ELECTROENCEPHALOGRAM (EEG) BASED EMOTIONAL LIGHTING DESIGN USING DEEP-LEARNING FOR A USER-CENTRIC APPROACH

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Abstract. This study proposes a methodology for using artificial intelligence (AI) and biometrics in spatial design. The research mainly applies a gated recurrent unit (GRU) model, a recurrent neural network (RNN), to analyze electroencephalogram (EEG) data and dynamically adjust lighting according to the user's emotional state. This study suggests an illumination adjustment system that modifies lighting according to the user's emotional state using the proposed method. Integration of EEG data can overcome the limitations of lighting systems. It can effectively target individual emotional responses. The GRU model represents a significant improvement in lighting design by addressing both cognitive and emotional user needs. The model's effectiveness in processing real-time data and adapting through incremental learning was evaluated. The model has shown a significant impact on emotional architecture and spatial design, with a focus on individual experience.

Keywords. : Gated Recurrent Unit, EEG, EEG Data Analysis, User-Centric Design, Emotional Lighting, Real-Time Data Processing, Affective Computing, BCI, BMI

1. Introduction

The use of artificial intelligence (AI) and biometrics in spatial design has facilitated adaptive and responsive environments, revolutionizing elements such as lighting, air quality, and user interfaces (Hsieh et al., 2022). These technological advancements have led to a burgeoning interest in the study of personalized spatial configurations, with deep learning algorithms contributing critically to the precision and speed of electroencephalogram (EEG) data analysis (Craik et al., 2019).

This study focuses on the application of a gated recurrent unit (GRU) model, a type of recurrent neural network (RNN), to analyze EEG data in real time and adjust lighting based on the user's emotional state (Kim et al., 2022). This approach transforms lighting design by enhancing its emotional and cognitive responsiveness and surpassing the constraints of existing lighting systems. (Eroglu et al., 2020). The

ACCELERATED DESIGN, Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2024, Volume 3, 381-390.

current lighting system is standardized to specific lux values for each circumstance. It is an environmental element that could vary depending on individual emotions and responses. However, although countries have different specified situational standards, illuminance values within the same setting differ among countries. Standardized lighting systems lack clear criteria and do not adequately reflect the diverse emotions and reactions of individual users. Therefore, to provide personalized and optimized lighting, this study presents an approach to analyze users' EEG data in real time.

This paper describes the research design, participant selection, and EEG data collection methods, as well as provides details on the experimental setup and data collection equipment in Chapter 2. Chapter 3 elaborates on the GRU model's training process, encompassing data processing, model training, and evaluation methods. Chapter 4 presents the model's evaluation results, introducing real-time data processing and incremental learning methods. Lastly, Chapter 5 explores the research's significance, technical limitations, and contributions to emotional architecture and human-centered space design. This paper offers a noteworthy contribution to the field of personalized space design utilizing EEG data, presenting a new perspective for research and practice in this area.

1.1. INTEGRATING AFFECTIVE COMPUTING WITH BCI/BMI IN SPATIAL DESIGN

The user-centered spatial design uses EEG data, focusing on brain-computer interface (BCI), brain-machine interface (BMI), and affective computing. BCI technology enables the direct connection of a user's EEG signals to a computer system, facilitating the translation of the user's thoughts, intentions, and emotional states into computer commands. BMI is an extension of BCI that uses the user's brain signals to control mechanical devices. Affective computing is the use of machine learning and artificial intelligence to create systems that can interpret and respond to a user's emotional state. These approaches enable systems to interact with users based on their intent and emotional state.

Tanaka et al. (2005) and Mai et al. (2021) made significant contributions to the development of systems using EEG signals. However, these studies had limitations in their ability to reflect the user's complex emotional state and decision-making process. Additionally, they were versatile enough for different environmental settings (Mai et al., 2021; Tanaka et al., 2005). This research aims to improve the user-centered spatial design by analyzing and processing EEG data.

1.2. ADVANCEMENTS IN EEG DATA PROCESSING TECHNOLOGY

Electroencephalography (EEG) is a crucial tool for understanding a person's emotional state, as it measures the brain's electrical activity. This study employs advanced neural networks, specifically GRU, to analyze EEG data effectively. GRU, a specialized version of Recurrent Neural Networks (RNN), is particularly good at learning from and remembering information over extended periods. This capability is vital for accurately modeling the time-dependent aspects of EEG signals and detecting changes in brain activity. (Wilaiprasitporn et al., 2020). Our research focuses on leveraging EEG data to innovate lighting adjustment methods that respond to individual emotional states. It is crucial to advance various analysis techniques, such as spectral estimation methods for EEG data. This study builds on previous research that has discussed spectral estimation methods in the works of Murugappan et al. (2008) to Craik et al. (2019), and is intended to enhance them by combining them with contemporary data processing techniques (Craik et al., 2019; Murugappan et al., 2008; Muthuswamy & Thakor, 1998; Subha et al., 2010). Illumination systems using EEG data have been developed based on research by Wahy & Mansor (2010) and Wu et al. (2019) (Wahy & Mansor, 2010; Wu et al., 2019). While these systems demonstrated the potential of EEG-based lighting adjustments, they also faced challenges in processing data in real-time and adapting quickly to changes in a user's emotional state. Our study addresses these challenges by effectively capturing EEG data's temporal dynamics using the GRU model and integrating this data into lighting systems to provide real-time, responsive adjustments.

This research proposes a novel approach to the design of contemporary spaces that leverages technological advances to optimize the user experience. The methodology of implementing EEG data and the GRU model addresses previous limitations and provides a significant contribution to the field of spatial design. The theoretical analysis of this research will have a significant function in elucidating the fundamental concepts and methodologies and exploring the extensive comprehension and practicality of the research findings.

2. Materials and Experiment

2.1. RESEARCH DESIGN AND PARTICIPANT

The experiment, approved by the Hanyang University Ethics Committee (HYU-2023-280), involved a single 27-year-old female subject, Subject A. This single-subject research design is particularly effective for detailed observation and analysis of individual behavioral changes, as demonstrated in various fields. Therefore, this study selected Subject A as the sole participant, enabling the precise collection and repeated measurements of EEG data. This approach facilitates the development of customized emotional lighting services tailored to individual needs.

2.2. DATA ACQUISITION

Prior to EEG data collection, all windows in the room are closed to minimize the influence of natural and extraneous light sources. The lighting environment and measurement equipment were verified with artificial lighting disabled, ensuring controlled conditions. To reduce the influence of external variables and enhance the participant's focus on spatial elements, earplugs were provided to block out external noise, which could significantly affect EEG measurements. The study was conducted in a lecture room within Hanyang University's architecture department. The room dimensions are 7620(L)×10430(W)×7620(H) mm, with a designated experimental space of 800×1200×2000 mm situated at the room's center for EEG data collection. The main experiments occurred in area 'A', while areas 'B' and 'C' were designated for light and temperature/humidity sensing, respectively. A light fixture in area 'D' was used to establish specific lighting conditions for the experiments.

The study utilized the Emotiv EPOC X headset, paired with EmotivPRO software, to capture EEG data, filtering out mains noise and harmonic frequencies. The software employed machine learning to analyze the EEG, distinguishing Performance Metrics (PM) that represent six emotional indicators: Stress (St), Engagement (En), Interest (In), Excitement (Ex), Attention (At), and Relaxation (Re). These metrics are critical for evaluating the participant's psychological and physiological reactions, offering insights into their mental state and engagement with tasks. (Salaken et al., 2020).

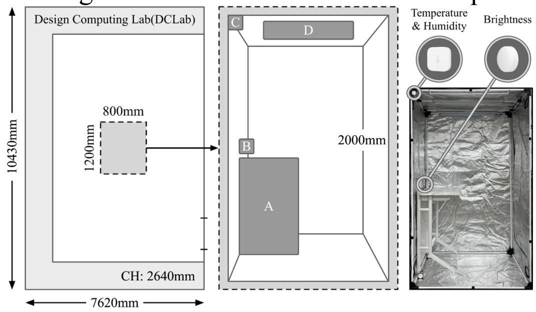

Figure 1. EEG Measurement Participant Environment

Stress (St) indicates the level of comfort in performing a task, with high levels often leading to negative outcomes. Engagement (En) indicates the level of attention and immersion in the task. This is evidenced by increased physiological arousal and beta-wave activation. Interest (In) can also be expressed as valence. It indicates interest or disinterest in the current activity. Excitement (Ex) indicates a positive state of physiological excitement and arousal, associated with activation of the sympathetic nervous system and distinct physiological responses. Attention (At) indicates attention to focus on a particular task and the frequency of task-switching, providing an indicator of deficient focus and distraction. Finally, the metric of Relaxation (Re) indicates one's ability to recuperate from a state of focus. Individuals can receive high scores on this metric, particularly when engaged in meditation. These indicators are crucial for evaluating task performance and mental state (Emotiv, 2023).

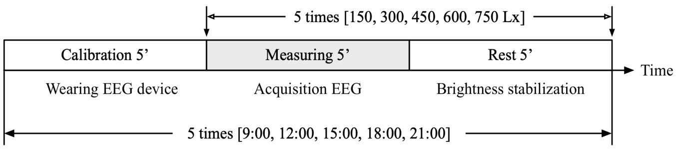

Figure 2. Experimental Procedure

The experiment was conducted on Subject A for three days to measure responses and collect training and test datasets. Over three days, Subject A participated in five daily sessions, each consisting of trials under varying lighting conditions (Figure 2). These trials, conducted at different times (9:00 a.m., 12:00 p.m., 3:00 p.m., 6:00 p.m., and 9:00 p.m.), involved equipment setup, EEG measurement, and light stabilization, adhering to predefined illuminance standards (KS A 3011:1998).

2.3. DATA PROCESSING AND ANALYSIS

EEG and sensor data are used to extract emotional measures for individuals and to construct data sets. The research methodology encompasses data collection, preprocessing, and feature extraction phases, outlined in a process diagram (Figure 3). During the data collection phase, raw EEG data and environmental condition data are obtained from various sensors. The environmental data includes physical measurements such as illumination, temperature, and humidity, collected in real-time by the Home Assistant system. To accurately assess an individual's cognitive state, the EmotivPro software processes EEG data to generate quantitative emotional metrics such as stress (St), attention (At), and engagement (En). Node-red, a visual programming tool, is utilized to integrate these two different types of time-series data in real-time. The data collection procedure is automated every 10 seconds and undergoes normalization during the pre-processing stage. This step adjusts the range and scale of the data, preparing them for consistent analysis in subsequent stages.

3. Methodology

3.1. GRU-BASED MODEL TRAINING PROCESS

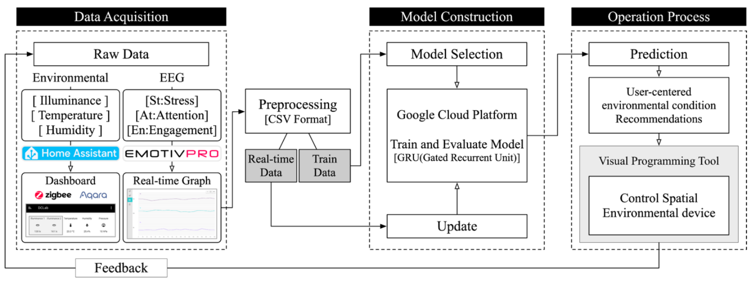

Figure 3. Process Diagram

The study employs GRNN for all phases, including data processing, model training, results evaluation, and interpretation. RNNs play a key role in ensuring continuous data analysis over time. The two representative RNN structures, GRU and LSTM, are compared and analyzed, and the GRU model is selected for real-time EEG and environmental sensor data acquisition and processing. The GRU model, with its simpler design and fewer parameters, outperforms the LSTM in real-time data processing by enabling quicker learning and reducing computational demands (Zhang et al., 2018).

The model's training process is systematically managed using the Google Cloud Platform (GCP), where the model generates predictions on environmental control conditions tailored to the subject's emotional response. The predictions are subsequently evaluated and optimized for accuracy (Hyseni et al., 2017). For model optimization, an automated tuning for hyperparameters was performed using the Optuna framework through Bayesian optimization methods. This technique uses past data to efficiently select new hyperparameters that can improve performance faster and more accurately than other optimization techniques. The selection of these conditions resulted from extensive trials and evaluations. The performance of the chosen hyperparameters is depicted in Figure 4, showcasing bins with minimal loss values. The resulting optimal hyperparameter combination is 48 GRU units, dropout rate 0.48, learning rate approximately 0.0038, number of epochs 180, and batch size 32 (Akiba et al., 2019).

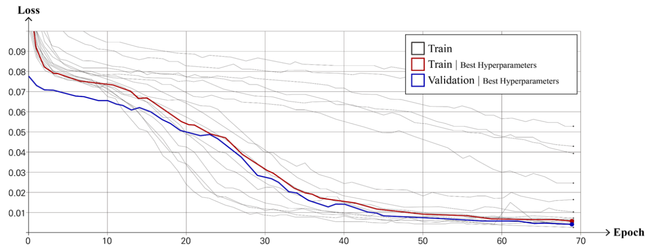

Figure 4. Hyperparameter Epoch Loss

The GRU training is constructed based on these hyperparameter values. It normalized the model data using MinMaxScaler, allocating 80% for training and 20% for testing. The performance of the trained model is evaluated using the test data, rather than the validation data, as it is insufficient. In the training process, predictions are based on consecutive data points, equivalent to 10 minutes of data. 'Features' include emotional indicators like Stress (St), Attention (At), and Engagement (En) values, while 'Targets' comprise environmental factors such as Lux (Illumination), Temp (Temperature), and Humi (Humidity). The GRU model effectively forecasts ideal environmental settings by identifying patterns between emotional indicators (Features) and environmental conditions (Targets).

3.2. PREDICTION AND RANKING OF DATA

A Python script performs the data's prediction and ranking. This script processes real-time data by supplying the model with 60 data points at once, each set representing 10 minutes. To extend the dataset, the script duplicates the last 30 data points from the input. This approach is not designed to ensure that the real-time data always comprises exactly 60 data points, but rather to make space for 30 consecutive predictions during the prediction process. The goal of the prediction process is to estimate future values, beginning with the sequence's 61st data point and continuing for each point thereafter. This method of sequential forecasting acknowledges the continuity of time series data and enables predictions for multiple future time points.

Based on the predictions, the system suggests the best environmental conditions, calculating a score from three key factors: Attention, Engagement, and Stress. The design ensures that higher levels of concentration and lower levels of stress result in higher scores. The scores for the variables At and En are determined by assigning higher scores to values closer to their maximum. Conversely, the score for St is attributed to higher values for lower stress levels. To calculate the final score, weights of 0.25 are assigned to Attention and Engagement each, and 0.5 to Stress, with these weights then added together. The resulting dataset is then organized in descending order by score and each data point is allocated a rank. This method calculates a relative score for each emotional metric and applies weights to derive a composite score that accurately reflects the user's environmental preferences.

The GRU model identifies the complex interaction between the user's emotional state and environmental conditions and utilizes this information to predict and rank environmental conditions that align with the user's preferences. This demonstrates a significant advancement in user-centered environmental design and sensing architecture.

4. Results and Validation

4.1. MODEL EVALUATION

The GRU models trained in this study were evaluated using standard metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 score (Abumohsen et al., 2023). These metrics are essential for measuring how accurately the models predict and understand data patterns. MSE and MAE measure how close the model's predictions are to the actual outcomes, helping gauge the model's accuracy. The R^2 score reflects how well the model captures the underlying data patterns.

The evaluation showed an MSE of approximately 0.002, an MAE of 0.03, and an R^2 score of 0.971, demonstrating the model's effectiveness in identifying the relationship between EEG data and environmental conditions for accurate predictions.

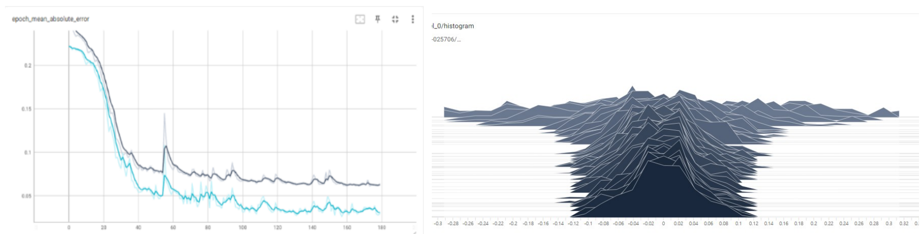

Figure 3. MAE (Mean Squared Error) | GRU model Kernel

Figure 5 illustrates a rapid decrease in the model's MAE in the initial learning phase, leading to a consistent reduction in errors and stable prediction accuracy over time. The right graph in Figure 5 evaluates the model's kernel distribution, highlighting how the model values different input features during training. A balanced distribution of weight values suggests the model equally considers various features without depending too heavily on any one feature.

The results underscore the model's proficiency in deciphering complex relationships between EEG signals and environmental parameters, thus enabling accurate environmental condition predictions based on emotional states.

4.2. ADJUSTING ENVIRONMENTS IN REAL-TIME BASED ON EMOTIONAL STATES

Through real-time data processing, prediction, and incremental learning, these advances personalized environmental conditions based on the user's emotional state. For setup, the system loads GRU models and scaling tools stored in Google Cloud Storage (GCS), using the Google Cloud Platform (GCP). Once data is collected in a specific bucket, the cloud storage trigger initiates and two main processes commence simultaneously.

Figure 6 illustrates two main activities: controlling lighting based on predictions made by cloud functions and Node-RED, and updating the GRU model with new data through incremental learning.

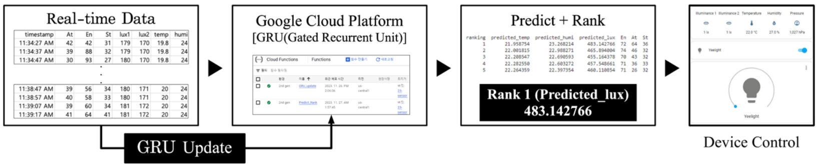

Figure 6. Real-time Process Diagram

The first process entails predicting and controlling lighting. An integral aspect of this process is the use and output of data. The Python script deployed in Cloud Functions handles the data triggered for collection. This algorithm ranks the prediction data, selects the highest-ranked illuminance value, and transmits it to the lighting control system. Predictive information is gathered via Google Cloud Pub/Sub and then transformed into a string message before being relayed to the Node-RED system. The illuminance value is subsequently adjusted to reflect the user's emotional state upon receipt of this data by the Node-RED system.

The second process involves continuously updating the model through incremental learning. This process efficiently incorporates real-time incoming data into the existing GRU model, allowing it to quickly adapt to changing data patterns over time. It provides a fast and effective solution to data availability and resource constraints in environments where data is constantly being generated. The model's responsiveness to real-time data flows is also enhanced.

This approach customizes environments by analyzing and visualizing users' emotions in real-time. It demonstrates how lighting adjustments can significantly affect stress management for users. These findings constitute significant contributions to the fields of user-centered spatial environment design and emotional architecture, offering a different perspective for future user-centered design approaches.

5. Discussion and Conclusion

This study presents the field of spatial design by using the application of artificial intelligence and biometrics. By applying a GRU model for real-time EEG data analysis, it innovatively adapted lighting to the user's emotional and cognitive states. This approach enables a user-responsive lighting system, offering a substantial improvement over traditional static lighting solution.

The GRU model used in the research is adept at understanding the complex interactions between EEG and environmental conditions, and accurately predicts and ranks environmental factors by users' preferences. This crucial advancement has the potential to surpass the limitations of existing lighting systems and enhance user productivity. Moreover, we have demonstrated methods for refining the accuracy of our model in an environment where data streams are generated continuously through real-time data processing and incremental learning. However, there are certain limitations to the incremental learning approach of the GRU models. Catastrophic

Forgetting is a phenomenon where previously learned information is gradually forgotten as the model is trained on new data. This can negatively impact the model's predictive accuracy if the data distribution changes over time. To overcome this limitation, data management strategies must be improved and the technological aspects of incremental learning methods must be enhanced. The findings of this study significantly contribute to the field of user-centered spatial environment design and emotional architecture. It highlights the importance of technological advances in personalized space organization and the improvement of the user environment.

The single-subject research design limits the generalizability of the results, and further research on user groups with diverse backgrounds is needed. On the technical side, there is a continuing requirement for enhancements in EEG data processing and analysis methods. Progress in these methodologies could further improve the quality of future studies.

Nevertheless, this study suggests human-centered architecture and spatial design that reflects the individual needs and preferences of each user by designing and creating spaces based on their emotions and responses. In particular, it emphasizes the importance of designing more inclusive and interactive spatial environments in future research by considering users' emotional responses, which can contribute to improving their satisfaction in space. It can also contribute to the development of technologies that automatically adjust environmental conditions such as lighting and temperature to reflect the user's emotional state, through convergence with smart home systems. This approach aims at human-centered space design and provides potential for research and practical applications in various fields.

Acknowledgements

This research was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2022R1A2C3011796)

References

Abumohsen, M., Owda, A. Y., & Owda, M. (2023). Electrical Load Forecasting Using LSTM, GRU, and RNN Algorithms. Energies, 16(5), Article 2283. https://doi.org/10.3390/en16052283

Akiba, T., Sano, S., Yanase, T., Ohta, T., Koyama, M., & Assoc Comp, M. (2019, Aug 04-08). Optuna: A Next-generation Hyperparameter Optimization Framework. [Kdd'19: Proceedings of the 25th acm sigkdd international conferencce on knowledge discovery and data mining]. 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD), Anchorage, AK.

Craik, A., He, Y. T., & Contreras-Vidal, J. L. (2019). Deep learning for electroencephalogram (EEG) classification tasks: a review. Journal of Neural Engineering, 16(3), Article 031001. https://doi.org/10.1088/1741-2552/ab0ab5

Eroglu, K., Kayikçioglu, T., & Osman, O. (2020). Effect of brightness of visual stimuli on EEG signals. Behavioural Brain Research, 382, Article 112486. https://doi.org/10.1016/j.bbr.2020.112486

Hsieh, M. C., Zhang, Y. Q., Dong, R., Lee, Y. C., & Ni, C. Y. (2022). Use of EEG signals, cortisol secretion, and task performance to evaluate the effects of different lighting environments on concentration level in a sustained attention task. International Journal of Industrial Ergonomics, 92, Article 103371. https://doi.org/10.1016/j.ergon.2022.103371

Hyseni, L. N., Ibrahimi, A., & Ieee. (2017, Jul 18-20). Comparison of the Cloud Computing Platforms Provided by Amazon and Google. [2017 computing conference]. Computing Conference, United Kingdon, London, ENGLAND.

Kim, J., Hwang, D. U., Son, E. J., Oh, S. H., Kim, W., Kim, Y., & Kwon, G. (2022). Emotion recognition while applying cosmetic cream using deep learning from EEG data; cross-subject analysis. Plos One, 17(11), Article e0274203. https://doi.org/10.1371/journal.pone.0274203

Mai, N. D., Lee, B. G., & Chung, W. Y. (2021). Affective Computing on Machine Learning-Based Emotion Recognition Using a Self-Made EEG Device. Sensors, 21(15), Article 5135. https://doi.org/10.3390/s21155135

Murugappan, M., Rizon, M., Nagarajan, R., Yaacob, S., Hazry, D., & Zunaidi, I. (2008, Jun 25-28). Time-Frequency Analysis of EEG Signals for Human Emotion Detection.IFMBE Proceedings [4th kuala lumpur international conference on biomedical engineering 2008, vols 1 and 2]. 4th Kuala Lumpur International Conference on Biomedical Engineering, Kuala Lumpur, MALAYSIA.

Muthuswamy, J., & Thakor, N. V. (1998). Spectral analysis methods for neurological signals. Journal of Neuroscience Methods, 83(1), 1-14. https://doi.org/10.1016/s0165-0270(98)00065-x

Salaken, S. M., Hettiarachchi, I., Crameri, L., Hanoun, S., Nguyen, T., Nahavandi, S., & Ieee. (2020, Aug 24-27). Evaluation of Classification Techniques for Identifying Cognitive Load Levels using EEG Signals.Annual IEEE Systems Conference [2020 14th annual ieee international systems conference (syscon2020)]. 14th Annual IEEE International Systems Conference (SysCon), Electr Network.

Subha, D. P., Joseph, P. K., Acharya, R., & Lim, C. M. (2010). EEG Signal Analysis: A Survey. Journal of Medical Systems, 34(2), 195-212. https://doi.org/10.1007/s10916-008-9231-z

Tanaka, K., Matsunaga, K., & Wang, H. O. (2005). Electroencephalogram-based control of an electric wheelchair. Ieee Transactions on Robotics, 21(4), 762-766. https://doi.org/10.1109/tro.2004.842350

Wahy, N., & Mansor, W. (2010). EEG based home lighting system. 2010 International Conference on Computer Applications and Industrial Electronics,

Wilaiprasitporn, T., Ditthapron, A., Matchaparn, K., Tongbuasirilai, T., Banluesombatkul, N., & Chuangsuwanich, E. (2020). Affective EEG-Based Person Identification Using the Deep Learning Approach. Ieee Transactions on Cognitive and Developmental Systems, 12(3), 486-496. https://doi.org/10.1109/tcds.2019.2924648

Wu, Y., Jin, Y. L., Yokoyama, A., Wang, C., Li, Y. F., Liu, Y., Wang, G. X., & Ieee. (2019, Oct 17-19). Live Demonstration: An EEG-Based Comparative Study of Light Color Effect on Mental Stress Relief Using an Integrated Mobile Application.Biomedical Circuits and Systems Conference [2019 ieee biomedical circuits and systems conference (biocas 2019)]. IEEE Biomedical Circuits and Systems Conference (BioCAS), Nara, JAPAN.

Zhang, D., Lindholm, G., & Ratnaweera, H. (2018). Use long short-term memory to enhance Internet of Things for combined sewer overflow monitoring. Journal of Hydrology, 556, 409-418. https://doi.org/10.1016/j.jhydrol.2017.11.018

Nguyen, E. (2019, August 6). Does EmotivPro automatically remove artifacts from the EEG data collected? Emotiv. Updated from original version of May 31, 2019. Retrieved December 1, 2023, from https://www.emotiv.com/knowledge-base/does-emotivpro-automatically-remove-artifacts-from-the-eeg-data-collected/

Emotiv. (2023, November 23). Performance Metrics. In EmotivPro V3 Guidebook. Retrieved November 30, 2023, from https://emotiv.gitbook.io/emotivpro-v3/data-streams/performance-metrics