Teleoperation of a Robot Arm in 2D Catching Movements using EMG Signals and a Bio-inspired Motion Law

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***Abstract*— This paper presents a methodology of robot arm teleoperation, using electromyographic (EMG) signals and a bio-inspired motion law. The methodology is implemented in planar catching movements, in situations that the user reaches and grasps objects lying on a table in front of him. EMG signals from the flexor and extensor muscles of both the elbow and the wrist joint are used to predict the elbow and wrist joint angle. This is done by using two auto-regressive moving average with exogenous output (ARMAX) models, one for each joint. A position tracker is attached in the user's upper arm, before the elbow joint, and is used for the application of the bio-inspired motion law. This law states that the trajectory of the human hand during planar reaching tasks lays on a straight line. Thus, by applying this motion law at the predicted hand trajectory, the errors of the joint angle estimation through the ARMAX model are reduced. The grasping intention of the user, after reaching the target is decoded through a discrimination algorithm based on feature extraction of the EMG signals from the forearm. The experimental results show that the two ARMAX model estimations for the joint angles, in conjunction with the motion law, are able to predict the user's motion with high accuracy, within different target points and various movement velocities.**

***Index Terms*— electromyographic (EMG) signal, robot teleoperation, auto-regressive model.**

I. INTRODUCTION

The presence of the robots in every-day life is becoming more noticeable. From this fact, the issue of teleoperation of robots in performing every-day tasks has received increased attention although, in these situations, complex interface sensors and machinery are inapplicable. A possible solution is the use of electromyographic (EMG) signals as the master-slave interface. EMG signals are recorded through small surface EMG electrodes, therefore the user's movement is not impeded. Apart from the interface issue, the resulting motion of the teleoperated robot is a critical issue. This issue is becoming crucial, when the robot is performing every-day tasks, like reaching and grasping objects on a table. In the case of those applications, the motion characteristics of the robot arm should replicate those of the human arm.

EMG signals have been used in many applications as driving signals not only for teleoperated robots, but also for prosthetic or orthotic devices. Fukuda [1] firstly introduced the teleoperation of a robot arm using EMG signals and a position tracking system. Wrist movement was extracted from an EMG pattern discrimination algorithm. Linear prediction models and pattern discrimination methods using neural networks [2] have been proposed in the past within this scope. A pattern classification technique which combines neural networks with a parametric Autoregressive (AR) model has been used for identifying finger motion based on EMG signals in [3]. A Hill-based muscle model, in conjunction with a position tracker was used by the authors for robot arm teleoperation, for smooth isometric elbow motions in [4]. In orthotic applications, Rosen et al. used a Hill-based muscle model for joint torque estimation in driving an exoskeleton arm [5].

There have been many studies in the motor control of the human upper limb in different kinds of tasks. The task that has attracted the most attention is that of reaching stationary targets. Flash and Hogan [6] have proposed that minimization of jerk closely matches human motion. From then, there has been a lot of research in the field of motor control, and it is widely proved that in point-to-point movements, like those of planar catching, the trajectory of the human hand lays on a straight line connecting initial and target points with enough accuracy [7]-[8]. This motion law is confirmed when the target point is visible to the human and the motion is unconstrained.

In this paper, a teleoperation methodology for an anthropomorphic robotic manipulator in planar reaching and grasping tasks is proposed and tested through a sufficient number of experiments. EMG signals from the main flexor (biceps brachii) and the main extensor (triceps brachii) muscle of the elbow are used to estimate the user's elbow angle during the reaching movement. Moreover, EMG signals from flexor carpi ulnaris and extensor carpi ulnaris are used to estimate the user's wrist motion. These estimates based on EMG signals were generated by using an auto-regressive moving average with exogenous output (ARMAX) model. Moreover, a position tracking system is placed in the user upper arm, before the elbow joint, in order to monitor the shoulder adduction-abduction. The motion law described above is used to correct the resulting trajectory of the hand, which is subject to elbow joint prediction errors. The grasping intention is decoded through a feature extraction based algorithm applied on the EMG signals from the muscles of the forearm. The resulting trajectory in conjunction with the estimate of the wrist joint angle is used to drive the shoulder, the elbow and the wrist joints of the robotic manipulator in real-time.

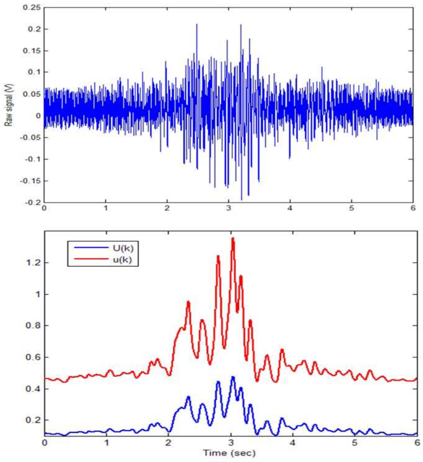

Fig. 1. Recorded, processed and final form of biceps brachii EMG signal during elbow flexion.

Thus, the main contribution of this paper is the extraction of accurate arm trajectories, using surface EMG signals and a bio-inspired law based on a human motor control. The experimental results show that the accuracy of the predicted trajectory is high, in various target points and motion velocities.

The rest of the paper is organized as follows: Section II gives a description of the methodology proposed, with the appropriate segregation of the distributed sub-problems. Section III illustrates the efficiency of the approach through a number of experimental results, while section IV concludes the paper.

II. METHODOLOGY

A. Elbow Joint

Biceps brachii and triceps brachii are selected as the main responsible flexor and extensor muscles of the elbow joint. Modeling the complex relationship between EMG signal and the motion of the corresponding joint can be accomplished through morphological modeling. This involves designing a model based on physical characteristics of the system. The large number of user-dependent parameters though, makes this solution impractical.

Therefore, instead of determining the structure of the system, the relationship between the EMG signal (input) and the joint motion (output) will be obtained considering the system as a *black box*.

Considering an EMG signal as a time varying stochastic process gives the possibility to model it as a zero-mean Gaussian distribution. Thus, the system proposed has two inputs and one output. The processed EMG signals from the flexor and extensor muscles are the two inputs, and the corresponding joint angle is the output. One of the important features of the proposed system is that it should incorporate time lag between the input (EMG signals) and the output (joint motion). The final model selected is an ARMAX model. The Z-transform equation of the system is

$$y_e(k) = \frac{B_e\left(z^{-1}\right)}{A_e\left(z^{-1}\right)} u_e(k) + \frac{C_e\left(z^{-1}\right)}{A_e\left(z^{-1}\right)} e(k) \tag{1}$$

where $y_e(k)$ the elbow joint angle, $u_e(k) = \left[\begin{array}{cc} u_{1e}(k) & u_{2e}(k) \end{array}\right]$ the processed EMG signals from the two muscles, $e(k)$ the model disturbance, z^{-1} represents the right shift in sample-time and $A_e\left(z^{-1}\right)$, $B_e\left(z^{-1}\right)$, $C_e\left(z^{-1}\right)$ polynomials of the form

$$\begin{array}{l} A_e\left(z^{-1}\right) = 1 + a_1 z^{-1} + \ldots + a_{na} z^{-na} \\ B_e\left(z^{-1}\right) = 1 + b_1 z^{-1} + \ldots + b_{na} z^{-nb} \\ C_e\left(z^{-1}\right) = 1 + c_1 z^{-1} + \ldots + c_{na} z^{-nc} \end{array} \tag{2}$$

where na, nb, nc their orders respectively. The model disturbance e can be regarded as a white Gaussian noise.

The identification phase of the system, consists of multiple catching movements performed by the user. The corresponding EMG signals were recorded and processed. The process of the raw EMG signals consists of full-wave rectification and low-pass filtering (4^{th} order Butterworth filter with a cut-off frequency of 6 Hz). Then the signals were normalized to their corresponding values recorded through maximum voluntary isometric contraction of each of the muscles. The input signals $\left[\begin{array}{cc} u_{e1}(k) & u_{e2}(k) \end{array}\right]$ of the ARMAX model were computed from the processed EMG signals $\left[\begin{array}{cc} U_{e1}(k) & U_{e2}(k) \end{array}\right]$ as shown below:

$$u_{ei}(k) = -\frac{1}{\ln\left(U_{ei}(k)\right)}, \quad i = 1, 2 \tag{3}$$

where

$$0 < U_{ei}(k) < 1, \quad i = 1, 2 \tag{4}$$

due to normalization to maximum value. This function is used to make the low increase in amplitude of the EMG during slow movements, more distinguishable. A typical raw EMG signal from biceps brachii during smooth elbow flexion, its processed form U_e, and its final form u_e are shown in Fig. 1.

The elbow joint angle is recorded through a system that consists of four markers and a camera with its axis perpendicular to the plane of movement. The positions of these markers are the shoulder (acromion), the elbow, the wrist and the hand (end of the palm). In this way the elbow joint angle can be computed through the catching movement. Then, the input signals (processed EMG signals from muscles acting on the elbow joint) and the elbow joint angle are inserted into the ARMAX model. The estimation of the coefficients of the polynomial is done through minimization of a quadratic prediction error criterion by a built-in function of the software package Matlab^{TM}. The order of the polynomial is selected to be 8 for $A_e\left(z^{-1}\right)$, $B_e\left(z^{-1}\right)$ and 5 for $C_e\left(z^{-1}\right)$. The identification data are approximately 10 elbow flexion-extension movements, and the estimation of the model takes about 4 minutes.

B. Wrist Joint

During the catching tasks, and because of the fact that the elbow is in pronosupination, the wrist flexion-extension is only of interest. The methodology used is similar to that

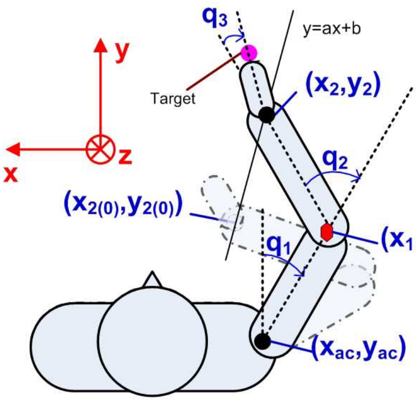

Fig. 2. 3-link model of the human arm.

used for the estimation of the elbow joint angle. Thus, EMG signals are recorded from flexor carpi ulnaris and extensor carpi ulnaris, and after processing they are used as input $\begin{bmatrix} u_{w1}(k) & u_{w2}(k) \end{bmatrix}$ to an ARMAX model of the form

$$y_w(k) = \frac{B_w(z^{-1})}{A_w(z^{-1})} u_w(k) + \frac{C_w(z^{-1})}{A_w(z^{-1})} e(k) \tag{5}$$

where $y_w(k)$ the wrist joint angle and $u_w(k) = \begin{bmatrix} u_{w1}(k) & u_{w2}(k) \end{bmatrix}$ the processed EMG signals from the two muscles.

During the identification procedure, the wrist angle is calculated using the system with the markers and the camera described above, with a similar procedure, as this for the elbow angle.

The coefficients of this ARMAX model are estimated with the same Matlab^{TM} function used for the elbow ARMAX model. The order of the corresponding polynomials is selected to be 12 for $A_w(z^{-1})$, $B_w(z^{-1})$ and 5 for $C_w(z^{-1})$. The identification data are approximately 10 wrist flexion-extension movements, and the estimation of the model takes about 5 minutes.

C. Shoulder Joint

During the planar catching movements, only adduction-abduction of the shoulder is used. Thus the estimation of the shoulder angle of the user's arm is done through a position tracker that is placed in the upper arm, before the elbow joint. The torso of the user is stable, and the position of the acromion, is a priori measured by the position tracker. The y-axis of the position tracker reference system is parallel to the upper arm, when the adduction-abduction angle is zero. Then, the shoulder angle is calculated by

$$q_1 = arctan2(x_1 - x_{ac}, y_1 - y_{ac}) \tag{6}$$

where (x_1, y_1), (x_{ac}, y_{ac}) are the positions of the tracker and the acromion respectively. These points are shown in Fig. 2. In this Figure, the modeling of the upper limb as a three-link planar arm is also shown.

D. Analysis and Application of the Bio-inspired Motion Law

The estimation of the elbow joint by the ARMAX model is not satisfactory for catching tasks. It is obvious that small prediction errors in the joint angle can result in large deviations from the desired target position. The use of the fact that the user hand trajectory lies on a straight line during the catching motion, can be used to correct in real time the predicted trajectory. The application of this law is based on the kinematic and differential kinematic analysis of the arm, without the wrist part, that is given below.

1) Kinematics: The position of the hand (x_2, y_2) is given by

$$\begin{array}{l} x_2 = -L_1 \sin(q_1) - L_2 \sin(q_1 + q_2) + x_{ac} \\ y_2 = L_1 \cos(q_1) + L_2 \cos(q_1 + q_2) + y_{ac} \end{array} \tag{7}$$

where L_1, L_2 the lengths of the upper arm and forearm respectively, (x_{ac}, y_{ac}) the position of the acromion with respect to the position tracker reference system and q_1, q_2 the joint angles of the shoulder and the elbow respectively. The positive direction of them is shown in Fig. 2.

2) Inverse Kinematics: If the equation of the line on which the hand is moving is

$$y = ax + b \tag{8}$$

where a, b the coefficients of the line, then using Eq.(7)

$$A\cos(q_2) + B\sin(q_2) = K \tag{9}$$

where

$$\begin{array}{l} A = L_2(\cos(q_1) + a\sin(q_1)) \\ B = -L_2(\sin(q_1) - a\cos(q_1)) \\ K = -aL_1 sin(q_1) - L_1\cos(q_1) + \\ \quad y_{2(0)} - ax_{2(0)} + ax_{ac} - y_{ac} \end{array} \tag{10}$$

where the initial position of the hand $(x_{2(0)}, y_{2(0)})$ is known to the system. This point belongs to the line, thus

$$y_{2(0)} = ax_{2(0)} + b \tag{11}$$

By solving the inverse kinematics and using Eq. (9), the elbow angle is given by

$$q_2 = f_1(q_1, a) \tag{12}$$

3) Differential Kinematics: Differenting Eq. (12) with respect to time

$$\dot{q}_2 = \frac{d(f_1(q_1, a))}{dt} = f_2(q_1, \dot{q}_1, a) \tag{13}$$

where $\dot{q}_1$, $\dot{q}_2$ angular velocities of shoulder and elbow angles.

The coefficient a of the line is given by

$$a = \frac{\dot{y}_2}{\dot{x}_2} \tag{14}$$

so by differenting Eq. (7) with respect to time, a is given by

$$a = f_3(q_1, \dot{q}_1, q_2, \dot{q}_2, a) \tag{15}$$

Substituting q_2, $\dot{q}_2$ from Eq. (12), (13) the coefficient a is given by

$$a = f_4(q_1, \dot{q}_1, a) \tag{16}$$

Utilizing Eq. (6) using the measurements of the tracking sensor $(x_1(t), y_1(t))$, the coefficient a can be estimated by solving the equation

$$a - f_4(q_1, \dot{q}_1, a) = 0 \tag{17}$$

The complexity of this equation does not permit an analytical solution, so it is solved by an iterative procedure. Then by using Eq. (11), the equation of the trajectory line is known.

If the line on which the hand trajectory should lie is known, a correction can be made in the estimation of the elbow angle through the ARMAX model. The correction is done in Cartesian space. So if $\hat{q}_2$ the estimation from the ARMAX model, then the corresponding estimation of the position of the hand in Cartesian space is $(\hat{x}_2, \hat{y}_2)$ where

$$\begin{aligned} \hat{x}_2 &= -L_1 \sin(q_1) - L_2 \sin(q_1 + \hat{q}_2) + x_{ac} \\ \hat{y}_2 &= L_1 \cos(q_1) + L_2 \cos(q_1 + \hat{q}_2) + y_{ac} \end{aligned} \tag{18}$$

The estimate for this point from the human motion law is $(\hat{x}_2', \hat{y}_2')$. The difference in these predictions is defined by

$$\left[\begin{array}{cc} \hat{e}_x & \hat{e}_y \end{array}\right]^T = k \left[\begin{array}{cc} \hat{x}_2' - \hat{x}_2 & \hat{y}_2' - \hat{y}_2 \end{array}\right]^T \tag{19}$$

where $k \in (0, 1)$. Then the error $\tilde{q}_2$ of the elbow angle is related to the hand position error through the function

$$\tilde{q}_2 = \frac{\partial(f_1(x_2, y_2, q_1))}{\partial x_2} \hat{e}_x + \frac{\partial(f_1(x_2, y_2, q_1))}{\partial y_2} \hat{e}_y \tag{20}$$

The formulation of those equations are found in [9].

The overall architecture of the correction of the hand trajectory using the bio-inspired motion law is depicted in Fig. 3. As it can be seen, there is a difference in the frequencies of the tracker (τ_1) and the EMG model estimation (τ_2) as $\tau_1 = 30Hz$, and $\tau_2 = 1KHz$. For this reason planning is needed to interpolate the tracker measurements to the ARMAX estimation frequency. It must be noted, that due to the fact that the tracker measurements are slow and noisy, the main driving command is this coming from the EMG signals and the ARMAX model estimation.

E. Grasping Discrimination

When the user hand reaches the target, a discrimination algorithm is used to predict the grasping. This algorithm is based on the EMG signals from both muscles recorded at the forearm. The variance (VAR) of the EMG signals is computed by

$$VAR_i = \frac{1}{n-1} \sum_{k=1}^{n} x_{ik}^2 \quad , i = 1, 2 \tag{21}$$

where i the number of different recorded muscles, n the number of samples in the moving window, and x_i the recorded EMG signals. The grasping discrimination is achieved through simultaneous monitoring of both variances. If they exceed a threshold value, the system decides that the user grasped the object, and the appropriate command is sent to the gripper attached at the end-effector of the robot manipulator.

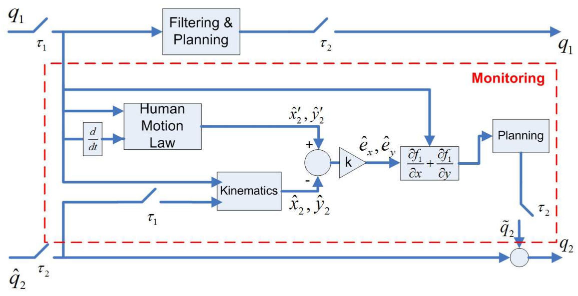

Fig. 3. Motion estimator architecture.

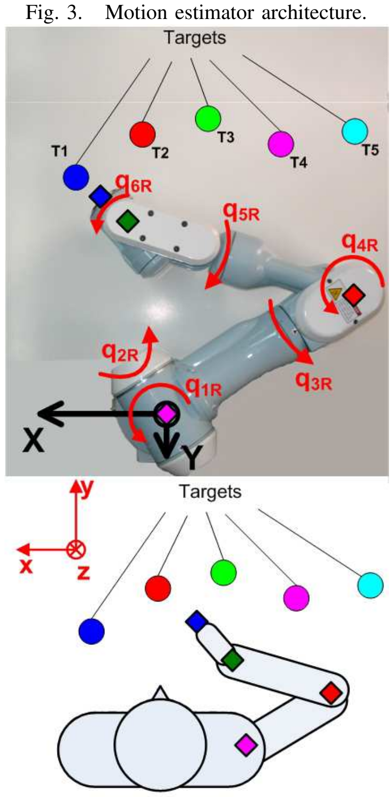

Fig. 4. Experimental set-up layout, targets and robot angles and reference system.

F. Robot Teleoperation

The shoulder, elbow and wrist joints of the robotic manipulator are being teleoperated by the user. The end-effector of the robot should be driven to the same target reached by the user. Although, due to the fact that the human arm has different lengths from those of the robot, an inverse kinematics analysis of the robot arm should be applied. In Fig. 4, the corresponding points of the human and robot arm are shown. The reference system of the robot, and all the joints are also depicted.

If $\left[\begin{array}{ccc} X & Y & Z \end{array}\right]^T$ the point of the robot that should be driven to the target, then by robot kinematic (see appendix)

$$\begin{aligned} X &= 0.45 \cos(q_{R1}) + 0.48 \cos(q_{R1} + q_{R4}) \\ &\quad + 0.07 \cos(q_{R1} + q_{R4} + q_{R6}) \\ Y &= 0.45 \sin(q_{R1}) + 0.48 \sin(q_{R1} + q_{R4}) \\ &\quad + 0.07 \sin(q_{R1} + q_{R4} + q_{R6}) \\ Z &= 0.317 \end{aligned} \tag{22}$$

having $q_{R2} = q_{R3} = \frac{\pi}{2} = const$, $q_{R5} = q_{R7} = 0 = const$, where $q_{Ri},\ i = 1, ..., 7$ the robot joint angles, and $Z = const$ for planar motion. The axis transformation that should be done between the axis of the position tracker and those of the robot reference system is given by

$$\begin{array}{l} X = x_2 - x_{ac} \\ Y = -\left(y_2 - y_{ac}\right) \end{array} \tag{23}$$

To reach the target in the desired way, the orientation of the end-effector with respect to the Z axis of the robot reference system should be equal to the orientation of the hand of the user with respect to the z axis of the tracker reference frame. Based on the relative positioning of the two reference system and the positive direction of the robot and human angles, the robot angles are related to those of human by

$$q_{R1} + q_{R4} + q_{R6} = -\left(q_1 + q_2 + q_3\right) = Q \tag{24}$$

where q_3 the human wrist joint angle. Thus, having the final estimates for (x_2, y_2), and the three human joint angles, the robot joint angles q_{R1}, q_{R4}, q_{R6} are computed by inverse kinematics:

$$\begin{array}{l} q_{R4} = arctan2\left(\pm\sqrt{1-K^2}, K\right) \\ q_{R1} = arctan2\left(B_R, A_R\right) \\ -arctan2\left(\pm\sqrt{1-\left(\frac{X'}{\sqrt{A_R^2+B_R^2}}\right)^2}, \frac{X'}{\sqrt{A_R^2+B_R^2}}\right) \\ q_{R6} = -q_{R1} - q_{R4} + Q \end{array} \tag{25}$$

where

$$\begin{array}{l} K = \frac{X'^2+Y'^2-0.4329}{0.4320} \\ X' = X - 0.07\cos\left(Q\right) \\ Y' = Y - 0.07\sin\left(Q\right) \\ A_R = 0.45 + 0.48\cos\left(q_{R4}\right) \\ B_R = -0.48\sin\left(q_{R4}\right) \end{array} \tag{26}$$

The positive solution for q_{R4} and the negative for q_{R1} are selected in order to mimic the human elbow and shoulder joint limits respectively.

III. Experiments

A. System Components

The robotic arm used is a 7-DoF anthropomorphic manipulator (PA-10, Mitsubishi Heavy Industries). The system is implemented through a network of two personal computers (PCs), which are connected through Ethernet (TCP/IP protocol), in a Linux environment. The processors specification of those PCs are Pentium 4, 2.8 GHz. The first PC is capable of acquiring in real time EMG signals and position tracker measurements, compute the estimated joint angles and calculate the desired robot joint angles. Then, through bidirectional communication, the second PC reads the current robot joint angles and sends the desired values. The second PC communicates with the robot controller through ARCNET protocol and controls the position of the robot joints in a frequency of 400 Hz.

Using a signal acquisition board (NI-DAQ 6036E) EMG signals are recorded through an EMG system (Bagnoli-16, Delsys Inc.). Single differential surface EMG electrodes (DE-2.1, Delsys Inc.) are used. EMG signal is pre-amplified with a gain factor of 1000 and sampled at 1.0 KHz. The position tracking system (Isotrak II, Polhemus Inc.) communicates with the PC through serial communication (RS-232) in a frequency of 30 Hz. The size of the position sensor is 2.83(W) 2.29(L) 1.51(H) cm, and sufficienlty portable for the user. The static accuracy is $\pm$2.4 mm for the axes x, y, z.

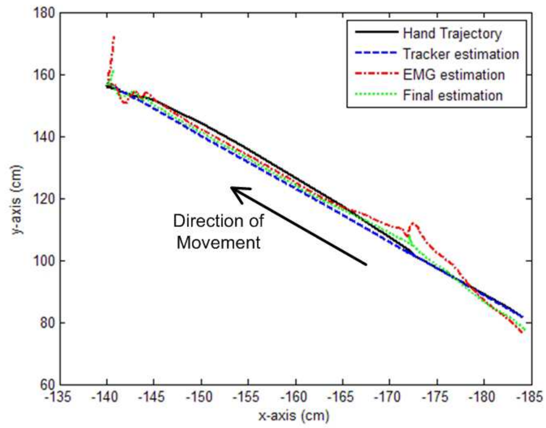

Fig. 5. System performance during reaching target T1: Correction of trajectory.

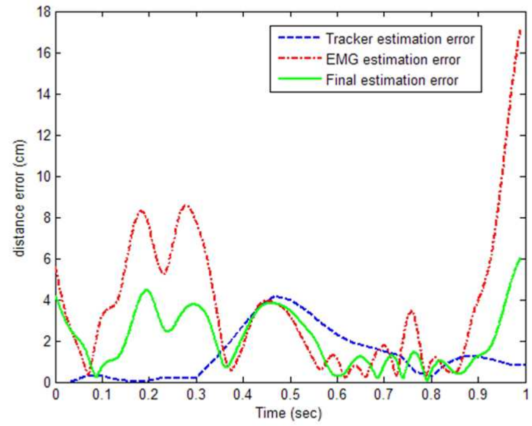

Fig. 6. System performance: Distance error.

B. Experimental Results

The proposed methodology was tested through a number of experiments, with four different subjects. All subjects were within 22-26 years old, body weight 75-95 Kg and height 1.70-1.90 m. During the identification phase, the acromion position is measured with the position tracker, such as the length of the upper arm, the forearm and the palm of the user. During the normal operation phase, subject A was seated in front of a table. The subject was told not to move his torso while moving his hand. A set of visible and reachable targets were placed in front of him as shown in Fig. 4. Four surface EMG electrodes were attached to record biceps brachii, triceps brachii, flexor carpi ulnaris and extensor carpi ulnaris and the position tracker was placed on the upper arm, before the elbow.

In Fig.5 the system performance is illustrated in Cartesian space, as the user reaches target T1. The trajectory line predicted utilizing the bio-inspired motion law is drawn for every tracking sensor measurement. As it can be seen it is close enough to the real trajectory. Using the correction of the ARMAX model estimation through the human motion law, the trajectory of the hand was corrected in real time. In Fig. 6 the decrease in the error in cartesian space due to the application of this technique is illustrated.

The system was tested through all the targets T1 to T5. It was proved that the system estimated the trajectory of the human hand with enough precision, even if the targets were at different orientation and distances.

The grasping discrimination was successfully implemented during the experiments. It must be noted that the subject was told to reach the targets with his/her fingers open, and the proper orientation of his/her wrist, in order to grasp the target object without deviating his/her hand position after the reaching phase.

IV. Conclusion

This paper proposes a methodology of robot arm teleoperation in 2-dimensional (2D) reaching and catching movements. The user-robot interface consists of four surface EMG electrodes and a position tracker. EMG signals were recorded from muscles of the elbow and wrist joint and were used to estimate elbow and wrist joint angles respectively. The EMG signals from the muscles of the forearm were also used to decode the user's intention for grasping. The application of a bio-inspired motion law, in the predicted hand trajectory was proved successful in correcting estimation errors, and calculating the user's hand trajectory with enough accuracy. The robustness and accuracy of the system was validated through a number of experiments with targets placed in different orientation and distances from the user. The methodology can be applied to any kind of teleoperated or orthotic devices.

Acknowledgment

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Appendix

We define seven successive coordinate frames at the center of rotation of the seven joints of the PA-10 manipulator, following the Denavit-Hartenberg notation. The homogeneous matrix relating two successive coordinate frames $\{i-1\}, \{i\}$ is given by

$$T_{i-1}^{i} = \begin{bmatrix} \cos q_i & -\cos\alpha_i \sin q_i & \sin\alpha_i \sin q_i & a_i \cos q_i \\ \sin q_i & \cos\alpha_i \cos q_i & -\sin\alpha_i \cos q_i & a_i \sin q_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (27)$$

Using the PA-10 Denavit-Hartenberg parameters (Table I), the total transformation matrix relating the user-corresponding frame at the robot with the base coordinate system $\{0\}$ is given by

TABLE I

D-H Parameters for PA-10 robot arm

$\alpha_i\ (rad)$	$a_i\ (m)$	$d_i\ (m)$
$-\frac{\pi}{2}$	0	0.317
$\frac{\pi}{2}$	0	0
$-\frac{\pi}{2}$	0	0.45
$\frac{\pi}{2}$	0	0
$-\frac{\pi}{2}$	0	0.48
$\frac{\pi}{2}$	0	0
0	0	0.07

$$T_0^7 = T_0^1 \cdot T_1^2 \cdot T_2^3 \cdot T_3^4 \cdot T_4^5 \cdot T_5^6 \cdot T_6^7 \quad (28)$$

The position of this point in space having $q_{R2} = q_{R3} = \frac{\pi}{2}$, $q_{R5} = q_{R7} = 0$, is given by the first three elements of the fourth column of T_0^7:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.45c_1 + 0.48c_{14} + 0.07c_{146} \\ 0.45s_1 + 0.48s_{14} + 0.07s_{146} \\ 0.317 \end{bmatrix} \quad (29)$$

where c_i, s_i stand for $\cos(q_{Ri})$ and $\sin(q_{Ri})$ respectively. The $c_{ij...}$ stands for $\cos(q_{Ri} + q_{Rj} + ...)$ and similarly for the $s_{ij...}$.

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