Estimating EMG Signals to Drive NeuroMusculoSkeletal Models in Cyclic Rehabilitation Movements*

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***Abstract*— A main challenge in the development of robotic rehabilitation devices is how to understand patient's intentions and adapt to his/her current neuro-physiological capabilities. A promising approach is the use of electromyographic (EMG) signals which reflect the actual activation of the muscles during the movement and, thus, are a direct representation of user's movement intention. However, EMGs acquisition is a complex procedure, requiring trained therapists and, therefore, solutions based on EMG signals are not easily integrable in devices for home-rehabilitation.**

This work investigates the effectiveness of a subject- and task-specific EMG model in estimating EMG signals in cyclic plantar-dorsiflexion movements. Then, the outputs of this model are used to drive CEINMS toolbox, a state-of-the-art EMG-driven neuromusculoskeletal model able to predict joint torques and muscle forces. Preliminary results show that the proposed methodology preserves the accuracy of the estimates values.

I. INTRODUCTION

Population aging and neurological diseases or injuries are the main causes of the increasing number of people with locomotion disorders. Despite the high effectiveness of therapists-based rehabilitation on restoring motor functionalities [5], [8], high cost and strong dependency on therapist skills limit their availability to the patients. To decrease the cost and speed up the recovery process, robotic technologies such as automated treadmill [4] or active orthoses [1], have been increasingly introduced in rehabilitation to assist the patient in the repetition of exercises. However, most of these devices are based on preprogrammed control strategy where the patient is not actively involved, reducing treatment effectiveness. Furthermore, subject monitoring is still demanded to the therapist during periodic manipulation. The development of a new generation of rehabilitation devices aims at overcoming these limitations, through the capability of understanding patient's intention and adapt to his/her current neuro-physiological state.

Knowledge of internal muscle forces, joint moments, and other dynamic variables during the movement could definitely help in monitoring patient condition, intention, and improvement during the rehabilitation treatment thus improving its effectiveness. Since in vivo muscle force measurements are not feasible, a promising solution is to develop approaches based on EMG-driven NeuroMusculoSkeletal (NMS) models [2]. These models (Sec. II-E) take as input electromyographic (EMG) signals, i.e. the electrical potential generated in the muscles, and estimate joint torques, muscle forces, and other internal dynamic parameters. Main advantages of using EMG signals are the strongly correlation with the subject's motion intention and the non-invasive acquisition procedure. However, EMGs quality is highly dependent on sensors placement, thus requiring professional skills, and can also be affected by electric and magnetic noise. These issues definitely prevent the possibility of using the approach in home-rehabilitation.

This scenario justifies the methodology proposed in this work. The objective is to investigate the possibility to use EMGs estimated by a model instead of the directly acquired ones as input for the EMG-driven NMS model. While the highly variability of EMG signals prevents to develop an EMG model for the general case, we tackled only the simple and cyclic movement of plantar-dorsiflexion (P-DF). Despite being a simple and cyclic movement, it has a great relevance in rehabilitation of ankle injuries as sprains or fractures [7]. After the development of the EMG model to estimate synthesized signals, those are used to drive CEINMS, an EMG-driven NMS modeling toolbox able to predict joint torques and muscle forces. This paper reports the first assessment of the methodology with an healthy subject performing a P-DF cyclic movement at six different controlled speeds. Previous results on five subjects performing P-DF movements already demonstrated that it is possible to achieve a good accuracy in EMGs prediction [9]. This work evaluates the possibility of their use as input for EMG-driven neuromusculoskeletal model to predict ankle torque. The main advantage of the proposed approach is that, once a subject- and task-specific EMG model has been defined, no EMG recordings are needed to drive the NMS model. EMG acquisition could, therefore, be limited to periodical recalibration of the model to account for patient improvements. Despite its applicability limited to repetitive movements, the proposed approach would enable the use of home-rehabilitation devices while monitoring the patient efforts.

II. METHODS

A. Equipments and Experimental Setup

For this preliminary study, we recruited one healthy subject, 25 years old, with a body mass of 64 kg and a height of 1.75 m. The participant had no disorder that could influence his movements, and provided written informed consent prior to participation. The study was conducted in accordance

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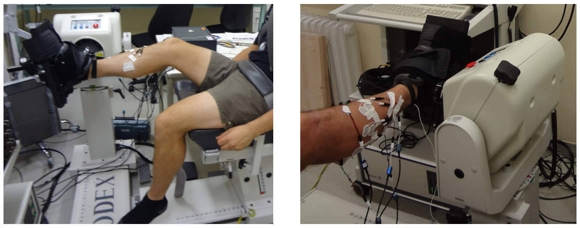

(a) (b)

Fig. 1. (a) Subject on S3P, (b) EMG electrodes placement on the subject [3]

with the Declaration of Helsinki. EMG signals were collected with a EMG-USB2 System (OT Bioelettronica, Turin, Italy) from the following muscles: Gastrocnemius Lateralis, Gastrocnemius Medialis, Soleus, Peroneus Longus, Tibialis Anterior. Electrodes were placed according to SENIAM recommendation [3]. A System 3 Pro (S3P) dynamometer (Biodex Corp., Shirley, NY) was used in isokinetic mode to drive the movement (trajectory and speed) of the subject. Motor joint torque and kinematic data measured by the S3P and signals from the EMG amplifier were synchronously acquired at a sample rate of 2048 Hz.

B. Experimental Procedure

The participant was asked to comfortably sit on the S3P with the right knee at 40° and the right foot on the S3P stand (Fig. 1(a)). Before the acquisition, he was shortly instructed on the procedure and practiced P-DF movements. Then, the subject was instructed to perform P-DF movements at the speed imposed by the S3P producing his maximum effort, trying somehow to speed up the movement. The subject was provided with a visual feedback on his current effort to help in the correct execution of the experiment. Each step was executed at six different speeds, chosen for feasibility and safeness for the subject: 30, 45, 60, 75, 90, and 120 °/s. For each step and speed, at least five acquisition were registered, each one including four P-DF repetitions. With the objective of evaluating the effect of the fatigue, additional data were acquired repeating the same acquisition setup but asking the subject to modulate his effort at 75, 50, 25 percent of his maximum following the visual feedback.

C. Data Processing

Raw EMG signals were high-pass filtered (Butterworth, IV order, 300 Hz), rectified, and low-pass filtered (Butterworth, IV order, 8 Hz) [6]. The resulting EMG linear envelopes were then normalized using the maximum EMG peak through all the acquisition.

D. EMG Model

The EMG model aims at estimating EMG signals from ankle speed and position during P-DF movements (Fig. 2).

Starting from nine P-DF cycles for each speed, mean EMG curves for each muscle were first computed. Then, curves at different speeds were time warped over 2000 samples to

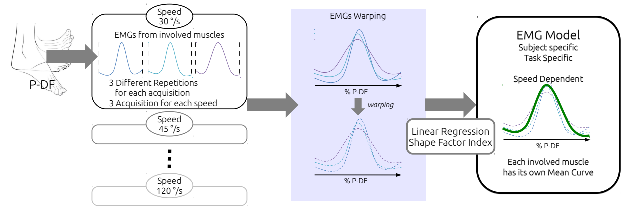

Fig. 2. EMG model schema.

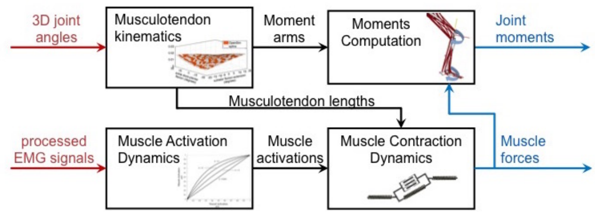

Fig. 3. Schematic structure of the EMG-driven NeuroMusculoSkeletal model.

release the time dependence (Eq. 1) and obtain EMG values for muscle m at speed s as a function of the sample k:

$$emg_{m,s}(t) \rightarrow emg_{m,s}(k) \quad (1)$$

Then, the resulting curves were combined to obtain a single average curve for each muscle:

$$EMG_m(k) = \frac{\sum_s emg_{m,s}(k)}{N_s} \quad (2)$$

From these curves, it is possible to estimate EMGs during the rehabilitation treatment. Starting from the time required to complete a P-DF cycle (input of the model), for each muscle, the previously computed average EMG curve is unwarped to match the current speed thus generating a first prediction of EMG signals. Finally, a shape factor is also introduced to account for the speed dependence of the EMG signal amplitude.

E. EMG-driven NMS Modeling

To estimate ankle torque and muscle forces expressed by the subject we used a subject-specific EMG-driven NeuroMusculoSkeletal (NMS) model. This model reproduces the process with which muscles transform neural commands into movement and can be used to estimate the forces generated inside the human body. Fig. 3 shows a schematic representation of an EMG-driven NMS model, composed of four blocks. The *Musculotendon Kinematics* block uses the joint angles measured by the S3P to compute musculotendon lengths and moment arms of the muscles. The *Muscle Activation Dynamics* block transforms normalized EMG signals into muscle activations, accounting for the non linearity that exists between muscle excitations and muscle forces. It also introduces a recursive filter to represent the muscle twitch response [6]. The *Muscle Contraction Dynamics* block combines together muscle activations and musculotendon lengths to generate estimates of the forces

TABLE I

COMPARISON BETWEEN ESTIMATED AND EXPERIMENTAL EMGS AT DIFFERENT SPEEDS, AVERAGED USING 3 TRIALS FOR EACH MUSCLE.

Speed (°/s)	RMSE ± STD	R^2± STD
30	0.09 ± 0.028	0.664 ± 0.146
45	0.079 ± 0.02	0.854 ± 0.07
60	0.072 ± 0.015	0.882 ±0.06
75	0.078 ± 0.018	0.9 ± 0.043
90	0.083 ± 0.016	0.879 ± 0.048
120	0.096 ± 0.012	0.861 ± 0.047

produced by the musculotendon units (MTUs). The model includes a set of muscle parameters, which are initially estimated from literature or measured from medical images, and then calibrated as described in [6]. Finally, once the forces produced by the muscles are available, the *Moments Computation* block projects these forces to the desired degrees of freedom (DOF). In summary, the EMG-driven NMS model can estimate muscle forces and joint moments at multiple DOFs using only 3D joint angles and EMG signals as inputs, either measured or estimated, as in our case. The implementation of this step is based on two different tools: the Calibrated EMG-Informed NMS Modelling Toolbox (CEINMS)[1], a state-of-the-art EMG-driven NMS model we have recently developed; and OpenSim[2] to develop a musculoskeletal anatomical model of the subject.

III. RESULTS

To validate the proposed approach, outputs of the two models were compared with experimental data from validation trials not previously used to build the models. First, EMG signals estimated by the model (Synt. EMGs) were compared with experimental ones to assess their accuracy and reliability, spanning all the muscles and different speeds. Then, both synthetic and experimental EMGs were used as input for the NMS model to predict ankle joint moments and muscle forces. Validation was performed comparing predicted and experimental ankle torques since muscle forces, albeit the most interesting output, cannot be measured in a non-invasive way.

A. *EMG Model Validation*

EMGs estimated by the model (Synt. EMG) were compared with measured ones for trials not used during the model creation procedure (Fig. 4). Tab. I reports root mean square error (RMSE) and Pearson product moment correlation R^2 for the different speeds. Achieved performance are quite promising, both in terms of R^2 and RMSE for almost every tested speed. Slightly worst performance at the lowest speed (R^2 close to 0.66) is possibly due to the difficulties of the subject in following the S3P at this extremely low speed. Indeed, Biodex Reference Manual suggests 60°/s as the lowest speed for reliable acquisitions of P-DF movements. However, these estimated EMGs will be useful to assess

[1]https://simtk.org/home/ceinms
[2]http://opensim.stanford.edu/

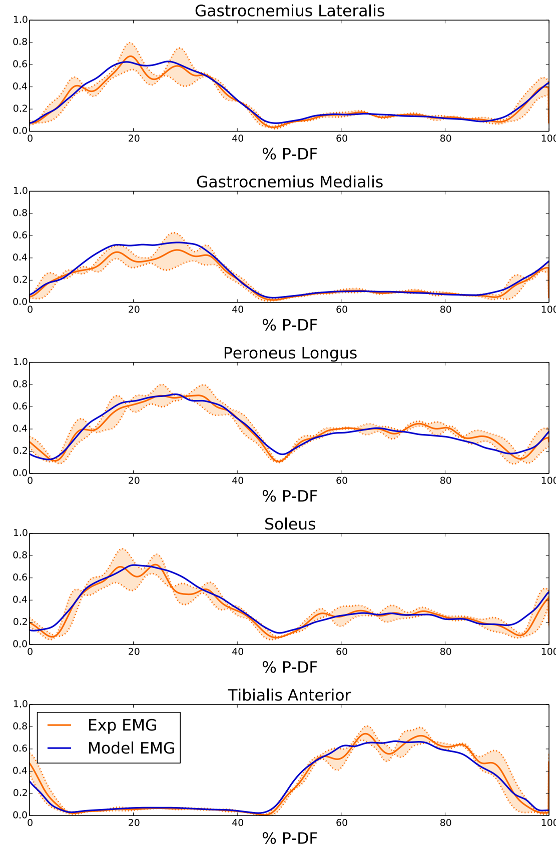

Fig. 4. Comparison between estimated EMG signals and measured ones for each recorded muscle. Results are reported as a percentage of the P-DF cycle at speed 60°/s. Light orange areas reports the ± STD intervals of the reference.

TABLE II

COMPARISON BETWEEN ESTIMATED AND EXPERIMENTAL EMGS ON DIFFERENT MUSCLES AVERAGED USING 3 TRIALS FOR EACH SPEED.

Muscle	RMSE ± STD	R^2± STD
Gastrocnemius Lateralis	0.068 ± 0.013	0.876 ± 0.087
Gastrocnemius Medialis	0.069 ± 0.015	0.867 ± 0.088
Peroneus Longus	0.094 ± 0.017	0.789 ±0.128
Soleus	0.089 ± 0.014	0.806 ± 0.139
Tibialis Anterior	0.094 ± 0.023	0.802 ± 0.048

the impact of higher errors on the behavior of NMS model (Sec. III-B). The analysis of the accuracy of the EMG model for the different muscles (Tab. II) shows an average RMSE of 0.083 ± 0.013, i.e. less than 10%. High values were also achieved for R^2 (0.848 ± 0.078), showing a good correlation between estimated and measured EMGs. Evaluation of effects of muscles fatigue were also investigated, obtaining no relevant differences.

B. *Torques Validation*

The second step of the validation procedure aimed at assessing the accuracy of the predicted ankle torque when estimated EMG signals are used as input for the NMS model (CEINMS) instead of the measured ones. First, torques predicted using measured EMGs were compared with the

TABLE III

TORQUE VALIDATION STATISTICAL RESULTS.

Speed °/s		Measured Vs Exp. CEINMS	Synt. CEINMS Vs Exp. CEINMS
30	RMSE ± STD	14.352 ± 1.818	8.667 ± 0.516
	R^2 ± STD	0.891 ± 0.031	0.928 ± 0.013
45	RMSE ± STD	13.912 ± 1.747	5.403 ± 1.169
	R^2 ± STD	0.85 ± 0.03	0.973 ± 0.013
60	RMSE ± STD	15.055 ± 2.095	5.003 ± 1.164
	R^2 ± STD	0.888 ± 0.019	0.981 ± 0.006
75	RMSE ± STD	12.273 ± 1.33	5.645 ± 1.431
	R^2 ± STD	0.895 ± 0.024	0.98 ± 0.008
90	RMSE ± STD	12.09 ± 0.679	6.377 ± 1.536
	R^2 ± STD	0.878 ± 0.014	0.977 ± 0.012
120	RMSE ± STD	12.302 ± 1.26	6.325 ± 1.42
	R^2 ± STD	0.883 ± 0.023	0.981 ± 0.011

experimental torques measured with the S3P (Tab. III-"Measured Vs Exp. CEINMS" column). A R^2 higher than 0.85 confirm a very good correlation, while RMSE shows a worst behavior. However, this error is mainly due to the prediction of the first peak, i.e. when the subject changes from dorsi to plantarflexion. This was partially expected since the subject reported difficulties in synchronously follow the S3P support in this phase, resulting in a experimental torque mainly due to the S3P contribution. Then, estimated EMG signals were used as input of the NMS model to assess the impact on the final predicted torque (Tab. III-"Synt. CEINMS Vs Exp. CEINMS" column). An overall R^2 of 0.97 ± 0.02 and RMSE of 6.24 ± 1.30 are very promising results for the proposed methodology as also clearly visible in Fig. 5.

IV. CONCLUSIONS

While EMG-driven NMS models are powerful tools able to provide information about muscle forces, joint torques, and other internal dynamic parameters, they require EMG signals as input. This prevents the use of the tools by untrained people and, therefore, in home-rehabilitation.

This work investigated the possibility to avoid EMGs measurements using EMGs estimated with a subject- and task-specific EMG model. In a previous work we have already demonstrated the possibility to accurately predict EMG in cyclic P-DF movements [9]. The preliminary results of this work demonstrate that the predicted ankle torque for plantar-dorsiflexion (P-DF) movements does not change significantly when EMGs estimated by a model are used as input of the NMS model. This opens the possibility to monitor patient's efforts during rehabilitation, allowing therapists to quantitatively assess the impact of the therapy. While the proposed approach is only applicable to simple, cyclic tasks, still the methodology has a high potentiality due to their relevance in rehabilitation treatments. We are currently applying this methodology to a larger set of people, including unhealthy subjects, to assess the reliability and the intra-subject variability of the obtained results.

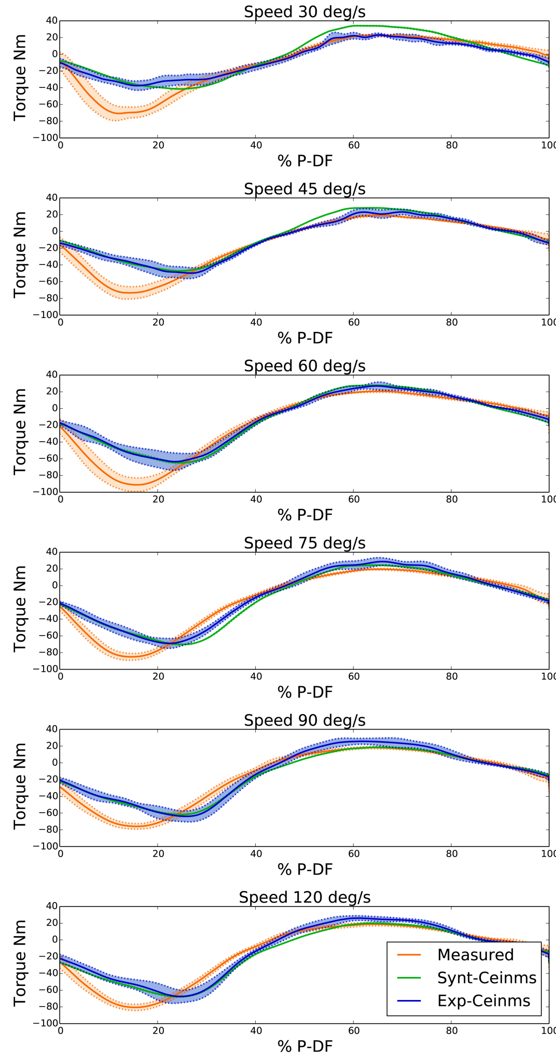

Fig. 5. Comparison between measured torques (orange line), and the ones estimated by CEINMS, either using experimental EMG signals as input (blue line), or estimated EMG signals (green line). Results are reported as a percentage of the P-DF cycle at each speed. The light areas report the ± STD intervals of the torque values.

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