Estimation of Time-varying Human Arm Stiffness Using Electromyogram Signal

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Abstract:
Human arm stiffness is important in movement stability in unstable or novel environments. Therefore measurement of the arm stiffness is necessary to study on control mechanisms involved in stabilization and adaptation to environments dynamics. Previous techniques, did not measure time-varying stiffness explicitly. Here we introduce a novel method to estimate arm stiffness using EMG signals. In this method, muscles activation levels are related to joints torques and stiffness. We derived analytical relations to calculate arm stiffness using joints dynamics. This method was used to find arm stiffness profile in 12 subjects, before a reaching movement task. Results imply that this method can be used to find time-varying profile of the arm stiffness.

Keyword: Time-Varying Stiffness, EMG, Arm model.

I. INTRODUCTION

Human is supposed to learn how to resist against disturbances during daily movement tasks [1]. Stiffness is assumed as a tunable portion of human arm resistance against out-world disturbances to perform stable movements [2]. Therefore, arm stiffness is one of the important variables that researchers are interested to measure in movement tasks. Stiffness value depends on many parameters like: arm configuration, activation level of muscles, co-contraction of muscles around the joint, reflexive gains and disturbance characteristics. Most previous researches are based on steady-state value of displacement (or force) responses of the arm, against servo controlled force (or displacement) disturbances and no major attention has been paid to time-varying stiffness of the arm [3, 4]. On the other hand, using inverse dynamics equations to find torques generated on joints is not sufficient to have a good estimation of joints stiffness. Because the net torque on joint is proportional to subtraction of flexor and extensor torques, while stiffness is related to addition of absolute values of flexor and extensor torques.

In this paper a new method is presented to investigate time-varying stiffness profile, before starting a reaching movement task. This method was used to find stiffness profile of 12 human subjects. Results indicate that this method can be used to study of time-varying stiffness of human arm.

II. METHODS

We used a complete musculoskeletal model of the human arm to estimate arm stiffness in response to mechanical perturbations. In this model, 6 muscles were considered as four uniarticular muscles (anterior and posterior parts of Deltiods, Biceps short head and Triceps lateral head) and two biarticular muscles (Biceps long head and Triceps long head). These muscles could flex or extend shoulder and elbow joints. This model was constrained to 2-DOF planar movements (Fig.1).

![Fig.1. Model of human arm with 6 muscles. Muscles are, 1- anterior part of Deltiods (DA), 2- posterior part of Deltiods (DP), 3-Biceps short head (BSH), 4-Triceps lateral head (TlaH), 5-Biceps long head (BLH) and 6-Triceps long head (TloH).](image)

EMG signals are assumed to contain information about both voluntary and reflexive signals that control muscles activities. On the other hand, it is possible to investigate time-varying activity of the muscles using EMG signals. EMG signals were rectified and filtered using a recursive filter in some previous researches [5, 6] to find activation levels of the muscles (Eq.1).
where \( e_i(t) \) is processed EMG, \( d_i \) is electromechanical delay and \( EMG_i(t) \) is rectified EMG signal of the muscle \( i \). \( \alpha_i \), \( \beta_i \) and \( \gamma_i \) are constants. A nonlinear function was used to map the processed EMG signal to activation level of the muscle (Eq.2).

\[
a(e) = \frac{e^{A e - 1}}{e^{A e - 1}} \\
-3 \leq A < 0
\]  

(Eq.2)

Where \( A_i \) indicates the nonlinearity index of the relation and \( a_i \) is activation level of the muscle. When \( A_i \) gets near to zero, relation would be more linear.

We used Hill-type model of the muscle to estimate muscle forces around the joints, using activation levels of the muscles (Eq.3).

\[
F_m = a_i F_i(l), F_v(l), F_{max} + F_p
\]  

(Eq.3)

Where, \( F_m \) is muscle force, \( F_i \) is nonlinear length-tension relation (Fig.2), \( F_v \) is force-velocity relation (Fig.3), \( F_{max} \) is maximum muscle force, \( F_p \) is nonlinear passive force and \( l \) is muscle length.

To find activation related stiffness, we used slope of the length-tension relation. This slope was scaled by activation level of the muscle. In other words, muscle stiffness was assumed to be controllable by excitation signals from spinal and supraspinal levels of CNS. Therefore, we could derive stiffness of the hand using estimated joints stiffness and arm configuration (Eq.4).

\[
K_v = - (J^T)^{-1} \left( \frac{\partial M}{\partial \theta} F_m + MK_m M^T + \frac{\partial J^T}{\partial \theta} F \right)
\]  

(Eq.4)

Where \( \theta \) is a vector which contains angles of shoulder and elbow, \( k_v \) is arm stiffness matrix, \( J \) is a Jacobian matrix, relating hand velocity to joints angular velocity (Eq.5), \( M \) is Jacobian matrix containing arm-moments of muscles (Eq.6 and Eq.7), \( F_m \) is a vector of six muscles forces, \( K_m \) is a diagonal matrix of muscles stiffness (Eq.8) and \( F \) is the applied disturbance to the hand.

\[
\tau = J^T F_e
\]  

(Eq.5)

\[
M = \begin{bmatrix}
\frac{\partial l_1}{\partial \theta_1} & \frac{\partial l_2}{\partial \theta_1} & 0 & 0 & \frac{\partial l_3}{\partial \theta_1} & \frac{\partial l_4}{\partial \theta_1} \\
0 & 0 & \frac{\partial l_1}{\partial \theta_2} & \frac{\partial l_2}{\partial \theta_2} & 0 & \frac{\partial l_3}{\partial \theta_2} \\
0 & 0 & 0 & \frac{\partial l_1}{\partial \theta_3} & \frac{\partial l_2}{\partial \theta_3} & \frac{\partial l_4}{\partial \theta_3}
\end{bmatrix}
\]  

(Eq.6)

\[
\tau = -M F_m
\]  

(Eq.7)

\[
k_m = \frac{\partial F_m}{\partial l_m} = \frac{\partial (a_i F_i(l_m))^2}{\partial l_m} = a_i F_v K_{ac}(l_m) + K_p(l_m)
\]  

(Eq.8)

In the other word, we used EMG signals in our method to estimate time-varying stiffness of the muscles (Fig.4) and forces (Fig.2). Using these data, we can estimate time-varying stiffness using Eq.4.
Fig. 4. Muscle stiffness with different activation levels

But these equations are limited by arm dynamics. In other words, Muscle forces can be used in arm dynamics equations to find joints angles and velocities as Eq.8.

\[ Q = M(q)\ddot{q} + V(q, \dot{q}) \]  

(Eq.8)

Where \( Q \) is joints angles matrix, \( M \) is Inertial part and \( V \) is viscose-damper part of the arm dynamics. Gravity has been compensated and therefore, there is no gravity related term in this equation. Complete model of the arm is presented in Fig.5.

Fig. 5. Musculoskeletal model used to estimate Joint stiffness using EMG signal: We used processed EMG as activation level of Hill-type muscle model and calculated muscle stiffness and muscle tensions using this model. Then joints torques were calculated based on arm moments. Response of a 2DOF arm model to the external disturbance and joints torques, were used to calculate joints kinematics and muscle kinematics as a result. Finally based on muscles forces, muscles stiffness, disturbance force and configuration of the hand, time-varying stiffness of the arm was estimated.

III. SETTING MODEL PARAMETERS

There are 2 steps to find good values for model parameters. First, we set some values which can be scaled to each subject. For example, mass of the forearm can be found knowing subjects weight. Parameters which could be scaled are presented in Table 1. Some other parameters, like center of gravity, Inertia tensors, forearm masses, muscles optimal lengths and tendons slack lengths were also scaled to each subject.

Table 1: Values used in the model for a man (68 kg, 75cm). all values are in mm.

<table>
<thead>
<tr>
<th>L_1</th>
<th>L_2</th>
<th>a_{1,1}</th>
<th>a_{1,2}</th>
<th>a_{1,3}</th>
<th>a_{1,6}</th>
<th>a_{2,3}</th>
</tr>
</thead>
<tbody>
<tr>
<td>310</td>
<td>340</td>
<td>60</td>
<td>50</td>
<td>33</td>
<td>42</td>
<td>47</td>
</tr>
<tr>
<td>a_{2,4}</td>
<td>a_{2,5}</td>
<td>a_{2,6}</td>
<td>b_1</td>
<td>b_2</td>
<td>b_3</td>
<td>b_4</td>
</tr>
<tr>
<td>38</td>
<td>30</td>
<td>38</td>
<td>125</td>
<td>170</td>
<td>124</td>
<td>192</td>
</tr>
</tbody>
</table>

In the second step, other parameters were estimated using recorded signals. For example, parameters in EMG-force relation of the muscles could be found in this step. We designed two supplementary experiments for this aim. In the first experiment, subjects were asked to apply forces in 16 different directions (Fig.6). Maximum voluntary forces and muscle activities of six muscles were recorded for each direction and each subject. These data were used to estimate values in Eq.2 using Genetic Algorithm (GA) optimization method.

Fig. 6. Experimental setup for supplementary experiments. Maximum voluntary forces and related EMG signals were recorded in 16 directions.
Second experiment was designed to tune EMG signal processing filter (Eq.1). In this experiment 7.5 N and 15 N forces were applied in 8 different directions by a 2-DOF robot. EMG filter parameters were estimated to decrease difference between applied and simulated forces. We used GA to find the best set of parameters which optimized the cost function.

IV. EXPERIMENTS

We used our explained method to investigate how human arm stiffness is regulated to resist against upcoming known disturbances based on EMG recordings. 12 human subjects participated in our experiments.

They adapted to a velocity dependant force field which was introduced during a planar reaching task. A 2DOF planar robot at computational motor control Lab in Johns Hopkins University was used for this aim. Subjects were instructed to move after a go cue to one of the 2 targets: 1- up-left 2-down-right (Fig.7). A 50ms force pulse was presented in some random trials to flex or extend the arm during preparatory period. Motion data and EMG signals recorded at 200Hz and 2kHz frequencies respectively.

![Fig. 7. Subjects moved towards one of 2 targets in the workspace: 1- up-left and 2-down-right. They adapted to a counter clock wise velocity dependent force field.](image)

Fig. 7. Subjects moved towards one of 2 targets in the workspace: 1- up-left and 2-down-right. They adapted to a counter clock wise velocity dependent force field.

V. RESULTS

Mechanical parameters, like lengths and tendon connection points were adjusted using subjects weights and heights. Parameters for activation levels were estimated using Genetic Algorithm (GA). Results for estimation of nonlinear parameter A (Eq.2) are presented in table 2. Maximum forces for 6 muscles were also estimated using GA. Results are presented in table 3.

<table>
<thead>
<tr>
<th></th>
<th>DA</th>
<th>DP</th>
<th>BSH</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA</td>
<td>-1.02 (0.33)</td>
<td>-0.36 (0.21)</td>
<td>-0.48 (0.18)</td>
</tr>
<tr>
<td>BLH</td>
<td>-0.59 (0.33)</td>
<td>-1.00 (0.27)</td>
<td>-0.61 (0.21)</td>
</tr>
</tbody>
</table>

Table2: Estimated values for nonlinear parameter A (for six muscles of 12 subjects). Values in parenthesis are standard mean of error.

<table>
<thead>
<tr>
<th></th>
<th>DA</th>
<th>DP</th>
<th>BSH</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA</td>
<td>942.9 (119.6)</td>
<td>1003.4(90.5)</td>
<td>948.4(107.5)</td>
</tr>
<tr>
<td>BLH</td>
<td>539.0(60.7)</td>
<td>915.4(40.4)</td>
<td>809.9(48.6)</td>
</tr>
</tbody>
</table>

Table3: Estimated values for maximum contraction forces (for six muscles of 12 subjects). Values in parenthesis are standard mean of error.

Model was simulated in workspace of the arm (Fig.8) to evaluate the tuned model. Simulated model tracks actual displacement data well, which means model parameters are tuned correctly. The error sizes for 12 subjects are presented in table 4.

<table>
<thead>
<tr>
<th>Subject</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Up-left disp. error [%]</td>
<td>15</td>
<td>11.9</td>
<td>16.6</td>
<td>12.4</td>
<td>11.6</td>
<td>16.1</td>
</tr>
<tr>
<td>Down-right disp. error [%]</td>
<td>13.2</td>
<td>9.9</td>
<td>12.6</td>
<td>15.4</td>
<td>9.3</td>
<td>13.8</td>
</tr>
</tbody>
</table>

Table4. Averaged displacement error for 12 subjects.

<table>
<thead>
<tr>
<th>Subject</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Up-left disp. error [%]</td>
<td>7.3</td>
<td>14.3</td>
<td>8.5</td>
<td>12.1</td>
<td>9.8</td>
<td>7.7</td>
</tr>
<tr>
<td>Down-right disp. error [%]</td>
<td>10.7</td>
<td>16.1</td>
<td>10.5</td>
<td>9.9</td>
<td>13.8</td>
<td>10.7</td>
</tr>
</tbody>
</table>

Fig.8. Workspace of human arm.
Simulation of the stiffness for different activation levels of muscles and disturbance forces implies that the model represents changes in parameters (e.g. different levels of muscles activation and applied disturbances). Simulation results for fully activated muscles and 1 N disturbance in X direction are presented in figures 9 and 10 respectively. Stiffness ellipse area shows the size of the stiffness and its orientation represents direction with maximum stiffness of the hand. This method of visualization was used by other researchers to represent stiffness matrix.

VI. DISCUSSION

Results show that the method can be used for estimation of stiffness profiles. Profiles are time-varying and it will help researchers to apply the proposed method to dynamic tasks, like movements. On the other hand, this method needs supplementary experiments and many parameters should be tuned with subject specific data. This method is useful for tracking changes in stiffness and precise value of the stiffness could not be found by this method.

REFERENCES