Estimating Arm Motion and Force using EMG signals: On the Control of Exoskeletons

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Abstract— **There is a great effort during the last decades towards building robotic devices that are worn by humans. These devices, called exoskeletons, are used mainly for support and rehabilitation, as well as for augmentation of human capabilities. Providing a control interface for exoskeletons, that would guarantee comfort and safety, as well as efficiency and robustness, is still an issue. This paper presents a methodology for estimating human arm motion and force exerted, using electromyographic (EMG) signals from muscles of the upper limb. The proposed method is able to estimate motion of the human arm as well as force exerted from the upper limb to the environment, when the motion is constrained. Moreover, the method can distinguish the cases in which the motion is constrained or not (i.e. exertion of force versus free motion) which is of great importance for the control of exoskeletons. Furthermore, the method provides a continuous profile of estimated motion and force, in contrast to other methods used in the literature that can only detect initiation of movement or intention of force. The system is tested in an orthosis-like scenario, during planar movements, through various experiments. The experimental results prove the system efficiency, making the proposed methodology a strong candidate for an EMG-based control scheme applied in robotic exoskeletons.**

I. INTRODUCTION

The coupling of human extremities with robotic devices has received increased attention during the last decades. Focusing on the upper extremity, there has been a wide research on the development and control of arm exoskeletons, towards providing both efficiency and safety for the users. The fact that exoskeletons are in physical contact with the human, and thus exchange power and information signals, makes their control exceptionally demanding [1]. Although the intention of the user wearing the exoskeleton is important, since it is essentially the predominant control signal, the means of interfacing with the user and consequently the decoding of his intention has not been sufficiently resolved yet.

Most of the previous developments in the field, use signals coming from either artificial sensors (e.g. force-torque sensors), or from the human limb itself, as control interface for the exoskeletons. Surface electromyographic (EMG) signals are frequently used, since their recording method doesn't entail any bulky mechanisms or machinery placed on the user. EMG signals correspond to muscle activity when the muscle contracts. Since muscle contraction causes not only motion, but also force exertion to the environment through the actuated limb, EMG signals can be proved very useful in cases where motion and force estimates are required.

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A lot of different methodologies have been proposed for the utilization of EMG signals to control robots coupled with humans. A Hill-based muscle model was used to estimate human joint torque in driving an exoskeleton in [2]. For rehabilitation purposes, Dipietro et al. [3] developed a training system for the upper limb movements of stroke patients, which incorporates EMG signals. Kiguchi et al. [4] used EMG signals for the control of an exoskeleton for human elbow and forearm motion assistance. EMG signals to force relationship were investigated in the past [5]. However, there is limited literature on combined motion and force estimation using EMG signals, which is undoubtedly a challenging issue for the control of wearable robotic systems. The authors in the past have developed a system for this scope [6]. However, it's applicability was restricted only to constrained motion, i.e. force was always present during motion. Consequently, the system could not resolve the case where both constrained and unconstrained motion was performed during the same trial (i.e. in a consecutive manner).

In this paper, a method for estimating a continuous profile of motion and force exerted by the upper limb, during unconstrained and constrained movement, using EMG signals recorded from 7 muscles, is proposed. The motion analyzed is restricted to a plane perpendicular to the user's torso, at the height of the shoulder. Seven bipolar surface EMG electrodes record the muscular activity of equal in number muscles acting on the shoulder and the elbow joints. The system architecture is divided into two phases: the training and the real-time operation. During the training phase the user is instructed to move his/her arm randomly on the plane. The user's wrist is coupled with the end-effector of a robotic manipulator, which is configured in such way permitting motion only on the aforementioned plane. The training phase is divided in two stages; at the first stage, the robot arm is compliant to the user's motion, therefore the motion is considered unconstrained. At the second stage, the robot arm exerts force at the user's wrist, therefore the motion is constrained. This is done through an artificial potential field on the plane of motion, that attracts the robot end-effector, and consequently the user's hand, to the center of the workspace.By using this attractive potential field, many situations occurring when a person interacts with the environment through an exoskeleton, are simulated (i.e. pushing, pulling or lifting an object).During both stages, muscular activity of the seven muscles, as well as the motion of the arm on the plane, are recorded. Using these training data, a switching model is trained to map muscles activation to both motion and exerted force. As soon as the model

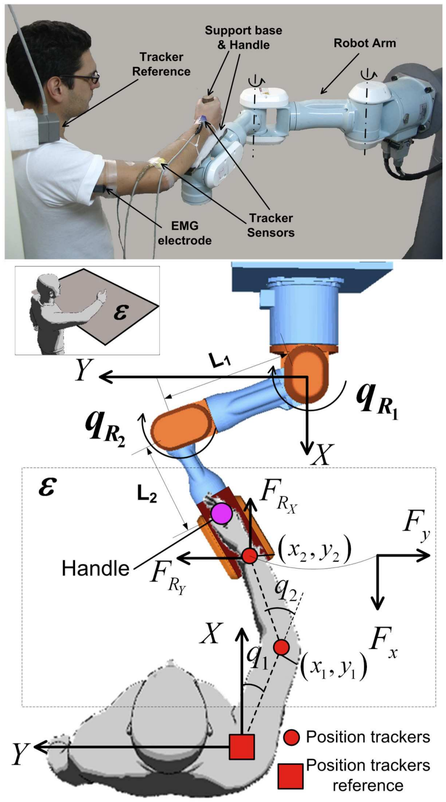

Fig. 1. Orthosis-like experimental setup.

is trained, the real-time operation phase commences. During this phase, EMG recordings are decoded to motion and force in real-time. The motion switches between constrained and unconstrained without notifying the user, while the switching is not known a priori to the system. The proposed method is assessed through an orthosis-like experimental setup.The experimental results show that the proposed method could be used for the control of wearable robotic devices and especially arm exoskeletons.

The rest of the paper is organized as follows: the proposed system architecture is analyzed in Section II, the experiments are reported in Section III, while Section IV concludes the paper.

II. Materials and methods

The motion analyzed in this paper is restricted to the plane ε as shown in Fig. 1. Consequently, only shoulder transverse adduction-abduction and elbow flexion-extension are analyzed. The main responsible muscles for the analyzed shoulder motion (i.e. deltoid (anterior), deltoid (posterior), deltoid (middle), pectoralis major) and for the elbow motion (i.e. biceps brachii, brachioradialis, triceps brachii) are recorded using surface EMG electrodes connected to an EMG acquisition system. The signals are pre-amplified with a gain factor of 1000 and acquired through a signal acquisition board using sampling frequency of 1kHz. Then, they are full-wave rectified, low-pass filtered (4^{th} order Butterworth filter) and normalized to their maximum voluntary isometric contraction value [7].

Measurement of the performed motion is accomplished by using a position tracking system. The tracker sensors are placed on the elbow and the wrist of the user, while their reference system is placed on the shoulder of the user as shown in Fig. 1. Since two rotational DoFs are of interest, the corresponding joint angles can be computed using the position tracker measurements, through the following equations.

$$\begin{aligned} q_1 &= \arctan 2\left(y_1, x_1\right) \\ q_2 &= \arctan 2\left(y_2 - y_1, x_2 - x_1\right) \end{aligned} \tag{1}$$

where q_1, q_2 the shoulder and elbow joint angles respectively and (x_1, y_1), (x_2, y_2) the coordinates of the sensors 1 and 2 respectively, with respect to the tracker reference system, as shown in Fig. 1.

The user's wrist joint is immobilized at zero position using straps on a support base equipped with a handle for the user's hand. The support base is mounted on the end-effector of a 7 degrees of freedom (DoFs) robotic manipulator, which is properly configured to support the user's hand against gravity. Two robotic joints are free to move, while the others are fixed through electromechanical brakes.In order to artificially create a constrained motion of the human arm, the robot arm was controlled in such way simulating a two-dimensional spring with variable stiffness. Thus, when the user moves his/her arm on the plane as shown in Fig. 1, he/she has to exert force to the environment (i.e. robot arm) in order to deform the virtual two-dimensional spring. A variable stiffness is used in order to achieve larger heterogeneity in exerted force profiles. For that reason, an artificial potential field $V\left(x_e, y_e\right)$ is defined as

$$V\left(x_e, y_e\right) = sgn\left(\frac{d}{2} - x_e\right) c\left(x_e\right) + sgn\left(y_e\right) \frac{F_y^{\max}}{d^2} y_e^3 \tag{2}$$

where $\left[\begin{array}{cc} x_e & y_e \end{array}\right]^T$ the end-effector position at the plane of motion, and

$$c\left(x_e\right) = \left(-\frac{4F_x^{\max}}{3d^2} x_e^3 + \frac{2F_x^{\max}}{d} x_e^2 - F_x^{\max} x_e + \frac{1}{6} F_x^{\max} d\right) \tag{3}$$

where $F_x^{\max}$, $F_y^{\max}$ the maximum forces exerted along the X, Y axes of the plane, $d = L_1 + L_2$ where L_1, L_2 the length of the robot links as shown in Fig. 1, while is the function $sgn\left(\cdot\right)$ the signus function. The potential field built on the plane of motion is designed in order to make the user exert force along the two axes of motion and in both directions (i.e. attractive and repulsive forces), while the magnitude of each force component is a 2^{nd} order function of the position at the corresponding axis. This is true since the force $\mathbf{F} = \left[\begin{array}{cc} F_x & F_y \end{array}\right]^T$ that the user exerts, is equal in magnitude and opposite in direction to the force $\mathbf{F}_R = \left[\begin{array}{cc} F_{R_X} & F_{R_Y} \end{array}\right]^T$ exerted by the robot arm due to the potential field V, which is given by $\mathbf{F}_R = -\nabla V\left(x_e, y_e\right)$ The potential across the plane of motion, is depicted in Fig. 2. As it can be seen, the proposed potential field generates forces along the two axes in both directions, since it is attractive to its center $\left[\begin{array}{cc} \frac{d}{2} & 0 \end{array}\right]^T$.

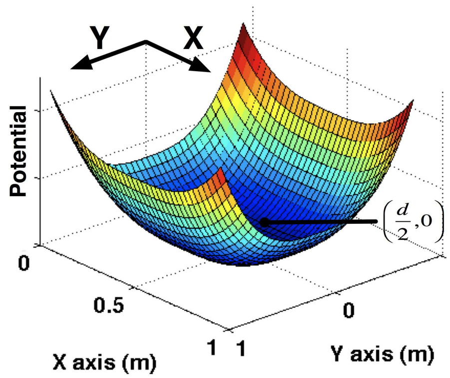

Fig. 2. Potential field on the robot workspace.

In order the robot arm to exert the above mentioned force to the user through the handle mounted at the support base as shown in Fig. 1, the following torque command should be sent to the motors of the actuated robotic joints:

$$\tau = \mathbf{I}\ddot{\mathbf{q}}_R + \mathbf{F_{fr}}\left(\dot{\mathbf{q}}_R\right) + \mathbf{J}^T\left(\mathbf{q}_R\right)\mathbf{F}_R \tag{4}$$

where $\tau = \left[\begin{array}{cc} \tau_1 & \tau_2 \end{array}\right]^T$ the torque vector sent to the motors of the robot arm, $\mathbf{I}$ the 2×2 tensor of inertia of the two DoF arm, $\mathbf{q}_R = \left[\begin{array}{cc} q_{R_1} & q_{R_2} \end{array}\right]^T$ the robot joint angles vector, $\mathbf{F_{fr}}$ the friction vector at each joint and $\mathbf{J}\left(\mathbf{q}_R\right)$ the two DoF arm Jacobian matrix given by:

$$\mathbf{J} = \left[\begin{array}{cc} -L_1 s_2 - L_2 s_{24} & -L_2 s_{24} \\ L_1 c_2 + L_2 c_{24} & L_2 c_{24} \end{array}\right] \tag{5}$$

where c_i, s_i correspond to $\cos\left(q_{R_i}\right)$ and $\sin\left(q_{R_i}\right)$ respectively, $i = 1, 2$, while c_{12}, s_{12} correspond to $\cos\left(q_{R_1} + q_{R_2}\right)$ and $\sin\left(q_{R_1} + q_{R_2}\right)$. The inertia tensor $\mathbf{I}$ and the friction terms for each joint have been identified in [8]. The Coriolis-Centrifugal forces of the robot are omitted since their contribution to the dynamic equation is considered negligible.

Therefore, using the above setup, a constrained (or unconstrained for zero force field) motion of the upper limb can be simulated. The question to be answered here is how using EMG recordings and training data (of both motion and force measured), one could train a decoding method for estimating both motion (shoulder and elbow motion) and force applied (along the two X , Y axes of the plane) using only EMG signals in real-time. Furthermore, this method should be robust enough to provide precise estimates, in both cases, i.e. constrained and unconstrained motion.

Since the number of muscles recorded is quite large (i.e. 7), a low-dimensional (low-D) representation of muscle activations will be used instead of individual activations. This is based on the muscle synergies during motion of the arm, that have been discussed in the biomechanics literature [9]. To deal with this, a dimensionality reduction technique is applied. The most widely used dimension reduction technique is principal component analysis (PCA). It is widely used due to its conceptual simplicity and the fact that relatively efficient algorithms exist for its computation. The central idea of PCA is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is achieved by transforming the data set to a new set of variables, the principal components (PCs), which are uncorrelated, and which are ordered so that the first few retain most of the variation present in all of the original variables. For more details about the method, the reader should refer to [10], [11]. The method application is briefly described in the following paragraph.

EMG signals recorded during training, are digitized and pre-processed resulting to M measurements for each of the 7 muscles corresponding to their activation. Let $\mathbf{z}_t = \left[\begin{array}{ccc} z_{1,t} & \ldots & z_{7,t} \end{array}\right]^T \in R^7$, represent activations of the 7 muscles at time t. A matrix $\mathbf{Z} = \left[\begin{array}{ccc} \mathbf{z}_1 & \ldots & \mathbf{z}_M \end{array}\right]$ is constructed for the M time instances in the training data, having the zero-mean activations of each muscle during training. Since each row of the matrix $\mathbf{Z}$ correspond to zero-mean muscle activation of each muscle, the covariance matrix $\mathbf{\Sigma}$ is given by

$$\mathbf{\Sigma} = \mathbf{Z}\mathbf{Z}^T \tag{6}$$

Since $\mathbf{\Sigma}$ is symmetric and positive semi-definite, there exists an orthonormal matrix $\mathbf{G}$ and a nonnegative diagonal matrix $\mathbf{\Lambda}$ such that

$$\mathbf{\Sigma} = \mathbf{G}\mathbf{\Lambda}\mathbf{G}^T \tag{7}$$

Each column of in $\mathbf{G}$ is an eigenvector and each diagonal entry in $\mathbf{\Lambda}$ is an eigenvalue which reveals the variance in the corresponding eigenvector direction. The total variance of the data is the sum of all these eigenvalues. Therefore, the eigenvectors with the highest eigenvalues describe most of the original data variance [11]. Describing the original variables with fewer dimensions d_L, is finally the goal of the proposed method. Many criteria have been proposed for choosing the right number of the PCs to keep, in order to retain most of the original data variance. The reader should refer to [11] for a complete review of these methods. Perhaps the most obvious criterion for choosing the number of fewer dimensions d_L, is to select a cumulative percentage of total variation which one desires that the selected PCs contribute, i.e. 80% or 90%. The required number of the PCs is then the smallest value of d_L, for which, this chosen percentage is exceeded. Indeed, after the application of the dimensionality reduction method on the muscle data recorded, it was found that a 2-dimensional (2D) space could describe most of the original 7D data variability. Details on dimensionality reduction on muscle activations can be found in [12].

Having enough training data, one can build a model that will use EMG signals to estimate motion and force exerted. In order to describe motion, the angular velocity of each joint is selected. This is done because the joint angular velocity distribution can be accurately enough modeled through a Gaussian distribution, a fact that alleviates the following analysis. Let $\mathbf{U}_t \in \mathbb{R}^2$ be a vector describing the 2D representation of muscles activation at time $t = kT$, where T the sampling period (1 $msec$ in our case), and $k = 0, 1, \ldots$. Let $\mathbf{y}_t = \left[\begin{array}{cccc} \dot{q}_{1_t} & \dot{q}_{2_t} & F_{x_t} & F_{y_t} \end{array}\right]^T$ be the desired output of the model, where $\dot{q}_{1_t}$, $\dot{q}_{2_t}$ the shoulder and elbow angular

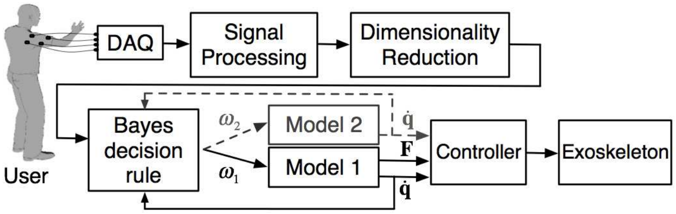

Fig. 3. Block diagram of the proposed method. The ω_1 case is depicted.

velocity respectively, and F_{x_t}, F_{y_t} the components of exerted force along the X, Y axes respectively, at time t. A decoding model of the following form is selected:

$$\begin{aligned} \mathbf{x}_{t+1} &= \mathbf{A}\mathbf{x}_t + \mathbf{B}\mathbf{U}_t + \mathbf{v}_t \\ \mathbf{y}_t &= \mathbf{C}\mathbf{x}_t + \upsilon_t \end{aligned} \tag{8}$$

where $\mathbf{x}_t \in \mathbb{R}^h$ a hidden state vector, h the dimension of this vector and $\mathbf{v}_t$, υ_t zero-mean Gaussian noise in process and observation equations respectively, i.e $\mathbf{v}_t \sim N(\mathbf{0}, \mathbf{W})$, $\upsilon_t \sim N(\mathbf{0}, \mathbf{Q})$, where $\mathbf{W}_{h\times h}$, $\mathbf{Q}_{4\times 4}$ are the covariance matrices of $\mathbf{v}_t$, υ_t respectively. Matrices $\mathbf{A}_{h\times h}$, $\mathbf{B}_{h\times 2}$ and $\mathbf{C}_{4\times h}$ represent the dynamics of the hidden states, the relation between the low-D embeddings of muscles activation and the hidden states dynamics, and the relation of the hidden states to the output variables of the model respectively.

Model training entails the estimation of the matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, $\mathbf{W}$ and $\mathbf{Q}$. Given a training set including the low-D embeddings of the muscle activations and the model output (i.e. joint velocities and force exerted), the model parameters can be found using an iterative prediction-error minimization (i.e. maximum likelihood) algorithm [13].

The model (8) was used to decode muscular activity to planar motion of the upper limb in the past [12]. Moreover, a model of similar structure was proved successful in decoding EMG signals to force exerted, but only when the force was always present [6]. In this paper, whether the force is present or not (i.e. the motion is constrained or not) is not known a priori. Therefore, the main objective is to combine two different models of the same form as in (8), and to effectively switch between them in real time, in order to decode EMG activity to both motion and exerted force, whether or no the motion is constrained. This is achieved through training of the two models at the two corresponding cases (constrained and unconstrained motion), and building a probabilistic framework that will decide the proper model to use at each time instance. The architecture proposed is depicted in Fig. 3.

The switching between the two models is based on the probability that exerted force is present, given the low-D embeddings of muscles activations and the joint angular velocities $\dot{\mathbf{q}} = \begin{bmatrix} \dot{q}_1 & \dot{q}_2 \end{bmatrix}^T$. Let $\mathbf{\Omega} = \{\omega_1, \omega_2\}$ be the set of the two possible classes, where ω_1 corresponds to exertion of force and ω_2 corresponds to free motion. Therefore, given a feature vector

$$\mathbf{S} = \begin{bmatrix} u_{L_1} & u_{L_2} & \dot{q}_1 & \dot{q}_2 \end{bmatrix}^T \tag{9}$$

where u_{L_1}, u_{L_2} the 2D embeddings of the 7 muscles activation, a classifier is built to decide whether the exerted force is zero or not, i.e. the class is ω_2 or ω_1 respectively, at each time step. This is done by using the Bayes theorem [14], that in our case is defined as

$$P(\omega_j|\mathbf{S}) = \frac{p(\mathbf{S}|\omega_j)\, P(\omega_j)}{p(\mathbf{S})}, \quad j = 1, 2 \tag{10}$$

where $P(\omega_j|\mathbf{S})$ the posterior probability, i.e. the probability of the class being ω_j given the feature vector $\mathbf{S}$, $p(\mathbf{S}|\omega_j)$ the class-conditional PDF, $P(\omega_j)$ the prior probability of the class being ω_j and $p(\mathbf{S}) = \sum_{j=1}^{2} p(\mathbf{S}|\omega_j)\, P(\omega_j)$ the evidence factor that can be viewed as a scale factor that guarantees the posterior probabilities sum to one. The two classes ω_1, ω_2 are considered equally likely to happen, thus $P(\omega_1) = P(\omega_2) = 0.5$. The class-conditional PDF $p(\mathbf{S}|\omega_j)$ represents the likelihood of ω_j with respect to the feature vector $\mathbf{S}$, i.e. the muscles activation and the performed motion. This density function is built during the training procedure, where EMG signals, force and position data are collected. Knowing when force is exerted (i.e. given the class ω_j), the PDF is fitted to a mixture of Gaussians distributions. A mixture of multivariate Gaussians is selected since it can model quite accurately the distribution of the data collected, and moreover, the fitting procedure[1] is simple and computationally fast. Thus the class-conditional PDF is defined as

$$p(\mathbf{S}|\omega_j) = \sum_{i=1}^{g_j} \pi_i^{(j)} f_i^{(j)}\left(\mathbf{S}, \mu_i^{(j)}, \Sigma_i^{(j)}\right), \quad j = 1, 2 \tag{11}$$

where $f_i^{(j)}\left(\mathbf{S}, \mu_i^{(j)}, \Delta_i^{(j)}\right)$ represents a multivariate Gaussian density function with $\mu_i^{(j)}$ the mean vector, and $\Delta_i^{(j)}$ the respective covariance matrix, $\pi^{(j)} = \begin{bmatrix} \pi_1^{(j)} & \dots & \pi_{g_j}^{(j)} \end{bmatrix}^T$ the vector of mixing proportions of the mixture, while the exponent (j) at each variable in (11) denotes the class-specific variable. The mixing proportions of each mixture sums to one, i.e. $\sum_{i=1}^{g_j} \pi_i^{(j)} = 1, \quad j = 1, 2$. Using training data, the two Gaussian mixture models (GMMs) defined in (11) are fitted. Then, during the real-time operation phase, using (10), a decision about the class can be made at each time step, according to the simple Bayes decision rule, i.e. decide ω_1 if $P(\omega_1|\mathbf{S}) > P(\omega_2|\mathbf{S})$; otherwise decide ω_2. This decision controls the switching between the two models of form (8), which is done at each time step, where a new feature vector $\mathbf{S}$ is available. Having decided if motion is constrained or not, and using recorded muscle activation, the appropriate decoding model provides the desired estimates for motion and force exerted.

III. Results

The proposed architecture is assessed through experiments on an orthosis-like setup as depicted in Fig. 1. The robot

[1] Expectation Minimization algorithm (EM) [15]

TABLE I

COMPARISON BETWEEN THE PROPOSED STATE-SPACE MODEL AND THE LINEAR-FILTER METHOD IN DECODING MOTION AND FORCE

Decoding model	Training time (sec)	CC_1	CC_2	CC_3	CC_4	$RMSE_1\ \left(\frac{rad}{\sec}\right)$	$RMSE_2\ \left(\frac{rad}{\sec}\right)$	$RMSE_3\ (N)$	$RMSE_4\ (N)$
State-space	28	0.97	0.96	0.97	0.98	0.05	0.06	1.59	1.73
Linear-filter	25	0.74	0.78	0.79	0.81	0.18	0.35	5.43	8.11

arm used is a 7 DoF anthropomorphic manipulator (PA-10, Mitsubishi Heavy Industries). The details of the experimental setup can be found in [6].

During the training, the user is instructed to move his/her arm randomly on the plane. The user's wrist is coupled with the end-effector of a robotic manipulator, which is configured in such way permitting motion only on the aforementioned plane. Initially, the force field is set to zero, therefore the robot arm is compliant to the user's induced motion, and so the motion is considered free. EMG signals and position data are collected for a period of 1 minute. Then, the force field is activated, while the user continues to perform random movements on the plane. Now the motion is constrained and in addition to the previous recordings, force data are also collected from the robot joint motor current readings. This stage lasts 1 minute too. The recorded data from both stages are used in the previously analyzed methods, to conclude to a switching system that can estimate motion and force exerted using only EMG recordings.

As soon as the model is trained, the real-time operation phase commences. During this phase, the user is instructed to move his arm on the plane, whether the force field is active or not. On the robot side, the force field is activated in a random way, therefore it's not known a priori neither to the user nor to the proposed system, when the motion is constrained or not. The position trackers are kept into place for offline validation purposes. The estimates for motion and force, along with the ground truth are shown in Fig. 4. As it can be seen, the proposed method could track the motion and the force exerted by the user's arm, with high accuracy, using only EMG recordings, even if the motion was changing from constrained to unconstrained in real-time.

Two criteria will be used for assessing the accuracy of the reconstruction of human motion and force using the proposed methodology. These are the root-mean-squared error (RMSE) and the correlation coefficient (CC). The latter describes essentially the similarity between the reconstructed and the true motion (or force) profiles and constitutes the most common means of reconstruction assessment for decoding purposes. Let $\hat{\mathbf{y}} = \begin{bmatrix} \hat{y}_1 & \hat{y}_2 & \hat{y}_3 & \hat{y}_4 \end{bmatrix}^T = \begin{bmatrix} \hat{\dot{q}}_1 & \hat{\dot{q}}_2 & \hat{F}_X & \hat{F}_Y \end{bmatrix}^T$ the estimated output vector of motion and force and $\mathbf{y}_{\mathrm{T}} = \begin{bmatrix} y_{1_{\mathrm{T}}} & y_{2_{\mathrm{T}}} & y_{3_{\mathrm{T}}} & y_{4_{\mathrm{T}}} \end{bmatrix}^T = \begin{bmatrix} \hat{\dot{q}}_{1_{\mathrm{T}}} & \hat{\dot{q}}_{2_{\mathrm{T}}} & \hat{F}_{X_{\mathrm{T}}} & \hat{F}_{Y_{\mathrm{T}}} \end{bmatrix}^T$ the corresponding true values of the variables, measured through the position tracker and the robot motors[2]. Then the RMSE and CC criteria are defined by

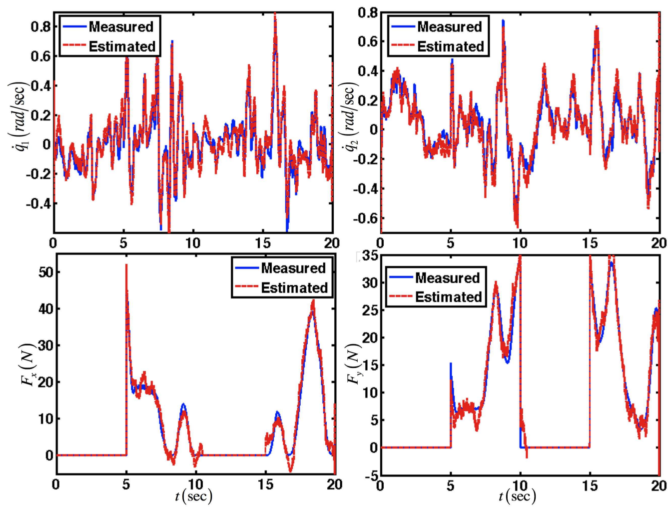

Fig. 4. Estimates for angular velocity and force exerted. The motion was changing from unconstrained to constrained every 5 sec.

$$RMSE_i = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(y_{i_{\mathrm{T}}k} - \hat{y}_{ik}\right)^2}, \quad i = 1,2,3,4 \tag{12}$$

$$CC_i = \frac{\sum_{k=1}^{n}\left(y_{i_{\mathrm{T}}k} - \bar{y}_{i_{\mathrm{T}}}\right)\left(\hat{y}_{ik} - \bar{\hat{y}}_i\right)}{\sqrt{\sum_{k=1}^{n}\left(y_{i_{\mathrm{T}}k} - \bar{y}_{i_{\mathrm{T}}}\right)^2 \sum_{k=1}^{n}\left(\hat{y}_{ik} - \bar{\hat{y}}_i\right)^2}}, \quad i = 1,2,3,4 \tag{13}$$

where $\bar{y}_i$ represents the mean of the i^{th} element of the output vector across n testing samples. Perfect matching between the estimated and true values corresponds to $CC = 1$. Table I lists the criteria values for a testing session of 1 minute during the real-time operation phase, including also the method training computation time, which was less than 30 seconds.

A worth-assessing characteristic of the method is the type of the decoding model used (i.e. linear model with hidden states). The authors believe that a comparison with

[2]Joint angular velocity is computed through differentiation with respect to time of the joint angles computed from (1), while exerted force is computed through robot joint torque (i.e. motor current) readings via the manipulator Jacobian matrix (5) and (4).

a well-known and of similar complexity algorithm, such as the linear filter method, is reasonable. Briefly, if $\mathcal{Y}_k$ the variables decoded (i.e. joints velocity and force exerted) at time $t_k = kT$ and $\mathcal{E}_{i,k-j}$ the muscle activation of muscle i at time t_{k-j}, the computation of the linear-filter entails finding a set of coefficients $\xi = \begin{bmatrix} a & r_{1,1} & \dots & r_{i,j} \end{bmatrix}^T$, so that

$$\mathcal{Y}_k = a + \sum_{i=1}^{v} \sum_{j=0}^{N} r_{i,j} \mathcal{E}_{i,k-j} \tag{14}$$

where a is a constant offset, $r_{i,j}$ are the filter coefficients, v is the number of muscles recorded, while the parameter N specifies the number of time bins used. A typical value of the latter is $100msec$, thus $N = 100$, for a sampling period of $1msec$. The coefficients can be estimated from training data using simple least-squares regression. In our case, for the sake of comparison, the same training data were used for both the state-space model and the linear-filter, and after training, both models were tested using the same testing data as before. Regarding the switching case, two models of the linear filter method were also used, for the case of unconstrained and constrained motion respectively, while the switching was controlled by using the same probabilistic framework used for the state-space model. Values for RMSE and CC for the linear filter method are also reported in Table I, for the sake of comparison with the state-space model.

In general the proposed methodology was proved very accurate in decoding EMG to both motion and force, despite the fact that the motion was varying from constrained to unconstrained in real time. Moreover, the proposed decoding model outperformed the mostly used one (i.e. linear filter), while the complexity of the method and the time of training was negligible.

IV. Conclusions and Discussion

In this paper, the authors have proposed a method for decoding EMG activity from muscles of the upper limb to motion and force exerted. The activation of 7 muscles of the shoulder and elbow joints were recorded and represented into a low-dimensional space, revealing muscle synergies during planar movements. Then, a switching method using linear state space models with hidden states, was used to decode low-D muscle embeddings to performed motion and force. A probabilistic framework was used in order to classify performed motion (to unconstrained or constrained) and decide which decoding model to use. Gaussian mixture models were also used in order to fit the density function of the data recorded during training. The system was used for estimating in real-time a continuous profile of motion and force exerted by the user to the environment, tested through an orthosis-like setup. The method was proved very accurate in estimating the desired profiles of motion and force.

The main novelty introduced here is that the proposed method is accurate enough in cases where constrained and unconstrained motion is present. Its importance becomes obvious if one realizes that this is the case where a person wears an exoskeleton and interacts with the environment (e.g. reaching targets or lifting objects). Moreover, the proposed method can provide a continuous profile of motion and force, in comparison with most of the previous works in the field that provide only discrete information about motion (i.e. initiation or ending of it). Highly efficient exoskeletons that have been built during the last years should be compliant, assisting and safe for the users, monitoring their intention of motion and force exerted. For this reason, the proposed method could be used for the robust control of highly efficient exoskeletons.

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