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Preface

For this edition of the Brazilian Conference on Biomedical Engineering (CBEB2020 – Congresso Brasileiro de Engenharia Biomédica), 665 papers were submitted, composed of 564 scientific articles (4-6 pages) and 101 Scientific Communications (Abstracts up to 2 pages). After the first round of reviews, 595 papers were accepted (514 full papers and 81 scientific communication). These 595 articles underwent a second review round, and at the end 551 papers (478 full papers and 73 scientific papers) were accepted to be presented at CBEB2020.

CBEB is promoted by the Brazilian Society of Biomedical Engineering (SBEB), with biannual periodicity, organized by researchers linked to a local research institution, with the collaboration of the entire scientific community linked to the area of Biomedical Engineering in Brazil. CBEB2020 was held on October 26-30, 2020 in Vitória (Brazil) and was organized in the following tracks:

- Clinical Engineering and Health Technology Assessment
- Biomaterials
- Tissue Engineering and Artificial Organs
- Bioengineering
- Biomedical Devices and Instrumentation
- Biomechanics and Rehabilitation
- Neuroengineering
- Biomedical Signal and Image Processing
- Biomedical Robotics, Assistive Technologies, and Health Informatics
- Biomedical Optics and Systems and Technologies for Therapy and Diagnosis
- Basic Industrial Technology in Health
- Special Topics

We would like to thank the sponsors CNPq and FAPES for making it possible to celebrate this event in times of uncertainty due to the COVID-19 pandemics.

October 26-30, 2020
Vitória - Brazil

Teodiano Bastos-Filho
Anselmo Frizera-Neto
Eliete Maria de Oliveira Caldeira

Soft Sensor for Hand-Grasping Force by Regression of an sEMG Signal

E. E. Neumann[1] and A. Balbinot[2]

[1] Msc. Student, UFRGS/PPGEE, Laboratory of Electro-Electronic Instrumentation (IEE), Porto Alegre, Brazil
[2] Principal Investigator, UFRGS/PPGEE, Laboratory of Electro-Electronic Instrumentation (IEE), Porto Alegre, Brazil

Abstract— **This paper presents the implementation of a soft sensor for hand-grasping force by the sEMG (Surface Electromyography) collect from 6 different muscles in the ventral regions of the forearm. This work is implemented in the envelope of the signal from sEMG by a low-pass filter with a cut frequency of $3Hz$, which maintains the information of the energy of the signal. An Artificial Neural Network (ANN) was applied for the regression of the force and was done an online application of the model as a soft sensor, and has as input the 6 channels of sEMG rectified and filtered. Four volunteers were tested to see the viability of the regression, all of them showed high R_{sq} for fitting the regression model, 0.99, 0.98, 0.98 and 0.97, respectively proving the capability of the application. The online performance demonstrated $16.66[N]$ of root mean square error, approximately 3.14% of a MVC (Maximal Voluntary Contraction) threshold of volunteer 01.**

Keywords— **Soft sensor, ANN, low-pass filter, hand-grasping force, sEMG.**

I. Introduction

The surface Electromyography (sEMG) is widely used in prosthesis control. Its adoption to control prosthesis, for instance, increases the life quality and gives greater autonomy to the user [1] [2] [3] [4]. As the signal is collected from the skin, some influences from other groups of muscles are captured even though the electrodes are placed in specific places as the central region of the targeted muscle [5]. The force applied by a prosthetic hand or by an exoskeleton is extremely delicate, and some quotidian tasks as hold a glass needs a force control to avoid harm to the user [1] [2] [6] [7] [8]. During the use of prostheses, the response must be fast to the user, with a maximum delay of 300 [ms] so that the user does not have the perception of delay [9].

The signal from sEMG contains some useful information of the body movements and the amplitude of the signal is directed linked with the force applied by the muscle [10]. The signal has a stochastic nature and has an amplitude in the range of 1-10 mV, and a frequency in the range of 15-500 Hz [1].

The goal in this study is the implementation of a soft sensor of grip-hand force in an online application, as [9] the model should not introduce a delay that is perceivable by the user.

To estimate the force made by the user, the sEMG signal is acquired from specifics superficial muscles located on the forearm. Then the signal is processed, rectified, enveloped and the data is located on a database. Therefore the data is processed and feeds an Artificial Neural Network (ANN), to regress the force applied on a dynamometer.

In some previous works related is possible to see the implementation of a force regression by the sEMG signal applied offline [11]. Where the regression was made by 6 channels of sEMG by the ELM (Extreme Learning Machine), SVM (Support Vector Machine) algorithms had the minor RMSE (Root Mean Square Error).

In [12] it is possible to see one application of the estimation of hand force using ANN (Artificial Neural Network), where the estimated force was tested online, with a different approach of movement of the hand.

In the work [13], it is possible to see the application of hand orthosis for an individual with Duchenne muscular dystrophy, to increase the maximum grasping force of the participant's, improving from 2.8 to 8N, controlled by sEMG.

In other previous works with a different approach [14] in the lower limb, the application is similar, without the use of an accelerometer to support the network.

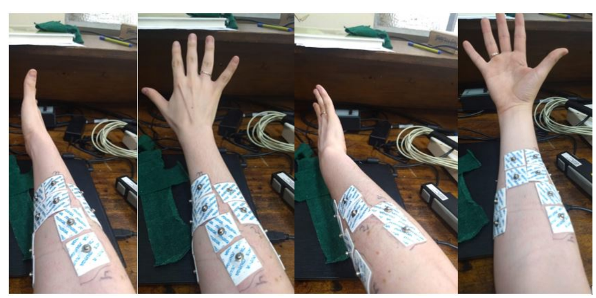

Fig. 1: Differential electrode position on forearm

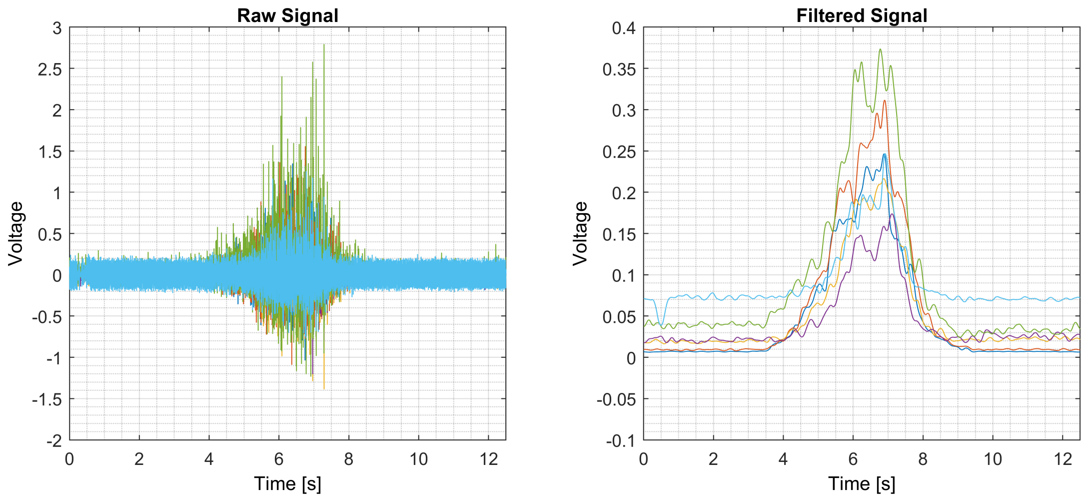

Fig. 2: A (Left) - Raw Signal of sEMG / B (Right) - Rectified and Filtered Signal

II. Protocol and Acquisition System

A. Protocol

All procedures performed in these studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This study was approved by the Institutional Review Board of Federal University of Rio Grande do Sul under the Certificate of Presentation for Ethical Appreciation number: 11253312.8.0000.5347.

As examined in [11], the combination of the 6 channels utilized revels the better regression of the force. Following previous guidelines [11], 6 muscles were chosen to perform the regression. They are superficial and can be captured from sEMG [15], being them: brachioradialis (BR),flexor carpi radialis (FCR), flexor carpi ulnaris (FCU), extensor carpi radiali (ECR), extensor carpi ulnaris (ECU), and extensor digitorum (ED), the position is showed in figure 1, with the superficial electrode fixed in the ventral muscle region on the skin.

To starts to acquire the signals, the volunteer is oriented to follow the standard position, sitting comfortably in an upright position, the arm should be pointing down and, the forearm resting on the support of the chair projected 90 degrees forward.

Due to the necessity of synchronization, one stimulus was shown to the volunteers 5 seconds before the analog gauge started to climb from zero to Maximal Voluntary Contraction (MVC). During the force application cycle, the user is induced to control his or her force, ramping until the MVC. Right after that, the slow release of the dynamometer is induced. The entirety of the cycle interval is 8 seconds, divided in 4 seconds of force application until the MVC and 4 seconds of slow-release until the relaxed state.

The interval between each press is 30 seconds and the movement is done repeatedly for 10 times each test. The database is composed of 4 volunteers and each one did 8 tests. Therefore, each volunteer has 80 press movements. The interval between tests is more than 5 minutes.

B. Acquisition

The acquisition of the sEMG was done by a Data Acquisition (DAQ) NI UBS-6289 from NATIONAL INSTRUMENTS (A/D of 18 bits), with a sample acquisition of $2kHz$ combined with a system acquisition SAS1000 V8 from EMG System do Brasil. The signal of force was collected by a dynamometer from EMG System do Brasil, and acquired by a DAQ-mx 6009 from NATIONAL INSTRUMENT with a sample acquisition of $2kHz$, which was characterized. The signal from one accelerometer was captured together for future implementations. All the signals were acquired by a routine in the software LabView, where was performed by a computer with 8 GB of RAM, processor i5.

III. Method

Due to the nondeterministic and stochastic nature of the sEMG, it is hard to regress the signal. Then it is common to this area of study to work with the features of the signal, as RMS and medium frequency. However, this work has an intent to run online, then no feature that requires processing

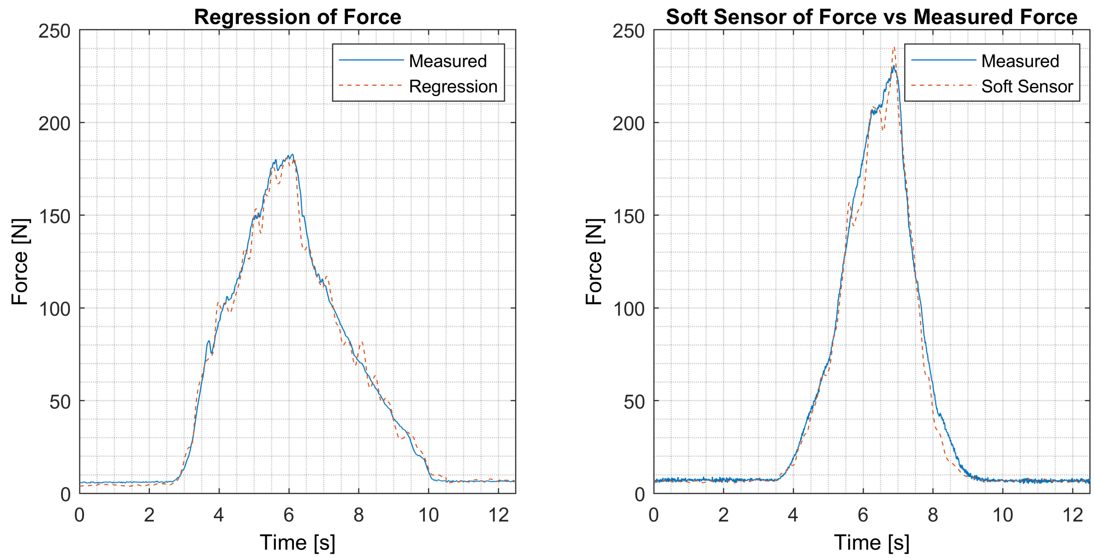

Fig. 3: A (Left) - Model regression of one movement of volunteer 02 / B (Right) - Response of the soft sensor in validation tests of volunteer 01

signal as frequency-domain is proper to efficiency. The goal is to use less processing as possible.

A. Dynamometer Characterization

The dynamometer used to capture the signal was characterized by the introduction of standard weights at the input and output voltage measurements, as shown in table 1, and the system's output and input function was regressed by iterations.

Table 1: Data collected from the dynamometer for characterization.

Weight [kgf]	Output [V]
0.0000	$0,105622$
0.2582	$0,112208$
0.4582	$0,123458$
0.6582	$0,129756$
1.2582	$0,157926$
1.4582	$0,167134$
1.6582	$0,177304$

B. Data processing

The first treatment of the signal was the rectified since the important feature for this work is the energy in the signal, which is linear and proportional by the force applied [11].

The exploration of envelope techniques for the sEMG signal exhibit that the use of RMS of the signal is common to envelop the signal of sEMG [10] [11], but thinking in an online application that requires a low process demand, was studied one low-pass filter that provides a possibility of a hardware application, using fewer computational resources. The filter applied to this work was a low-pass Butterworth of 4th order with a cut frequency of 3 Hz and yet remaining the energy of the signal.

C. Regression

The data of each volunteer was separated into 6 of 8 trials to training the model and 2 of 8 to test the model of regression. The model used in this work is ANN, where the input layer is formed by 6 neurons equivalent to each channel of the sEMG processed with the implemented filter, The model used in this work is ANN, where the input layer is formed by 6 neurons equivalent to each channel of the sEMG processed with the implemented filter.

The hidden layer has 100 neurons defined by a sweep from 40 till 100. With hyperbolic tangent sigmoid activation transfer function on each neuron and the method of back-propagation of the error was tested with the Levenberg-Marquart and the Bayesian regularization method. Lastly, the output neuron has a linear function.

Then for the validation, a network pre-trained with the volunteer's data and Bayesian back-propagation method is implemented in the LabView by the MatLab block. Letting all processes run in LabView software with MatLab in a back run.

IV. Results

A. Dynamometer Characterization

The curve fitting of the data collected on the Table 1 into a linear equation result in the transfer function observed in equation 1 where x is weight in kgf, and $f(x)$ is voltage, with a R_{sq} of 0.9961.

$$f_x = 0.04409x + 0.1028 \tag{1}$$

B. Data processing

The result of the data processing to envelope the signal and keep the energy proved to be promising, and the rectifier and filter can be applied to hardware to consume less processing power of the machine. The resulting signal is observed in figure 2.

C. Model Regression

The 6 channels of the filtered signal from figure 2 and the ANN model for regression has made by 6 neurons in the input layer, 100 neurons in the hidden layer, the used method of back-propagation error were Bayesian. The set of trials 1,2,3,4,5, and 7 was used to train the model, and the set of trials 6 and 8 was used to validate the model. The signal was segmented to 4 seconds before the movement, the movement, and 4 seconds after the movement.

Table 2: Mean Square Error (MSE) of the test set and the R from regression of each volunteer trained by the network model.

Volunteer	Test set MSE	Regression R
Volunteer 01	4.9910^{-4}	$R = 0.992627$
Volunteer 02	2.2310^{-3}	$R = 0.989760$
Volunteer 03	3.1010^{-3}	$R = 0.989372$
Volunteer 04	3.2610^{-3}	$R = 0.97977$

As the results of Mean Square Error (MSE) in table 2, the regression of the force accomplishes by the sEMG signal from the 6 selected group of muscles works, for exemplification in figure 3.a is possible to observe the response of the regression. The results of the volunteer 01 have the best fit and the lower MSE.

D. Online Performance

As shown in figure 2, the force can be regressed by an ANN with the 6 channels of sEMG, an ANN is implemented in the LabView by a MatLab block pre-trained.

For the model validation, was performed 6 trials each with 10 moves only performed by the volunteer 01. The response of the soft sensor in figure 3.b shows the possibilities to regress the signal of sEMG into force. Thus, the soft sensor shows the capabilities to measure the force applied to an object without really measure the force. The maximum punctual absolute error was $0.3163[V]$, that can be applied to the sensibility of equation 1 than the force is approximately $70.3[N]$, that occur in the point of transition of the MVC to the release of the dynamometer.

The Root Mean Square Error (RMSE) for all the 6 trial of 10 movements each, is $0.0283[V]$ equivalent to $6.28[N]$, approximately 3.14% of the MVC. Beyond the use of the soft sensor, with a threshold value of force, the system has the capability of identifying the MVC, although each volunteer has a different threshold [16], for the volunteer 01, was determined by visual inspection an MVC of $200[N]$.

V. Discussion

The database is limited to the specific positioning from which the data was collected. For greater robustness and use of prostheses, the database should be expanded with variations of posture and grip position of the dynamometer for better generalization of the model used in the soft sensor.

It is interesting to continue the database by introducing volunteers who do not have forearm muscles or have a partial amputation of the forearm, conducting the study of the position of the electrodes, displacing, or adding electrodes in the ventral regions of the chest muscles of the volunteer in future work. Since humans also can adapt and learn with the systems.

This kind of envelope is capable of being applied in hardware, and that was the intent to use this kind of envelope of the signal, that will require less software performer, and can be scalable to a portable computer like a RaspBerry as [14]. Since the force regression doesn't work with classes, it was a smooth transition of the output signal.

VI. Conclusion

The biological signal was captured by electrodes as Figure 1, and as pre-processing was rectified than pass through a low-pass filter with a cut frequency of $3Hz$ as displayed in Figure 2, the energy of the signal was retained as the information of the movement in the pre-processed signal by the envelope technical applied.

As the results point, the regression of force to a soft sensor implementation is possible, as the figure 3.b shows the response of the soft sensor in use. Also, until a subtle change in the pattern of the position of the electrode or the hold position of the dynamometer can influences the system [16], to prevent that instability is recommended to in each trial refix the electrodes to train the network with different positions always targeting the ventral position of the muscle, as demonstrated in [15].

The demonstrated RMSE is approximately 3.14% of the MVC value of volunteer 01, clearly occurs with greater intensity at the point of greatest volunteer effort, not least because several factors influence it, such as the presence of small volunteer tremors in the execution of their maximum strength. The database did not deal with trials of forces below the MVC.

For future works, we recommend using haptic technologies to give feedback of force to the user in conjunction with the soft sensor implemented in this work. The soft sensor shows a promissory response to the sEMG signal, keeping the morphology of the force applied into the dynamometer, demonstrating the higher error just into the peak of force in MVC. We also recommend the hardware application of the filter with the purpose of the envelope the signal. This method of the envelope is viable to use in online application orthosis or prothesis and can be combined with some classified system of movements as done in [1].

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

ACKNOWLEDGEMENTS

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Author: Eduardo Egewarth Neumann
Institute: UFRGS
Street: Av. Osvaldo Aranha,103
City: Porto Alegre
Country: Brazil
Email: eduardo.en00@gmail.com