PREDICTING ARM MOVEMENTS FROM TORSO ORIENTATIONS: A SUPPORT VECTOR REGRESSION APPROACH

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Abstract: This study focuses on improving biomechanical analysis and rehabilitation methods using predictive modeling. It aims to create a reliable predictive model using Support Vector Regression (SVR) to predict arm movements based on torso orientation. By processing data from Inertial Measurement Units attached to participants' torsos and arms, the study explores the potential of SVR in physical therapy. The model's accuracy is evaluated using statistical metrics like Mean Absolute Error and coefficient of determination R^2, demonstrating its effectiveness in predicting human movements. This work supports advancements in rehabilitation, setting a precedent for future research into adaptive, high-accuracy predictive modeling in health-related applications.
Key words: Biomechanical Modeling, Inertial Measurement Units (IMUs), Human Movement Analysis, Predictive Analytics, Rehabilitation Technologies.

1. INTRODUCTION

In the field of biomechanical analysis and rehabilitation, understanding and predicting human limb movements accurately is a big challenge that has significant implications for the development of assistive technologies and therapeutic strategies. As human movements are inherently complex and dynamic, the ability to model these movements precisely offers substantial benefits in various applications, from physical therapy to the enhancement of athletic performance and beyond. This study focuses on the development of a predictive model using Support Vector Regression (SVR) to estimate arm movements based on the orientation of the torso. This approach uses the robust capabilities of SVR, known for its effectiveness in managing non-linear data and complex relationships, making it particularly suitable for the nuanced interactions between different body segments.

The research starts with a thorough review of the current state of the art, identifying gaps in existing models that typically struggle with the variability and complexity of human motion. Recognizing these gaps, this study formulates a clear problem statement aimed at creating a new predictive model tailored to the specific dynamics of torso and arm movements. To address this, the research employs a detailed methodology starting from data collection using Inertial Measurement Units (IMUs) placed strategically on the torso and arms of subjects performing a range of movements. This data is then analyzed to understand distributions, variances, and potential biases that could impact the model's performance. This preparation is used for the training of the SVR model, which is tested and validated against metrics such as Mean Absolute Error (MAE) and the coefficient of determination (R²) to ensure its effectiveness in real-world scenarios.

The goal of this research is not only to contribute a functional model to the biomechanics community but also to offer insights into the specific relationships between torso movements and corresponding arm motions. By achieving a deeper understanding through this predictive modeling, the findings could significantly enhance the precision of movement analysis in clinical settings, ultimately leading to better-designed assistive devices and more effective rehabilitation techniques. This paper presents a comprehensive

examination of the model development process, from theoretical groundwork to practical application, and discusses the broader implications of this work in advancing human movement analysis.

2. THE STATE OF THE ART

Exoskeletons for upper limb support play a critical role in enhancing motor function, particularly for individuals with musculoskeletal impairments or neurological injuries. These devices employ a range of mechanisms—from passive to fully active control systems—to provide rehabilitation, assistive support, or both, depending on the user's needs. Among these systems, electromyography (EMG)-controlled exoskeletons are widely adopted due to their ability to intuitively decode the user's motor intentions through muscle activation signals, especially for those recovering from shoulder joint injuries or muscular disorders. These systems replicate natural movement patterns, enabling users to engage in daily tasks with improved ease and autonomy.

A significant body of work has emerged focusing on control system designs for upper limb exoskeletons. For instance, Sui [1] proposed a cable-driven, passive exoskeleton prototype that integrates gravitational balance mechanisms to reduce muscular effort. Similarly, the Auxilio exoskeleton combines textile interfaces with cable-driven actuation for lightweight and adaptive rehabilitation [2]. The RUPERT IV system introduces pneumatic actuators governed by Proportional-Integral-Derivative (PID) and Iterative Learning Controllers (ILC), optimizing real-time control during repetitive motor tasks [3]. Additionally, L-Exos incorporates force sensors and serial kinematic structures for responsive feedback and assistance during movement [4]. These innovations underscore the growing diversity of control strategies tailored to the complexity of human limb dynamics and user-specific rehabilitation demands.

Recent research emphasizes the integration of Artificial Intelligence (AI) to further enhance control strategies in exoskeletons. AI-based systems, particularly those utilizing Artificial Neural Networks (ANNs), have demonstrated success in predicting arm movement angles from EMG data [5]. To account for the variability of limb motion dynamics, Tang et al. [6] proposed a multi-sensor fusion strategy incorporating gyroscopes to improve joint angle estimation. These sensor-driven AI models, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, show promise in learning and adapting to user-specific motion patterns for real-time applications.

Given the challenges of EMG signal variability and system complexity, research has shifted toward minimal sensor setups that use torso orientation data to estimate arm movement. For example, Liang et al. [7] highlighted the effectiveness of Inertial Measurement Units (IMUs) in biomechanics for both activity recognition and force estimation. These IMU-based systems offer a non-invasive, low-cost approach to predict musculoskeletal dynamics. Rahman et al. [8] demonstrated accurate estimation of elbow joint angles using three IMUs and validated their personalized calibration algorithm against electro-goniometers. Similarly, Zhang et al. [9] reviewed computational methods for translating IMU data into joint angles, validating their accuracy relative to optoelectronic systems.

Affordable sensing approaches have also gained attention. For instance, Buttera [10] presented visual-inertial sensor-based techniques for cost-effective and precise kinematic estimation, making these technologies more accessible in home rehabilitation settings. Further developments in multi-sensor fusion, as demonstrated by Trigili et al. [11], combine various sensing modalities to enhance the intuitiveness and responsiveness of soft exoskeleton control, bringing the systems closer to natural limb coordination.

Additionally, Li et al. [12] introduced a CNN-LSTM framework capable of handling inter-subject variability in surface EMG signals, essential for subject-independent and home-based applications. Their approach is particularly suited for bilateral training in stroke rehabilitation, providing a robust method for synchronous upper limb movement prediction.

Efforts have also focused on real-world usability and ergonomic design. Studies by

Gaponov et al. [13] and Wei et al. [14] analyzed how wearable exoskeletons can be made more acceptable for long-term use, emphasizing comfort, weight distribution, and user interface design. These aspects are vital for translating laboratory prototypes into real-world solutions.

The literature reveals a growing consensus around the feasibility of predicting upper limb movements using torso orientation data, supported by advancements in machine learning, sensor fusion, and exoskeleton design. By minimizing sensor requirements and utilizing intelligent models such as Support Vector Regression, future systems can become more adaptable, cost-effective, and scalable for diverse user populations. The current study builds upon this foundation, introducing a regression-based model to infer shoulder-level arm movements from IMU-derived torso orientation data, contributing to the development of lightweight, intelligent assistive technologies.

3. METHODOLOGY

The methodology employed in our research to develop and evaluate a machine learning model for predicting arm movements based on torso movements encompasses a structured approach, which organizes the research process into a series of methodical steps, as shown in Figure 1.

The initial phase involves a comprehensive review of existing literature related to the use of machine learning in predicting limb movements, focusing particularly on models that integrate body posture data. The goal is to understand the current technologies, algorithms, and techniques used in similar contexts and to identify successful practices and limitations. Based on the insights gained from the state-of-the-art, we identify specific gaps in the existing research, particularly areas where current models may fail to accurately predict complex limb movements or where they lack adaptability to different individuals or movement types.

We then formulate the research problem and define the specific objectives that our study aims to address. This includes the development of a model capable of using torso orientation to

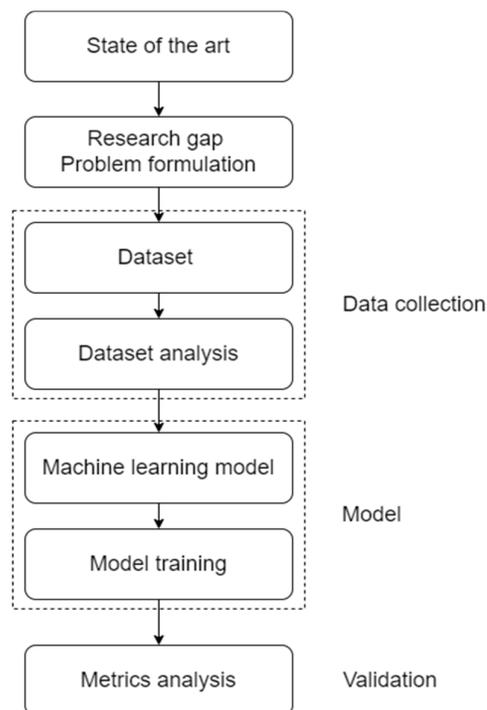predict arm movement with high accuracy across varied human activities.

Fig. 1. Research methodology.

Despite the progress in integrating AI with upper limb exoskeletons, significant gaps remain, particularly in enhancing AI's capacity to work with IMUs. Current AI systems generally rely on static algorithms that are not adequately tailored to accommodate the dynamic nature of human movement or the complexity of real-time physiological data. There is a critical need for the development of advanced AI models that can effectively process and integrate complex data streams from IMUs and other sensors. These models should be capable of continuous learning from user interactions and be adaptive enough to modify exoskeleton behavior based on nuanced changes in user motion and conditions. Moreover, existing systems fall short in their decision-making capabilities, particularly in interpreting subtle signals from IMUs to predict and adjust to user intentions. Enhancing AI's ability to seamlessly synthesize information from IMUs and provide anticipatory adjustments could greatly improve the customization, responsiveness, and overall efficacy of

rehabilitative exoskeletons, highlighting a vital area for future research and development.

The central research problem in our study is to develop and validate a predictive model capable of estimating arm movements based on the orientation of the torso with high accuracy. This problem arises from the need to enhance biomechanical analyses and support applications in physical therapy and rehabilitation, where precise modeling of body movements is crucial for treatment efficacy and the development of assistive technologies.

The specific objectives of our research are:

- Dataset construction and preprocessing, including variance analysis, to prepare the dataset for effective training and validation of the model.
- Model development, namely a SVR model that uses torso movement data as inputs to predict corresponding arm movements.
- Model validation using appropriate metrics such as MAE and R^2 to assess its accuracy and reliability.

These objectives aim to guide the structured exploration of the capabilities of SVR models in exoskeleton control, focusing on the translation of torso movements into predictive outputs for arm movements. The successful development and validation of this model could lead to significant advancements in motion analysis, rehabilitation practices, and the design of biomechanical devices.

The dataset used in this study comprises orientation and movement data collected from IMU sensors placed on the 7 subjects' torsos and arms. Data collection involves 3 sessions per participant where participants repetitively (at least 10 times) perform a range of predefined movements to capture a diverse array of motion patterns. This step is crucial for ensuring the model is trained and validated on realistic and varied data.

Before model development, an extensive analysis of the dataset is conducted. This includes examining the properties of the data such as distribution, variance, and potential biases. The relationship between input (torso movements) and output variables (arm movements) is explored using statistical methods to ensure the data is suitable for training a predictive model.

The core of our methodology involves selecting and configuring a machine learning model to fit our data and research objectives. For our study, we utilize SVR, chosen for its effectiveness in handling non-linear relationships and its robustness against overfitting in scenarios involving complex human movements.

This phase involves training the SVR model on the prepared dataset. Training entails tuning various parameters of the model, such as the kernel type and regularization parameters, to optimize performance. We use a portion of 80% of the dataset to train the model, ensuring it learns to generalize from the input data to predict arm movements accurately.

After training, the model's performance is evaluated using several metrics, such as MAE and R^2. These metrics help assess how well the model predicts arm movements and indicate areas where further tuning or additional data might be needed to improve accuracy.

Each of these steps is methodically laid out to ensure that the research is comprehensive, robust, and tailored to effectively address the identified research gaps.

4. EXPERIMENT

4.1 Data Collection

Collecting training data was the basement to ensure that the model could learn the relevant correlations between human body positions, specifically between the torso and the arm. During this experiment, two IMU sensors were utilized. The first sensor was placed on each subject's torso, specifically between the shoulder blades on the back, to capture movements and the orientation of the torso for determining the correct position of the arm in the developed model. The second sensor was attached to the right arm, midway between the shoulder and elbow. This placement was chosen to obtain precise measurements of the arm's angles and acceleration, necessary for position estimation. All data were recorded in a CSV file, a storage method that facilitated subsequent data processing and analysis, allowing for adjustments and optimization of the machine

learning model to meet the project's requirements as accurately as possible.

The data collection process for constructing the training dataset was structured into three distinct sessions, each aimed at capturing specific types of arm movements in coordination with the torso. This approach aimed to diversify the data to train a machine learning model capable of interpreting and responding correctly to various types of human movements. In the first session, the subjects repeatedly performed the arm movement from up to down at least ten times, synchronized with the torso movement. This session was designed to collect data on vertical movements, simulating the lifting and lowering of objects or natural gestures in the vertical plane. The second session focused on the arm's front-to-back movement, also performed at least ten times in sync with the torso. This aimed to capture the dynamics of the arm in antero-posterior movements, such as pushing or pulling an object. The third session involved repeating a circular arm movement at least ten times, coordinated with the torso, to collect data on complex, rotational movements useful in assessing arm coordination and agility.

Upon completing the three sessions, the collected data were aggregated into a consistent dataset, from which 80% was to be used for training the model, and the remaining 20% for its validation. Random selection of the training and validation subsets ensures that the model is tested on unseen data during training, providing a realistic evaluation of its performance and generalization.
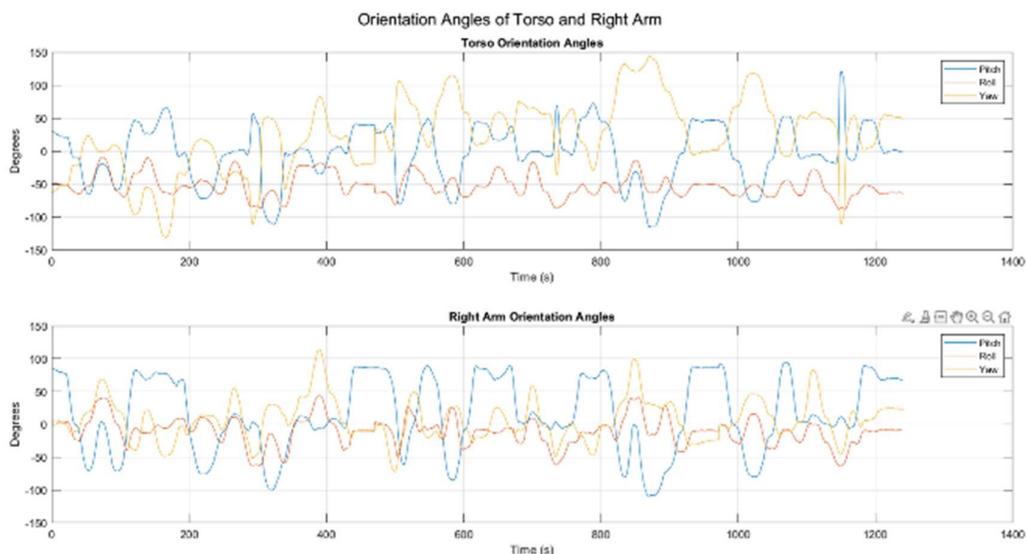

Fig. 2. Data for the circular movements.

Figure 2 presents a detailed visualization of the orientation angles of both the torso and the right arm over a period of approximately 1200 seconds, captured during the experimental data collection.

The graph is divided into two panels, with the top panel displaying the orientation angles of the torso (Pitch, Roll, and Yaw) and the bottom panel showing the corresponding orientation angles of the right arm. From the three orientation angles of the torso, further will be considered only Pitch and Roll as the Yaw orientation is not relevant for the current case and could introduce biases due to torso orientation.

This visual data is instrumental in understanding how movements of the torso correlate with those of the right arm, providing essential insights for the development of predictive models that aim to accurately estimate arm positions based on torso movements.

4.2 Data Analysis

The statistical analysis of our dataset reveals insights for SVR model aimed at predicting arm movements from torso orientations. Input 1 and Output 1 show high variances of 1881.5095 and

3227.4534, respectively, indicating a diverse range of dynamic movements, which present both a challenge and an opportunity for modeling complex patterns. In contrast, Input 2 and Output 2 demonstrate lower variances (297.0783 and 461.5714), suggesting more uniform and constrained movements. Output 3, with a variance of 984.5195, strikes a balance, offering moderate diversity in arm movements. Mean values provide further behavioral insights; both Input 1 and Input 2 show a predilection towards negative values (-3.5566 and -52.7608), while the outputs hover around more central values with Output 1 at 14.117, Output 2 at -10.6444, and Output 3 at 7.1739, indicating prevalent positions or typical movement patterns.

These statistics are important for fine-tuning the SVR model, ensuring it captures the broad spectrum of human movements effectively, enhancing its utility in biomechanical applications and rehabilitation scenarios.
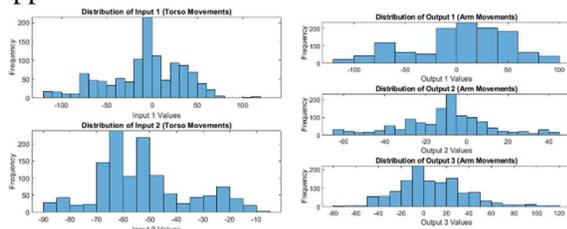

Fig. 3. Distributions.

Figure 3 illustrates the distributions of torso and arm movements across different measurement values, providing critical insights for our research on predicting arm movements from torso orientations using SVR. For the inputs, Input 1 shows almost a normal distribution around 0. Input 2, on the other hand, exhibits a left-skewed distribution with a concentration of data points around -60, indicating a tendency towards certain negative values which might be associated with a specific type of movement or bending.

The output variables, representing different dimensions of arm movements, show varied distribution shapes that are crucial for our predictive modeling.

Output 1 has a nearly uniform distribution across a range from -100 to 100, hinting at a balanced occurrence of arm movements throughout this range without a distinct bias towards any specific angle. Output 2 displays a normal distribution centered around zero, suggesting that most arm movements in this dimension are near a neutral position, with fewer occurrences of extreme movements. Lastly, Output 3 has a right-skewed distribution with most data concentrated around smaller positive values and extending up to 120, which may represent a specific type of arm movement that occurs more frequently in one direction. These distributions help in understanding the nature and variability of the movements recorded and have significant implications for the design and tuning of our SVR model. The variability and skewness in the data might require specific considerations in the model training process, such as handling imbalanced data or applying transformations to achieve better predictive performance.

Understanding these distributions allows for more informed feature engineering and model selection, ultimately contributing to the development and refinement of a robust predictive model for arm movements based on torso orientations.

The correlation matrix (figure 4) provides the relationships between the two input variables related to torso movements and the three output variables corresponding to arm movements. In the matrix, warmer colors (yellow, orange) indicate positive correlations, while cooler colors (blue, purple) signify negative correlations, with the scale moving from -1 to 1. Notably, Input 1 shows a strong positive correlation with Output 1, suggesting a significant direct relationship where torso movements captured by Input 1 are likely to predict corresponding movements in Output 1. Conversely, Input 1 has a negative correlation with Output 3, indicating that as values for Input 1 increase, those for Output 3 tend to decrease. Input 2 exhibits a substantial positive correlation with Output 2, highlighting its predictive strength for these specific arm movements. These relationships underscore critical dynamics that could inform the predictive model's structure, suggesting that specific inputs are better predictors for certain outputs, which is essential for optimizing the model for accuracy and efficiency in real-world applications. Such insights could be important in enhancing models

used in biomechanics, physical therapy, and sports science, ensuring that predictions are both precise and meaningful.
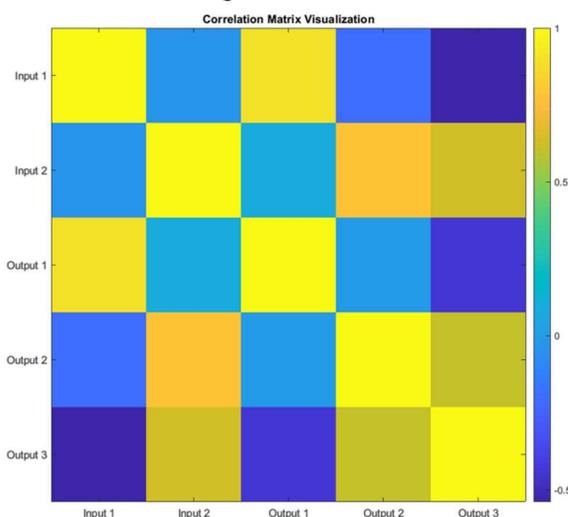

Fig. 4. Correlation matrix.

4.3 Machine Learning Model

The use of SVR model regression in modeling the relationship between torso and arm movements is particularly justified due to SVR's robustness in handling high-dimensional data and its effectiveness in regression tasks that involve complex, nonlinear relationships. SVR is adept at finding a hyperplane in a multidimensional space that best fits the data, making it ideal for the precise estimation required in biomechanical applications. In the context of this specific problem, where the goal is to predict arm movement based on torso orientation—a task characterized by continuous and often nonlinear interactions—the Gaussian kernel used in SVR provides the necessary flexibility to capture subtle nuances in human movement. Furthermore, SVR's capacity to minimize error within a certain threshold (defined by epsilon in the SVR settings) ensures that the model is not only sensitive to data patterns but also resistant to overfitting, making it a robust choice for developing predictive models in rehabilitation and human movement analysis. This approach, therefore, ensures that the model can generalize well across different subjects and conditions, providing reliable and accurate predictions crucial for designing effective upper limb exoskeletons.

The MATLAB code described is a complex machine learning model specifically designed for training and evaluating a SVR model. This model is aimed at predicting arm movement values based on a set of input data that captures torso movements.

The SVR model is trained for each response dimension using MATLAB's `fitrsvm` function. This function is configured to standardize the data and utilize a Gaussian kernel while optimizing other specific kernel parameters. The standardization process is crucial as it ensures that the model is not biased by the scale of the data, allowing for more accurate predictions. The use of a Gaussian kernel helps in handling non-linear relationships between the inputs and outputs effectively.

For each response dimension, a specific model is created and stored facilitating the management of multiple response models simultaneously.

Once the models are trained, predictions are made using the trained models, and the model's accuracy is assessed through the MAE for each response dimension. Furthermore, R^2 is calculated, which measures the proportion of variation in the dependent data that is predictable from the model.

5. RESULTS

The model's prediction accuracy results are quantified using the MAE and R^2. The MAE values for the three output dimensions—8.890041, 4.778525, and 8.600046—indicate the average deviation of the model's predictions from the actual measurements, in degrees. These errors suggest a medium level of precision, with variances dependent on the range of measured values, which span from [-90, 90°] for the first dimension and [-30, 120°] for the third.

Furthermore, the R^2 values—0.921378, 0.883412, and 0.836123 for the three dimensions, respectively—reveal how well the model's predictions fit the actual data. An R^2 value closer to 1 indicates an excellent fit, suggesting that the model can explain a significant portion of the variance observed in the data. While the first dimension shows a high degree of fit, indicating a strong alignment

between predicted and real values, the third dimension's lower R² value points to a less effective model performance in capturing and explaining variance in that part of the dataset.

Overall, the model demonstrates a good predictive capability, with varying performances across different output dimensions. Improvements could be achieved by utilizing more precise IMU sensors, enhancing the accuracy and reliability of predictions. This detailed analysis and visualization of model performance are indispensable for refining the predictive capabilities of SVR models used in biomechanical applications, particularly in the context of movement prediction for rehabilitation and human motion analysis.

For the first output dimension, the graph exhibits wide fluctuations in values, oscillating between approximately [-150, 100]. The SVR model follows the trends and oscillations of the actual values with considerable accuracy, closely mirroring the amplitude and frequency of the waves. However, there are notable discrepancies, particularly near the peaks and troughs, where the model fails to capture all the details precisely (for example, in the areas around samples 800-1000 and at the end of the measurement interval).

The second output dimension shows variations between approximately [-60, 40]. The predictions and actual values are generally aligned, but some deviations are noticeable, especially at the turning points of the graph.
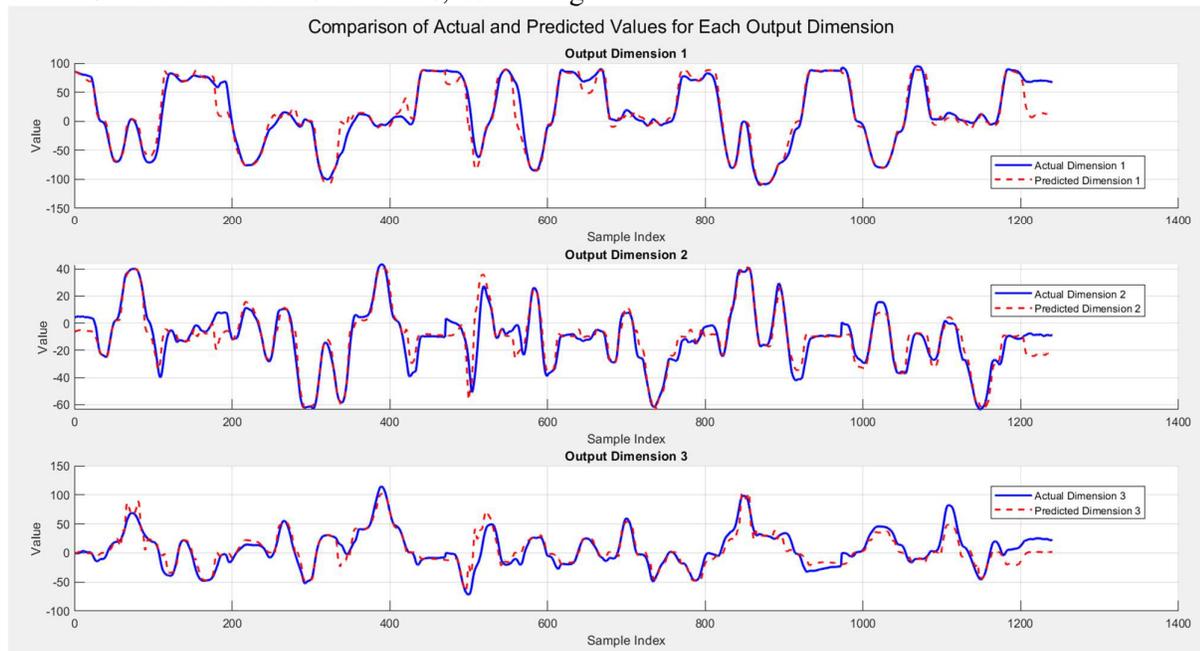

Fig. 5. Real versus predicted data.

Compared to the first dimension, the model appears to have slightly less accuracy here, as evidenced by the gaps between the red and blue lines.

The third output dimension has values fluctuating between [-100, 150]. The predictions of the SVR model display a generally good trend in following the actual values, with accuracy comparable to or perhaps slightly better than the other two dimensions. Even so, there are moments where the predictions do not perfectly

match the actual values, such as around sample 600 and at the end of the analyzed time period.

The graph effectively demonstrates the SVR model's ability to faithfully approximate the behavior of the real data dynamics across all three dimensions, although there are variations in the level of precision and accuracy.

6. CONCLUSIONS

Our study employed SVR to predict arm movements based on torso orientation,

leveraging statistical methods and machine learning techniques. The results demonstrated that the model could effectively capture the nuanced relationships between torso and arm dynamics, as evidenced by strong correlations between specific inputs and outputs. This predictive capability is crucial in applications such as rehabilitation, where understanding and anticipating limb movements can significantly enhance therapy outcomes.

The analysis revealed a normal and skewed distribution in the movement data, which highlights the complexity of human motion and the challenge it poses for predictive modeling. Despite these complexities, the SVR model achieved notable accuracy, as reflected by the metrics analysis that incorporated MAE and R^2. These metrics underscored the model's ability to predict with a high degree of fidelity, suggesting its robustness and reliability in handling real-world data scenarios.

However, this study is not without limitations. The most significant is the reliance on a limited dataset, which may not fully capture the diversity of human movements across different demographics or conditions. Additionally, correlation analysis, while insightful, assumes linear relationships, and the real-world dynamics of the human movement can exhibit non-linear behaviors that our current model might not fully account for.

Another limitation of this research is the challenge of applying the developed model outside of controlled environments, which is a common issue in the field of predictive modeling. The environments in which the model was tested are standardized and do not fully capture the variability and unpredictability of real-world settings. Factors such as different user behaviors, environmental disturbances, and unmodeled physical interactions can affect the performance of the model. These conditions could lead to some discrepancies between the predicted and actual arm movements.

Also, the precision of the Inertial Measurement Units (IMUs) used in the study is a limitation of the research. While the IMUs are effective for capturing movement data, their accuracy is not perfect, and the sensors can introduce measurement errors into the data

collection process. These inaccuracies can propagate through the predictive model, affecting the reliability of the output predictions. Improvements in sensor technology or the integration of additional sensor types could enhance the accuracy of data capture, thus improving the overall effectiveness of the predictive model.

Looking ahead, there are several ways for enhancing the predictive model. Incorporating a larger and more diverse dataset would be a primary goal, as this would help the model learn a broader array of movement patterns and improve its generalizability. Employing more advanced machine learning techniques, such as deep learning, which can capture non-linear relationships and complex interactions more effectively, might also enhance predictive accuracy.

Moreover, real-time data processing and feedback implementation could transform this model into a dynamic tool for use in adaptive systems, such as real-time motion tracking and adjustment in physical therapy or advanced robotics.

Additionally, incorporating a multimodal sensor approach could improve data accuracy and reliability. By combining traditional IMUs with other types of sensors, such as optical or force sensors, the system can achieve a more comprehensive data capture, reducing reliance on any single source of potentially noisy data. These improvements would broaden the practical deployment of the technology in everyday rehabilitative and assistive scenarios, thereby overcoming current limitations and advancing the field of biomechanical predictive modeling.

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Predicția mișcărilor brațului pe baza orientării trunchiului: o abordare prin regresie cu vectori suport

Acest studiu se concentrează pe îmbunătățirea analizei biomecanice și a metodelor de reabilitare utilizând modelarea predictivă. Obiectivul principal este crearea unui model predictiv fiabil folosind Regresia cu Vector Suport (SVR) pentru a prezice mișcările brațelor pe baza orientării trunchiului. Prin procesarea datelor de la Unitățile de Măsurare Inerțială (IMU) atașate pe trunchiul și brațele participanților, studiul explorează potențialul SVR în fizioterapie. Acuratețea modelului este evaluată utilizând metrici statistice precum Eroarea Medie Absolută (MAE) și coeficientul de determinare R^2, demonstrând eficacitatea sa în predicția mișcărilor umane. Această lucrare se încadrează în tendințele actuale de aplicare a inteligenței artificiale în reabilitare, reprezentând un pas pentru cercetări viitoare în domeniul modelării predictive adaptive și de precizie în aplicații legate de reabilitarea motorie.

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