**Bibliography**

[1] Md. A. Ahamed, Md. A.-U. Ahad, Md. H. A. Sohag, and M. Ahmad, “Development of low cost wireless biosignal acquisition system for ECG EMG and EOG,” in 2015 2nd International Conference on Electrical Information and Communication Technologies (EICT), Dec. 2015, pp. 195–199, doi: 10.1109/EICT.2015.7391945.

This research paper aims to demonstrate that three biosignals (EEG, EMG, and EOG) can be monitored using a device which is wireless, portable, and battery powered. This is an extremely useful technology to consider as it is in alignment with our priority of minimal and non-invasive hardware. The team found that their device transmitted effectively up to 9 meters away from the receiver using a Bluetooth connection and was able to function continuously for about 22 hours. If a rechargeable power source were to be used instead, this could prove an efficient wearable technology for the purposes of live monitoring.

[2] P. Arpaia, N. Moccaldi, R. Prevete, I. Sannino, and A. Tedesco, “A wearable EEG instrument for real-time frontal asymmetry monitoring in worker stress analysis,” IEEE Transactions on Instrumentation and Measurement, pp. 1–1, 2020, doi: 10.1109/TIM.2020.2988744.

Using only three points of contact with dry EEG electrodes, this team was able to identify stress responses in the subject with 98% accuracy. The wearable device used transmitted the collected data via wireless internet connection to a local Raspberry Pi unit, which then forwarded the data to their server for analysis. This is a very similar method to that which we are using, and for the same reasons. This paper was able to effectively demonstrate that accurate EEG data could be collected while imposing fewer movement restrictions than traditional methods.

[3] E. Bak, G.-H. Choi, and S. B. Pan, “ECG-Based Human Identification System by Temporal-Amplitude Combined Feature Vectors,” IEEE Access, vol. 8, pp. 42217–42230, 2020, doi: 10.1109/ACCESS.2020.2976688.

The goal of this work was to evaluate the efficacy of differentiating individuals based solely on ECG sensor data. The team tested a wide variety of feature vectors, mainly focusing on the relative temporal positions of the fiducial points in the ECG. Achieving an identification accuracy of 94%, this research shows string indication of unique and identifiable characteristics within subject’s ECG. While this is not of great importance with regard to current space missions where identity is not a concern, this could prove useful technology as we enter into the age of commercial spaceflight.

[4] J. M. Eklund and N. Khan, “A bio-signal computing platform for real-time online health analytics for manned space missions,” in 2018 IEEE Aerospace Conference, Mar. 2018, pp. 1–8, doi: 10.1109/AERO.2018.8396819.

[5] M. Elgendi and C. Menon, “Machine Learning Ranks ECG as an Optimal Wearable Biosignal for Assessing Driving Stress,” IEEE Access, vol. 8, pp. 34362–34374, 2020, doi: 10.1109/ACCESS.2020.2974933.

Similar to the paper by P. Arpaia et al., [2] the main focus of this research was on monitoring the stress levels of subject. In contrast, however, their goal was to identify what individual biosignal produced the highest correlation with subject stress using interaction principal component analysis. They concluded that, in identifying stress during a time period in which a subject is driving, ECG data was the most accurate, followed by GSR. During their analysis, they also noted a significant correlation between heart rate and EMG data. The main limitation in this study was the small sample size, which was taken from a database of stress recognition in drivers.

[6] D.-H. Kim, E. Lee, J. Kim, P. Park, and S. Cho, “A Sleep Apnea Monitoring IC for Respiration, Heart-Rate, SpO2 and Pulse-Transit Time Measurement Using Thermistor, PPG and Body-Channel Communication,” IEEE Sensors Journal, vol. 20, no. 4, pp. 1997–2007, Feb. 2020, doi: 10.1109/JSEN.2019.2950367.

[7] P. Lakkamraju, M. Anumukonda, and S. R. Chowdhury, “Improvements in Accurate Detection of Cardiac Abnormalities and Prognostic Health Diagnosis Using Artificial Intelligence in Medical Systems,” IEEE Access, vol. 8, pp. 32776–32782, 2020, doi: 10.1109/ACCESS.2020.2965396.

[8] J.-H. Lee, J. M. Hwang, D. H. Choi, and S.-O. Park, “Noninvasive Biosignal Detection Radar System Using Circular Polarization,” IEEE Transactions on Information Technology in Biomedicine, vol. 13, no. 3, pp. 400–404, May 2009, doi: 10.1109/TITB.2009.2018623.

This paper discusses and verifies the efficacy of measuring an individual's heart and respiration rate through clothing and without direct contact. While this technology has existed for some time, they improved upon the methodology by using a small circular polarity antenna, roughly the size of a deck of cards (100mm x 50mm x 13 mm). This research takes a large step in the direction of non-invasive health monitoring systems and could be used as part of a more extensive data collection and monitoring system for our project. The only caveat is that their experiment required that the subject be motionless for the duration, but this could still be utilized in a less frequent, more comprehensive examination.

[9] L. A. Martínez-Tejada, N. Yoshimura, and Y. Koike, “Classifier comparison using EEG features for emotion recognition process,” in 2020 IEEE 18th World Symposium on Applied Machine Intelligence and Informatics (SAMI), Jan. 2020, pp. 225–230, doi: 10.1109/SAMI48414.2020.9108746.

[10] Y. Ming, D. Wu, Y.-K. Wang, Y. Shi, and C.-T. Lin, “EEG-Based Drowsiness Estimation for Driving Safety Using Deep Q-Learning,” IEEE Transactions on Emerging Topics in Computational Intelligence, pp. 1–12, 2020, doi: 10.1109/TETCI.2020.2997031.

[11] G. Retsinas, P. P. Filntisis, N. Efthymiou, E. Theodosis, A. Zlatintsi, and P. Maragos, “Person Identification Using Deep Convolutional Neural Networks on Short-Term Signals from Wearable Sensors,” in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), May 2020, pp. 3657–3661, doi: 10.1109/ICASSP40776.2020.9053910.

Similar to the work done by E. Bak et. al. [3], this paper focuses on identification of individuals using hear rate data. In contrast, however, these researchers also incorporated accelerometric and gyroscopic data captured from smartwatch worn by the subjects. They found that a great deal of device-specific noise from the accelerometer and gyroscope was affecting their data, causing the neural networks to identify subject based on the devices they wore rather than the intended data set. This is certainly a factor that future endeavors must account for, especially considering the application to a weightless environment where the orientation and acceleration of subject is much less predictable.

[12] R. Toderean, “Classification of Sensorimotor Rhythms Based on Multi-layer Perceptron Neural Networks,” in 2020 International Conference on Development and Application Systems (DAS), May 2020, pp. 204–207, doi: 10.1109/DAS49615.2020.9108910.

[13] H.-Y. Wu, M. Rubinstein, E. Shih, J. Guttag, F. Durand, and W. T. Freeman, “Eulerian Video Magnification for Revealing Subtle Changes in the World,” p. 8.