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Clusterization of multi-channel electromyograms into muscle-specific activations to drive a subject-specific musculoskeletal model: towards fast and accurate clinical decision-making*[1]

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***Abstract*— Current clinical decision-making is based on rapid and subjective functional tests such as 10 m walking. Moreover, greater accuracy can be achieved at the expense of rapidity and costs. In biomechanical laboratories, advanced technologies and musculoskeletal modeling can quantitatively describe the biomechanical reasons underlying gait disorders. Our work aims to blend clinical rapidity and biomechanical accuracy through multi-channel (MC) electromyography (EMG) clustering and real-time neuro-musculoskeletal (NMS) modeling techniques integrated into a sensorized wearable garment that is quick to set up. Here we present a unique pipeline that goes from MC EMG signals to ankle torque estimation following two steps: (1) non-negative matrix factorization (NNMF)-based EMG clustering for the extraction of muscle-specific activations and (2) subject-specific EMG-driven NMS modeling. The results show the potential of NNMF as an electrode clustering tool, as well as the ability to predict joint torque during movements that were not used for the EMG clustering.**

***Clinical Relevance*— The integration of advanced signal processing and real-time musculoskeletal modeling integrated into a smart wearable garment has a good potential to become a promising tool for diagnosis. It could provide a window on the musculoskeletal reasons of the subjects' dysfunctional muscle activity for fast and accurate clinical decision-making.**

I. Introduction

Worldwide, one of the leading causes of motor disability is stroke. One in four adults over the age of 25 will have a stroke in their lifetime and the forecast of the spreading of this disease sees the number of strokes increasing the double [1]. Furthermore, the majority of patients surviving a stroke keeps physical disabilities and, due to the impact of the stroke on each individual, choosing the correct rehabilitation treatment is complicated. Two are the key aspects in movement rehabilitation clinical environments, motor assessment accuracy and rapidity. Currently, it remains unknown what muscle functions are used during a motor activity and how the muscle strength changes during treatment. Clinical decision-making is indeed relying on simplistic but rapid tools to assess the patients' motor function, the functional ambulatory categories (FAC), i.e. 10m walk [2]. The evaluation is rather subjective and varies between the clinicians' knowledge and experience. On the other hand, in biomechanical laboratories, the availability of advanced technologies, such as motion tracking systems, electromyography (EMG), and force plates, combined with musculoskeletal modeling techniques can give more accurate insights into the actual patients' state. However,

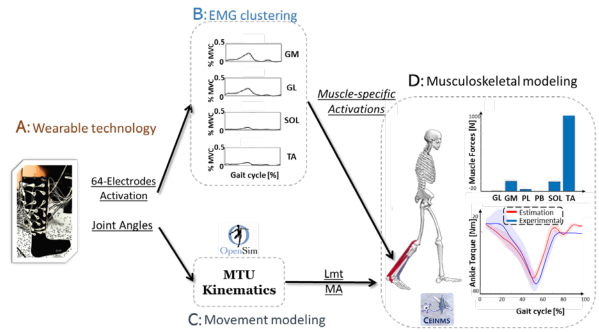

Figure 1: Schematics representation of the proposed technology: (A) fully wearable soft sensorized garment; (B) signal processing techniques to reduce the 64 electrodes space in 4 MTU activations; (C) transform the joint angles in MTU length and moment arm

the accuracy is achieved at the expense of rapidity so that the lengthy setup, such as the process of manual muscle localization for electrode placement, joint angle measurements, and the time-consuming post-processing of the data prohibit the translation of advanced technologies in clinics. Our work aims to balance clinical rapidity and biomechanical accuracy to provide clinicians with an asset to quickly and quantitatively characterize patients' motor deficits and recovery trends. We propose (see Fig. 1) to use advanced signal processing techniques and real-time (RT) neuro-musculoskeletal (NMS) modeling integrated into a smart wearable garment thereby avoiding lengthy post-processing of movement data. The wearable garment is a lower leg sock instrumented with a large-scale multi-channel (MC) EMG grid and inertial motion unit (IMUs) sensors. It can allow reducing the setup time as well as enhancing repeatability in muscle selection and preventing human errors when manually identifying muscles and electrodes' location. The smart clothing together with advanced signal processing techniques can provide muscle activations and muscle-tendon unit (MTU) kinematics. Those are necessary to finally model in RT the subject-specific NMS properties.

In the last decades, EMG-driven modeling has been developed and used to estimate human-generated muscle forces and resulting joints torques in real-time [3], [4] over a wide range of tasks and degrees of freedom (DOF). Although, in these studies, the setup included expensive and time-consuming technologies as well as susceptible to human error. We want to further improve existing RT NMS modeling frameworks linking them to an innovative smart wearable technology sensorized with MC-EMG in combination with

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clustering techniques. The wearable garment and the clustering technique allow using the RT NMS in clinical environments where rapidity and accuracy are necessary for optimal subject-specific rehabilitation strategy.

We then present the experimental protocol and the results for (1) the automatic extraction of 4 muscle-specific activations from an MC-EMG grid and (2) ankle torques estimation during locomotion at different speeds using offline EMG-driven NMS modeling.

II. EXPERIMENTS

Three healthy participants (66% male, age = 27 ± 1 years, height = 1,7 ± 0.09 m, mass = 75 ± 17,7 kg) with no recurrent or recent lower limb injuries participated. The study was approved by the University of Twente and all the participants provided informed written consent.

A. *Experimental protocol*

The protocol included the recording of EMG data, markers trajectories and ground reaction forces (GRF). The surface EMG signals were recorded at 2048 Hz from the right lower leg using a wearable garment with an integrated grid of 64 monopolar dry electrodes. Furthermore, 33 reflective markers were placed on the subject's body and the markers' trajectories were recorded at 128 Hz from a motion tracking system (Qualisys Oqus, Qualisys AB, Sweden). Finally, the GRFs were recorded at 1024 Hz using an instrumented treadmill (M-Gait, MotekForce Link, The Netherlands).

The experimental protocol consisted in 5 tasks. First, the subjects were asked to stand on a static pose for few seconds and then to perform a maximal voluntary contraction (MVC). Afterward, the subjects performed locomotion tasks at the speed of 1km/h, 3km/h, and 5 km/h.

III. METHODS

A. *EMG clustering method*

The 64 EMG electrodes space was reduced into a 4 muscles space. The dimensionality reduction was obtained in two steps (see Fig. 2), both based on non-negative matrix factorization (NNMF) [5] on 64 normalized linear envelopes.

The first step of the clustering consisted of applying NNMF on the 64 normalized linear envelopes of the slowest speed to extract 2 synergistic behaviors explained by two decomposed matrixes. The primitives' matrix suggested in which percentage of the gait cycle the activation occures while the weights highlighted how much each electrode activated in these moments. From the second matrix two main active zones were identified, a cluster of electrodes that contributes to the activation of the Triceps Surae (TS) during the push-off phase and a cluster related to Tibialis Anterior (TA) contraction. To automatically distinguish the primitives of the TS and TA muscle groups, a sorting algorithm based on the main primitive peaks' position was applied. Afterward, the main active electrodes from TA synergy were extracted and link to the TA. From the TS synergy, is not possible to automatically extract clusters of electrodes specific for Gastrocnemius Medialis (GM) and Lateralis (GL), and Soleus (SOL).

The second step of the proposed clustering method consisted of applying the NNMF a second time. The NNMF is

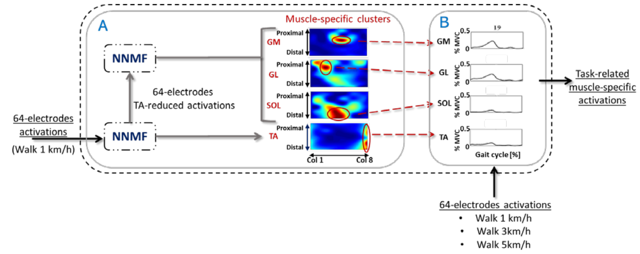

Figure 2: Schematic representation of the implemented clustering methodology that includes 2 steps: (A) extraction of muscle-specific cluster via NNMF and (B) determination of task-related muscle-specific activations

a parts-based representation that can recognize different additive details of the non-negative input object able to reconstruct the input. The NNMF is here used to extract from the TS activation three different muscle-specific contributions GM, GL, and SOL. The inputs matrix of the second NNMF were the normalized linear envelopes deducted of the reconstructed envelopes from the TA synergy. To associate the most active channels of the three synergies to each muscle we used the anatomical information: the SOL is supposed to be in a distal position to the knee joint, while the GM is medial, and the GL is lateral with respect to the TA. Once extracted 4 electrodes' groups, the muscle-specific activations, from now on referred to as automatic activations (A_a), are computed for each locomotion speed. This is done by averaging the normalized linear envelopes of each electrode's cluster.

To validate the A_a, manual muscle activations (A_m) were computed using two adjacent electrodes manually selected from the multi-channel grid on top of each muscle belly.

B. *Movement modeling*

The open-source software OpenSim [6] is used to model the subject-specific musculoskeletal geometry. The OpenSim default model (a 12-segment, 19 DOF) is first scaled to match the subject-specific anthropometry. For this, marker data of a static trial are used. Secondly, the scaled model and the markers' trajectories are inputs to the inverse kinematics (IK) to retrieve joint angles. Afterward, the joint angles are transformed into musculotendon units (MTUs) lengths (Lmt), and moment arms (MA). Lastly, the inverse dynamics takes the scaled model, the IK, and GRFs to compute the experimental joint moments (T_{exp}).

C. *Musculoskeletal modeling*

The CEINMS toolbox [7] allows estimating subject-specific neuromechanical properties during movements. To accurately predict joint torque, the NMS model needs to be calibrated to match the subject-specific parameters that describe how MTUs activate and contract. These values vary non-linearly across individuals and need to be optimized to best match the individual's physiology and anatomy. For each locomotion speed, we took the first 8 seconds of the MTU activations, Lmt, MA, and the T_{exp} to obtain a subject-specific and task-related calibrated model for both input conditions: A_m and A_a. Finally, we estimated torque (T_{est}) during each walking task using the related calibrated model and the process data for Lmt, MA, and MTU activations in both manual (T^m_{est}) and automatic (T^a_{est}) conditions.

D. Data processing

The raw EMG data were inspected to find channels with large voltage fluctuations. The channels with a standard deviation larger than 20 times the median absolute deviation from the median among all channels, were put to zero. The inspected EMG data were then band-pass filtered between 20 Hz and 450 Hz using a zero-lag 2nd order Butterworth filter and fully rectified. The rectified signals were further inspected to remove noise. The *filloutliers* Matlab function was used to find local outliers with a specified moving method, (*movmedian*), according to a window length fixed to *0.3* times the sampling frequency. All the samples outside of the 3.5 percentiles were replaced with a filling method based on shape-preserving piecewise cubic spline interpolation. Afterward, the signals' content removed by the *filloutliers* function was extracted and checked to recover signal information detected as noise. To do so all the samples with a value higher than 2 times the local median (window length as defined previously) of the fully rectified signals were put to zero. The resultant not-noisy content was added to the output of the *filloutliers* function and low pass filtered at 5 Hz using a zero-lag 2nd order Butterworth filter. The resultant EMG linear envelopes were normalized using the maximum values among all the locomotion trials. Finally, the silent channels, i.e. normalized linear envelope at zero, were reconstructed averaging the 4 neighbor electrodes' envelopes.

The markers trajectories and GRF were processed using MotoNMS [8] Matlab scripts.

C. Statistical analysis

Gait cycles were automatically segmented via a heel strike detection algorithm on GRF. The square of the Pearson coefficient (R^2) value was computed for each locomotion task between the mean across all gait cycles of A_m and A_a. The R^2 value is computed also for each gait cycle between the A_m and A_a. Similarly, the R^2 end the root mean square (RMS) values were computed between the mean across all gait cycles of the T_{exp} and both T^m_{est} and T^a_{est}.

IV. Results

A. EMG clustering

Fig.3 shows the comparison between A_m and A_a, averaged across all gait cycles (see Tab.1 for the correspondent R^2 values) of each subject during each locomotion speed. The automatic activations reproduce with good accuracy the shape of the automatic activation for GM and SOL and decrease for TA and GL where both amplitude and shape slightly differ.

TABLE 1: R^2 BETWEEN MANUAL AND AUTOMATIC ACTIVATIONS AMONG ALL GAIT CYCLES AND ALL SUBJECTS

Speed	*TA*	*GM*	*GL*	*SOL*
1 km/h	0,60 ± 0,29	0,62 ± 0,31	0,37 ± 0,25	0,61 ± 0,31
3 km/h	0,56 ± 0,17	0,89 ± 0,12	0,60 ± 0,21	0,82 ± 0,09
5 km/h	0,40 ± 0,21	0,85 ± 0,15	0,57 ± 0,19	0,80 ± 0,10

B. Musculoskeletal modeling

Fig.4. shows that the T^m_{est} and T^a_{est} can reproduce the overall shape of the T_{exp} with less accuracy at increasing locomotion speeds (see Tab. 2). Both dorsi and plantar flexion peaks show to be more underestimated by the NMS model as well as the walking velocity increased. The estimated torques are backwards with respect to the T_{exp} due to synchronization problem between the motion tracking and the EMG systems.

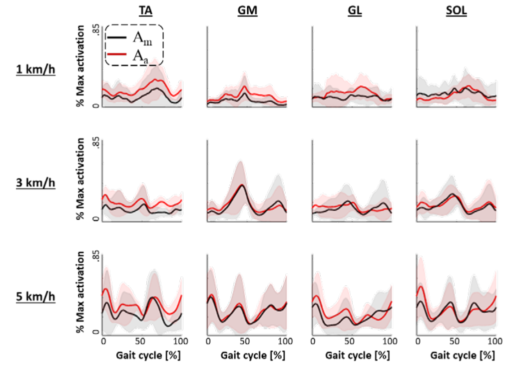

Figure 3: Comparison between Am (black line) and Aa (red line) of each specific muscle, averaged across all gait cycles of each subject during each locomotion speed.

TABLE 2 TORQUE SIMILARITY INDEXES ACROSS ALL SUBJECTS

	R^2		RMS	
Speed	*TA*	*GM*	*GL*	*SOL*
1 km/h	0,79 ± 0,03	0,77 ± 0,08	1,43 ± 0,61	2,34 ± 1,76
3 km/h	0,61 ± 0,08	0,72 ± 0,12	2,84 ± 1,83	2,87 ± 0,77
5 km/h	0,57 ± 001	0,74 ± 0,02	0,59 ± 0,23	0,13 ± 0,10

V. Discussions

We show preliminary results on a unique pipeline that goes from MC-EMG to estimated ankle torque through two steps: NNMF-based EMG clustering for the extraction of muscle-specific activation and subject-specific EMG-driven NMS modeling.

Previous studies have already used NNMF as a dimensionality reduction algorithm for several purposes as image classification [9], biological data mining [10], and more recently for muscle synergies extraction [11][12]. The last application provides the a priori knowledge on which we based the clustering methodology. According to the literature during locomotion, the multi-muscles in the leg are activated by 4 control signals that contract different muscle groups in specific functional moments of the gait cycle [13], [14]. Just two of these control signals are related to lower-leg muscles,

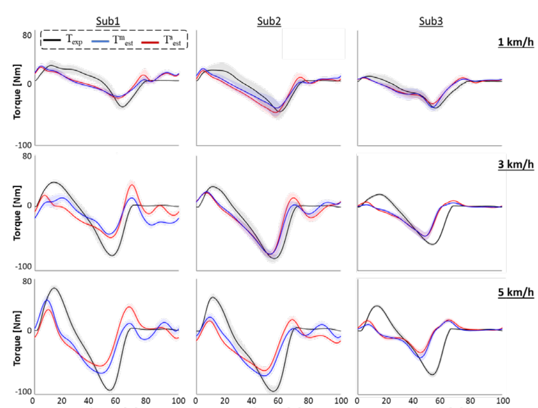

Figure 4: Comparison between the average across all gait cycles of the estimated ankle torques T^m_{est}, T^a_{est} and the experimental torque T_{exp}. The columns divide the graphs between the 3 subjects while the rows divide the graph by the locomotion speed.

one activating the TS during the push-off and one contracting the TA during the swing and in preparation for the heel strike.

The results of the first step show the potential of NNMF as a tool for associating electrodes with unrevealed positions to specific lower leg muscles. The NNMF can automatically identify muscles' locations during a simple locomotion task. In this way, both lengthy procedures for the manual identification of individual muscles and the human error introduced by electrodes' placement could be avoided. Furthermore, the NNMF-based clustering could lead to higher consistency in muscles' identification, as well as higher repeatability across different training sessions. This is because it is based on quantitative evidence of muscle activations instead of subjective manual muscles' identification. Therefore, the extracted muscle-specific electrodes could describe how the muscles activate over different movements not used during the EMG clustering and better quantify the motor development across time. The method worked well for GM and SOL, but it seems to match with less accuracy the manual activation of GL and TA. The main assumption we made was the possibility to extract from 64 channels 2 muscle synergies during locomotion activating TS muscles and TA. This assumption might exclude other lower-leg muscles that can contribute to both the push-off phase and to dorsiflexion during the swing phase and in preparation for the heel strike. From the distribution of the channels automatically selected for TA and GL, it seemed that in both clusters other contributes might be included. One of the plantar flexor muscles group not included in the EMG clustering is the Peroneus Longus (PL) also quite close to the GL. Similarly, weaker dorsi-flexors can activate and be detected via surface EMG. Therefore, the poorer accuracy for TA and GL could open the NNMF-based clustering to the identification of more dorsi- and plantar-flexors muscles.

The output of the second step suggests that in both conditions, manual and automatic NMS modeling, the estimated torques do not differ considerably. Therefore, the flexible sensorized garment together with NNMF-based clustering non only allow reproducing NMS simulations as accurate as using the standard set-up, which includes manual placed bipolar electrodes but also enables rapid set up. However, the estimation needs to be improved to better match the negative peak of experimental torque's plantar flexion. For this purpose, the estimation is quite sensitive to the accuracy of the NMS calibration and the quality of the EMG signal, being the NMS an EMG-driven approach.

The study presents aspects that could be improved and that could as well improve the results. (1) The used garment is currently available in a single size that cannot fit all subjects with the same tightness and hence could cause movements between the electrodes and the skin. (2) The used EMG electrodes are dry and more susceptible to noise. The use of a conductive gel or salty water could improve the quality of the EMG signals. (3) Just three subjects and locomotion were included in this study. More data can help to have a more exhaustive comprehension of the goodness of the NNMF-based clustering method. (4) The clustering method is based on two assumptions: a single locomotion task can activate the main lower leg muscles and during that task, the most active muscles are TA, GM, GL, and SOL. Further studies should consider a combination of movements that sequentially activate the muscles, as well as including more muscles to be detected and helpful for a more accurate diagnosis.

VI. Conclusions

In this study, we show preliminary results towards an advanced technology that integrates advanced signal processing techniques and NMS modeling into a smart wearable garment. An easy set-up and quantitative insights on internal musculoskeletal properties have a good potential to become a resource for clinicians. It will give them rapidity and quantitative evidence on the muscle strength, as well as biomechanical causes of the gait disorder and hence help tailor the rehabilitation treatment to the patient-specific needs.

Acknowledgment

The garment is developed in collaboration with TMSi.

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