Intelligent Motion Planning for Man-Machine Interactive Redundant Manipulator

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Abstract There are many researches about man-machine interaction. Especially, the human neuro-biological signals can be applied for various problems such as controlling a mechanical device and/or interfacing human with the computer. It is one of very interesting topics that human can use many kind of devices without learning specific knowledge of them if the devices can be controlled according to human intention. In this paper, we proposed an motion planning method for a system with redundant manipulator, which is controlled by human's neuro-biological signals, especially, EOG (Electrooculogram). We used fuzzy classifier to translate the EOG into the user's intention. We found the optimal motion planner for this redundant manipulator that can move to the desired point. We used neural networks to find the inverse kinematics solution of the manipulator. We also showed the performance of the proposed motion planner with several simulations.

Keywords: Motion Planning, Neural Network, Redundant Manipulator, Man-Machine Interaction

1 Introduction

Controlling robots by human thought was a science fiction. However, it's being realized in some applications nowadays. Owing to the rapid growth of research and technique of human body, we could put the knowledge into the human computer interface[1]. There are many researches on using human neuro-biological signals for various problems such as controlling a mechanical device and/or interfacing human with the computer. It is one of the very interesting topics that human can use various devices without learning specific knowledge of them if they can be controlled according to human intention. In this paper, we will consider the motion planner of a robot manipulator, which is controlled by EOG as shown in Figure 1[2].

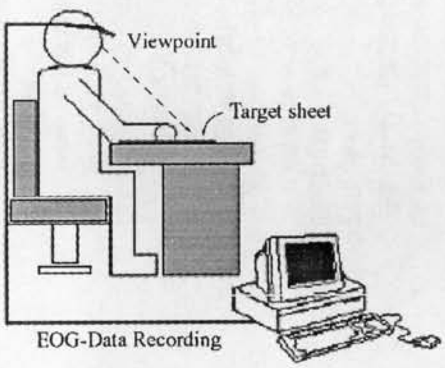

Fig.1 Human Computer Interface

The motion planning of robot manipulators is one of the most challenging problems in robotics. This problem can be solved either in the joint space or in the task space. Motion planning in the task space for the desired trajectory is usually considered as an inverse kinematics problem. The closed-form solution is hard to obtain and can be given only for the certain types of robot manipulators. This is particularly true in the case of a robot with a redundant degree of freedom (DOF), i.e., the dimension of the joint space is larger than the dimension of the task space. However, a redundant manipulator is using in many application, because it has advantages especially in the obstacle avoidance.

The inverse kinematics problem with mechanical redundancies has historically been solved using the generalized inverse method. This method was first introduced to the robot control by Whitney in 1969[3]. The inverse kinematics solution for the redundant robot is not unique without extra design criteria. Therefore, several design objectives, such as obstacle avoidance[4] singularity avoidance[5], torque minimization[6], energy minimization[7], etc. are used to get an appropriate solution. The problem can be also solved with an iterative method[8].

In this paper, the system with redundant manipulators controlled by human's neuro-bilogical signals is described. For this system, a new intelligent motion planning method for the redundant manipulators is proposed. Also, it interprets user's command using fuzzy classifier and it uses the neural networks to solve the inverse kinematics problem. To obtain the optimal trajectories, several criteria for the tracking error and the energy minimization are used.

This article is organized as follows. In section Ⅱ, the inverse kinematics problem of a redundant robot is formulated. Then the structure of the proposed method is described in section Ⅲ. The experiment setup and results are given in section Ⅳ. Finally, we conclude this paper in section Ⅴ.

2 Motion Planning of Redundant Robot

The forward kinematics of robots can be solved with various techniques[9, 10]. Consider a redundant manipulator with n degrees of freedom, which manipulates in m-dimensional task space ($n > m$). And then, the discrete-form forward kinematics at step k can be formulated as

$$\begin{pmatrix} r_1(k) \\ r_2(k) \\ \vdots \\ r_m(k) \end{pmatrix} = \begin{pmatrix} f_1(\theta_1(k), \theta_2(k), \cdots, \theta_n(k)) \\ f_2(\theta_1(k), \theta_2(k), \cdots, \theta_n(k)) \\ \vdots \\ f_m(\theta_1(k), \theta_2(k), \cdots, \theta_n(k)) \end{pmatrix} \quad (1)$$

where $\theta_i(k)$ denotes the joint variables, $r_i(k)$ is the manipulation variables in m-dimensional space and $f_i(k)$ is the function that describes the forward kinematics.

Suppose $\theta_i(k)$ be represented as

$$\theta_i(k+1) = \theta_i(k) + \Delta\theta_i(k) \quad (2)$$

Then Eq. (1) becomes

$$\underline{r}(k+1) = \underline{f}(\theta_1(k) + \Delta\theta_1(k), \theta_2(k) + \Delta\theta_2(k), \cdots, \theta_n(k) + \Delta\theta_n(k)) \quad (3)$$

There can be many configurations of the joints for the same position in the task space. To decide the desired trajectory, the other measure or constraints are needed to choosing one configuration among the candidates. Doing this, we introduce two criteria for the minimization of the moving energy and the tracking error. Therefore, the motion planning problem of a redundant robot can be formulated as an optimization problem as follows:

$$\underset{\Delta\theta(k)}{Minimize}\ \Phi = \sum_{i=1}^{n} w_{\theta_i} \Delta\theta_i(k)^2 + \sum_{i=1}^{n} w_{r_i}(r_{di}(k) - r_i(k))^2 \quad (4)$$

subject to

$$\underline{r}(k+1) = \underline{f}(\theta_1(k) + \Delta\theta_1(k), \theta_2(k) + \Delta\theta_2(k), \cdots, \theta_n(k) + \Delta\theta_n(k)) \quad (5)$$

where r_{di} is the desired end-effect position, w_{θ_i} and w_{r_i} are the relevant weights. The underline (__) means that quantity is a vector. In Eq. (4), the first term on the right-hand side is introduced to minimize the energy of the system which closely related to control effort of the manipulator and the second term is applied to minimize the tracking error. We use the dynamic programming procedure to solve this optimization problem.

3 Proposed Motion Planning Method

The control structure of the developed system is shown in Figure 2. The main objective of this research is to design an intelligent motion planner for a redundant robot manipulator controlled by human neuro-biological signals. First, we consider the command interpreter that translates the neuro-biological signals into the corresponding motion commands. Next, we consider the proposed intelligent motion planner of redundant manipulators.

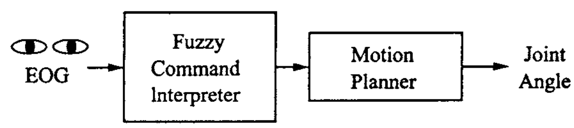

Fig.2 Control Structure of the System

A. Command Interpreter

The user's intention must be interpreted as the commands which are used to control the robot manipulator. There are many kinds of neuro-biological siganls, such as EEG (Electroencephalogram), EMG (Electromyogram) and EOG (Electrooculogram). We use the EOG signal generated from human, when he sees the objects, in order to control the robot. As the human looks at a point, the horizontal EOG and vertical EOG signals are generated and these signals are recorded through the electrodes using the human computer interface. The EOG data are collected during the experiment in which the human move his attention on the predefined three different target positions for five seconds from the default target point on the test sheet shown in Figure 3. The sampling time is 10 ms. Figure 4 shows the horizontal, vertical EOG and the corresponding target positions represented by the certain values.

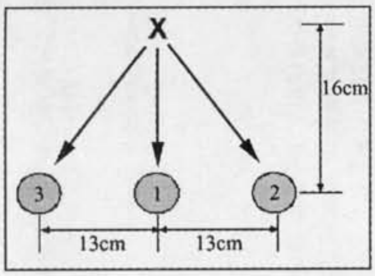

Fig.3 Target Sheet

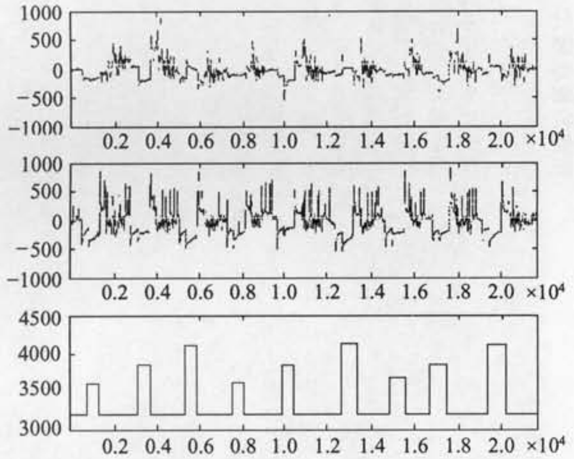

Fig.4 The Horizontal and Vertical EOG Signal

We need to classify the target points with the EOG signals. The intelligent classifier is needed because the EOG signals contain considerable noise as you see from Figure 4. We use a fuzzy classifier to interpret the EOG signals. To construct the fuzzy classifier, we proposed the structure and parameter optimization technique[11] using evolutionary algorithm. In this method, the Takagi-Sugeno fuzzy model is used and the structure and parameters of fuzzy models are simultaneously optimized by the evolutionary algorithm. The fitness function is defined to minimize the tracking error, the number of rules, and the degree of overlapped portion of each membership function. With these terms, we can get the fuzzy classifier with small number of rules which are well-separated in the input domain. We use the data of the third row in the Figure 4 as training set and the desired output are the different values given by the corresponding classification results.

Using the obtained fuzzy classifier, we can get the target value that the robot has to move. Because the Takagi-Sugeno model's output is continuous value and it is a classification problem, we use some heuristics to discretize the results. So, we take the closest class from the fuzzy model's output. And then, the filtering technique is used to reduce the effect of noise. This filter uses the data for previous 1 second. Finally, the motion planner can be used to find the optimal trajectories.

B. Intelligent Motion Planner

The proposed motion planning method is based on neural network. Neural network is a powerful tool in classification and function approximation, where the input is high dimensional and noisy. We use neural network to approximating the inverse kinematics of the manipulator. Because the manipulator is a redundant one, there can be several solutions for the same point. So, the inverse kinematics can not be learned by one neural network. To solve this, we fix some joint variables so that the other joint variables can be obtained uniquely. In this case, the inverse kinematics for that fixed joint value can be trained using one neural network. So, we require as many number of neural networks as the number of joint angle configurations we choose. In Figure 5, the structure of the proposed motion planner is shown. Each neural network is in charge of the inverse kinematics for the each configuration.

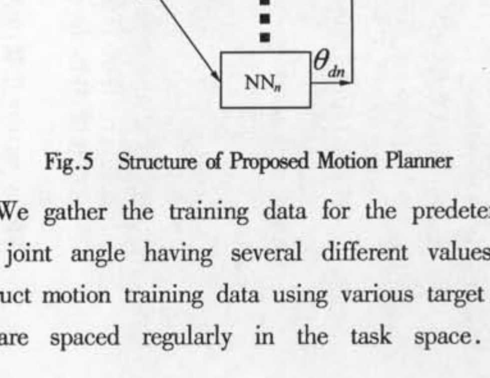

Fig.5 Structure of Proposed Motion Planner

We gather the training data for the predetermined fixed joint angle having several different values. We construct motion training data using various target points that are spaced regularly in the task space. After constructing motion training data, we train the neural network. The inputs of the neural network are the desired positions in the task coordinate, i.e., x-, y-coordinates, etc., and the outputs are each joint angle. Finally, we can get the multiple models with several different configurations of the joint angles.

Next, we have to select the joint configuration among multiple models at each time step. The desired trajectories are generated as close to the line connecting the initial and final states as possible. We apply the dynamic programming procedure to obtain the optimal solution for the problem as in Eq. (4). With the given weights and time steps, we can get the optimal joint configurations following the trajectories that minimize the objective function.

4 Experiments

The actual robot manipulator and the defined joint angles are shown in Figure 6 and Figure 7. It has 4 degrees of freedom and the experimental setup is as follows: The control module for the manipulator is based on 8-bit processors. Each control module can control 2 motors simultaneously and total 3 control modules are used. Motion commands are communicated through RS-232C serial connections between the host computers and each control module and only the position information is transmitted.

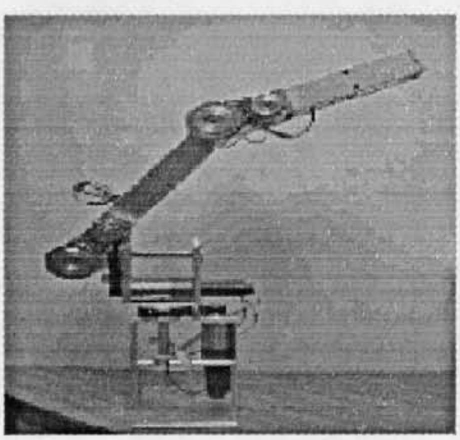

Fig.6 Redundant Robot Manipulator

The task is to help a human eating with a spoon. The desired trajectories are the segment from one of 3 points as shown in the Figure 3 to one's mouth. As the human looks at each point, the fuzzy classifier informs to the control system which points the human looks at. Then according to the point index given by the fuzzy classifier, the 2-dimensional target point is sent to the control module for the robotic manipulator. After receiving the target point, the manipulator moves according to the series of motion commands produced by the proposed motion planner.

First, we tested the command interpreter. We trained the fuzzy classifier using the data shown in Figure 4. The target positions are normalized to have the values from −10 to 10. After the training, we could get the fuzzy model that has 4 and 3 membership functions for the horizontal and vertical EOG signals, respectively and totally 12 (4 × 3) rules. Because the output of fuzzy model was continuous one like in Figure 8, we chose the target point as the closest point from the output. And the filtering mentioned above is also used. The final classification results are shown in Figure 9.

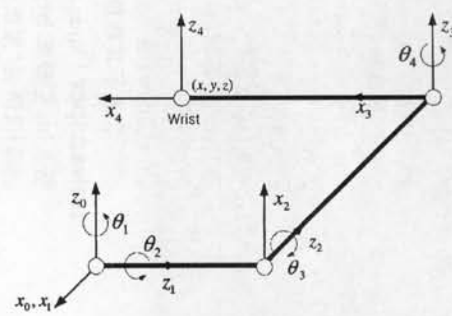

Fig.7 Joint Angle Configuration

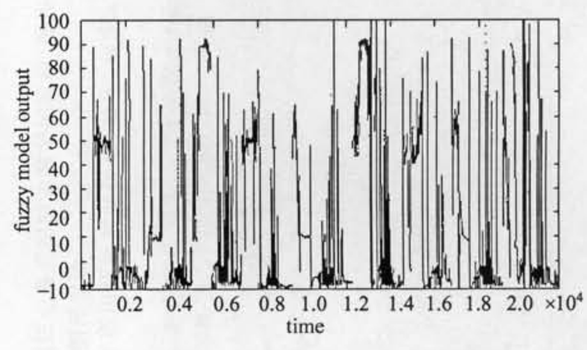

Fig.8 Output of Fuzzy Classifier

Second, we tested the neural network used to learn the inverse kinematics. We choose the third joint as fixing joint because it is a counterpart of the human's elbow and it can play an important role in obstacle avoidance. The neural network used was a feed-forward multilayer perceptron which has one input, two hidden layers, and one output layer. The inputs are the coordinates in Cartesian space and the outputs are the 3 joint angles. These layers have 3, 20, 20 and 4 nodes respectively,

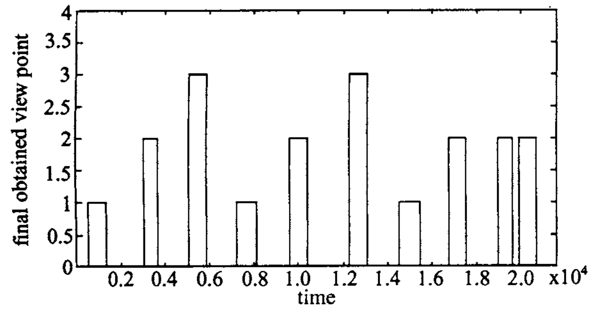

Fig.9 Command Interpretation Result

and a bipolar sigmoid function was used. The 343 training data which are uniformly distributed in Cartesian space were obtained.

The tracking result with a circular motion is shown in Figure 10. In this figure, the third joint, θ_3, was fixed as 0. The neural network can approximate the inverse kinematics and the difference between the desired trajectory and the trajectory with the configurations calculated from neural network is very small. With this approach, we could move the manipulator even when new target point, which was originally not in the training data set, was given.

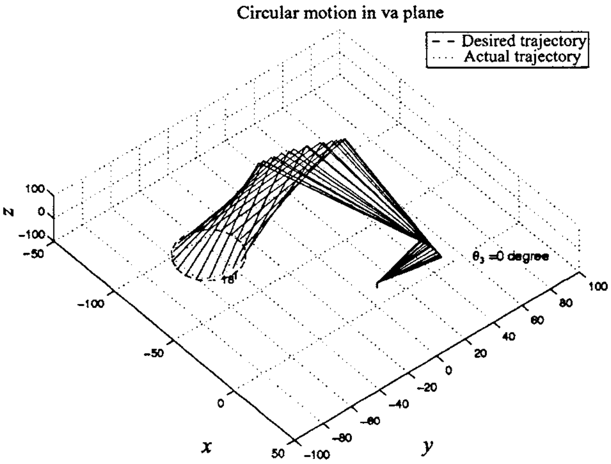

Fig.10 Tracking Result of Neural Networks

Finally, we tested the proposed motion planner. In Figure 11 and Figure 12, we show the results with the energy minimization criteria only. So, we used the weights, $w_{\theta_i} = 1$ and $w_{r_i} = 0$ for all i. In this figure, we note that θ_3 was not changing during the experiment and this means that the only one neural network model was chosen during the experiment and the angle of the third joint is 30 degrees.

Next, the results with both energy minimization and tracking error criteria are shown in Figure 13 and Figure 14. We used the weights, $w_{\theta_i} = 1$ and $w_{r_i} = 1$ for all i. In this case, the neural network model was selected to minimize the error rather than the energy. Therefore, the different configurations of the joint angle are selected. The angles of the third joint are 0 and 5 degrees and this means that the robot arm is almost unfolded.

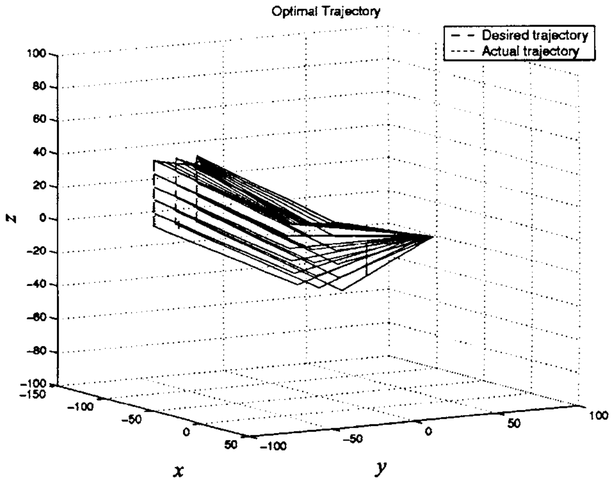

Fig.11 Result with Energy Minimization Criteria

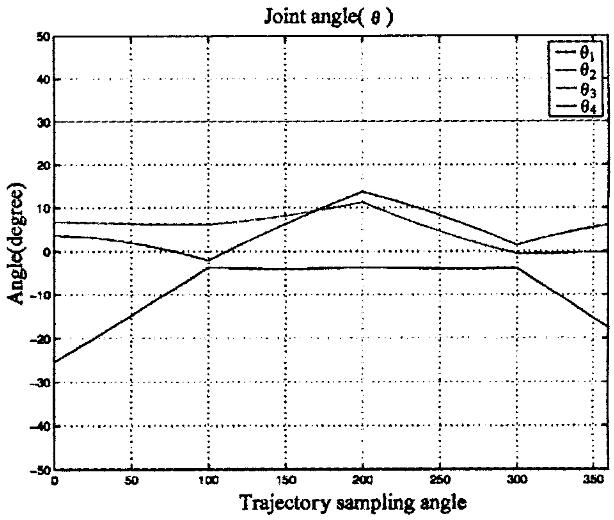

Fig.12 Joint Angle with Energy Minimization Criteria

In both cases, the planner generated the optimal path and joint angles and showed good performances. We can adjust the weights as desired performance property.

5 Conclusion

In this paper, the system with redundant manipulators controlled by human's neuro-bilogical signals is described. The manipulator is controlled by the EOG signals and the fuzzy classifier is used to interpret user's

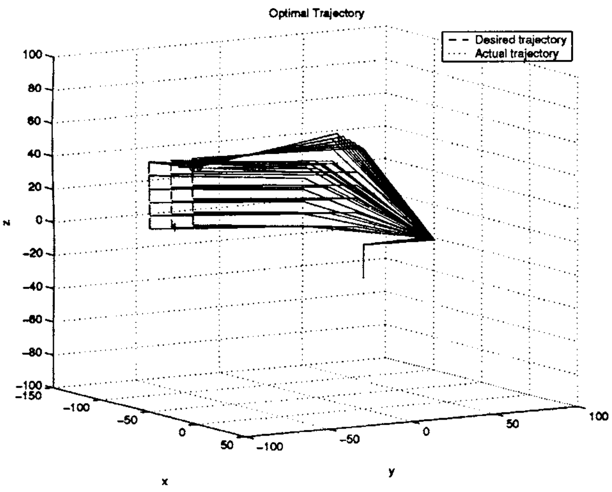

Fig. 13 Result with Energy Minimization and Tracking Error Criteria

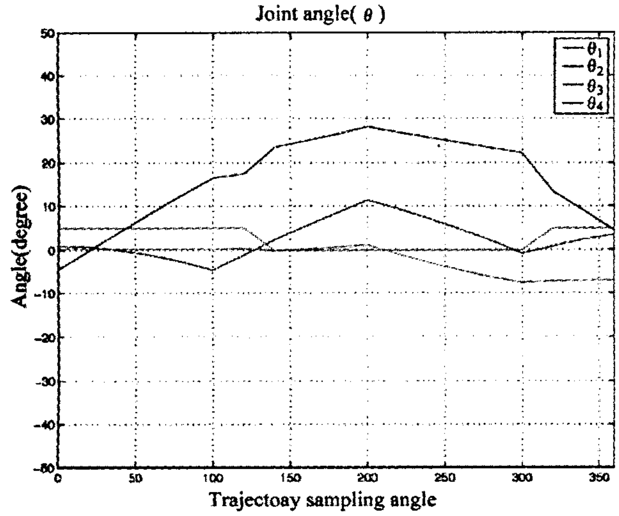

Fig. 14 Joint Angle with Energy Minimization and Tracking Error Criteria

intention. As the human fixes his eyes on the target points, the robotic manipulator is controlled tracking relevant trajectories by the proposed intelligent motion planner. The proposed motion planner can find several candidate motions with predefined target points with neural network and then produces the optimal motions according to the given EOG signals.

Although only 2 dimensional target points are used in this paper, it is not a difficult problem to extend the proposed approach to the 3 dimensional target points.

Acknowledgment

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