International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

COPY RIGHT

IJIEMR Transactions, online available on 18th October 2024. Link

https://ijiemr.org/downloads.php?vol=Volume-13 &issue= Issue 10

DOI:10.48047/IJIEMR/V13/ ISSUE10/50

Title: " PHYSIOLOGICALLY BASED STRESS DETECTION IN REAL-TIME FOR HAZARDOUS OPERATIONS"

Volume 13, ISSUE 10, Pages: 345- 352

Paper Authors
SRIKANTH REDDY KONNI, AIMAN FATHIMA

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

PHYSIOLOGICALLY BASED STRESS DETECTION IN REAL-TIME FOR HAZARDOUS OPERATIONS

[1]SRIKANTH REDDY KONNI, [2]AIMAN FATHIMA
[1]Assistant Professor, Department of CSE, Sree Chaitanya College of Engineering, Karimnagar
[2]Student, Department of CSE, Sree Chaitanya College of Engineering, Karimnagar

ABSTRACT

Real-time stress detection is a useful tool for stress reduction and job performance optimisation during hazardous operations training. Stress detection systems use physiological cues to build a machine learning model that classifies stress levels in unseen data. Sadly, the time-series structure of physiological data and individual variations restrict the applicability of generalised models, making real-time monitoring and post-hoc stress identification more difficult. A personalised stress detection system that chooses a customised subset of characteristics for model training was assessed in this research. After the fact, the system was assessed for deployment in real time. Additionally, the error resulting from indirect approximations was evaluated for classical classifiers in comparison to an ideal probability classifier (Approximate Bayes; ABayes), which served as a benchmark. The three stressor levels that the healthy individuals had to complete were either a basic laboratory-based activity (N-back, n = 14) or a difficult virtual reality one (responding to spacecraft emergency fires, n = 27). Assessments were made of breathing, electrodermal activity, blood pressure, and heart rate. Window sizes and customised features were contrasted. Comparisons were made between the classification performance of random forests, decision trees, support vector machines, and ABayes. The findings show that three stress levels may be more accurately classified using a customised model with time series intervals than using a generalised model. In contrast to ABayes, holdout performance and cross-validation differed for classical classifiers, indicating inaccuracy from indirect approximations. The chosen characteristics varied depending on the activities and window size, but blood pressure was determined to be the most noticeable. One benefit of personalised models is their capacity to take individual differences into account; this feature is expected to become more prevalent in detection systems of the future.

1. INTRODUCTION

Even with intensive emergency response training, the stress of a crisis might impair a person's ability to react appropriately in an actual emergency. Stress may set off a series of potentially altering physiological processes. Cognitive resources, situational awareness, decision-making, and behavioural habits [1].A high-stress situation's incapacity to handle the stress might impair work performance, increasing the chance of mission failure, injury, or death [2]. Therefore, greater training may help create resilience to this situational stress and provide better results. Therefore, tailoring the level of stress in training situations based on real-time monitoring of an individual's stress reactions may result in a safer management of real-world hazardous operations [3], [4].

Machine learning-based stress detection has proven difficult for a number of reasons. Individual variances exist in the evaluation of stressful events and the body's reaction to them. By expanding their models to a large population, or the "average" response, several stress detection techniques have tried to minimise technological complexity [3]. Personalised stress detection methods, however, could be more resilient to individual variations since the stress reaction to a particular circumstance is mostly subjective [5, 6].

The second difficulty stems from the potential issues associated with the time series nature of physiological information. There are links between features and timing in the physiological stress response. The machine learning premise that the data are independently and identically distributed may be broken by these correlations, producing biassed outcomes [7].

Interpreting how closely model predictions match the actual conditional probabilities of a subject's stress levels is another difficulty. Stress detection models use conventional machine learning techniques that estimate the likelihood that a person is under stress based on their physiological reactions. These algorithms use data-driven approximations. Nevertheless, these approximations are often imprecise and lack a reference point for analysis. A classifier with the same parameters as the Bayes theorem will have the lowest likelihood of mistake, according to traditional statistics research, which states that the Bayes theorem is theoretically the best answer [8]. To get the conditional probability of each class, the Bayes theorem use an empirical density distribution as a genuine prior probability. The classifier chooses the maximal a posteriori class, or the class with the largest posterior probability of occurrence. Algorithms for machine learning make an effort to approximate the density distributions. A classifier that approximates Bayes becomes an optimal Bayes classifier if the classifier's density estimates converge to the actual densities, meaning that the predicted probability mirrors the true probability of occurrence. However, since the method makes assumptions about things like predictor independence, these approximations may vary widely in accuracy [9]. As a result, understanding the logic of the model might be challenging. Because they are often triggered by the same neuroendocrine axis, physiological systems are known to have a high degree of reliance when it comes to a stress response [10]. Multivariate kernel density estimators may be used by academics to demonstrate how classifiers can take dependencies into consideration [11]. For the purpose of stress detection, it may be useful to compare supervised machine learning classifiers to a benchmark optimum classifier, which approximates Bayes using a density distribution calculated by multivariate kernel density estimation.

New methods for time series analysis for physiologically based stress

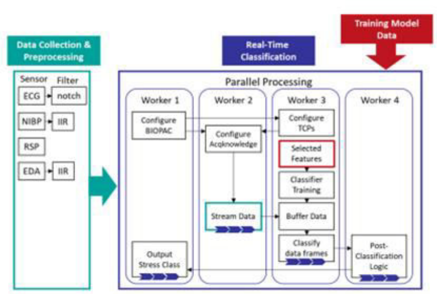
International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

detection are required in order to enable real-time and continuous monitoring of stress levels [12]. In order to better match student reactions to training settings or to better analyse individual stress during staged or actual operations, closed-loop automation may be made possible via real-time stress detection [13]. Multivariate kernel density estimators may aid in improving detection accuracy in datasets with repeated measurements at numerous periods that exhibit uncertainty due to randomness or incompleteness, such as multiple measures of physiological data [11].

This study aims to evaluate the validity, objectivity, and reliability of a personalised model technique in order to solve these issues. In order to account for individual variations in physiology, the first study issue concerns objectivity and asks if stressor levels may display unique levels in personalised characteristics utilised for the classification model. This will provide assurance that the training data represent different ground truth levels and that the model is appropriately developed for the given context. The system's reliability is the subject of the second research question, which assesses the time-series interval approach's performance using a post-hoc model that compares window sizes, classifier validation methods, features chosen for each individual, and a standard laboratory cognitive task with a challenging job-specific task. In contrast to a Bayes classifier called Approximate Bayes (A Bayes), which uses multivariate kernel density estimation to obtain direct approximations of optimal stress classes, the third research question concentrates on the validity of the system by attempting to determine whether indirect approximations have an impact on traditional supervised machine learning classifiers.

This study is a component of a larger initiative to create VR training scenarios that use real-time stress monitoring to dynamically adjust a virtual environment [14], [15], and [16]. The experiment will evaluate a time-series interval approach to stress detection for a post-hoc model of physiological response data, its accuracy in detecting participant stress using a collected during stressful tasks, and provide the architecture for a real-time stress detection system that uses this classification methodology in order to address these research questions within the limitations of the larger system. Post-hoc validation of a machine learning pipeline enables applications for stress monitoring and real-time stress detection.

2. SYSTEM ARCHITECTURE



3. EXISTING SYSTEM

The physiological stress response involves the interaction between the nervous system and the endocrine system that aims to maintain physiological integrity under changing environmental demands. The time course of the physiologic responses to stress varies by system and by the intensity and duration of the stressor; they are neither physiologically independent nor statistically orthogonal. After the psychological appraisal of a stressor, neural ganglia pathways are activated almost instantaneously to evoke very rapid responses via local neurotransmitters. For example, disinhibition of heart rate via vagal withdrawal occurs within milliseconds while a sympathetically-mediated increase in heart occurs after a few seconds (5-10 s) [10]. Sympathetic and sudomotor activity results in the opening of eccrine sweat glands on hands and feet, which occur about 1-5 seconds after stimuli [17]. On the other hand, the physiologic responses due to circulating chemicals take longer to manifest. Epinephrine is secreted from the adrenal medulla and range from milliseconds to minutes to exert their cardiovascular effects. Whereas, cortisol is initiated by the adrenal cortex 5–10 min after stressor onset and peak between 20 and 30 min [18]. These processes can act exclusively or in conjunction on target organs to potentiate (e.g., memory, muscle activation) or attenuate organ function (e.g., digestion, reproduction).

Stress detection, by means of classifying these physiological responses into levels of stress via machine learning, continues to evolve and is motivated by the potential utility of continuously monitoring stress levels in real-time [12], [21]. Stress detection systems have been developed for drivers in semi-urban scenarios [22], [23], patients undergoing virtual reality therapy [24], individuals in working environments [25], and people that need help managing daily stress [21], [26], [27], [28], [29], [30]. Stress detection can also be applied to a variety of human-machine interfaces (HMIs) which may monitor stress, but also infer the cognitive state of the user to adapt system functionality [31]. Examples of HMIs that may use stress detection include wearable devices, voice recognition systems, eye tracking systems, facial expression analysis, and brain/body computer interfaces [12], [32]. However, these HMIs may not be able to accurately detect stress in all individuals, and the accuracy of stress detection may vary depending on the specific technology and approach used [33].

These detection systems collect information about stress responses from either objective physiological sensors or subjective psychological metrics, in the form of independent variables called features, which are then used to classify the stress level. Commonly used sensors include electrodermal activity (EDA), electrocardiogram (ECG), respiration (RSP), electroencephalogram (EEG), skin temperature (ST), and blood volume pulse (BVP) [33]. For an ECG signal, stress indices have been primarily inferred from changes in the time intervals between heartbeats, which measure Heart Rate Variability (HRV) using time-domain, frequency-domain, or nonlinear analysis. HRV metrics have been associated with sympathetic and parasympathetic activation. However, attempting to detect stress levels from signal amplitude alone neglects the

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

time series nature of physiological data. Physiological systems may be simultaneous and coupled (e.g., breathing can modulate heart rate), contain both deterministic and stochastic components, and may be correlated when measured over long periods of time [34]. Stress sensor signals are continuous ordered attributes; therefore, they are best characterized by features that quantify the distribution of data points, variation, correlation properties, stationarity, entropy, and nonlinear properties [35].

Disadvantages

• The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to find Stress Detection.

• Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.

• Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.

4. PROPOSED SYSTEM

This paper describes the development of a personalized physiological-based stress detection system to classify acute stress using feature selection on intervals of the time-series data. To train the machine learning model, participant physiological signals were collected for three stressor levels during either a spaceflight emergency fire procedure on a VR International Space Station (VR-ISS) [46], [47] or a well-validated and less-complex N-back mental workload task [48].

Several previous studies have detected stress induced by N-back tasks via machine learning methods, both alone [48], [50] and with another job-specific task [51]. Therefore, comparing a jobs pecific VR-ISS task to the N-back using the same personalized approach is a way to assess the system's reliability can work for multiple stress detection tasks. Each participant had features selected at different interval window sizes, then those personalized features trained the classifier model, and subsequently tested the classifier's predictive accuracy. Since the stress response is complex and often unique, the analysis will explore which features are selected most for individuals depending on window size, and how this changes classification

performance. Classifier performance was assessed using both holdout and cross-validation validation techniques to simulate how the model may perform on unseen data as an analog for deployment in real-time.

Advantages

The novelty and contribution of this research is to show that stress detection may benefit from using personalized time series approaches to quantify temporal patterns in physiological signals, to assess whether traditional classifiers are limited in approximating the optimal Bayes solution, that certain features may be better at different windows sizes, and that this approach has a suitable performance for detecting stress for a VR spaceflight emergency training procedure.

5. IMPLEMENTATION

Modules Description

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Stress for Hazardous Operations Detection Status, View Stress for Hazardous Operations Detection Status Ratio, Download Predicted Data Sets, View Stress for Hazardous Operations Detection Status Ratio Results, View All Remote Users.

View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT STRESS FOR HAZARDOUS OPERATIONS DETECTION TYPE, VIEW YOUR PROFILE.

6. CONCLUSION

The objective, valid, and reliable nature of a real-time stress detection system employing a personalised time-series interval technique was assessed in this study in order to handle the problems of wide variations in individual stress response and the time-series character of physiological data. Both the easy and difficult activities were able to reach different stress levels, making them suitable for use as ground truth for machine learning. The window widths were analysed to determine which characteristics and/or sensors were appropriate for different time periods. It was discovered that the customised model performed better than the generalised model. Additionally, it assessed the impact of supervised machine learning classifiers' indirect approximations in comparison to A Bayes, the benchmark optimum classifier. The performance of the classifier might be somewhat to moderately impacted by indirect approximations (-11% to +14% of A Bayes). Comparing the present results to previous studies on multi-class stress detection, it seems that a personalised system performs promisingly. When choosing HMIs, sensors, and model characteristics, researchers should exercise caution since they may not take into consideration intra- and inter-individual variations in stress physiology. Subsequent research endeavours will go deeper into these customised stress detection systems with the objective of executing strategies that take into consideration the varying times of an individual's stress reaction and physiological indicators.

REFERENCES

[1] J. E. Driskell, E. Salas, J. H. Johnston, and T. N. Wollert, Stress Exposure Training: An Event-Based Approach (Performance Under Stress). London, U.K.: Ashgate, 2008, pp. 271–286.

[2] I. Barshi and D. L. Dempsey, ''Risk of performance errors due to training deficiencies: Evidence report,'' Nat. Aeronaut. Space Admin. (NASA), NASA Johnson Space Center, Houston, TX, USA, Tech. Rep., JSC-CN-35755, 2016.

[3] M. Gjoreski, M. Luštrek, M. Gams, and H. Gjoreski, ''Monitoring stress with a wrist device using context,'' J. Biomed. Inform., vol. 73, pp. 159–170, Sep. 2017, doi: 10.1016/j.jbi.2017.08.006.

[4] M. Zahabi and A. M. A. Razak, ''Adaptive virtual reality-based training: A systematic literature review and framework,'' Virtual Reality, vol. 24, no. 4, pp. 725–752, Dec. 2020, doi: 10.1007/s10055-020-00434-w.

[5] Y. S. Can, B. Arnrich, and C. Ersoy, ''Stress detection in daily life scenarios using smart phones and wearable sensors: A survey,'' J. Biomed. Informat., vol. 92, Apr. 2019, Art. no. 103139, doi: 10.1016/j.jbi.2019.103139.

[6] A. O. Akmandor and N. K. Jha, ''Keep the stress away with SoDA: Stress detection and alleviation system,'' IEEE Trans. Multi-Scale Comput. Syst., vol. 3, no. 4, pp. 269–282, Oct. 2017, doi: 10.1109/tmscs.2017.2703613.

[7] M. Verleysen and D. Franaois, ''The curse of dimensionality in data mining and time series prediction,'' in Proc. Int. Work-Conf. Artif. Neural Netw. Berlin, Germany: Springer, 2005, pp. 758–770, doi: 10.1007/11494669_93.

[8] S. Tong and D. Koller, ''Bayes optimal hyperplanes? Maximal margin hyperplanes,'' in Proc. IJCAI, 1999, pp. 1–5.

[9] I. Rish, ''An empirical study of the naive Bayes classifier,'' in Proc. IJCAI Workshop Empirical Methods Artif. Intell., 2001, vol. 3, no. 22, pp. 41–46.

[10] F. Shaffer, R. McCraty, and C. L. Zerr, ''A healthy heart is not a metronome: An integrative review of the heart's anatomy and heart rate variability,'' Frontiers Psychol., vol. 5, p. 1040, Sep. 2014, doi: 10.3389/fpsyg.2014.01040.

[11] B. Kim, Y.-S. Jeong, and M. K. Jeong, ''New multivariate kernel density estimator for uncertain data classification,'' Ann. Oper. Res., vol. 303, nos. 1–2, pp. 413–431, Aug. 2021.

[12] E. Smets, W. De Raedt, and C. Van Hoof, ''Into the wild: The challenges of physiological stress detection in laboratory and ambulatory settings,'' IEEE J. Biomed. Health Informat., vol. 23, no. 2, pp. 463–473, Mar. 2019, doi: 10.1109/JBHI.2018.2883751.

[13] D. Jones and S. Dechmerowski, ''Measuring stress in an augmented training environment: Approaches and applications,'' in Foundations of Augmented Cognition: Neuroergonomics and Operational Neuroscience. Berlin, Germany: Springer, 9744, pp. 23–33, 2016, doi: 10.1007/978-3-319-39952-2_3.

[14] T. T. Finseth, ''Adaptive virtual reality stress training for spaceflight emergency procedures,'' Ph.D. dissertation, Aerosp. Eng., Iowa State Univ.,
2021.

[15] T. Finseth, M. C. Dorneich, N. Keren,W. D. Franke, S. Vardeman, J. Segal, A. Deick, E. Cavanah, and K. Thompson, ''The effectiveness of adaptive training for stress inoculation in a simulated astronaut task,'' in Proc. Human Factors Ergonom. Soc. Annu. Meeting, Baltimore, MD, USA,
2021, pp. 1541–1545.