Identifying Electromyography Sensor Placement using Dense Neural Networks

Paolo Cappellari[1], Robert Gaunt[2], Carl Beringer[2], Misagh Mansouri[2] and Massimiliano Novelli[2]
[1]*College of Staten Island, City University of New York, U.S.A.*
[2]*RNEL, University of Pittsburgh, Pittsburgh, U.S.A.*

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Abstract: Neural networks are increasingly being used in medical settings to support medical practitioners and researchers in performing their work. In the field of prosthetics for amputees, sensors can be used to monitor the activity of remaining muscle and ultimately control prosthetic limbs. In this work, we present an approach to identify the location of intramuscular electromyograph sensors percutaneously implanted in extrinsic muscles of the forearm controlling the fingers and wrist during single digit movements. A major challenge is to confirm whether each sensor is placed in the targeted muscle, as this information can be critical in developing and implementing control systems for prosthetic limbs. We propose an automated approach, based on artificial neural networks, to identify the correct placement of an individual sensor. Our approach can provide feedback on each placed sensor, so researchers can validate the source of each signal before performing their data analysis.

1 INTRODUCTION

Artificial neural networks (ANN) (LeCun et al., 2015) are being used in many fields, including computer vision, speech/audio recognition, bio-informatics, etc. Practical evidence gathered from ANN powered applications shows results that are comparable and often better of those achievable by humans. For instance, in the computer vision field, deep learning techniques can accurately identify objects in pictures (Lin et al., 2013; Szegedy et al., 2016); in natural language processing, they are used for language modeling (Luong et al., 2015; Józefowicz et al., 2016) to achieve speech recognition, machine translation, part-of-speech tagging, parsing, handwriting recognition, amongst other applications.

Most of the work with ANNs focus on automatic classification of images and textual data. There are areas, however, where data are not immediately usable and/or represent very different underlying signals, like in the medical domain. Some studies using deep learning already exist in the medical domain, e.g. (Liang and Hu, 2015; Rubin et al., 2017), and a number of challenges, e.g. (Kaggle, 2014; Kaggle, 2015) have been published to see how deep learning can help with specific problems.

In the area of prosthetic limbs control for amputees, intramuscular electrodes could be used to record the bioelectric activity from muscles in the residual limb and in turn used to control the movement of a prosthesis. These sensors record the electromyography (EMG) activity in the set of muscles that collaboratively contribute to the execution of a movement. In current commercial myoelectric systems, EMG signals are acquired from just a few sensors on the surface of the residual limb. One potential challenge in the design of advanced prostheses based on fully implanted systems and intramuscular EMG is to assess, from the immediate sensor readings, the identity of the specific muscle that a given sensor is recording from. Given that in the forearm, for example, there are approximately 28 muscles that control the wrist and fingers and are often coactivated, it is not a trivial task to simply identify the signature of a muscle based on hand and wrist movements.

In this work, we present a neural network approach to identify which muscle a particular sensor is recording from using noisy data where the validity of the labelling is uncertain.

Paper Structure. The paper is structured as follows: in the remainder of this section, we discuss the background and motivation for this research, the research aims, and the contribution; in Sec. 2, we pre-

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sent the related research; in Sec. 3, we provide details about the experimental setup, data collection and the initial pre-processing of the acquired raw data; in Sec. 4, we present a process to transform such raw data into usable information for the neural network; in Sec. 5, we describe the neural network architecture and configuration; in Sec. 6 we detail our evaluations and we discuss the results; and finally, in Sec. 7, we draw our conclusions.

1.1 Background and Motivation

The loss of a limb can have significant effects that place limitations on a person's activities of daily living. In many instances of limb loss however, muscles remain in the residual limb that can be voluntarily activated by attempting to move the missing limb. For example, in the case of a wrist disarticulation (hand missing at the wrist) or a transradial amputation (hand missing mid-forearm), nearly all the muscles that control the wrist and fingers remain intact.

This muscle activity can be monitored via electromyography (EMG). Briefly, when a muscle contracts, it generates an electrical potential associated with the flow of calcium ions in the muscle fibers. As more fibers in a muscle are recruited, the amplitude of this signal, after some simple signal processing, increases. This electrical potential can be monitored by a sensor (an electrode) either placed on the surface of the skin over a muscle, or surgically placed into the muscle itself. A single sensor, usually, monitors a specific muscle, or part of it. Multiple sensors are placed in multiple muscles to monitor the overall behavior of a limb, as limb movement is the result of the activity of many muscles.

1.2 Research Aims

Positively identifying the muscle associated with a specific sensor is not a trivial task. Consider the control of the hand: there are more than 20[1] muscles at work in the forearm alone. The activity of many of these muscles are highly correlated across many different coordinated movements, and producing isolated activity of specific muscles is a very difficult for subjects. This is especially true in amputees that may not have attempted to move certain muscles for many years. As a result, identifying the placement of an EMG sensor can be a challenging and time-consuming task. Misplacing a sensor may lead to changes in the outcome of specific data analysis processes and ultimately prosthesis control. The focus of this work is to use a dense neural network to identify the relationship between a specific sensor and the underlying muscle. In short, we seek to label each sensor with the correct muscle name. To accomplish this, we will use a data set consisting of EMG and kinematic data collected from a number of able-bodied individuals performing structured hand and finger movements. Here, each EMG sensor has been targeted to a specific muscle under ultrasound guidance, but in certain cases we know that these labels are incorrect, either due to electrode migration or slight errors in targeting. The challenge is to validate each EMG signal, to capture any mislabeling within the data collected during each experiment, and provide a method to continually validate the correctness of the labelling throughout the experiment, given that the sensors can shift position with muscle contraction.

[1] https://en.wikipedia.org/wiki/Forearm#Muscles

1.3 Contribution

ANNs are capable of discovering and associating meaning to complicated and/or noisy data. During the past number of years, ANNs have been used to identify patterns and trends that humans cannot (easily) find, which make them a potentially ideal method to identifying EMG sensor labels. Most of the existing works that focus on recognizing movements by monitoring EMG signals assume that the monitoring device is properly configured and deployed. With this work we make the following contributions:

- Automatic collection and enrichment of low level sensor values with the experiment contextual information;
- A method for feature extraction of both EMG values of muscle activity patterns and kinematic measurements of related movements, to succinctly represent a rehabilitation session's data;
- The automatic classification of sensor (mis-)placement using an artificial neural network.

This approach to sensor identification could have several benefits. First, it could reduce the time that researchers or prosthetists require to identify a muscle when setting up or programming a prosthetic control system, and second, it could be used to automatically track changes in the sensor locations that could occur over time.

2 RELATED RESEARCH

Over the years, EMG signals have been used in many diagnostic, research and rehabilitation applications.

In particular surface EMG signals, that is signals recorded from skin surface, have been used in prosthesis control (Khezri and Jahed, 2011; Chu et al., 2006; Soares et al., 2003), analysis of functional electrical stimulation (FES) (Kocyigit et al., 1996), human-machine interaction (HCI) (Zazula et al., 1998), pathological tremor analysis (Dideriksen et al., 2011), and muscle fatigue analysis (Steens et al., 2012). The main characteristic of surface EMG sensors, as opposed to intramuscular ones, is that are non-invasive and thus easier to use in a broad range of applications. On the other hand, surface sensors cannot be used to monitor the activity of deep muscles as the electrical activity of more superficial muscles always appears larger in amplitude. Further, surface EMG sensors typically have low spatial resolution and cannot distinguish between the activity of even superficial muscles that are immediately adjacent. Intramuscular sensors are used to study single motor unit activity which is necessary for analyzing neuropathies, such as myopathes and diseases of neuromuscular junctions (Merletti and Farina, 2009).

To date, there has been limited attention to the challenges surrounding the identification of high-density intramuscular sensors. In simple systems, with just a few sensors, this issue is less problematic. However, as intramuscular systems containing dozens of electrodes are developed, addressing this issue becomes paramount. In (Kamavuako et al., 2011; Kamavuako et al., 2012), authors build an ANN to estimate grasping force of a hand movement given the EMG signals. In this work, the researchers break the input EMG signals in contiguous chunks of 200 milliseconds to extract entropy values, which are then associated to the subject's grasping force. Altogether, these values are provided as input to train the ANN, which can then estimate grasping force by just reading the EMG signals.

In (Matsumura et al., 2002), authors use an ANN to recognize wrist movements/positions by analyzing EMG signals. Signals are transposed into the frequency domain by evaluating the Fast Fourier Transform, which is then classified into a number of categories representing possible positions of the wrist (neutral, up and down, right and left, wrist to inside, wrist to outside), achieving an accuracy ranging from about 50% to 90%.

In (Gandolla et al., 2017), authors predict a set of hand grasp movements by using a sequence of ANNs. The approach processes 10 EMG signals simultaneously, with the goal of predicting the subject's movement intention so to command a robotic hand. A first network performs a subject's specific clustering on the input EMG signals. When the clustering detects that more than one hand grasp task, then the output of the first network is passed to a second ANN that classifies hand grasp tasks within the cluster. The results show an overall accuracy around 76%.

In (Atzori et al., 2016a) authors use convolutional neural networks to classify more than 50 hand movements from EMG signals. Input signals are broken down into intervals so to achieve real-time control of the prosthesis. Overall, the network was able to achieve an accuracy ranging between 60-70%. Researchers observed that the accuracy improves when the class of movements to classify is reduced, reaching the 90% when only 11 movements are considered, as also noted by (Atzori et al., 2016b).

Other works, e.g. (Yang et al., 2017), extend on the conventional rehabilitation setting by leveraging the use of virtual reality so to provide patients with a more familiar life-like scene, or tackle the issue of develop a EMG controlled exoskeletons (Mulas et al., 2005; Moital et al., 2015).

Finally, in (Karlik, 2014) authors provide a survey of the different machine learning approaches for EMG signal characterizations, including ANNs. Authors briefly present the surveyed works, discussing performance, pros and cons of each. While some of these reports discuss the processing of EMG signals, none of the approaches surveyed emphasize the correctness of the input EMG labels themselves, which is the primary goal of this work, and one where complexity scales as the number of sensors increases.

3 DATA ACQUISITION AND ANALYSIS

This section describes the experimental setup used to record raw data, the physical movements performed by the subjects, and how the data are stored and manipulated to make it processable by an ANN.

3.1 Experimental Setup

All procedures described here were approved by the Institutional Review Boards at the University of Pittsburgh and the Army Research Lab. Informed consent was obtained from the participants prior to any study procedures being performed. The experiments and data collection sessions typically lasted 8 hours and are briefly described here. At the beginning of the experiment, a physician used ultrasound guidance to place 16 fine-wire intramuscular EMG sensors (Motion Lab Systems, Baton Rouge, USA) into a set of wrist and finger extrinsic hand muscles of the forearm. Each sensor was labeled with a code represen-

Table 1: Muscle names and associated labels.

Label	Muscle name
FPL	flexor pollicis longus
APL	abductor pollicis longus
ED2	extensor digitorum index
ED3	extensor digitorum middle
ED4	extensor digitorum ring
ED5	extensor digitorum pinky
EIND	extensor indicis
ED_M	extensor digit minimi
EPL	extensor pollicis longus
ECR_LO	extensor carpi radialis longus
ECU	extensor carpi ulnaris
FDS2	flexor digitorium superficialis index
FDP2	flexor digitorum profundus index
FDS3	flexor digitorium superficialis middle
FDP3	flexor digitorum profundus middle
FDS4	flexor digitorium superficialis ring
FDP4	flexor digitorum profundus ring
FCR	flexor carpi radialis
FCU	flexor carpi ulnaris
SUP	supinator
PTER	pronetor teres

ting the muscle that was targeted for implantation. Table 1 shows the muscle codes used in our experiments.

Subjects were asked to execute specific movements while researchers tested electrical connections, signal quality, and attempted to confirm sensors location. Once the EMG sensor setup was validated, the forearm was wrapped with protective gauze and the subject was asked to wear a glove that had been instrumented with kinematics sensors (The Motion Monitor, Chicago, USA), as shown in Fig. 1(a). The kinematic sensors enabled the tracking of all finger, thumb and wrist joint kinematics in 3D space.

The subjects were seated on a comfortable chair and were able to rest their forearms on the table between recordings. A wide screen television was placed in front of the subjects where videos explaining the type of movements were shown. The complete setup can be seen in Fig. 1(b)

Subjects were asked to perform a variety of repetitive hand movements. During each movement EMG and kinematic signals were recorded. Each recording where data was acquired is called trial. The trials of interest for the purpose of this paper are single joint movement trials where the subject was asked to maintain a specific wrist posture (neutral, flexed, extended, pronated, and supinated) and to move the selected finger in flexion and extension 10 times for the duration of the trial as indicated by the video shown. Each subject was required to perform all the combinations between wrist positions and finger selected at the speed of 1 movement per second, while only for some of them a slower version (2 seconds per movement) were

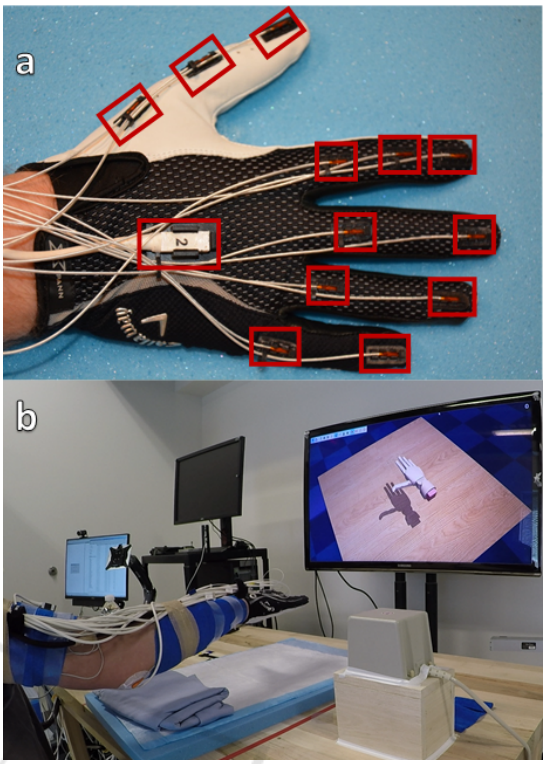

Figure 1: Glove with embedded kinematics sensors (a). Complete experimental setup (b).

collected due to time constrains. The duration of each trial was set to allow the subject to complete 10 repetitions of flexion and extension at the requested speed. For each trial, 2 data files were generated and saved: one containing EMG signals and one with kinematics signals. These signals were acquired on different computers with EMG files containing 32 single-ended signals, sampled at 30 kHz. Kinematics files included 23 hand joints relative positions, which were sampled at 100.2 Hz.

3.2 Raw Data Storage

Once the experiment is completed, researchers transfer EMG and kinematic data in their raw proprietary format to a central disk storage, in a directory structure dedicated to the subject with all file names properly assigned for easy management. Once there, they are converted to a more accessible format and imported in our data framework which allows fast retrieval and has query capabilities. At this time the full raw data for each trial is accessible to any lab member having access rights for processing and analysis.

4 DATA PREPARATION

In this section, we describe how we transform the recorded EMG and kinematic data into a representation that captures relevant features of the signals and that can be processed by a neural network. We perform the following transformation steps: signal filtering, and feature extraction.

4.1 Signal Filtering

EMG signals are typically transformed from their raw state into a filtered representation prior to use in analysis or prosthesis control. As described in (Kamavuako et al., 2009), to extract an estimate of muscle activation, we performed the following 3 filtering steps: high pass filter at 100 Hz to remove motion artifacts, rectify the signal (compute the absolute value of the signal), and low pass filter at 10 Hz. Fig. 2 illustrates the difference between EMG signals before (on left) and after (on right) these filtering steps.

Kinematic signals are low-pass filtered at 10Hz. These signals do not require additional frequency filtering, as their wavelets are not noisy, see Fig. 3. Nevertheless, we apply a smoothing filter to soften signals peaks and asperities.

In figure, it can be observed a flat kinematic activity at both the beginning and the end of the signals: these are the intervals between the start of the signal recording and the start of the actual articulation movement, and the between the end of the physical exercise and the halt of the recording. We are interested at the time window where the rehabilitation movement occurs. Given the latencies of the system and the response time of the subject, such window is not constant across trials and subjects. To isolate the movement window, we have implemented an algorithm to detect the beginning and the end of the movement in the trials. This start/end times are calculated on the kinematic signals, and applied to both EMG and kinematic datasets to remove unnecessary data.

Briefly, the algorithm first finds the period of the movement, then calculates the start and end times. The period of each signal is calculated by transforming the signal in the frequency domain so to isolate its harmonic with highest energy, which in this type of trials is the frequency of the movement, from which the signal period can be extracted. Periods from all signals are aggregated and the median is computed to calculate the value of the overall movement period. The start/stop time of each input signal is calculated as follows: (i) we find the peaks of the signal (in the time domain), (ii) we extract the time at which the first and last peaks occur, and (iii) we off-set the latter by a quarter period in advance and in delay, respectively. The start of the movement is considered to be the minimum value across all the start computed from the kinematics signal, while the end is the max value between all the ends. During the process, some signals do not report peaks so they are not included in this computation.

4.2 Feature Extraction

In this section we describe how we encode EMG and kinematic signals in a compact format that is both descriptive of the trial and processable by an ANN.

To prepare the continuous time EMG and kinematic data for the ANN, we extracted representative and salient features from the input signals. The primary features chosen for this analysis were the cross-correlations between the EMG signals and between EMG and kinematic signals. All subjects performed the same set of movements and we assume that the time-varying patterns of muscular activity required to produce these movements are similar. As a result, we therefore assume that the cross-correlations between muscle activations and kinematics contains unique features that can be discovered by a neural network when properly trained.

For each subject and trial, we calculated two different sets of cross-correlations. First, we calculated the cross-correlation between each filtered EMG signal and all other filtered EMG signals, and second, we calculated the cross-correlations between each filtered EMG signal and each filtered kinematic variable. This simple feature extraction approach reduced the multi-channel continuous time series data to a 16 by 38 matrix, consisting of 16 EMG signals and 16 EMG signals plus 22 kinematic. Fig. 4 shows a heat map representation of the subset of the correlation matrix obtained from the EMG signals from a single trial, where the red and white indicate high and low correlation values, respectively.

5 SIGNAL CLASSIFICATION MODELING

In the following section we detail the architecture of the ANN; the rationale for the selection of the training, validation and test data; and, the training of the artificial neural network for our classification task.

5.1 Neural Network Architecture

After feature extraction, each trial can be represented with a relatively small amount of data, representable

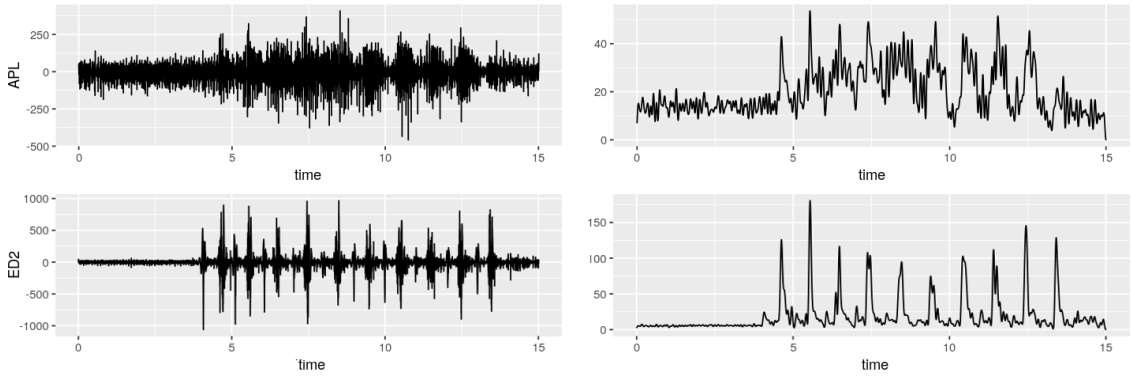

Figure 2: A sample of EMG signals for a few sensors before (on left) and after (on right) frequncy filtering.

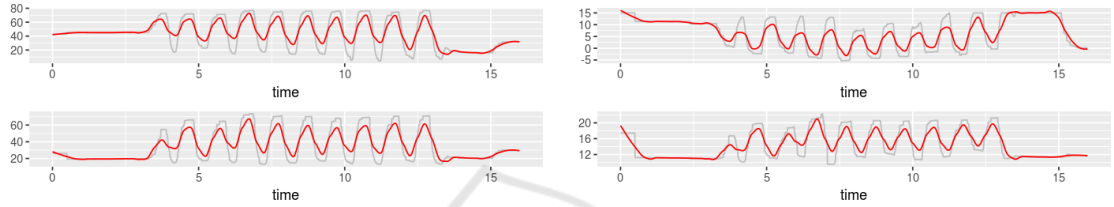

Figure 3: A sample of kinematics signals for a few sensors.

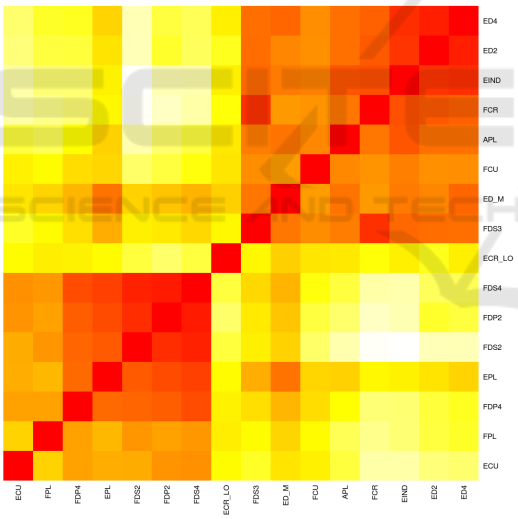

Figure 4: Sample Heat map of correlation matrix between data from all EMG sensors.

by the correlation matrix. In this matrix (or table), a single trial consists of 16 rows (one for each EMG signal) and 38 columns describing the correlations of the other EMG sensors and kinematic variables to each EMG signals. Multiple trials are combined together in the table by concatenating the matrices vertically to form a table with 38 columns and a number of rows equal to 16 multiplied by the number of trials. This kind of input can be managed by a neural network with a relatively simple neural network architecture, in contrast to other approaches that use images thus requiring deep neural networks, e.g. (Rubin et al., 2017). Our neural network is a *dense neural network* composed of the following layers:

- An input layer with 100 inputs, which correspond the number of our features; activation is ReLU;
- 3 hidden layers completely interconnected of size 200, 300 and 200 neurons, with ReLU activation function;
- The output layer with 21 neurons matching the labels of the targeted muscle present in the raw data with a softmax activation.

The output of our neural network is a set of 21 numbers with value between 0 and 1 indicating the probability that the input is the muscle indicated by the label assigned to the specific output. To assign the correct label, we threshold the probabilities at 0.5, anything above is considered 1, while below is 0.

5.2 Training, Validation, and Test Sets

In supervised learning, input data has to be separated into three sets: training, validation, and test. The first set is used to train the network; the second to validate the quality of the trained network during the training process, on data for which classification result is known; and, the third represent unseen data to the network and it is used to evaluate the prediction accuracy when the training is done. With our goal being the correct labeling (classification) of the muscle associated with each EMG sensor represented by the input

features across multiple type of movements, we devised the following input sets:

- `Full-Random`: at each training cycles observations belonging to each set are selected randomly from the input data sets according to the following proportions: 70% for training, 15% for validation, and 15% test.
- `Subject-specific`: data from one of the subject is completely removed from the data set and used as test set. The remaining data is organized accordingly: 85% for training; and, 15% for validation

Datasets built using the `Full-Random` are common to the majority of the approaches using ANNs. This approach is the simplest and basically rely on the amount of input observations in order to be able to discover patterns. With `Subject-specific`, we remove all data belonging to one subject from the training and validation sets. In doing so, we are able to evaluate how the network behaves when presented with data that, in its entirety, has not been seen before, thus the network could not have assimilated any pattern from it.

Results from training the network with these three different types of sets will be described in Sec. 6.

5.3 Neural Network Training

The input to our neural network is the tabular representation of the cross-correlation matrices representing the various trials. In preparing the input for the neural network, we had to convert the categorical variables to so-called one-hot encodings. Specifically, each observation in our tabular representation is composed of the following data:

- a one-hot encoding describing the type of movement (56 boolean inputs);
- the cross-correlation values between one EMG channel and all the other EMG channels, that is 21 inputs with values between -1 and 1;
- the cross-correlation between one EMG signal (the same as above) and all the kinematics signals, that is 23 inputs with value between -1 and 1;
- a one-hot encoding describing which EMG signal is the source of all correltions, that is what muscle the EMG sensor is monitoring.

We created one model for each of our input sets defined in Sec. 5.2. To create each model, we run the training cycle process for 100 epochs, with batch size of 16 data samples. For a proper evaluation of the model, we repeated the training cycle 1000 times for each type of input sets. The next section presents the results of our experiments.

6 EVALUATION

This section presents the evaluation of our approach to automatic classification of EMG sensor placement. The goal is to correctly associate each EMG input channel with the correct muscle label, confirming the information provided during the experimental setup where electrodes were placed under ultrasound guidance, or, in case of different prediction, marking the specific channel for more scrutiny and study.

For evaluating our approach, we built a prototype system using R, python, and keras. The input data was composed of the signals collected from 6 subjects; each subject undergo between 24 and 55 trials, for a total of 204 trials in total. In the reminder of this section we present: the results obtained when using the `Full-Random` input set, the results obtained when using the `Subject-Specific` input set, and a discussion of the discoveries.

6.1 Full-Random Model

Fig. 5 shows the progression of the model accuracy over 1000 training cycles when trained on the `Full-Random` input set. The model reached an average accuracy of 99.27% with a standard deviation of 0.04 on the training set, and an accuracy of 90.10% with a standard deviation of 0.01 on the validation set.

The test set results over the thousands iterations computes to an average accuracy of 90.02% with a standard deviation of 0.0148. Fig. 6 show the box plot of model accuracy and loss on the test set. The vast majority of training cycles perform well, while a minority exhibit lower performance.

We proceeded by analyzing the accuracy on each individual muscle label to investigate whether the classification model was performing better for some muscles than for others. Fig. 7 shows that the muscle label classification performs well, except for ED3, ED5, and ED_M, to some extent.

We then analyzed the prediction accuracy for every muscle of each subjects. Fig. 8 shows the neural network predictions for the first 8 channels, enumerated from left to right by row, of subject 1. As we can see, channels 1, 2, and 3, with labels ECR_LO, ECU, and FDP4, are predicted correctly almost all the times. For channels 4, and 8, the prediction is not as good as for the previous group. For channels 5, 6, and 7, the neural network performed poorly.

Lastly, we checked the accuracy over the same muscle across different subjects. Fig. 9 shows predictions for channel FDP4 across all subjects. We can observe that FDP4 is not present for subject 2, which

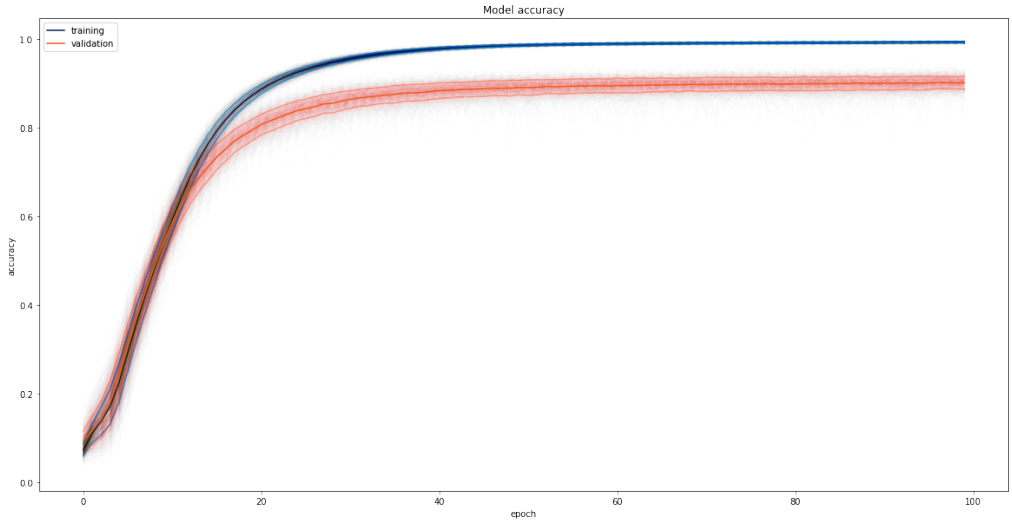

Figure 5: Progression of accuracy during 100 epochs on training (blue) and validation (red) sets. Solid line is the average value with plus and minus one std. The cloud contains each single training cycles.

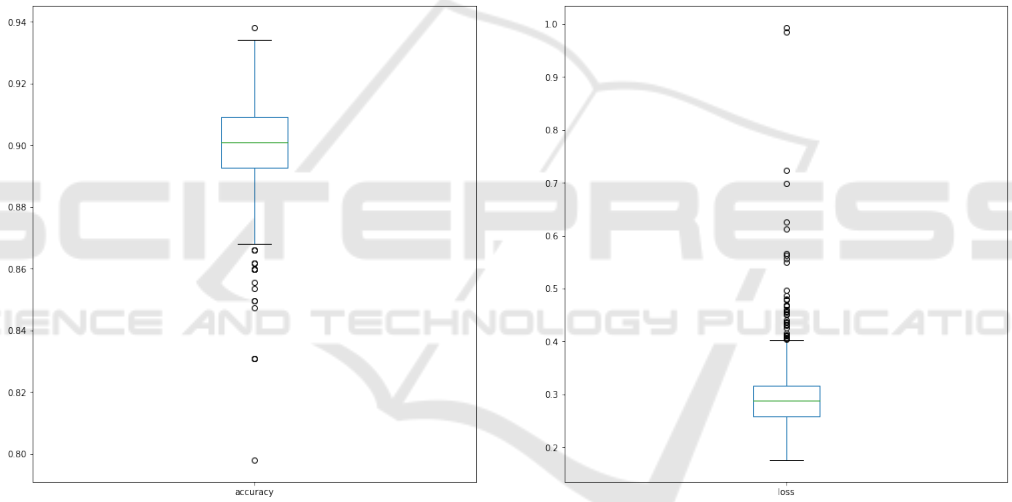

Figure 6: Box plot of accuracy and loss for test set over the thousand training cycles.

likely means that for the trial no sensor was placed in the associated muscle. For all the remaining 5 subjects, we can say that the prediction is fairly accurate.

6.2 Subject-specific Model

With regards to the `Subject-specific` input sets, we relegated data from a single subject to the test set, while data from all other subjects composed the training and validations set. The model accuracy was similar to the `Full-Random` configuration, where the network achieved 99.03% and 90.19% accuracy for the training and validation sets, respectively. With data from the test subject, that had never been seen by the network during training 88.17% of the EMG sensors were identified as recording signals from the muscle that was assigned under ultrasound guidance.

Fig. 10 shows the accuracy for first 8 channels for subject 1. It can be observed that the prediction accuracy was: very high for channels 1, 2, 3, 5 and 8, high for channels 4 and 6, and low/poor for channel 7.

6.3 Discussion

Validation of placement of fine-wire electrodes in the extrinsic hand muscles and other locations has typically been accomplished by qualitative comparison of EMG activity generated by the movement being performed (Birdwell et al., 2011; Burgar et al., 1997; Rudroff, 2008). The applications of small amounts of current through EMG electrodes to stimulate a muscle contraction has alternatively been used (Bird-

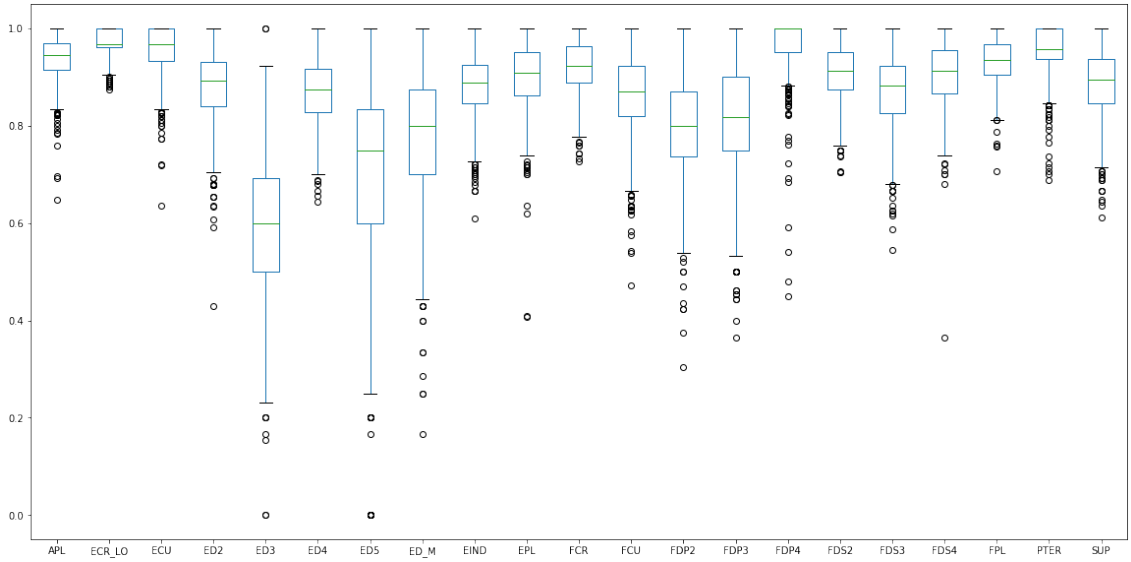

Figure 7: Box plot for accuracy for each muscle.

well et al., 2013; Park and Harris, 1996), but this method may not be applicable for prosthetic limb users. To the best of our knowledge, our approach is the first of its kind to use a machine-learning algorithm to validate electrode location.

The neural network model we developed delivers very good performance in labeling EMG channels with the identity of the muscle that was targeted during implant, especially when considering the relatively small amount of subjects and trials composing the training data. In analyzing the results from the evaluation, we noted several interesting findings.

In the individual muscle labelling experiment for the `Full-Random` input set, see Fig. 7, we discovered that one reason why channels were under-performing is that the input signals for those channels do not appear for all monitored subjects. As a consequence, the model had a smaller number of samples to use to infer signal patterns, thus impacting the overall accuracy.

In the per subject muscle labelling experiment for the `Full-Random` input set, see Fig. 8, the poor performance on channels 5, 6, and 7 could be caused by the presence of inconsistencies in the initial labelling provided by the physician for these channels. To validate this hypothesis, domain expert researchers have to review the experimental data and analyze the dynamics of the signal in relation to the movement.

Finally, we looked at the incorrect predictions to investigate whether there is a correlation between the actual (correct) muscle and the incorrect predicted value. We built a directed graph of the wrong predictions, see Fig. 11 which show an excerpt of this graph for a single example. The graph exhibits some interesting patterns including that the ANN confused muscles within two separate groups: extensors and flexors. This figure also shows that some of the muscle are not predicted at all, and they lead to the use of the “none” label.

7 CONCLUSIONS

Artificial neural networks show great application potential across a range of different domains. In this paper, we focused on how to support physician and medical researchers in assessing whether a set of intramuscular electromyography sensors are placed in the targeted muscle or not. We presented a number of data processing steps which take raw sensor data and transforms it in usable information that enables domain specialists to perform their tasks more efficiently and effectively, improving both the rehabilitation sessions as well as the quality of the data analysis resulting from the multiple recording trials.

We have presented a novel approach that combines a dense neural network architecture with a compact cross-correlation matrix describing the rehabilitation trial sensor readings. We have developed a prototype system and evaluated it on real data. The experiments demonstrated that our approach achieves an accuracy around 90% in classifying the muscle from which sensor readings are coming from. This is a very promising result, especially when considering that: in our experiments the classification imprecision on specific muscles was caused by lack of data regarding such muscles, possibly muscle mis-labelling; and that the amount of observations available to train the net-

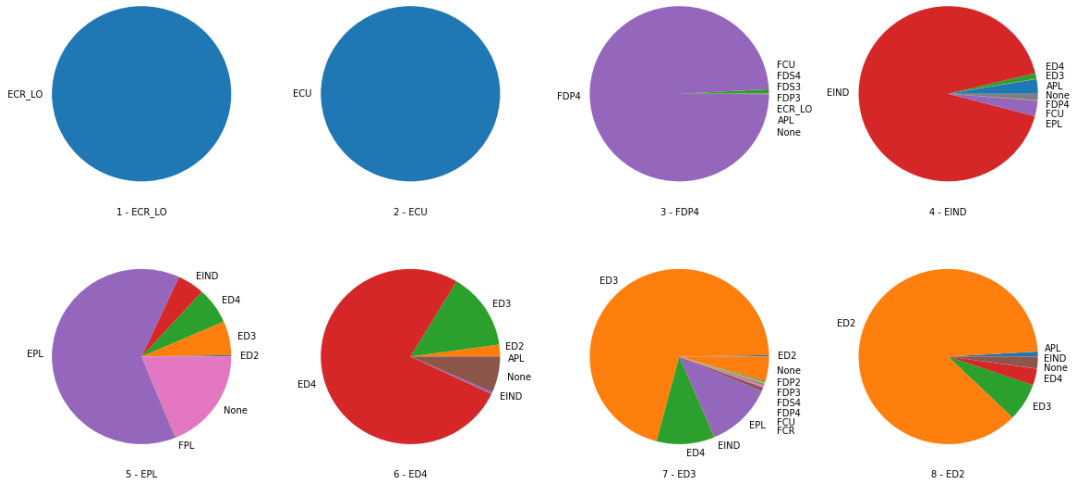

Figure 8: Excerpt of the first 8 channels from Subject 1 individual channel predictions. Each pie chart represent the predictions for one channel which is indicated right below with the label that was assigned during experimental setup

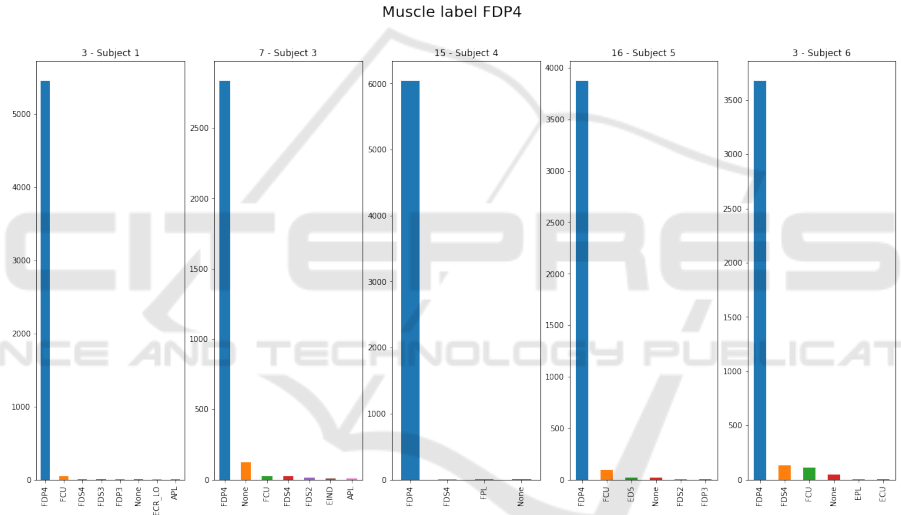

Figure 9: Muscle FDP4 predictions across subjects.

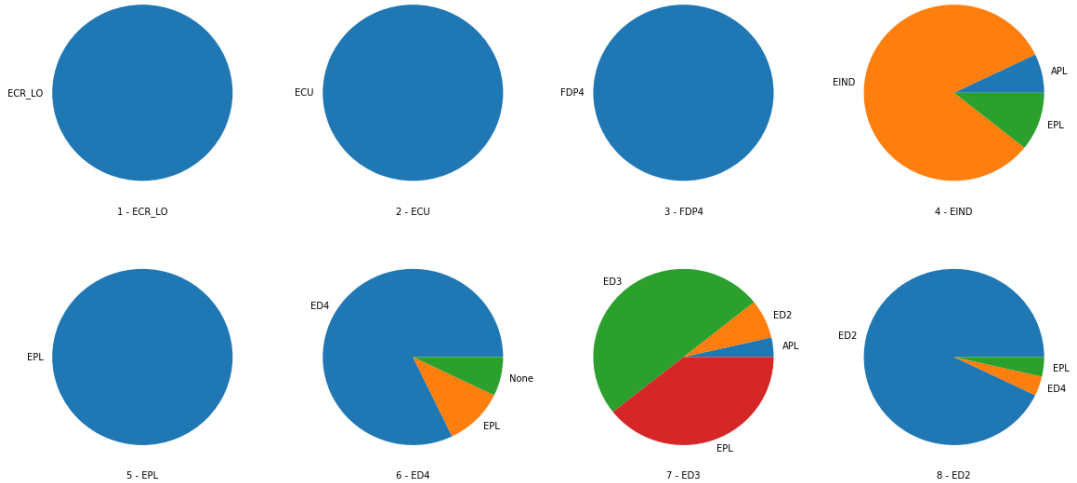

Figure 10: Excerpt with the first 8 channels from the predictions on all channels with subject 1 data as a test set.

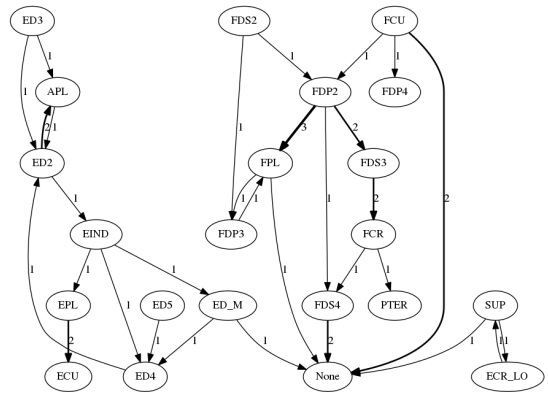

Figure 11: Directed graph of the wrong predictions: edge thickness indicates the number of occurrences of the mistaken label.

work was limited in general, when compared to other works using neural networks.

The results of this study can help with validating the implanted muscle identity using the pattern of EMG activity. We used ultrasound techniques as an initial tool to validate the predicted results. Future work will focus on validating the predicted muscles identities using the EMG pattern with the probability of migration of each EMG sensor in the neighboring muscle compartment based on the geometrical vicinity. Also, we are planning to extend this work to improve classification accuracy by obtaining access to a larger amount of observations, further enriching the trials' metadata, and trying different neural network architectures and parameters.

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