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Simultaneous Control of Human Hand Joint Positions and Grip Force via HD-sEMG and Deep Learning

Farnaz Rahimi [1], Mohammad Ali Badamchizadeh [1], Raul C. Sîmpetru [2], Sehraneh Ghaemi [1], Bjoern M. Eskofier [2,3,4,5], and Alessandro Del Vecchio [2]

[1]Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz 5165677861, Iran
[2]Department Artificial Intelligence in Biomedical Engineering, Friedrich-Alexander-University Erlangen-Nuremberg, Erlangen 91052, Germany
[3]Translational Digital Health Group, Institute of AI for Health, Helmholtz Zentrum München – German Research Center for Environmental Health, Neuherberg, Germany
[4]Chair of AI-supported Therapy Decisions, LMU München, Munich, Germany
[5]Institute of AI in Medicine, LMU Hospital, Munich, Germany

Corresponding authors:
First: Alessandro Del Vecchio (e-mail: alessandro.del.vecchio@fau.de)
Second: Mohammad Ali Badamchizadeh (e-mail: mbadamchi@tabrizu.ac.ir)

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ABSTRACT In myoelectric control, simultaneous control of multiple degrees of freedom can be challenging due to the dexterity of the human hand. Numerous studies have focused on hand functionality, however, they only focused on a few degrees of freedom. In this paper, a 3DCNN-MLP model is proposed that uses high-density sEMG signals to estimate 20 hand joint positions and grip force simultaneously. The deep learning model maps the muscle activity to the hand kinematics and kinetics. The proposed models' performance is also evaluated in estimating grip forces with real-time resolution. This paper investigated three individual dynamic hand movements (2pinch, 3pinch, and fist closing and opening) while applying forces in 10% and 30% of the maximum voluntary contraction (MVC). The results demonstrated high accuracy in estimating kinetics and kinematics. The average Euclidean distance across all joints and subjects was 11.01 ± 2.22 mm and the normalized root mean square error for offline and real-time force estimation were found to be 2.17 ± 0.79 %MVC and 5.10 ± 1.81 %MVC respectively. The results demonstrated that by leveraging high-density sEMG and deep learning, it is possible to estimate human hand dynamics (kinematics and kinetics), which is a step toward developing more accurate systems for controlling prosthetic devices and assistive technologies.

INDEX TERMS Deep learning, surface Electromyography, real-time, multi-DoF prediction, grip force

I. INTRODUCTION

The human hand is a complex and highly functional part of the body, doing a wide range of movements in daily life activities. It comprises multiple joints, leading to its dexterity. Accurate and precise controlling of these multiple degrees of freedom (DoF) is essential for developing prosthetic devices. Biosignals are extensively employed in human-machine interfaces (HMIs) [1], [2]. Among these signals, Electromyography (EMG) is prominently used for controlling myoelectric devices. Surface EMG (sEMG) [3] is a non-invasive method for capturing the electrical activity generated by ensembles of motor units (MUs) from the surface of the skin (Figure 1a). It contains valuable information on muscle contractions, therefore making it a suitable option for controlling rehabilitation systems, like exoskeletons and prosthetics. Recent developments in myoelectric control [4]–[6] have facilitated the prediction of kinematics and kinetics, but remain limited in their ability to fully control hand functions as it is still challenging to decode the joint forces into control signals. Most of the studies primarily focused on estimating discrete hand gesture recognition [6], [7], grip forces [8], and joint angles [9] from sEMG patterns, therefore a limited number of DoFs could be controlled, resulting in restricted motion output. Natural hand movements are not limited to discrete

TABLE 1: List of Acronyms

Acronym	Definition	Acronym	Definition
ACC	Accelerometer	MAE	Mean Absolute Error
CNN	Convolutional Neural Network	MCP	Metacarpophalangeal Joint
DIP	Distal Interphalangeal Joint	ML	Machine Learning
DoF	Degree of Freedom	MLP	Multilayer Perceptron
EMG	Electromyography	MVC	Maximum Voluntary Contraction
GELU	Gaussian Error Linear Unit	NRMSE	Normalized Root Mean Square Error
HD-sEMG	High-Density Surface Electromyography	PCC	Pearson Correlation Coefficient
LSTM	Long Short-Term Memory	PIP	Proximal Interphalangeal Joint
sEMG	Surface Electromyography	SVR	Support Vector Regression

patterns. Continuous estimation and adjustment of the control signals lead to smoother and more natural movements of prosthetics. Therefore continuous controlled strategies are preferred to discrete classification-based control [10]–[12].

Research on myoelectric control has mainly focused on either kinematics or kinetics in isolation [13]–[18]. Various algorithms have been developed for estimating isometric finger or grip forces [13], [19]–[21]. Similar algorithms have been used, focusing mainly on kinematics, for instance, wrist joint angle estimation [14], [15], and finger joint angles [16], [17]. However, for more effective myoelectric control, it is crucial to address both kinetics and kinematics simultaneously.

For the human hand, the wrist and finger motions together with the forces exerted, largely determine its functionality. Therefore recent studies have focused on the simultaneous estimation of wrist/finger motion and forces [22]–[26] to have a better understanding of the human hand. The aforementioned studies have good results in simultaneous estimation, however, they only evaluated a few DoFs. For wrist motion, three DoFs were studied including wrist flexion/extension, abduction/adduction, and pronation/supination. Considering grip force in total 4 DoFs have been estimated in [22] and [23]. Finger angles and forces are studied in [24] considering the same number of DoFs. In our previous study [25] four hand gesture types and five individual finger forces were estimated simultaneously considering 6 DoFs in total. Sun et al. [26] estimated the finger curvatures in five DoFs and grip force in one DoF. However, the human hand has a complex anatomy. It has 5 digits and 15 joints. Simultaneous estimation of multiple DoFs from sEMG is challenging due to the complexity of modeling the large input-output space. Additionally, multiple muscles from superficial to deep are involved in hand movements and there are inter-dependencies between finger movements, which means that the movement of a single finger or a single DoF within the same finger cannot be performed completely independently [27]. Therefore only a few studies have focused on replicating the multi-DoF movements of the human hand. Numerous studies have successfully predicted continuous joint angles but with a smaller number of DoFs [4], [28], [29]. Recent advancements in machine learning (ML) have paved the way for studying all hand joints to reconstruct the full human hand. Previous studies [30], [31] utilized different artificial neural networks to continuously estimate hand joint angles from the sEMG signals. Other studies [32], [33] focused on analyzing hand movements by reconstructing the full human hand kinematics as 3D points in Euclidean space. These studies have good results for kinematics but they have overlooked the forces. The estimation of both kinetics and kinematics with a high number of DoFs is not well addressed in the literature which is essential for a practical and intuitive prosthetic hand. Considering the lack of research in multi-DoF kinetics and kinematics estimation, in this paper, a deep learning model is proposed to construct the full human hand. The model predicts the 3D Cartesian positions of 20 hand joints, corresponding to the metacarpophalangeal (MCP), proximal interphalangeal (PIP), distal interphalangeal (DIP), and fingertip of each of the five digits, while simultaneously estimating grip force representing the complete movement and force dynamics of the hand.

This paper further investigates the real-time estimation of grip forces, focusing on the kinetics of the human hand to enhance the effectiveness of force control in prosthetic devices.

The main contribution of this paper is to address the following key points within the state of art:

- **Multi-DoF kinetics and kinematics estimation**
  Considering the lack of research on simultaneous kinetics and kinematics estimation, this paper aims to estimate both hand joint movements and exerted grip forces. There are only a few studies [22]–[25] on this issue limited to a few DoFs for wrist motion and grip force. In this paper, we took a distinct path by estimating 20 human hand joint positions and grip forces (21 DoFs) over 3 movements.
- **Real-time grip force estimation**
  The efficiency of the deep learning model in kinematics estimation is investigated in [5]. In the current paper, grip forces are estimated with real-time resolution to evaluate the performance of the deep learning model in kinetics estimation.

II. STATE-OF-THE-ART IN SIMULTANEOUS KINETICS AND KINEMATICS PREDICTION

Despite growing interest in human motion decoding, simultaneous estimation of kinematics and kinetics remains a challenging and relatively unexplored task. Only a limited number of studies has addressed this problem using

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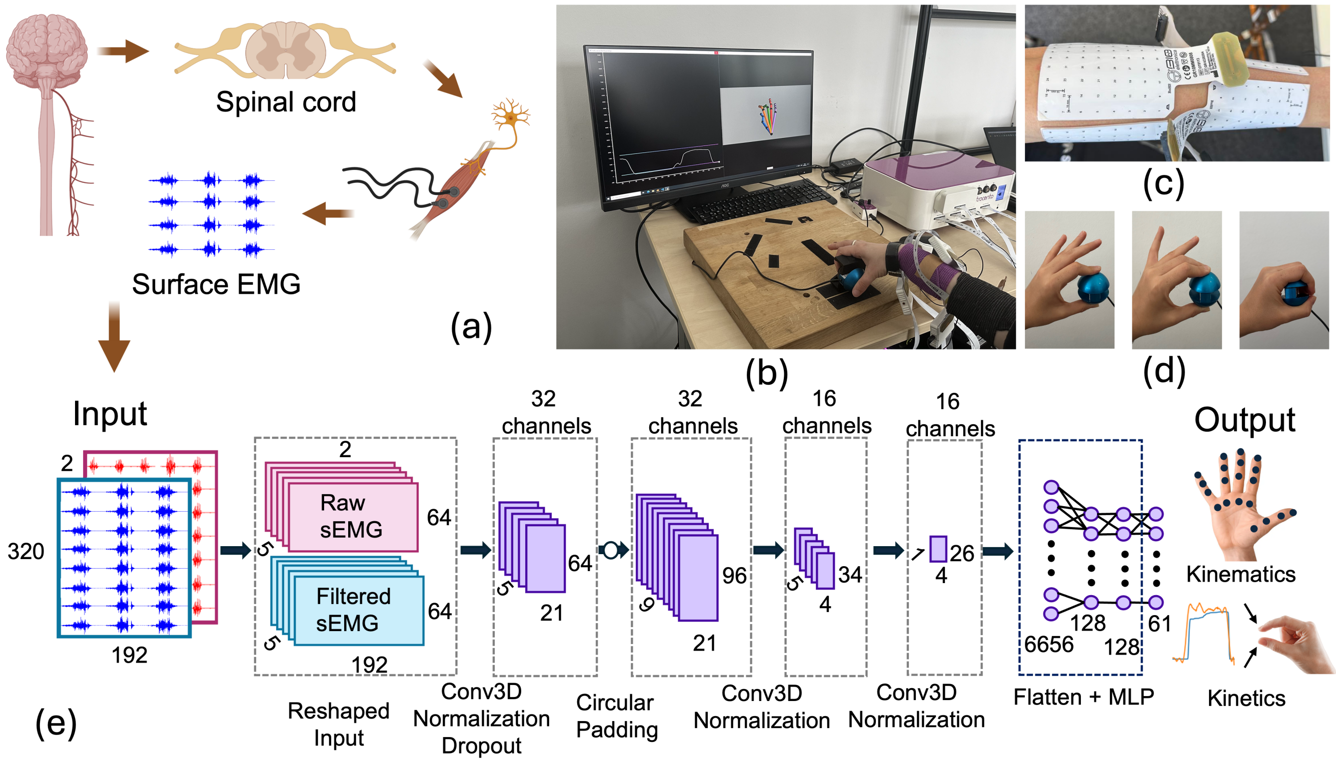

FIGURE 1: Overview of the study. (a) Neuromuscular pathway showing the flow of signals from the brain through the spinal cord to muscles. (b) Experiment setup. The participant is following the hand videos while reaching the predefined force level. (c) Three EMG grids are placed around the arm under the elbow and two grids proximal to the distal ulnar head. (d) Three hand movements performed during the experiment, 2pinch, 3pinch and grasp. (e) Deep learning model architecture for predicting hand joint positions and forces.

sEMG signals (Table 2). Early approaches primarily relied on bipolar sEMG, or augmented with auxiliary sensors such as accelerometers or inertial measurement units. Mao et al. [23] combined sEMG with acceleration signals to estimate grip force alongside wrist angles, demonstrating improved robustness compared to using sEMG alone. More recent studies have adopted high density sEMG (HD-sEMG) to capture spatial patterns of muscle activation [22], [24], [34]. Different machine learning and deep learning models have been developed for EMG prediction. Mao et al. [23] used support vector regression (SVR), whereas more recent studies have increasingly adopted recurrent architectures because of their ability to model the temporal dependencies and nonlinear, time-varying characteristics of simultaneous myoelectric decoding. For instance, Zhang et al. [35] employed a long short-term memory (LSTM) model for joint-angle and interaction-force estimation, Li et al. [22] proposed a graph-driven GCN-LSTM framework for simultaneous estimation of wrist angles and grasp force, and in our previous work, Rahimi et al. [25] used a 3DCNN-LSTM architecture to estimate digit-tip forces together with hand postures under simulated real-world conditions. More recently, Li et al. [34] further integrated motor-unit activity with an LSTM-based framework for real-time simultaneous estimation of wrist angles and grasp force.

Despite these advances, the number of simultaneously predicted DoFs in the literature remains limited. Most existing studies focus on a small set of outputs, typically combining one force variable with one or a few kinematic variables. Even in more advanced studies, the decoding space is still restricted to relatively low-dimensional tasks such as grip force with wrist angles or a limited set of finger kinetics and kinematics. This indicates that, despite recent progress in sensing and model architectures, simultaneous estimation is still limited to low-complexity and simple tasks.

III. METHODS

A. DATA ACQUISITION

The data acquisition setup is shown in Fig. 1b. Nine healthy right-handed individuals participated in the study, comprising four men and five women aged between 23 and 30 years. They signed an informed consent before the experiments. The experiments were in agreement with the Declaration of Helsinki and approved by the Friedrich-Alexander University ethics committee (n. 21-150 3-B). The participants were asked to shave their forearms before the experiment and clean the skin with alcohol. Five sEMG grids each measuring 8 rows by 8 columns with an interelectrode distance of 10 mm (OT Bioelettronica, Turin, Italy) were attached around the

TABLE 2: Summary of relevant studies on simultaneous kinetics and kinematics estimation.

Paper	EMG modality	Model	Target	No. DoF	No. subjects
Zhang et al. (2022) [35]	sEMG	LSTM	Wrist angle + Interaction force	2	8
Mao et al. (2023) [23]	sEMG	SVR	Wrist angles + Grip force	4	9
Roy et al. (2023) [24]	HD-sEMG	Neural approach	Joint angles + Finger forces	4	7
Li et al. (2024) [22]	HD-sEMG	GCN-LSTM	Wrist angle + Grip force	2	12
Rahimi et al. (2024) [25]	HD-sEMG	3DCNN-LSTM	Digit-tip forces + Hand postures	6	11
Li et al. (2025) [34]	HD-sEMG	LSTM	Wrist angle + Grip force	2	10

forearm and wrist (Figure 1c). The self-adhesive bandages were used to firmly secure the electrode grids and ensure they remained fixed during the testing. The analog HD-sEMG signals were recorded in monopolar mode with a 150× amplification. The sampling frequency was 2048 Hz, signals were bandpass filtered between 10–500 Hz and converted to digital format using a multichannel amplifier with a 16-bit analog-to-digital converter (EMG-Quattrocento, OT Bioelettronica, Turin, Italy). The grip force was recorded using a force dynamometer (COR2, OT Bioelettronica, Turin, Italy) connected to EMG-Quattrocento. The force dynamometer was calibrated prior to the experiments with different weights to obtain the force values in Newtons. The HD-sEMG and the grip force were recorded simultaneously and synchronized directly at the source. The participants sat in front of a desk with a screen in front of them to follow the video of the movements. The force dynamometer was fixed on the desk, and the participants had to press it to follow the predefined force trajectories.

In order to have a generalized model and avoid restricting it to a specific hand skeleton, the ground truth kinematics data were recorded from a single individual, then it was used to generate a reference movement video to guide the other individuals to mimic the same movements during the experiments. Four cameras simultaneously recorded the movements from four different angles. The videos were first processed with Deeplabcut [36], a markerless kinematics software, and then aligned in 3D space using Anipose [37]. Based on the recorded kinematic data for one subject, a video was created for each movement. The videos were displayed to the participants, and they were asked to follow them to have a consistent frequency for repeating the movements (detailed explanation in Cakici et al. [38]). These kinematics were then used as the shared reference trajectory for training the model, shared across all participants. This made it possible to skip the kinematics recording for each participant and allowed subjects who could not move their hands to take part in the study in the future. The kinematics data in this paper were previously used in [5] but from a different perspective. In the previous study, the hand exercises were performed vertically. However, in this paper, the hand was aligned horizontally to the ground to grip the force dynamometer, so the kinematics were rotated by 90 degrees to match this new alignment.

The exercises included 2-finger pinch (thumb and index finger), 3-finger pinch (thumb, index, and middle fingers), and opening and closing the fist as a single movement (Figure 1d). Each movement was performed for 60 seconds and repeated twice, once at 10% and once at 30% of the participant's Maximum Voluntary Contraction (MVC) with short rest periods provided between trials.The movements were performed in the following order: 2-finger pinch, 3-finger pinch, and fist opening and closing. Each movement was first performed at 10% MVC and then at 30% MVC. Before the start of each exercise, a task-specific MVC was recorded for each hand movement. Participants performed a single trial in which they executed the same movement and pressed the force dynamometer as hard as possible. After measuring MVC, real-time visual feedback was provided, displaying both the hand movements and the target line representing the desired 10% or 30% MVC force (Figure 1b). Participants were instructed to follow the hand kinematics video while pressing the force dynamometer to reach the specified force level and then release it.

B. PREPROCESSING

The collected data required preprocessing before being fed to the network. Each window of the sEMG signal was low-pass filtered ($<$ 20 Hz) with a 4th-order digital Butterworth filter and appended to the raw windows, so that each input to the network consisted of both raw and low-pass filtered sEMG. Low-pass filtered sEMG has been shown to improve the performance of deep learning models [33], [39]. The sEMG and force data were recorded in non-overlapping windows of 64 samples. Simultaneously, the timestamps corresponding to each segment in the video frames were calculated. After recording, these intervals were used to save the synchronized kinematics and EMG data. According to [5], windows of 64 samples of sEMG did not provide enough temporal information; therefore, three consecutive windows were combined to form a longer 192-sample window with an increment of 64 samples. The kinematics and forces do not vary significantly in 94 ms (192 samples), so the average of the windows was taken as the model output. This simplified the model's output from a matrix to a vector for each sEMG window. In the proposed implementation, a sliding window over 64-sample segments was used instead of non-overlapping 192-sample windows to maintain real-time update rates. This design enabled a steady rate of 32 predictions per second (one prediction every 64 samples at 2048 Hz.)

C. EMG AUGMENTATION

Deep learning models require a large amount of data for training. Therefore, the collected data were augmented using three different augmentation methods. In this paper, three augmentation methods were used. First, Gaussian noise [40] was added to each sEMG channel to have a signal-to-noise ratio of 5. This helps the model to learn realistic noisy conditions. The other augmentation method was the Magnitude wrapping technique [40]. Each sEMG channel was multiplied by a curve sampled from a normal distribution. The wrapped signal had the same characteristics as the original sEMG signal, but the amplitude varied according to the wrapping curve. This slight variation simulated the potential electrode displacement during the experiments. Finally, the Wavelet decomposition [40] was applied to reconstruct distorted sEMG signals. Data augmentation was applied only to the training set to avoid data leakage. This resulted in a four fold increase in data and prepared the model for real-life conditions and challenges.

D. MODEL

The model employed in this paper (Figure 1e) is an adaptation of one from our earlier paper [5]. The prior model was outputting either kinematics or kinetics. The main contribution of this work is the simultaneous estimation of both, real-time force prediction, and the investigation of how force influences the overall prediction performance. To achieve this, the model is modified to output all hand joint positions in 3D space as well as the grip force simultaneously. The input tensor is the combined raw and low-pass filtered sEMG windows with the shape of 2 (raw and filtered sEMG inputs) $\times$ 320 (number of channels) $\times$ 192 (number of samples per window). To apply grid-wise normalization [5], the channels are split by the number of grids into a 4D tensor of shape 2 $\times$ 5 (number of sEMG grids) $\times$ 64 (number of electrodes per grid) $\times$ 192. The model begins with a 3D convolutional layer (kernel size = 1 $\times$ 1 $\times$ 31, stride = 1 $\times$ 1 $\times$ 8, number of outputs = 32). This layer processes individual channels using a 31-sample receptive field (15.2 ms) to extract task-relevant features from the raw sEMG signal. The activation function used for the convolutional layers is GELU [41], and each convolutional layer is followed by an Instance Normalization layer [42]. Then there is a 3D dropout layer (p = 0.25) to prevent overfitting. The next layer is a circular padding (2 for back and front; 16 for top and bottom) which extends the extracted features dimension and preserves the recording's synchronicity for the subsequent layer. The second 3D convolutional layer has a kernel size of 5 $\times$ 32 $\times$ 18 with dilation of 1 $\times$ 2 $\times$ 1 and 16 output channels. This layer looks at all 5 grids at once and extracts the features of the grid combination. The last 3D convolutional layer has a kernel size of 5 $\times$ 9 $\times$ 1 with 16 output channels, to filter out the unnecessary information and collect the most relevant details. The extracted features from the previous convolutional layers are flattened and fed into a simple perceptron with three layers. The first two layers have 128 neurons with GELU activation functions, and the last layer is the output.

The model output is the 3D hand skeleton including all 20 joint values in 3 dimensions (60D) and a grip force (1D). The wrist position is constant and excluded from the output. The model is adapted to learn fewer tasks (2pinch, 3pinch, and fist closing and opening) by reducing the number of channels per layer. Mean absolute error is chosen as the loss function and AdamW [43] with the AMSGrad [44] correction is used for model optimization. The parameters used for training the model are fully explained in [5].

The models were trained and evaluated in a subject-specific manner. Each participant had a model trained from scratch on their own data and tested on the same subject after transfer learning. HD-sEMG signals are highly subject-specific, so a model trained on one user does not generalize directly to others. For unseen users, a separate patient-specific model can be trained using data collected from that individual, allowing accurate estimation of hand kinematics and forces.

E. REAL-TIME INTERFACE

Real-time control provides immediate feedback to achieve natural and intuitive control and improves performance and user engagement. This paper focuses mainly on real-time force estimation as kinematics has previously been studied in [5]. The real-time experiment was conducted on separate days with one or two-day intervals between sessions. After collecting data on the first session, the model was trained, and the offline results were calculated. The placement of the sEMG grids was slightly different in two separate sessions as it was impossible to attach them in the same position. Therefore, during the second session, each movement was repeated for 30 seconds, and the data were used to transfer learning. The trained model was retrained for 12 epochs with new data to be adapted to the new electrode positions preparing it for real-time predictions. The sEMG and force data were recorded in non-overlapping windows of 64 samples. As previously noted a window of 64 did not contain enough temporal information, in offline experiments, three windows of data were combined to create a window of 192 samples. In the real-time application, the model needed to wait for two additional sEMG windows to make useful predictions. This means that the model required a 93.75 ms warm-up time. After this warm-up period, the model generated 32 predictions per second after receiving each new sEMG window (31.25 ms). The model output was refined using the real-time filter introduced in [5] to remove the jitter and correct the predictions. This filter performed well in real-time experiments as it has no delays and uses the memory of previous predictions to reconstruct predictions accurately.

F. STATISTICAL ANALYSIS

Statistical analyses were conducted using the paired, two-sided Wilcoxon signed-rank test implemented in SciPy. This non-parametric test was chosen to assess differences between paired groups without assuming a normal distribution of the data. To control for the increased risk of errors due to multiple comparisons, p-values were adjusted using the Bonferroni correction method implemented in Statsmodels. Adjusted p-values $\leq$ 0.05 were considered as statistically significant differences between groups.

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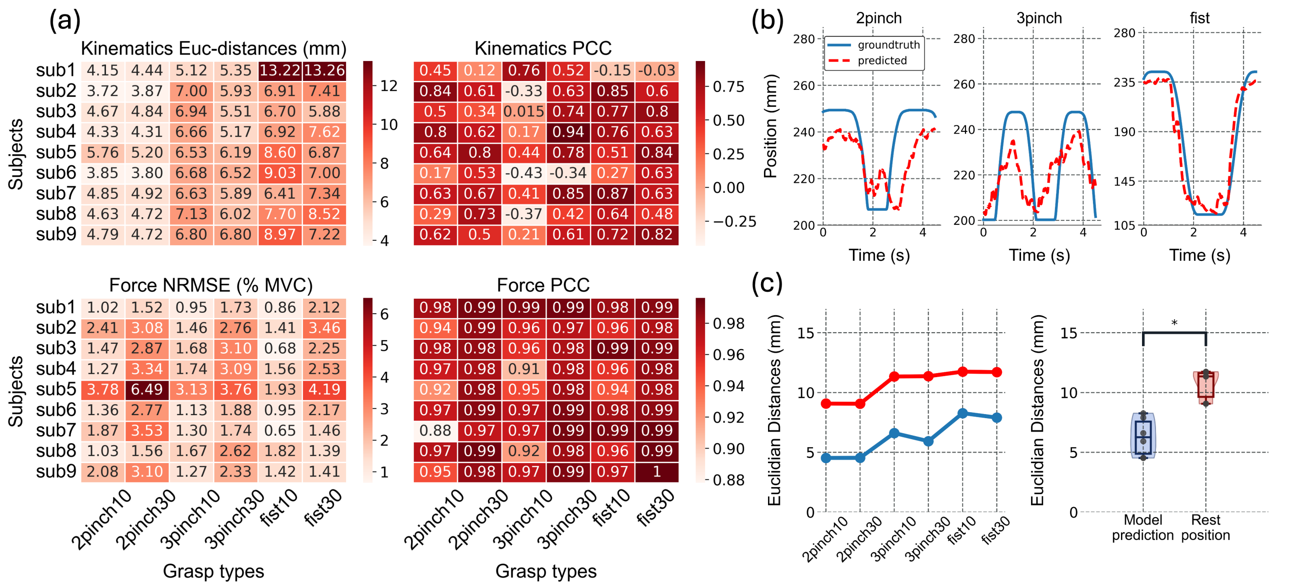

FIGURE 2: The proposed model performance. (a) Heatmaps of error metrics for kinematics and force estimation across all subjects and postures: Kinematic errors represented by Euclidean Distance and PCC, averaged over fingertip and DIP joints and 3 axes; Force estimation errors represented by NRMSE (%MVC) and PCC (10 and 30 represent the relative force level). (b) Index fingertip movement prediction across different postures for subject 3 (joint no. 5 and axis z). (c) The proposed model's kinematics prediction performance compared to the steady prediction of rest position across all subjects. The Euclidean distances for model prediction are statistically significantly lower from the steady rest position (Wilcoxon signed-rank test, $p \leq 0.05$), with a mean difference of $-4.42\,\mathrm{mm}$ (95% CI $[-5.15, -3.69]$).

IV. RESULTS

The acquired data from each subject were split into training and testing sets with an 80-20 ratio to train subject-specific models. The data were split using a contiguous block strategy, for each subject and movement, the middle 20% of the continuous time series was held out as the test set, and the remaining 80% was used for training. Four boundary windows at the transitions partially overlap both sets due to the 192-sample concatenation, which were removed from the test sets to avoid train-test leakage. The training set was further divided into training and validation sets. The deep learning model was trained with the training set for 50 epochs. To evaluate the model's performance, Pearson correlation coefficient (PCC) and normalized root mean square error (NRMSE), computed as RMSE divided by the subject's MVC, were used as error metrics for force prediction. The prediction error for kinematics was calculated in Euclidean distance in millimeters (mm) to represent the hand joint position error in 3D along with PCC. The model effectively predicted hand joint positions along with the applied forces demonstrating its performance in simultaneous prediction of both kinetics and kinematics.

A. KINEMATICS PREDICTION PERFORMANCE

The mean kinematic prediction error, averaged across all subjects, 20 joints, three spatial dimensions (X, Y, and Z), and all time steps, was 11.01 ± 2.22 mm. Given the functional importance of distal joints in grasp control, Figure 2a reports errors specifically for the fingertip and DIP joints as proximal joints tend to yield lower errors and may result in overly optimistic performance estimates. Overall, Euclidean errors were lowest for the 2pinch, and increased for the 3pinch and fist movements (average = 6.65 ± 1.10). This ordering reflects the increasing number of fingers involved as well as the broader range of motion, particularly in the fist movement, where all digits flex across a wide range of joint angles. The PCC between predicted and actual joint positions was predominantly positive, with a majority of values falling in the range of 0.5–0.87, indicating moderate to strong linear correspondence. However, several subjects exhibited near-zero or even negative correlations, indicating that the model did not consistently capture the temporal dynamics of distal joint movements across individuals. Figure 2b illustrates the movement of the index fingertip for subject 3. The figure shows changes in the fingertip's position along the Z-axis during 2pinch, 3pinch, and fist opening and closing movements.

In order to further investigate the model's performance in predicting kinematics, a statistical analysis (Wilcoxon signed-ranked test) is done to examine the absolute Euclidean distances across tasks under two different conditions. The proposed model's prediction for distal joints is compared to a baseline condition where the model has a steady output and predicts the rest state for all movements regardless of the task. Figure 2c shows the mean Euclidean distance over all subjects for each task. Results indicate that the model prediction is statistically significantly different ($p = 0.03$) from the rest state, with a mean difference of $-4.42\,\mathrm{mm}$ (95%

CI [−5.15, −3.69]) demonstrating the model's ability to accurately predict the hand joint positions and consequently the hand movements.

B. FORCE PREDICTION PERFORMANCE - OFFLINE

According to Figure 2a the deep learning model accurately predicted the forces across various hand movements and force levels. The applied forces correspond to 10% and 30% of the subject's MVC. The mean NRMSE and PCC over all subjects are 2.17 ± 0.79 % MVC and 0.97 ± 0.01 respectively. The results demonstrate that the model achieved reliable force predictions, and effectively interprets sEMG signals to predict forces with high accuracy and reliability. The force prediction results for subject 1 are shown in Figure 3a.

C. FORCE PREDICTION PERFORMANCE - REAL-TIME

This paper focuses on force estimation with real-time resolution to evaluate the model's performance in real-time force estimation. The model's performance for force estimation is evaluated through further experiments and analysis. After training the model with offline training data, a separate session was conducted for real-time experiments. Following the transfer learning process, the participants performed the same experiments with real-time feedback shown to them to have a proportional control on the applied and predicted forces. The model was outputting the force with 32 predictions per second after the warm-up period. The mean NRMSE and PCC over all subjects for real-time experiments was 5.10 ± 1.81 % MVC and 0.92 ± 0.04 respectively. The NRMSE for force prediction was higher in real-time experiments compared to offline analysis across all movement types (2pinch: Δ = 3.71% MVC, 95% CI [1.44, 5.98]; 3pinch: Δ = 2.82% MVC, 95% CI [1.62, 4.03]; fist: Δ = 2.35% MVC, 95% CI [1.05, 3.66]). This reduction in performance might be because of the shifts in electrodes as the real-time experiments were conducted several days after the offline experiments and it is challenging to place the sEMG grids in the exact same position as during the offline experiments. These shifts can lead to variations in signal acquisition affecting the model's prediction. However, despite these challenges, the model was still able to accurately detect and predict forces demonstrating its robustness to different conditions. The real-time force prediction results for subject 1 are shown in Figure 3b.

D. ABLATION STUDY

To systematically evaluate the contribution of individual components in the proposed framework, a series of ablation studies were conducted. Regarding HD-sEMG spatial resolution, a dedicated ablation study by Simpetru et al. [45] systematically quantified the impact of spatial resolution by evaluating electrode subsets ranging from 25 to 320 channels. A deep learning model similar to the one proposed here was used to predict kinematics only. They reported a strong positive correlation between the number of electrodes and predictive accuracy. Therefore this analysis was not repeated in the present work and the ablation studies were focused on

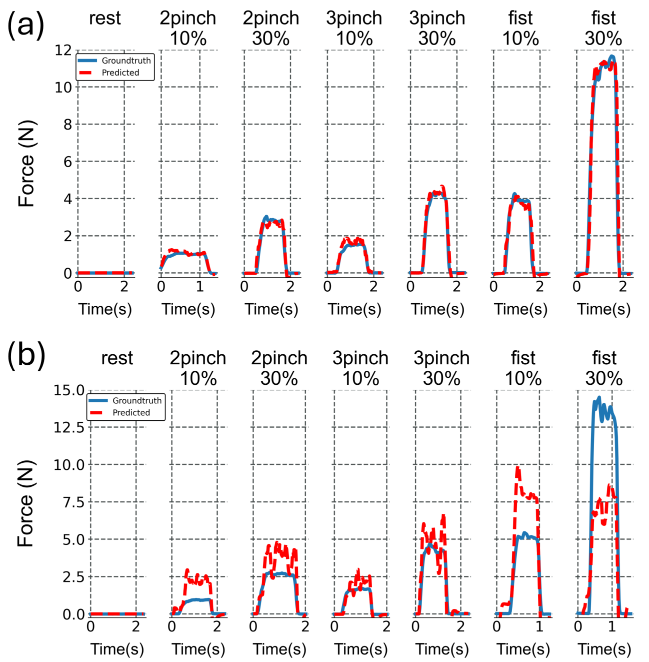

FIGURE 3: Force estimation results for subject 1 across various postures and force levels. The 10% and 30% values indicate force levels as a percentage of MVC. (a) Offline force estimation results. (b) Real-time force estimation results.

model architecture and input signal design. To evaluate the contribution of low-pass filtering, the 3DCNN-MLP model was trained on raw sEMG without low-pass filtered inputs. As shown in Figure (Figure 4), a force NRMSE of 4.05 ± 3.30 %MVC and a kinematics Euclidean error of 5.89 ± 1.17 mm were achieved by this variant. While the kinematics error was lower than that of the proposed model, the force estimation error was significantly higher and exhibited considerably greater variability. To assess the contribution of model depth, two simplified variants of the proposed architecture were evaluated: one retaining only a single Conv3D layer and one retaining two Conv3D layers, compared to the full model with three Conv3D layers. As shown in Figure 4, there was a gradual decline in performance as the number of layers was reduced. For kinematics prediction, error increased consistently with decreasing model depth. For force estimation, no statistically significant difference was observed between the two-layer variant and the full model; however, a statistically significant increase in error was found for the single-layer variant, suggesting that the Conv3D layers enhance performance by extracting more informative features. Finally, a bidirectional LSTM-based architecture was explored as an alternative to the CNN-based model. In this variant, the per-grid normalized HD-sEMG input was flattened into a time-series sequence and projected to a 128-dimensional embedding via a linear layer with GELU activation and Layer Normalization. The sequence was then processed by a bidirectional LSTM (hidden size 128), followed by a unidirectional LSTM (hidden size 64).The last hidden state was concatenated with the temporal mean of all hidden states to obtain a global summary of the input window. This combined representation was then passed through a linear output layer to produce the final predictions. The LSTM model performed well for kinematics prediction, however, it showed significantly higher errors for force estimation. Overall, the best performance across both force and kinematics prediction tasks was achieved by the proposed 3DCNN-MLP model with three Conv3D layers, demonstrating the importance of both input preprocessing and sufficient model depth in effectively leveraging HD-sEMG signals.

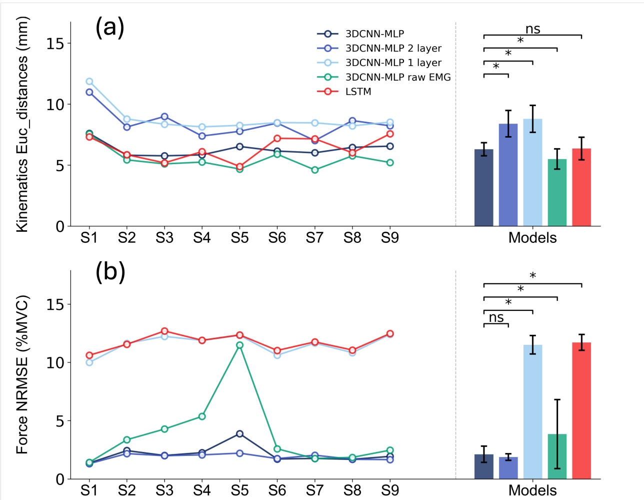

FIGURE 4: Ablation study results comparing model architectures across subjects. (a) Kinematics Euclidean distance (mm) and (b) Force NRMSE (%MVC) for each subject (S1–S9). Lines represent individual subject performance; bars show the mean ± standard deviation. Statistical comparisons between the proposed 3DCNN-MLP and each ablation variant were performed using the Wilcoxon signed-rank test with Bonferroni correction (* $p \leq 0.05$, ns: not significant)

V. DISCUSSION

The main goal of this paper was to study the human hand focusing on the joints movements and forces exerted during movements. The human hand has an intricate structure with numerous joints. Extensive research has been conducted on the human hand to understand its functionality and replicate its movements. Most of the research has focused on human hand discrete movements and obtained accurate performances. Recent studies moved toward continuous hand movement estimation as it provides a more accurate representation of natural movement. Additionally, to develop an accurate model of the hand it is essential to consider the forces involved in holding or gripping objects. The combination of kinetics and kinematics estimation is overlooked in the literature or restricted to limited DoFs (such as simultaneous estimation of wrist angle and forces (2 DoFs) or movement types and forces.). These approaches fail to capture the full functionality of the human hand. This paper aims to fill the existing gap by simultaneously estimating kinetics and kinematics across a higher number of DoFs (> 20).

A. COMPARISON TO OTHER RELATED WORKS

There are a few studies on simultaneous and continuous estimation of kinetics and the kinematics of the human hand. The most recent similar study [22] proposed a graph-driven method for simultaneous and proportional estimation of wrist joint angles and grip forces. Similar to our study, they used HD-sEMG to capture the forearm muscle information and tried three different wrist movements. The participants followed the wrist trajectories and applied forces in 30% and 60% of their MVC. A new deep learning model based on graph CNN and LSTM was proposed to capture spatial and temporal information and estimate the wrist angle and the force exerted simultaneously. The proposed method's performance is compared with other deep learning models including LSTM, Conv-LSTM, and CNN. The graph CNN-LSTM achieved the best results among other models with the average PCC of 91.9% for force and 89.6% for wrist angle estimation over all subjects. In another similar study [23], wrist angle and grip force are studied during three wrist movements. Support vector Regression (SVR) is used to estimate both kinetics and kinematics. They have compared different feature sets such as the combination of EMG and Acceleration (ACC) signals. The best performance of the proposed method for force estimation using only EMG signals is $92.42 \pm 0.87\%$ and using the combined EMG and ACC features they have achieved 95.32 ± 1.35 % correlation. The wrist angle correlation using only EMG and EMG + ACC features are $84.41 \pm 4.48\%$ and 96.44 ± 0.96 % respectively.

As summarized in Table 3, our proposed deep learning model achieves strong performance, with a correlation of $97.6 \pm 0.01\%$ for offline grip force estimation and $92.1 \pm 0.04\%$ in real-time. These results are comparable to, and in some cases exceed, those reported in related studies. However, it is important to note that differences in data collected, electrode configurations, and experimental designs across studies prevent a strictly direct comparison.

B. FORCE LEVEL AND MOVEMENT TYPE EFFECT ON PREDICTION

The proposed model's performance for predicting force and hand kinematics was evaluated across different force levels and movement types. Figure 5 shows the performance metrics across subjects, with individual data points representing each subject's result. For force prediction, the NRMSE differed significantly between the 10% and 30% MVC conditions for all three movement types (Figure 5a), indicating that the model produces larger errors at higher force levels. This is consistent with the well-known nonlinear relationship between sEMG and force at elevated contraction levels, where increasing complexity of motor unit recruitment and firing rate modulation makes accurate prediction more challenging [46]. Across different movement types within each force

TABLE 3: Average PCC scores for kinematics and force estimation across different methods

	Li et al. [22]		Mao et al. [23]		Proposed method
method	GCN+LSTM	LSTM	SVR		3DCNN + MLP
input	EMG		EMG	EMG + ACC	EMG
channels no.	192 channels		7 channels	14 channels	320 channels
DoFs no.	2 DoFs (1 Wrist angle + 1 Force)		4 DoFs (3 Wrist angles + 1 Force)		21 DoFs (20 hand joint positions + 1 Force)
Force Level	30% and 60% MVC		under 30% MVC		10% and 30% MVC
Grip force	91.9	88.7	92.42	95.32	**97.6**

level, no statistically significant differences were observed (Figure 5b), suggesting that the model's force prediction performance is robust to movement type. For kinematics prediction, no statistically significant difference in Euclidean distance error was found between the two force levels across any movement type (Figure 5c), indicating that varying force level does not substantially affect the accuracy of kinematic estimation. However, kinematics prediction accuracy did vary significantly across movement types (Figure 5d). Specifically, Euclidean distances followed a clear ordering with the fist movement yielded the highest distances, followed by the 3pinch, and then the 2pinch, reflecting the increasing number of fingers involved and the broader range of motion, particularly in the fist movement.

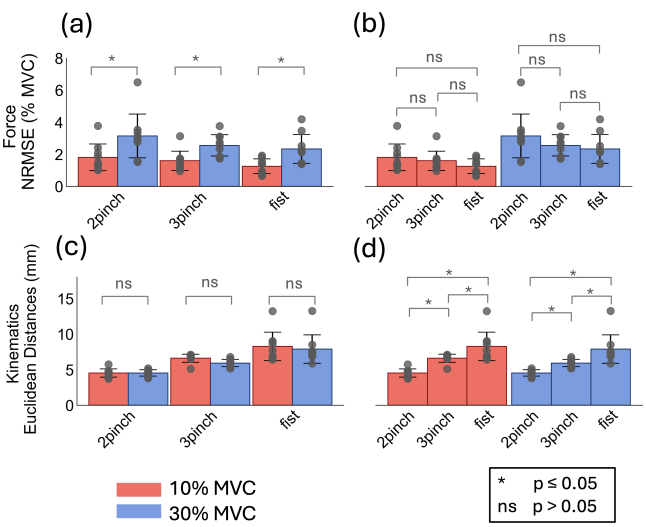

FIGURE 5: Model prediction comparison across different force levels and movement types. (a) force estimation error (NRMSE) across different force levels for each movement type. (b) force estimation error across different movement types at each force level. (c) kinematics estimation error (Euclidean distance) across different force levels for each movement type. (d) kinematics estimation error across different movement types at each force level. Statistical analysis was performed using the Wilcoxon signed-rank test with Bonferroni correction (* $p \leq 0.05$, ns: not significant)

C. LIMITATIONS AND FUTURE WORK

This study has several limitations. The number of hand movements was restricted to three grasp types (2pinch, 3pinch, and fist), thereby limiting the generalization of the results to new and untested grip types and movements. Future experiments should include a broader range of hand movements. The lack of amputees is another limitation of this study which affects the study's applicability to real clinical scenarios, as amputees are the main users of prosthetics. Future research should consider amputees to evaluate the model's performance in practical scenarios. Real-time kinematics prediction was previously studied in [5], where the model successfully estimated 20 joint positions concurrently in real-time. Building on this work, the present study adapted and evaluated the model's ability to predict real-time forces, demonstrating strong real-time performance. However, the model currently has limitations in performing simultaneous kinetics and kinematics real-time predictions, which requires further investigation. Moreover, a comprehensive robustness analysis under controlled electrode shift and calibration conditions is necessary to fully assess model stability and performance in real-time prediction. Another limitation of this study is the large number of EMG electrodes. Future studies should investigate strategies to reduce the number of electrodes while maintaining accurate kinematics and kinetics predictions.

VI. CONCLUSION

In this paper, a method combining HD-sEMG signals and deep learning techniques was presented to estimate 20 hand joint positions and grip forces simultaneously during three hand movements (2pinch, 3pinch, and fist closing and opening). The study involved 9 individuals performing three dynamic hand movements while applying forces at two different force levels (10% and 30% MVC). Given the limited research on simultaneous multi-DoF kinematics and kinetics estimation, our approach demonstrated superior performance in estimating 21 DoFs (20 hand joint positions and one force), facilitating comprehensive control of the human hand. Additionally, forces were examined with real-time resolution, aiming to enhance the model's effectiveness for real-time applications.

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FARNAZ RAHIMI received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from the University of Tabriz, Tabriz, Iran, in 2016, 2018, and 2024, respectively. From 2022 to 2023, she was a visiting researcher with the Neuromuscular Physiology and Neural Interfacing Laboratory at Friedrich-Alexander-Universität Erlangen-Nürnberg, Erlangen, Germany. Her research interests include signal processing, data science, and machine learning.

MOHAMMAD ALI BADAMCHIZADEH was born in Tabriz, Iran, in 1975. He received the B.S. degree in electrical engineering and the M.Sc. and Ph.D. degrees in control engineering from the University of Tabriz, Tabriz, in 1998, 2001, and 2007, respectively. He is currently a Professor in the Faculty of Electrical and Computer Engineering, University of Tabriz. His current research interests include adaptive control, stability of systems, and system identification.

RAUL C. SÎMPETRU received the M.Sc. degree in Biomedical Engineering in 2023 from FAU Erlangen-Nürnberg. He is currently a research associate at the Neuromuscular Physiology and Neural Interfacing Laboratory, FAU Erlangen-Nürnberg, where he investigates neural manifolds underlying motor control and decodes motor intentions from EMG signals. He developed MyoGestic, an open-source EMG framework for real-time decoding of spared motor dimensions in individuals with neural lesions, enabling intuitive control of virtual hands and prostheses. His research interests include neural signal decoding, adaptive myocontrol, and assistive neurotechnology.

SEHRANEH GHAEMI received the B.Sc. degree in power engineering from Amir Kabir University, Tehran, Iran, in 1999, and the master's and Ph.D. degrees in control engineering from the University of Tabriz, Tabriz, Iran, in 2003 and 2010, respectively. She is currently a Professor in the Control Department, Faculty of Electrical and Computer Engineering, University of Tabriz. Her main research interests include fuzzy systems, evolutionary algorithms, and intelligent control.

BJÖRN M. ESKOFIER (Senior Member, IEEE) received the degree in electrical engineering from Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), in 2006, and the Ph.D. degree in biomechanics from the University of Calgary, Calgary, AB, Canada, under the supervision of Prof. Dr. Benno Nigg. In 2016, he was a Visiting Professor with the Prof. Paolo Bonato's Motion Analysis Laboratory, Harvard Medical School (February-March). In 2018, he was a Visiting Professor with the Prof. Alex Sandy Pentland's Human Dynamics Group, MIT Media Laboratory (March-August). Since April 2023, he has been an Associate Principal Investigator and the Leader of the Research Group Translational Digital Health, Helmholtz Zentrum München. From April 2023 to August 2023, he was a Visiting Professor with the Prof. Scott Delp's NMBL Laboratory that is part of Stanford University's Schools of Engineering and Medicine. He was the head of the Machine Learning and Data Analytics (MaD) Laboratory, FAU, Erlangen, Germany and as of 2025, he has joined LMU Klinikum München as Director of the Institute for Artificial Intelligence in Medicine and holds the Chair for AI-Supported Therapy Decisions at Ludwig-Maximilians-Universität München. He authored more than 400 peer-reviewed articles, holds five patents, started three spinoff startup companies, and is in a supporting role for further startups. Dr. Eskofier received several medical-technical research awards, including the Curious Mindsaward 2021 in Life Sciences by Manager Magazin and Merck. He is also active in the organization of several IEEE and ACM meetings (e.g., BSN, BHI, EMBC, IJCAI, ISWC, and UbiComp), most recently as the General Chair of BHI 2023. He was the Area Editor of the IEEE OPEN JOURNAL OF ENGINEERING IN MEDICINE AND BIOLOGY and an Associate Editor of the IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS.

ALESSANDRO DEL VECCHIO received a PhD in Neuroscience and he later conducted post-doctoral research at the Department of Bioengineering Imperial College London. In 2020, he joined the Department of Artificial Intelligence in Biomedical Engineering (AIBE) at Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU) as an Assistant Professor and, in 2025, became Full Professor. He is the founding head of the Neuromuscular Physiology and Neural Interfacing Laboratory at FAU. His research centers on decoding spinal motor neuron activity, neuromuscular physiology, and the development of advanced human–machine and neural interfaces for rehabilitation, prosthetics, and assistive technologies. He is a recipient of the DFG Emmy Noether, the Medical Valley Award, and the Journal of Physiology Best Paper Prize.