EMG-based Position and Force Estimates in Coupled Human-Robot Systems: Towards EMG-controlled Exoskeletons

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This paper presents a methodology for the control of robots, in position and force, using electromyographic (EMG) signals recorded from muscles of the shoulder and elbow. A switching model is used for decoding muscular activity to both joint angles and force exerted from the human upper limb to the environment. The proposed method is able to estimate those variables in cases where no force is exerted to the environment (unconstrained motion), as well as in cases where motion is accompanied with force exertion (constrained motion). The switching model is trained to each subject, a procedure that takes only a few minutes, using a torque-controlled robot arm coupled with the human arm. After training, the system can decode position and force using only EMG signals recorded from 7 muscles. The system is tested in a orthosis-like scenario, in planar movements, through various experiments covering the cases aforementioned. The experimental results prove the system efficiency, making the proposed methodology a strong candidate for an EMG-based controller for robotic exoskeletons.

1 Introduction

Robotic devices coupled with human upper extremities have received increased attention during the last decade. More specifically, there has been a wide research on the control of exoskeletons, towards providing both efficiency and safety. The most challenging issue in the control of exoskeletons is the fact that they are in physical contact with the human and exchange power and information signals [1].

Most of the previous developments in the field, use signals coming from either artificial sensors (e.g. force-torque sensors), or 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. This is the case where an exoskeleton is to be controlled, since human intended motion and force should be estimated and incorporated in its controller.

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, Krebs et al. [3] developed a training system for the upper limb movements of stroke patients, which incorporates EMG signals. In this setup however, only the onset of the patient's attempt to move is detected by monitoring EMG signals and not the whole profile of motion and force exerted. Generally, there is limited literature on combined position and force estimation using EMG signals, which is undoubtedly a challenging issue for the control of coupled human-robot systems. The authors in the past have developed a system for this scope [4]. 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. Furthermore, motion was not estimated using the EMG recordings, but using a position tracking system.

In this paper, a method for estimating a continuous profile of motion and force exerted by the upper limb, during un-constrained and constrained movements, 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. Using this field, the motion is constrained in both directions of motion (i.e. towards the user's body or not), thus both the flexor and extensor muscles of the analyzed joints are activated. By using the aforementioned 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 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, where EMG signals are decoded to both motion and force exerted, in real-time. 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 2, the experiments are reported in Section 3, while Section 4 concludes the paper.

2 Materials and methods

The set-up used for the present study is shown in Fig. 1. User's motion is restricted to the plane, thus 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. A signal pre-processing algorithm is applied to EMG signals to remove noise. Measurement of joint angles is accomplished by using a position tracking system (Isotrak II, Polhemus Inc.). 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. The user's wrist joint is immobilized at zero position by means of 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 (PA-10, Mitsubishi Heavy Industries), 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 such configuration allowing the robotic arm to move on the same plane that the user's arm moves. The robot arm was controlled in such a 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 (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 details on the generation of the 2-dimensional force field as well as the realization of this, through the appropriate torque control at the robot joints, the reader should refer to [4].

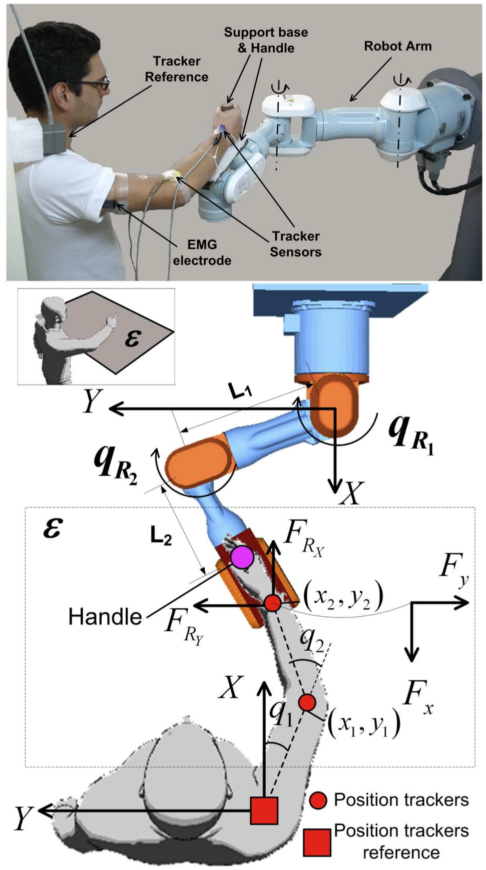

Fig. 1. Orthosis-like experimental setup.

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 position 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 has been discussed in the biomechanics literature [5]. Indeed, after the application of the dimensionality reduction method on the 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 [6].

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[1]. 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 $\mathbf{y}_t = \left[\, \dot{q}_{1_t} \ \dot{q}_{2_t} \ F_{x_t} \ F_{y_t} \,\right]^T$ be the desired output of the model, where $\dot{q}_{1_t}$, $\dot{q}_{2_t}$ the shoulder and elbow angular velocity respectively[2], and F_{x_t}, F_{y_t} the components of exerted force along the X, Y axes respectively, at time t. The model selected is defined as

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

where $\mathbf{x}_t \in \mathbb{R}^d$ a hidden state vector, d 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 $\mathbf{W} \in \mathbb{R}^d$, $\mathbf{Q} \in \mathbb{R}^4$ are the covariance matrices of $\mathbf{v}_t$, υ_t respectively. Matrices $\mathbf{A}_{d\times d}$, $\mathbf{B}_{d\times 2}$ and $\mathbf{C}_{4\times 2}$ 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. Details on the model structure can be found in [6].

The authors have used the model (1) to decode muscular activity to planar motion of the upper limb in the past [6]. Moreover, a model of similar structure was proved successful in decoding EMG signals to force exerted, but only when the force was always present [4]. 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 (1), 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. 2.

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 $\dot{\mathbf{q}} = \left[\, \dot{q}_1 \ \dot{q}_2 \,\right]^T$. 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. Moreover, since the observed muscular activity is also affected by the performed motion (i.e. different angular velocity is caused by different muscle activity), the joint velocity $\dot{\mathbf{q}}$ should also be considered in the

[1] Joint angular velocity distribution can be modeled through a Gaussian distribution, a fact that alleviates the following analysis.

[2] With q_1 corresponding to the shoulder adduction-abduction and q_2 the elbow flexion-extension angle.

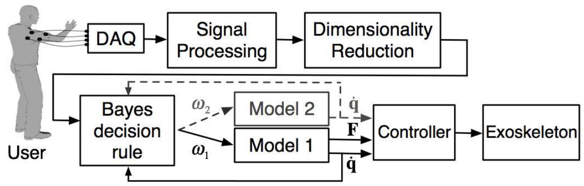

Fig. 2. Block diagram of the proposed method. The ω_1 case is depicted.

proposed framework. Therefore, given a feature vector $\mathbf{S} = \left[\, u_{L_1}\ u_{L_2}\ \dot{q}_1\ \dot{q}_2 \,\right]^T$, 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 Bayes theorem [7], that in our case is defined as

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

where $P\left(\omega_j|\mathbf{S}\right)$ the posterior probability, i.e. the probability of the class being ω_j given the feature vector $\mathbf{S}$, $p\left(\mathbf{S}|\omega_j\right)$ the class-conditional PDF, $P\left(\omega_j\right)$ the prior probability of the class being ω_j and $p\left(\mathbf{S}\right) = \sum_{j=1}^{2} p\left(\mathbf{S}|\omega_j\right) P\left(\omega_j\right)$ 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 $P\left(\omega_1\right) = P\left(\omega_2\right) = 0.5$. The class-conditional PDF $p\left(\mathbf{S}|\omega_j\right)$ 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[3] is simple and computationally fast. Thus the class-conditional PDF is defined as

$$p\left(\mathbf{S}|\omega_j\right) = \sum_{i=1}^{g_j} \pi_i^{(j)} f_i^{(j)} \left(\mathbf{S}, \mu_i^{(j)}, \varSigma_i^{(j)}\right), \quad j = 1, 2 \tag{3}$$

where $f_i^{(j)} \left(\mathbf{S}, \mu_i^{(j)}, \varSigma_i^{(j)}\right)$ represents a multivariate Gaussian density function with $\mu_i^{(j)}$ the mean vector, and $\varSigma_i^{(j)}$ the respective covariance matrix, $\pi^{(j)} = \left[\pi_1^{(j)} \ldots \pi_{g_j}^{(j)}\right]^T$ the vector of mixing proportions[4] of the mixture,

[3] Expectation Minimization algorithm (EM) [8]

[4] Mixing proportions sum to one, i.e. $\sum_{i=1}^{g_j} \pi_i^{(j)} = 1$

while the exponent (j) at each variable in (3) denotes the class-specific variable. Using training data, the two Gaussian mixture models (GMMs) defined in (3) are fitted. Then, using (2), 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 (1), which is done at each time step, where a new feature vector $\mathbf{S}$ is available. Then, using recorded muscle activation, the selected model provides the desired estimates for motion and force exerted. Therefore, a switching system that can predict motion and force exerted in real time, using only muscle recordings and prior knowledge gained through the training data, has been realized.

3 Results

3.1 Experiment Design

The proposed architecture is assessed through experiments on an orthosis-like setup as depicted in Fig. 1. The robot arm used is a 7 DoF anthropomorphic manipulator (PA-10, Mitsubishi Heavy Industries).

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.

After the training procedure, the real-time operation commences. The position trackers are kept into place for offline validation purposes. EMG signals are only used, and through the switching model architecture, estimates for both joint angular velocities and force exerted are provided. The estimates for motion and force, along with the ground truth are shown in Fig. 3. 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.

3.2 Method assessment

Two criteria will be used for assessing the accuracy of the reconstruction of human motion and force using the proposed methodology. These are the

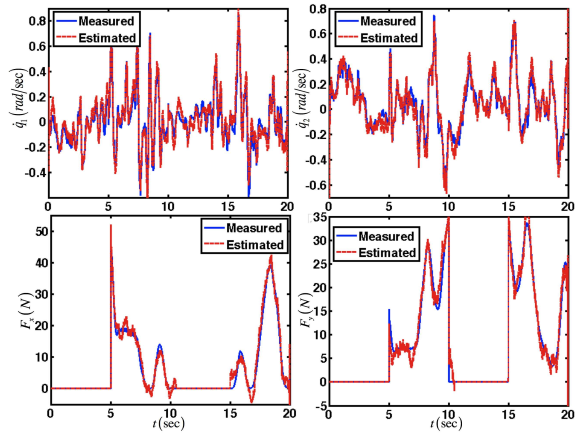

Fig. 3. Estimates for angular velocity and force exerted. The motion was changing from unconstrained to constrained every 5 sec.

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 $\hat{\mathbf{y}} = \left[\hat{y}_1\ \hat{y}_2\ \hat{y}_3\ \hat{y}_4\right]^T = \left[\hat{\dot{q}}_1\ \hat{\dot{q}}_2\ \hat{F}_X\ \hat{F}_Y\right]^T$ the estimated output vector of motion and force and $\mathbf{y}_\mathrm{T} = \left[y_{1_\mathrm{T}}\ y_{2_\mathrm{T}}\ y_{3_\mathrm{T}}\ y_{4_\mathrm{T}}\right]^T = \left[\hat{\dot{q}}_{1_\mathrm{T}}\ \hat{\dot{q}}_{2_\mathrm{T}}\ \hat{F}_{X_\mathrm{T}}\ \hat{F}_{Y_\mathrm{T}}\right]^T$ the corresponding true values of the variables, measured through the position tracker and the robot motors[5]. Then the RMSE and CC criteria are defined by

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

$$CC_i = \frac{\sum\limits_{k=1}^{n}\left(y_{i_\mathrm{T}k} - \bar{y}_{i_\mathrm{T}}\right)\left(\hat{y}_{ik} - \bar{\hat{y}}_i\right)}{\sqrt{\sum\limits_{k=1}^{n}\left(y_{i_\mathrm{T}k} - \bar{y}_{i_\mathrm{T}}\right)^2 \sum\limits_{k=1}^{n}\left(\hat{y}_{ik} - \bar{\hat{y}}_i\right)^2}}, \quad i = 1,2,3,4 \tag{5}$$

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 and II list 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.

[5] Joint angular velocity is computed through time-differentiation of the joint angles, while exerted force is computed through robot joint torque (i.e. motor current) readings via the manipulator Jacobian matrix.

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.

Table 1. Assessment of decoding motion and force using correlation coefficient criterion.

Decoding model	Training time (sec)	CC_1	CC_2	CC_3	CC_4
State-space	28	0.97	0.96	0.97	0.98

Table 2. Assessment of decoding motion and force using the root-mean-squared error.

Decoding model	Training time (sec)	$RMSE_1$ $(\frac{rad}{\sec})$	$RMSE_2$ $(\frac{rad}{\sec})$	$RMSE_3$ (N)	$RMSE_4$ (N)
State-space	28	0.05	0.06	1.59	1.73

4 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 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. 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.

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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