_t)\frac{P(s_t \mid y_t)}{P(s_t)} \approx k(y_t)\frac{\mathcal{N}(s_t \mid f(y_t), Q(y_t))}{\mathcal{N}(s_t \mid 0, S)} \quad (2)$$

where $k(\cdot)$ is a normalizing constant, $f(\cdot), Q(\cdot)$ the conditional mean and covariance of s_t, respectively. The advantage of such approximation is that $f(\cdot), Q(\cdot)$, and S are easier to learn from training data than the full conditional density (see Burkhart et al., 2020 for details). In particular, the conditional mean f can be learned using a number of regression methods; here we adopted a neural network regression (Burkhart et al., 2020).

Before DKF training, the signals were smoothed by applying the Savitzky-Golay filter (Savitzky and Golay, 1964). To evaluate the performance of the model, the normalized Root Mean Squared Error (nRMSE) was calculated. DKF was trained as many times as the number of LOOCV iterations, and the average of all the computed nRMSE values for each iteration was used to determine the overall nRMSE value.

6 RESULTS AND DISCUSSION

Results of the evaluation of the models are presented in this section, along with a discussion on the importance of each individual device. Only the stress labels were taken into account for the evaluation, and different tests were run for each model.

6.1 Discrete SSM performance

In order to evaluate the results of in terms of classification, confusion matrices and accuracy scores were reported. Based on the affective states designed for the different game phases, different classification tasks were distinguished:

1. using baseline, low stress, medium stress, and high stress as classes, a four-class problem was defined;
2. using baseline, low stress, and high stress as classes, a three-class problem was defined;
3. using the baseline condition acting as the no-stress class and the other states acting as the stress class, a binary problem was defined.

Each setup defined by the classification problem was run sixteen times (the number of folds in LOOCV), and the accuracy measures are averaged over all runs of the repeated LOOCV.

As it can be seen in Figure 3a, the first classification task revealed that the collected VR-based data perform better for the high stress condition. The features have difficulties, in fact, in distinguishing between different stress levels, particularly the low stress state.

Figure 3b shows the results of the second classification problem. The model proved to be valid at recognizing the data in the high stress class and quite good at recognizing the baseline data. In this case, a great deal of the low stress data is incorrectly classified as high stress.

The third classification task is the one that led to the best results, which are shown in the confusion matrix illustrated in Figure 3c. The algorithm proves to be able to discriminate between the two classes, the best score is achieved with the baseline class.

In Table 4, the accuracy scores for all the described classification tasks are reported.

The binary problem was the one in which the model performed better, reaching the accuracy of 84.4%. Overall, results provided evidence that discrete SSMs were good at distinguishing between a state of stress and a state of baseline, but they could hardly classify different stress levels.

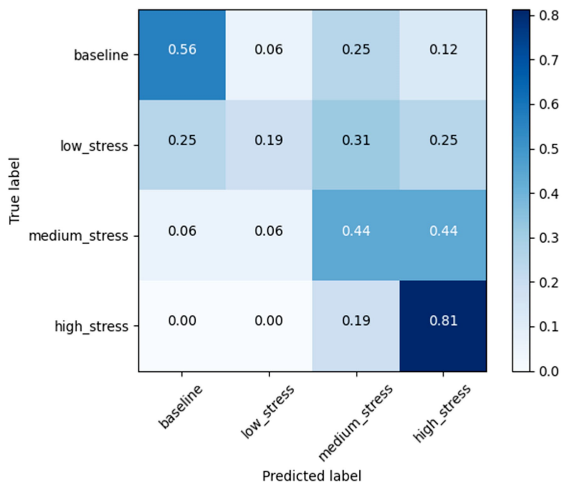
Table 4: Accuracy scores of the model for all the classification tasks.

Accuracy score		
Four-class	Three-class	Two-class
50.0	56.2	84.4

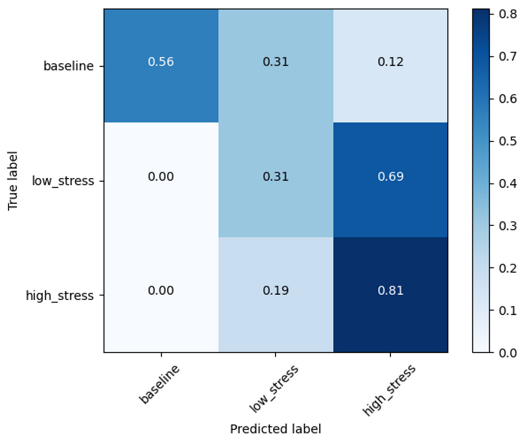
6.2 Continuous SSM performance

As a preliminary qualitative evaluation, the actual label curve $\{l_t\}_{t=1}^{T}$, defining the self-assessed stress level, and the predicted stress curve were also plotted and compared with the purpose of visualizing and scrutinizing the results.

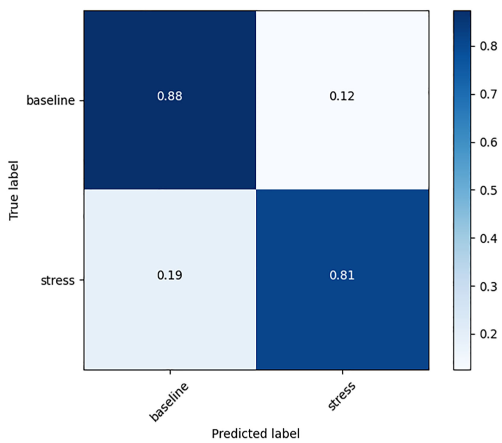
The two curves were plotted for each fold of LOOCV procedure, hence for each test subject. Fig-



(a) Confusion matrix of the four-class problem.



(b) Confusion matrix of the three-class problem.



(c) Confusion matrix of the two-class problem.

Figure 3: Confusion matrices of all the classification tasks using VR-based features.

ure 4 shows one typical example of the inferred latent stress level dynamics, which refers to the trial involving subject 13 as the test and all the other subjects as training set. The red line indicates the inferred stress curve, whilst the blue line represents the actual label curve $\{l_t\}_{t=1}^{T}$. Even though the model was able to identify the general trend of the stress level dynamics, these results suggest that the continuous SSM is not accurate enough, at least in the current experimental setting, to make the model fully reliable for game control purposes.

A quantitative evaluation was thus performed in terms of the nRMSE values obtained by comparing the target (self-assessment) and estimated perceived stress curves. The computed nRMSE values are reported in Table 5. The three different input types are compared, nRMSE was calculated for each iteration of LOOCV process using each subject as test set in turn, and then the nRMSE average with respect to all the iterations was computed.

Table 5: The nRMSE values computed for each trial in which the DKF model was run. Subject column indicates the subject who was left out during LOOCV iteration, and AVG is the average value across all trials.

subject	nRMSE
01	0.44
02	0.39
03	0.59
04	0.42
05	0.61
06	0.49
07	0.89
08	0.57
09	0.60
10	0.73
11	0.50
12	0.45
13	0.43
14	0.44
15	1.0
16	0.80
AVG	0.57

6.3 Discussion

The VR-based data provide quite generalizable measures: behavioral and movement data, such as controllers and head velocities, which keys are pressed and at what pressure level, are indicative of the users' emotional states. Information gathered from *Quest 2* devices proved to be useful to identify the perceived stress level of the players. This suggests that, in the

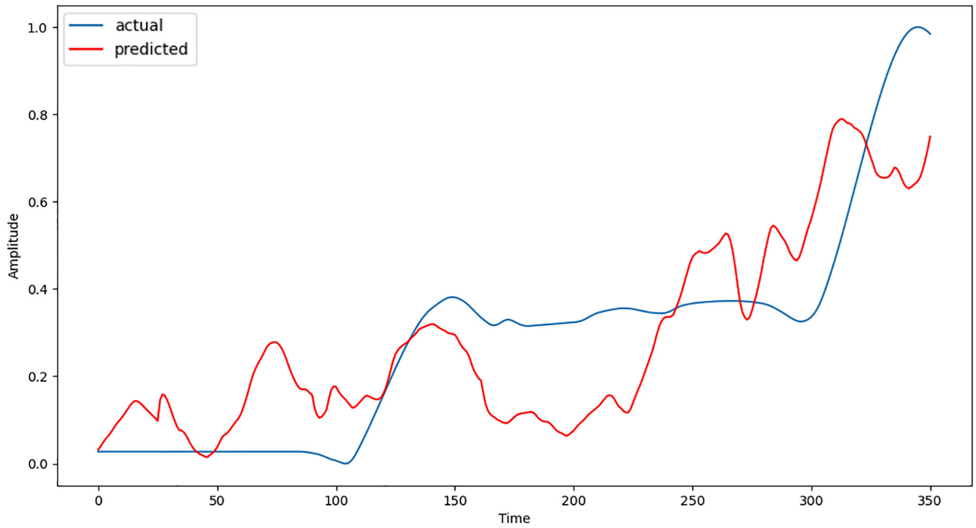


Figure 4: Curves of the actual stress labels and the stress labels predicted by DKF for the VR-based features, using subject 13 as test set.

context of video games, the VR-based features can offer a rich understanding of the affective states. The analyzed context, in fact, differs from any other real context, and players' mental states are strongly related to game events and actions they can do.

7 CONCLUSION

The present work aimed at a preliminary investigation concerning the assessment of players' perceived stress level in VR-based video games. The developed systems can in principle be applied to video games of the same genre, with the same structure and elements as the one developed in this project: a survival horror video game with a baseline phase for calibration and stress elements established on the features of perceived stress defined by Lebois et al. (2016).

When comparing how the utilized algorithms performed on the various tasks, it becomes apparent that the binary state discrete model produced the highest accuracy scores. The achieved classification accuracies are up to 84.4% using the VR-based data.

In conclusion, the results obtained are encouraging and this preliminary study can be useful as a starting point for future research. Further work is required to gather more data from a major number of subjects, and to take the questionnaires into account. Questionnaire answers were not included in the development of the presented model. Training the models using different classes of players who have the same profile (Yannakakis and Togelius, 2018) would result in a more personalized experience.

The potential benefits of the explored approach are twofold: a system incorporating a stress-dependent control can adapt the content of the game in response to the players' experiential state; stress level modelling/inference can help in developing new game mechanics relying on such index to provide a customized experience for players.

Video games are increasingly being used in the field of mental health (Colder Carras et al., 2018; Pallavicini et al., 2018a). The enjoyment and intrinsic motivation often associated with video games make them a powerful and attractive tool to provide psychological support to people. According to studies, video games can help individuals cope with their stressful life experiences (Pallavicini et al., 2021; Maarsingh et al., 2019). A stress-based serious game that incorporates biofeedback techniques into the game could assist people with stress to handle their emotional and physiological responses to stressors, improving their abilities in everyday life and their mental health.

Ongoing research is focused on two aspects. The first concerns the integration of physiological information (electrodermal activity) with behavioural data for stress level assessment. This aspect paves the way to consider the relationship between the stress response and the affective state of the user.

The second, more generally, relates to the use of stress/affective assessment for the development of affective feedback-based video games. In this perspective, feedback from players' affective states (Bersak et al., 2001) is incorporated into the development of new game content and mechanics, manipulating gameplay so to keep the players in the flow state.

REFERENCES

Ahmed, F., Bari, A. H., and Gavrilova, M. L. (2019). Emotion recognition from body movement. *IEEE Access*, 8:11761–11781.

Bersak, D., McDarby, G., Augenblick, N., McDarby, P., McDonnell, D., McDonald, B., and Karkun, R. (2001). Intelligent biofeedback using an immersive competitive environment. In *Paper at the designing ubiquitous computing games workshop at UbiComp*, pages 1–6. Citeseer.

Bishop, C. M. (2006). *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Springer-Verlag New York, Inc., Secaucus, NJ, USA.

Boccignone, G., Conte, D., Cuculo, V., and Lanzarotti, R. (2017). Amhuse: a multimodal dataset for humour sensing. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction*, pages 438–445.

Bradley, M. M. and Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of behavior therapy and experimental psychiatry*, 25(1):49–59.

Burkhart, M. C., Brandman, D. M., Franco, B., Hochberg, L. R., and Harrison, M. T. (2020). The discriminative kalman filter for bayesian filtering with nonlinear and nongaussian observation models. *Neural computation*, 32(5):969–1017.

Cohen, S., Kamarck, T., and Mermelstein, R. (1983). A global measure of perceived stress. *Journal of health and social behavior*, pages 385–396.

Colder Carras, M., Van Rooij, A. J., Spruijt-Metz, D., Kvedar, J., Griffiths, M. D., Carabas, Y., and Labrique, A. (2018). Commercial video games as therapy: A new research agenda to unlock the potential of a global pastime. *Frontiers in psychiatry*, 8:300.

Csikszentmihalyi, M. and Csikzentmihaly, M. (1990). *Flow: The psychology of optimal experience*, volume 1990. Harper & Row New York.

Frommel, J., Schrader, C., and Weber, M. (2018). Towards emotion-based adaptive games: Emotion recognition via input and performance features. In *Proceedings of the 2018 Annual Symposium on Computer-Human Interaction in Play*, pages 173–185.

Fullerton, T. (2014). *Game design workshop: a playcentric approach to creating innovative games*. CRC press.

Girin, L., Leglaive, S., Bie, X., Diard, J., Hueber, T., and Alameda-Pineda, X. (2021). Dynamical variational autoencoders: A comprehensive review. *Foundations and Trends in Machine Learning*, 15(1-2):1–175.

Herbold, S. (2020). Autorank: A python package for automated ranking of classifiers. *Journal of Open Source Software*, 5(48):2173.

Higgins, E. T. (1989). Self-discrepancy theory: What patterns of self-beliefs cause people to suffer? In *Advances in experimental social psychology*, volume 22, pages 93–136. Elsevier.

Karg, M., Samadani, A.-A., Gorbet, R., Kühnlenz, K., Hoey, J., and Kulić, D. (2013). Body movements for affective expression: A survey of automatic recognition and generation. *IEEE Transactions on Affective Computing*, 4(4):341–359.

Kleinsmith, A. and Bianchi-Berthouze, N. (2012). Affective body expression perception and recognition: A survey. *IEEE Transactions on Affective Computing*, 4(1):15–33.

Lazarus, R. S. (1993). From psychological stress to the emotions: A history of changing outlooks. *Annual review of psychology*, 44(1):1–22.

Lebois, L. A., Hertzog, C., Slavich, G. M., Barrett, L. F., and Barsalou, L. W. (2016). Establishing the situated features associated with perceived stress. *Acta Psychologica*, 169:119–132.

Maarsingh, B. M., Bos, J., Van Tuijn, C. F., and Renard, S. B. (2019). Changing stress mindset through stressjam: a virtual reality game using biofeedback. *Games for health journal*, 8(5):326–331.

Marín-Morales, J., Llinares, C., Guixeres, J., and Alcañiz, M. (2020). Emotion recognition in immersive virtual reality: From statistics to affective computing. *Sensors*, 20(18):5163.

Mishra, P. and Ratnaparkhi, S. (2018). Hmm based emotion detection in games. In *2018 3rd International Conference for Convergence in Technology (I2CT)*, pages 1–4. IEEE.

Pallavicini, F., Ferrari, A., and Mantovani, F. (2018a). Video games for well-being: A systematic review on the application of computer games for cognitive and emotional training in the adult population. *Frontiers in psychology*, 9:2127.

Pallavicini, F., Ferrari, A., Pepe, A., Garcea, G., Zanacchi, A., and Mantovani, F. (2018b). Effectiveness of virtual reality survival horror games for the emotional elicitation: Preliminary insights using resident evil 7: Biohazard. In *International Conference on Universal Access in Human-Computer Interaction*, pages 87–101. Springer.

Pallavicini, F., Pepe, A., Mantovani, F., et al. (2021). Commercial off-the-shelf video games for reducing stress and anxiety: systematic review. *JMIR mental health*, 8(8):e28150.

Savitzky, A. and Golay, M. J. (1964). Smoothing and differentiation of data by simplified least squares procedures. *Analytical chemistry*, 36(8):1627–1639.

Schell, J. (2008). *The Art of Game Design: A book of lenses*. CRC press.

Sykes, J. and Brown, S. (2003). Affective gaming: measuring emotion through the gamepad. In *CHI'03 extended abstracts on Human factors in computing systems*, pages 732–733.

Vachiratamporn, V., Legaspi, R., Moriyama, K., and Numao, M. (2013). Towards the design of affective survival horror games: An investigation on player affect. In *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, pages 576–581. IEEE.

Yannakakis, G. N. and Togelius, J. (2018). *Artificial intelligence and games*, volume 2. Springer.