2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

On Lightmyography: A New Muscle Machine Interfacing Method for Decoding Human Intention and Motion

Mojtaba Shahmohammadi, Anany Dwivedi, Poul Nielsen, Andrew Taberner, and Minas Liarokapis

Abstract— **Recognising and classifying human hand gestures is important for effective communication between humans and machines in applications such as human-robot interaction, human to robot skill transfer, and control of prosthetic devices. Although there are already many interfaces that enable decoding of the intention and action of humans, they are either bulky or they rely on techniques that need careful positioning of the sensors, causing inconvenience when the system needs to be used in real-life scenarios and environments. Moreover, electromyography (EMG), which is the most commonly used technique, captures EMG signals that have a nonlinear relationship with the human intention and motion. In this work, we present lightmyography (LMG) a new muscle machine interfacing method for decoding human intention and motion. Lightmyography utilizes light propagation through elastic media and the change of light luminosity to detect silicone deformation. Lightmyography is similar to forcemyography in the sense that they both record muscular contractions through skin displacements. In order to experimentally validate the efficiency of the proposed method, we designed an interface consisting of five LMG sensors to perform gesture classification experiments. Using this device, we were able to accurately detect a series of different hand postures and gestures. We also compared LMG data with processed EMG data.**

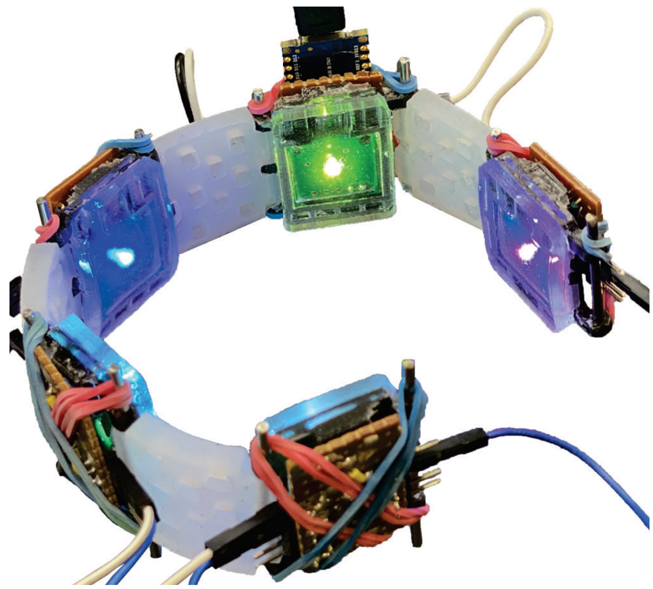

Fig. 1. The proposed lightmyography armband that consists of five sensing modules (LMG sensors).

I. Introduction

The need for effective human-machine communication is becoming more important due to the rapid development of intelligent devices that can be used in a broad range of applications in modern society. Numerous studies have focused on this topic and plenty of interfaces have been proposed to enhance communication between the humans and machines, improving accuracy, robustness, usability, and intuitiveness of interactions. The available interfaces are mainly categorised into hand-held controllers, vision-based controllers, voice based controllers, and wearable interfaces. Hand-held controllers such as joysticks are the most widely-used interfaces; however, they can be bulky, fatiguing, and usually are not suitable for portable devices. Another disadvantage of hand-held interfaces is that they are not suitable for the control of prosthetic devices. On the other hand, vision-based methods are usually quite convenient in terms of usability, but they suffer from the same portability and compactness issues, while in the case of voice based interfaces, ambient noises limit their applicability [1].

Mojtaba Shahmohammadi, Anany Dwivedi, and Minas Liarokapis are with the New Dexterity research group, Department of Mechanical Engineering, Faculty of Engineering, The University of Auckland, New Zealand. E-mails: {msha851, adwi592}@aucklanduni.ac.nz, minas.liarokapis@auckland.ac.nz

Poul Nielsen and Andrew Taberner are with the Auckland Bioengineering Institute, The University of Auckland, New Zealand. E-mails: p.nielsen@auckland.ac.nz, a.taberner@auckland.ac.nz

Wearable interfaces that capture the human kinematics or the muscular activity offer suitable solutions for the control of robotic and prosthetic devices. Such interfaces can be developed using for example electromyography (EMG) or forcemyography (FMG) sensing modules [2]–[4]. These are non-invasive techniques that focus on recording the muscle contractions on the surface of the skin. EMG based interfaces use the electrical activity of the human muscles to decode the user's intent. EMG based interfaces have been successfully used for applications such as using virtual keyboards [5], controlling exoskeletons [6], and operating prosthetic devices [7], etc. FMG based interfaces have also been investigated in several studies as an alternative to EMG based interfaces [8], [9]. Both techniques offer intuitive, hands-free, non-fatiguing interaction with computers and intelligent machines such as prosthetic devices.

EMG based interfaces typically require sophisticated electronics for data acquisition and processing, utilisation of gel-based electrodes, proper selection of the muscle groups, and proper positioning of the EMG sensors, rendering their integration in portable devices challenging. [10], [11]. To solve this issue and to create portable and practical muscle machine interfaces, several researchers have focused on developing appropriate armbands that incorporate numerous EMG or FMG sensors in a compact form. [12]–[14].

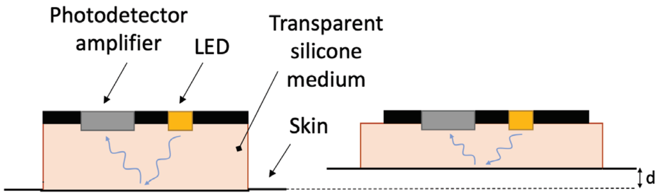

Fig. 2. A drawing demonstrating the working principle of lightmyography. Light gets emitted from an LED and transmitted through an elastic medium. A photodetector amplifier is used to detect the light that is reflected on the skin surface. On the right side of the image, the movement of the skin due to muscle contraction, during the execution of a gesture, compresses the silicone medium and changes the intensity of the light received by the photodetector amplifier.

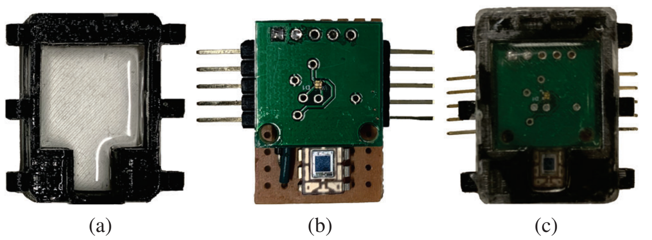

Fig. 3. Different components of one of the device's LMG sensors: a) a silicone element molded on a 3D printed base, b) electronic parts of the sensing module consisting of a small RGB LED and a OPT101 photodetector amplifier, and c) the electronic parts are inserted into the silicone module to complete the assembly of the LMG sensor.

In this work, we present a new muscle-machine intefacing method that we call lightmyography (LMG) and we create a wearable, lightweight LMG armband that can allow for decoding of human gestures (see Fig. 1). Most of the parts of the proposed armband are either 3D printed or molded using silicone rubber. The device consists of five LMG sensing modules, each housing an LED and a photodetector. To validate the efficiency of the LMG method and the proposed armband, the device has been employed in decoding five different gestures and its performance has been compared with the performance of an EMG based interface that uses a commercially available bioamplifier. The results demonstrate that the LMG based muscle machine interface offers promising performance and has the potential to become an efficient solution for the intuitive control of robotic and bionic devices.

The rest of the paper is organized as follows: Section II presents the working principle of lightmyography, the design of the armband, and the methods used, section III explains the experiments conducted and the methods used to evaluate the performance of the armband in decoding various hand gestures. Section IV discusses the results, while section V concludes the paper.

II. Working Principle, Design, and Methods

In this section, we present the working principle of lightmyography as well as the materials and the methods that we used to develop the LMG based arm band.

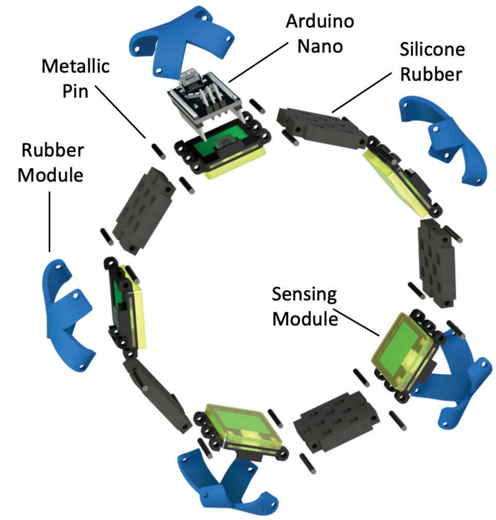

Fig. 4. Exploded view of the device. The proposed device consists of five sensing modules connected together in a circular shape by using silicone rubber elements. An arduino nano is attached on top of one of the sensing modules to make the device both portable and stand alone. Metalic pins are connecting together the different LMG sensors and silicone rubber elements so as to make adding or removing modules easier. Finally, rubber elements provide the required pretension for each LMG sensor.

A. Working Principle of Lightmyography

The design of the device is based on the fact that the change in the position and orientation of a reflecting surface can change light intensity at a fixed point away from the reflective surface. So, by having a flexible compressible medium between a reflecting surface and a photodetector, it is possible to detect movements in the reflecting surface. In the proposed design, an LED sends a light signal to arm skin through a compressible silicone medium. Then, a photodetector amplifier receives the reflection of the light signal from the skin. However, the gain of the photodetector amplifier changes when the target muscle under the skin moves and compresses or decompresses the silicone medium. Fig. 2 shows a schematic of how lightmyography works.

B. Design of the Lightmyography Based Wearable Band

For the design of the armband we tested two different silicones with different optical densities (Smooth-On Dragon skin 10 and Solaris). With Solaris, the gain of the photodetector amplifier was higher, and the changes were more detectable due to its lower optical density. Hence, in the final design of the LMG armband Solaris was used as the medium between the LED and the skin. For the photodetector amplifier, we use OPT101 from Texas instruments. In order to increase the amount of achievable compression in the silicone medium, and to decreases the relative moving distance between the skin and sensors, a 3D printed base is attached to the silicone part. This has been done by molding part of the silicone part inside the 3D printed base. Then, we added rubber bands between the 3D printed base and the PCB to keep the silicone medium pretensioned. This reduces the synced movement of skin and the sensors on the PCB. Fig. 3 shows one module of the device.

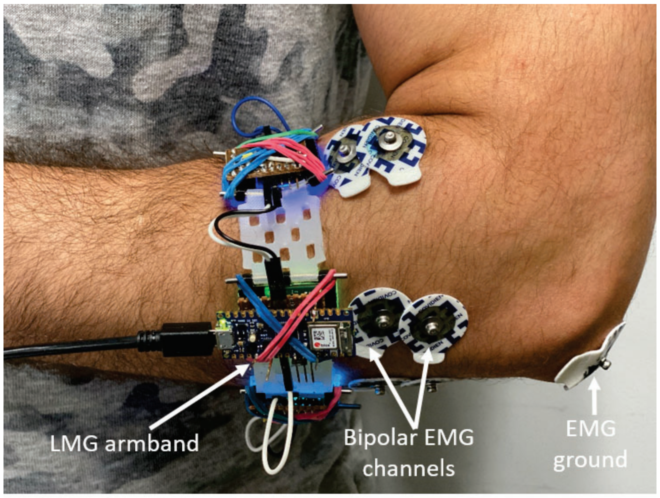

Fig. 5. The placement of the optical armband and the EMG electrodes. The ground of the EMG bioamplifier is placed at the elbow where muscular activity becomes minimal.

The device consists of five modules to monitor different muscle groups at the same time during gesture execution. The modular design of the device makes it possible to add or remove modules easily if required. It is achieved by using elastic elements made out of Smooth-On dragon skin 10 to connect the different modules of the LMG band with the help of metallic pins. An exploded view of the device is presented in Fig. 4.

III. Experiments

In order to evaluate the performance of the proposed LMG band interface, gesture execution data was collected from nine subjects (ages = 25 year $\pm$ 4 year, five males and four females, and upper forearm circumference of 25 mm $\pm$ 4 mm). Two subjects (both males) were left-hand dominant, while seven subjects (three males and four females) were right-hand dominant. The study was approved by the University of Auckland Human Participants Ethics Committee (UAHPEC), reference number #019043. Prior to the study, participants provided written and informed consent to the experimental procedures.

A. Data Collection

During the experiments, the subjects were asked to perform five different gestures: rest, power, pinch, tripod, and finger extension. The data collection procedure for each gesture started with 10 seconds of rest followed by 10 seconds of gesture execution, repeating five times. Visual cues in the form of a three second counter were provided to the subjects on the computer screen to switch between the gesture and the rest phases. A software trigger was sent to the data recording script to label the gesture and the rest phases for developing machine learning models using supervised learning schemes. For data collection, the LMG armband was placed in the upper half of the forearm where the majority of the muscle groups (extensor digitorum, flexor digitorum superficialis, flexor digitorum profundus, and flexor pollicis longus) responsible for the movements of the digits are located [15]. In order to compare the performance of the armband with the state-of-the-art EMG bioamplifiers, data from five bipolar EMG channels was collected at the same time as the data from the armband using g.tec's g.USBamp bioamplifier. For the EMG data, a sampling rate of 1200 Hz was used, and the acquired data were filtered using a Butterworth bandpass filter of 5 Hz and 500 Hz. The machine learning models were developed using the Root Mean Square (RMS) feature, which was extracted from the raw EMG signals. For extracting the RMS value, a moving window of 170 ms was used with a stride of 17 ms. Fig. 5 shows the placement of the armband and the EMG electrodes. The RMS value is defined as:

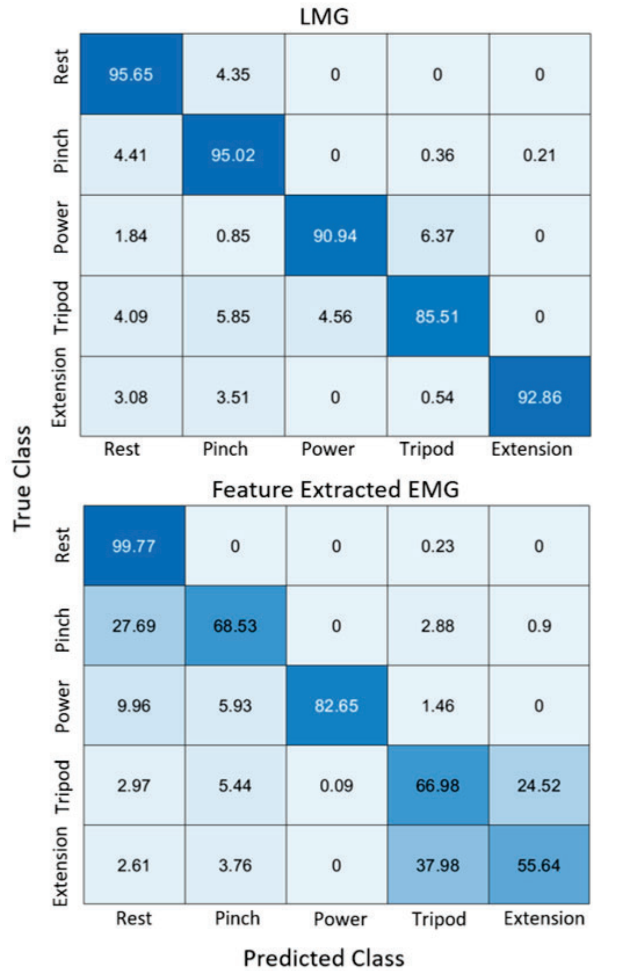

Fig. 6. Confusion matrix for decoding the gestures using LDA based model trained using the two different sets of data. The matrix presents the confusion in classifying gestures over five folds for Subject 9. All the values in the confusion matrices are percentages.

$$RMS = \sqrt{\frac{1}{N}\left(\sum_{k=1}^{N}(x_k)^2\right)}, \tag{1}$$

where N is the size of the window applied to the data.

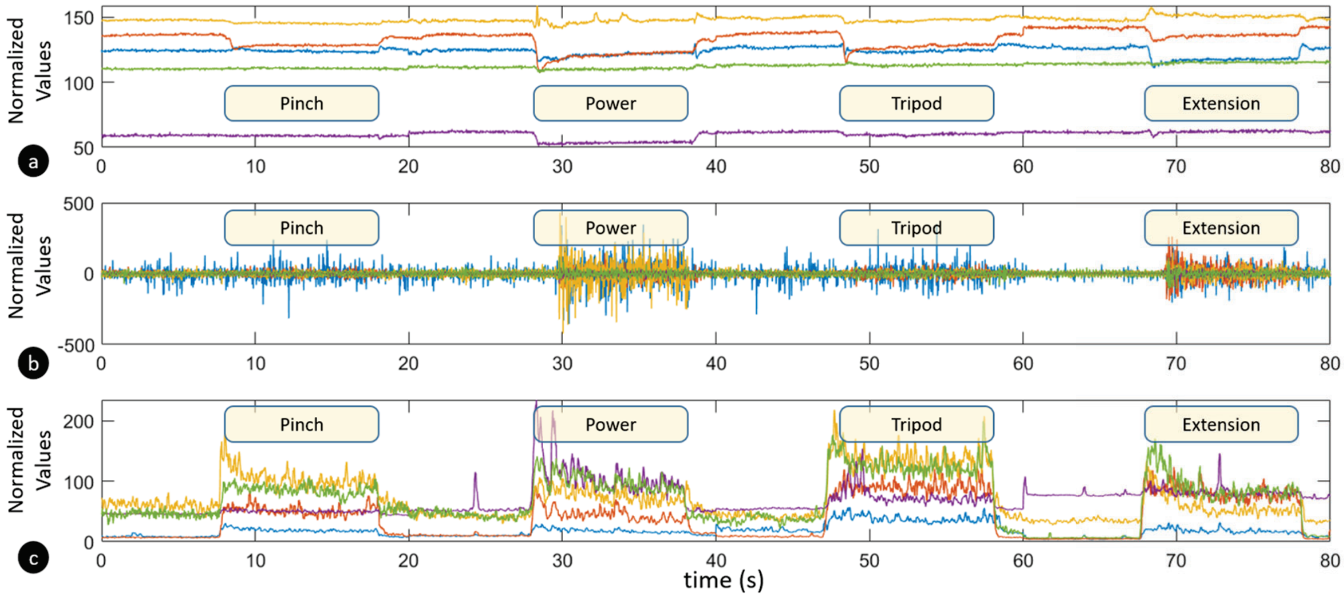

Fig. 7. The LMG and EMG values during pinch, power, tripod, and extension gesture. Subfigure a) shows the activation values for the LMG sensors, subfigure b) shows the raw EMG activations, while subfigure c) shows the processed EMG signals (RMS values).

TABLE I
ACCURACY VALUES (EXPRESSED AS PERCENTAGES) FOR THE GESTURE DECODING MODELS DEVELOPED USING LIGHTMYOGRAPHY (LMG) AND ELECTROMYOGRAPHY (EMG) DATA

Data Source	**LMG**			**EMG**		
Learning Model	**LDA**	**SVM**	**RF**	**LDA**	**SVM**	**RF**
Subject 1	94.68%	93.99%	89.22%	87.32%	86.54%	93.63%
Subject 2	82.16%	83.49%	81.45%	76.30%	78.93%	82.36%
Subject 3	90.48%	93.17%	88.55%	93.18%	96.05%	94.58%
Subject 4	71.83%	78.12%	85.56%	64.63%	60.15%	88.70%
Subject 5	86.20%	88.90%	84.02%	77.52%	82.51%	82.64%
Subject 6	81.56%	85.46%	83.86%	77.43%	93.85%	92.14%
Subject 7	92.33%	95.61%	96.16%	71.49%	86.46%	87.94%
Subject 8	88.50%	88.09%	89.84%	78.71%	76.48%	89.49%
Subject 9	92.00%	91.54%	90.79%	74.71%	87.26%	88.08%

B. *Classification Methods*

Before developing the machine learning models, it was made sure that all the five classes of different gestures (rest, power, pinch, tripod, and extension) are balanced. Since the classes are balanced, the chance performance (in case of random guessing the gesture class) for the learning algorithm should be $\sim 20\%$.

To compare the performance of the armband with the EMG bioamplifier, three different machine learning techniques were used, namely: i) Linear Discriminant Analysis (LDA) classifier [16], ii) a Support Vector Machine (SVM) based multiclass classifier [17], and iii) a Random Forest (RF) classifier [18]. The SVM based classifier was developed using a nonlinear RBF kernel. The classifiers were trained and validated using the 5-fold cross validation method.

IV. RESULTS

This section presents the gesture decoding accuracy for the LMG band and the EMG bioamplifier. To do this, we trained machine learning models on two different sets of data. The first set was developed using the data from the LMG band, while the second set using the RMS feature extracted from the raw EMG data. For each set, three different machine learning schemes were employed to decode the human intention (as discussed in Section III-B).

Table I presents the gesture decoding accuracies achieved using different machine learning schemes on each of the sets. Out of the two sets, the models trained on the data using the LMG armband perform better than those trained using feature extracted EMG. Fig. 6 presents the confusion matrices for decoding the gestures using two different interfaces and an LDA based classifier. The results presented are from Subject 9 (see Table I) over five folds of cross validation. From the confusion matrices, it can be seen that the inter-class mis-classifications while discriminating the gestures decoded from the LMG data are significantly lower as compared to when decoded using the feature extracted EMG data. An example of the LMG, raw EMG, and feature extracted EMG recordings is shown in Fig. 7.

V. CONCLUSION

In this work, we introduced a new type of muscle machine interfacing method that we call lightmyography and we presented a wearable, lightweight LMG based armband for muscle-machine interaction. The proposed armband is composed of 3D printed parts as well as parts molded using silicone rubber. It consists of five sensing modules, each housing an LED and a photodetector. To validate the efficiency of the LMG method and the proposed armband, the device has been employed in decoding five different gestures and its performance has been compared with the performance of an EMG based interface that uses a commercially available bioamplifier. In the results section, it can be noticed that the models trained and tested on the LMG data perform better than those trained and tested on the EMG data.

Regarding future directions for the proposed armband, we plan to add inertial measurement units (IMUs) to achieve better decoding performance by identifying the orientation of the user's arm. During the experiments, it was noticed that the tightness of the band around the arm significantly affects performance, so the next version of the armband will have adjustable band dimensions as well as adjustable pretension in each of the sensing modules. Also, casing will be designed around each sensing module to reduce the effect of ambient light on the LMG based decoding capabilities. We also plan to investigate the impact of the wavelength of the emitted light in different silicon mediums. A comprehensive sensitivity analysis and a parametric study of the physical design characteristics and the required data collection, processing, and human intention and motion decoding systems will also be conducted.

References

[1] A. Dwivedi, Y. Kwon, and M. Liarokapis, "Emg-based decoding of manipulation motions in virtual reality: Towards immersive interfaces," in *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2020, pp. 3296–3303.

[2] T. S. Saponas, D. S. Tan, D. Morris, R. Balakrishnan, J. Turner, and J. A. Landay, "Enabling always-available input with muscle-computer interfaces," in *Proceedings of the 22nd annual ACM symposium on User interface software and technology*, 2009, pp. 167–176.

[3] E. Cho, R. Chen, L.-K. Merhi, Z. Xiao, B. Pousett, and C. Menon, "Force myography to control robotic upper extremity prostheses: a feasibility study," *Frontiers in bioengineering and biotechnology*, vol. 4, p. 18, 2016.

[4] A. Dwivedi, L. Gerez, W. Hasan, C.-H. Yang, and M. Liarokapis, "A soft exoglove equipped with a wearable muscle-machine interface based on forcemyography and electromyography," *IEEE Robotics and Automation Letters*, vol. 4, no. 4, pp. 3240–3246, 2019.

[5] M. A. Rahim and J. Shin, "Hand movement activity-based character input system on a virtual keyboard," *Electronics*, vol. 9, no. 5, 2020. [Online]. Available: https://www.mdpi.com/2079-9292/9/5/774

[6] C. Fleischer and G. Hommel, "A human–exoskeleton interface utilizing electromyography," *IEEE Transactions on Robotics*, vol. 24, no. 4, pp. 872–882, 2008.

[7] C. Castellini and P. Van Der Smagt, "Surface emg in advanced hand prosthetics," *Biological cybernetics*, vol. 100, no. 1, pp. 35–47, 2009.

[8] X. Jiang, L.-K. Merhi, Z. G. Xiao, and C. Menon, "Exploration of force myography and surface electromyography in hand gesture classification," *Medical engineering & physics*, vol. 41, pp. 63–73, 2017.

[9] M. Connan, E. Ruiz Ramírez, B. Vodermayer, and C. Castellini, "Assessment of a wearable force-and electromyography device and comparison of the related signals for myocontrol," *Frontiers in neurorobotics*, vol. 10, p. 17, 2016.

[10] A. Dwivedi, G. Gorjup, Y. Kwon, and M. Liarokapis, "Combining electromyography and fiducial marker based tracking for intuitive telemanipulation with a robot arm hand system," in *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 2019, pp. 1–6.

[11] J. Kim, S. Mastnik, and E. André, "Emg-based hand gesture recognition for realtime biosignal interfacing," in *Proceedings of the 13th international conference on Intelligent user interfaces*, 2008, pp. 30–39.

[12] A. Kadkhodayan, X. Jiang, and C. Menon, "Continuous prediction of finger movements using force myography," *Journal of medical and Biological Engineering*, vol. 36, no. 4, pp. 594–604, 2016.

[13] V. P. Rachim and W.-Y. Chung, "Wearable noncontact armband for mobile ecg monitoring system," *IEEE transactions on biomedical circuits and systems*, vol. 10, no. 6, pp. 1112–1118, 2016.

[14] Y. T. Wu, M. K. Gomes, W. H. da Silva, P. M. Lazari, and E. Fujiwara, "Integrated optical fiber force myography sensor as pervasive predictor of hand postures," *Biomedical engineering and computational biology*, vol. 11, p. 1179597220912825, 2020.

[15] R. J. Stone and J. A. Stone, *Atlas of skeletal muscles*. McGraw Hill, 2003.

[16] A. J. Izenman, "Linear discriminant analysis," in *Modern multivariate statistical techniques*. Springer, 2013, pp. 237–280.

[17] W. S. Noble, "What is a support vector machine?" *Nature biotechnology*, vol. 24, no. 12, pp. 1565–1567, 2006.

[18] L. Breiman, "Random forests," *Machine learning, Springer*, vol. 45, no. 1, pp. 5–32, 2001.