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Feasibility Study of Upper Limb Control Method Based on EMG-Angle Relation

The paper describes the method of predicting the angular position of the human upper limb using EMG signals. A neural network with fuzzy logic was used for this purpose. The main goal of the work, namely to demonstrate that a neural network with fuzzy logic is a useful tool for predicting motion based on EMG signals, has been completed. Two EMG signals from those muscles of the human arm that show the greatest activity during the load lifting are used. When determining the driving torques, the differences between the intended and the actual angular position are taken into account, and a simplified dynamics model was used for the calculations. In order to validate the method, the actual and predicted angles are compared and the differences between the moments determined on the basis of anticipated angular positions and the moments provided by the OpenSim simulator using real angular positions are examined.

Keywords: Hand prosthesis, thumb position, motion transmission, lateral and opposite grasp.

1 Introduction

The electromyography (EMG) technique senses the electrical activity which is the response to a nerve's stimulation of the muscle. The force developed by the muscle to some extent correlates with EMG activation of the muscle however the activation patterns of individual muscles vary with a lot of factors - i.e. the speed, the load or the tiredness. The coordinated activity of antagonistic muscles produces the movement. Most commonly EMG activity is assessed with surface electrodes, but it should be noted that it can only consider the muscle fibers, which are in close proximity to the skin. The fundamental advantage of EMG sensing is such that it allows to anticipate the motion before it is realized therefore the EMG signals are commonly used to control prostheses, or exoskeletons. The difficulty is that the motion of each joint is achieved by coordinated work of a lot of muscle groups and not each of them can be accessed by sensors. Moreover the muscles can actively only contract. Therefore the EMG based control methods must apply the artificial intelligence methods to derive the relation between the EMG and the intended movement. Some amount of research is devoted to the estimation of angular positions based on EMG activity. Au and Kirsch [1] had developed a time-delayed artificial neural network that uses EMG signals from six groups of elbow and shoulder muscles to predict the three movements of the shoulder (horizontal flexion-extension, abduction-adduction and internal-external rotation), as well as elbow flexion-extension. Wang and Buchanan [2] devised an artificial network for quantifying muscle activity using EMG signals. The state of the art indicates that a lot of researchers are working on the methods delivering the EMG-forces or EMG-driving torques relation. Among the numerous works it can be mentioned the following articles. Koike and Kawato [3] reconstructed human arm movement in a horizontal plane and estimated dynamic joint torques from sEMG signals using a neural network model. Su *et al.* [4] exploited a nonlinear regression model technique to define the relation between sEMG signals and the interaction forces. In more recent approaches the general mapping between the EMG activity and motion patterns is studied by Hahn *et al* [5]. Many researchers are focusing on decoding EMG signals using artificial intelligence methods for pattern recognition-based control schemes. This in-

cludes EMG classification using artificial neural networks or other machine learning approaches [6], [7]. In works using fuzzy logic approaches, the focus is also on the classification of muscle activity [8]. Despite numerous studies on the relationship between sEMG signals and the motion features of the human limbs, as well as the works on motion generation methods, There is still some gap in incorporating identified EMG-motions relations to the efficient control systems. Moreover majority of the research focuses on the lower limbs, with less attention devoted to the upper limbs [9], [10]. One of the actual trends is to use the fuzzy logic neural networks in exoskeletons control taking into account the root mean square (RMS) feature of EMG signals [11,12]. A new approach using the the artificial neural network with fuzzy logic is presented, here the neural network with fuzzy rules is used to reconstruct the upper limb motion based on the EMG signals. Additionally the control concept using the feedback information is provided and tested numerically on a two-link arm modeling the upper limb. The fuzzy Logic neural network was used to deliver the mapping between the EMG signals and the planned angular positions. The simplified dynamic model was used next to produce the actuating torques basis one difference between the actual joint positions and planned joint positions. With low amount of numerical calculations, the method is convenient for a real-time application. The proposed strategy was verified in two ways – using motion data provided by the VICON motion capture system, and by dynamic simulations using the Opensim package. The paper is structured as follows: Sec. 2 gives the problem statement and control concept, Sec. 3 outlines the biomechanics of the upper limb, section 4 presents the used dataset, Sec. 6 summarizes obtained results comparing both – angular trajectories and torques. Discussion and conclusions are given in Sec. 7.

2 Statement of the problem

Despite of a lot of works most of existing EMG based control methods are based solely on signals classification methods that attribute EMG features to a discrete set of movements. An effective means of estimating the continuous movements of multiple joints is still lacking [13], regardless of some interesting proposals such as [6]. Often are used artificial neural networks or other machine learning approaches [7], [6] including the fuzzy logic but the focus is still on the classification [8]. Even if muscular activity is

delivered by surface sensors and from limited amount of muscles it still contains 'hidden' information about the movement. Thus, as the literature confirms, it is possible to forecast based on EMG signals the intended motion and/or force in a smooth continuous way. The above observation was the motivation for this work. A new approach using an artificial neural network with fuzzy logic to reconstruct the movement of the upper limb based on EMG signals is presented. In addition, the concept of limb motion control using feedback information is presented and tested on a simple example. The elaborated method is planned to be used with a simple exoskeleton of the upper limb. The device is currently at the preliminary design stage and is intended for children with neuromuscular diseases. These children can no longer walk and fully manipulate the upper limbs, their mobility is limited to the wheelchair. Therefore, such an exoskeleton will increase their mobility, and thus their living conditions.

3 The outline of the method and assumptions

The proposed control method consists of following stages (actually realized only in simulation):

design stage: design a fuzzy logic artificial network delivering the intended angular positions basis on processed set EMG signals (data set used for learning),

application stage: apply the processed EMG signals to the designed neural network (data set used for testing) and obtain the intended angular positions,

application stage: compare the actual angular position (using the recorded data set) evaluate the required angular increment,

application stage: evaluate required control torques using the simplified dynamics model.

The block diagram of the proposed control concept is shown in Fig. 1. Verification of the method was made by: comparing of

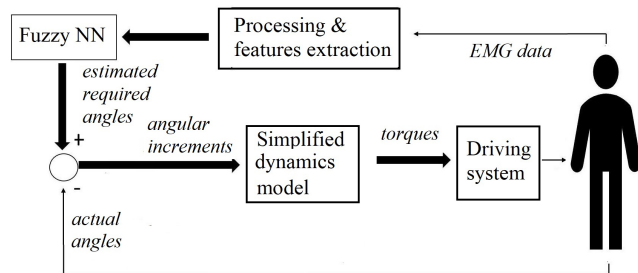


Fig. 1 The concept of control system. Thick lines are indicating the part which uses the data evaluated using presented methods.

predicted angular trajectories with the real ones; comparing the calculated torques with the torques obtained using dynamic simulation performed with OpenSim, which is a professional software with high precision human body models. To animate the motion in OpenSim the real motion trajectories are applied. Following the need of developed exoskeleton and simplifying the studies two degree of freedom (*DoF*) model of a human arm was used (Fig. 2). Moreover the mapping between EMG and the angular position was made using two EMG signals as it will be described later.

The simplified model of the upper limb consists of two parts the upper arm (arm) and the forearm with two joints, shoulder and elbow, with one *DoF* each (Fig 2a). In fact, the shoulder is a complex joint performing omnidirectional motion, while the elbow is a hinge joint as it bends and straightens like a hinge. Another displacement is also possible in the region where the radius meets the humerus, what allows turning the hand palm up

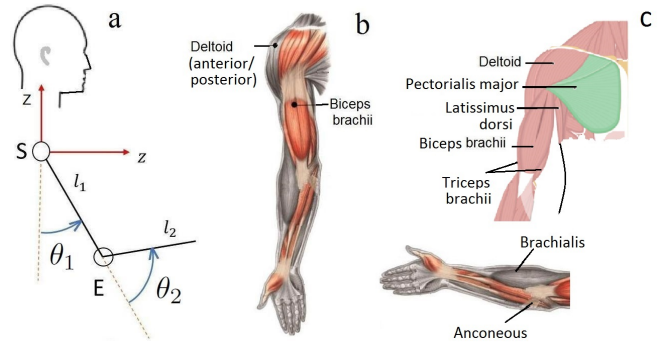


Fig. 2 Simplified kinematic model of the upper limb (a): S – shoulder joint, E – elbow joint, l_1 – length of upper arm, l_2 – length of forearm, view of the limb with indicated muscles group taken into account is this study (b), the main muscle groups of the upper limb (c).

and down. However applied simplification was sufficient for this work. The reference frame is attached to the center of the shoulder (S). Parameters l_1 and l_2 are the lengths of the upper arm and the forearm, respectively, θ_1 and θ_2 represent the rotation angles of the shoulder and the elbow joints around the x-axis producing the flexion/extension motion in the sagittal plane. The general form of dynamic model is expressed as follows:

$$\mathbf{D}(\theta)\ddot{\theta} + \mathbf{C}(\theta, \dot{\theta}) + \mathbf{G}(\theta) = \mathbf{D}_r\Gamma + \mathbf{J}^T\mathbf{F} \quad (1)$$

where $\theta(2 \times 1) = (\theta_1, \theta_2)^T$, $\dot{\theta}$, and $\ddot{\theta}$ – are the vector of the angular positions, velocities, and accelerations, $\Gamma(2 \times 1)$ – is the actuating torques vector, $\mathbf{D}(\theta)(2 \times 2)$ is the inertia matrix, $\mathbf{C}(\theta, \dot{\theta})(2 \times 1)$ is the vector of centrifugal and Coriolis forces, $\mathbf{G}(\theta)(2 \times 1)$ is a gravity force vector, $\mathbf{J}^T(2 \times 2)$ is transposed Jacobian matrix and \mathbf{F} is the force vector (2×1) due to the load hold by the hand. The main muscles involved during the shoulder flexion are the Pectoralis major and the Anterior Deltoid, and during the extension – the Latissimus dorsi, and the Posterior deltoid¹. The elbow flexion is achieved by Triceps brachii and Anconeus while the extension by Brachialis, Biceps brachii (Fig 2c).

4 Dataset and parameters

The dataset used in this work is provided by the Warsaw Children Memorial Hospital. It covers 12 sub-sets. The data are recorded for healthy male adult person 33 years old, 1.83m tall, weighting 90kg. Analyzing the motion dynamics the upper limb parameters are taken from the anthropomorphic data [14–16] taking into account the gender, weight and the height of the tested person. The actor performed the flexion/extension motion of the elbow holding different loads in the hand (0, 1, 2, and 5kg). The trials are arranged in three cases of four trials each, depending on the position of the person. In the first case, the person stands in the force platform. In the second cases, the person stands on two platforms, while in the third case, the person is seated. Movement in the elbow joint covered the full range of motion, that is, from the upright position (the limb 'hangs' along the trunk) to the position where the elbow joint is maximally bent. In this scenario, the movement of the shoulder joint is limited to a small extent required for the correct positioning of the hand. The dataset includes the EMG data recorded using 16 electrodes attached to the main muscles of the upper limb, the angular positions of the body joints acquired by the motion capture systems, the force moments (torques) in the joints and the forces. All data are collected using the VICON system, the surface electrodes are attached to the body according to the common standard. The recording rate for

¹<https://teachmeanatomy.info/>

EMG signals is 100Hz. The raw EMG signals are amplified to the range of 0 – 5V and processed using Butterworth filter and then processed. All pre-processing including joint torques evaluation is made using the VICON software. Taking into account that the main aim is to deliver the proof of concept only two EMG signals are used. The most active muscles, relevant for recorded human activity where chosen, namely the Deltoid and Biceps Brachii (Fig. 2b). The Deltoid is a strong muscle that the contribution is crucial for a lot of athletic and every day activities (as carrying, swimming, loads handling). Biceps contributes to flexion and supination (outward rotation) of the forearm. It supports and stabilizes the deeper (and stronger) Brachialis muscle during lifting and lowering the forearm. Such limitation allowed to reduce the amount of needed fuzzy logic rules but created the foundation for EMG-angular position mapping. The features extracted from EMG signals are the *RMS* and the maximum fractal length (*MFL*), obtained using a software package, developed with Matlab by T. Jingwei *et al* [17]. The feature *RMS* characterizes the signal power:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}, \quad MFL = \log_{10} \left(\sqrt{\sum_{i=1}^{N-1} (x_{i+1} - x_i)^2} \right) \quad (2)$$

where x_i is the signal value at i – th sample and N is the number of samples in a data segment. Root mean square (*RMS*) represents the square root of the average power of the EMG signal for a given period of time. The maximum fractal length (*MFL*) represents the density of action potential, or in the other words, the muscle contraction strength [18], application of a logarithmic scale reduces sensitivity to the noises.

5 Fuzzy Neural Network (NN)

The *RMS* and the *MFL* of the EMG are used as inputs for the fuzzy NN to predict the angular trajectories. The first quantity characterizes the amplitude of the EMG signal, while the second one is proportional to the strength of muscle contraction. The fuzzy NN combines fuzzy logic and NN technique. While fuzzy logic deals with the imprecision and the uncertainty of the data, the NN offers an adaptability. The fuzzy NN is governed with the following IF-THEN rules [19]: – if x is A_1 and y is B_1 , then $f = C_1$, – if x is A_2 and y is B_2 , then $f = C_2$. The IF-THEN rules define the state of the output depending on the state of the inputs, following such principle: IF the input variables are in a certain state, THEN the output will have the specific state. Available in Matlab Mandani type [20] of fuzzy NN is applied. The fuzzy NN consists of five layers. The fuzzification layer takes the input values and determines the membership functions belonging to them. The inference layer generates the firing strengths for the rules with product method. In the implication and the aggregation layers, the computed firing strengths are normalized and aggregated respectively. The defuzzification layer gives the output. For the elbow three fuzzy sets are used: low, medium, and high (Fig. 3a). Each set represents the intensity of the muscle activation. When the input belongs to the low fuzzy set, the muscle is resting, when it belongs to the medium, the muscle is powering the motion in moderate way, and when it belongs to the high, the contraction of the muscle is very intense. To increase the accuracy of the results for both types of input, the medium fuzzy set is divided into two subsets: medium low (medL) and medium high (medH). The Gaussian functions are used to define the membership (comparing to standard linear function), these functions increase the prediction sensitivity and allow to obtain smoother results. All applied functions have almost the same width. Similar fuzzy logic is applied for the output (Fig. 3b). The relationships between the inputs and the output are defined through the following IF-THEN rules:

1. If (*RMS* is low) and (*MFL* is low) then (angle is low)
2. If (*RMS* is medL) and (*MFL* is medL) then (angle is medL)

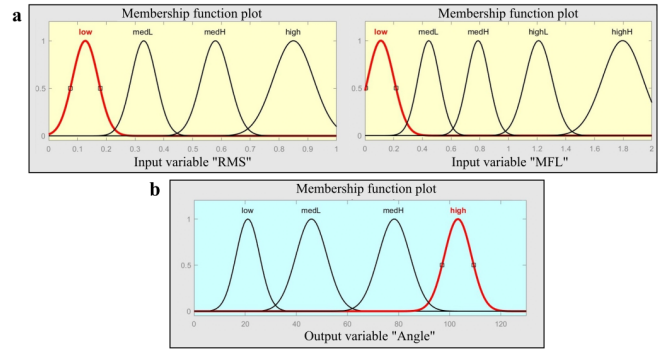


Fig. 3 The elbow: Membership functions– input (a), membership functions – output (b).

3. If (*RMS* is medL) and (*MFL* is low) then (angle is medL)
4. If (*RMS* is medH) and (*MFL* is medL) then (angle is medH)
5. If (*RMS* is medH) and (*MFL* is medH) then (angle is medH)
6. If (*RMS* is medH) and (*MFL* is high) then (angle is high)
7. If (*RMS* is high) and (*MFL* is high) then (angle is high)

The fuzzy NN of the shoulder is more complicated in implementation as the movements recorded in the given dataset are limited in range however the logic of the membership functions is the same as for the elbow (Figs. 4a and 4b). For the *RMS* we noticed that merging the medium and the high sets into one set gives better results. To characterize the output status depending on the inputs, the following IF-THEN rules are formulated:

1. If (*RMS* is low) and (*MFL* is low) then (angle is low)
2. If (*RMS* is low) and (*MFL* is med) then (angle is low)
3. If (*RMS* is low) and (*MFL* is high) then (angle is med)
4. If (*RMS* is high) and (*MFL* is low) then (angle is med)
5. If (*RMS* is high) and (*MFL* is med) then (angle is high)
6. If (*RMS* is high) and (*MFL* is high) then (angle is high)

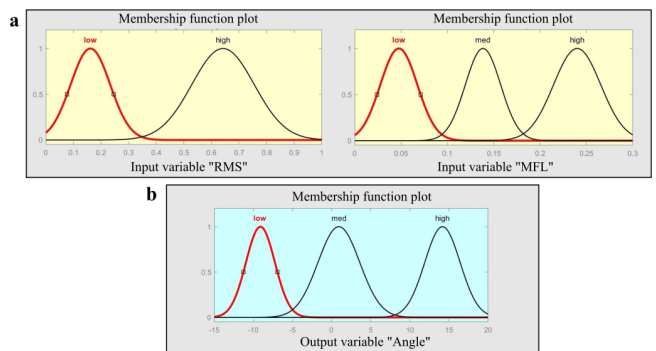


Fig. 4 The shoulder: membership functions – input (a), membership functions – output (b).

6 Validation of the method

Testing the control concept The accuracy of the angular prediction and of the evaluation of the torques is investigated first. The evaluation of the torques requires the calculation of the term on the right side of Eq. (1). The predicted angular velocities and accelerations are obtained by discretization using Euler's method with the sampling frequency 100Hz. To overcome the effect of noise, the output of the fuzzy NN and the predicted angular velocities are filtered with function *smoothdata* function of Matlab®. Predicted angles are compared with the registered angles corresponding to the recorded EMG signals. Having in mind that the EMG signals indicate the intended movement before it is effectively performed, it is obvious that the angular trajectories delivered by fuzzy NN are ahead of the real trajectories. Therefore for the purpose of validation, it is necessary to apply the time shift. Fig. 5 shows that the angular trajectories obtained from fuzzy NN and the real ones, good similarity is seen especially for the trajectories of the elbow joint. The difference between the shifted output from the fuzzy NN,

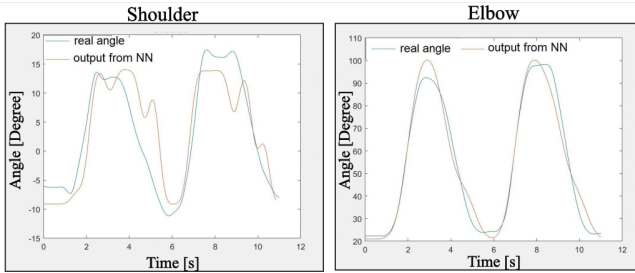


Fig. 5 Real and predicted trajectories for shoulder and elbow.

and the real angle delivered by the motion capture system is also studied. As the presented material has the character of feasibility studies we will be not going to the details by discussing particular differences. The results are validated using the Bland & Altman method [21] and considering the differences between generated and real angles. Fig. 6 the difference between real and inferred angle as a function of their mean is illustrated. Additionally the mean value of the these differences and confidence intervals (range of agreement) are given. The 95% confidence interval is firstly applied. As it can be seen for both joints some values are outside 95% range (marked by dotted red line). Next the 99% and 99.9% ranges are tested. The green lines mark the 99.9% range for shoulder and 99% range for elbow. All data lay within these ranges, therefore it can be concluded that with 99.9% confidence the angular error is within the range -15.1° ; 13.6° for the shoulder and with 99% confidence the error is within 13.2° ; 11.7° range for the elbow. In the case of shoulder the 95% range is significantly exceeded for the shoulder position being near to the resting position (the average is around zero). In the case of elbow it happens for the larger angles ranging 80° ; 90° . These results show that there is room for improvement. Additionally the real torques (from the data set) and torques calculated using the simplified model Eq. (1) and intended angular positions are compared. Results are shown in Fig. 7a. Similarly as for angular trajectories, the real torques are slightly ahead of the inferred torques and there are some with smaller discrepancies for the elbow joint.

6.1 Validation of simplified dynamic model using OpenSim. As described above the results obtained for the shoulder, which is a complex joint with flexibility's and sliding of the bones, demonstrate bigger discrepancy. Therefore, it is found to be useful to compare the torques delivered by simplified model (1) and detailed dynamical model. OpenSim simulator [22] is used for this purpose. The angular trajectories delivered by the fuzzy NN

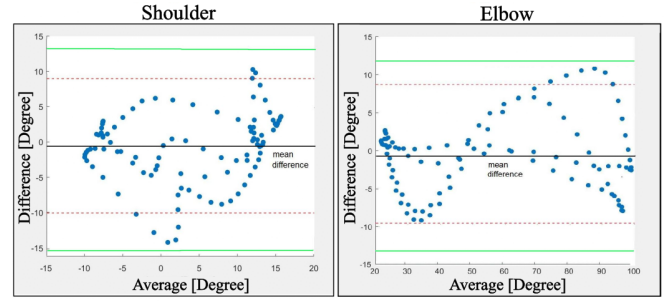


Fig. 6 Results of Bland-Altman method, shoulder and elbow data.

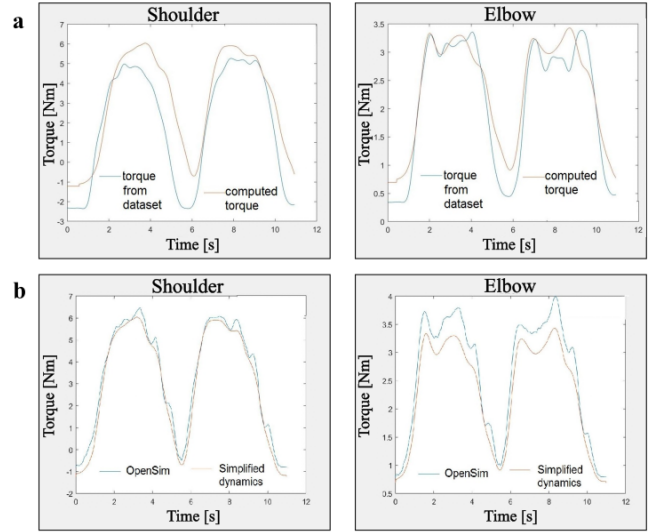


Fig. 7 Comparison of the torques: torques computed using the simplified model of dynamics and torques provided by the dataset (a), torques obtained using OpenSim software and the torque calculated using simplified dynamical model and the angles delivered by fuzzy NN (b).

are applied. The OpenSim model called *Arm26*² with two *DoF* (flexion/extension of the shoulder and flexion/extension of the elbow) and with three main muscle groups (Biceps, Triceps, and Brachialis) is used. After scaling the physical parameters of the model according to the subject characteristic, the motion is simulated using *Arm26* module. Results are presented in Fig. 7b. The torque curves obtained by both methods show good a similarity however these obtained using OpenSim have more fluctuations comparing to the results obtained using simple two-link model represented by (1). It is caused by the fact that the OpenSim arm model is much more complicated. However in some time intervals, especially during the flexion, the two trajectories overlap perfectly. The results confirm the correctness of simplified model.

7 Discussion and conclusions

Based on the comparisons with the true dataset and using the results provided by the OpenSim software, proposed method of intended motion estimation and motion control using fuzzy logic NN and simplified dynamical model is concluded as being feasible. Applied dynamic model can be farther enriched with more *DoF* and compliant elements for 3D movements. In farther studies it would also be advisable to include data recorded for several

²<https://github.com/opensim-org/opensim-models/blob/master/Models/Arm26/arm26.osim>

persons. It is also interesting to answer if there are any significant differences between the data recorded for adults and the data for children. Moreover, it is necessary to study situation when a person performs movements while dynamically interacting with the environment, which causes a variable load on the motion apparatus. It is necessary to answer the question of how such interaction influences the estimation of intended movements. In this case, the feedback loop of the control system should contain a corrective element, that would make the person wearing the assisting device, correctly accomplish the intended task. In presented work the prediction accuracy is enough to get the proper shape and range of motion. Taking into account that only two EMG signals are used there is large room for improvements. The developed fuzzy NN should be farther enhanced considering more EMG inputs and accordingly, more fuzzy rules. Such upgrading should be used for fine tuning of the prediction. Additionally comparing with the other research, in this work more features of EMG signals are used, namely besides of typically applied *RMS* the *MFL* feature (summed up to current time instant) is used. Differently than in majority of the works foretasted are the angular positions but not the torques. The torques are calculated basis on the difference between the current and inferred position. Such strategy allows for incorporating the simple safety mechanism in the controller, using the position error. If such error, evaluated as the difference between the intended position and the current position, exceeds some (realistically defined) threshold the controller should not force the movement. Such condition, adopted from robot control systems, is logically natural as a human never changes its joint position tremendously. To impose similar constraint in pure torque control method is problematic as it is more troublesome to estimate the range of torque change, especially when the hand (or leg) is loaded or the dynamic interaction is involved. Despite of some shortcomings, the presented studies sufficiently justify the feasibility of the control method. The research plans are to father extend the dynamic model allowing to consider more complicated movements and the complexity of the shoulder joint. However the numerical simplicity must be kept.

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