An Intelligent Approach to Mitigate the Effects of Dynamic Movements in FMG technique for Upper Limb Prosthesis.

Muhammad Bilal [*], Muhammad Usman Qadir [**], Muhammad Awais Khan [***], Izhar-Ul-Haq **‍**

[*] Mechatronics Department, University of Engineering and Technology Peshawar

Abstract- This research paper aims to advance the clinical applicability of Force Myography (FMG) technology, particularly for the benefit of individuals with disabilities. FMG is employed to map muscle deformation resulting from gesture recognition, utilizing force-sensing resistors mounted on a flexible band wrapped around a person's area of effect to detect muscle stiffness. Even residual limbs with minimal muscle tissue can facilitate effective human-machine interfaces for appropriate actions using FMG.

Machine learning algorithms play a critical role in providing highly accurate results. Despite significant progress in precision over the past two decades, there remains a substantial gap between laboratory testing and clinical trials. This paper seeks to address this disparity by exploring methods for enhancing FMG performance outside of controlled laboratory environments, thereby improving its potential for real-world applications and positively impacting the lives of disabled individuals.

Index Terms- Disabled, Force-Sensing-Resistors, FMG, Gesture recognitions, Machine Learning

I. INTRODUCTION

The loss of a limb profoundly impacts individuals, who often seek assistance from prosthetics clinics. Popular bionic hands like Otto Bock's Michelangelo hand, Touch Bionics' i-Limb, and Steeper Group's Bebionic3 are available, but their utilization remains low due to cost and usability issues.

Current methods, like sEMG, face challenges due to cost and signal quality degradation over time. Force Myography (FMG) emerges as a promising alternative, offering durability and sweat resistance. However, FSR values inconsistency during daily activities poses a significant challenge for trans-radial amputees, leading to dissatisfaction and abandonment of prosthetics.

This research aims to develop a robust system capable of interpreting user intent accurately despite FSR fluctuations. Objectives include analyzing muscle contractions' impact on FSR readings, optimizing FSR sensor placement, employing advanced signal processing and machine learning techniques, and exploring sensor fusion approaches. The proposed system aims to enhance control accuracy and improve the quality of life for amputees relying on robotic prosthetics.

In summary, this research focuses on implementing an efficient FMG system to classify limb positions and movements accurately, addressing the challenges faced by trans-radial amputees and advancing prosthetic control systems.

II. ADVANCEMENTS IN THE FMG-BASED PROSTHETIC CONTROL: OVERCOMING CHALLENGES AND MEETING USER NEEDS

This literature review aims to summarize existing research on Force Myography (FMG) techniques and their application in prosthetic development, particularly for trans-radial amputees.

Limb loss is a significant global health concern, with estimates suggesting a rise to 3.6 million cases in the United States by 2050. Upper limb amputations, especially trans-radial ones, pose unique challenges for rehabilitation and prosthetic development.

The Be Bionic i-limb prosthesis, developed by Össur, is an advanced device designed to replicate human hand functionality and appearance. Featuring individually powered fingers, including an articulating thumb, it offers exceptional dexterity and grip strength. Myoelectric signals from residual muscles control its movements, enabling precise finger and thumb control.

A key feature is its adaptability to various grip patterns and hand positions, with pre-set options like pinch, power grip, or key grip. Users can customize settings through mobile apps, enhancing usability. Moreover, cosmetic coverings closely resemble natural hands, boosting comfort, confidence, and integration into daily life.

In conclusion, the Be Bionic i-limb prosthesis offers a highly advanced, customizable solution for upper limb deficiencies or amputations. Its myoelectric technology, coupled with multiple grip patterns and aesthetic considerations, ensures exceptional functionality and user acceptance.

III. HARNESSING FMG TECHNOLOGY FOR DYNAMIC MOVEMENTS: DESIGN AND HARDWARE FRAMEWORK

This study aims to address the challenges of dynamic movements using force myography (FMG). It involves designing an FMG band, collecting data with force-sensitive resistors (FSRs) and an inertial measurement unit (IMU), and training a machine learning model for limb position and movement classification.

In recent years, custom FMG bands tailored for specific applications have emerged. The band is adjustable and features durable outer material and soft inner lining for comfort. A single FSR, strategically positioned to target forearm muscles, allows precise detection of muscle contractions, enhancing limb movement representation.

The custom FMG band includes a buffer circuit for FSRs, connected to the Arduino Portenta H7 microcontroller, ensuring accurate and stable readings. Additionally, a 3.7-volt battery and Bluetooth HC-06 module are integrated for long-lasting power and wireless data transmission.

The Arduino Portenta H7, with its dual-core Cortex-M7 and Cortex-M4 microcontrollers, is ideal for acquiring signals from both the MPU6050 IMU and FSRs. The IMU, MPU-6050, measures acceleration and rotation, enhancing gesture recognition accuracy. A moving average filter smoothens accelerometer data, improving accuracy further.

Machine learning techniques, particularly the random forest classifier, are employed for limb position prediction. Supervised learning with a training dataset enables accurate prediction, crucial for real-time applications. The trained model is loaded onto the Portenta H7 microcontroller for real-time control of the prosthetic device.

Performance comparison reveals the effectiveness of the random forest classifier compared to other methods like Linear Discriminant Analysis and Support Vector Machines. Despite their advantages, the random forest classifier is chosen for its ability to handle large datasets and provide accurate results.

Validation on the experimenter's hand yields over 98% accuracy. Further validation may involve testing on other participants and assessing robustness under various conditions.

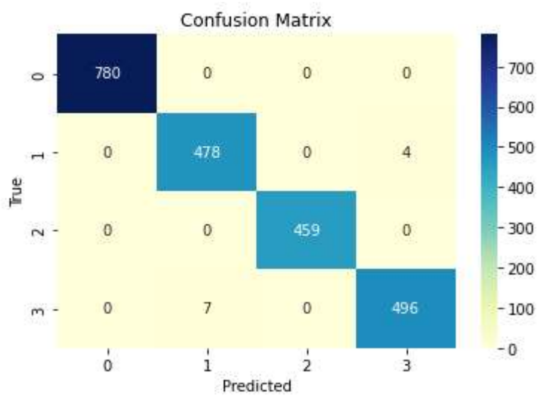
In conclusion, this chapter explores the design, development, and implementation of an FMG system for dynamic movement detection and classification. By optimizing design, hardware, and software components, it lays the foundation for improved prosthetic control using FMG technology, ultimately enhancing the lives of amputees.

IV. COMPREHENSIVE ANALYSIS OF PROSTHETIC CONTROL: DATA COLLECTION AND PERFORMANCE EVALUATION

The study involved collecting data on four limb positions: Stationary, Butterfly, Flag, and Bend/Fold. Force-sensitive resistors (FSRs) and an inertial measurement unit (IMU) were used to collect data both statically and dynamically. A moving average filter improved accelerometer data quality during acquisition.

In the stationary position, the arm is relaxed, serving as a baseline for the FMG system. The lateral extension, represented by the Butterfly position, engages shoulder and upper arm muscles, crucial for accurate gesture classification. The Bend/Fold position deactivates FSRs to prevent false signals during arm compression.

The FMG system achieved 95% accuracy in dynamic testing, focusing on real-world scenarios. Four limb positions facilitated gesture control system operation, adjusting FSRs in real-time based on muscle contractions and arm position. A low delay time (<300 milliseconds) ensured a comfortable user experience.
The confusion matrix evaluated the classifier's performance. Most predictions were correct, with some misclassifications between positions 1 and 3, suggesting areas for improvement.



In conclusion, Chapter 4 examined data collection methods and outcomes, emphasizing the development of an effective prosthetic control system. The confusion matrix analysis provided insights into system performance, highlighting its potential for practical applications in upper limb prosthetics, with implications for improving quality of life for amputees.

V. CONCLUSION AND FUTURE SCOPE OF THE PROJECT

The study aimed to enhance prosthetic limb control during dynamic movements using force myography (FMG). A custom FMG band with FSRs and an IMU was designed, and a Random Forest model was trained to classify four limb positions: Stationary, Butterfly, Flag, and Bend/Fold.

The high accuracy of over 98% on the experimenter's hand demonstrates the FMG technique's potential for precise limb movement detection, even during dynamic activities. The confusion matrix showed minimal misclassifications, indicating the model's ability to distinguish between limb actions accurately.

The moving average filter improved accelerometer data quality, contributing to overall system accuracy. Implementing the trained model on the Portenta H7 microcontroller enabled real-time prosthetic control, showcasing the approach's practicality.

Future research could involve testing on a larger, diverse group, exploring long-term system reliability, and investigating alternative machine learning algorithms for improved accuracy. Integrating EMG sensing could enhance system robustness.

In summary, this study showcased FMG's potential combined with machine learning for prosthetic control during dynamic movements, paving the way for advanced, user-friendly prosthetic devices.

The study focused on refining prosthetic limb control during motion using FMG. A custom FMG band was crafted, leveraging FSRs and an IMU, while a Random Forest model was trained to classify four limb positions. Achieving over 98% accuracy on the experimenter's hand underscored FMG's precision, even in motion. The confusion matrix revealed few misclassifications, validating the model's accuracy. A moving average filter bolstered accelerometer data quality, aiding real-time control via the Portenta H7 microcontroller. Future directions include broader testing, exploring alternative algorithms, and integrating EMG sensing for improved robustness. This research marks a significant step toward more sophisticated prosthetic control systems, promising enhanced user experiences.

References

[1] K. Ziegler-Graham, E. J. MacKenzie, P. L. Ephraim, T. G. Travison, and R. Brookmeyer, "Estimating the prevalence of limb loss in the United States: 2005 to 2050," Arch Phys Med Rehabil, vol. 89, no. 3, pp. 422–429, 2008, doi: 10.1016/j.apmr.2007.11.005.

[2] M. Wininger, "Pressure signature of forearm as predictor of grip force," The Journal of Rehabilitation Research and Development, vol. 45, no. 6, pp. 883–892, Dec. 2008, doi: 10.1682/JRRD.2007.11.0187.

[3] L. F. Lucaccini, P. K. Kaiser, and J. Lyman, "The French electric hand: Some observations and conclusions," Bull. Prosthet. Res, vol. 10, no. 6, pp. 31–51, 1966.

[4] D. Ferigo, L.-K. Merhi, B. Pousett, Z. G. Xiao, and C. Menon, "A Case Study of a Force-myography Controlled Bionic Hand Mitigating Limb Position Effect," Journal of Bionic Engineering, vol. 14, no. 4, pp. 692–705, 2017, doi: https://doi.org/10.1016/S1672-6529(16)60435-3.

[5] R. L. Abboudi, C. A. Glass, N. A. Newby, J. A. Flint, and W. Craelius, "A biomimetic controller for a multifinger prosthesis," IEEE Transactions on Rehabilitation Engineering, vol. 7, no. 2, pp. 121–129, 1999.

[6] P. Lukowicz, F. Hanser, C. Szubski, and W. Schobersberger, "Detecting and interpreting muscle activity with wearable force sensors," in International Conference on Pervasive Computing, 2006, pp. 101–116.

[7] A. Radmand, E. Scheme, and K. Englehart, "High-density force myography: A possible alternative for upper-limb prosthetic control," J Rehabil Res Dev, vol. 53, no. 4, pp. 443–456, 2016, doi: 10.1682/jrrd.2015.03.0041.

[8] G. Lei, S. Zhang, Y. Fang, Y. Wang, and X. Zhang, "Investigation on the Sampling Frequency and Channel Number for Force Myography Based Hand Gesture Recognition," Sensors, vol. 21, no. 11, p. 3872, 2021, [Online]. Available: https://www.mdpi.com/1424-8220/21/11/3872

[9] Z. G. Xiao and C. Menon, "A Review of Force Myography Research and Development," Sensors, vol. 19, no. 20, p. 4557, 2019, [Online]. Available: https://www.mdpi.com/1424-8220/19/20/4557

[10] C. Connolly, "Prosthetic hands from Touch Bionics," Industrial Robot, vol. 35, no. 4, pp. 290–293, 2008, doi: 10.1108/01439910810876364.

[11] E. Biddiss and T. Chau, "Upper-limb prosthetics: critical factors in device abandonment," Am J Phys Med Rehabil, vol. 86, no. 12, pp. 977–987, Dec. 2007, doi: 10.1097/PHM.0b013e3181587f6c.

[12] F. Cordella, A. L. Ciancio, R. Sacchetti, A. Davalli, A. G. Cutti, E. Guglielmelli, and L. Zollo, "Literature Review on Needs of Upper Limb Prosthesis Users," Front. Neurosci., vol. 10, May 2016, doi: 10.3389/fnins.2016.00209.

[13] Cordella, F., Ciancio, A. L., Sacchetti, R., Davalli, A., Cutti, A. G., Guglielmelli, E., & Zollo, L. (2016). Literature Review on Needs of Upper Limb Prosthesis Users. Frontiers in Neuroscience, 10. https://doi.org/10.3389/fnins.2016.00209

[14] D. Farina et al., "The Extraction of Neural Information from the Surface EMG for the Control of Upper-Limb Prostheses: Emerging Avenues and Challenges," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 22, no. 4, pp. 797-809, July 2014.

[15] L. A. Miller, R. D. Lipschutz, B. Stubblefield, et al., "Control Strategies for Integration of Electric Powered Prosthetic Limbs," IEEE Engineering in Medicine and Biology Magazine, vol. 20, no.

[16] Össur. (n.d.). i-limb. Retrieved from https://www.ossur.com/en-us/prosthetics/arms/i-limb

[17] Touch Bionics by Össur. (n.d.). i-limb ultra. Retrieved from https://www.touchbionics.com/products/active-prosthetic-hands/i-limb-ultra

[18] Atkins, D. J., Heard, D. C., & Donovan, W. H. (1996). Epidemiologic overview of individuals with upper-limb loss and their reported research priorities. Journal of Prosthetics and Orthotics, 8(1), 2-11.

[19] Cordella, F., Ciancio, A. L., Sacchetti, R., Davalli, A., Cutti, A. G., Guglielmelli, E., & Zollo, L. (2016). Literature review on needs of upper limb prosthesis users. Frontiers in Neuroscience, 10, 209.

[20] Biddiss, E., & Chau, T. (2007). Upper limb prosthesis use and abandonment: a survey of the last 25 years. Prosthetics and Orthotics International, 31(3), 236-257.

[21] Kyberd, P. J., & Hill, W. (2011). Survey of upper limb prosthesis users in Sweden, the United Kingdom and Canada. Prosthetics and Orthotics International, 35(2), 234

[22] Castellini, C., & van der Smagt, P. (2013). Surface EMG in advanced hand prosthetics. Biological Cybernetics, 108(1), 141-153. doi: 10.1007/s00422-012-0538-9

[23] Gijsberts, A., & Caputo, B. (2013). Exploiting Independent Task Execution for Improved Generalization in Continuous EMG Decoding. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 21(5), 769-777. doi: 10.1109/TNSRE.2013.2250521

[24] Krasoulis, A., Kyranou, I., Erden, M. S., Nazarpour, K., & Vijayakumar, S. (2017). Improved prosthetic hand control with concurrent use of myoelectric and inertial measurements. Journal of NeuroEngineering and Rehabilitation, 14(1), 71. doi: 10.1186/s12984-017-0276-1

[25] Jiang, N., Vujaklija, I., Rehbaum, H., Graimann, B., & Farina, D. (2014). Is Accurate Mapping of EMG Signals on Kinematics Needed for Precise Online Myoelectric Control? IEEE Transactions on Neural Systems and Rehabilitation Engineering, 22(3), 549-558. doi: 10.1109/TNSRE.2013.2287383

[26] Zhou, R., Hu, H., & Liu, Y. (2006). A Real-Time EMG Pattern Recognition System Based on Linear-Nonlinear Feature Projection for a Multifunction Myoelectric Hand. IEEE Transactions on Biomedical Engineering, 53(11), 2232-2239. doi: 10.1109/TBME.2006.883695

[27] Novak, D., & Riener, R. (2015). A survey of sensor fusion methods in wearable robotics. Robotics and Autonomous Systems, 73, 155-170. doi: 10.1016/j.robot.2014.08.012

[28] Oskoei, M. A., & Hu, H. (2008). Myoelectric control systems—A survey. Biomedical Signal Processing and Control, 2(4), 275-294. doi: 10.1016/j.bspc.2008.07.003

[29] Amft, O., & Troster, G. (2008). Recognition of dietary activity events using on-body sensors. Artificial Intelligence in Medicine, 42(2), 121-136. doi: 10.1016/j.artmed.2007.11.007

[30] Cho, E., Chen, R., & Merhi, L. K. (2017). Force Myography for Monitoring Grasping in Individuals with Stroke with Mild to Moderate Upper-Extremity Impairments: A Preliminary Investigation in a Controlled Environment. Frontiers in Bioengineering and Biotechnology, 5, 32. doi: 10.3389/fbioe.2017.00032

[31] Yun, Y., Kim, H. C., & Kim, J. (2016). A Real-Time Hand Gesture Recognition and Human-Computer Interaction System. Sensors, 16(5), 630. doi: 10.3390/s16050630

[32] Merhi, L. K., & Menon, C. (2017). Integrating Force Myography Into a Commercially Available Myoelectric Controlled Prosthetic Hand. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 25(10), 1766-1774. doi: 10.1109/TNSRE.2017.2675090

[33] Jiang, X., Merhi, L. K., & Menon, C. (2017). Exploring wrist-worn sensors to assess force myography: a comparison of force myography and electromyography. Biomedical Physics & Engineering Express, 3(5), 055014. doi: 10.1088/2057-1976/aa85f9

[34] Razak, A. H., & Linares, J. M. (2016). An Overview of Force Myography Signal Processing for Human-Machine Interfaces. In 2016 2nd International Conference on Robotics and Automation Engineering (ICRAE), 119-123. doi: 10.1109/ICRAE.2016.7738813

[35] Ahmadi, S., Oyekoya, O., & Connolly, J. D. (2017). An investigation into the efficacy of avatar-based systems for student learning. Computers & Education, 111, 83-99. doi: 10.1016/j.compedu.2017.03.010

[36] Al-Timemy, A. H., Bugmann, G., Escudero, J., & Outram, N. (2013). Classification of finger movements for the dexterous hand prosthesis control with surface electromyography. IEEE Journal of Biomedical and Health Informatics, 17(3), 608-618. doi: 10.1109/JBHI.2013.2244890

[37] Englehart, K., & Hudgins, B. (2003). A robust, real-time control scheme for multifunction myoelectric control. IEEE Transactions on Biomedical Engineering, 50(7), 848-854. doi: 10.1109/TBME.2003.813539

AUTHORS

First Author – Muhammad Bilal, B.Sc. Electrical Engineer, NUCES Fast,

Second Author – Muhammad Usman Qadir, M.Sc Mechatronics, Lab Engineer, Dept of Mechatronics, University of Engineering and technology Peshawar, Pakistan.

Third Author – Muhammad Awais Khan, M.Sc Mechatronics, Dept of Mechatronics, University of Engineering and technology Peshawar, Pakistan.

Fourth Author – Izhar-Ul-Haq, Ph.D. (Loughborough University, UK), Professor at Dept of Mechatronics of The University of Engineering and technology Peshawar, Pakistan.