Modeling subjective fear using skin conductance: a preliminary study in virtual reality

Andrea Baldini[1*], Sergio Frumento[2], Danilo Menicucci[2], Angelo Gemignani[2],
Enzo Pasquale Scilingo[1], Alberto Greco[1]

Abstract— **Reliably measuring fear perception could help evaluate the effectiveness of treatments for pathological conditions such as specific phobias or post-traumatic stress syndrome (e.g., exposure therapy). In this study, we developed a novel virtual reality (VR) scenario to induce fear and evaluate the related physiological response by the analysis of skin conductance (SC) signal. Eighteen subjects voluntarily experienced the fear VR scenario while their SC was recorded. After the experiment, each participant was asked to score the perceived subjective fear using a Likert scale from 1 to 10. We used the cvxEDA algorithm to process the collected SC signals and extract several features able to estimate the autonomic response to the fearful stimuli. Finally, the extracted features were linearly combined to model the subjective fear perception scores by means of LASSO linear regression. The sparsification imposed by the LASSO procedure to mitigate the overfitting risk identified an optimal linear model including only the standard deviation of the tonic SC component as a regressor ($p = 0.007$; $R^2 = 0.3337$). The significant contribution of this feature to the model suggests that subjects experiencing more intense subjective fear have a more variable and unstable sympathetic tone.**

I. INTRODUCTION

Fear is an emotion commonly experienced in response to potentially dangerous or threatening cues but, when poorly regulated, it can result in excessive manifestations and persist in everyday situations, with implications in different pathological conditions. Indeed, the long-term exposition to fear could cause impairment of memories and difficulties in regulating emotions [1]. Moreover, when fear translates into irrational feeling, it could affect humans' mental health by originating conditions like specific phobias or post-traumatic stress syndrome. Such pathological states substantially impact daily life due to the adverse effects on our decision-making, learning, and thinking processes.

One of the most effective clinical approaches to treat phobias is exposure therapy [2]: a psychological treatment that gradually exposes pathological subjects to irrationally fearful objects. In this context, measuring fear perception could help evaluate the effectiveness of the treatment as well as standardize and control the exposure sessions.

* The research leading to these results has received partial funding from the Italian Ministry of Education and Research (MIUR) in the framework of the CrossLab project (Departments of Excellence), and from European Union H2020 Program under grant agreement n 824153 of the project "POTION-Promoting Social Interaction through Emotional Body Odours".

[1] A. Baldini and A. Greco are with the Department of Information Engineering, University of Pisa, Italy, 56122.

[2] S. Frumento, D. Menicucci and A. Gemignani are with the Department of Surgical, Medical, Molecular and Critical Area Pathology, University of Pisa, Italy, 56122.

* Corresponding author: andrea.baldini@phd.unipi.it

In clinical practice, the common approach to assess emotions relies on psychometric scales and self-reported measures. Indeed, several self-assessment questionnaires have been already developed and applied to evaluate the fear induced by specific phobias (e.g., height [3], [4], spiders [5]) in the exposure therapies context [6]. However, each self-reported questionnaire has potential issues concerning reliability and replicability mainly due to its subjective nature, leading to biased measures. Thus, in the last years more objective methods have been proposed to estimate psychophysiological states by analyzing their physiological correlates in response to emotional stimuli (e.g., fearful stimuli) [7], [8]. Such a physiological response is regulated by the parasympathetic and sympathetic branches of the autonomic nervous system (ANS) and is manifested by variations in different peripheral anatomic signals. One of the most studied sympathetic nervous system (SNS) correlates in fear studies is the skin conductance (SC) [9], which has been recently used to assess anxiety disorders [10], and investigate the fear learning and conditioning processes [11].

Nevertheless, despite the extensive use of SC in fear studies, to the best of our knowledge, a model of the systematic relationship between the skin conductance response patterns and fear perception level is still missing. Such an analysis is complicated by the subject-dependent response to fearful stimuli and by difficulties in reliably, reproducibly and controllably eliciting specific emotions.

In the last decades, most affective computing studies have attempted to induce fear by using mainly passive and unengaging media such as the Internation Affective Picture System (IAPS) and the International Affective Digitized Sounds (IADS) or the so-called film clip paradigm [12]. However, the sense of presence and engagement represents a crucial aspect of fear elicitation protocols [13]. The recent advancements in computer vision and computational tools have enabled virtual reality (VR) technologies in fear studies. In this context, the opportunity to design virtual simulations that faithfully mimic real-world situations can pave the way to fear elicitation protocols that contemporarily involve discrete responses and situational fear [14].

In this preliminary study, we developed a virtual scenario to induce situational fear and investigate specific SC components able to explain the subjective perception of fear. In particular, we designed three different virtual scenarios in which subjects could freely navigate. The SC signals were recorded during the virtual exploration through a wearable device. Afterwards SC signals were processed to extract

Manuscript 1420 submitted to 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Received January 31, 2022.

specific features reflecting both tonic and phasic sympathetic activation and to linearly combine them to explain the level of subjective fear reported. To this aim, we adopted a cross-validated LASSO regression procedure to build the best linear model associating the physiological response and psychological perception to a fearful virtual environment.

II. MATERIALS & METHODS

A. Study population & experimental protocol

Eighteen healthy subjects (12 females), aged between 18 and 35, voluntarily participated in the experiment. The study was approved by the bioethical commitee of the University of Pisa (n. 14/2019). Before beginning the experimental sessions, the subjects were asked to sign the informed consent and fill in the S.T.A.I. Y-1 questionnaire. Only subjects with a S.T.A.I. Y1 score less than 45 (i.e., threshold of a high anxious state) were included in the experiment. The experimental protocol (see Figure 1) consisted of four sessions showing three different VR scenarios, as follows:

- Session 1, Rest (*R*): the participants were immersed for three minutes in a void space and they were asked to relax.
- Session 2, Neutral (*N*): each subject visited a virtual living room for three minutes, representing a neutral situation in terms of emotional stimulation.
- Session 3, Fear (*F*): the participants explored for five minutes a virtual scenario purposely designed to induce subejctive fear.
- Session 4. Recovery (*V*): the participants were immersed for three minutes in the same void space to recover.

We adopted the Oculus Rift S (Lenovo and Facebook Technologies, USA) to render and update the VR scenarios and a Shimmer 3GSR+ unit to record the SC signals sampled at 50.33 Hz throughout the experiment.

After the experiment, each subject was asked to self-assess the fear felt (*SASF*) during the *F* session by using a Likert scale whose levels spanned from 1 to 10.

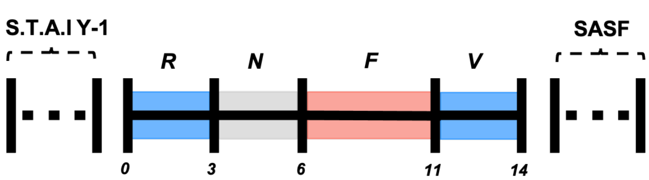

Fig. 1. The experimental timeline. R=Rest session. N=Neutral session. F=Fear-inducing session. V=Recovery session

B. Virtual environment design

We designed the three VR scenarios using the Unity3D game engine. Subjects could navigate within the scenarios using the Oculus touch controller. The speed of the movements was limited to minimize possible motion sickness effects. To control the emotional impact of the environments we dealt with lightining conditions and colours temperature [15]. The VR environments were developed as follows:

1) Rest scenario: The *R* and *V* sessions were characterized by a void space displaying only a black text on a neutral warm coloured background. The black text invited the participants to relax and the background colour was accurately selected to avoid arousing effects.

2) Neutral scenario: The *N* scenario was designed to help the subjects adapt to the immersive virtual environment and to train them to move using the Oculus touch controller. To control the emotional impact of this session, the lights were configured with neutral colour temperature and equally divided between direct and indirect [15]. In addition, the objects within the scenario were of neutral colours [15].

3) Fear scenario: The *F* session represented a virtual abandoned hospital of $550m^2$ following horror movies and games specific guidelines [16]. Accordingly, we set flickering dimmed lights to favour darkness and provide suspenseful audio. The participants could navigate within the low-light environment using a virtual flashlight bound to the non-dominant hand. To enhance the fear-inducing effect of the environment, we included a series of virtual horror contents combining both sight and auditory sensory channels stimulation.

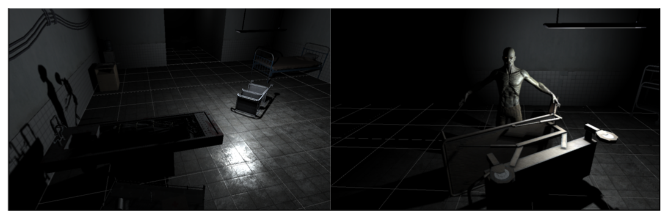

Fig. 2. F session design. On the left side=virtual abandoned hospital. On the right side=example of virtual horror content.

C. SC decomposition & feature extraction

To monitor the SNS activity, we recorded and analyzed the SC signal throughout the whole experiment. Indeed, the SC describes variations in the electrical properties of the skin and represents one of the most direct measures to observe the SNS dynamics. The SC signal is comprised of two main components: a slow-varying component (i.e., the skin conductance level; SCL) and fast-varying fluctuations (i.e., the skin conductance response; SCR). These operate with different timescale and relationships with exogenous stimuli. The SCL reflects the sympathetic tone of the subject [17] and contains information about the general psychophysiological state [18]. The SCRs arise in response to external stimuli. We used the cvxEDA algorithm [19] to decompose the SC signal in its components (i.e., SCL and SCRs) and jointly estimate the sympathetic bursts of the SMNA underlying the SCRs.

Once the SC signals were decomposed, we processed the SCL, the SCRs and the SMNA signals to extract several features (Table I). In particular, the SCL signals were segmented using non-overlapped time windows of 20 seconds. For each segment, we extracted the mean value (*SCLmean*) and the standard deviation (*SCLstd*). Likewise, we used a

Manuscript 1420 submitted to 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Received January 31, 2022.

shorter non-overlapped time window of 5 seconds to analyze the SCRs and the SMNA signals. More specifically, we estimated the mean value of the SCR component (SCRmean), and the amplitude of the maximum peak (PeakMax), the spikes number (NPeak) and the sum of the peaks amplitude (AmpSum) from the SMNA signal. In addition, we computed the SC spectral power in the frequency band 0.04-0.15 Hz (EDAsymp) within non-overlapped time windows of 60 seconds. Finally, we computed the difference between averaged values within the time segments considering the features extracted from the *F* and the *R* session.

TABLE I

LIST OF INVESTIGATED SC FEATURES

Feature	Description
SCLmean	SCL mean value
SCLstd	SCL standard deviation
SCRmean	SCR mean value
PeakMax	Maximum amplitude within the SMNA spike train
NPeak	Number of peaks within the SMNA spike train
AmpSum	Sum of the peak amplitudes within the SMNA spike train
EDAsymp	SC spectral power in the frequency band 0.04-0.15 Hz

D. Statistical analysis: LASSO regression

We modeled the collected *SASFs* as a function of the extracted features. To select the best linear model explaining the *SASFs*, we adopted the LASSO (least absolute shrinkage and selection operator) linear regression [20]. The LASSO is a model that implements a regularization technique based on L^1-norm particularly suited to handle multicollinearity and mitigate the overfitting risk in the regression models. A typical LASSO problem considering n features can be formulated as the following minimization problem (Eq. 1):

$$\min_{\beta \in R^n} \{ \|y - X\beta\|_2^2 + \lambda \|X\beta\|_1^1 \} \tag{1}$$

Where y represents the dependent variable to be modeled (i.e., the *SASFs*), X is the design matrix containing the SC features, β defines the coefficients vector, and λ is a regularization parameter controlling for the sparsity of the solution.

Given the high number of regressors compared to the number of observations, to facilitate model interpretability and comparisons between regressors, we applied the LASSO model after z-scoring the SC features. Then, the model was evaluated in terms of mean squared error (MSE) according to a 9-folds cross-validation. The cross-validation was accomplished for a geometric sequence of 100 different values of λ ranging from $1.39e-4$ to 1.39. The SC features were ranked by analyzing the relative coefficient at the different λ coefficient values. Afterwards, the statistical significance of the selected features was evaluated through an *exact post-selection inference* procedure [21] to overcome the overfitting issues affecting the standard way of conducting inference in regression models. Then, the values of β and λ that minimized the *MSE* were considered to fit the best model explaining the *SASFs*.

III. RESULTS

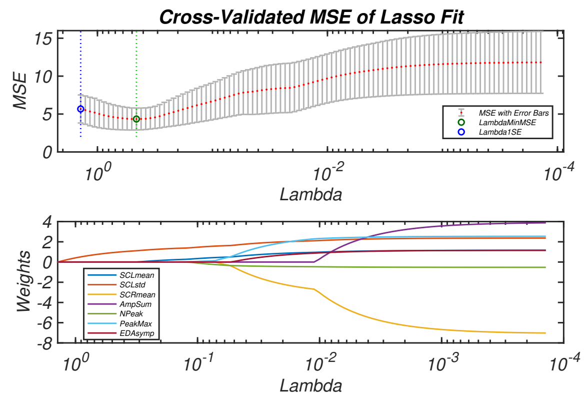

Fig. 3. The upper figure shows the Mean Squared Error (MSE) of the least absolute shrinkage and selection operator (LASSO) regression model estimating the SASFs at different values of λ. The intervals of confidence for each considered λ were obtained through a 9-folds cross-validation. The bottom figure shows the value of each regressor coefficient at different values of λ.

The anxiety of each participant was classified as low/moderate (i.e., S.T.A.I. Y-1 score less than 45); thus, no subjects were excluded from the experimental sessions. The *SASFs* scores evaluating the subjective fear felt during the virtual exploration of the abandoned hospital was equal to 7.50 ± 1.50.

The feature selection process imposed by the LASSO L^1-regularization reduced the dimensionality of the feature set by finding a sparse optimal model (Figure 3). The SC features were ranked according to the trend of the relative coefficients shown in Figure 3. The Table II reports such a feature ranking.

TABLE II

LASSO FEATURE RANKING. λ_0 INDICATES THE VALUE OF THE λ PARAMETER IMPOSING THE BETA COEFFICIENT OF THE RELATIVE SC FEATURE EQUAL TO ZERO.

Feature	Rank	λ_0
SCLstd	1	1.03993
SCLmean	2	0.3158
PeakMax	3	0.1647
NPeak	4	0.1246
SCRmean	5	0.0780
EDAsymp	6	0.0530
AmpSum	7	0.0111

The model that minimized the mean squared error ($\lambda = 0.4582$) within the 9-folds cross-validation framework imposed coefficients equal to zero for six of the seven extracted features. Thus, according to the results produced by the LASSO algorithm, only *SCLstd* was included in the best model. The *exact post-selection inference* showed the statistical significance of this feature ($p = 0.007$) at the value of

Manuscript 1420 submitted to 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Received January 31, 2022.

lambda that minimized the MSE. The model accounted for the 33.73% of the *SASFs* variability.

The model was the following (Eq. 2):

$$SASF = 6.4118 + 0.9701 \cdot TonicStd \tag{2}$$

The model (Eq. 2) minimum MSE was equal to 4.3439.

IV. Discussion

In this study, we combined a VR fear-inducing scenario with a LASSO regression to investigate the SC features able to explain the processes underlying the perception of situational fear. Our work confirms the capability of VR to induce genuine emotional states in ecological, reproducible and highly-controllable experimental environments. While the traditional laboratory conditions can only administer discrete and decontextualized emotional stimuli, VR allows for an experimental manipulation of the whole environment where the emotional reactions are elicited and consciously perceived. For what concerns the proposed VR scenario, the high median value of the *SASFs* scores suggested that it represented a suspenseful context inducing a high level of subjective fear (i.e., situational fear). Interestingly, the psychophysiological correlates of such situational fear (consciously reported) are distinguishable from those of fight-or-flight responses to discrete fearful stimuli (that do not necessarily involve consciousness; [22]). Indeed, the analysis based on LASSO regression revealed an optimal linear model for the available dataset, including only *SCLstd* as a regressor rather than fast reactions typical of the fight-or-flight response to discrete stimuli. This mechanism could represent a possible etiology and therapeutic target for mental disorders sharing an irrational fear for specific animals, objects or situations (e.g., specific phobias, post-traumatic stress disorder, panic disorder). Future works will explore the physiological reaction induced by the discrete stimuli within the proposed virtual scenario.

V. CONCLUSIONS

This study proposes a novel virtual scenario able to induce situational fear providing at the same time a flexible tool to investigate possible physiological correlates of this emotion. In this work, we analyzed both fast- and slow-varying components of the SC signal by using a LASSO regression model explaining the self-reported situational fear. This analysis could be considered the first step towards an objective measurement of fear perception entirely based on sympathetic dynamics, preferable to possibly unreliable subjective reports.

References

[1] R. G. Parsons and K. J. Ressler, "Implications of memory modulation for post-traumatic stress and fear disorders," *Nature neuroscience*, vol. 16, no. 2, pp. 146–153, 2013.

[2] Y. Choy, A. J. Fyer, and J. D. Lipsitz, "Treatment of specific phobia in adults," *Clinical Psychology Review*, vol. 27, no. 3, pp. 266–286, 2007.

[3] S. A. Steinman and B. A. Teachman, "Cognitive processing and acrophobia: validating the heights interpretation questionnaire," *Journal of anxiety disorders*, vol. 25, no. 7, pp. 896–902, 2011.

[4] D. Huppert, E. Grill, and T. Brandt, "A new questionnaire for estimating the severity of visual height intolerance and acrophobia by a metric interval scale," *Frontiers in neurology*, vol. 8, p. 211, 2017.

[5] J. Szymanski and W. O'Donohue, "Fear of spiders questionnaire," *Journal of behavior therapy and experimental psychiatry*, vol. 26, no. 1, pp. 31–34, 1995.

[6] D. Watson, S. N. Garfinkel, C. D. G. van Praag, D. Willmott, K. Wong, F. Meeten, and H. D. Critchley, "Computerized exposure therapy for spider phobia: Effects of cardiac timing and interoceptive ability on subjective and behavioral outcomes," *Psychosomatic Medicine*, vol. 81, p. 90–99, 2019.

[7] S. D. Kreibig, F. H. Wilhelm, W. T. Roth, and J. J. Gross, "Cardiovascular, electrodermal, and respiratory response patterns to fear-and sadness-inducing films," *Psychophysiology*, vol. 44, no. 5, pp. 787–806, 2007.

[8] D. M. Vianna and P. Carrive, "Changes in cutaneous and body temperature during and after conditioned fear to context in the rat," *European Journal of Neuroscience*, vol. 21, no. 9, pp. 2505–2512, 2005.

[9] B. G. Wallin, "Sympathetic nerve activity underlying electrodermal and cardiovascular reactions in man," *Psychophysiology*, vol. 18, no. 4, pp. 470–476, 1981.

[10] L. Gualniera, J. Singh, F. Fiori, and P. Santosh, "Emotional behavioural and autonomic dysregulation (ebad) in rett syndrome – eda and hrv monitoring using wearable sensor technology," *Journal of Psychiatric Research*, vol. 138, pp. 186–193, 2021.

[11] R. Faghih, P. Stokes, M.-F. , R. Zsido, S. Zorowitz, B. Rosenbaum, H. SONG, M. Milad, D. Dougherty, E. Eskandar, A. Widge, E. Brown, and R. Barbieri, "Characterization of fear conditioning and fear extinction by analysis of electrodermal activity," *Conference proceedings: ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, vol. 2015, pp. 7814–7818, 08 2015.

[12] H. H. Sik, G. T. Halkias, C. Chang, J. Gao, H. K. Leung, and B. W. Y. Wu, "Modulation of the neurophysiological response to fearful and stressful stimuli through repetitive religious chanting," *Journal of Visualized Experiments*, no. 177, 2021.

[13] C. Coelho, J. Tichon, T. J. Hine, G. Wallis, and G. Riva, "Media presence and inner presence: the sense of presence in virtual reality technologies," in *From communication to presence: Cognition, emotions and culture towards the ultimate communicative experience*. IOS Press, Amsterdam, 2006, pp. 25–45.

[14] D. Liao, Y. Huang, Z. Tan, J. Yang, and X. Xu, *Design of Virtual Reality Scenes with Variable Levels of Fear Evocation*, 06 2018, pp. 103–115.

[15] J. Marín-Morales, J. L. Higuera-Trujillo, A. Greco, J. Guixeres, C. Llinares, E. P. Scilingo, M. Alcañiz, and G. Valenza, "Affective computing in virtual reality: emotion recognition from brain and heartbeat dynamics using wearable sensors," *Scientific Reports*, vol. 8, no. 1, 2018.

[16] E. Soares de Lima and T. Demarque, "Auditory hallucination: Audiological perspective for horror games," 10 2013.

[17] S. Ghiasi, A. Greco, R. Barbieri, E. P. Scilingo, and G. Valenza, "Assessing autonomic function from electrodermal activity and heart rate variability during cold-pressor test and emotional challenge," *Scientific reports*, vol. 10, no. 1, pp. 1–13, 2020.

[18] A. Greco, G. Valenza, J. Lazaro, J. Garzon-Rey, J. Aguilo, C. D. la Camara, R. Bailon, and E. Scilingo, ""acute stress state classification based on electrodermal activity modeling"," *"IEEE Transactions on Affective Computing"*, "2021".

[19] A. Greco, G. Valenza, A. Lanata, E. P. Scilingo, and L. Citi, "cvxeda: A convex optimization approach to electrodermal activity processing," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 4, pp. 797–804, 2016.

[20] R. Tibshirani, "Regression shrinkage and selection via the lasso," *Journal of the Royal Statistical Society: Series B (Methodological)*, vol. 58, no. 1, pp. 267–288, 1996.

[21] J. D. Lee, D. L. Sun, Y. Sun, and J. E. Taylor, "Exact post-selection inference, with application to the lasso," *The Annals of Statistics*, vol. 44, no. 3, pp. 907–927, 2016.

[22] S. Frumento, D. Menicucci, P. K. Hitchcott, A. Zaccaro, and A. Gemignani, "Systematic review of studies on subliminal exposure to phobic stimuli: Integrating therapeutic models for specific phobias," *Frontiers in Neuroscience*, vol. 15, 2021.