Electromyography Signal Analysis to Obtain Knee Joint Angular Position

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Keywords: Electromyography, Knee Rehabilitation, Polynomial Adjustment, Locally Weighted Projection Regression.

Abstract: Knee injuries are due to several causes and affect a large part of the population. In all of the cases, rehabilitation is required to recover the joint mobility and strength. In this context, the use of technology, especially the development of assistive devices may offer advantages to the patients, e.g. allow to perform correctly the exercises, adapt to the users' needs and help to comply with the prescribed physical therapy. These devices may have specific requirements focused on not harming the patient. This is why control strategies are needed, and therefore feedback sensing is highly important. In this paper we present an algorithm to determine the knee joint angular position from surface Electromyography (EMG) measurements, using a curve fit from a polynomial adjustment method and a Locally Weighted Projection Regression (LWPR) method. We validate our approach, comparing the data obtained from the curve fitting with the measurements obtained with position sensors. In this way, results show that indeed we can explain the joint angular position with the EMG data taken in knee flexion-extension motion, applying a polynomial adjustment approach and the LWPR method.

1 INTRODUCTION

The amount of people suffering knee impairments caused by accidents, cord injury, arthritis, and aging is increasing (Koller-Hodac et al., 2010). To recover partially or completely the normal functions, or to avoid the joint degeneration, a rehabilitation process is required in all cases. Part of the treatment includes physiotherapy, which implies different procedures to reduce pain and swelling, and to recover mobility and strength (Huo et al., 2016), (Umivale, 2011). Traditionally, the subjects must attend limited therapy sessions that most of the times are not enough to recover the joints normal function (Jensen and Lorish, 1994). Other times the subjects do not comply with the prescribed treatment reducing its effectiveness (Khan and Scott, 2009). Additionally, the treatment evaluation is usually done in a visual or verbal way, therefore it can be subjective (Umivale, 2011).

In some cases, as part of the treatment the physician prescribes the use of elements as orthoses, elastic bands, and so on, to improve the subjects' condition. However, the traditional orthoses are rigid structures which limit the user's natural motion, and may cause discomfort. This is why recently, there has been an increasing interest in the development and use of assistive robotic devices for physical rehabilitation (see e.g. (Fang et al., 2018) or (Koller-Hodac et al., 2011)), which are oriented to improve the traditional rehabilitation methods, allowing the treatment completion, as well as the adaptation to the users' rehabilitation process and requirements.

Several assistive devices are already available in literature. For example, (Ren et al., 2017) address a wearable ankle robotic device in passive and active training in acute stroke. As part of the design, authors report the need of controllers. This device senses and tracks the patient's motion (or intent of motion) of the ankle without harm. It is worth to mention that important considerations must be made for designing systems oriented to stroke patients; however, this topic is out of the scope of our paper.

Other assistive devices in literature do not have a feedback control system, but use measurements (e.g. electromyography (EMG)) to control the system in open loop. This is the case of the upper limb exoskeleton in (Mghames et al., 2017), which is implemented with a Variable Stiffness Actuator (VSA). Authors obtain an analogy of the open loop control parameters with those of the human muscle system, tuning in that way the mechanical system parameters. The feed-forward control inputs are obtained by directly mapping the estimation of the muscle activation, using EMG sensors. This approach shows in-

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deed the importance of obtaining EMG signals, which could further be used in closed loop (feedback) control strategies. Moreover, in (Yap et al., 2015) authors present the design of a soft wearable hand exoskeleton with pneumatic actuation. The device is novel and allows to perform different hand therapy exercises. However, the authors discuss the need of a feedback system, which may include sensing elements to make the device more robust and accurately controlled. Other assistive devices are presented in (Li and Cheng, 2017), or (Wang et al., 2009), just to name a few. In all cases, the need of an accurate control strategy is addressed, for which a sensing system and signal processing algorithms are required.

On the other hand, control strategies for assistive devices must track the desired reference accurately, e.g. angular position, velocities and forces, so there is no harm for the user (Ren et al., 2017). In order to design and implement such strategies, information from the system and from the patient must be obtained. For instance, joint angular position is important to correct the system's action. Moreover, EMG data could help to evaluate parameters such as stiffness and position (intended motion), to control assistive systems like those based on the use of variable stiffness actuators (VSA), or series elastic actuators (SEA) (Ajoudani et al., 2012). As well, the EMG signal can be used to track the process progress (Altobelli et al., 2015; Fang et al., 2018; Akhtar, 2016; Garabini et al., 2017; Ema et al., 2017; Earp et al., 2013; Chen et al., 2018). A common approach to recognize the intent of motion in walking is to sense the ground forces of the foot and joint angles using inverse models (Ajoudani et al., 2012). Nevertheless, the EMG signal is a promising interface between the user and the system mainly for two reasons; first, the easy way to obtain it in a non invasive way by means of electrodes over the skin; second, the direct relation between the EMG and the muscular activity, closely related to the intent of motion (Ito et al., 2015). Therefore, sensing systems and algorithms to obtain and process EMG data are useful in assistive devices. Besides, reducing computational cost and economic cost are usually design parameters which can be satisfied by limiting the number of sensors while obtaining the required information. This can be achieved by using EMG sensors and an acqurate algorithm that allows obtaining the angular position from these data. After the data acquisition, the EMG signal needs preprocessing (i.e. filtering, amplification and sampling) (Freriks and Hermens, 2000).

We are interested in exploring the EMG-joint angle relationships, which can be determined by using fitted EMG-joint angle curves. For this, two different methods of Polynomial fitting to find the joint angular positions from the EMG signals are used and compared, namely a Polynomial Adjustment method, and a Locally Weighted Projection Regression method (LWPR). Other algorithms have been already developed in literature with this purpose. For example, in (Chen et al., 2018) the authors evaluate the root mean square value (RMS) from the electromyogram voltage signal, to determine the intended motion in flexion-extension action, employing a fuzzy logic algorithm. Another approach is reported in (Ito et al., 2015), where authors determine the wrist angle using a bilinear model which takes into account the muscle elasticity and viscosity, and the contracting force of the flexor and extensor muscles. In general, this kind of algorithms present advantages because they can be run online, while the one presented in this paper can only be applied offline. However, in our approach we certainly reduce the computational cost, in terms of the running time of the algorithm. Moreover, in general the EMG signal level depends on some features as the muscular mass, muscle elasticity and viscosity, or the skin color, but some of the algorithms that obtain information from EMG data do not adapt to the specific features of the individuals. Our approach, normalizes the EMG signal each time so it can be adjusted to each individual. Efforts to obtain musculo-tendon forces related to the joint angles during the elbow flexion-extension movement have also been addressed. For instance, in (Pang and Guo, 2013), authors use the Hill-based muscular model using the triceps and the biceps forces to calculate the joint angle. This kind of approaches are interesting in the study of intended motion but are different from ours because they search the relationship of the EMG signal with forces, while we are interested in obtaining the angular position from EMG data.

In this paper we present an algorithm to determine the joint angular positions using a curve fitting in two cases, i.e. a polynomial adjustment method and alternatively a LWPR method. We compare the results and performance of both methods and we validate our approach by comparing the data obtained from the curve fitting with the measurements taken in the same conditions with position sensors NOTCH[1]. The muscles from which we obtain the EMG signal are the Vastus lateralis and the Vastus medialis, whose contraction is mainly related to the knee extension. For the validation we calculate the correlation coefficient (CC) between the angular position measured with the NOTCH and the angular position obtained by applying the two approaches from the EMG signal. In the case of the polynomial adjustment approach, the

[1] https://wearnotch.com/

CC is about 52%, while in the LWPR case the CC is around 37%, considering the whole knee flexion-extension motion. These results indicate that either the polynomial adjustment and the LWPR methods allow to explain the extension of the knee, being the former method better than the latter. First, we give a theoretical background on the curve fitting methods. Then, we address the experiment performed with 20 participants. We use these data to develop and test the algorithm in two cases, first using polynomial adjustment and then the LWPR method, and we validate the results comparing them with angular positions obtained from the NOTCH. Afterwards, we present and discuss the results obtained.

2 THEORETICAL BACKGROUND

As introduced before, the EMG signal is related to the intention of motion. This means that from the EMG measurements we can also get the angular position (Ajoudani et al., 2012), (Ito et al., 2015). This relationship can be obtained as a curve fitting of the EMG data, using a proper method. However, this relationship is complex and vastly individualized, i.e. it depends on the physical characteristics of each person. Several factors contribute to the EMG voltage level, including the distance or orientation of the sensor on the muscles or different physical features of people. This is why a normalization is required and is proposed in this paper.

Besides, to validate the results, the curves obtained from the fitting need to be compared to the joint angular position data. This is done by calculating the correlation coefficient. In the process of fitting, large amount of data and the algorithm have to be processed and this may take some time depending on the information available. In this way, the computational cost is important and there is a trade off between this cost and the obtained results.

In this section, we present the theoretical elements required to develop an algorithm that allows to determine the knee joint angular position from EMG data in a flexion-extension motion, i.e. the two methods for the curve fitting that will be used.

2.1 Polynomial Adjustment

The polynomial adjustment method gives as a result the coefficients of a mathematical function that describes the joint angle in terms of the EMG signal. This method uses a Vandermonde matrix $V \in \mathbb{R}^{(n+1)\times(n+1)}$,

$$V p = Y \,, \tag{1}$$

which can be written as

$$\begin{pmatrix} 1 & x_0 & x_0^2 & \dots & x_0^{n-1} \\ 1 & x_1 & x_1^2 & \dots & x_1^{n-1} \\ 1 & x_2 & x_2^2 & \dots & x_2^{n-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_n & x_{n^2} & \dots & x_n^{n-1} \end{pmatrix} \begin{pmatrix} p_0 \\ p_1 \\ p_2 \\ \vdots \\ p_n \end{pmatrix} = \begin{pmatrix} y_0 \\ y_1 \\ y_3 \\ \vdots \\ y_n \end{pmatrix} . \tag{2}$$

The columns of the matrix V relate the vector x of independent variables of the system. $p \in \mathbb{R}^{n+1}$ is the vector of the polynomial coefficients. $Y \in \mathbb{R}^{n+1}$ is the vector of dependent variables. The coefficients vector of the polynomial fit p are calculated from (1) as a Gaussian reduction.The polynomial order n depends on the motion speed and on how precise the adjustment is desired. In the experiment presented in this paper, we use a polynomial fit of order $n = 20$, because the test is made either for slow and rapid contractions, so the polynomial needs to reach every signal peak.

After the Gaussian reduction, the adjusted polynomial $p(x)$ of order n can be defined as

$$p(x) = p_0 x^n + p_1 x^{n-1} + \dots.. + p_n x + p_{n-1} \,. \tag{3}$$

Notice that x is the EMG signal voltage normalized.

2.2 Locally Weighted Projection Regression LWPR

LWPR is a non-parametric technique in high dimensional space that provides a useful representation as well as training algorithms for learning about complex phenomena based on incremental training. It uses statistically cross validation to learn from data acquired. For nonlinear function approximation, LWPR uses piece-wise linear models (Vijayakumar et al., 2006). This method allows to obtain a model from the EMG signal x, which is then compared with the validation signal from the NOTCH sensor. The EMG signal is different on each person, due to different features. The model obtained is adaptable according to each subject. The prediction $\hat{y}$ of each point of the angular position, with K samples is described by

$$\hat{y} = \frac{\sum_{k=1}^{K} w_k \, y_k}{\sum_{k=1}^{K} w_k} \,, \tag{4}$$

where w_k is a weight for each data point $(x_i\,,\, y_i)$, considering a Gaussian kernel, and it is defined as

$$w_k(x) = e^{-\frac{1}{2}(x) D_k(x)} \,. \tag{5}$$

Here, $D_k(x)$ is a metric distance. The algorithm finds the best approximation of the joint angular position for each subject. The details on the derivation of this method are out of the scope of this paper. For further details, the reader is encouraged to review for example (Vijayakumar and Schaal, 2000; Vijayakumar et al., 2006).

3 EXPERIMENT

To establish a relationship between the EMG signal and the knee angular position we evaluate the maximum-effort contractions made by the vastus lateralis and vastus medialis muscles in the flexion-extension action. To evaluate the algorithms presented on section 2, we carried out an experiment which is reported here. We present the experimental setup and we describe how data was acquired, processed and validated.

3.1 Measurement Setup

We invited 20 healthy participants, i.e. 10 women and 10 men of ages 20 to 45; height 150 cm to 175 cm, and mass 50 to 85 Kg. The participants were informed about the procedure and signed an informed consent. The test consisted on performing maximal isokinetic knee flexion and extension. EMG data and joint angular position data were acquired from noninvasive EMG sensors and Notch position sensors.

In general, each joint in the body is actuated by at least a pair of muscles (agonist-antagonist). Then, the knee flexion is mainly related to the contraction of the Hamstrings (Biceps Femoris, the Semitendinosus and the Semimembranosus) muscles, and the extension is mainly related to the contraction of the vastus medialis (VM), the vastus lateralis (VL) and the rectus femoralis (RF) muscles. According to (Stegeman and Hermens, 2007), to obtain information of the knee joint motion, the EMG sensors must be placed on these muscles. In this paper, we only show the information from the VM and VL (related to the extension), because we are interested in obtaining position from EMG, therefore, we assume that if the algorithms work for the knee extension they will provide also accurate information in the case of flexion and also for other muscles actuating other joints. To use the EMG sensors properly, we have taken into account the recommendations of the SENIAM project[2] (Stegeman and Hermens, 2007). Then, EMG electrodes and NOTCH sensors were placed as shown in Figure 2. The trials were defined to be carried out in sitting position with the legs stretched (i.e. flexed at 100º . Then each person was asked to perform a complete flexion-extension movement (from 0º to 150º) for seven times, continuously with a total duration of 15 seconds (see figure 1).

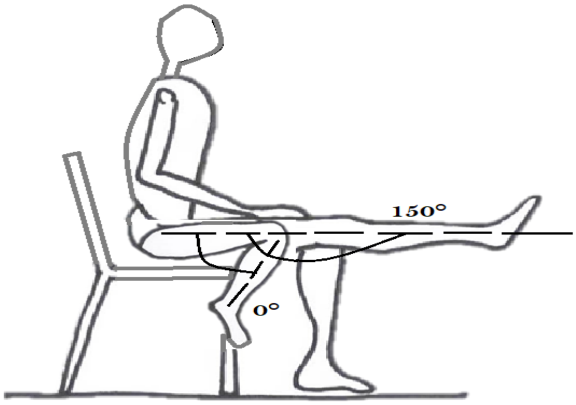


Figure 1: Flexion-extension movement. An angular position of 150ºindicates that the leg is completely extended, and at 0º, it is completely flexed.

3.2 Data Acquisition and Pre-processing

Data for the surface EMG signal was acquired with a sampling frequency $f_{sE} = 1\ KHz$ using the MyoWare^{TM} Muscle Sensor (AT-04-001). Two self-adhesive surface electrodes of diameter 0.5 cm were placed in a bipolar configuration over the VM and VL muscles. The signal was digitally filtered using a Butterworth band-pass filter of twentieth-order, with a lower cutoff frequency of $f_{Lc} = 0.1\ Hz$ and a higher cutoff frequency of $f_{Lc} = 10\ Hz$. The main idea of this filter is to eliminate non important frequencies and noise. NOTCH data were sampled at $f_{sN} = 250\ Hz$. This system saves the information on a smartphone. Then, the data can be sent to a computer in order to read and graph the joint angular position signal, which is used in the experiment to validate the performance and accuracy of the algorithms.

3.3 Processing and Post-processing

Once the signal is acquired and pre-processed, data is normalized by dividing each value by the maximum value of the signal. Afterwards, LWPR and polynomial adjustment algorithms were applied separately. Then, in order to validate the results of the algorithms,

[2] Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles (SENIAM) is a European concerted action in the Biomedical Health and Research Program (BIOMED II) of the European Union that provides recommendations for sensors and sensor placement procedures and signal processing methods for SEMG. More information can be found on: http://www.seniam.org/

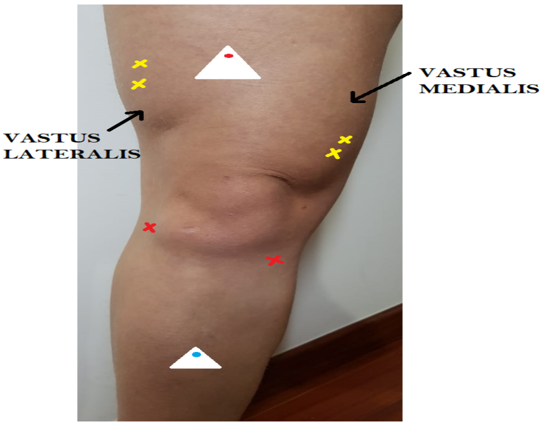


Figure 2: NOTCH and EMG sensors positions. Yellow markings show the position of the electrodes in the bipolar configuration. Red markings indicate the position of the EMG sensors' ground. The white triangles show the NOTCH sensors position.

we compared them to the NOTCH signal. For this, the signal output from the algorithms is amplified and shifted in time, because the EMG signal provides the intention of motion. Additionally, we are working with the normalized signal, and the NOTCH sensor gives the angular position in the corresponding units. Therefore, to determine the amplification gain, we relate the maximum and the minimum points of the normalized EMG signal with the NOTCH signal.

3.4 Validation

The correlation coefficient (CC) allows to determine the linear correlation or similarity between two variables, and $-1 \leq CC \leq 1$, where -1 means a complete inverse linear relation between two signals, 0 indicates no correlation between signals, and 1 denotes the complete correlation between the signals. We compare the joint angular position calculated from the EMG signal in both muscles, the vastus medialis and vastus lateralis, with the joint angular position measured by the NOTCH sensors. Given that the two signals have a different number of samples, to compare the signals, we generated another vector with the samples of the NOTCH signal corresponding to the same instant of time as the output of each algorithm. The CC was evaluated using MATLAB [3].

The computational complexity classifies the computational problems due to their inherent difficulty, to determine whether a certain problem could be solved with a number of resources. The computational complexity can be calculated as the number of operations required to perform a task, or the total required processing time. Other works, such as (Peng, 2008), analyze it by quantum theory. In this document, we will calculate the processing time for the algorithms implemented using the LWPR method and the polynomial approximation, running on an ASUS G5551VW PC with Intel Core i7-6700HQ processor, RAM of 16 GB and NVIDIA GeForce GTX 960M graphic card.

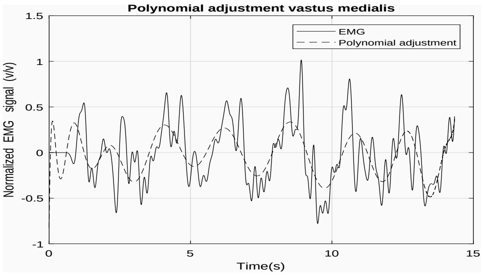
4 RESULTS AND DISCUSSION

The data in the experiment were obtained from the twenty participants that performed the flexion-extension exercises. These data were used for the analysis. In this section, to illustrate the results, we report the mean correlation coefficient CC_{mean}, considering all the participants. In the same way, we show the maximum computational cost applying the two different methods (adjusted polynomial and LWPR), as well as the delay of the signals. The delay represents the time difference between the post-processed signals and the validation signal from the NOTCH sensor. Then, to exemplify the behavior of the EMG signals of the VM and VL, as well as the results of applying both methods (separately) to obtain the angular position, we chose the results of one participant to report it in the Figures in this section. Afterwards, we compare these results with the NOTCH sensor measurements to validate them.

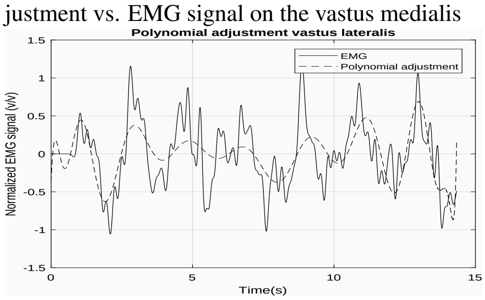
Figure 3 shows the results of applying the polynomial adjustment method to both muscles, the VM and the VL. Observe that the polynomial adjustment curve follows the EMG signal trend even if it does not reach the signal amplitude. As indicated before, the polynomial obtained is of degree 20, which can predict any signal peak. It is worth to remark that a polynomial with a higher degree does not guarantee better results but it implies a higher computational cost. Other approaches may use lower degree polynomials, e.g. (Earp et al., 2013) that obtains a 4th degree polynomial, but the motion in that case is slow, while here it can be either fast or slow.

To validate the polynomial adjustment method we compare the post-processed signal with the NOTCH signal obtained from the same experiment and at the same time. Figure 4 shows the VM and the VL muscles with the polynomial adjustment and the validation signal, where we can see that the algorithm takes approximately three seconds to follow the NOTCH signal. It is worth to remark that the highest peak on the Notch signal represents the subject's muscle maximum-effort contraction. As a result, for the knee extension the angular position signal corresponds to the NOTCH output for the VM

[3]https://la.mathworks.com/help/matlab/ref/corrcoef.html

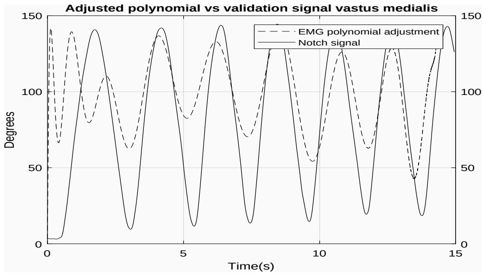


(a) Knee angular position from the Polynomial adjustment vs. EMG signal on the vastus medialis

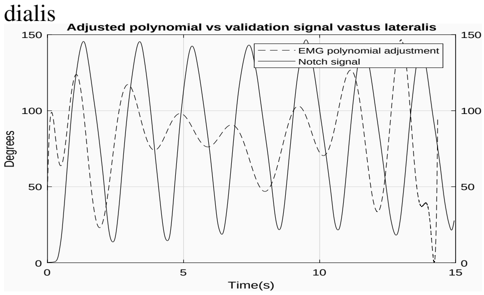


(b) Knee angular position from the Polynomial adjustment vs. EMG signal on the vastus lateralis

Figure 3: Knee angular position obtained from the Polynomial adjustment method and EMG signal from the vastus lateralis and the vastus medialis muscles.



(a) Knee angular position from the Polynomial adjustment vs. Validation signal on the vastus medialis



(b) Knee angular position from the Polynomial adjustment vs. Validation signal on the vastus lateralis

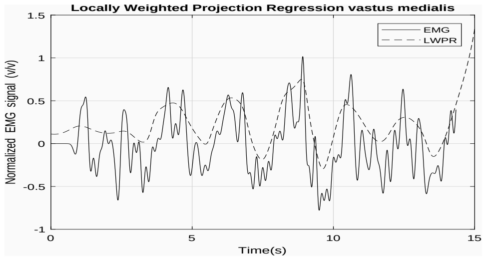
Figure 4: Knee angular position from the Polynomial adjustment compared to the validation signal of NOTCH sensors on the vastus lateralis and the vastus medialis muscles.

muscle in time and amplitude, while for the flexion the polynomial adjustment follows the trend, but does not reach the amplitude. The main reason for this is that the VM and the VL are contracted mainly in the knee extension. The mean correlation coefficient is $CC_{mean} = 0.558$, which indicates that half of the signal (the portion corresponding to the extension) is correctly predicted. Additionally, the VM muscle reveals better results than the evaluation of the VL muscle.

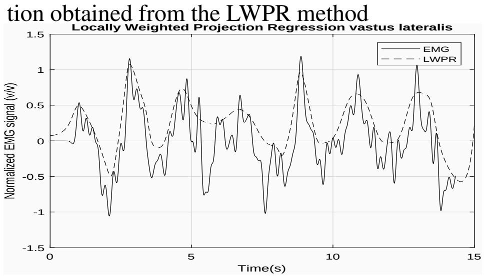
The results of the application of the LWPR method are shown in Figure 5. As presented in section 2.2, each point of the joint angular position is estimated from the EMG signal for each user. Figures 5(a) and 5(b) show the angular joint position obtained from the application of the LWPR approach for the VM muscle, and for the VL muscle respectively. In the former case, the algorithm works properly after 2.5 s of execution. This means that the first data, up to 2.5 s are not valid and we do not consider them for the validation. It can be seen that LWPR algorithm tries to follow the maximum peaks of the signal for both muscles, but it presents problems in following the minimum values for the VL and the VM, different from the polynomial approach that works better in following both the minimum and maximum peaks.

Tables 1 and 2 show the correlation coefficient (CC) obtained when comparing the NOTCH signal with the outputs of the algorithms after the signal post-processing. As a result, for the VM muscle, $CC_{mean} = 0.356$ and $CC_{mean} = 0.558$ for the LWPR and the polynomial adjustment respectively. On the other hand, for the VL muscle, $CC_{mean} = 0.3741$ and $CC_{mean} = 0.500$ for the LWPR and the polynomial adjustment respectively. These results can also be observed in Figures 4(a), and 6(a) previously analyzed, where the polynomial adjustment reaches better results than the LWPR method. The CC shows that the approaches of each algorithm explain the knee extension, because the VM and VL muscles are mainly contracted when the knee is extended. However, in order to evaluate the total range of motion during the knee flexion-extension, it is necessary to use the signals obtained from other muscles such as the hamstring. The VM EMG data allows to explain better the joint angular position than the VL. This can be seen comparing the CC, that in the first case is of about 50% while in the latter is about 37%.

Finally, to evaluate the computational cost in terms of the time required to finish the processing, we tested the algorithms on an ASUS G5551VW with Intel Core i7-6700HQ processor, RAM of 16 GB and an NVIDIA GeForce GTX 960M graphic card. The time required by the LWPR method was 310.55 s, while the time required for the polynomial adjustment was

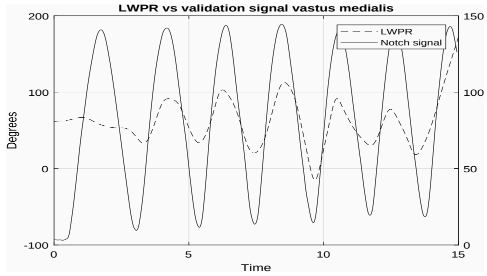


(a) Polynomial set in the VM: knee angular position obtained from the LWPR method

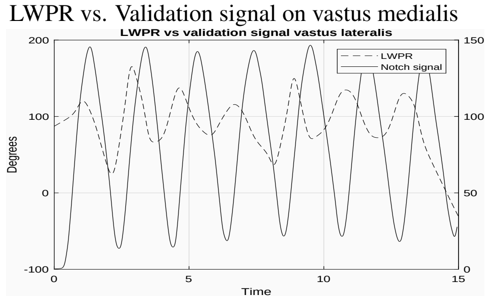


(b) Polynomial set in VL: knee angular position obtained from the LWPR method

Figure 5: Knee angular position from the LWPR method and EMG signal from the vastus lateralis and the vastus medialis muscles.



(a) Knee angular position obtained from the LWPR vs. Validation signal on vastus medialis



(b) Knee angular position obtained from the LWPR vs. Validation signal on vastus lateralis

Figure 6: Knee angular position obtained from the LWPR method compared with the validation signal of the vastus lateralis and the vastus medialis.

0.222 *s*. The former method spends more time because of the learning processes and the prediction of the required parameters.

Table 1: Validation data on vastus medialis.

Vastus medialis		
Metod	CC_{mean}	Delay(s)
LWPR	0.356	-0.325
P adjustment	0.558	-0.114

Table 2: Validation data on vastus lateralis.

Vastus lateralis		
Metod	CC_{mean}	Delay(s)
LWPR	0.3741	-0.775
P adjustment	0.500	-0.74

5 CONCLUSION

We have presented an algorithm to determine the joint angular positions from surface Electromyography (EMG) measurements with the aim of using these data for control systems of assistive devices. Two approaches have been explored, i.e. a polynomial adjustment method and a LWPR method. These methods allow a curve fitting to obtain joint angular position from EMG. To validate the obtained curves, we compared the data obtained from the curve fit with the measurements obtained with position sensors NOTCH. In order to obtain EMG data from the flexion-extension motion, an experiment was carried out, in which 20 subjects participated. As a result, we found that the polynomial adjustment method evaluating the EMG signal over the vastus medialis muscle reached a higher similarity compared to the NOTCH sensor signal. This test allowed to obtain similar signals from the curve fitting of the EMG data, compared with the NOTCH sensor in the extension of the knee. This results are coherent because the muscles from which we obtained the EMG data (i.e. the vastus lateralis and the vastus medialis) are the main muscles involved in the knee extension. Future work will be oriented to use signals from other muscles to explain completely the flexion-extension range of motion. This analysis can be done using more EMG sensors. We expect to use real time algorithms but as a drawback the computational cost will be incremented.

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REFERENCES

Ajoudani, A., Tsagarakis, N. G., and Bicchi, A. (2012). Tele-impedance: Towards transferring human impedance regulation skills to robots. In *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, pages 382–388. IEEE.

Akhtar, A. (2016). *Estimation of distal arm joint angles from EMG and shoulder orientation for transhumeral prostheses*. PhD thesis.

Altobelli, A., Bianchi, M., Catalano, M. G., Serio, A., Baud-Bovy, G., and Bicchi, A. (2015). An instrumented manipulandum for human grasping studies. In *Rehabilitation Robotics (ICORR), 2015 IEEE International Conference on*, pages 169–174. IEEE.

Chen, J., Zhang, X., Cheng, Y., and Xi, N. (2018). Surface emg based continuous estimation of human lower limb joint angles by using deep belief networks. *Biomedical Signal Processing and Control*, 40:335–342.

Earp, J. E., Newton, R. U., Cormie, P., and Blazevich, A. J. (2013). Knee angle-specific emg normalization: The use of polynomial based emg-angle relationships. *Journal of Electromyography and Kinesiology*, 23(1):238–244.

Ema, R., Wakahara, T., and Kawakami, Y. (2017). Effect of hip joint angle on concentric knee extension torque. *Journal of Electromyography and Kinesiology*.

Fang, C., Ajoudani, A., Bicchi, A., and Tsagarakis, N. G. (2018). Online model based estimation of complete joint stiffness of human arm. *IEEE Robotics and Automation Letters*, 3(1):84–91.

Freriks, B. and Hermens, H. (2000). *European recommendations for surface electromyography: results of the SENIAM project*. Roessingh Research and Development.

Garabini, M., Della Santina, C., Bianchi, M., Catalano, M., Grioli, G., and Bicchi, A. (2017). Soft robots that mimic the neuromusculoskeletal system. In *Converging Clinical and Engineering Research on Neurorehabilitation II*, pages 259–263. Springer.

Huo, W., Mohammed, S., Moreno, J. C., and Amirat, Y. (2016). Lower limb wearable robots for assistance and rehabilitation: A state of the art. *IEEE Systems Journal*, 10(3):1068–1081.

Ito, S., Inui, D., Tateoka, K., Matsushita, K., and Sasaki, M. (2015). Wrist angle estimation based on bilinear model using electromyographic signals from circularly-attached electrodes. In *2015 54th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)*, pages 1167–1172.

Jensen, G. M. and Lorish, C. D. (1994). Promoting patient cooperation with exercise programs. linking research, theory, and practice. *Arthritis and Rheumatism*, 7:181–189.

Khan, K. M. and Scott, A. (2009). Mechanotherapy: how physical therapists' prescription of exercise promotes tissue repair. *British Journal of Sports Medicine*, 43(4):247–252.

Koller-Hodac, A., Leonardo, D., Walpen, S., and Felder, D. (2010). A novel robotic device for knee rehabilitation improved physical therapy through automated process. In *2010 3rd IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics*, pages 820–824.

Koller-Hodac, A., Leonardo, D., Walpen, S., and Felder, D. (2011). Knee orthopaedic device how robotic technology can improve outcome in knee rehabilitation. In *2011 IEEE International Conference on Rehabilitation Robotics*, pages 1–6.

Li, H. and Cheng, L. (2017). Preliminary study on the design and control of a pneumatically-actuated hand rehabilitation device. In *2017 32nd Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, pages 860–865.

Mghames, S., Laghi, M., Santina, C. D., Garabini, M., Catalano, M., Grioli, G., and Bicchi, A. (2017). Design, control and validation of the variable stiffness exoskeleton flexo. In *2017 International Conference on Rehabilitation Robotics (ICORR)*, pages 539–546.

Pang, M. and Guo, S. (2013). A novel method for elbow joint continuous prediction using emg and musculoskeletal model. In *2013 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pages 1240–1245.

Peng, W. (2008). Energy analysis method of computational complexity. In *2008 International Symposium on Computer Science and Computational Technology*, volume 2, pages 682–685.

Ren, Y., Wu, Y., Yang, C., Xu, T., Harvey, R. L., and Zhang, L. (2017). Developing a wearable ankle rehabilitation robotic device for in-bed acute stroke rehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(6):589–596.

Stegeman, D. and Hermens, H. (2007). Standards for suface electromyography: The european project surface emg for non-invasive assessment of muscles (seniam). 1.

Umivale, P. S. (2011). Patología de la rodilla: Guía de manejo clínico.

Vijayakumar, S., D'Souza, A., and Schaal, S. (2006). Incremental online learning in high dimensions. *Neural computation*, 17:2602–34.

Vijayakumar, S. and Schaal, S. (2000). Locally weighted projection regression: An o(n) algorithm for incremental real time learning in high dimensional spaces. In *Proceedings of the Seventeenth International Conference on Machine Learning (ICML 2000)*, volume 1, pages 288–293, Stanford, CA. clmc.

Wang, P., McGregor, A. H., Tow, A., Lim, H. B., Khang, L. S., and Low, K. H. (2009). Rehabilitation control strategies for a gait robot via emg evaluation. In *2009 IEEE International Conference on Rehabilitation Robotics*, pages 86–91.

Yap, H. K., , Nasrallah, F., Goh, J. C. H., and Yeow, R. C. H. (2015). A soft exoskeleton for hand assistive and rehabilitation application using pneumatic actuators with variable stiffness. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pages 4967–4972.