Volitional PD computed torque control design of a 2-DOF finger model for cylindrical grip movement assistance with sEMG signal classification

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***Abstract*—In this paper, we present a two-link finger model design for a hand exoskeleton that performs cylindrical grip movements. Movement intention was initially detected with sEMG signal classification from a subset of the Ninaweb dataset. Then, a simulated PD Computed Torque Control (PD CTC) allowed for accurate movements given a defined intention. A high accuracy of classification was obtained using a single random forest classifier and a very small error was obtained for the fingers when following the desired trajectories.**

***Keywords*—rehabilitation, random forest, volitional control, computed torque, hand exoskeleton, sEMG signal classification.**

I. Introduction

Since cylindrical grip exercises improve motor skills during rehabilitation therapy in post-stroke patients [1], we propose the design of a volitional sEMG-controlled hand exoskeleton for assisted therapy. The volitional control movement of the exoskeleton system is commanded by the user through measured sEMG signals. A random forest classifications of these was performed to identify grip and release movements. Furthermore, fingers were modeled with 2 degrees of freedom and a PD torque computed control was used for their movements. A block diagram of the overall system is shown in Fig. 1.

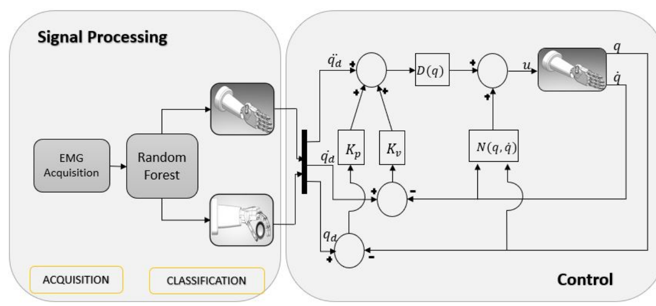

Fig. 1. Process block diagram

II. Signal Acquisition

Given that cylindrical grasping movement is an activity of daily living (ADL), intention-sensing via surface electromyography (sEMG) is commonly used to easily control the assistance hand exoskeleton as in [2]. In order to make these measurements, electrodes are placed around the arm, eight of them were placed in an elastic band around the forearm and two additional ones at the Flexor Digitorum superficialis and at the Extensor Digitorum muscles as shown in Fig. 2. Some important characteristics of these two muscles are mentioned in Table I [3]. Since only movement classification was carried out, targeted placement of electrodes was not required [4].

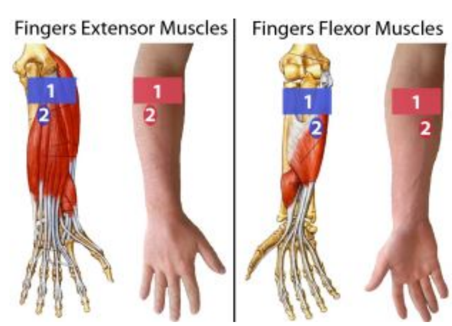

Fig. 2. Localization of electrodes [4]

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TABLE I
MUSCLES AND THEIR CHARACTERISTICS

Muscles	Distal Attachment	Main Actions
Flexor Digitorum Superficialis (FDS)	Middle phalanges of medial four digits	Flexes middle and proximal phalanges at PIP and MCP joints of medial 4 digits.
Extensor Digitorum (ED)	Extensor expansion of medial four digits	Extends MCP and interphalangeal joints of medial four digits and extends hand at wrist joint.

III. CLASSIFICATION OF MOVEMENT INTENTION

The sEMG signal classification was based on the Ninaweb dataset [5] and on further research [6] that clustered different types of movements. Among these we focused on cylindrical grip movements which are shown in Fig. 3.

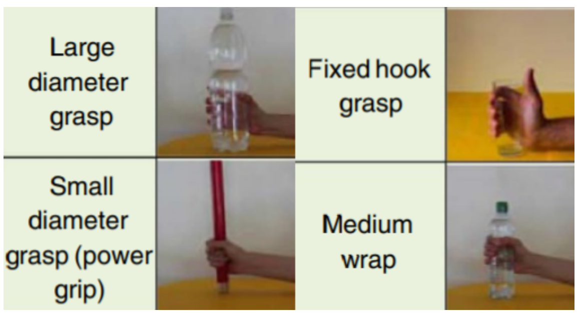

Fig. 3. Cylindrical grasps [5]

Even though most research around this dataset has been done on the performance of classification algorithms for all of its labeled hand movements [7]–[9], only a few of them provide results for each of these, such as [10]. Based on the results from [10] and our own tests, classical machine learning algorithms provided better results than deep learning algorithms when classifying cylindrical grasps only. However, more feature engineering was required. Following a similar approach from [5], around 1/3 of the data was used for testing and 1/4 of the remaining was used for validation purposes. Before performing any classification, the data was passed through a first order Butterworth low-pass filter with a cutoff frequency of 1 Hz.

An account of Matlab-based algorithms for sEMG signal feature extraction is offered in [11]. Among these, the time domain statistics features (TD) were suitable for achieving high accuracy on unseen data. The input parameters were the time domain features extracted from measurements across 10 channels. A time window of 200 ms was chosen after testing from the range of windows recommended in [12] which sufficed for our purposes. Furthermore, the outputs were the labels that corresponded to each of the 4 desired movements plus the resting state. These were then sent to the control system to initiate or stop the fingers movement of grasping or releasing.

IV. MECHANICAL DESIGN

The mechanical design of the hand prototype was developed in SolidWorks. In this design, the fingers are considered as a two-degree-of-freedom system in which the coordinate systems are located at each joint. The biometric aspects of the hand are based on that of a 25-29 year old male [13]. The design of a 2-DOF finger model is shown in Fig. 4.

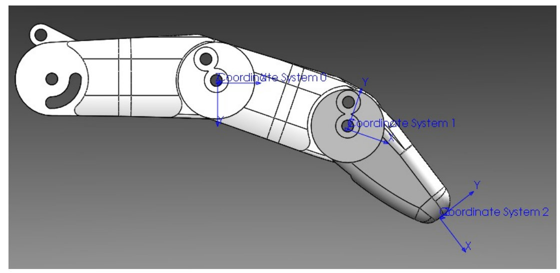

Fig. 4. Mechanical design of a 2-DOF finger model

V. DYNAMIC MODEL

Exoskeletons fingers can be modeled as a planar manipulator with 2 rotational degrees of freedom [14].

A. *Denavit-Hartenberg*

The Denavit-Hartenberg representation or convention is a systematic method for describing the kinematic relationship between a pair of adjacent links.

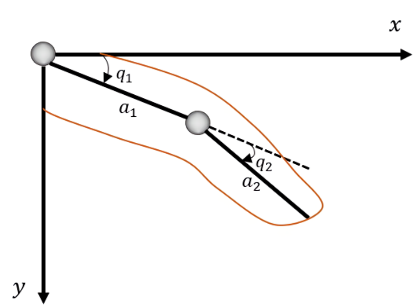

Fig. 5. Kinematic representation of the two-degree-of-freedom model for the human finger

TABLE II
DENAVIT-HATENBERG REPRESENTATION (D-H)

Joint(i)	$\theta_{(i)}$	$d_{(i)}$	$a_{(i)}$	$\alpha_{(i)}$
1	q_1	0	a_1	0
2	q_2	0	a_2	0

B. Direct kinematics

At present there are different methods to solve the problem of direct kinematics, but the most common case is the use of homogeneous transformation matrices, using the method of the systematic representation of *Denavit-Hartenberg*.

$$T_n^0(q) = \begin{pmatrix} n_n^0(q) & s_n^0(q) & a_n^0(q) & o_n^0(q) \\ 0 & 0 & 0 & 1 \end{pmatrix} \qquad (1)$$

$$\begin{pmatrix} c(q_1+q_2) & -s(q_1+q_2) & 0 & a_1 c(q_1) + a_2 c(q_1+q_2) \\ s(q_1-q_2) & c(q_1+q_2) & 0 & a_1 s(q_1) + a_2 s(q_1+q_2) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

This matrix $T_n^0(q)$ represents both the position and the orientation of the model of the worked finger along the base reference system shown in Fig. 5.

C. Euler-Lagrange approach

It is an energy-based approach, where the dynamic model can be derived using the Lagrange equations:

$$\frac{\mathrm{d}}{\mathrm{d}t}\left(\frac{\partial L}{\partial \dot{q}_i}\right) - \frac{\partial L}{\partial q_i} = \tau_i \qquad i = 1, ..., n \qquad (2)$$

where:

$$L = T - U \qquad (3)$$

Taking the necessary derivatives for equation 2 leads to the following equation of motion:

$$D(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) + F(\dot{q}) = \tau \qquad (4)$$

VI. Control Design

Since traditional control systems do not provide good performance, a PD type computed torque control algorithm is implemented. Previous work indicates that this type of controller shows good performance in the case of exoskeleton systems [15]. The equations for the dynamics of the robotic arm with rigid link [16] are given below:

$$D(q)\ddot{q} + N(q,\dot{q}) = \tau \qquad (5)$$

where:

$$N(q,\dot{q}) = C(q,\dot{q})\dot{q} + G(q) + F(\dot{q}) \qquad (6)$$

Finally, the proposed control law remains as follows:

$$u = D(q)(\ddot{q}_d + K_v\dot{e} + K_p e) + N(q,\dot{q}) \qquad (7)$$

where $e(t)$ is the tracking error, whose equation is:

$$e(t) = q_d(t) - q(t) \qquad (8)$$

with $q_d(t)$ being the desired joint angle and $q(t)$ being the real joint angle. The control system is shown in Fig. 6.

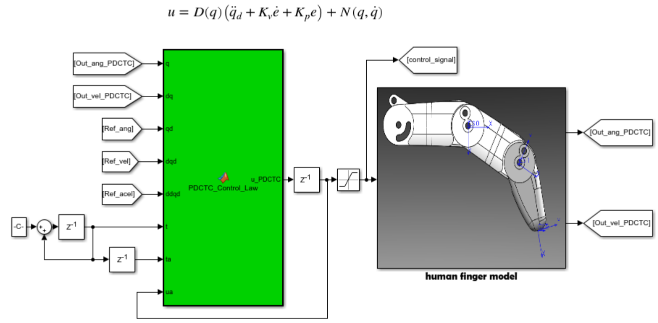

Fig. 6. Control structure for the PD type computed torque controller

VII. Results

A. sEMG Classification

Even though the training performed with Random Forests (RF) and Support Vector Machines (SVM) showed significantly high accuracy, when more data was processed, the performance scaled poorly both in accuracy and time. For this reason, only the Random Forests classifier was used.

The classification model worked best when considering data from one subject only giving accuracies above 90%. When fitting for groups of 10 or 20 subjects, the model gave accuracies in the range of 60-70%. Also, when resting position was considered as a separate classification process, accuracies dropped down to around 80% for individuals but showed a smaller raise for groups. These results are shown in Table III.

TABLE III
Model Performance

Mode of training	**Accuracy**
1 subject including resting	90.72 %
1 subject with 2 classifiers	80.94 %
10 subjects including resting	70.38 %
10 subjects with 2 classifiers	73.46 %

B. PD type computed torque control - PDCTC

Regarding the trajectory position control, the exoskeleton system follows the trajectory with good performance as shown in Fig. 7.

In Fig. 8, computed torque signals were very small because a DC electric micro-motor was used. Also, the errors shown were minimal and in the order of 10^{-5} for both joints.

Finally, the design parameters used in the proposed controller structure are shown in Table IV.

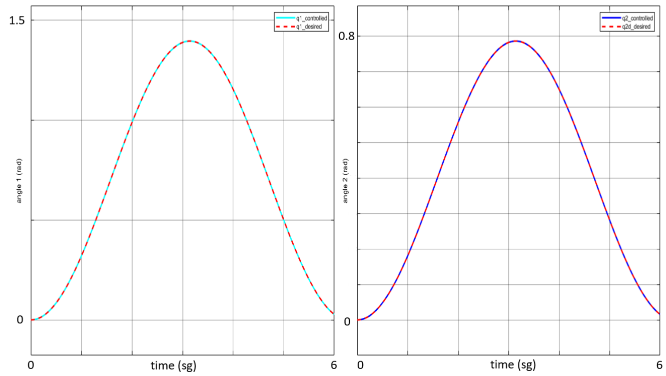

Fig. 7. Trajectory tracking for each joint in Rad

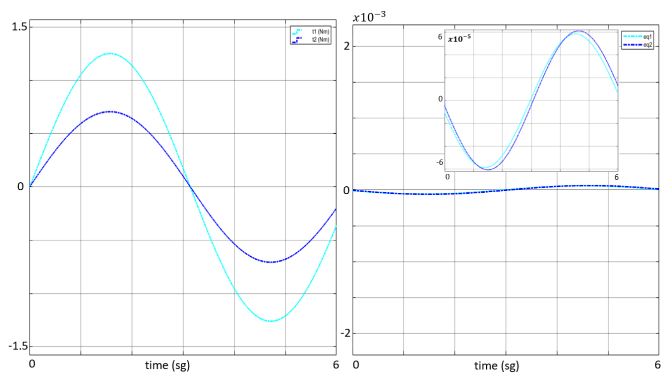

Fig. 8. Left-computed torque in N.m, right-errors for each joint in Rad

TABLE IV
DESIGN PARAMETERS

Joint(i)	$Kv_{(i)}$	$Kp_{(i)}$
1	90	65000
2	190	77000

VIII. CONCLUSIONS

Based on the achieved accuracies, the classification of movement intention worked better when training was done with only one classifier (including the resting state) and was performed exclusively with a final user thus giving accuracies over 80%. Also, considering that only electrode measurements were taken into account, including other sensors such as accelerometers might improve classification [17]. The control design applied to the hand exoskeleton allowed it to follow a defined trajectory with an error in the order of 10^{-5}, which is negligible when compared to the overall magnitude that is being tracked, meaning that it would not endanger the user. The presented model constitutes a feasible process, though its strongly dependent on each of its parts to work properly. Further research might include specific trajectories and controllers as well as alternative pipelines for making this process more robust.

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