Assessment of Muscle Fatigue using a Probabilistic Framework for an EMG-based Robot Control Scenario

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Abstract— **Human-robot control interfaces have received increased attention during the last decades. With the introduction of robots in every-day life, especially in developing services for people with special needs (i.e. elderly or impaired persons), there is a strong necessity of simple and natural control interfaces. In this paper, electromyographic (EMG) signals from muscles of the human upper limb are used as the control interface between the user and a robot arm. EMG signals are recorded using surface EMG electrodes placed on the user's skin, letting the user's upper limb free of bulky interface sensors or machinery usually found in conventional human-controlled systems. The proposed interface allows the user to control in real-time an anthropomorphic robot arm in three dimensional (3D) space, by decoding EMG signals to motion. However, since EMG changes due to muscle fatigue are present in this kind of control interface, a probabilistic framework has been developed, which can detect in real-time the muscle fatigue level. By complying to those fatigue-related signal changes, the proposed method can provide accurate decoding of motion through long periods of time. The system is used for the continuous control of a robot arm in 3D space, using only EMG signals from the upper limb. The method is tested for a long period of operation, proving that muscle fatigue does not affect the decoder accuracy. The efficiency of the method is assessed through real-time experiments including random arm motions in 3D space.**

I. INTRODUCTION

Although, robots came to light approximately 50 years ago, the way humans can interface with them and finally control them is still an important issue. The human-robot interface plays a role of the utmost significance, especially since the use of robots is increasingly widening to everyday life tasks (e.g. service robots, robots for clinical applications). A large number of interfaces have been proposed in previous works. However, most of the previous works propose complex mechanisms or systems of sensors, while in most cases the user should be trained to map his/her action (i.e. three dimensional (3D) motion of a joystick or a haptic device) to the desired motion for the robot. In this paper a new mean of control interface is proposed, according to which, the user performs natural motions with his/her upper limb. Surface electrodes recording the electromyographic (EMG) activity of the muscles of the upper limb are placed on the user's skin. The recorded muscle activity is transformed to kinematic variables that are used to control the robot arm.

EMG signals have often been used as control interfaces for robotic devices. However, in most cases, only discrete control has been realized, focusing only for example at the directional control of robotic wrists [1], or at the control of multi-fingered robot hands to a limited number of discrete postures [2]. Quite recently Thakor et al. [3] achieved to identify 12 individuated flexion and extension movements of the fingers using EMG signals from muscles of the forearm of an able-bodied subject. However, controlling a robot by using only finite postures can cause many problems regarding smoothness of motion, especially in the cases where the robot performs every-day life tasks. Therefore, effectively interfacing a robot arm with a human entails the necessity of continuous and smooth control.

An important factor that is present in the EMG-based controlled systems, though never been investigated until now, is the muscle fatigue, and how it affects the EMG signal decoding. Muscle fatigue is reflected by certain changes in its electromyogram signal [4]. All the algorithms that have been proposed in the past use stationary models for translating EMG signals to motion. Therefore, EMG changes due to fatigue are not incorporated in the previously used models, making the aforementioned methods applicable only for short time periods.

In this paper, a muscle fatigue-dependent methodology for controlling an anthropomorphic robot arm using EMG signals from the muscles of the upper limb, is proposed. Surface EMG electrodes are used to record from 11 muscles of the shoulder and the elbow. 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 in random patterns with variable speed in the 3D space. A position tracking system is used to record the arm motion during reaching. The procedure lasts for 4 minutes, with no resting periods, in order to investigate muscle fatigue and EMG changes due to fatigue. Four DoFs are analyzed (i.e. two for the shoulder and two for the elbow). To tackle the dimensionality problem, the activation of the 11 muscles recorded and the 4 joint angle profiles are represented into two low-dimensional spaces via the appropriate technique. The mapping between those two low-dimensional spaces is realized through a linear model whose parameters are identified using the previously collected data. Changes in EMG signals due to muscle fatigue are monitored for all the recorded muscles. Then, through the appropriate multivariate modeling and a Bayesian classifier, the condition of the muscles (with respect to their fatigue) is identified. Having represented the muscles condition in discrete phases of fatigue, a set of models are trained instead of one stationary model. In this way, the changes in EMG signals

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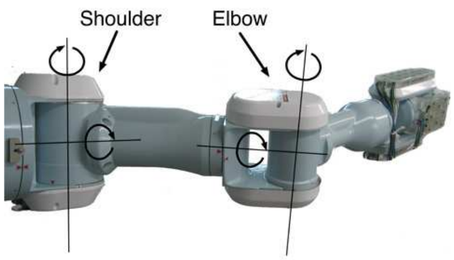

Fig. 1. The controlled robot arm is equipped with two rotational DoFs at the shoulder, and two at the elbow.

due to fatigue are incorporated into the decoding model, since a set of fatigue-dependent models is trained instead of one. Therefore, the accuracy of the decoding method is not affected by muscle fatigue, and the methodology can be used for long periods of time without any efficiency deterioration. As soon as the training phase has finished, the real-time operation phase commences. A control law that utilizes these motion estimates is applied to the robot arm actuators. In this phase, the user can teleoperate the robot arm in real-time. The efficacy of the proposed method is assessed through a large number of experiments, during which the user controls the robot arm in performing random movements in the 3D space.

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

A. Background and Problem Definition

The motion of the upper limb in the 3D space will be analyzed, not including though the wrist joint for simplicity. Therefore the shoulder and the elbow joints are of interest. Since the method proposed here will be used for the control of a robot arm (PA-10, Mitsubishi Heavy Industries), equipped with 2 rotational DoFs at each of the shoulder and the elbow joints as shown in Fig. 1, we will model the human shoulder and the elbow as having two DoFs too, without any loss of generality. In fact, it can be proved from the kinematic equations of a simplified model of the upper limb, that the motion of the human shoulder can be addressed by using two rotational DoFs, with perpendicularly intersecting axes of rotation. The elbow is modeled with a similar pair of DoFs corresponding to the flexion-extension and pronation-supination of this joint. Hence, 4 DoFs will be analyzed from a kinematic point of view. It must be noted that a detailed kinematic model of the upper limb is out of the scope of this paper, since the robot to be controlled is equipped with a limited number of DoFs for the joints analyzed.

For the training of the proposed system, the motion of the upper limb should be recorded and joint trajectories should be extracted. For this scope, a magnetic position tracking system was used, equipped with two position trackers and a reference system, with respect to which the 3D position of the trackers is provided. In order to compute the 4 joint angles, one position tracker is placed at the user's elbow joint and the other one at the wrist joint. The reference system is placed on the user's shoulder. The set-up as well as the 4 modeled DoFs are shown is Fig. 2. Let $\mathbf{T_1} = \begin{bmatrix} x_1 & y_1 & z_1 \end{bmatrix}^T$, $\mathbf{T_2} = \begin{bmatrix} x_2 & y_2 & z_2 \end{bmatrix}^T$ the position of the trackers with respect to the tracker reference system. Let q_1, q_2, q_3, q_4 the four joint angles modeled as shown in Fig. 2. Finally, by solving the inverse kinematic equations the joint angles are given by:

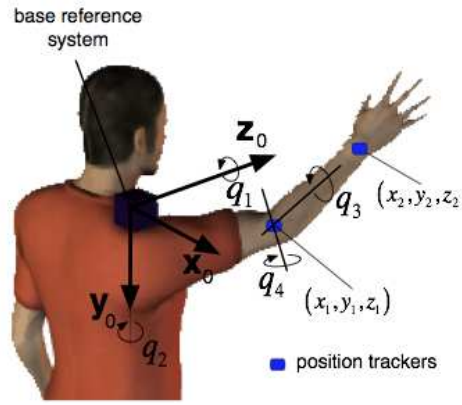

Fig. 2. The user moves his arm in the 3D space. Two position tracker measurements are used for computing the four joint angles. The tracker base reference system is placed on the shoulder.

$$\begin{aligned} q_1 &= \arctan 2\left(\pm y_1, x_1\right) \\ q_2 &= \arctan 2\left(\pm\sqrt{x_1^2 + y_1^2}, z_1\right) \\ q_3 &= \arctan 2\left(\pm B_3, B_1\right) \\ q_4 &= \arctan 2\left(\pm\sqrt{B_1^2 + B_3^2}, -B_2 - L_1\right) \end{aligned} \tag{1}$$

where

$$\begin{aligned} B_1 &= x_2 \cos(q_1)\cos(q_2) + y_2 \sin(q_1)\cos(q_2) - z_2 \sin(q_2) \\ B_2 &= -x_2 \cos(q_1)\sin(q_2) - y_2 \sin(q_1)\sin(q_2) - z_2 \cos(q_2) \\ B_3 &= -x_2 \sin(q_1) + y_2 \cos(q_1) \end{aligned} \tag{2}$$

where L_1 the length of the upper arm. The length of the upper arm can be computed from the distance of the first position tracker from the base reference system, while the length of the forearm L_2 can be computed from the distance between the two position trackers. It must be noted that since the position trackers are placed on the skin and not in the center of the modeled joints, the lengths L_1, L_2 may vary as the user moves the arm. However, it was found that the variance during a 4 minute experiment was less than 1cm (i.e. approximately 3% of the mean values for the lengths L_1, L_2). Therefore, the mean values of L_1, L_2 for a 4 minute experiment were used for the following analysis.

Regarding muscle recordings, a group of 11 muscles, mainly responsible for the analyzed motion, is recorded: deltoid (anterior), deltoid (posterior), deltoid (middle), pectoralis major, teres major, pectoralis major (clavicular head), trapezius, biceps brachii, brachialis, brachioradialis and triceps brachii.

B. Muscle Fatigue Related EMG Changes

It is widely reported in the biomechanics and physiology literature that prolonged or repeated contractions of skeletal muscles lead to impaired muscle function, i.e. development of fatigue [4]. It has been also reported that EMG signal changes with muscle fatigue [4]. In this work, the way these changes are illustrated in the EMG recordings will be investigated in order to build a method able to identify muscle condition with respect to fatigue in real-time. The quantification of muscle fatigue will then lead us to build a set of models for decoding EMG signals to motion, in such a way that EMG changes will not affect the decoding accuracy.

As noted before, the system requires a training period of 4 minutes, without resting periods. During this period, EMG signals from 11 muscles are recorded. After signal preprocessing, a set of signal features are computed. These are listed below:

- Integral of absolute value (IAV)
- Zero crossing (ZC)
- Variance (VAR)

For details about these signal characteristics the reader should refer to literature [5].

The calculation of the previously defined signal features for the training period of 4 minutes, showed that there is an increase in their values with respect to the experiment time that is related to muscle fatigue. Similar behavior was noticed for all the recorded muscles.

C. Muscle Fatigue Assessment

From the above analysis, a feature vector $\mathbf{S}$ can be defined, including the three aforementioned signal characteristics that can be computed at each time bin for each muscle. The feature vector $\mathbf{S}_m^{(i)}$ for each muscle i, $i = 1, \ldots, 11$, for the time bin $m = 1, 2, \ldots$, is defined by:

$$\mathbf{S}_m^{(i)} = \left[\begin{array}{ccc} IAV_m^{(i)} & ZC_m^{(i)} & VAR_m^{(i)} \end{array} \right]^T \tag{3}$$

The time bin m spans from time $(m-1)NT$ to mNT, where T the sampling period, i.e. $T = 1$ msec. and $N = 100$ the width of the time bin.

The purpose of the work, as described above, is to quantify in a sense the muscle fatigue, in order to be able to decide about the muscle condition and switch between different models for EMG-based motion decoding. In other words, a measure of fatigue $f^{(i)}$ for each muscle i should be defined. Then, a set $\mathbf{f}^{(i)}$ of possible *fatigue states* can be defined as shown below

$$\mathbf{f}^{(i)} = \left\{ f_1^{(i)}, f_2^{(i)}, \ldots, f_n^{(i)} \right\} \tag{4}$$

where n the number of fatigue states for the muscle i.

Muscle fatigue is mainly caused by the repetitive force exertion of the muscle. Muscle force, as reported in the literature with the form of the well-known Hill muscle model, is related to muscle length and muscle contraction velocity (i.e. rate of change of the length) [6]. These muscle characteristics are directly related to the angular position and velocity of the actuated joint through a simplified musculoskeletal model of the arm. From the above, it is evident that the joint angle and the angular velocity should be incorporated in our analysis of muscle fatigue. This is because an increase at a signal characteristic (e.g. the $IAV^{(i)}$) of the muscle i can be caused by large force exertion and not necessarily muscle fatigue. Muscle force can not be easily measured though. Therefore, its result, i.e. the angle and the angular velocity of the actuated joint, will be incorporated to the muscle fatigue analysis, a practice that is consistent to the concept of the aforementioned models. Moreover, since muscle actuate usually in more than one DoFs, with the latter defined as in Fig. 2, the fatigue analysis of the 7 muscles of the shoulder (i.e. deltoid (anterior), deltoid (posterior), deltoid (middle), pectoralis major, teres major, pectoralis major (clavicular head) and trapezius) will incorporate the two DoFs of the shoulder, and respectively for the 4 muscles of the elbow (i.e. biceps brachii, brachialis, brachioradialis and triceps brachii). Therefore, we can define a fatigue-related feature vector for each of the two muscle groups, i.e. $\mathbf{F}_m^{(i)} = \left[\begin{array}{ccccccc} IAV_m^{(i)} & ZC_m^{(i)} & VAR_m^{(i)} & q_{1m} & \dot{q}_{1m} & q_{2m} & \dot{q}_{2m} \end{array} \right]^T$, $i = 1, \ldots, 7$, $m = 1, \ldots$, the feature vector for the 7 muscles of the shoulder, and $\mathbf{F}_m^{(i)} = \left[\begin{array}{ccccccc} IAV_m^{(i)} & ZC_m^{(i)} & VAR_m^{(i)} & q_{3m} & \dot{q}_{3m} & q_{4m} & \dot{q}_{4m} \end{array} \right]^T$, $i = 8, \ldots, 11$, $m = 1, \ldots$, the feature vector for the 4 muscles of the elbow, computed at each time bin m, while q_{1m}, q_{2m}, q_{3m}, q_{4m} the joint angles at time bin m computed by (1), and $\dot{q}_{1m}$, $\dot{q}_{2m}$, $\dot{q}_{3m}$, $\dot{q}_{4m}$ the respective angular velocities computed through time differentiation of the joint angles.

In order to define the level of fatigue for the muscle i at each time instance m, according to the measured feature vector $\mathbf{F}_m^{(i)}$, we need to compute the conditional probability of the muscle being at the fatigue state $f_{(j)}^{(i)}$, $j = 1, \ldots, n$, n the possible fatigue states, given the feature vector $\mathbf{F}_m^{(i)}$, i.e. $P\left(f_{(j)}^{(i)} | \mathbf{F}_m^{(i)}\right)$. This is done by using the Bayes theorem [7], that in our case is described by the following equation.

$$P\left(f_{(j)}^{(i)} | \mathbf{F}_m^{(i)}\right) = \frac{p\left(\mathbf{F}_m^{(i)} | f_{(j)}^{(i)}\right) P\left(f_{(j)}^{(i)}\right)}{p\left(\mathbf{F}_m^{(i)}\right)}, \quad j = 1, \ldots, n \tag{5}$$

where $p\left(\mathbf{F}_m^{(i)} | f_{(j)}^{(i)}\right)$ the probability density function (PDF) of the feature vector $\mathbf{F}_m^{(i)}$ given the fatigue state $f_{(j)}^{(i)}$, $P\left(f_{(j)}^{(i)}\right)$ the prior probability of the fatigue state being $f_{(j)}^{(i)}$ and

$$p\left(\mathbf{F}_m^{(i)}\right) = \sum_{j=1}^{n} p\left(\mathbf{F}_m^{(i)} | f_{(j)}^{(i)}\right) P\left(f_{(j)}^{(i)}\right) \tag{6}$$

the evidence factor that can be considered as a scale factor that guarantees the posterior probabilities sum to one. The n fatigue states for each muscles i are considered equally likely to happen, i.e.

$$P\left(f_{(1)}^{(i)}\right) = P\left(f_{(2)}^{(i)}\right) = \ldots = P\left(f_{(n)}^{(i)}\right) = \frac{1}{n} \tag{7}$$

However the PDF of the feature vector $\mathbf{F}_m^{(i)}$ given the fatigue state $f_{(j)}^{(i)}$, $p\left(\mathbf{F}_m^{(i)} | f_{(j)}^{(i)}\right)$, the so-called *likelihood* term, needs to be computed. This is going to be achieved using the data collected through the training period. Since there is no specific relation between the coefficients of the feature vector, a flexible method of modeling will be used called Finite Mixture Models.

Finite mixtures of distributions provide a mathematical-based approach to the statistical modeling of a wide variety of random phenomena [8]. In our case, where more than one components (i.e. features) are to be modeled, that are not independent, a multivariate mixture model will be used. Moreover, a common assumption in practice is to take the component densities to be Gaussian. Therefore, a multivariate Gaussian Mixture Model (GMM) will be used for modeling the multivariate density of the feature vector $\mathbf{F}_m^{(i)}$. Let $\mathbf{F}_m^{(i)}$ the observed feature vector of muscle i at time instance m during the training procedure. The PDF of this can be modeled using a GMM that is defined by

$$p\left(\mathbf{F}_m^{(i)}\right) = \sum_{h=1}^{g} \pi_h \phi_h \left(\mathbf{F}_m^{(i)}, \mu_h, \mathbf{\Sigma}_h\right) \tag{8}$$

where $\phi_h\left(\mathbf{F}_m^{(i)}, \mu_h, \mathbf{\Sigma}_h\right)$ represents a multivariate Gaussian density function with $\mu_\mathbf{h}$ the mean vector, $\mathbf{\Sigma}_h$ the respective covariance matrix, and $\pi = \begin{bmatrix} \pi_1 & \ldots & \pi_g \end{bmatrix}^T$ the vector of mixing proportions of the mixture, which sum to one.

Using the training data collected, the parameters of the GMM, i.e. π, μ, $\mathbf{\Sigma}$, are fitted using the Expectation Minimization (EM) algorithm [8]. The number of the Gaussian components g is determined by using the Akaike criterion, which is a widely-used measure of goodness of fit of an estimated statistical model.

In our case, the mixture components can be used for clustering the signal characteristics, into clusters that will represent essentially the fatigue level. This can be done once the mixture models has been fitted, using a probabilistic clustering of the data into g clusters that can be obtained in terms of the fitted posterior probabilities of component membership for the data. An outright assignment of the data into g clusters is achieved by assigning each data point to the component to which it has the highest posterior probability of belonging.

Relating the fatigue level to the g clusters is feasible, since the multivariate data modeled are selected to vary with the muscle fatigue level. Therefore, the set of fatigue levels defined in (4) for muscle i, can be redefined having g_i *states*, i.e.

$$\mathbf{f}^{(i)} = \left\{f_1^{(i)}, f_2^{(i)}, \ldots, f_{g_i}^{(i)}\right\} \tag{9}$$

where g_i the number of the components fitted to the data collected from muscle i.

Therefore, from the aforementioned analysis and after the training period, the muscle fatigue level can be assigned to each muscle i at each time instance m using (5). For each muscle i, the feature vector $\mathbf{F}_m^{(i)}$ is computed. Then for each of the fatigue levels j, $j = 1, \ldots, g_i$, the conditional probability of the muscle being at the fatigue level $f_{(j)}^{(i)}$ can be computed using (5), where

$$\begin{aligned} & p\left(\mathbf{F}_m^{(i)} | f_{(j)}^{(i)}\right) = \sum_{h=1}^{g_i} \pi_h \phi_h \left(\mathbf{F}_m^{(i)}, \mu_h, \mathbf{\Sigma}_h\right) \\ & P\left(f_{(1)}^{(i)}\right) = P\left(f_{(2)}^{(i)}\right) = \ldots = P\left(f_{(g_i)}^{(i)}\right) = \tfrac{1}{g_i} \\ & p\left(\mathbf{F}_m^{(i)}\right) = \sum_{j=1}^{g_i} p\left(\mathbf{F}_m^{(i)} | f_{(j)}^{(i)}\right) P\left(f_{(j)}^{(i)}\right) \end{aligned} \tag{10}$$

Having computed $P\left(f_{(j)}^{(i)} | \mathbf{F}_m^{(i)}\right)$ for each fatigue level $f_{(j)}^{(i)}$, $j = 1, \ldots, g_i$, a decision about the fatigue level assignment to the muscle i can be made, according to the simple Bayes decision rule, i.e.

$$\begin{aligned} & \text{decide} \quad f_s^{(i)} \quad \text{if} \quad P\left(f_s^{(i)} | \mathbf{F}_m^{(i)}\right) \geq P\left(f_h^{(i)} | \mathbf{F}_m^{(i)}\right), \\ & h = 1, \ldots, g_i \end{aligned} \tag{11}$$

where $f_s^{(i)}$ the final fatigue assignment for muscle i. The above procedure is implemented for all the recorded muscles, at each time instance in real time.

During the training period, it was noticed that the EMG signal characteristics of each recorded muscle were varying isotropic. Due to this fact, the components g_i for each muscle i were found to be equal in number among the recorded muscles, while the switching among the fatigue states, computed from (5), (10), (11), for each muscle was noticed to happen almost at the same time instance. This can be explained by the above reasons:

- Fatigue-related signal characteristics from all muscles were varying isotropic during arm motion.
- Muscles usually act in synergies, therefore it's more likely that they suffer fatigue in an approximately synchronous manner.
- Arm motion performed by the user covered most of the arm kinematic workspace, in terms of joint configuration, and dynamic workspace in terms of joint velocity, activating all the recorded muscle isotropically and not wearing out only a subset of them.

The decision for the global fatigue state f_G is made using the fatigue states of all the muscles, $f_s^{(i)}$, $i = 1, \ldots, 11$, by deciding which of the states is most *popular* among the muscles. Let P_h be the sets that include the muscles whose fatigue state is h, $h = 1, \ldots, g$. Thus, if Π the union of the sets P_h, $h = 1, \ldots, g$,

$$\Pi = P_1 \bigcup P_2 \ldots \bigcup P_g \tag{12}$$

we have, $\overset{=}{\Pi} = 11$ the total number of the population of the sets, which coincides with the number of muscles. If we denote an allocation rule $r_B\left(f_G\right)$ for assigning the global fatigue state f_G to one of the possible fatigue states, where $r_B\left(f_G\right) = f_l$ implies that the global fatigue state is assigned to the lth fatigue state ($l = 1, \ldots, g_i$), then the optimal rule for the allocation of f_G is defined by: $r_B\left(f_G\right) = \arg\max_h \overset{=}{P}_h$, where $\overset{=}{P}_h$ the population number of the set P_h, $h = 1, \ldots, g$. The above rule essentially means that the global fatigue state f_G is the one that describes the fatigue state of the majority of the recorded muscles.

D. Fatigue-related Switching Decoder

Since the number of muscles recorded is quite large (i.e. 11), a low-dimensional (low-D) representation of muscle activations will be used instead of individual activations. The most widely used dimension reduction technique is principal component analysis (PCA). During the training period, the EMG recordings from each muscle are preprocessed, i.e. full-wave rectified, low-pass filtered and normalized to their maximum voluntary isometric contraction value [6]. Then they are represented into a low-dimensional space, using the PCA algorithm. It was found that a 2-dimensional (2D) space could represent most the original high dimensional data variance (more than %96). The authors have used the dimensionality reduction for muscle activations in the past for planar movements of the arm [9]. Therefore the details of the method application are omitted. Furthermore, the dimensionality reduction technique will also be used for representing the arm motion in a low-dimensional space, revealing motion primitives that are extensively discussed in the literature. Therefore, by using the PCA algorithm the analyzed 4-DoF motion, described in joint angles (i.e. q_1, q_2, q_3, q_4), is represented into a 2-dimensional space. Indeed it was found that most of the original data variance (%97) was represented using a 2-dimensional space.

Having represented the muscle activations and the performed joint kinematics into two low-dimensional spaces, one can build a model that will use the EMG low-dimensional embeddings to estimate performed motion. Let $\mathbf{U}_t \in \mathbb{R}^2$ the 2-dimensional vector of the low-dimensional representation of the 11 muscle recordings, at time $t = kT, \quad k = 1, \ldots$. Let $\mathbf{y}_t \in R^2$ be the low-dimensional embedding of the arm joint angles at the same time instance. The model that will be used for decoding the EMG activity to performed motion is defined as

$$\begin{aligned} \mathbf{x}_{t+1} &= \mathbf{A}\mathbf{x}_t + \mathbf{B}\mathbf{U}_t + \mathbf{v}_t \\ \mathbf{y}_t &= \mathbf{C}\mathbf{x}_t + \upsilon_t \end{aligned} \tag{13}$$

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 $\mathbf{W} \in \mathbb{R}^d$, $\mathbf{Q} \in \mathbb{R}^2$ are the covariance matrices of $\mathbf{v}_t$, υ_t respectively. Details about the model structure and the fitting procedure can be found in [9].

A distinct model of the form (13) is used for each of the g possible global fatigue states. Therefore, during training, data belonging to each one of the possible global fatigue levels are only used for the corresponding decoding model. I.e. the model h, $h = 1, \ldots, g$, is trained using data only when the global fatigue level is f_h.

During real-time operation, the g trained models are used to transform the low-dimensional embeddings of muscle activations to low-dimensional embeddings of joint angles. The switching among the models is discrete, however, smoothness in the transitions and the output model estimations is guaranteed since the initial hidden-state vector of a model, immediately after a switching, is calculated through the observation equation of the model previously used[1]. In Fig. 3 the total architecture of the method for the real-time motion decoding is depicted.

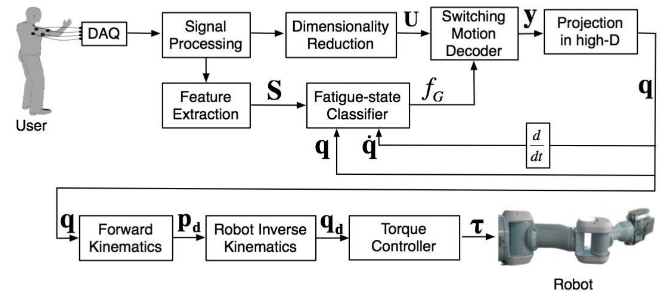

Fig. 3. The block diagram of the proposed methodology. $\mathbf{q}$ is the vector of the four joint angles decoded from the EMG signals, while $\mathbf{p_d}$ the pose vector computed through the human arm kinematics given the four joint angles.

E. Robot Control

A 7 DoF anthropomorphic robot arm (PA-10, Mitsubishi Heavy Industries) is used. In order to control the robot arm using the desired joint angle vector $\mathbf{q_d}$[2], an inverse dynamic controller is used, defined by:

$$\tau = \mathbf{I}(\mathbf{q_r})(\ddot{\mathbf{q}}_\mathbf{d} + \mathbf{K_v}\dot{\mathbf{e}} + \mathbf{K_P}\mathbf{e}) + \mathbf{G}(\mathbf{q_r}) + \mathbf{C}(\mathbf{q_r}, \dot{\mathbf{q}}_\mathbf{r})\dot{\mathbf{q}}_\mathbf{r} + \mathbf{F_{fr}}(\dot{\mathbf{q}}_\mathbf{r}) \tag{14}$$

where $\tau = \begin{bmatrix} \tau_1 & \tau_2 & \tau_3 & \tau_4 \end{bmatrix}^T$ is the vector of robot joint torques, $\mathbf{q_r} = \begin{bmatrix} q_{1r} & q_{2r} & q_{3r} & q_{4r} \end{bmatrix}^T$ the robot joint angles, $\mathbf{K_v}$ and $\mathbf{K_p}$ gain matrices and $\mathbf{e}$ the error vector between the desired and the robot joint angles, i.e.

$$\mathbf{e} = \begin{bmatrix} q_{1d} - q_{1r} & q_{2d} - q_{2r} & q_{3d} - q_{3r} & q_{4d} - q_{4r} \end{bmatrix}^T \tag{15}$$

$\mathbf{I}$, $\mathbf{G}$, $\mathbf{C}$ and $\mathbf{F_{fr}}$ are the inertia tensor, the gravity vector, the Coriolis-centrifugal matrix and the joint friction vector of the four actuated robot links and joints respectively, identified in [10]. The vector $\ddot{\mathbf{q}}_\mathbf{d}$ corresponds to desired angular acceleration vector that is computed through simple differentiation of the desired joint angle vector $\mathbf{q_d} = \begin{bmatrix} q_{1d} & q_{2d} & q_{3d} & q_{4d} \end{bmatrix}^T$ using a necessary low-pass filter to cut off high frequencies. More details about the controller can be found in [9].

III. RESULTS

The proposed architecture is assessed through remote teleoperation of the robot arm using only EMG signals from the 11 muscles as analyzed above. The robot arm used is a 7 DoF anthropomorphic manipulator (PA-10, Mitsubishi Heavy Industries). The details of the experimental setup can be found in [11].

Real and estimated motion data were recorded for 3 minutes during the real-time operation phase. The real joint angle

[1]This is feasible since the $\mathbf{C}$ matrix of each model has been defined as a full-rank matrix through the fitting procedure.

[2]The vector of joint angles decoded from EMG signals.

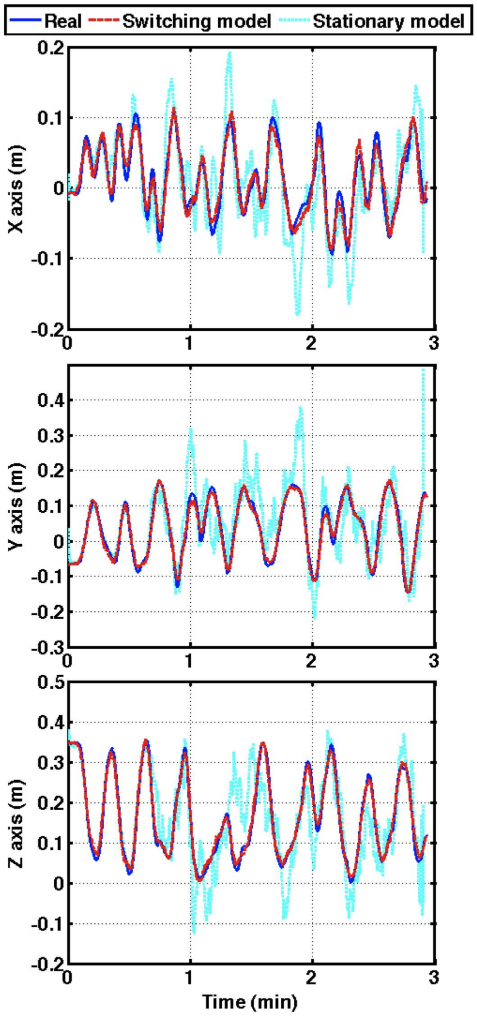

Fig. 4. Real and estimated hand trajectory along the x, y, z axes, for a 3 minute period. Estimates from the proposed switching method are quite close to the ground truth during the whole 3 minute test, while the stationary model accuracy decreases after a period of approximately 30 seconds.

profiles were computed from the position tracker sensors, which were kept in place (i.e. on the user's arm) for offline validation reasons. The estimated user's hand 3D trajectory along with the ground truth are depicted in Fig. 4. As it can be seen the method could estimate the hand trajectory with high accuracy, compensating for EMG changes due to muscle fatigue. The latter is shown in Fig. 4, where the estimates based on a stationary decoding model of the same form of (13), that didn't compensate for muscle fatigue, are shown. As it can be seen, using a stationary model, the accuracy of the estimates decreases with time, due to muscle fatigue.

IV. Conclusions and discussion

In this paper, a muscle fatigue-dependent methodology for controlling an anthropomorphic robot arm using EMG signals from the muscles of the upper limb, was proposed. A probabilistic framework was designed in order to assign to each of the muscles recorded, a *fatigue state*. Then, a switching model was built in such way to compensate EMG changes related to muscle fatigue. The proposed method was tested in a real-time teleoperation task of a robot arm in the 3D space, lasted for about 3 minutes. It was shown from the experimental results that the proposed method could estimate the human arm motion using only EMG signals with high accuracy.

The novelty of the method proposed here can be centered around two main issues. First, the proposed method is not affected by EMG changes due to muscle fatigue. Since EMG is widely known as a non-stationary signal, the fact that the proposed method can compensate for EMG changes through time (mainly caused by muscle fatigue), is quite important for the field. The second important issue presented here is that, to the best of our knowledge, this is the first time a continuous profile of 3D arm motion (including 4 DoFs) is extracted using only EMG signals. Most previous works extract only discrete information about motion, while there are some works that estimate continuous arm motion, constrained though to isometric movements, single DoF, or very smooth motions [12].

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