EMG-based Teleoperation of a Robot Arm Using Low-Dimensional Representation

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***Abstract*— In robot teleoperation scenarios, the interface between the user and the robot is undoubtedly of high importance. In this paper, electromyographic (EMG) signals from muscles of the human upper limb are used as the control interface between the user and a remote robot arm. The proposed interface consists of surface EMG electrodes, placed at the user's skin at several locations on the arm, letting the user's upper limb free of bulky interface sensors or machinery usually found in conventional teleoperation systems. The motion of the human upper limb entails the activation of a large number of muscles (i.e. more than 30 muscles, not including finger movements). Moreover, the human arm has 7 degrees of freedom (DoFs) suggesting a wide variety of motions. Therefore, the mapping between these two high-dimensional data (i.e. the muscles activation and the motion of the human arm), is an extremely challenging issue. For this reason, a novel methodology is proposed here, where the mapping between the muscles activation and the motion of the user's arm is done in a low-dimensional space. Each of the high-dimensional input (muscle activation) and output (arm motion) vectors, is transformed into an individual low-dimensional space, where the mapping between the two low-dimensional vectors is then feasible. A state-space model is trained to map the low-dimensional representation of the muscles activation to the corresponding motion of the user's arm. After training, the state-space model can decode the human arm motion in real time with high accuracy, using only EMG recordings. The estimated motion is used to control a remote anthropomorphic robot arm. The accuracy of the proposed method is assessed through real-time experiments including motion in two-dimensional (2D) space.**

I. INTRODUCTION

Robot arms are versatile tools found in a wide range of applications. In recent years, applications where humans and robot arms interact, have received increased attention. The case where the interaction entails the human controlling a remote robot is called robot teleoperation. The latter case requires a user interface to translate the operator commands to the robot. A large number of interfaces have been proposed on this issue in previous works, where some examples of them can be found in [1], [2], [3]. However, most of them involve complex mechanisms or systems of sensors, that the user should be acquaint with, resulting to a feeling of discomfort for non-experts. Moreover, in most of the cases the user should be trained to map his/her action (i.e. three-dimension (3D) motion of a joystick or a haptic device) to the resulted motion of the robot. In this paper, a new mean of interface is proposed, according to which, the user can directly control a robot arm, by performing natural motions with his/her own arm, without any bulky mechanism coupled with the arm. While the user moves his/her the arm, electromyographic (EMG) activity is recorded from selected muscles, using surface EMG electrodes. Through a decoding procedure the muscular activity is transformed to kinematic variables that are used to control the remote robot arm. Using the proposed interface the user doesn't need to be acquaint with the interface mapping, since the only thing that he/she has to do, is to perform natural arm movements in order to directly control the teleoperated anthropomorphic robot arm.

EMG signals have been used as control signals for robotics devices in the past. Fukuda [4] proposed a human-asstising manipulator teleoperated by EMG signals and arm motions. In this case wrist motion of the robot arm was controlled using the muscular activity from the muscles of the forearm. However discrete only postures of the wrist were identified through EMG signals, rather than a continuous representation of the wrist motion. EMG signals have also been used for the control of prosthetic hands, such as the Utah artificial arm [5], the Boston arm [6] and the Waseda hand [7]. A five-fingered hand was also controlled using EMG signals from muscles of the forearm in [8], [9]. In most of the above cases, EMG signals were used for providing binary control variables (e.g. starting or stopping the robot motion) or for commanding discrete postures to the robot, using classifications algorithms. However, a continuous representation of the user's motion will be essential for a dexterous robot arm teleoperation. The authors have used in the past EMG signals for the continuous control of a single degree of freedom (DoF) of a robot arm in [10], as well as two DoFs during planar catching tasks in [11]. However in these cases, a small number of muscles were recorded, while the user's motion was stereotyped (i.e. smooth elbow flexion-extension and 2D over-simplified center-out reaching tasks respectively).

The human motor control system is undoubtedly one of the most investigated physical systems. Its complexity in terms of the several control units (neurons) stimulating the large number of motor units (muscles) actuating the numerous DoFs on the human body, has always been an intriguing attraction for many scientific areas. Focusing on the human upper limb, approximately 30 individual muscles actuate the 7 DoFs that a human arm has (i.e. 3 at the shoulder, 2 at the elbow, 2 at the wrist). Therefore, the analysis of muscle activations with respect to the performed arm motion entails the use of a high-dimensional vector of variables (i.e. muscle activations). However, recent work in the field of biomechanics proposes that muscles are activated by the nervous system in a sense of patterns, called time-varying

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muscle synergies [12]. In other words, skeletal muscles act collectively and in an ordered way for actuating the arm joints. This finding suggests that muscle activations can be represented into a low-dimensional space, where such synergies are being considered instead of individual activations. A low-dimension representation is also feasible at the arm kinematic level (i.e. joint angles) according to movement primitives, suggested at several studies in the biomechanics [13]. A mapping between the two low-dimensional spaces could result to a robust decoding method, able to conclude to a continuous representation of the human arm motion from multiple muscle recordings, and finally to be used as the control algorithm for an EMG-based robot control scenario.

In this paper, a methodology for controlling a remote anthropomorphic robot arm is proposed, using EMG signals from the muscles of the human upper limb. Eight muscles of the shoulder and elbow joints are recorded and processed in real time. The human arm motion is restricted to a plane perpendicular to user's torso at the height of the shoulder. The teleoperation architecture is divided into two phases: the training and the real-time operation. During training, the kinematics of the human arm (i.e. joint angles) are recorded using a position tracking system, while the activations of eight muscles are recorded simultaneously. Then, the recorded muscle activations are transformed into a low-dimensional space using a dimensionality reduction technique. The joint angles recorded are transformed into a low-dimensional space too. It is shown that very few dimensions for both muscle activations and joint angles are able to represent most of the data variability. The mapping between the two low-dimensional spaces is achieved through a state-space model identified using the data collected during the training phase. When the state-space model is identified, the real-time operation phase commences. During this phase, the state-space model estimates the user's motion by using only the recorded muscle activations in real-time. The motion estimates are finally inputed in a control law in order to actuate the remote robot arm. During the system operation, the user has visual contact with the arm, thus he/she is able to teleoperate it in real-time. The efficiency of the method is assessed through a number of experiments, during which the user controls the robot arm in performing random planar motions.

The rest of the paper is organized as follows: the system architecture is presented in Section II, where each method used is analyzed. The experimental procedure assessing the method efficiency is reported in Section III, while Section IV concludes the paper.

II. Materials and methods

A. System and problem definition

Dealing with the complexity of the skeletal muscles of the upper limb and their contribution to the motion of the multiple DoFs of the arm is definitely a challenging issue. In this paper, a methodology to tackle this complexity is presented, in order to finally conclude in a complete representation of the human arm motion using only muscle activation recordings. The efficiency of the method is assessed using real-time experiments, where the user's arm motion is restricted to a plane π perpendicular to user's torso at the height of the shoulder, as shown in Fig. 1a. Thus the motion in joint space is restricted to two DoFs: shoulder transverse adduction-abduction and elbow flexion-extension, allowing the definition of two joints angles, q_1 and q_2 respectively.

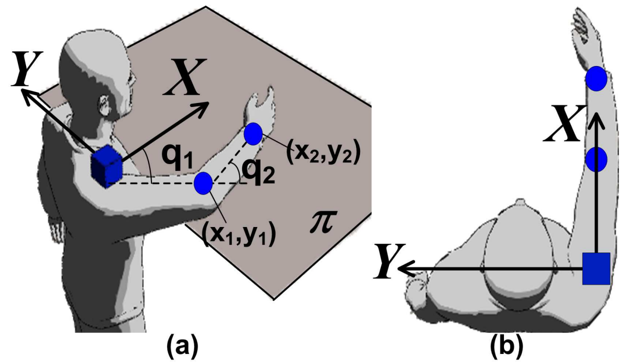

Fig. 1. a) The user's motion is restricted to the plane π. Position tracking reference and sensors are shown in blue cube and circles respectively. b) Definition of zero-angle configuration.

B. Data pre-processing

There are several muscles acting at the two DoFs analyzed here. Some of those muscles act simultaneously at both joints, making the analysis of two separate systems rather problematic. Based on biomechanics literature [14], a group of eight muscles, mainly responsible for the analyzed motion, are recorded: deltoid (medial), deltoid (anterior), pectoralis major (sternal head), pectoralis major (clavicular head), biceps brachii, brachialis, brachioradialis and triceps. Surface EMG electrodes are used for recording, placed on user's skin following the directions given in [14]. Raw EMG signals after amplification are digitized using a sampling frequency of 1 kHz. Then, they are full-wave rectified, low-pass filtered (using a 4^{th} order Butterworth filter) and normalized to their maximum voluntary isometric contraction value [15]. The resulted signal is defined in the literature as the neural excitation, denoted here by $r(t)$, where t denotes time. Neural excitation is coupled with muscle activation with the intracellular processes of calcium activation and deactivation, which are usually approximated by first-order dynamics as shown below [16].

$$\frac{du(t)}{dt} + \left(\frac{1}{\tau_{act}}\left(\beta + (1-\beta)\, r(t)\right)\right) u(t) = \frac{1}{\tau_{act}} r(t) \quad (1)$$

where $u(t)$ is the muscle activation, τ_{act} the time constant of full excitation of the muscle ($r(t) = 1$) and β the ratio between τ_{act} and the time constant for full relaxation of activation (τ_{deact}), i.e.

$$\beta = \frac{\tau_{act}}{\tau_{deact}}, \quad \beta \in (0, 1) \quad (2)$$

Using values for the above constants taken from literature [15], and numerically solving the differential equation (1) at each time step, the muscle activation $u(t)$ is computed for each of the recorded muscles.

During the system training phase, the user's arm joint angles should be recorded in order to be related to muscle activations. A position tracking system is used, consisting of a reference system and two sensors. The sensors are placed at the elbow and at the user's wrist as shown in Fig. 1a. Defining user's angles equal to zero when the arm is fully extended (see Fig. 1b), and aligning the reference axis with the user's arm in this position using the readings from the sensors, joint angles q_1 and q_2 can be computed by:

$$\begin{aligned} q_1 &= \arctan 2\left(y_1, x_1\right) \\ q_2 &= \arctan 2\left(y_2 - y_1, x_2 - x_1\right) \end{aligned} \tag{3}$$

where (x_1, y_1), (x_2, y_2) the coordinates of the sensors 1 and 2 respectively, with respect to the tracker reference system. The frequency of the position tracker measurements is 60 Hz. Using an anti-aliasing FIR filter these measurements are re-sampled at the frequency of 1 kHz, to be consistent with the muscle activations measurements.

Having computed the muscle activations $u_k^{(i)}$ of each muscle i at time kT, where T the sampling period and $k = 1, 2, ...$, and the corresponding joint angles q_{1k} and q_{2k}, the mapping between them still remains an issue. The dimensions of the variables to be correlated (i.e. 8 muscle activation to be correlated to 2 joint angles) makes the problem of mapping rather difficult. In order to tackle this dimensionality issue, a dimension-reduction technique is applied.

C. Dimension reduction

The problem of dimension reduction is introduced as an efficient way to overcome the curse of the dimensionality when dealing with vector data in high-dimensional spaces and as a modeling tool for such data. It is generally defined as the search for a low-dimensional manifold that embeds the high-dimensional data. More formally, the problem of dimension reduction can be stated as follows: suppose we have a sample of D-dimensional real vectors drawn from an unknown probability distribution. The fundamental assumption that justifies the dimension reduction is that the sample actually lies, at least approximately, on a manifold of smaller dimension than the data space. The goal of dimension reduction is to find a representation of that manifold (i.e. a coordinate system) that will allow to project the data vectors on it and obtain a low-dimensional, compact representation of the data. In our case, two manifolds are going to be found: muscle activation data will be embedded into the first, while kinematic data (joint angles) will be embedded into the second. Then the mapping between the two sets of low-dimensional data will be feasible.

Principal component analysis (PCA) is the most widely used dimension reduction technique, due to its conceptual simplicity and to the fact that relatively efficient algorithms exist for its computation. For details about the method, the reader should refer to [17].

Following the PCA algorithm, we can conclude to a transformation of the muscle activations and joint angles to another reference systems. It is noted that the muscle activations and the joint angles are seen as completely different data sets. The PCA algorithm will be implemented twice: once for finding a new representation of the muscle activation data, and then one more time for the representation of joint angles. Below we briefly describe the procedure, since the algorithm is the one presented above.

During the training phase the user is instructed to move the arm on the plance π as shown in Fig 1a. While the user moves the arm, m muscle activation and joint angle measurements are computed from the surface EMG recordings and position tracking data, using eq. (1), (3). Let $\mathbf{U} = \begin{bmatrix} \mathbf{u^{(1)}} & \mathbf{u^{(2)}} & \dots & \mathbf{u}^{(8)} \end{bmatrix}^T$ be a $8 \times m$ matrix containing the m samples of muscle activations from each of the 8 recorded muscles, i.e. $\mathbf{u^{(i)}} = \begin{bmatrix} u_1^{(i)} & u_2^{(i)} & \dots & u_m^{(i)} \end{bmatrix}^T$, $i = 1, \dots 8$, $m \in \mathbb{N}$. Similarly, let $\mathbf{Y} = \begin{bmatrix} \mathbf{y^{(1)}} & \mathbf{y^{(2)}} \end{bmatrix}^T$ be a $2 \times m$ matrix containing m samples of the two joint angles, i.e.

$$\begin{aligned} \mathbf{y^{(1)}} &= \begin{bmatrix} q_{1_1} & q_{1_2} & \dots & q_{1_m} \end{bmatrix}^T \\ \mathbf{y^{(2)}} &= \begin{bmatrix} q_{2_1} & q_{2_2} & \dots & q_{2_m} \end{bmatrix}^T \end{aligned} \tag{4}$$

where q_{1_k}, q_{2_k}, $k = 1, \dots m$ denote the k^{th} measurement of the joint angle q_1 and q_2 respectively. Concerning the muscle activations, mean values of each muscle activation data set are subtracted from the corresponding measurements. Then the covariance matrix $\mathbf{F}$ is computed and using spectral decomposition, it is written as

$$\mathbf{F} = \mathbf{G}\mathbf{J}\mathbf{G}^T \tag{5}$$

where $\mathbf{J}$ is the 8×8 diagonal matrix with the eigenvalues of $\mathbf{F}$ and $\mathbf{G}$ is the 8×8 matrix with column vectors the eigenvectors of $\mathbf{F}$. The principal component transformation of the muscle activation data can now be defined as

$$\mathbf{M} = \mathbf{G}^T\mathbf{K} \tag{6}$$

where $\mathbf{K}$ is the $8 \times m$ matrix computed from $\mathbf{U}$ by subtracting the mean value for each muscle across the m measurements. Apparently, if all the 8 eigenvectors are included in $\mathbf{G}$, then the new representation of the data, as this is defined by the $\mathbf{M}$ matrix, is equivalent (from a dimension point of view) with the original. However, due to the calculation of the principal components of the data, we can easily find the significance of each one of these components in representing the original data. Here is where the notation of dimensionality reduction comes into it. We can form a *feature vector* $\mathbf{V}$ that would be able to decrease the dimensionality of the original data. $\mathbf{V}$ is basically a matrix of vectors that is constructed by taking the most significant eigenvectors of the data. The significance of each eigenvector is determined by the corresponding eigenvalue (i.e. variance). The bigger is the eigenvalue, the more significant is the corresponding eigenvector. An analytical approach can be found in [17]. A method usually adopted for selecting the number of the most significant eigenvectors is to compute the ratio between each eigenvalue (i.e. variance) and the sum of all the eigenvalues. This is called the *explained variance* of each eigenvector and can be defined by

$$\nu_i = \frac{\lambda_i}{\sum_{l=1}^{8} \lambda_l} = \frac{\lambda_i}{trace\left(\mathbf{J}\right)}, \quad i = 1, 2, \ldots, 8 \tag{7}$$

where λ_i are the eigenvalues, and $trace\left(\mathbf{J}\right)$ denotes the sum of the diagonal elements of the $\mathbf{J}$ matrix which coincides with the sum of the eigenvalues. As it can was seen, by using only the first three eigenvectors out of the total eight, we can represent more than 90% of the original data. This suggests a dramatic reduction in the dimensionality of the data. The feature vector $\mathbf{V}$ can now be defined as a 8×3 matrix, each column of which is the selected eigenvector taken from $\mathbf{G}$. Therefore the low-dimensional representation of the muscle activation data can defined by (6), using only the first three eigenvectors, i.e.

$$\mathbf{\Xi} = \mathbf{V}^T \mathbf{K} \tag{8}$$

where $\mathbf{\Xi}$ is the $3 \times m$ matrix describing the low-dimensional representation of the muscle activations of 8 muscles during planar arm motions.

Similarly for the case of joint angles, we found that only one dimension is sufficient to describe the two-dimensional data of joint angles (variance explained: 97%). Therefore the low-dimensional representation of the joint kinematics can be defined by

$$\mathbf{Q} = \mathbf{H}^T \mathbf{R} \tag{9}$$

where $\mathbf{Q}$ is the vector describing the low-dimensional representation of the joint kinematics during planar arm motions. Matrices $\mathbf{H}$ and $\mathbf{R}$ are of size 2×1 and $2 \times m$ and their definition is equivalent to this of the matrices $\mathbf{V}$ and $\mathbf{K}$ in the case of muscle activations.

Applying a dimension reduction technique, the high-dimensional data of muscle activations and corresponding joint angles were represented into a manifold of fewer dimensions. More specifically, only three dimensions are enough to describe the muscle activation of 8 muscles, while one dimension can describe the kinematic variables (joint angles) with enough accuracy. From a neuro-physiological point of view, this low-dimensional representation proves that muscles act in synergies while actuating a human joint, as well as, arm DoFs act in a collective way, suggesting the formulation of motor primitives. However the aim of this paper is not to prove the presence of internal coordination mechanisms of the human motor control, but to efficiently extract them, and using the proper mathematical formulation, employ them for controlling robotic devices. How this low-dimensional representation facilitates the mapping between muscle activations and corresponding arm motion is shown immediately after.

D. Decoding arm motion from EMG

Having computed the low-dimensional representation of the muscle activations and the corresponding human joint angles, we can define the problem of decoding as follows: find a function f that can map muscle activations to arm motion in real-time, being able to be identified using training data. Generally, we can define it by

$$\mathbb{Y} = f\left(\mathbb{U}\right) \tag{10}$$

where $\mathbb{Y}$ denotes human arm kinematic variables and $\mathbb{U}$ muscle activations. A large number of algorithms have been previously used for decoding human motion from EMG [4], [18], [19]. However in most of these works the decoding was addressed in a sense of classification, not concluding to a continuous representation of the kinematics which would be necessary for the dexterous robot control. Specifically in our case, the aim is the formulation of the decoding function f, that can be used for the continuous representation of the arm joint angles using measured muscle activation in real-time.

From a physiological point of view, a model that would describe the function of skeletal muscles in actuating the human joints would be generally a complex one. Using such a model for real-time decoding would be problematic. For this reason, we can adopt a more flexible decoding model in which we introduce "hidden", or "latent" variables we call $\mathbf{x}$. These hidden variables can model the unobserved, intrinsic system states, and thus facilitate the correlation between the observed muscle activation $\mathbb{U}$ and joint angles $\mathbb{Y}$. In this case, (10) can be re-written as shown below

$$\mathbb{Y} = f\left(\mathbb{X}, \mathbb{U}\right) \tag{11}$$

where $\mathbb{X}$ denote the set of the "hidden" states. Moreover, we can assume a linear relation between the hidden states and the muscle activations and joint angles. The latter assumption results to the specific formulation of the joint angles decoding problem using the following state space model

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{B}\xi_k + \mathbf{w}_k \\ z_k &= \mathbf{C}\mathbf{x}_k + v_k \end{aligned} \tag{12}$$

where $\mathbf{x}_k \in \mathbb{R}^d$ is the hidden state vector at time instance kT, $k = 1, 2, \ldots$, (T being the sampling period), d the dimension of this vector, $\xi_k \in \mathbb{R}^3$ is the vector of muscle activations and $z_k \in \mathbb{R}$ is the vector of the observed joint kinematics (i.e. joint angles). It must be noted that the decoding is defined using the low-dimensional representation of the muscle activations and the arm joint angles established earlier in this paper. That is the reason $\xi_k \in \mathbb{R}^3$ (the low-dimensional representation of muscle activations has three dimensions), and $z_k \in \mathbb{R}$ (the low-dimensional representation of joint angles has one dimension). From this point, ξ, z will be called muscle activations and joint angles respectively, implying the low-dimensional representation of the original data sets. The matrix $\mathbf{A}$ determines the dynamic behavior of the hidden state vector $\mathbf{x}$, $\mathbf{B}$ is the matrix that relates muscle activations ξ to the state vector $\mathbf{x}$, while $\mathbf{C}$ is the matrix that represents the relationship between the joint angle representation z and the state vector $\mathbf{x}$. $\mathbf{w}_k$ and v_k represent zero-mean Gaussian noise in the process and observation equations respectively, i.e. $w_k \sim N\left(\mathbf{0}, \mathbf{W}\right)$, $v_k \sim N\left(0, \sigma^2\right)$, where $\mathbf{W} \in \mathbb{R}^{d \times d}$ is the covariance matrix of $\mathbf{w}_k$ and σ^2 the variance of v_k.

Model fitting entails the estimation of the following parameters: matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, noise covariance matrix $\mathbf{W}$ and variance σ^2. Given a training set of length m, including muscle activations and joint angles, the model parameters can be found using an optimization procedure. More specifically, an iterative prediction-error minimization (i.e. maximum likelihood) algorithm is used [20]. In the experiments reported below we used a standard implementation of the optimization procedure in Matlab™ System identification Toolbox. The system input (i.e. muscle activations), included in the training set of length m, is the low-dimensional representation of muscle activations measured during the training phase, i.e. the matrix $\mathbf{\Xi}$ defined in (8): $\mathbf{\Xi} = \begin{bmatrix} \xi_1 & \xi_2 & \dots & \xi_m \end{bmatrix}^T$, $\xi_k \in \mathbb{R}^3$, $k = 1, \dots, m$. The system output (i.e. joint angles), included in the training set of length m, is the low-dimensional representation of joint angles measured during the training phase, i.e. the $\mathbf{Q}$ matrix defined in (9) : $\mathbf{Q} = \begin{bmatrix} \mathcal{Q}_1 & \mathcal{Q}_2 & \dots & \mathcal{Q}_m \end{bmatrix}^T$, where $\mathcal{Q}_k \in \mathbb{R}$ is the one-dimensional representation of the two joint angles at time instance kT, $k = 1, \dots m$. Finally, the dimensionality d of the state vector should be selected. This is done in parallel with the estimation procedure, by deciding the number of states, greater of which, the additional states do not contribute to the model input-output behavior. The way to conclude to this is by using the singular values of the covariance matrix of the system outputs [20].

E. Robot control

Having the model parameters identified by using training data, user's arm motions can be directly decoded from muscle activations using eq. (12) during the real-time operation phase. More specifically, user's shoulder and elbow joint angles during planar motions, can be decoded from recorded muscle activations. It must be noted, that the decoding model outputs the low-dimensional representation of the kinematic variables. However, knowing the feature vector $\mathbf{H}$ (see (9)), we can easily transform the decoded data back to the original high-dimensional space (i.e. two-dimensional variable consisting of the shoulder and elbow joint angles).

Let $\hat{q}_1$, $\hat{q}_2$ the estimated (i.e. decoded) shoulder and elbow joint angles respectively. Since the aim of the architecture presented here is the robot arm direct teleoperation, the human joint angles estimates will drive the corresponding robotic joints. A 7 DoF anthropomorphic robot arm (PA-10, Mitsubishi Heavy Industries) is used. Only two DoFs of the robot are actuated (shoulder and elbow correspondingly) while the others are kept fixed at zero position. The arm is horizontally mounted to mimic the human arm. The robot arm along with the actuated DoFs is depicted in Fig. 2. The robot motors are controlled in torque. In order to control the robot arm using the estimated human arm joint angles, an inverse dynamic controller is used, defined by:

$$\tau = \mathbf{I}\left(\ddot{\mathbf{q}}_{\mathbf{h}} + \mathbf{K}_{v}\dot{\mathbf{e}} + \mathbf{K}_{\mathbf{p}}\mathbf{e}\right) + \mathbf{F}_{\mathbf{fr}}\left(\dot{\mathbf{q}}_{\mathbf{r}}\right) \qquad (13)$$

where $\tau = \begin{bmatrix} \tau_{r1} & \tau_{r2} \end{bmatrix}^T$ the vector of robot joint torques, $\mathbf{q}_h = \begin{bmatrix} \hat{q}_1 & \hat{q}_2 \end{bmatrix}^T$ the vector of the estimated human joint angles, $\mathbf{q}_r$ the corresponding robot joint angle vector, $\mathbf{e}$ the error vector between human and robot joint angles, $\mathbf{K}_v$, $\mathbf{K}_\mathbf{p}$ gain matrices and $\mathbf{I}$, $\mathbf{F}_{\mathbf{fr}}$ the inertia tensor and the joint friction vector of the two actuated robot links and joints respectively, identified in [21]. Human estimated joint angle acceleration vector $\ddot{\mathbf{q}}_{\mathbf{h}}$ is computed through simple differentiation of the estimated joint angle vector $\mathbf{q}_{\mathbf{h}}$, using a necessary low-pass filter to cut high-frequencies generated.

III. Results

A. System components

The robot arm used is a 7 DoF anthropomorphic manipulator (PA-10, Mitsubishi Heavy Industries). Two personal computers (PCs) are used, running Linux operating system. One of the PCs communicates with the robot controller through the ARCNET protocol in the frequency of 500 Hz, while the other acquires the EMG signals and the position tracker measurements (during the training phase). The two PCs are connected through serial communication (RS-232) interface for synchronization purposes. EMG signals are acquired using a signal acquisition board (NI-DAQ 6036E, National Instruments) connected to an EMG system (Bagnoli-16, Delsys Inc.). Single differential surface EMG electrodes (DE-2.1, Delsys Inc.) are used. The position tracking system (Isotrak II, Polhemus Inc.) used during the training phase is connected with the PC through serial communication interface (RS-232). The size of the position sensors is 2.83(W) 2.29(L) 1.51(H) cm.

The proposed methodology was tested in a planar motion teleoperation scenario depicted in Fig. 2. During the training phase the user moved his arm on the plane perpendicular to his torso at the height of the shoulder, following random profiles. EMG signals from eight muscles were recorded, while simultaneous measurements of the shoulder and elbow joint angles were computed from the position tracker measurements. Experimental measurements for a time period of one minute were acquired. A model of the form shown in (12) was estimated, using the low-dimensional representation of the training data. A second-order model was found to be able to accurately correlate the low-dimensional representations of the muscle activation and the human joint angles. Since the data were recorded, the model estimation procedure lasted only 10 sec. Since the model was estimated, the real-time operation phase took place. The user moved randomly his arm on the plane. Only EMG signals were used in order to estimate human joint angles and use them in the control law (13) to drive the robot arm. Human joint angles are estimated in the frequency of the muscle activation, which is 1 kHz. These estimates are up-sampled in real-time to meet the robot control frequency (500 Hz). During the testing phase, the position tracker measurements for the human joint angles are not used to control the robot, however they are recorded for the sake of assessing the accuracy of the method later. Fig. 3 shows the estimated human joint angles during

TABLE I

METHOD EFFICIENCY COMPARISON BETWEEN HIGH AND LOW-DIMENSIONAL REPRESENTATION OF DATA

Representation dimensionality	Time (sec)	Order	CC_1	CC_2	$RMSE_1$ (°)	$RMSE_2$ (°)	CC_x	CC_y	$RMSE_x$ (cm)	$RMSE_y$ (cm)
Low	10	2	0.99	0.92	1.76	3.95	0.98	0.96	1.1	1.2
High	610	6	0.88	0.82	9.0	4.1	0.59	0.85	3.2	12.3

the testing phase along with the ground truth. As it can be seen the method was able to estimate both human joint angles with high accuracy. The elbow joint angle has slightly larger error than the shoulder. This might happened because during the planar movements, the motion of the elbow was restricted to small displacements, generating noisy profiles at the muscle activation level. The robot joint trajectory coincides with the estimated human joint angles, since the proposed controller has an accuracy of 0.15 deg in trajectory tracking experiments proved elsewhere [21]. The accuracy of the reconstruction of the human joint angles is reported using two different criteria: the root-mean-squared error (RMSE) and the correlation coefficient (CC), describing the similarity between the reconstructed and the true joint angle profiles. If $\hat{q}_1$, $\hat{q}_2$ are the estimates for the true joint angles q_1, q_2 respectively, then the RMSE and the CC are defined as follows:

$$RMSE_i = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(q_{ik} - \hat{q}_{ik}\right)^2}, \quad i = 1,2 \tag{14}$$

$$CC_i = \frac{\sum_{k=1}^{n}\left(q_{ik} - \bar{q}_i\right)\left(\hat{q}_{ik} - \bar{\hat{q}}_i\right)}{\sqrt{\sum_{k=1}^{n}\left(q_{ik} - \bar{q}_i\right)^2 \sum_{k=1}^{n}\left(\hat{q}_{ik} - \bar{\hat{q}}_i\right)^2}}, \quad i = 1,2 \tag{15}$$

where $\bar{q}_i$ represents the mean of the i^{th} joint angle across n testing samples. It must be noted that perfect matching between the estimated and the true angles would result to $CC = 1$. The values of those criteria during a testing time period of 10 sec were: $RMSE_1 = 1.76\ deg$, $RMSE_2 = 3.95\ deg$, $CC_1 = 0.99$, $CC_2 = 0.92$. Furthermore, the error in the position of the user's hand was computed, since in some teleoperation scenarios this is also of great importance. The estimated and real hand position was computed from the estimated and real joint angles respectively, measuring the length of the user's upper arm and forearm and using simple kinematic equations. It must noted that the position of a point just behind the user's wrist was computed, in order not to include the unobserved wrist joint angle in the calculations. The values of the estimation criteria were: $RMSE_x = 1.1\ cm$, $RMSE_y = 1.2\ cm$, $CC_x = 0.98$, $CC_y = 0.96$, where subscripts x, y denote quantities along the two axes of the motion plane, as shown in Fig. 1.

A worth-assesing characteristic of the method is the use of the low-dimensional representation of the muscle activation and human kinematic variables. In order to conclude if this approach finally facilitated the decoding method, we tried to estimate a model given by (12) using the high-dimensional data for muscle activations and human joint angles. I.e. the input vector ξ had length equal to eight (8 muscles recorded), while the output vector $\mathbf{z}$ had length equal to two (2 joint angles). The same training and testing data were used as above in order the comparison to be logical. The results are shown in Table I. As it can be seen the decoding method using the high-dimensional data concluded to a model of order 6, required 10 minutes to be trained, while the results were worst than those of the proposed decoding in the low-dimensional space. This result proves the efficiency of the proposed methodology in the task of the EMG-based dexterous control of robots.

IV. CONCLUSIONS AND DISCUSSION

In this paper a new mean of robot teleoperation was introduced. EMG signals recorded from muscles of the user's shoulder and elbow were used for extracting kinematic variables (i.e. joint angles) in order to control an anthropomorphic robot arm. Activations from eight different muscles were used in order to estimate the motion of two DoFs of the user's arm during planar motions. Muscle activations were projected on a low-dimensional manifold, suggesting correlations between muscles, i.e. muscle synergies. It was found that only three (out of eight) principal components of the original data were enough to describe the original variability. In addition, the arm kinematics during planar motion (shoulder and elbow motion) were found also able to be projected to a low-dimensional manifold, suggesting the presence of substantial motor primitives in human arm motion. However the aim of this paper is not to prove the presence of internal coordination mechanisms of the human motor control, but to efficiently extract them, and using the proper mathematical formulation, employ them for controlling robotic devices. Thus, dealing with the low-dimensional representation of the muscles activations and arm kinematics, a decoding model was built to map one to the other. A state-space model was used, having the efficiency to simulate the internal, unobserved mechanisms of the system, via the "hidden" state vector. Our results of reconstructing human motion and controlling a remote robot arm in real time prove the proposed method efficiency, while suggest the application of the method to multiple DoFs of the human arm.

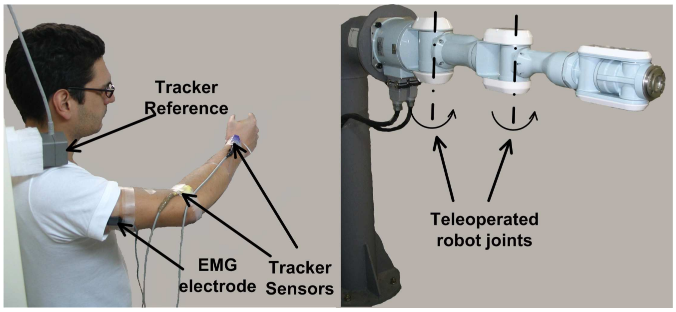

Fig. 2. Planar motion teleoperation setup. Left: user performs planar motion. The position tracker is used only during training. Right: Horizontal mounting of the robot arm. Two joints (robotic shoulder and elbow) are teleoperated by the user.

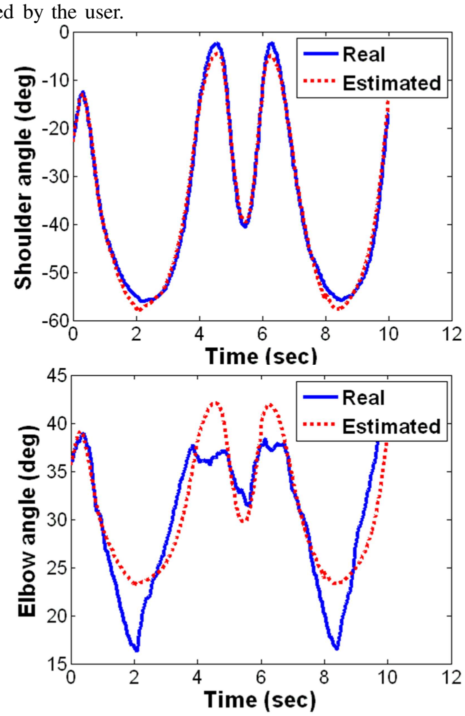

Fig. 3. Real and estimated joint angles for shoulder and elbow.

The generic structure of the proposed method suggests many important directions for further research. One of them is the application of different linear dimensionality reduction techniques (e.g. factor analysis, independent component analysis (ICA)) and nonlinear (e.g. nonlinear PCA, principal curves, multidimensional scaling (MDS)), in order to investigate towards a better representation of the high-dimensional data. Moreover, in the decoding part, a number of different model should be investigated, like Bayesian algorithms or hidden Markov models (HMM).

With the use of EMG signals and robotic devices in the area of rehabilitation receiving increased attention during the last years, our method could be proved beneficial in this area. Moreover, the proposed method can be used in a variety of applications, where an efficient human-robot interface is required. For example, prosthetic or orthotic robotic devices mainly driven by user-generated signals can be benefitted by the proposed method, concluding to a user-friendly and effective control interface.

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