Robotic Perception and Action Project Report EMG Classification using deep learning

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***Abstract*—This report summaries the content of the work. The project consisted in classifying a a dataset of EMG signal of a ....with respect to a class of movements, by means of machine learning algorithms taught in class.**
We have managed to reach an accuracy of 85%

I. Introduction

THIS demo file is intended to serve as a "starter file". The template can be found here [?]:
http://www.ieee.org/conferences_events/conferences/publishing/templates.html

The study on the specific field, thanks to the progress in technology has increased a lot in the last year also thanks to the progress of the Artificial Intelligence. The possibility to study and analyse the signal obtained from a certain gesture could make big progress for the sake of amputees if then applied at the robotic arm technology.

By using the software MATLAB we analyzed a dataset of EMG using machine learning techniques explained in class.
signals elaborating a spesific LSTM structure in order to reach the highest accuracy as possibile. We did a comparison using two kind of supervised learning analysis, that are LSTM using the signal and DNN usign the features extracted from the signal.

II. Related Work

III. Elaborating the project

We took a dataset of rami khushaba. It is composed by EMG signal of 8 subjects, six males and two females, aged between 20-35 years were recruited to perform the required fingers movements. The subjects were all normally limbed with no neurological or muscular disorders.

The datasets were recorded using eight EMG channels (DE 2.x series EMG sensors) mounted across the circumference of the forearm and processed by the Bagnoli desktop EMG system from Delsys Inc., as shown in Fig.2. A 2-slot adhesive skin interface was applied on each of the sensors to firmly stick them to the skin. A conductive adhesive reference electrode, dermatrode reference electrode, was placed on the wrist of each of the subjects during the experiments. The collected EMG signals were amplified using a Delsys Bagnoli-8 amplifier to a total gain of 1000. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) was used to sample the signal at 4000 Hz; the signal data were then acquired using Delsys EMGWorks Acquisition software. The EMG signals were then bandpass filtered between 20-450 Hz with a notch filter implemented to remove the 50 Hz line interference. Fifteen classes of movements were collected during this experiment including: the flexion of each of the individual fingers, i.e., Thumb (T), Index (I), Middle (M), Ring (R), Little (L) and the combined Thumb-Index (T-I), Thumb-Middle (T-M), Thumb-Ring (T-R), Thumb-Little (TL), Index-Middle (I-M), Middle-Ring (M-R), Ring-Little (RL), Index-Middle-Ring (I-M-R), Middle-Ring-Little (M-RL), and finally the hand close class (HC) as shown in Fig.3.

*** When collecting data, the subjects were asked to perform each of the aforementioned fifteen movements, and hold that movement for a period of 20 seconds in each trial (only first 5 sec from each trial used in the paper). You can study what happened to the muscle, in terms of fatigue on this data, or do classification on it. Three trials are available (6 used in the paper, 3 provided here), allocate two of them for training and one for testing. You can even chop the extra data if you think 5 seconds are more than enough for each trial.

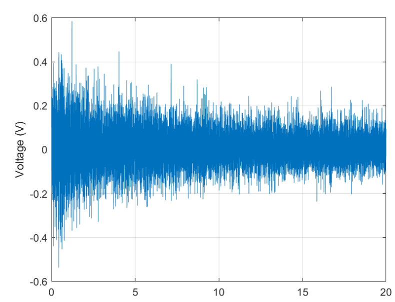

Fig. 1. Example of a figure caption.

We did a preprocessing of the signal starting from filtering it. To do that we started plotting the fft to see it if the filter was necessary: we Compute two sided spectrum, Divide by L for normalisation of the power of the output for the length of the input signal and Compute signal sided spectrum by taking the positive part of double

As you can see the signal was not filtered. So we did it applying a forth order Butterworth bandpass filter between 20 and 450 Hz and a notch filter at 50 Hz (more precisely from 48 to 52 Hz). You can see from the pictures below the differences from the raw signal to the one filtered

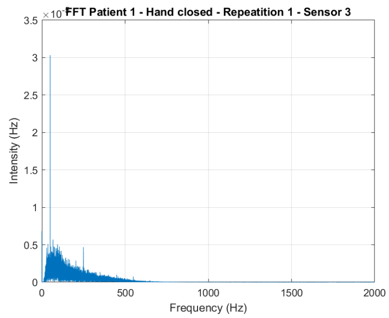

Fig. 2. Example of a figure caption.

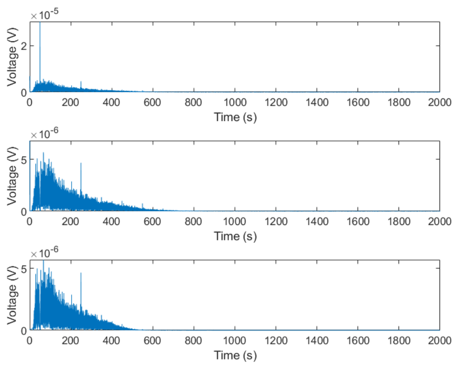

Fig. 3. Example of a figure caption.

Backing to time domain, the signal conditioning was not finished: we rectified it taking the absolute value And normalized

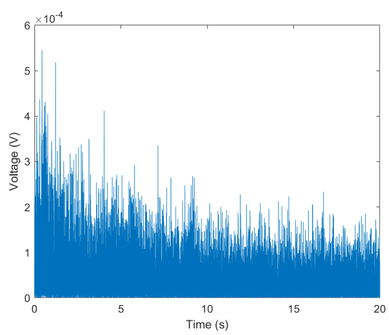

Fig. 4. Example of a figure caption.

between 0 and 1: Now we are ready for the implementation with LSTM.

CITAZIONI: Even though the time consumption and dimension for TD features were faster and smaller than other features, recognition performance was not satisfactory as claimed by Tsai et al. [29].
normalization is a crucial step and changes in EMG amplitude can influence the normalization result, affecting recognition performance.

A. *LSTM*

For the labeling we gave a number at each movement converting the xls file into a number taking care that each

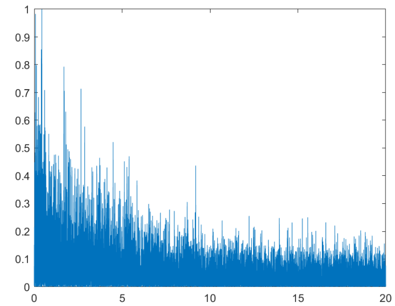

Fig. 5. Example of a figure caption.

movement had a different value. In this way we were not worried about assigning other type of label and something like that.

We feed the network with a cell array of Nx1 cells, which include matrices of 8x100 value. N is the total number of segments given to the network. We decided to split the signal in small segment of 0.5 sec in order to make easier the work for the neural network and increasing the final accuracy.
The 8 rows of the matrix represent the input of the network, the 8 sensor channel attached to the subjects, from which we got the EMG signals, while 100 columns are the value we took from each window, using a function to got the 100 bigger values.

B. *Feature extraction*

Besides the analysis with LSTM we followed another method, more classic, consisting on extracting manually a set of features from the signals, giving them as inputs to a neural network in order to reach the same goal of the previous study.

There exist three types of EMG features: time-domain (TD), frequency-domain (FD) and time-frequency-domain (TFD) features.
Angkoon Phinyomark et al said that EMG features based on frequency-domain are not good in EMG signal classification. Moreover we discovered that many features are redundant, and their power changes depending also on the type of classifier you use for the process.
In the end we opted for the ones that Angkoon Phinyomark et al considered the recommendation for each group in which features can be divided:

- MAV from energy information method
- WL from complexity information method
- WAMP from frequency information method
- AR from prediction model method
- MAVSLP from time-dependence method

1) Mean absolute value (MAV):

$$\text{MAV} = \frac{1}{N}\sum_{n=1}^{N}|x_i| \tag{1}$$

2) Waveform length (WL):

$$\text{WL} = \sum_{n=1}^{N-1}|x_{i+1} - x_i| \tag{2}$$

3) Willison amplitude (WAMP):

$$\text{WAMP} = \sum_{n=1}^{N-1} [f(|x_n - x_{n+1}|)] \tag{3}$$

where $f(x) = \begin{cases} 1, & \text{if } x \geq \text{threshold} \\ 0, & \text{otherwise} \end{cases}$

4) Auto-regressive coefficients (AR):

$$x_i = \frac{1}{N} \sum_{p=1}^{P} a_p x_{i-p} + w_i \tag{4}$$

5) Mean absolute value slope (MAVSLP):

$$\text{MAVSLP}_k = \text{MAV}_{k+1} - \text{MAV}_k, \quad k = 1, ..., K-1 \tag{5}$$

We also add RMS since appears to be the best parameter compared to MAV, MAX, SSC, ZC and WL as it provides a quantitative measure for electrode selection [3].

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2} \tag{6}$$

Feature in time domain do not need any transformation, which calculate based on raw EMG time series [3]. For this reason we used the raw signal, only filtered with Notch at 50 Hz and band-pass between 20 and 450 Hz.

C. DNN

Once extracted the features we feed the network writing a MATLAB function that returns a vector with all the features. A vector for each segment in which we divided the 20 sec sequence. Choosing 0.5 sec, we got 40 segments.

IV. Experimental results

Add a Section about experimental results and verification of your output.

Any number, both final and intermediate results should be described. Even the experimental setup, and the measurement environment should be described. The measure should be reproducible by the readers. Listing the models of the instrument is not important (e.g., oscilloscope TD98445....), while the type of instrumentation or the type of measure is fundamental to repeat the experiment.

In case, please, provide a shared folder (e.g., github, gitlab, Google Drive, ...) where the code is available for repeat the experiments, the achieved results are available for a comparison.

V. Conclusion

sdasdadasdasd
Context/Scenario $\Rightarrow$ Challenges $\Rightarrow$
$\Rightarrow$ What you have done $\Rightarrow$
$\Rightarrow$ most important achievements, with key numbers.

References

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