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Motion Trajectory Estimation for Hand Grasping States Using a Deep Learning Approach

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Abstract: Predicting the final grasp tendency at the start of movement in prosthetic hands is crucial for improved control. Biological data, such as 3D movement and muscle activity, have been using by researchers to predict the final grasp. Early prediction of the intended grasp allows the prosthetic device to initiate control actions before the motion is complete, resulting in faster and more intuitive responses. Most machine learning algorithms are trained to predict the gesture of the final grasp. The aim of this study is to accurately estimate the final grasp state using inertial measurement unit (IMU) data. This estimation, based on movement trajectories, will allow prosthetic devices to respond more quickly to user actions. Deep Learning model was trained using movement data collected from a prosthetic hand controlled certain gesture trajectories without any human involvement. Data such as acceleration, angular velocity, and orientation were gathered through IMU sensors to create 3D orientation matrices representing the movement process. A deep convolutional neural network was used for training, with data labeled by the final grasp states. The deep learning algorithm successfully predicted the final hand motion with 93% accuracy. This trained model enables the generation of smooth supervisory trajectories, facilitating faster and more accurate control of the prosthesis. The proposed model demonstrates significant potential in improving prosthetic hand control by predicting the final hand movement at an early stage of motion, contributing to more responsive and effective prosthetic devices.

Keywords: trajectory estimation, deep learning, prosthesis

1. Introduction

Controlling prosthetic hands is regarded as one of the most important tools for improving the quality of life for prosthetic users. To create any movement in prosthetic hands, the controller must first determine the type of motion that the user tends to perform. Determination of the movement traditionally relies on biological signals, such as electromyogram (EMG) data which capture muscle activity [1–3]. The ability to predict the final grasp type from early-stage motion improves responsiveness by allowing the system to begin executing control strategies sooner, reducing delay and enhancing the fluidity of interaction between the user and the prosthetic hand.

Processing such signals can be unreliable and complex because of the challenges related to signal noise, variability between users, and complexity in real-time control [4, 5]. These difficulties necessitate alternative approaches. One of these approaches is motion orientation and trajectory. The concept of motion orientation and trajectory in prosthetic hands refers to more than just the path of movement. It involves understanding the factors that affect how the hand moves and interacts with its surroundings [6, 7]. The trajectory depends on the kinematic capabilities of the prosthetic hand. It also depends on the changing environment and the coordination between the user's intentions and movements [8].

Using advanced motion trajectory planning can significantly improve the performance of a prosthetic hand. It enhances precision and dexterity. Whether the task involves reaching, grasping, or executing complex movements, an optimized trajectory ensures the prosthetic hand operates efficiently [9, 10]. A well-designed motion trajectory improves the user's comfort and overall experience, reducing the physical and cognitive effort needed to use the prosthesis [11, 12].

It is necessary to understand the functional movements of the human hand to develop prosthetic systems with the capability to mimic the dexterity and control of natural grasping behavior. Functional hand movement depends on the sophisticated coordination of anatomical components and biomechanical forces that are responsible for precise manipulation during activities of daily living. Recent research has stressed the complexity of hand prehension and the requirement for systematic classification of grasp types and motion patterns [13]. Biomechanical studies have shed light on the coordination of the joints and muscle groups of

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the hand in functional activities, emphasizing how these patterns help achieve stable and adaptive grasping [14]. Furthermore, it has been shown that hand coordination strategies are not just task dependent but also mirror highly optimized motor control mechanisms specialized for daily activities [15]. Both ergonomic and functional evaluations still provide useful paradigms for the quantification of hand performance and the comprehension of normal and pathological movement patterns [16, 17]. The integration of such research into prosthetic system design guarantees that the control strategies are compatible with the natural functional abilities of the hand. Therefore, our research focuses on movement classes that account for a large percentage of everyday hand activities to close the gap between machine learning-based prediction and biomechanically driven grasp function.

Motion estimation in Cartesian space is one of the most challenging tasks for almost any dynamic system. Accurate measurement equipment and a suitable data analysis system are needed to measure movement, determine its behavior and produce meaningful information from the obtained data. To acquire and collect information from motion, inertial measurement unit (IMU) devices have attracted much attention from industrial applications to daily activities [18–20]. Generally, an IMU consists of accelerometers and gyroscopes, which can be used to measure angular and linear acceleration in different axes. These small, lightweight sensors are used to track the prosthetic hand's motion by measuring the hand's changes in orientation and position. The data collected by the IMU are then used to estimate the hand's position and orientation. These data can be used to track the hand's rotation, orientation, and movement, and this information can be used to control the prosthetic hand's or fingers' direction.

Deep learning (DL) algorithms are the most popular approaches in data science [21–23]. These algorithms can interpret data to predict patterns. Data fed into a DL are transformed into meaningful representations [24]. The power of DL in data analysis has led researchers to design models capable for various fields such as computer vision, speech recognition, medical research, robotics, genetics, transportation, etc. [25–28].

Convolutional neural networks (CNN) as DL models are particularly suited for classification tasks due to their ability to capture both spatial and temporal relationships in the data [29–31]. CNNs can automatically learn the features needed for classification from raw data allowing it to make predictions or control decisions based on high-dimensional and complex input. They simplify the process and improve accuracy. Furthermore, CNN is a powerful technique that has been applied to various problems in prosthetics, including control of hand motion and orientation [32–34].

In the context of prosthetic hand motion trajectory, CNNs have shown strong potential for learning complex patterns in both the kinematics and dynamics of movement, as well as user intention [35, 36]. When trained on motion data collected via wearable sensors, these models can predict intended hand trajectories and orientations, enabling prosthetic systems to mimic natural movement or adapt to varying grasping forces [37].

Recent developments in intention prediction systems have incorporated cognitive control architectures and neural learning to recognize user intention in real time, particularly within assistive robotics [38]. These approaches typically combine multimodal sensor data with advanced classifiers to generalize across different user behaviors. Even though some prior research has focused on lower-limb movements such as gait using IMU signals and CNN-based feature extraction techniques [39, 40], the methodological foundations are applicable to upper-limb prosthetics as well. These studies highlight the effectiveness of time-frequency analysis and convolutional architectures in extracting meaningful features from IMU data, regardless of the limb in question. This supports the idea that intention prediction techniques developed for gait or full-body motion analysis can inform upper-limb applications, especially when viewed from a sensor modality and data-processing perspective.

Recent advances in wearable devices such as muscle-driven control systems [41] and cognitive computing for flow status prediction [42] reflect the growing trend of integrating soft actuators and AI models in assistive technologies, complementing data-driven sensing approaches like the one presented in this study.

The development of lightweight, embedded IMU systems further supports this transition. Studies have demonstrated how such sensors can be integrated into intelligent orthotics and prosthetics to enhance motion tracking and control [43]. Similarly, gesture recognition systems designed for individuals with neurological disorders have successfully combined temporal signal preprocessing with artificial neural networks to classify motion intentions based on wrist-worn devices [44]. Additionally, CNN-based models originally developed for detecting fine-grained hand motions in sports contexts—such as swing analysis in tennis or golf—offer insights into how hand motion patterns can be modeled and classified in real-world environments [45]. These applications reinforce the versatility of DL in motion intention recognition across domains. Recent reviews emphasize the growing preference for IMU-based control systems due to their robustness, cost-efficiency, and ease of use compared to EMG-based counterparts [1, 2, 18]. Feature extraction methods optimized for embedded implementation [18], wearable electromechanical sensor designs [34], and the integration of sensor fusion strategies [10, 46] reflect a growing focus on intelligent, user-centered design in modern prosthetic development.

In this study, we propose a novel pipeline that projects IMU-based 3D motion trajectories onto 2D images, so that matured CNN models can be utilized for final grasp prediction with minimal hardware overhead. In comparison with purely EMG-based solutions, our approach alleviates the effects of skin-electrode impedance and user signal variation [8] while preserving real-time performance. Our innovations are the single-sensor approach with onboard embedded GPU processing, a novel CNN model that captures salient spatiotemporal features from partial trajectories, and extensive validation with multiple daily-living grasp types. This specifically responds to the growing demand for affordable, user-friendly prosthetic options.

2. Materials and Methods

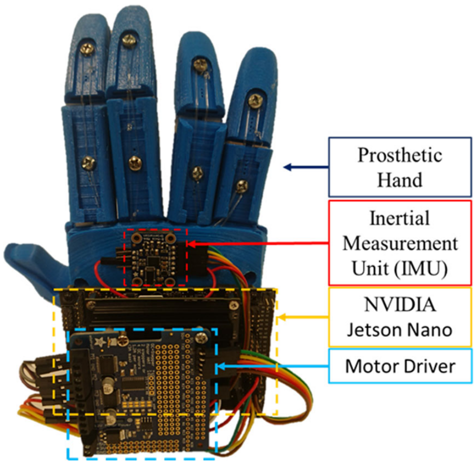
The pre-designed and 3D-implemented prosthetic hand is used to collect data and conduct verification. The prosthetic hand used in this study has 6 degrees of freedom in total: five for individual finger flexion-extension and one for thumb abduction/adduction. Although a full kinematic chain analysis is beyond the scope of this study, this configuration aligns with the theoretical estimation derived from Grübler's criterion for planar mechanisms as given in Equation (1) [47].

$$DOF = 3(n-1) - 2j \tag{1}$$

Here n is the number of links, and j is the number of joints. Each finger joint acts as a single DOF revolute joint, and the total DOF of 6 reflects the functional movement capabilities of the device used for data collection.

As seen in Figure 1, the system includes the IMU, motor driver, and main control unit (MCU). As seen in Figure 2 for collecting

Figure 1
The prosthetic hand and hardware setup attached



motion data, BNO05518 MEMS IMU has been chosen for its affordability and accessibility. NVIDIA Jetson Nano is selected as the MCU due to its ability to meet the system's specific requirements. This board has a GPU featuring 128 CUDA cores. This feature empowers the system to perform DL algorithms in real-time duties efficiently.

2.1. Data collection

During the data collection process, acceleration data related to hand movements are obtained using the IMU sensors. The sensor is placed on the hand as seen in Figure 1 and collected acceleration data in the x, y and z axes at a rate of 63 Hz.

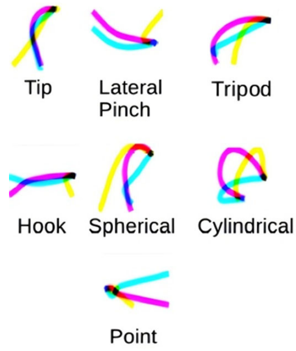
The collected acceleration data are used to create a 3D trajectory of hand movements as seen in Figure 3. These trajectories formed the basis for estimating grasping states. Common hand movements in daily life, such as grasping positions and pointing states, are analyzed. The trajectories of different grasping and pointing movements are defined with the unique characteristics of each movement.

The processing structure of motion measurements, which involves converting the acquired data into a 3D motion curve and then displaying it as an image, is clearly summarized in Figure 3.

All experimental data were obtained using a prosthetic hand setup that operates independently without any human involvement. Acceleration and angular velocity data were collected solely from an inertially instrumented prosthetic hand mounted on a controlled hardware setup.

The dataset contains 7 different movement classes, and these specific behaviors are chosen as they accounted for a substantial

Figure 3
3D trajectory curve stacked image representations



portion, approximately 80%, of the actions performed by individuals in their daily lives [48–50]. Each set contains 120 samples, and a total of 840 samples were collected. This dataset is used to train the CNN model and is divided into 70% for training, 15% for validation, and 15% for testing, with a stratified split applied to maintain class balance. The whole process begins with measurement, preprocessing, and training of CNN as illustrated in Figure 4.

2.2. CNN architecture

The model is built using convolutional layers to extract image features, followed by dense layers for classification. In the constructed model, a 48 × 48 image file is fed into the model, passing through several convolution layers. Sixty-four filters construct the first convolutional layer with an 11 × 11 kernel size and the same padding. The architecture was optimized through iterative experiments, where the 11 × 11 kernel in the first layer was chosen to capture broader motion patterns, followed by smaller kernels for fine-grained features. Dropout rates and filter counts were selected based on validation performance and common best practices to balance generalization and accuracy.

The ReLU (rectified linear unit) is selected as the activation function because it improves the convergence rate during training and eliminates the vanishing gradient problem. Also, it helps to reduce computational complexity, as it is computationally efficient. Outputs of activation functions pass through maximum pooling operation with a pool size of 2 × 2 and 2 × 2 stride. Finally, a dropout operation with a 0.25 dropout rate is applied to the pooled data to suppress the overfitting tendency of the model. The constructed CNN model is shown in Table 1.

A similar strategy is followed for the subsequent two convolutional layers with different filter counts and kernel sizes.

Figure 2
Connection schema for hardware setup

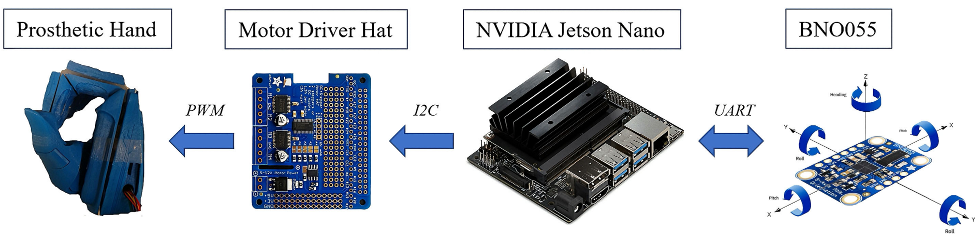


Figure 4
Prosthetic hand grasping detection system

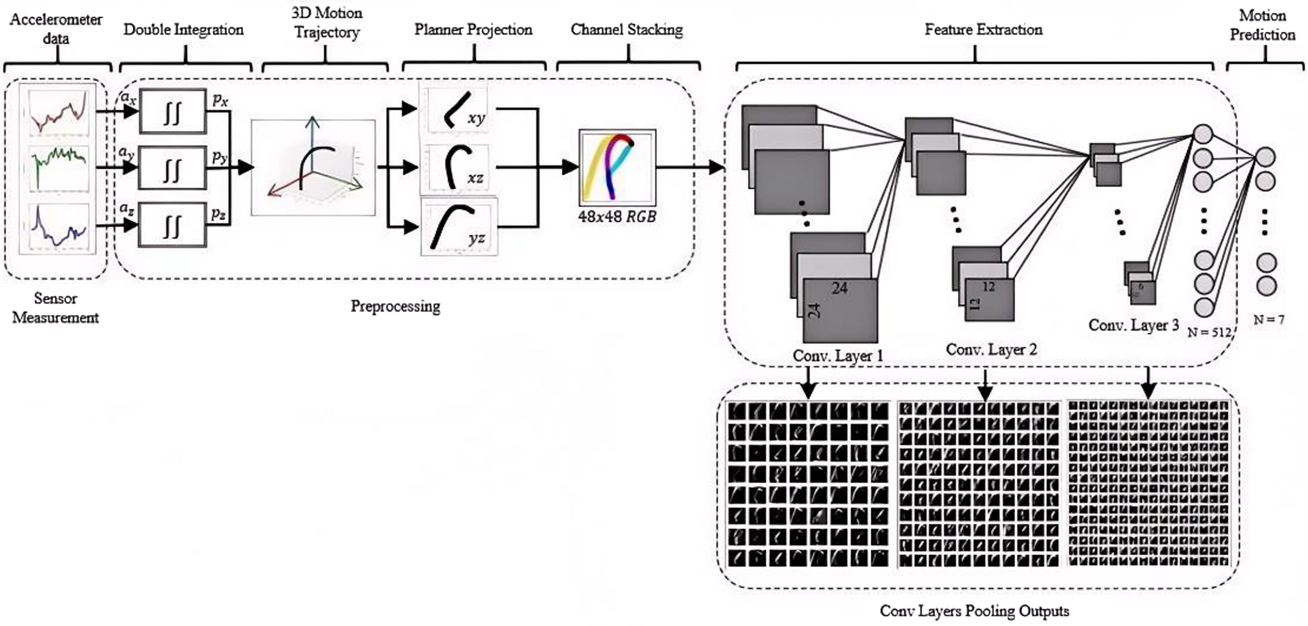


Table 1
Convolutional deep neural network structure

Layer	Description
Input	48 × 48 image files
Convolution	64 filters of size 11 × 11
Activation function	RELU
Max Pooling	2 × 2 pooling with 2 × 2 stride
Dropout	0.25 cut ratio to increase generally
Convolution	128 filters of size 5 × 5
Activation function	ReLU
Max Pooling	2 × 2 pooling with 2 × 2 stride
Dropout	0.25 cut ratio to increase generally
Convolution	256 filters of size 3 × 3
Activation function	ReLU
Max Pooling	2 × 2 pooling with 2 × 2 stride
Dropout	0.25 cut ratio to increase generally
Fully connected	Fully connected layers with 512 units
Activation function	ReLU
Dropout	0.5 cut ratio to increase the generality
Fully connected	Fully connected layer with 7 units
Activation function	Softmax layer

Parameters of each layer are also shown on the given CNN model representation in Table 1. The output of the last convolutional layer is fed into a fully connected layer with 512 units with ReLU activation. A dropout layer with a 0.5 rate is inserted to increase the generality and decrease the overfitting.

Softmax activation is selected as the output layer activation function in CNNs for several reasons; since this work deals with multi-class classification problems, the Softmax function can handle multiple classes simultaneously. It also is a probability distribution function that maps the output of the last layer of the CNN to a probability distribution over the possible classes to ensure that the network's production is a valid probability distribution. Finally, a previous classification dense layer is connected to the model with seven units, where 7 holds the number of classes followed by a Softmax activation as output.

2.3. Training procedure

A robust CNN model capable of predicting movement trajectories in prosthetic hands is developed through a structured process. First, the IMU data produced by the prosthetic hand while performing various grasping tasks are collected, and these data provide the input features for model training. The collected data are divided into a training set to be used in model training and a validation set to evaluate its performance. IMU data are normalized to ensure consistent scaling of the data, which facilitated stable learning of the model.

Cross-entropy has been used as a loss function for training process. Throughout the training, the model performance on the validation dataset is constantly monitored. Hyperparameters are adjusted to avoid overfitting. This process is repeated by fine-tuning the parameters and hyperparameters of the model until the desired performance is achieved.

3. Results

The test accuracy of the model is calculated as 93%. The performance of the model is evaluated using precision, recall, and $F1$-Score metrics, as shown in Tables 2 and 3. These metrics provided valuable insights into the model's ability to classify various motion classes.

Percentage of data to confidence level is shown in Figure 5. This shows that for point and spherical movements, the confidence level does not drop below 0.8 after reaching the halfway point of the movement. Overall, from the halfway point to the end of the grasping movement, the confidence level remains above 0.65 for all movement types. The proposed system has shown promising results in improving the operating speed and usability of

Table 2
Confusion matrix for prosthetic hand grasping detection system

	Cyl	Hook	Pinch	Point	Sph	Tip	Trip
Cyl.	18	0	0	0	0	1	0
Hook	0	17	0	0	0	0	2
Pinch	0	0	19	0	0	0	0
Point	0	0	0	19	0	0	0
Sph.	0	0	0	0	18	0	1
Tip	0	0	0	0	0	17	2
Trip	0	0	0	0	0	3	17

Table 3
Precision, recall, and F1-Score information for prosthetic hand grasping detection system

	Precision	Recall	F-1 Score	Support
Cyl.	1	0.95	0.97	19
Hook	1	0.89	0.94	19
Pinch	1	1	1	19
Point	1	1	1	19
Sph.	0.95	0.95	0.95	19
Tip	0.81	0.85	0.83	20
Trip	0.77	0.85	0.81	20

prosthetic hands and has provided a more intuitive and efficient user experience.

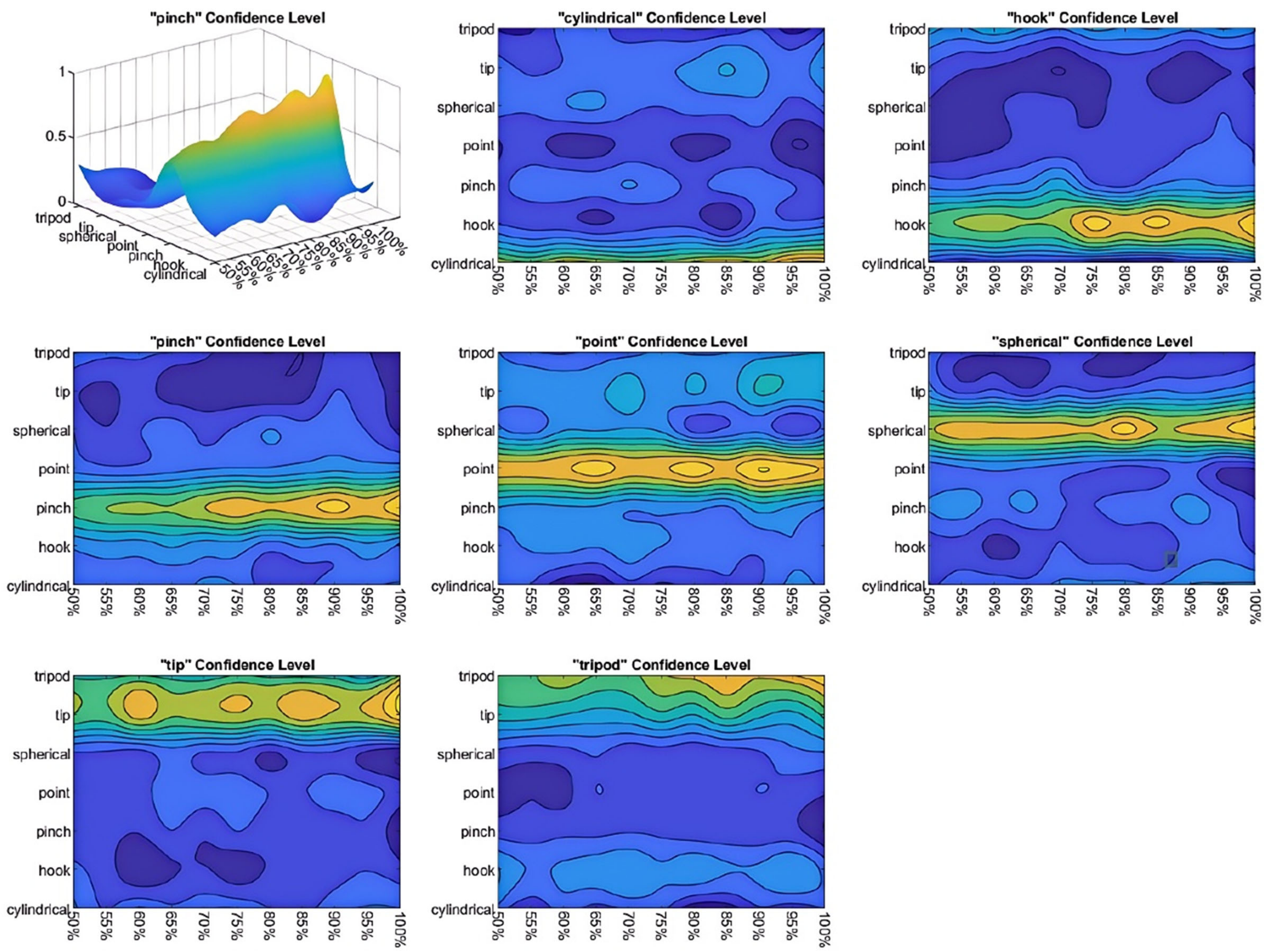
The confusion between Tip and Trip likely results from similar inertial patterns during the early motion phase, where their trajectories have high overlap. This suggests that fine-grained class separation may benefit from temporal modeling or additional sensing inputs in future work.

4. Discussion

The objective of this research was to enhance motion trajectory estimation for prosthetic hands through the implementation of DL techniques. Findings show that an impressive degree of accuracy (93%) is achievable with the utilization of IMU-based data and a CNN model. Interestingly, recent research still underscores the potential of wearable sensor technologies, specifically IMUs, in rehabilitation, activity monitoring, and prosthetics due to their portability and comparative low susceptibility to noise [18–20]. Their efficacy has been proved not just in simple motion classification but also in more complex activities such as path planning and gait recognition, thus showing the promise of continuous improvement of algorithms designed for the operation of a prosthetic hand.

Compared to EMG-only techniques, IMU-based techniques are less affected by complications from changing electrode-skin contact, muscle fatigue, and between-user variations [5, 10]. Yet every approach has its limitations as well; for example, motion artifacts

Figure 5
Confidence levels for each motion using various subsets of the collected test data



and external accelerations can ruin IMU performance when sensor placement is not ideal, or the hand comes into contact with objects that impart forces not related to the intended movement of the user.

While CNN models have already proven to be robust to the removal of these artifacts [23, 24], continued improvements in data preprocessing (i.e., sensor fusion, filtering, segmentation) remain crucial to ensure reliability, especially in real-world daily-living scenarios.

One direction for ongoing research is multimodal sensor fusion, pairing IMUs with other signals such as EMG or muscle synergy data [5, 10]. Fusing these complementary sensing modalities has the promise of enhancing both control precision and responsiveness, even if the increased system complexity would require greater onboard higher-level processing [30]. In this regard, previous research has shown that more recent architectures—such as recurrent neural networks and Transformers—are better able to maintain temporal dependencies and thus could be used to advance real-time motion prediction [23, 31]. User-centered design principles, as explored in literature on human-machine collaboration, call for the provision of intuitive control in the context of prosthetic devices [9, 36]. As this study illustrates, by anticipating the ultimate shape of the hand, prostheses can be rendered more responsive, decreasing cognitive load and enhancing quality of life overall [12, 18].

Furthermore, current research on virtual and augmented reality training systems shows that IMU-based solutions can also be used for immersive rehabilitation and skills learning [12]. The systems can offer the potential to integrate motion data, user interaction, and game-based training exercises to create a comprehensive and user-centered strategy for prosthesis adaptation. While the current dataset provided promising results, we acknowledge that the limited number of samples per class may affect generalizability. In future work, we plan to expand the dataset with more diverse and larger-scale motion recordings to further validate the robustness of the model across users and scenarios. Follow-up work can expand the dataset to include a more varied range of fine-grained grasp types and test the system's robustness in real-world settings with varying users. Hardware acceleration (e.g., quantization or model pruning for embedded GPUs) can further reduce latency for onboard processing, essential for fluency in prosthetic hand control. Future work will also include benchmarking against simpler architectures such as MLPs and classical machine learning models using raw IMU features, in order to assess trade-offs between model complexity and prediction performance. Ultimately, clinical trials involving subjects with differences in limbs will be important for quantifying the real-world impacts of the system, thus enabling comprehensive integration of IMU-based trajectory estimation into prosthetic hand design and control.

5. Conclusion

In conclusion, integrating DL algorithms and motion-sensing technology represents a pioneering approach to advancing prosthetic hand control. By accurately anticipating motion trajectories and grasping actions, individuals can attain a seamless and proficient user experience, ultimately enhancing their overall well-being. Utilizing an affordable yet dependable IMU enables the capture and analysis of intricate motion data. At the same time, a deep CNN model extracts valuable patterns and facilitates precise prediction of grasping actions. Our research findings, demonstrating an impressive accuracy rate of 93%, testify to the transformative potential of incorporating intelligent predictive systems into prosthetics hands. The practical application of this research holds tremendous promise in elevating the functionality and usability of prosthetic hands, empowering individuals to seamlessly execute a diverse range of tasks with remarkable dexterity and ease.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in GitHub respiratory at https://github.com/BioAstLab/MotionTrajectoryEstimation.

Author Contribution Statement

Erdem Erdemir: Conceptualization, Methodology, Software, Investigation, Resources, Writing – review & editing, Visualization, Supervision, Project administration. **Erkan Kaplanoglu:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration. **Cihan Uyanik:** Software, Validation, Formal analysis, Resources, Data curation, Writing – review & editing. **Gazi Akgun:** Validation, Data curation, Writing – original draft.

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