TIPTEKNO'24 MEDICAL TECHNOLOGIES CONGRESS
10-12 October 2024
Yasmin Bodrum Resort, Muğla, Türkiye

Investigating the Effect of Noise Levels on Mental Tasks Using Artificial Intelligence

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***Abstract*— The impact of stress on daily life has been a subject of interest in the last decades. The utilization of numerous electrical and electronic devices as well as increased land and air transportation densities constantly create noise which is a significant contributor to stress. In this study, the relationship between environmental noise, cognitive workload, and stress is investigated. Electroencephalogram (EEG) and photoplethysmogram (PPG) signals of 30 volunteers were recorded simultaneously while performing a 2-back task with different background noise levels. Features were then extracted from the processed signals to be classified with various machine learning algorithms. Results show that medium noise levels result in increased accuracy for the 2-back task which indicates keeping the noise levels at an acceptable level would be better for work and learning environments.**

Keywords—eeg; ppg; machine learning; n-back task; noise; environment; artificial intelligence; working memory

I. INTRODUCTION

In recent years, stress-related disorders have become a significant concern to global health. Stress affects individuals across various areas such as working and learning environments as well as residence areas [1]. Modern civilization has been found to be experienced in a world associated with a continuously rising environmental noise, which is seen as one of the major factors attributing to the rise in stress levels. Noise pollution means unwanted or harmful outdoor sounds, a serious concern in urban areas, and has been related to several adverse health effects, such as impaired cognitive performance, raised stress levels, and generally lowered well-being [2].

While several studies have been carried out in this field, not much is known about the details of mechanisms involved in environmental noise effects on mental workload and stress [3, 4]. Virtually all research undertaken so far has focused on psychological effects, with a large emphasis placed on subjective methods to measure cognitive strain or stress; these could be less than ideal for describing physiological responses triggered by noise exposure [5 – 7].

Electroencephalogram (EEG) which is a biological signal recorded noninvasively over the scalp to record the electrical activity of the brain, provides information related to neural processes involved in attention, memory, and mental workload. The need to develop evidence-based strategies that effectively mitigate the negative impacts of noise on mental health and cognitive function has become increasingly critical. In this context, machine learning models are employed to classify and predict cognitive, and stress responses derived from EEG and photoplethysmogram (PPG) data. Two machine learning models, namely Support Vector Machine (SVM) and Random Forest (RF), are particularly well-suited for this task due to their distinct strengths in handling complex, high-dimensional data [8, 9].

Several features can be extracted from the EEG that contain useful information regarding stress estimation. Time-domain features are Hjorth parameters (activity, mobility, and complexity), skewness and kurtosis, peak-to-peak amplitude, and sub-band power. Hjorth parameters quantify the variance of the signal's amplitude, frequency content, and waveform complexity, giving useful insight into the dynamic properties of the EEG signal [10]. Skewness and kurtosis of the signal contain information regarding the asymmetry and peak amplitude of the signal. The peak-to-peak amplitude represents the overall range of the signal. Sub-band power features, which indicate the specific frequency bands, all proved to be useful in understanding the relationship between EEG activity and cognitive processes. In addition, this set of features provides a coherent framework to analyze EEG data and mental state assessment under different conditions.

In this study, an experimental design is proposed for the investigation of the relationship between environmental noise, cognitive workload, and stress. The subjects were exposed to different levels of noise while performing a cognitive task, and their EEGs and PPGs were recorded. With the help of the several features extracted from the biological signals recorded and a machine learning classifier a better environment concerning cognitive performance and stress management, especially at offices, schools, or public spaces can be inferred. A multimodal approach with EEG and PPG enables a better understanding of brain activity when subjected to noise and physiological stress.

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II. Materials and Methods

A. Dataset

The study includes 30 participants, divided evenly in gender, whose ages ranged from 20 to 27 years old. All the participants were right-handed and they self-reported that they had no prior disorders and medications that might impair their cognitive abilities. All the EEG and PPG data were recorded at X, using a BitBrain Versatile-32 EEG recording device, and a prototype PPG smart-band. Only relevant EEG channels were selected for recording which are AF3, AF4, F3, F4, FC5, FC6, T7, T8, P7, P8, F8, F7, following 10-20 electrode placement convention.

B. Experimental Procedure

In the cognitive test, participants were exposed to different noise levels during a 2-back task, which assesses the functioning of the working memory and attention [11]. It is a sensitive method for detecting minor variations in the cognitive workload and, implicitly, the level of stress. For this, a custom 2-back test was prepared using MATLAB, R2023a (Fig. 1). During the experiment, three noise conditions were introduced: a quiet environment, 70 dB of aircraft noise, and finally, 80 dB of aircraft noise. These values of noise were aimed at simulating real auditory stressors that might impact cognitive performance.

The test was to be continuously measured by the response of the brain signals and the physiological responses of the participants both in the EEG and in the PPG. Therefore, the results are sorted based on participants' responses into three groups: "correct", "miss", and "false alarm". "Correct" refers to participants' responses when they rightly identified the 2-back match. A "miss" is when the participant fails to respond to a matching stimulus altogether. A "false alarm" is when a subject responds when the present letter does not match the letter two steps before.

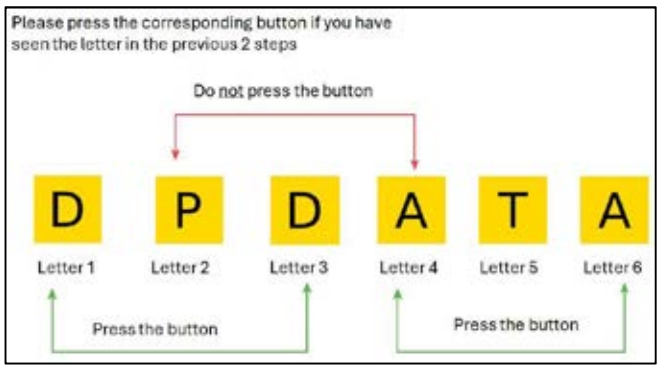


Fig. 1. Custom 2-back task used in the experiment.

C. Pre-processing

To remove noise in the EEG signal, a band-pass filter was used, with a passband of (1-50) Hz. This frequency range contains the relevant information regarding working memory; therefore, sub-bands such as high-gamma were omitted from the signal. Around 1-second regions of interest were then identified which coincided with the button-press events from the participants during the experiment.

D. Feature Extraction

Several features were extracted from the pre-processed EEG data. These features include Hjorth parameters, activity, mobility, and complexity, quantifying amplitude variance, frequency content, and waveform complexity of a signal [12]. Other features extracted were skewness and kurtosis, which estimate the asymmetry and peak of the distribution of the signal, respectively. For PPG data, heart rate variability and other time-domain features were extracted to relate the physiological stress responses under different noise conditions. Finally, sub-band powers of the EEG signal, namely, delta (1-4) Hz, theta (4-8) Hz, alpha (8-12) Hz, beta (12-25) Hz, and gamma (>25) Hz [13]. Extracted features were then used for the training of several machine learning algorithms to find a correlation between the levels of noise and stress.

III. Results and Discussion

A. Distribution of Correct and Incorrect Samples

Fig. 2 illustrates the proportional distribution of correct and incorrect responses across different noise conditions, silent, medium noise, and high noise environments. Fig. 2 reveals that the highest proportion of correct answers occurred in the middle noise level condition of 70 dB. These results suggest that a medium level of noise may facilitate performance on this cognitive task. On the other hand, both extremes of noise, loud levels, and complete silence were less appropriate for performing accurate responses to tasks since more mistakes were found in these two cases.

These findings contradict the hypothesis that the best cognitive performance would occur in a silent environment. It can be assumed that the first silent condition was perceived by the participants as a kind of practice phase, so due to a learning effect, their performance in the second medium noise condition was improved. This insight could be very important for further research and practical applications, for it would mean that adjusting the noise level could optimize cognitive performance in various settings.

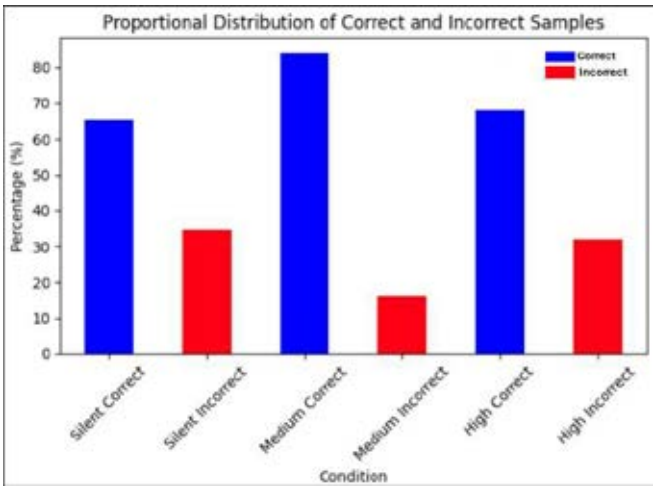


Fig. 2. Proportional distribution of incorrect and correct samples indicated by colors. Blue indicates correct answers, whereas red indicates incorrect ones. "Silent", "medium", and "high" indicate the levels of noise intensity.

B. Machine Learning Model Performance – Silent Condition

In this study, two different machine learning models were trained under various conditions and features. The SVM and RF models were trained for two different prediction targets, under noisy conditions and silent conditions. Under silent conditions, the correctness of the questions marked by the subjects based on EEG data was classified. Under noisy conditions, the goal was for the machine learning algorithms to predict under which noise conditions the subjects marked the correct answers. Both SVM and RF models were trained using all the features extracted from the EEG channels and were used with the default parameters. Data was split into train and test sets following 80% and 20% convention, respectively.

The accuracy of the SVM model reached 73%, whereas the RF reached up to 74% for the silent condition. A channel-based classification was also performed with SVM. Channel-based classification notably increased the classification performance. The best-performing channels were AF4 with 79.2% and F8 with 78.9% accuracy. A confusion matrix for the best-performing channel-based classifiers was given in Fig. 3. The RF model did not perform well enough; therefore, the results were omitted.

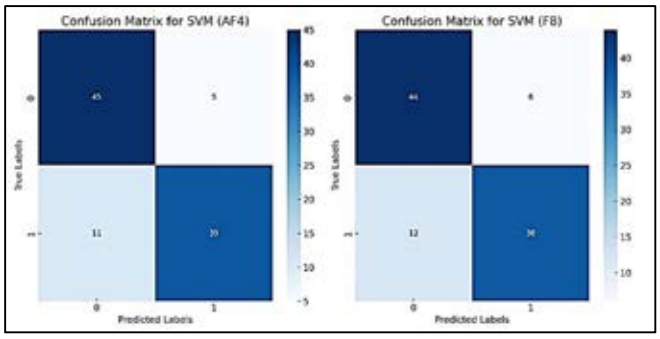


Fig. 3. Confusion matrices for channel-based SVM classifiers for AF4 and F8 channels, respectively.

C. Machine Learning Model Performance – Noisy Condition

The noisy condition yielded accuracies of 75.6% for SVM and 73.7% for RF. By applying heuristics, the important features used for this SVM model were indicated. Features can be sorted from most to least significant ones as complexity, activity, mobility, skewness, kurtosis, peak-to-peak amplitude, and sub-band powers, respectively (Fig. 4). Due to time limitations, a feature selection algorithm could not be employed.

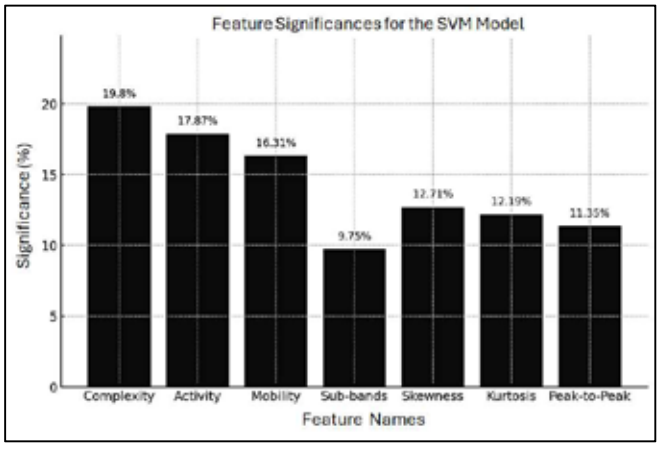


Fig. 4. Feature significances for the SVM model.

D. Correlation of the PPG with the Classification Results

Heart rate during exercise remains stable, thereby indicating that exercising under such conditions is related to a low level of mental workload and stress. Thus, though there is no significant change in heart rate with background or low-level aircraft noise, there is a significant increase in the heart rate when there is high-level aircraft noise, suggesting higher stress and greater mental workload. Therefore, high-level noise continuously distracts such individuals, causing them stress throughout the day, hence their sleep quality is poor, and this consequently decreases their general health and quality of life. The high-level aircraft noise initially significantly raises the heart rate, before leveling off, indicating that while there may be a very high degree of stress experienced at the start, they do adjust to the noise. This adjustment, however, does not prevent the long-term effects of chronic exposure to high noise levels causing chronic stress and consequent hypertension and other health problems. On the other hand, medium-level noise causes a drop in the heart rate implying that participants feel more relaxed (Fig. 5).

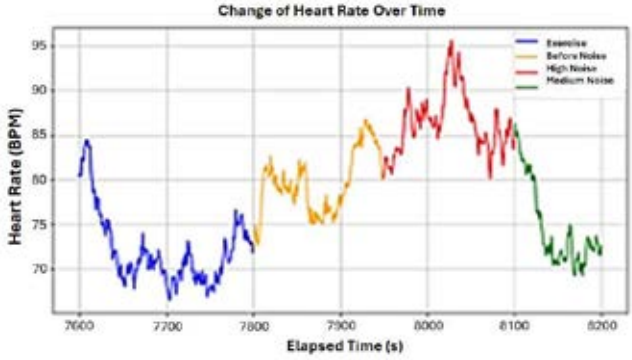


Fig. 5. Change of heart rate over time for different conditions. Different stages of the experiment were color-coded as follows; blue: exercise, yellow: before noise, red: high noise, green: medium noise.

IV. CONCLUSION

This study aimed to investigate how noise affects cognitive and physiological responses, by classifying features extracted from EEG and PPG signals. The methodology involved EEG signals to record brain activity as well as PPG signals to get the heart rate simultaneously when given an n-back task under different levels of noise. Preprocessing of the EEG data included band-pass filtering, normalization, and the extraction of Hjorth parameters: activity, mobility, complexity, EEG sub-band powers, skewness, kurtosis, and peak-to-peak amplitude.

The model was trained to achieve relatively high metrics. For the silent condition, models reached up to 73% and 74% accuracy for the SVM and RF models, respectively. On the other hand, under noisy conditions, 75.6% and 73.7% were reached with the same algorithms, respectively. Furthermore, channel-based classification for the silent condition reached up

to 79.2% for the AF4 channel and 78.9% for the F8 channel. A feature significance analysis revealed that the Hjorth parameters, together with skewness, kurtosis, and peak-to-peak amplitude, are more important predictors of cognitive workload and stress than frequencies of sub-bands which are to be exploited further in future studies.

Results revealed that participants performed better under medium-noise conditions which goes against the common knowledge that silent environments are the best to work and study. Furthermore, an elevated heart rate was revealed in the PPG results in moderate noise, indicating that the noise at such points was quite stressful. Surprisingly, it was less apparent in the silent and high-noise surroundings, most probably because of adaptation to the latter.

These findings underline the negative effects on the health of people who are exposed to chronic noise, for instance, those living near airports with continuous exposure leading to increased strain and concurrent health risks. The necessity of personalized workspaces is highlighted in terms of optimization with respect to noise based on individual noise levels and preferences. Carrying on from the studies [14, 15], this study shows that it is possible to extract valuable insights from several biological signs related to attention which is impacted by one of the most common environmental conditions, noise.

ACKNOWLEDGMENT

This study is supported by Scientific and Technological Research Council of Turkey (TUBITAK) 2209-B program with project number 1199B472338877.

The authors would like to thank Altug Gunes, Berkay Ilber Tunakan, Can Mungan, Duygu Koybasi, Ege Ozan Dundar, Ugur Emre Ozubelli, and Dr. Faezeh Yeganli for their contributions during the data acquisition and analysis process.

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