IMU-Based Exoskeleton Control: Torso Movements and AI

Marius Leonard Olar
University of Petrosani, Romania
Monica Leba
University of Petrosani, Romania
Andreea Cristina Ionică
University of Petrosani, Romania
Victor Triohin
University of Petrosani, Romania

Abstract

This study introduces a new control system for an upper limb exoskeleton, leveraging Inertial Measurement Unit (IMU) sensors placed on the user's trunk. The system employs two distinct control methodologies to enhance the exoskeleton's responsiveness and accuracy in assisting arm movements. The first method utilizes the torso's motion, integrating IMU data to calculate the arm's movement limits synchronously with the torso, ensuring the exoskeleton's movements are in harmony with the user's natural motion patterns. The second method adopts a more advanced approach, employing a neural network to predict the user's intended arm movement based on the torso's dynamics. This predictive model allows for a more intuitive interaction between the user and the exoskeleton, potentially improving the efficiency and satisfaction in its use. By comparing these methods, the paper aims to evaluate their effectiveness in providing a seamless and natural extension of the human body through the exoskeleton, offering insights into future developments for assistive technologies.

Keywords: Exoskeleton, IMU sensors, Torso movement, Neural network, Control system, Movement prediction, Assistive technology
JEL classification: L63, L86

Paper type: Research article
Received: 5 February 2024
Accepted: 28 May 2024

DOI: 10.54820/entrenova-2024-0024

Introduction

The accurate prediction and analysis of human movement using wearable sensor technology have gained significant attention in recent years, driven by advancements in sensor design, data processing algorithms, and machine learning techniques. This thriving field of research holds promise for a wide range of applications, from enhancing athletic performance and rehabilitation outcomes to developing sophisticated human-computer interaction systems. Among the various technologies employed, Inertial Measurement Units (IMUs) have emerged as particularly valuable tools due to their ability to capture comprehensive motion data in real-time.

IMUs, which typically combine accelerometers, gyroscopes, and magnetometers, offer a non-invasive means of quantifying body segment orientations and movements. When placed on different parts of the body, such as the trunk and limbs, these sensors can provide detailed insights into complex motor behaviours. This capability is of great interest not only to bio-mechanists and physical therapists but also to engineers and designers working on the next generation of wearable devices.

The human arm's movement, with its wide range of motion and intricate coordination, presents a particularly interesting subject for study. Understanding arm motion relative to the trunk is crucial for numerous activities, including reaching, lifting, and gesturing. Such movements are fundamental not only in daily activities and sports but also in clinical scenarios where recovery from injury or neurological conditions is the focus. However, the dynamic and three-dimensional nature of arm movements poses challenges for accurate measurement and analysis.

Recent developments in neural networks, a class of powerful machine learning models, offer a promising approach to interpreting the complex data derived from IMUs. Neural networks are well-suited to modelling non-linear relationships and handling high-dimensional data, making them ideal for analysing the nuanced patterns inherent in human movement.

By training these models on data captured from IMUs placed on the body, researchers can develop algorithms capable of predicting limb positions and movements with high accuracy.

This study aims to leverage the strengths of IMU sensors and neural network modelling to predict arm movement angles based on trunk orientation. Such predictions not only contribute to our understanding of body kinematics but also have practical implications in areas ranging from rehabilitation medicine, where they can inform therapy strategies, to interactive technologies, where they can improve user interfaces. By focusing on the relationship between trunk and arm movements, this research addresses a gap in the current literature and lays the groundwork for future innovations in wearable technology and motion analysis.

In this context, the following sections detail the methodology employed in capturing and processing IMU data, the design and training of the neural network model, and the evaluation of its performance in predicting arm movements. Through rigorous analysis and validation, this study seeks to demonstrate the potential of combining wearable sensors with machine learning to enhance our understanding and capability in the field of human motion analysis.

This introduction sets the stage for a comprehensive examination of using IMU data and neural network models to predict arm movements relative to the trunk, highlighting the scientific and practical significance of the research.

Literature review

In the field of biomechanics research and the development of assistive technologies, non-invasive methods for capturing human arm movements have increasingly become critical for monitoring and controlling human body movements. Among these methods, Electroencephalography (EEG), Surface Electromyography (sEMG), and Inertial Measurement Units (IMU) are the most commonly employed techniques (Ihab, 2023; Laksono et al., 2020; Ghattas, 2021). These technologies offer a varied perspective on human arm movements, allowing researchers and engineers to understand and manipulate movements in a non-invasive and efficient manner.

Electroencephalography (EEG) can record the electrical activities of the brain, which can be used to monitor human arm movements. Recent studies have demonstrated that EEG signals can be employed to detect the motor intentions of subjects and to control assistive devices via brain-computer interfaces (BCIs) (Meng et al., 2016). Furthermore, EEG can be integrated with electrical stimulation technologies to facilitate functional recovery in cases of brain injuries or neurological conditions (Ramirez-Nava et al., 2023).

Surface Electromyography, through the use of sEMG electrodes, is another non-invasive method practiced in measuring the electrical activity of muscles during movements (Li et al., 2020). sEMG sensors placed on the skin's surface can detect the electrical signals generated by muscle activity and provide detailed information about muscle contractions and how they contribute to human arm movements (Sattar et al., 2021). This method is frequently used in biomechanics, rehabilitation, and in developing prototypes of motion-controlled assistive devices.

Inertial Measurement Units are compact devices that combine accelerometers, gyroscopes, and magnetometers to measure the movements and orientation of an object in space (Bhattacharjee, 2022). When capturing human arm movements, IMUs can be attached to different segments of the arm to record and monitor three-dimensional movements, angular velocity, and acceleration (Gu et al., 2023; Digo et al., 2022). These devices are useful in developing motion monitoring systems, exoskeleton prototypes, and virtual reality devices involving human arm movements.

Each of these technologies—EEG, sEMG, and IMUs—brings unique benefits and challenges to the study of human motion. EEG offers insights into the preparatory phases of movement and can potentially predict motion intention before muscular activity begins. sEMG provides direct measures of muscle activation, valuable for understanding the mechanics of movement and the coordination of muscles during physical tasks. IMUs give a direct and practical means to quantify and analyze the kinematics of movement without the constraints of a laboratory setting.

Together, these modalities form a complementary suite of tools that, especially when combined with advanced computational models such as neural networks, hold great promise for advancing our understanding of human movement and developing new technologies to assist those with motor impairments. The convergence of these technologies has opened up novel possibilities in rehabilitative strategies, athletic training, and human-computer interaction, leading to an increased quality of life and enhanced capabilities for individuals across various applications.

Methodology

Participants

A total of 4 participants were recruited for this study. Inclusion criteria required participants to be free from any musculoskeletal, neurological, or cognitive conditions that could affect their ability to perform arm movements. All participants provided informed consent prior to participation.

Instrumentation

Participants' movements were captured using a system composed of two Inertial Measurement Unit (IMU) sensors. One sensor was securely placed on the trunk, and the other was positioned on the right arm. Each IMU sensor was capable of capturing tri-axial accelerometer, gyroscope, and magnetometer data, providing comprehensive information about the orientation, acceleration, and angular velocity of the trunk and arm. The study used only the orientation information.

Data Collection

Participants were asked to perform a series of predefined arm movements, ranging from simple (e.g., arm lifting) to complex (e.g., reaching for an object), under various conditions. The experiment was conducted in a controlled laboratory environment to minimize external interferences. Each movement was performed more than 15 times to ensure data reliability. The IMU sensors recorded data at a sampling rate of 10 Hz.

Data Processing

The raw data from the IMU sensors were pre-processed to extract relevant features for predicting arm movement. This included filtering for noise reduction, normalization, and segmentation of movement episodes. Rotation angles around the world x, y, and z axes were computed from the IMU data to represent the orientation of the trunk and arm in three-dimensional space.

Neural Network Model

A feedforward neural network was designed to predict the arm movement angles based on the trunk's orientation and movement data. The network comprised an input layer, one hidden layer with 30 neurons, and an output layer with three neurons corresponding to the predicted rotation angles of the arm around the x, y, and z axes. The network was trained using the backpropagation algorithm with the following parameters: a learning rate of 0.1, a maximum of 2000 epochs, and a performance goal of 10^{-6}.

Training Procedure

The dataset was divided into training (70%) and validation (30%) sets. The neural network was trained on the training set, with the validation set used to tune the model parameters and prevent overfitting. The performance of the trained model was then evaluated on a new test data set using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) to assess prediction accuracy.

Results and Discussion

Neural Network Training Performance

The training of the neural network, structured with one hidden layer consisting of 30 neurons, was aimed at predicting arm movement angles using data derived from IMU sensors placed on the trunk and right arm. The network topology included three input neurons corresponding to the trunk IMU data and three output neurons for the arm's rotation angles.

Training Procedure and Outcomes

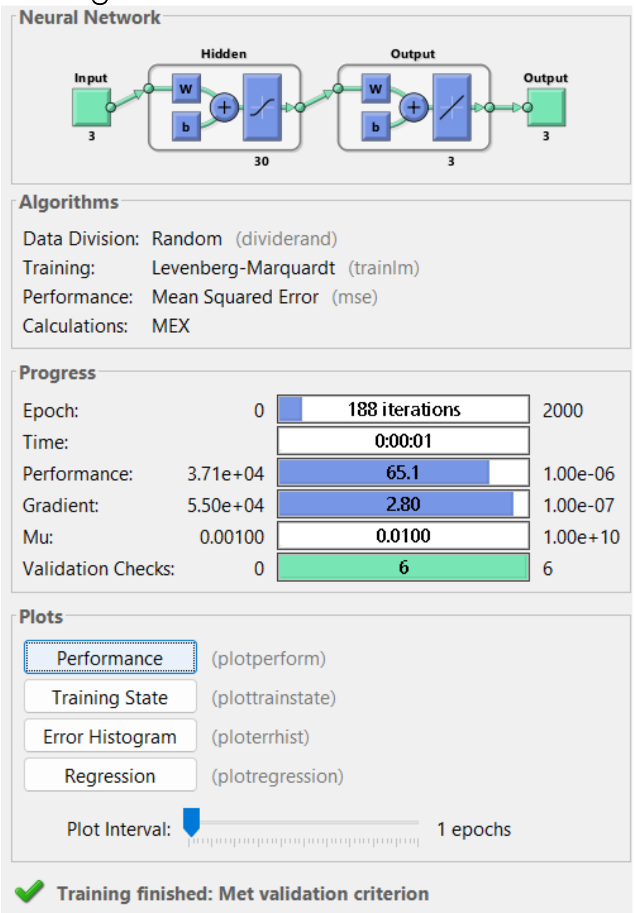
The training employed the Levenberg-Marquardt optimization algorithm, renowned for its efficacy in non-linear regression tasks and rapid convergence in medium-sized networks. The data division strategy was randomized, a common practice to ensure that the model is exposed to a diverse range of data scenarios during training iterations.

The network underwent 183 iterations, a subset of the maximum 2000 epochs prescribed, signalling early cessation of training as per the validation performance. This early stopping is indicative of the model's swift convergence towards a solution that meets the validation criteria.

The performance metric used was Mean Squared Error (MSE), and the final recorded MSE was approximately 3.71e+04. Despite the relatively large error magnitude suggested by MSE, it is essential to contextualize this value within the specific range and scale of the target angles, which span from -30 to 120 degrees. However, the MSE alone is insufficient for a comprehensive evaluation and must be considered alongside other performance metrics and the model's predictive capabilities.

The learning rate (Mu) was dynamically adjusted during training, balancing between 0.00100 and 0.01000. The number of validation checks, which halts training if the validation error increases consecutively, was six - reaching the limit to trigger an early stop to prevent overfitting.

Figure 1
Training of the neural network



Source: Author's illustration

Interpretation and Analysis

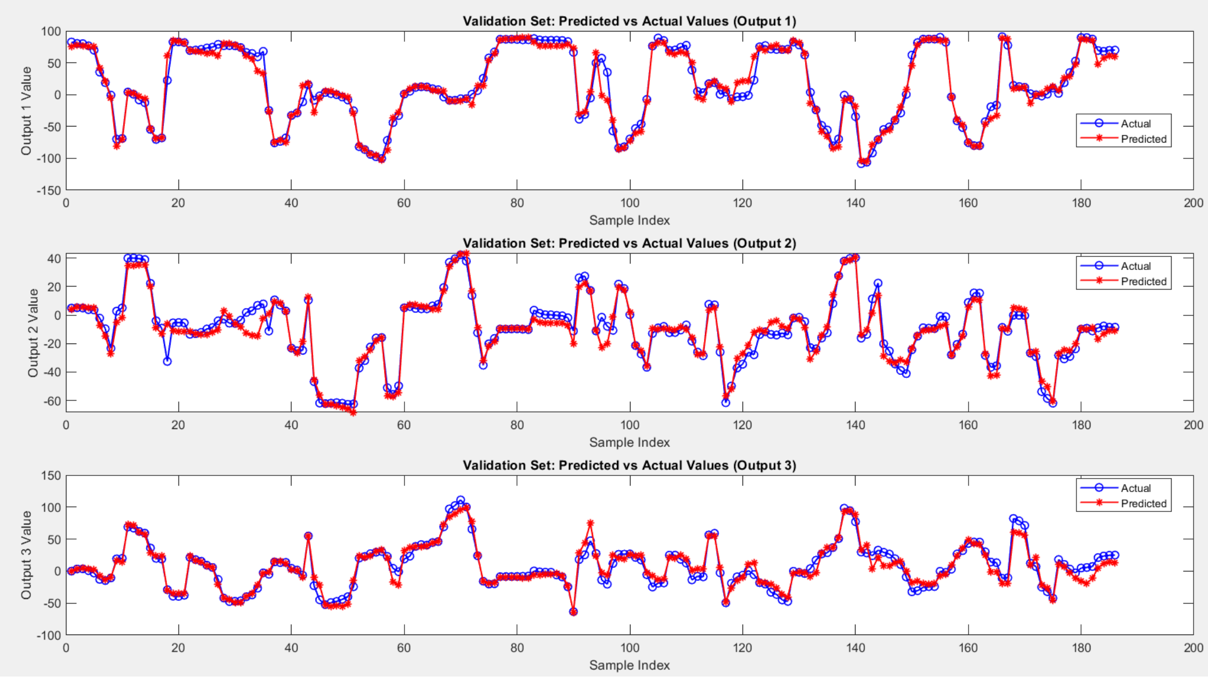
The training process demonstrates a mixed outcome. On one hand, the network's swift convergence is a positive indicator, suggesting a potentially effective model structure and learning algorithm choice. On the other hand, the final MSE and gradient values indicate that the model's predictions are not as close to the actual values as desired, but taking into account the use case of the model it is good to be used as it is.

The model's current performance provides a foundation upon which improvements can be made. Further research will focus on enhancing the neural network's predictive accuracy through architectural adjustments, advanced feature engineering, enriched training datasets, and rigorous hyperparameter optimization. The goal is to develop a robust model that can reliably predict arm movement angles relative to the trunk in real-time, paving the way for advancements in rehabilitative therapies and interactive technologies.

Presentation of Neural Network Validation Performance

In the validation phase of our neural network model, the predicted values for arm movement angles were compared against the actual values obtained from IMU sensors. This comparison was visualized across three distinct outputs, each corresponding to rotation angles around different axes.

Figure 2
Validation set predictions



Source: Author's illustration

Figure 2 illustrates the results of this comparison. Each subplot represents one of the three outputs, showing the predicted versus actual values across the same validation dataset.

The first plot showcases the prediction of the rotation angle around the first axis (Figure 2, top plot). The predicted values closely track the actual values, with only minor discrepancies between the two. This tight alignment is indicative of the model's strong performance for this particular movement component.

The second plot (Figure 2, middle plot) reveals the network's predictions for the rotation angle around the second axis. Here, we observe greater variance between the predicted and actual values compared to Output 1. While the general trend is captured by the model, some deviations suggest room for improvement, particularly in capturing the nuances of movement around this axis.

In the third plot (Figure 2, bottom plot), which represents the rotation angle around the third axis, the model's predictions again closely follow the actual values. However, occasional peaks and troughs indicate instances of over- or under-estimation by the neural network model.

Across all three outputs, the model demonstrates an overall satisfactory predictive capability, as denoted by the recurring coherence between the predicted and actual data points. However, the periodic deviations that are more pronounced in certain segments of the plots underscore the challenges inherent in capturing the dynamic and complex nature of human arm movements.

The presence of outliers and sporadic prediction errors could be attributed to various factors, such as sensor noise, non-linear dynamics of human movement not captured by the model, or potential overfitting to the training data despite satisfactory validation results. These outliers are critical in informing future improvements to the model, highlighting the need for further refinement of the network architecture or training process.

In summary, the illustrated performance in Figure 2 demonstrates the neural network's capability to predict arm movement angles with a high degree of accuracy. The minor discrepancies observed between the predicted and actual values open avenues for further research. Modifying the network structure, exploring advanced regularization techniques, or enriching the dataset with a broader range of movement patterns may help to enhance the precision of predictions and the model's robustness to new, unseen data.

Conclusion

The present study explored the feasibility of utilizing a feedforward neural network model to predict arm movement angles from IMU data collected from sensors positioned on the human trunk and arm. Our findings demonstrate the potential of such computational approaches to accurately interpret complex kinematic data and provide meaningful predictions of limb orientation in three-dimensional space.

The neural network, comprising an input layer, a hidden layer with 30 neurons, and an output layer with three neurons, was trained using the Levenberg-Marquardt optimization algorithm. The validation results, including a mean squared error (MSE) of 287.6327, root mean squared error (RMSE) of 16.9597, mean absolute error (MAE) of 13.0389, and an R-squared (R^2) of 0.77716, suggest a moderate degree of accuracy in the neural network's predictive capability. Visual inspection of the plotted validation set further substantiates these metrics, showing a strong correspondence between the predicted and actual values, with some room for improvement in certain areas.

These results underscore the complex challenge posed by modelling human motion—a task compounded by the inherent variability and complexity of biomechanical movements. While the network has shown proficiency in capturing the overall movement trends, occasional deviations and outlier predictions point to the necessity for further model optimization.

Moving forward, enhancements to the network architecture could include the addition of more layers or neurons, experimenting with different activation functions, and implementing advanced regularization techniques to improve generalizability. Moreover, expanding the dataset with a wider array of movement patterns and potentially integrating additional sensor modalities could refine the network's training and support its applicability in real-world scenarios.

In conclusion, the integration of IMU sensor data with neural network modelling holds significant promise for applications in rehabilitation, sports science, and human-computer interaction. By advancing our computational models and deepening our understanding of the data they process, we can aspire to realize systems that not only predict but also enhance human movement with greater precision and utility. The outcomes of this research lay a foundation for future investigations and technological innovations in the realm of motion analysis and beyond.

References

1. Bhattacharjee, A., & Bhatt, C. (2022). Human Arm Motion Capture Using IMU Sensors. In Smart Energy and Advancement in Power Technologies: Select Proceedings of ICSEAPT 2021, Volume 2 (pp. 805-817). Singapore: Springer Nature Singapore.
2. Digo, E., Gastaldi, L., Antonelli, M., Pastorelli, S., Cereatti, A., & Caruso, M. (2022). Real-time estimation of upper limbs kinematics with IMUs during typical industrial gestures. Procedia Computer Science, 200, 1041-1047.
3. Ghattas, J., & Jarvis, D. N. (2021). Validity of inertial measurement units for tracking human motion: a systematic review. Sports biomechanics, 1-14.

4. Gu, C., Lin, W., He, X., Zhang, L., & Zhang, M. (2023). IMU-based motion capture system for rehabilitation applications: A systematic review. Biomimetic Intelligence and Robotics, 3(2), 100097.
5. Ihab, A. S. (2023). A comprehensive study of EEG-based control of artificial arms. Vojnotehnički glasnik, 71(1), 9-41.
6. Laksono, P. W., Sasaki, M., Matsushita, K., Suhaimi, M. S. A. B., & Muguro, J. (2020, April). Preliminary research of surface electromyogram (sEMG) signal analysis for robotic arm control. In AIP Conference Proceedings (Vol. 2217, No. 1). AIP Publishing.
7. Li, K., Zhang, J., Wang, L., Zhang, M., Li, J., & Bao, S. (2020). A review of the key technologies for sEMG-based human-robot interaction systems. Biomedical Signal Processing and Control, 62, 102074.
8. Meng, J., Zhang, S., Bekyo, A., Olsoe, J., Baxter, B., & He, B. (2016). Noninvasive electroencephalogram based control of a robotic arm for reach and grasp tasks. Scientific Reports, 6(1), 38565.
9. Ramirez-Nava, A. G., Mercado-Gutierrez, J. A., Quinzaños-Fresnedo, J., Toledo-Peral, C., Vega-Martinez, G., Gutierrez, M. I., & Gutiérrez-Martínez, J. (2023). Functional electrical stimulation therapy controlled by a P300-based brain–computer interface, as a therapeutic alternative for upper limb motor function recovery in chronic post-stroke patients. A non-randomized pilot study. Frontiers in Neurology, 14, 1221160.
10. Sattar, N. Y., Kausar, Z., Usama, S. A., Farooq, U., & Khan, U. S. (2021). EMG based control of transhumeral prosthesis using machine learning algorithms. International Journal of Control, Automation and Systems, 19, 3522-3532.

About the authors

Marius Leonard Olar, Ph.D. student Eng. and assistant at University of Petrosani, Romania with a thesis that approaches upper limb exoskeleton design and control. He graduated Computer Engineering specialization both bachelor and master at the University of Petrosani, Romania. His main research interests are robotic systems and design. The author can be contacted at e-mail: **mariusolar@upet.ro**

Prof. Monica Leba is a Ph.D. supervisor in field of System Control Engineering in Computer and System Control Engineering Department at University of Petrosani, Romania. She has a PhD in System Control Engineering from University of Petrosani, a bachelor's degree in applied informatics and Master's Degree in Computer Engineering from University of Petrosani. She is a member of IEEE and IFAC, Computers for Control Technical Committee. Her research interests are in applied informatics, modelling-simulation, algorithms design. She has more than 100 refereed research articles in international journals, conferences and international patents prizes. The author can be contacted at e-mail: **monicaleba@upet.ro**

Prof. Andreea Cristina Ionica is a Ph.D. supervisor in the field of Management and Engineering, Professor of Management in Management and Industrial Engineering Department at University of Petrosani, Romania. She holds a Bachelor's Degree in Engineering (1992), a PhD (2004) in Industrial Engineering, a Bachelor's Degree in Economics (2002) from University of Petrosani and a Postgraduate Diploma (1998) from Institut National Polytechnique de Lorraine, France. The published papers address interdisciplinary and innovative research topics. She has more than 100 refereed research papers in international journals and conferences and international prizes for patents. The author can be contacted at e-mail: **andreeaionica@upet.ro**

Victor Triohin, Ph.D. student Eng. and research assistant at University of Petrosani, Romania with a thesis that approaches artificial intelligence applications. He graduated System Control Engineering bachelor and Computer Engineering master specialization both at the University of Petrosani, Romania. His main research interests are game development and artificial intelligence. The author can be contacted at e-mail: **victortriohin@upet.ro**