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An Electromyographic-driven Musculoskeletal Torque Model using Neuro-Fuzzy System Identification: A Case Study

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ABSTRACT

The purpose of this study was to estimate the torque from high-density surface electromyography signals of biceps brachii, brachioradialis, and the medial and lateral heads of triceps brachii muscles during moderate-to-high isometric elbow flexion-extension. The elbow torque was estimated in two following steps: First, surface electromyography (EMG) amplitudes were estimated using principal component analysis, and then a fuzzy model was proposed to illustrate the relationship between the EMG amplitudes and the measured torque signal. A neuro-fuzzy method, with which the optimum number of rules could be estimated, was used to identify the model with suitable complexity. Utilizing the proposed neuro-fuzzy model, the clinical interpretability was introduced; contrary to the previous linear and nonlinear black-box system identification models. It also reduced the estimation error compared with that of the most recent and accurate nonlinear dynamic model introduced in the literature. The optimum number of the rules for all trials was 4 ± 1, that might be related to motor control strategies and the % variance accounted for criterion was 96.40 ± 3.38 which in fact showed considerable improvement compared with the previous methods. The proposed method is thus a promising new tool for EMG-Torque modeling in clinical applications.

Key words: *Electromyography, musculoskeletal model, neuro-fuzzy system identification, voluntary isometric contraction*

INTRODUCTION

Surface electromyography (sEMG) is an electrical signal containing information about the physiological processes occurring during muscle contraction.[1] Motor unit (MU) is the functional unit of muscle that consists of an alpha motor neuron and all fibers innervated by that neuron. When action potentials are generated in the motor neuron, the fibers associated with that MU contract. The spatio-temporal summation of action potentials of different MUs generates the EMG signal.[1,2] sEMG amplitude represents "muscle activity" from the skin surface, that has a close relationship with the strength of contraction and muscle force.[3-5] Under ideal conditions, there is a quasi- or curvilinear relationship between the sEMG amplitude and the force exerted by a muscle.[6] Contraction of different muscles makes organs move and builds body gestures. The contraction strength of each muscle is important because the force produced by a single muscle cannot be measured, and only the total force is available which is provided by all the active muscles acting on a joint.[7] Therefore, muscle force is usually estimated based on surface EMG measurement, also called forward dynamics in biomechanics.[8]

One of the applications of muscle force estimation from electromyogram is in prosthetics. Finding a proper prosthesis that provides a good pretension and functional movement is an important aim in rehabilitation of amputees.[9] Positioning the hand in space is the primary role of the arm and the primary role of the hand is interaction with the environment.[10] The main problems for patients wearing prostheses is proper controlling the force, for example, to grab a hammer without letting it slip or an egg without breaking it.[11] Thus, it is expected for the prostheses to provide the same relationship between the central nervous system and peripheral joints/muscles that natural commands do.[12] sEMG is a noninvasive method, and the user is freed of straps and harnesses.[13] EMG can be recorded by electrodes placed on the skin of the patients[11] and a terminal device (a hand or a hook) is operated by an electric motor and sometimes together with a microprocessor.[9] Myoelectric sensors detect the muscle contraction level of the residual limb and therefore the amputees can control the mechanical prosthesis by muscle activity.[14]

In each movement, different agonist-antagonist muscles work together. Furthermore, the force of a single muscle

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could not be measured noninvasively. Thus, estimation of load sharing using sEMG could be a suitable method for movement analysis, e.g. for gait analysis. An EMG-force processing approach is employed to determine individual ankle muscle forces during gait,[15] and to specify the moment of every component of surrounding muscles, ligaments, and articular surfaces, that together makeup the total joint moment where inverse dynamics analysis is unable to do.[15-17] This load sharing is a basis to recognize joint function, disease, and injury,[16] and can be employed in ergonomics as well.

Other application of estimating force from EMG is in motion assist control devices. In these devices, the operator's intension is realized by EMG-force models. A power assist control is thus useful for people with gait disorder or aged people.[18]

In the field of ergonomics, an important principle is the prevention of musculoskeletal disorders (MSD). The musculoskeletal system comprises of bones and joints with their neighboring structures, as well as muscles, tendons and ligaments. MSD is a basis cause of temporary and permanent disability pensions. The most common MSD that are found in working population are upper extremity disorder and low-back pain.[19] A reason with this disorder is imposing heavy loads on the muscles. Therefore, the main activity of ergonomics is the estimation of physical damage and physiological implications. To prevent MSD, recognizing the load placed on individual muscles, ligaments, and every part is needed. Using EMG-force estimation, the over-loaded parts are recognized; thus providing the possibility to train people for its removal.[20]

The torque signal derived from EMG has also applications in rehabilitation. For example, muscle activation and movement patterns would be altered in individuals following stroke. If affected muscles and their contribution to the pathological pattern are known using EMG-force model, it might be possible to develop more effective rehabilitation therapies and to assess the effect of an intervention and to achieve better motion. These EMG-driven biomechanical models use EMG as inputs rather than trying to understand how muscles are activated in a given movement.[21,22]

Related Works

Since the time of Inman and Ralston and Lippold in 1952, the shape of the relationship between surface EMG and muscle force has been studied.[4] One of the major studies in this area was performed by Clancy and Hogan in 1997.[23] They used EMG of flexor and extensor muscle groups and limited the model relationship between muscle group torque contribution and EMG amplitude to be the sum of the basic functions with a linear dependence on a set of tunable parameters. In their work, various degrees of polynomials were used. In this situation, the problem of finding parameters became a linear least squares (LSs) problem. They also applied single-/multiple-channel and unwhitened/whitened/adaptively-whitened[24] EMG amplitude processors to study their effects. They could improve the torque estimation by different strategies such as using temporal whitening of EMG waveforms, combination of multiple EMG waveforms that improved the EMG amplitude estimation, and finally using agonist-antagonist co-contraction model in a wide range of torques. Accordingly, multi-channel adaptively-whitened processor with the 3rd degree polynomial was determined as the best approximator.

Another model was presented by Hoozemans and Van Deen in 2004[25] to predict handgrip forces using surface EMG of six forearm muscles. They used multiple linear regression (MLR) models for this prediction. Although promising, the conditions of using MLR and the validity criteria of the results could not be usually met in other real-world applications. Normality and homoscedasticity are two standard assumptions of regression diagnostics and model evaluation that must be met when using MLR.

In 2012, Clancy *et al*. investigated the relationship between EMG signals of biceps and triceps brachii and elbow torque, using linear and nonlinear dynamic model, different types of EMG amplitude processors, and advanced system identification techniques.[12] EMG amplitudes were estimated using single-and four-channel and adaptively-whitened[24] processors first. Every processor consisted of a high-pass filter, a first degree demodulator, and a down-sampler. Then, these amplitudes were mapped to the elbow torque using parametric models determined by system identification methods. They applied both agonist and antagonist muscles to account for co-contraction. Consequently, the torque estimation procedure was improved using advanced EMG amplitude processors (multi-channel and whitened), longer training data duration, and determining model parameters by pseudo-inverse and ridge regression besides linear LSs method. Wiener and Hammerstein nonlinear models were also investigated, because of their fewer parameters. The performance of the dynamic, nonlinear, parametric models with the second or third degree polynomial functions of EMG amplitude were better than linear, wiener, and Hammerstein models.

The other nonlinear model proposed for EMG-torque relationship considered the torque as an unknown coefficient of EMG envelope of a muscle with an unknown power,[26] and the total torque was considered as the sum of these functions for several muscles.[27] Minimizing mean square error between the measured and estimated torque signal could be done by Interior-Reflective Newton Algorithm (IRNA).[28] Furthermore, particle swarm optimization (PSO) method was applied for finding unknown coefficients in.[27] This new study showed nearly the same error as IRNA for estimating the torque, however the IRNA needs initializations of some of the parameters and constraints found by trial-and-errors to find the optimum, which is random for PSO. Furthermore, this model does not need predefined musculoskeletal parameters (e.g. parallel elastic stiffness and damping).

Staudenmann *et al*.[29] showed an improvement in estimating torque using high-density sEMG of triceps muscle and principal component analysis (PCA). This method showed decrease of phase cancellation, because every MU activity was recorded separately. Moreover, it was not compulsory to place electrodes in line with muscle fiber by this method. They found out that PCA preprocessing improves the performance of sEMG-based muscle force estimation.

Most of the clinical studies performed in this area are based on either calculating correlation/regression coefficients from sEMG and muscle force[30-32] or fitting biomechanical models with predefined physiological parameters or complex biomechanical simulations.[33,34] In the former methods, no physiological activation pattern is provider while in the later ones, additional kinematical information is required. The goal of our study was proposing a modeling approach based on classical system identification theory to model muscle force using only sEMG of the involving muscles. In this area, variety of linear/nonlinear black-box models have been proposed.[2,4,23,24,27,29,35] None of which could provide qualitative/quantitative motor control strategies. Thus, we took a rather different approach, that is, grey-box modeling by incorporating expert-based fuzzy systems in which the fuzzy rules could be interpreted to physiological mechanisms.

This paper is organized as follows: First, the recording protocol will be explained. The following section, explains the description of the modeling methods, containing signal preprocessing and proposed neuro-fuzzy modeling method. Then, the results of the proposed method are presented. Next, clinical interpretations and limitations, comparison with the other works, and directions for future work are mentioned. Part of this work has been presented in the abstract from in ISEK 2014 conference.[36]

MATERIALS AND METHODS

Experimental Data

The participants of this study were four healthy male subjects with the average age 21.3 ± 2.8 years; height 174.3 ± 2.6 cm; and body mass 71.0 ± 3.4 kg.[27] A written informed consent in accordance with the declaration of Helsinki was confirmed by each participant. Surface EMG signals from biceps brachii (BB), brachioradialis (BR), Lateral and Medial heads of [Triceps Brachii Lateral and Medial words (TBL) and Triceps Brachii (TBM)] were recorded during isometric voluntary flexions-extensions contractions while the elbow angle was flexed at 90°. For acquiring signals from the BB muscle, a two-dimensional adhesive array consisting of 65 electrodes of circular shape (5 columns and 13 rows, 8 mm inter-electrode distance, LISiN– Spes Medica, Battipaglia, Salerno, Italy) was used on its distal half, and for detecting signals of BR, TBL, and TBM, three linear arrays with 8 electrodes (inter-electrode distance of 5 mm) were applied.

The muscle innervation zones (IZ) were located using a 16 electrode array (5 mm electrode length, 1 mm diameter, 5 mm inter-electrode distance). The main IZ was located prior to the electrode-array placement for each muscle and the adhesive arrays were placed either proximally or distally from the main IZ location based on the subject's anatomical features. The reference electrode was placed at the wrist. Prior to the placement of the electrodes, the skin was gently abraded using abrasive paste (Meditec–Every, Parma, Italy). After amplification of the monopolar EMG signals (multi-channel surface EMG amplifier, EMG-USB, LISiN-OT Bioelectronica, Torino, Italy) and band-pass filtering (3 dB bandwidth, 10-750 Hz), they were sampled at 2048 Hz with a resolution of 12 bits. For measurement of the torque signal, an isometric brace used for limb fixation was applied, and after amplifying (Force Amplifier MISO-II, LISiN, Politecnico di Torino, Italy), it was sampled at 2048 Hz. The torque signal was displayed on a screen as a feedback for the participants, and was recorded at the same time with the EMG signals. At the first step of the experiment, three maximal voluntary contractions at isometric flexion and extension states (fMVC, eMVC) with 5 s duration were performed and the maximum was selected as the reference flexion and extension MVC. The subjects performed three series of flexion-extension torque ramps lasting about 100 s each. Each series consisted of four isometric ramps from n% eMVC to n% fMVC and back (with $n = 30, 50, 70$) which every cycle lasted about 25 s. In order to train the subjects to follow the ramp target on the biofeedback screen, few ramps were performed first. Single differential (SD) signals were computed along the fiber direction and it was used in all processes.[27]

Neuro-fuzzy Method

All analysis was performed offline in Matlab. For each muscle, EMG amplitude estimation of 100 s SD EMG trial signals, a 15 Hz high-pass filter (fifth-order Butterworth) was utilized in the forward and reverse time directions, and then a first-order demodulator (rectifier) was used. EMG signals were then decimated by a factor of 100 using a low-pass filter with cut-off frequency of 16.4 Hz acting as smoothing phase of EMG amplitude estimation.[12] Principal component (PC's)[29] were then extracted from each of four muscles and combined in such a way to reach one useful channel for each recording electrode. The number of PCs used, was determined based on cumulative percent variance (CPV) method. This study examined sum of the lower components with CPV of 99%.

The torque signal was also decimated by a factor of 100 using an eighth-order low-pass Chebyshev Type 1 filter with a cut-off frequency of 8.2 Hz and then smoothed by a 10-points moving average filter. This process caused the EMG dataset's bandwidth to be 10 times of that of torque frequency band to predict.[35,37] The mean of the inputs and output was removed and EMG amplitudes were then normalized by dividing by their maximum absolute values.

Electromyography amplitudes of four muscles were related to joint torque using neuro-fuzzy models.[38,39] Four estimated EMG amplitude signals were applied as the model inputs and the processed torque signal was considered as the model output. A Takagi-Sugeno-Kang (TSK) fuzzy inference system (FIS) was selected as fuzzy system, because it is more general and more flexible than Mamdani type.[40,41] A TSK FIS is a set of r rules ($i = 1, r$), each of which has the following form:[39,42,43]

$$\text{IF } x_1 \text{ is } A_1^i \text{ and } x_2 \text{ is } A_2^i \ldots \text{ and } x_n \text{ is } A_n^i \text{ then } y^i = f^i(x_1,\ldots,x_n) \quad (1)$$

The antecedent of each rule (#i) is the fuzzy and proposition, where A_j^i is a fuzzy set on the j^{th} premise variables. The consequent is a crisp function f^i of the input vector. The TSK inference system uses the weighted mean criterion to recombine all the local representations. In modeling, linear TSK FIS is used where the crisp function is defined as:

$$f^i = b^i + \sum_{j=1}^{n} a_j^i \times x_i \quad (2)$$

Where b^i and a_j^i are the offsets and linear weights respectively.

A software tool for neuro-fuzzy identification and data analysis, version 0.1[44] was used for the modeling in which Gaussian membership function, linear TSK, and weighted combination method of rules were used in the FIS. The initialization of the architecture was provided by a hyper-ellipsoidal fuzzy clustering procedure inspired by Babuska and Verbruggen, 1997.[45,46] In the optimization procedure, the linear parameters of the consequent models were estimated using the LS approach[47] while the parameters of the input membership functions were tuned using Levenberg–Marquardt nonlinear optimization algorithm.[38]

For each subject and each MVC percentage, the best complexity (number of rules) was determined based on a 10-fold cross-validation procedure and complexity analysis on the training data.[48] The range of rule numbers was specified between 4 and 11 rules, a-prior. It was observed that more than 11 rules caused over-fitting in many cases while using <4 rules, it was possible to capture the dynamics of the system. Then the model was produced with a given complexity, and finally it was evaluated using the test data. Finally, a two-sided 10 point moving average filter was applied to the estimated torque signal to remove possible fluctuations.

Validation

For each trial, the difference between measured (y) and estimated ($\tilde{y}$) torque signals was calculated using % Variance Accounted For (VAF) criteria.[49] The VAF formula is represented in the EQ.3.

$$\%VAF = 100 \times \left(1 - \frac{\text{var}(y - \tilde{y})}{\text{var(y)}}\right) \quad (3)$$

Moreover, a nonlinear dynamic model proposed by Clancy *et al*.[12] (3rd-degree polynomial, 28th-order dynamic model, whose model parameters were determined using the pseudo-inverse method), was implemented and applied on the same data sets for comparison. In each 100s trial, an epoch of 17 s of the torque signal (selected arbitrarily as to contain a flexion peak and an extension peak and environs) was used for training and the rest of the samples were used as test data.

RESULTS

Here, the procedure used for selecting optimal number of fuzzy rules is discussed in details [Figure 1]: Displays the root mean square error (RMSE) central tendency and dispersion when changing the number of rules from 4 to 11 for the subject no. 4 at 70% MVC.

Based on the mean and standard deviation of the 10-fold cross-validation analysis, five and ten rules are possible candidates. However, when changing the number of fuzzy rules from 5 to 10, the number of unknown parameters in the FIS increases from 65 to 130 [Table 1]; thus increasing the probability of over-fitting.

The over-fitting problem could be assessed based on the model selection criteria. One of which is the Akaike information criterion (AIC)[50] whose cost function could be defined as:

$$V_{AIC} = V_N(\theta) \times (1 + 2 \times \frac{\dim(\theta)}{N}) \quad (4)$$

Where, V_{AIC} is the AIC RMSE, V_N is the RMSE in the training set, θ is the vector of the unknown parameters and N is the number of data samples used for training. Thus, there will be a penalty for increasing the number of unknown parameters. Accordingly, five fuzzy rules were selected to represent EMG and muscle force relationship for the 4th subject @ 70% MVC. Furthermore, the RMSE of the

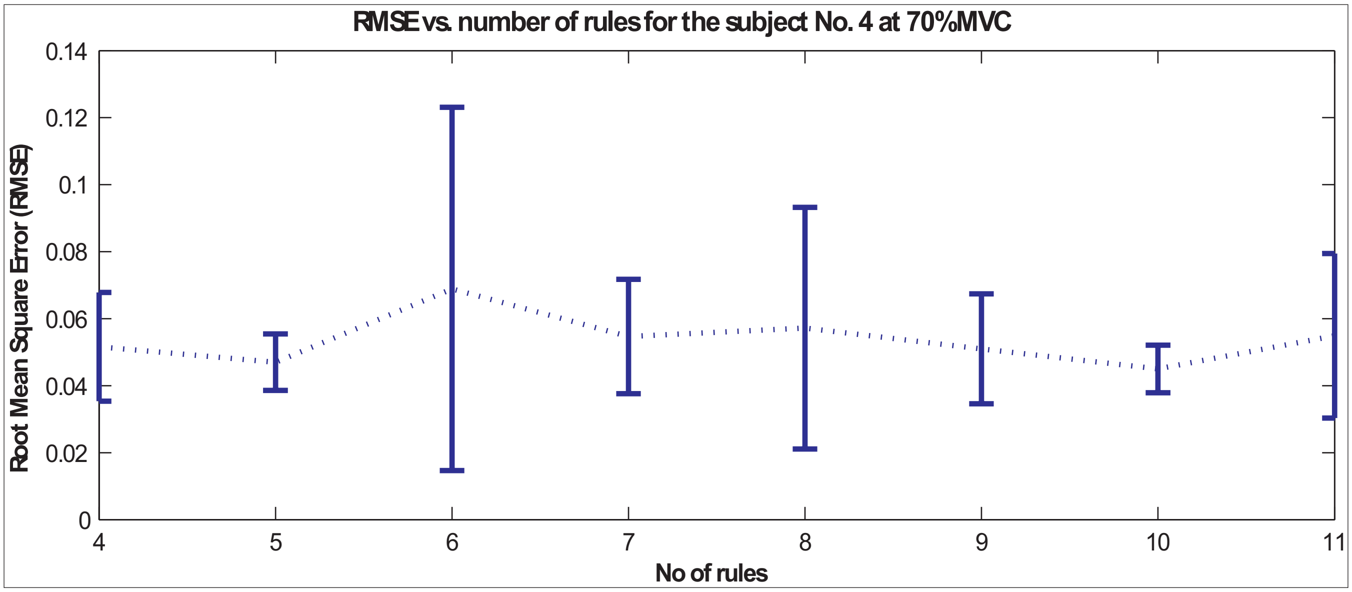

Figure 1: 10-fold cross-validation of the root mean square error versus the number of fuzzy rules for the 4th subject at 70% maximal voluntary contractions

proposed FIS with 5 rules during learning (optimization) procedure was shown in [Figure 2].

The optimal number of fuzzy rules to model EMG-torque extracted from the subjects participating in the study at different MVC's were reported in [Table 2].

Extracted fuzzy rules could be related to the different physiological mechanisms with which neuromuscular system produces force. First, the Gaussian membership functions act like muscle activation dynamics with which EMG signal is nonlinearly transformed into muscle activation signal.[26] Second, the dissimilarity (distance) between different fuzzy rules could be calculated using the generalized Minkowski metrics[51] considering the shape of input membership functions and the linear parameters of the consequent TSK FIS. This distance was shown for the 4th subject [Table 3]. Setting the distance cut-off threshold to 25%,[52] it might be possible to infer that two physiological mechanism are kept when increasing the muscle force from 30%MVC to 50%MVC while one control mechanism could be preserved when increasing the muscle force from 50%MVC to 70%MVC. This finding is in agreement with the fact that at low levels of MU recruitment, the force increment due to recruitment is small, whereas in forceful contractions, the force increment becomes much larger.[53] Thus MU recruitment requires new motor control strategy at higher levels of muscle contraction, resulting in fewer similar rules. However, this finding is sensitive to the distance cut-off threshold.

Table 4 shows the performance of the proposed neuro-fuzzy torque estimation in comparison with that of the nonlinear dynamic method proposed by Clancy *et. al.*, 2012. In the entire MVC's, the average % VAF of the

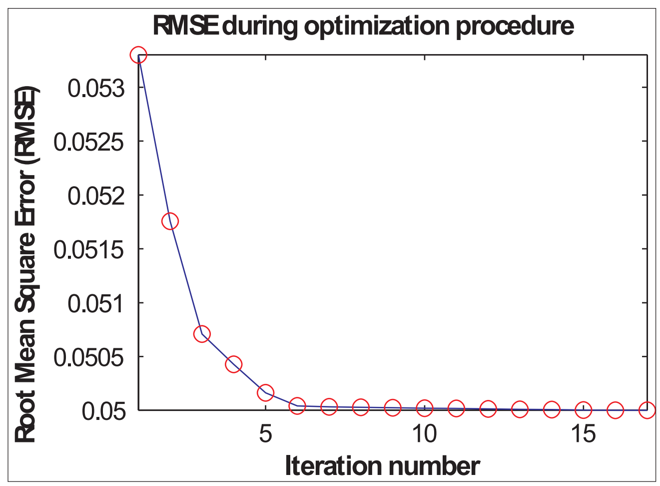

Figure 2: The root mean square error of the proposed fuzzy inference system with 5 rules during optimization procedure on the training set for the subject no. 4 at 70% maximal voluntary contractions

Table 1: The number of unknown parameters of the proposed fuzzy system for tuning as a function of number of fuzzy rules*

Number of rules	Number of unknown parameters
4	52
5	65
6	78
7	91
8	104
9	117
10	130
11	143

*The proposed fuzzy linear TSK system has four inputs and one output and all of the input fuzzy membership functions are Gaussian. TSK – Takagi-Sugeno-Kang

proposed method is higher, while its dispersion is *almost* lower than those of nonlinear methods (in 30% and 50%

Table 2: The optimal number of fuzzy rules extracted for the subjects participated in the experiment at different MVC percentages

% MVC	Subject			
	1	2	3	4
30	3	4	4	5
50	4	5	4	5
70	5	-	4	5

Note that the quality of the EMG data recorded for the second subject at 70% MVC was not good enough for the estimation procedure; thus was excluded from the analysis. EMG – Electromyography; MVC – Maximal voluntary contraction

Table 3: The distance between fuzzy rules extracted for the 4th subject (30% MVC vs. 50% MVC and 50% MVC vs. 70% MVC) in percentage (0: Identical rules, 100: Completely different rules)

30% versus 50%	50% MVC				50% versus 70%	70% MVC			
	R1	R2	R3	R4		R1	R2	R3	R4
30% MVC					50% MVC				
R1	44	42	41	41	R1	39	27	32	30
R2	48	46	46	45	R2	45	30	37	25*
R3	21*	24	23	23	R3	43	29	35	30
R4	21	19	21	18*	R4	43	28	36	25

R – Fuzzy rule; MVC – Maximal voluntary contraction. *The possible related fuzzy rules chosen based on the minimum distance measure (threshold)

Table 4: Comparison of proposed method and the nonlinear dynamic method proposed by Clancy *et al*., 2012 in average for all subjects

MVC percentage (number of subjects)	% VAF (mean±SD)	
	Proposed neuro-fuzzy model	Nonlinear dynamic model
30 MVC (4)	95.58±2.85 Minimum=91.38, maximum=97.55	80.86±13.12 Minimum=65.92, maximum=92.82
50 MVC (4)	98.54±0.78 Minimum=97.57, maximum=99.19	91.06±6.14 Minimum=83.44, maximum=96.30
70 MVC (3)	94.64±5.37 Minimum=88.50, maximum=98.48	89.74±5.16 Minimum=86.08, maximum=96.4

MVC – Maximal voluntary contraction; VAF – Variance accounted for; SD – Standard deviation

MVC, but 70%MVC). Thus, the accuracy and efficiency of the proposed method is acceptable in comparison with the most recent nonlinear methodology introduced in the literature. Meanwhile, the new modeling proposed in this study showed indispensable improvements in terms of accuracy and precision of % VAF.

An example of the predicted and measured torque signal using the proposed method was shown in [Figure 3] for the second subject at 50% MVC. In this example, an epoch of 17 s was used for training while the rest was used for testing the proposed FIS. As shown, the estimated torque signal follows the measured signal quite well (% VAF = 99.15).

DISCUSSIONS AND CONCLUSIONS

Biological systems are inherently nonlinear and modeling such systems needs nonlinear models.[54] Nonlinear models make it possible to capture additional subtle behavior in relationship between inputs and output.[27] Moreover, nonlinear processes are unique, that is, they do not have many common properties and in this way their system identification and modeling is a challenging task. An important factor in nonlinear system modeling and identification is universalness, which is the capability of describing a wide class of structurally different systems.[55] It is possible to use some equations that accurately model the discussed system, but since the relationship between the input and output of the system is not so derivable in biological systems, black-box method may be better to use.[56]

Other models which could be applied for nonlinear modeling are black-oriented models; Hammerstein, Wiener, and Volterra[57] models; linear-in-the-parameter models; signal dependent quasi-linear models, and gate function models.[58] Most nonlinear system identification methods are based on the nonlinear autoregressive with eXogenous input (NARX) model. Its large number of inputs is one of the problems of this model. As a result, the use of NARX models for high-order dynamic processes is not practical. Another drawback is that identification data are assumed to be well-distributed over the range of interest and a persistent excitation should generate it.[59]

In general, researchers believed that it is very cumbersome to identify a nonlinear system by traditional methods. So, neural network or other intelligent function approximation approaches are advised. When a system cannot be defined in precise mathematical equations, fuzzy models are also useful. If nonfuzzy or traditional representations are wanted to be used, a well-structured model is required. In addition, there are a lot of uncertainties, unpredictable dynamics and etc., especially in biological systems that cannot be mathematically modeled. Fuzzy modeling can be helpful for these applications.[60] Besides, we can insert the human knowledge and experiences in it and therefore, it would contain intuitive and comprehensible rules. Fuzzy system is a popular intelligent method of modeling, which is simple and highly intuitive. Recent results showed that the fusion of neural networks and fuzzy systems is very efficient for nonlinear system modeling.[61] Besides, it was proved that fuzzy systems are universal approximators.[62] Consequently, neuro-fuzzy systems were used in our study to estimate the force through the analysis of the sEMG.

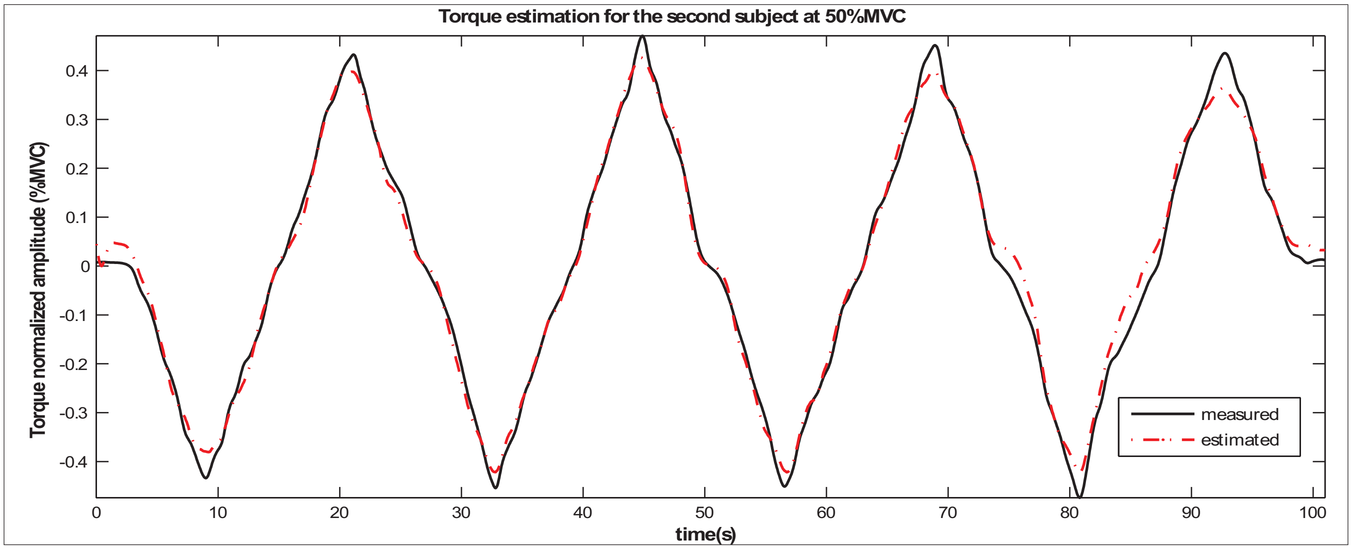

Figure 3: The estimated and measured torque signal using the proposed method for the second subject at 50% maximal voluntary contractions

In this article, surface EMG signals from electrode-arrays on BB, BR, TBL, TBM and the elbow torque signal were recorded during isometric voluntary ramp contractions. A neuro-fuzzy method was used to estimate the torque from these EMG signals. These collected signals for each participant corresponded to 30%, 50% and 70% of maximum voluntary flexion-extension contractions. SD signals along the fiber direction were used and PCA was applied for each of four muscles. After estimating the EMG amplitudes using averaged rectified value method, they were mapped to the torque signal using a neuro-fuzzy model. In this model, for each trial signal, the optimum number of rules was found and then an epoch of 17 s epoch signal were used to train the model.

The proposed fuzzy model resulted in %VAF (mean ± standard deviation) $=96.40 \pm 3.38$ for all trial signals. For the comparison, the Clancy's nonlinear dynamic model was implemented. Using the 3rd-degree polynomial, 28th-order dynamic model, the pseudo-inverse method with the tolerance of 5.6×10^{-3}, the best performance achieved was %VAF (mean ± standard deviation) $=86.99 \pm 9.6$. The new method improved the torque estimation results. Although the Clancy's nonlinear method was originally applied on random excitation EMG signals, its universal nonlinear structure allows adaptation with slow-varying signal in case of isometric ramp contractions. Meanwhile, slow isometric signal decreases the nonstationary properties of the signal; thus increasing the model performance.

Due to the rule-based structure of neuro-fuzzy model, interpretability is one of its advantages, and therefore the less number of rules resulted in more interpretability and generalization, but this decrease should not make the system dynamic be eliminated. The majority of cases achieved 4 or 5 optimal rules. The optimum number of fuzzy rules for each participant was different and was depended on the percentage of MVC [Table 2]. Furthermore, the common fuzzy rules at different contraction levels were identified using the distance-based analysis. Using the similarity threshold of 25%, rule no. 4 (30% MVC) was similar with all of the rules (50% MVC) [Table 3]. In this case, the most similar rule (R4) was chosen to have a one-to-one mapping. This is, in principal, similar with "merging fuzzy rules" in a fuzzy system in which the most similar rules are merged first.[63] In the meanwhile, the similarity was confirmed subjectively by checking the resulting fuzzy rules in terms of the shape of the input membership functions and their weights. However, this supervision did not change the similarity-based quantitative analysis. Since the computational complexity of using the tuned neuro-fuzzy method is low, it could be efficient for online applications, such as prosthesis control.

A limitation of this work was the constant posture signal recordings and also isometric contractions in which real dynamic physiological rule-based could not be assessed. Using the proposed method for dynamic contraction will be the focus of our future research. In the meanwhile, the data was not recorded at lower force levels (<30% MVC). This might be important for some applications such as prosthesis control in which the level of effort is quite low. However, since the algorithm could provide a good fit at 30%, 50%, and 70% MVC, we expect that we could have good fit on low force level EMG. In such contractions, the complexity of the EMG signal is lower since fewer MUs are recruited and (or) their firing rates are not high.

In the present study, each ramp contraction (cycle) was 25 s long. Increasing the contraction velocity has an impact on the performance of the proposed method. The velocity of the contraction not only affects the wide-sense stationary properties of the EMG signal, but it also affects the biomechanical force-velocity relationship in the hill-type models.[64] Increasing the contraction speed, the number of samples in an epoch must be reduced as to adapt the algorithm with the force fluctuations.

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