EMG-based Teleoperation of a Robot Arm in Planar Catching Movements using ARMAX Model and Trajectory Monitoring Techniques

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Abstract— **This paper presents a methodology of teleoperating a robot arm, using electromyographic (EMG) signals and a trajectory monitoring technique based on human motion analysis. EMG signals from the flexor and extensor muscles of the elbow joint are used to predict the human elbow joint angle, using an auto-regressive moving average with exogenous output (ARMAX) model. A position tracker is attached in the user upper arm, before the elbow joint. It has been identified from previous works on human physiology that the trajectory of the human hand during planar catching tasks lays on a straight line. This motion law is used in order to monitor and refine the trajectory of the human hand that is predicted through EMG and the ARMAX model. The experimental results show that the ARMAX model estimation for the elbow angle, in conjunction with the trajectory monitoring technique, is able to predict the user motion with high accuracy, within different target points unknown to the system, and various hand velocities.**

I. INTRODUCTION

As the robots come closer to humans, the issue of teleoperation in performing every-day movements has received increased attention. In these applications, there is an increasing demand for a direct and more natural means of interface between the user and the teleoperated robot. The user's motion should not be impeded by complicated interface sensors or machinery. A possible approach is the use of electromyographic (EMG) signals as the master slave interface because it has the advantage of being both convenient and natural for the master. Moreover, in many cases, the robot should replicate the way that the human arm is moving, in order to be able to perform human-like motions, and so to be more adaptive in constrained environments. For example, during catching of objects lying on a table, the robot arm should perform the motion in a way similar to that of the human arm, avoiding complicated configurations or motion profiles, which could result in collision with the table surface.

Most previous research on teleoperation of robots through EMG signals used pattern discrimination techniques in order to extract user intended motion. Fukuda [1] firstly introduced the way of 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 neural networks have also been used in the past for extracting user intended motion [2]. A pattern classifier technique which combines neural networks with parametric Autoregressive (AR) model has been used for identifying finger motion based on EMG signals in [3]. A Hill-based muscle model was used for joint torque estimation in driving an exoskeleton arm [4]. A Hill-based muscle model, in conjunction with a position tracker was used in teleoperating a robot arm, for smooth isometric elbow motions in [5].

Previous studies in directional control of planar human arm movement have defined 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[6]-[8]. This motion law is confirmed when the target point is visible to the human and the motion is unconstrained.

In this paper, a methodology for teleoperating an anthropomorphic robotic manipulator in planar catching tasks is proposed and tested through real-time experiments. Surface EMG signals from the flexor (biceps brachii) and the extensor (triceps brachii) muscle of the elbow are used to compute the user's elbow angle. An auto-regressive moving average with exogenous output (ARMAX) model is used to map the EMG signals to the elbow angle. 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 resulted trajectory of the hand, which is subject to elbow joint prediction errors. The resulted trajectory is used to drive the shoulder and the elbow joints of the robotic manipulator in real-time. So the main contribution of this paper is the extraction of accurate arm trajectories, using surface EMG signals and a monitoring technique based on a human motion law. The experimental results show that the accuracy of the predicted trajectory is high, in various target points and hand 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.

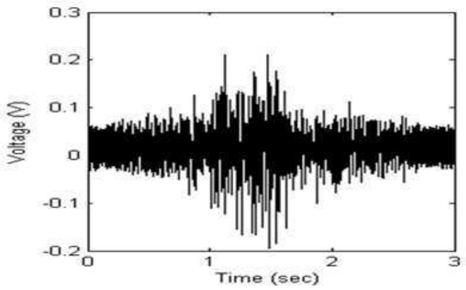

Fig. 1. Raw EMG signal from biceps brachii during elbow flexion

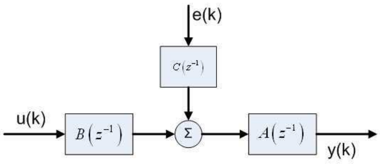

Fig. 2. ARMAX model.

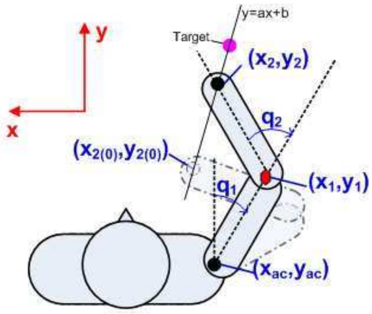

Fig. 3. User's arm points, joint angles and reference system

II. Methodology

The shoulder and the elbow joints of the robotic manipulator are teleoperated for point-to-point catching movements. The user's shoulder joint motion estimation will be based on measurements from the position tracker. The elbow joint motion estimation will be based mainly on EMG signals, through a correction from the motion law that will be analyzed further below. This section will describe in details each part.

A. Elbow Joint

Biceps brachii and triceps brachii are selected as the main responsible flexor and extensor muscles respectively, of the elbow joint. A typical form of EMG signal from biceps brachii as recorded during flexion of the elbow joint is depicted in Fig. 1. Modeling the complex relationship between EMG signal and the motion of the corresponding joint can be based on 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, rather than 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*. The *black box* type of modeling is referred to as system identification [10].

Parametric system identification is basically a simplification of equations for dynamic systems. The system proposed here has two inputs and one output: the processed EMG signals from the two muscles, and the elbow joint angle respectively. The system should incorporate time lag between input and output, which is an inherent characteristic of the musculoskeletal model. This delay is known as electro-mechanical delay (EMD) and is defined as the temporal disassociation between the EMG signal and the applied muscle force. Furthermore, considering EMG signal as a time varying stochastic process gives the possibility to model it as a zero-mean Gaussian distribution [9]. So EMG can be represented by an auto-regressive (AR) model. The model finally selected is an ARMAX model, whose structure is shown in Fig. 2. The equation (Z-transform) for this system is

$$A\left(z^{-1}\right)y\left(k\right) = B\left(z^{-1}\right)u\left(k\right) + C\left(z^{-1}\right)e\left(k\right) \qquad (1)$$

where $y\left(k\right)$ the elbow joint angle, $u\left(k\right) = \left[\begin{array}{cc} u_1\left(k\right) & u_2\left(k\right)\end{array}\right]$ the processed EMG signals from the two muscles, $e\left(k\right)$ the model disturbance, z^{-1} represents the right shift in sample-time and $A\left(z^{-1}\right)$, $B\left(z^{-1}\right)$, $C\left(z^{-1}\right)$ polynomials of the form

$$\begin{array}{l} A\left(z^{-1}\right) = 1 + a_1 z^{-1} + \ldots + a_{na} z^{-na} \\ B\left(z^{-1}\right) = 1 + b_1 z^{-1} + \ldots + b_{na} z^{-nb} \\ C\left(z^{-1}\right) = 1 + c_1 z^{-1} + \ldots + c_{na} z^{-nc} \end{array} \qquad (2)$$

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

In the identification phase, the user performed a variety of catching movements, in different directions and distances. EMG signals and the elbow joint angle were recorded. Three markers placed in the shoulder, elbow and wrist of the user respectively. A camera with its axis perpendicular to the plane of movement was used to record the markers displacement in order to compute elbow joint angle. 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 $\left[\begin{array}{cc} u_1\left(k\right) & u_2\left(k\right)\end{array}\right]$ of the ARMAX model were computed from the processed EMG signals $\left[\begin{array}{cc} U_1\left(k\right) & U_2\left(k\right)\end{array}\right]$ as shown below:

$$u_i\left(k\right) = -\frac{1}{\ln\left(U_i\left(k\right)\right)}\ , \quad i = 1,2 \qquad (3)$$

where

$$0 < U_i\left(k\right) < 1, \quad i = 1,2 \qquad (4)$$

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.

The coefficients of the polynomials are estimated through minimization of a quadratic prediction error criterion, implemented by a built-in function of the software package

Matlab^{TM} version 7. The order of the polynomials was selected to be 10 for $A\left(z^{-1}\right)$, $B\left(z^{-1}\right)$ and 5 for $C\left(z^{-1}\right)$. A typical number of identification experiments is 10, and the estimation of the model takes about 2 minutes.

B. Shoulder Joint

The human shoulder has been modeled as a 3 degrees of freedom (DoF) mechanism in the literature. In planar movements, only adduction-abduction of the shoulder is used. So the user's upper limb, can be modeled here as a two link mechanism[1] as shown in Fig. 3. 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

$$q_1 = Arctan2\left(x_1 - x_{ac}, y_1 - y_{ac}\right) \tag{5}$$

where (x_1, y_1), (x_{ac}, y_{ac}) are the positions of the tracker and the acromion respectively.

C. Correction of Elbow Joint Angle Estimation Through Monitoring of Hand Trajectory

The accuracy of estimation of the elbow joint motion from EMG signals, using the previously analyzed ARMAX model is not satisfactory for point-to-point catching tasks. Small prediction errors can result in large deviations from the desired target position. For this reason, it is proposed that the predicted trajectory of the user's arm should be monitored and corrected in real time, based on the human motion law for point-to-point tasks. This law defines that the trajectory of the hand (specifically the user's wrist) can be accurately enough approximated by a straight line.

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

$$\begin{aligned} x_2 &= -L_1 \sin\left(q_1\right) - L_2 \sin\left(q_1 + q_2\right) + x_{ac} \\ y_2 &= L_1 \cos\left(q_1\right) + L_2 \cos\left(q_1 + q_2\right) + y_{ac} \end{aligned} \tag{6}$$

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. 3.

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

$$y = ax + b \tag{7}$$

where a, b the coefficients of the line, then by substituting from Eq.(6) it is

$$A\cos\left(q_2\right) + B\sin\left(q_2\right) = K \tag{8}$$

[1]The user's hand is excluded

where

$$\begin{aligned} A &= L_2\left(\cos\left(q_1\right) + a\sin\left(q_1\right)\right) \\ B &= -L_2\left(\sin\left(q_1\right) - a\cos\left(q_1\right)\right) \\ K &= -aL_1 sin\left(q_1\right) - L_1\cos\left(q_1\right) + \\ &\quad y_{2(0)} - ax_{2(0)} + ax_{ac} - y_{ac} \end{aligned} \tag{9}$$

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

$$y_{2(0)} = ax_{2(0)} + b \tag{10}$$

By solving the inverse kinematics and using Eq. (10), the elbow angle is given by

$$q_2 = f_1\left(q_1, a\right) \tag{11}$$

where

$$\begin{aligned} f_1\left(q_1, a\right) &= Arctan2\left(B, A\right) - \\ &-Arctan2\left(\pm\sqrt{1 - \left(\frac{K}{p}\right)^2}, \frac{K}{p}\right) \end{aligned} \tag{12}$$

with

$$p = \sqrt{A^2 + B^2} \tag{13}$$

From Eq. (11) is obvious that for a straight line trajectory, elbow angle is dependent on the shoulder angle, and the line coefficients.

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

$$\dot{q}_2 = \frac{d\left(f_1\left(q_1, a\right)\right)}{dt} = f_2\left(q_1, \dot{q}_1, a\right) \tag{14}$$

where $\dot{q}_1$, $\dot{q}_2$ angular velocities of shoulder and elbow angles. Function $f_2\left(q_1, \dot{q}_1, a\right)$ is given in the appendix.

The coefficient a of the line is given by

$$a = \frac{\dot{y}_2}{\dot{x}_2} \tag{15}$$

so by differenting Eq. (6) with respect to time, a is given by

$$a = f_3\left(q_1, \dot{q}_1, q_2, \dot{q}_2, a\right) \tag{16}$$

Substituting q_2, $\dot{q}_2$ from Eq. (11), (14) the coefficient a is given by

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

where f_4 is given in the appendix. Utilizing Eq. (5) using the measurements of the tracking sensor $(x_1(t), y_1(t))$, the coefficient a can be estimated by solving the equation

$$a - f_4\left(q_1, \dot{q}_1, a\right) = 0 \tag{18}$$

The complexity of this equation does not permit an analytical solution, so it is solved by an iterative procedure. Then by using Eq. (10), the equation of the trajectory line is known.

Consequently, if the line on which the hand should move is known, a correction can be made in the estimation of elbow angle by the ARMAX model. The correction is done in Cartesian space. So if $\hat{q}_2$ the estimation from the ARMAX model, then $(\hat{x}_2, \hat{y}_2)$ is the corresponding estimation of the position of the hand in Cartesian space. The estimation 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 $\tilde{q}_2$ at the elbow angle is related with the error at the position of the hand though the function

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

where g is a function deriving from Eq. (6), by solving with respect to q_2.

It must be noted that the values of the coefficients a, b of the trajectory line are changing at every position tracker measurement. For this reason, the values of k are dependent on the change of the coefficients a, b. If the change is large, then the values are considered as disturbance and the value of k decreases. The total architecture of the motion estimator through the monitoring technique is shown in Fig. 4. The τ_1, τ_2 are the frequencies of the tracker and the EMG model estimation respectively. It is $\tau_1 = 30Hz$, and $\tau_2 = 1KHz$. Thus planning is needed to interpolate slow measurements.

It must be noted, that the ARMAX model estimation through the correction analyzed above is the main driving command, because of the fact that

- its frequency is 1 KHz, which is much higher than the tracker frequency (30 Hz)
- and the tracker measurements are subject to noise.

D. Robot Teleoperation

The fact that the final estimation of user motion is done in joint space (q_1, q_2), gives the possibility to the system to be adaptive to any teleoperated robot, whether this robot is a remotely-controlled robotic manipulator or an exoskeletal mechanism. In this paper, the main aim is to teleoperate a robotic manipulator in order to reach some targets in a plane. The targets of the robot are in the same arrangement as those of the human, as shown in Fig. 5. The corresponding points between human and robot are indicated with circles of the same color. However, the dimensions of the human arm are not equivalent to those of the robot arm. Consequently, inverse kinematics analysis for the robot arm should be applied in order to drive the robot arm at the correct target. 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 kinematics of the robot (see appendix)

$$\begin{array}{l} X = 0.45\cos\left(q_{R1}\right) + 0.48\cos\left(q_{R1} + q_{R4}\right) \\ Y = 0.45\sin\left(q_{R1}\right) + 0.48\sin\left(q_{R1} + q_{R4}\right) \\ Z = 0.317 \end{array} \tag{21}$$

having $q_{R2} = q_{R3} = \frac{\pi}{2} = const$, $q_{R5} = q_{R6} = q_{R7} = 0 = const$, where q_{Ri}, $i = 1, ..., 7$ the robot joint angles, and $Z = const$ for planar motion. The axis transformation that

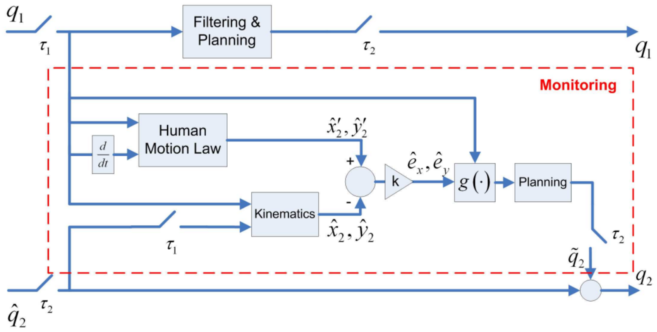

Fig. 4. Architecture of motion estimation through the monitoring technique

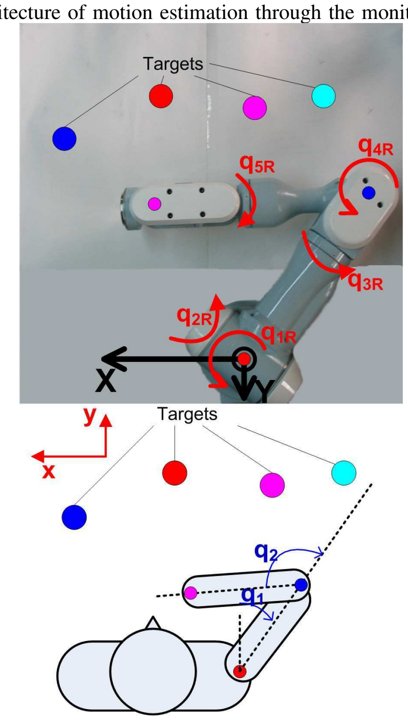

Fig. 5. Experimental set-up, targets and corresponding human-robot points

should be done between the axis of the position tracker and those of the robot reference system is given by

$$\begin{array}{l} X = x_2 - x_{ac} \\ Y = -\left(y_2 - y_{ac}\right) \end{array} \tag{22}$$

Thus, having the final estimation for (x_2, y_2), the robot joint angles q_{R1}, q_{R4} are computed by inverse kinematics:

$$\begin{array}{l} q_{R4} = Arc\tan 2\left(\pm\sqrt{1 - \left(\frac{X^2+Y^2-0.4329}{0.4320}\right)^2}, \frac{X^2+Y^2-0.4329}{0.4320}\right) \\ q_{R1} = Arc\tan 2\left(B_R, A_R\right) \\ -Arc\tan 2\left(\pm\sqrt{1 - \left(\frac{X}{\sqrt{A_R^2+B_R^2}}\right)}, \frac{X}{\sqrt{A_R^2+B_R^2}}\right) \end{array} \tag{23}$$

where

$$\begin{array}{l} A_R = 0.45 + 0.48\cos\left(q_{R4}\right) \\ B_R = -0.48\sin\left(q_{R4}\right) \end{array} \tag{24}$$

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 manipulator (PA-10, Mitsubishi Heavy Industries). The total methodology is implemented in a personal computer (PC) (Pentium 4, 2.8 GHz), in a Linux environment. This PC is connected through Ethernet cable (TCP/IP protocol) with a second PC which communicates with the robot controller through ARCNET protocol 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.

B. Experimental Results

The operation of the system is divided in two parts: the calibration phase, and the normal operation phase. During the calibration phase the user performs a small number of catching movements, in different directions and distances. Using methodology already analyzed, the ARMAX model is estimated. The acromion position is measured with the position tracker, such as the length of upper arm and forearm of the user. The calibration phase takes no more than 10 minutes. Then the normal operation phase takes place. The system was tested by four different subjects. All subjects were within 22-26 years old, body weight 75-95 Kg and height 1.70-1.90 m.

During 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. 5. Two surface EMG electrodes were attached to record biceps brachii and triceps brachii, and the position tracker was placed on the upper arm, before the elbow joint.

In Fig. 6 the system performance is illustrated. As it can be seen, both the elbow angle estimated by the ARMAX model and by the tracker deviate from the real one. However, by applying the monitoring technique, the error is reduced.

The system performance is more evident in Cartesian space (Fig. 7). The trajectory line predicted utilizing the human motion law is drawn for every tracking sensor measurement. As it can be seen it is close enough to the real trajectory. Using this monitoring technique, the trajectory of the hand was corrected in real time. In Fig. 7 the decrease in the error in cartesian space due to the application of the monitoring technique is illustrated. The system had similar performance among all the subjects and the targets reached. These targets were selected randomly and were not included in the calibration procedure.

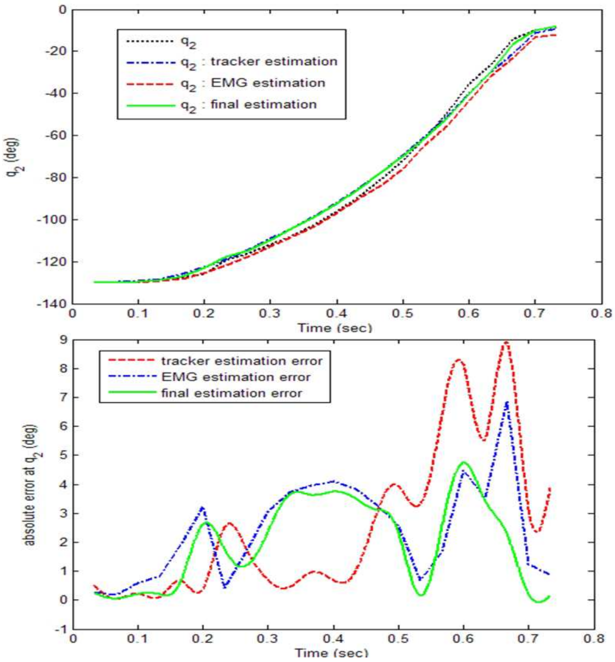

Fig. 6. System performance in joint space

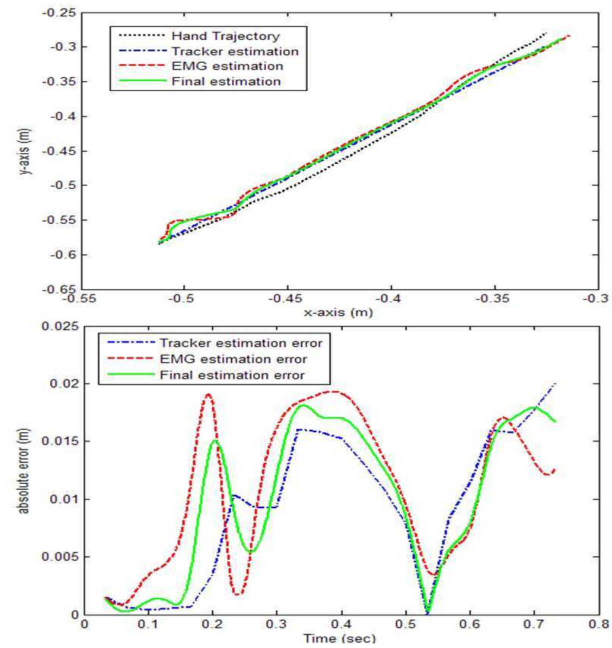

Fig. 7. System performance in Cartesian Space. Error is defined as the Euclidean distance from the human hand trajectory

C. Conclusion

This paper proposes a methodology of a robot arm teleoperation in two-dimensional catching tasks, through signals coming from both human muscles and artificial sensor. The human upper limb motion is predicted with high accuracy, using EMG signals from muscles acting on the elbow joint, and position measurements from a position tracker. Based on a pre-defined human motion law, the predicted trajectory is refined in real time. Experiments conducted show the accuracy and robustness of the system, in slow and fast catching motions, with targets being placed in different directions and distances. The methodology can be applied to any kind of teleoperated or orthotic robot.

In our future research, EMG signals from muscles acting on human wrist will be acquired in order to control the wrist of the robot arm. Grasping discrimination through EMG will be developed in order to teleoperate the robot in catching and fetching tasks. The expansion of the methodology to elbow pronation-supination is a future objective too.

ACKNOWLEDGMENT

The authors want to acknowledge the contribution of the European Commission through contract NEUROBOTICS (FP6-IST-001917) project.

APPENDIX

1) Human Differential Kinematics: Using Eq. (12) the elbow joint angular velocity is given by

$$\dot{q}_2 = \frac{d\left(f_1\left(q_1, a\right)\right)}{dt} = f_2\left(q_1, \dot{q}_1, a\right) \tag{25}$$

$$f_2 = -\left(w_2 \Big/ w_1\sqrt{1-\left(\frac{w_3}{w_1}\right)^2}+1\right)\dot{q}_1 \tag{26}$$

$$\begin{aligned} w_1 &= L_2\sqrt{(1+a^2)} \\ w_2 &= aL_1c_1 - L_1s_1 \\ w_3 &= ax_{2(0)} - y_{2(0)} - ax_{ac} + y_{ac} + L_1c_1 + aL_1s_1 \end{aligned} \tag{27}$$

By s_i, c_i the $\sin(q_i)$, $\cos(q_i)$ are denoted respectively.

From Eq. (6), (11), (14)-(16) the coefficient a is given by

$$a = f_4\left(q_1, \dot{q}_1, a\right) \tag{28}$$

where

$$f_4 = \frac{r_1}{r_2} \tag{29}$$

$$\begin{aligned} r_1 &= -\tfrac{1}{w_1w_5}L_1\left(w_4\sin\left(\theta_1-\theta_2-q_1\right)+w_1w_5s_1\right)\dot{q}_1 \\ r_2 &= \tfrac{1}{w_1w_5}L_1\left(w_4\cos\left(\theta_1-\theta_2-q_1\right)-w_1w_5s_1\right)\dot{q}_1 \end{aligned} \tag{30}$$

$$\begin{aligned} &\theta_1 = Arc\tan\left(w_5, -\tfrac{w_3}{w_1}\right), \quad \theta_2 = Arc\tan\left({}^{w_4}\!/_{w_6}\right) \\ &w_4 = L_2\left(ac_1 - s_1\right), \quad w_5 = \sqrt{1-\left({}^{w_3}\!/_{w_1}\right)^2} \end{aligned} \tag{31}$$

2) Robot Kinematics: We define five successive coordinate frames at the center of rotation of the first five 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

$$T_{i-1}^{i} = \begin{bmatrix} \cos q_i & -\cos\alpha_i\sin q_i & \sin\alpha_i\sin q_i & a_i\cos q_i \\ \sin q_i & \cos\alpha_i\cos q_i & -\sin\alpha_i\cos q_i & a_i\sin q_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{32}$$

TABLE I

D-H PARAMETERS FOR THE FIRST 5 JOINTS OF PA-10

α_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

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

$$T_0^5 = T_0^1 \cdot T_1^2 \cdot T_2^3 \cdot T_3^4 \cdot T_4^5 \tag{33}$$

The position of this point in space having $q_{R2} = q_{R3} = \frac{\pi}{2}$, $q_{R5} = q_{R6} = q_{R7} = 0$, is given by the first three elements of the fourth column of T_0^5:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.45\cos\left(q_{R1}\right) + 0.48\cos\left(q_{R1}+q_{R4}\right) \\ 0.45\sin\left(q_{R1}\right) + 0.48\sin\left(q_{R1}+q_{R4}\right) \\ 0.317 \end{bmatrix} \tag{34}$$

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