Elbow Joint Angle Estimation by Using Integrated Surface Electromyography

U. Mamikoglu, G. Nikolakopoulos, M. Pauelsen, D. Varagnolo, U. Röijezon and T. Gustafsson

***Abstract*— Electromyography (EMG) signals represent the electrical activation of skeletal muscles and contain valuable information about muscular activity. Estimation of the joint movements by using surface EMG signals has great importance as a bio-inspired approach for the control of robotic limbs and prosthetics. However interpreting surface EMG measurements is challenging due to the nonlinearity and user dependency of the muscle dynamics. Hence it requires complex computational methods to map the EMG signals and corresponding limb motions. To solve this challenge we here propose to use an integrated EMG signal to identify the EMG-joint angle relation instead of using common EMG processing techniques. Then we estimate the joint angles for elbow flexion-extension movement by using an auto-regressive integrated moving average with exogenous input (ARIMAX) model, which takes integrated EMG measurements as input. The experiments showed that the suggested approach results in a 21.85% average increase in the estimation performance of the elbow joint angle compared to the standard EMG processing and identification.**

I. INTRODUCTION

Musculoskeletal modelling has a great potential to contribute to a better understanding of human movement and to lean in significant improvements in various clinical and engineering applications. Specifically, personalized musculoskeletal models are useful for medical purposes, such as diagnosis of muscle injuries and disorders [1]. Personalized models for patients can also provide valuable information about their muscular conditions and help in designing treatments. However building and training personalized muscular models is a challenging task. In all these application areas, the common existing need is for accurate and efficient tools that operate in a simple, fast and cheap manner.

As depicted in Figure 1, training musculoskeletal models means to identify the interactions between neuromuscular activation levels and the induced musculoskeletal forces. However this requires: *a)* direct measurements of efferent nerve pathways, something that can be impractical or even impossible; *b)* measuring muscular architectures and forces, something that can be cumbersome, since it requires complex setups.

Instead of performing the previous *a)* and *b)* approaches, one may approximate activation levels with EMG measurements, and forces with joint angles, as suggested in Figure 2. This way of operating is usually referred to as *EMG-driven*

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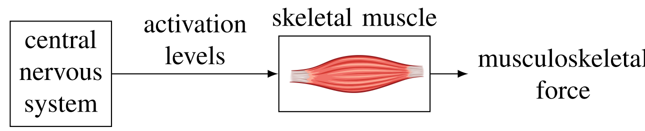

Fig. 1: Schematics of the transformation from muscular activation levels into muscular force.

modelling, a subject that has gained big importance in musculoskeletal research.

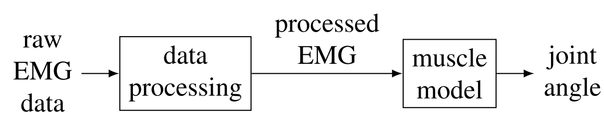

Fig. 2: General setting for performing modelling of muscles.

Before expressing our contributions, we review some literature dedicated to the *EMG-driven* modelling. We start our review by considering that this modelling identify works by identifying the muscle dynamics through measurements of the muscle activity and estimation of either the muscular force or the corresponding joint angle. This modelling scheme usually consists of two steps: 1) initial EMG preprocessing (following recommendations such as in [2]), and 2) identification of the muscle dynamics.

As schematized in Figure 2, step 2) can be performed by using either parametric (such as Hill's muscle models) or non-parametric approaches (such as machine learning techniques). An example of a parametric approach is in [3], where the authors used Hill's muscle models to estimate the muscular force as a function of muscle length and contraction velocity; the results are here a dynamic model of the forearm and wrist parts of the user's upper limb, information consequently used to estimate the elbow joint angle. The same authors identified in [4] the dynamics of elbow joint angles from EMG measurements by combining system identification tools with hand-trajectory correction algorithms based on the human motion laws. An example of a non-parametric approach relating EMG signals with joint angles are instead [5], [6], dealing with neural network mappings; [7], proposing fuzzy systems technologies; and [8], [9], exploiting non-parametric classification techniques.

The techniques cited above suffer nonetheless of some drawbacks: analyses based on parametric Hill's models suffer of a large number of user-dependent parameters, plus of requiring knowledge on the dynamics of the muscle's force-length and force-lengthening velocity relations. E.g., [3],

[4] required correcting the information from the motion-trackers to reduce the elbow joint angles estimation error. Analyses based on machine learning techniques, instead, require training sets defined over a predefined (and thus limited by definition) set of movements.

We thus aim at defining a new way of performing parametric EMG-driven identification that avoids the problems stated before, and that stem from the fact that integrated EMG has a relation with the muscular force production that is approximately linear [10]. This fact indeed suggests that also the model "integrated EMG-joint angle" is linear – something that opens up the possibility of using ARIMAX models for learning purposes.

In this paper we thus study this approach, and verify its generalization capabilities through dedicated experimental results. We thus show that using our integrated EMGs approach leads to a simple model of the joint movements with improved accuracy as 21.85% on average in estimating the joint angles, and this without the necessity of training a pre-specified set of movements or introducing a large number of user-defined parameters.

The rest of the paper is organized as follows. Section II introduces the proposed data preparation and system identification methodology. Section III describes the human experiments and simulation results of elbow joint angle estimation based on surface EMG measurements. Section IV finally contains the concluding remarks and the directions for future work.

II. Methodology

We estimate the elbow joint angle during lower arm flexion and extension movements by relating the EMG measurements to the elbow joint angles. The upper arm and the wrist joint are assumed to be fixed during the movements for simplicity. Hence, we assume that the only muscle that is responsible for the elbow flexion/extensions is the biceps brachii. In the first step we then obtain the EMG measurements from the biceps brachii and the elbow joint angles. We then model the EMG-joint angle dynamics by using the processed EMG and the joint angles as input and output, respectively. In the following subsections we describe the data processing and modelling methods in more details.

A. Preliminary Data Processing

A common approach to analyse the EMG signal prior to the muscle modelling consists of a high pass filter with a cut-off frequency of 30 Hz, rectification and a low pass filter with cut-off frequency (f_{cut}) between $6-2$ Hz depending on the speed of movements and normalization to the Maximum Voluntary Contraction (MVC) [11]. The high pass filter removes the motion artifacts and the baseline noise. Then the EMG signal is rectified and a low pass filter is implemented to both EMG and kinematic data.

This filtering operation has been controversial since the EMG signals contain information in $[10, 400]$ Hz bandwidth, which indicates that this scheme could lead to an incomplete interpretation of the signals and result in a loss of valuable information for the modelling purposes [12]. For the final step, maximum amount of force that a participant can produce, in a specific muscle during an isometric exercise was measured. Each EMG measurement taken from the participant's muscle was normalized according to the MVC, which resulted in a reference amplitude that allowed the EMG to be expressed as a percentage of this amplitude. However, it is well known that muscle force depends on the muscle length and the lengthening velocity. Therefore, the normalization of the signal to MVC was proven in [13] to be inaccurate, when isokinetic contraction occurred in the muscle during the experiments, which is usually the case to estimate the joint movements. Moreover it is important to remove the trends in the data prior to the modelling, since the EMG is a nonstationary signal. Consequently, this processing approach exhibited various drawbacks that could decrease the accuracy of joint movement estimations based on EMG measurements.

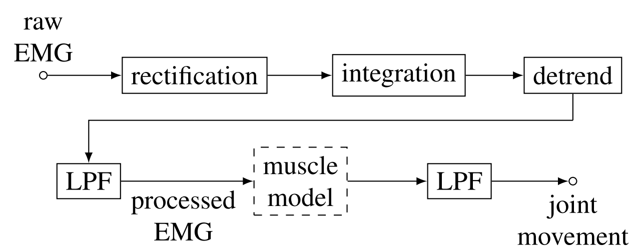

Fig. 3: A flow chart representing the suggested joint movement estimation based on processed EMG.

It has been reported in the literature that the relationship between the EMG signals and the muscular force can be approximated as linear. In this article we investigate if identifying linear models using integrated EMG as inputs leads to increase the accuracy of the estimation of joint angles. For this purpose, we rectified the EMG signal $u(t)$ and integrated over the whole interval $[t_0, t_f]$, i.e., set:

$$u_i(t) = \int_{t_0}^{t_f} |u(t)| dt \qquad (1)$$

where $u_i(t)$ represents the integral of the absolute value of the EMG signal. Moreover, removal of trends prior to the system identification has been important in the presence of unknown disturbances in the data [14]. Hence, polynomial fitting has been used to remove the trends in the EMG signal by fitting the data to a polynomial $u^*(t)$ of degree n, i.e., by setting:

$$u^*(t) = p_1 t^n + p_2 t^{n-1} + \ldots + p_n t + p_{n+1} \qquad (2)$$

where the coefficients of the polynomial are denoted as $\boldsymbol{p} = [p_1, p_2, \ldots, p_{n+1}]$. Subtracting the polynomial $u^*(t)$ from the integrated EMG $u_i(t)$ then results in the detrended signal:

$$\tilde{u_i}(t) = u_i(t) - u^*(t). \qquad (3)$$

In a similar approach, the mean from the angle data has been removed. Then the EMG signal and the joint angles were filtered with a zero-lag 2nd order low pass filter with a cut-off frequency 1 Hz in order to remove the noise and modelling errors. The resulting data set for modelling the musculoskeletal dynamics consisted of previously recorded and processed EMG and joint angles. Estimation of the joint movement was based on the obtained model, which took raw EMG measurements as input (illustrated in Figure 3). Figure 4 depicted a typical form of EMG signal measured from biceps brachii, corresponding integrated EMG signal, which was acquired using the approach described above and the processed joint angle.

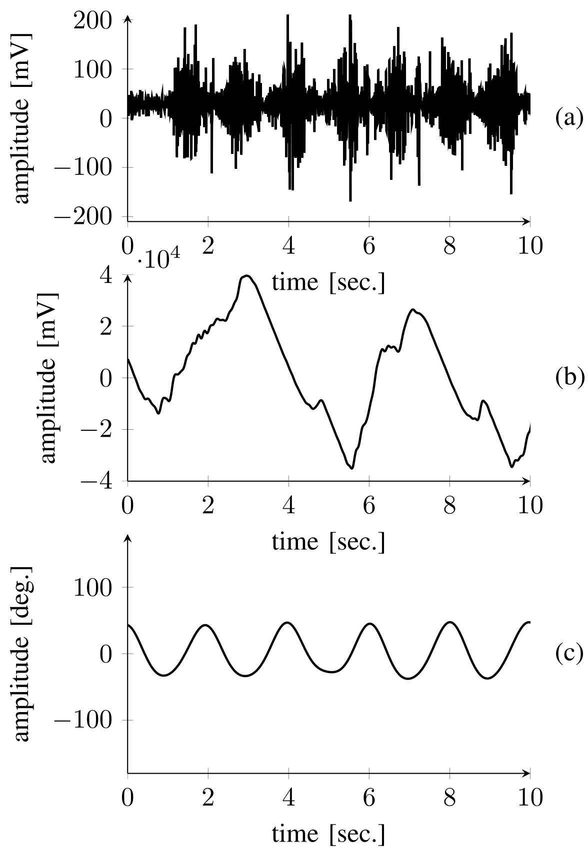

Fig. 4: a) Raw EMG signal measured from biceps brachii during elbow flexion/extension, b) Processed EMG signal, c) Processed elbow joint angle.

B. EMG to Joint Angle Estimation

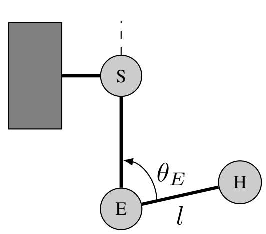

Fig. 5: A two-link representation corresponding to the upper and the lower arm and to the shoulder (S) and elbow (E) joints of the human body. H represents the hand.

Modelling the muscle dynamics is the problem of deriving analytical rules relating the muscle activation to the movement of the corresponding joint, while surface EMG signals provide a measure for the muscle activation. Muscle activation signals and EMG are related as:

$$u(t) = \phi(a(t)) + v(t) \tag{4}$$

where ϕ represents a function relating the neuromuscular activation signal $a(t)$ to the measured EMG values and $v(t)$ is the measurement noise. Moreover, muscular force and activation EMG are related as:

$$\begin{aligned} F(t) = H(a(t)) \quad &= H(\phi^{-1}(u(t) - v(t))) \\ &\approx H(\phi^{-1}(u(t)) + w(t) \end{aligned} \tag{5}$$

with H to represent a muscle model, where the input and the output are the processed EMG signal $u(t)$ and the muscle force $F(t)$, respectively, while $w(t)$ denotes the modelling errors. Similarly, muscle torque can be related to the joint angle measurements as:

$$T(t) = F(t)l(\theta_E) \tag{6}$$

where $T(t)$ is the corresponding torque on the joint and l is the length of muscle moment arm depending on the joint angle θ_E. In case the muscle torque (or force) measurements are not possible or impractical, joint angle can be measured to relate the muscular activation and joint movements. Therefore the musculoskeletal activity in the joint can be considered as a system in which the EMG signal and the joint angles are input and output, respectively.

Rather than determining the structure and estimating the parameters of this system, modelling based on input-output data, i.e., *system identification* can be implemented [14]. This approach has been widely used in the literature because of its performance and simplicity. A general tool in system identification is auto-regressive moving average with exegenous input (ARMAX) modelling. In cases where data show evidence of non-stationarity including an initial differencing step reduces the non-stationarity and yields an ARIMAX model. In order to address the non-stationarity of EMG, the processed EMG and joint angle data were related in an ARIMAX model structure such as:

$$A(q)y(t) = B(q)\tilde{u}(t - n_k) + \frac{C(q)}{1 - q^{-1}} e(t) \tag{7}$$

where $y(t)$ represented the output as elbow joint angle, $\tilde{u}$ the processed EMG signal, n_k input delay, $e(t)$ the model disturbance and the model coefficients:

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + \ldots + a_{n_a} q^{-na} \\ B(q) &= b_1 + b_2 q^{-1} + \ldots + b_{nb} q^{-n_b+1} \\ C(q) &= 1 + c_1 q^{-1} + \ldots + c_{n_c} q^{-n_c+1} \end{aligned} \tag{8}$$

Model order selection: It is required to determine the orders of the mathematical model n_a, n_b, n_c and the input delay n_k given by 7 and 8. We chose the model orders so to minimize the Akaike Information Criteria (AIC) index [15]. The coefficients of the polynomials in 8 were estimated through minimization of a quadratic prediction error criterion in Matlab.

III. Experiments

A. Subjects and Setup

We estimated the elbow joint angles during elbow flexion and extension of the lower arm. Four healthy participants, two women and two men 27 to 44 years old, of different stature and strength, participated in the experiments. During the experiments the participants were told to keep their upper arm fixed and only move their lower arm. The participants had full range of motion of the elbow joint and repeated the movements carrying a weight. The weight for each participant was chosen proportional to the maximum force, which was produced during the MVC in order to stimulate the muscles of the participants proportional to their strengths. The experiments were conducted with angular velocities of $180^\circ\,\mathrm{s}^{-1}$ to $90^\circ\,\mathrm{s}^{-1}$, which resulted in isokinetic contractions in the relevant muscle.

The surface EMG electrodes were placed on biceps brachii of each subject in a bipolar configuration. The distance between electrodes was set at 2 cm and all signals were checked to ensure inter electrode impedance, which was less than $5k\Omega$. The EMG measurements were recorded by using a 16-channel wireless EMG (Noraxon) at a sampling frequency of 1500 Hz. The EMG activity of each subject was additionally recorded for the MVC. Simultaneously with the EMG acquisition, 3D movements were assessed with a camera system (Qualisys Pro Reflex capture) at a sampling frequency of 200 Hz. A data set consisting of raw EMG and joint angles were collected from the participants. This data sets of the participants included elbow flexion/extension movements of constant speed $90^\circ\,\mathrm{s}^{-1}$ and changing speed ($180^\circ\,\mathrm{s}^{-1}$ to $90^\circ\,\mathrm{s}^{-1}$).

B. Experimental Results

We determined the model orders n_a, n_b, n_c and input delay n_k for both identification methods and for each participant as shown in Table I, while the polynomial order n for the trend removal was 3.

TABLE I: ARIMAX model orders obtained for the standard and suggested identification methodology denoted as *std* and *sug*, respectively.

Data set	n_a		n_b		n_c		n_k	
	std	sug	std	sug	std	sug	std	sug
P1	3	9	4	4	3	3	5	5
P2	3	8	3	4	1	1	2	4
P3	3	9	2	8	1	1	3	1
P4	3	7	2	5	1	1	1	2

We estimated the elbow joint angles for each participant by using the EMG measurements and the ARIMAX models given in Table I and compared these estimations with directly measured elbow joint angles during the elbow flexion

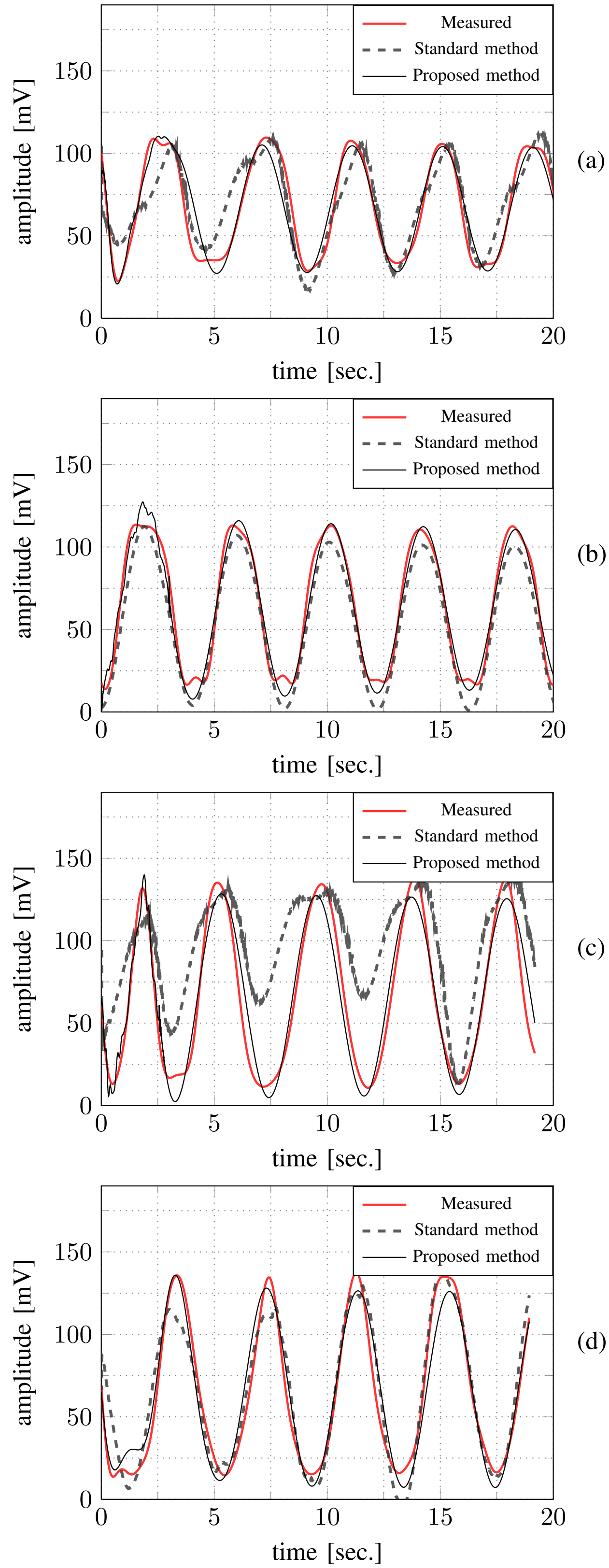

Fig. 6: Comparison of the measured elbow joint angles during constant speed flexion/extension with the estimated values based on the suggested identification methodology and the standard approach. Simulations (a) based on data set P1, (b) based on data set P2, (c) based on data set P3, (d) based on data set P4.

and extension. The estimated elbow joint angles based on integrated EMG (black), standard processed EMG (gray) and measured angle values (red) were plotted. Figure 6 illustrated the performance of the estimation of elbow joint angles for the participants during constant speed contractions. In the depicted results, it was observed that the estimated elbow joint angles deviated from the measured values with both of the methods. However, modelling based on the integrated EMG reduced the deviations in the estimations.

Additionally, we evaluated the results by using Normalized Root-Mean-Square Error (NRMSE):

$$\text{NRMSE} = \left(\frac{||\theta - \hat{\theta}||}{||\theta - \text{mean}(\theta)||} \right) \tag{9}$$

with the norm being the Euclidean one. Then we obtained the fitness values:

$$\text{fit} = 1 - \text{NRMSE} \tag{10}$$

which have been represented in Table II for each participant and for both estimation approaches. These results indicated that the integrated EMG based identification methodology has estimated the elbow joint angles, with an average accuracy of 93.7%, whereas it was 72.8% for the standard approach. The suggested approach achieved an increase in the estimation of the elbow joint angles between 12.6% to 41.4% for each participant. During the experiment, the third participant reported fatigue, which has been observed in Figure 6 c, since the estimation performance of the standard approach decreased significantly due to the changing dynamics in the muscle. The elbow joint angles, during elbow flexion/extension movements, have been also estimated, with a changing speed from $180^\circ\,\text{s}^{-1}$ to $90^\circ\,\text{s}^{-1}$ and these have been compared with estimations from directly measured elbow joint angles. Figure 7 illustrated the performance of the estimation of elbow joint angles for the participants. The fitness values of the estimations with the changing speed movements were represented in Table III. In this case, it has been observed that the estimation performance decreased for both of the identification approaches, when compared to the constant speed movements. However, the suggested approach still resulted in an increase in the fitness values since the average values were 59.7% and 82.5% for the standard and suggested methods, respectively. The effect of fatigue on the joint angle estimations was again higher in the standard approach as observed from Figure 7c. Moreover Figure 7b

TABLE II: Fitness value between measured and simulated values for the constant speed contractions.

Data set	**Standard method**	**Suggested method**
P1	0.781	0.907
P2	0.804	0.967
P3	0.525	0.939
P4	0.802	0.938

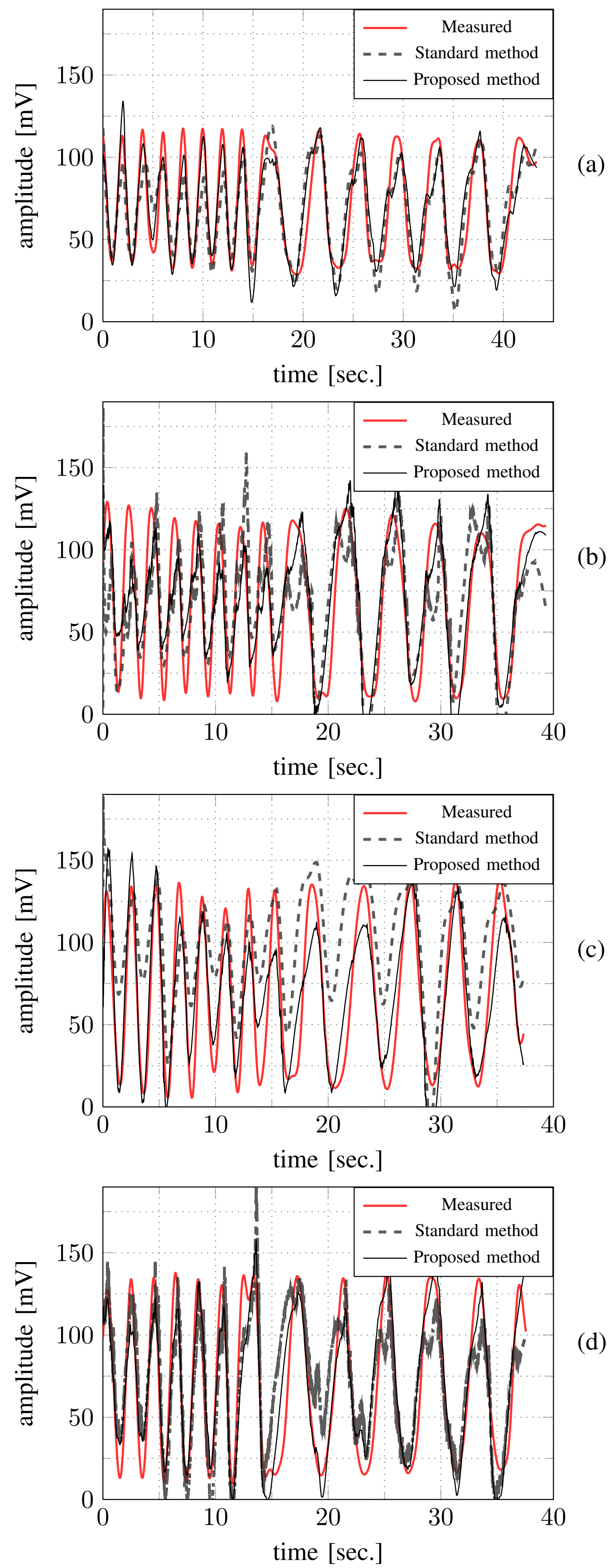

Fig. 7: Comparison of the measured elbow joint angles during changing speed flexion/extension with the estimated values based on the suggested identification methodology and the standard approach. Simulations (a) based on data set P1, (b) based on data set P2, (c) based on data set P3, (d) based on data set P4.

and Figure 7d indicated that the joint angle estimations, with the standard approach, contained higher oscillations especially around the maximum and minimum values.

TABLE III: Fitness value between measured and simulated values for the changing speed contractions.

Data set	Standard method	Suggested method
P1	0.750	0.823
P2	0.457	0.777
P3	0.539	0.800
P4	0.644	0.850

IV. Conclusions

We proposed a methodology for estimating the dynamics of the elbow joint angles starting from Electromyography (EMG) measurements of biceps brachii. The novelty relies on the consideration that the model from integrated EMG signals to joint angles is approximately linear; this implies that it is possible to perform classical identification steps based on auto-regressive integrated moving average with exogenous input (ARIMAX) models. To test the validity of this methodology we measured surface EMG plus elbow joint angles from a set of participants performing elbow flexion and extensions. The experimental data enabled us to identify muscular dynamics through ARIMAX models, and later estimate the elbow joint angles during elbow flexion/extension by using only the EMG measurements.

The experimental results showed that the suggested modelling increased the accuracy of estimation of the elbow joint angle during isokinetic contractions compared to the standard approach in a simple and efficient manner. The increase in the performance of the estimation was significantly higher (up to 41.4%) when the flexion/extension movements consisted of different speeds. Our approach can be further developed to be used in medical and robotic applications where it is impractical to measure or estimate additional physiological parameters other than surface EMGs for examining muscular dynamics.

In our future research, EMG signals from lower leg muscles will be acquired and used in the control of forwards-backwards movements in a robotic leg. The system identification methodology will be based on surface EMG measurements from multiple muscles, i.e., tibialis anterior and gastrocnemius. A future objective is to articulate the robotic leg in two degrees of freedom, in order to perform forwards-backwards and inwards-outwards movements around the ankle.

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