Intelligent Motion Planner for Redundant Manipulators Controlled by Neuro-Biological Signals

Chang-Hyun Kim, Min-Soeng Kim and Ju-Jang Lee

Dept. of Electrical Engineering and Computer Science, Korea Advanced Institute of Science and Technology
373-1, Guseong-dong, Yuseong-gu, Daejeon, 305-701, Korea
(Tel: +82-42-869-8032; Fax: +82-42-869-5432; E-mail: sunnine@odyssey.kaist.ac.kr,
mibella@webmail.kaist.ac.kr, jjlee@ee.kaist.ac.kr)

Abstract: There are many researches on using human neuro-biological signals for various problems such as controlling a mechanical object and/or interfacing human with the computer. It is one of very interesting topics that human can use various instruments without learning specific knowledge if the instruments can be controlled as human intends. In this paper, we proposed an intelligent motion planner for a redundant manipulator, which is controlled by humans neuro-biological signals, especially, EOG (Electrooculogram). We found the optimal motion planner for the 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: Redundant manipulator, Motion planner, Inverse kinematics, Neural network, Fuzzy system, Electrooculogram

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 object and/or interfacing human with the computer. It is one of the very interesting topics that human can use various instruments without learning specific knowledge if the instruments can be controlled as human intends. In this paper, we will consider the motion planner of a robot manipulator, which is controlled by EOG as shown in Fig. 1 [2].

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, a new intelligent motion planner for the redundant manipulators controlled by human's neuro-biological signals is proposed. It uses the neural networks to solve the inverse kinematics problem. To obtain the optimal trajectories, several criteria for the tracking and the energy minimization are used.

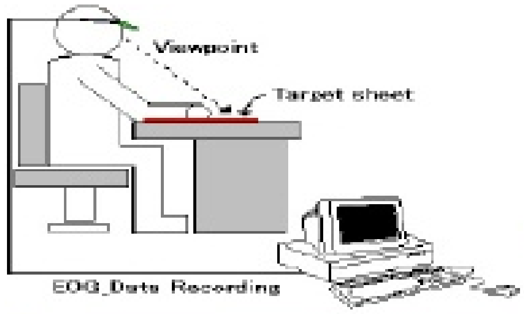

Fig. 1. Human Computer Interface

This article is organized as follows. In section 2, the inverse kinematics problem of a redundant robot is formulated. Then the structure of the proposed method is described in section 3. The experiment setup and results are given in section 4. Finally, we conclude this paper in section 5.

2. Motion Planning for Redundant Robot

The forward kinematics of robots can be solved with various techniques [8-9]. 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

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

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

$$\theta_i(k+1) = \theta_i(k) + \Delta\theta_i(k) \tag{2}$$

then Eq. (1) becomes

$$\begin{pmatrix} r_1(k+1) \\ r_2(k+1) \\ \vdots \\ r_m(k+1) \end{pmatrix} = \begin{pmatrix} f_1(\theta_1(k)+\Delta\theta_1(k), \theta_2(k)+\Delta\theta_2(k), \ldots, \theta_n(k)+\Delta\theta_n(k)) \\ f_2(\theta_1(k)+\Delta\theta_1(k), \theta_2(k)+\Delta\theta_2(k), \ldots, \theta_n(k)+\Delta\theta_n(k)) \\ \vdots \\ f_m(\theta_1(k)+\Delta\theta_1(k), \theta_2(k)+\Delta\theta_2(k), \ldots, \theta_n(k)+\Delta\theta_n(k)) \end{pmatrix} \tag{3}$$

We introduce two criteria for the energy minimization and the tracking error. The motion planning problem of a redundant robot can be formulated as an optimization problem as follows:

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

subject to

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

where r_{id} is desired end-effect position vector, w_{θ_i} and w_{r_i} are relevant weights. In Eq. (4), the first term on the right-hand side is introduced to minimize the energy which closely related to control effort and the second term is applied to minimize the tracking error. This optimization problem can be solved using the dynamic programming procedure.

3. Intelligent Motion Planner

The objective of this research is to design an intelligent motion planner for a redundant robot manipulator by human neuro-biological signals. There are many kinds of neuro-biological siganls, such as EEG (Electroencephalogram), EMG (Electromyogram) and EOG (Electrooculogram). We use the EOG signal generated by human when he sees the objects. As the human looks at a point, the horizontal EOG and vertical EOG signals are generated and recorded with electrodes using the human computer interface. The user's will must be interpreted as the commands that control the robot manipulator. Therefore, we use a fuzzy classifier to achieve this objective, and finally we get the target point that the robot will move. After that, the motion planner find the optimal trajectories.

The proposed motion planning method is based on neural networks. Neural networks are 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 a fixed point. To solve this, we fix some joint variables so that the other joint variables can be obtained uniquely. We gather the training data for the 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 networks. The inputs of the neural networks are the desired x-, y- coordinates, etc. and the outputs are each joint angle. Finally, we get the multiple models with several different joint angles.

Next, we have to select the joint configurations among multiple models at each time step. To do this, 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 trajectories that minimize the objective function. In Fig. 2, the structure of the proposed motion planner is shown.

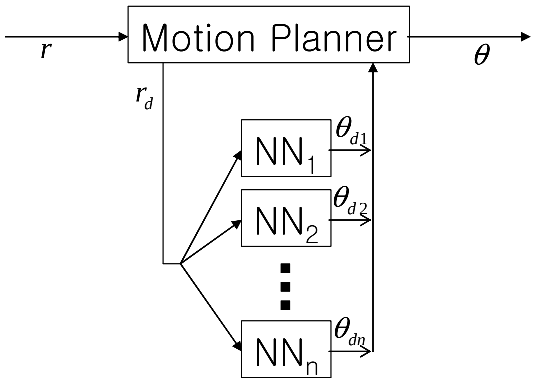

Fig. 2. Structure of Proposed Motion Planner

4. Experiments

The actual robot manipulator and the defined joint angles are shown in Fig. 3 and Fig. 4. It has 4 degrees of freedom and 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. The desired goal point for the manipulator is one of 3 points as shown in the Fig. 5. 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 neural networks. 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, and a bipolar sigmoid function was used. The

Fig. 3. Redundant Robot Manipulator

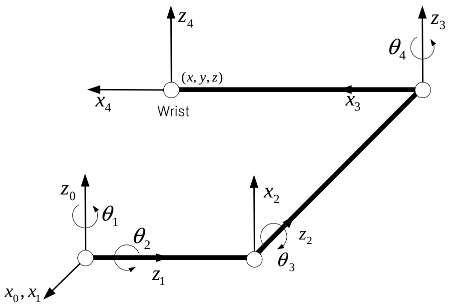

Fig. 4. Joint Angle Configuration

343 training data which are uniformly distributed in Cartesian space were obtained. The tracking result with a circular motion is shown in Fig. 6. In this figure, θ_3 was fixed as 0. With this approach, we could move the manipulator even when new target point, which was originally not in the training data set, was given.

Next, we tested the proposed motion planner. In Fig. 7 and Fig. 8, we show the results with angle differences criteria only. We used the weights, $w_{\theta_i} = 1$ and $w_{r_i} = 0$ for all i. Next, the results with both angle differences and tracking error criteria are shown in Fig. 9 and Fig. 10. We used the weights, $w_{\theta_i} = 1$ and $w_{r_i} = 10$ for all i. In both cases, the planner generated the optimal path and showed good performances. We note that θ_3 was not changing in Fig. 8. We can adjust the weights as desired performance property.

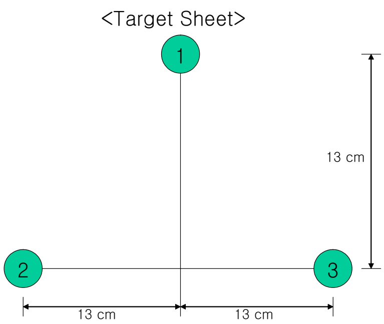

Fig. 5. Target Sheet

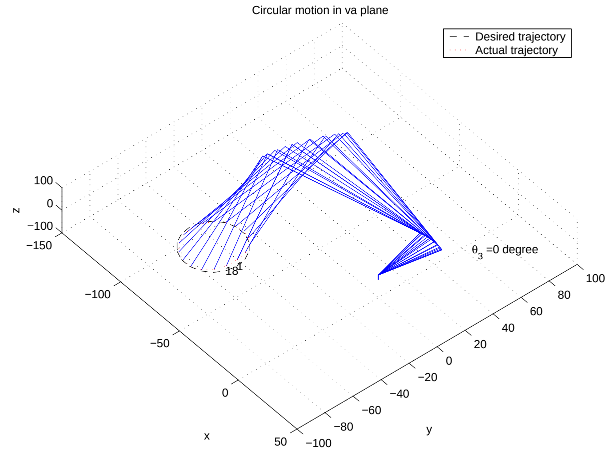

Fig. 6. Tracking Result of Neural Networks

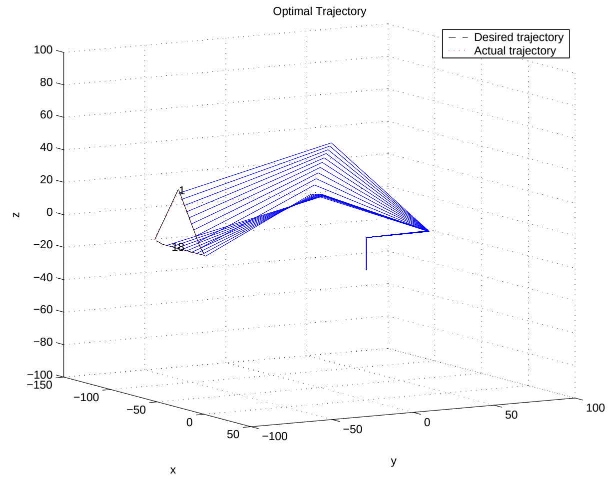

Fig. 7. Tracking Result with Difference Criteria

5. Conclusion

In this paper, an intelligent motion planner for the redundant manipulator is proposed. The manipulator is controlled by the EOG signals. As the human fixes his eyes on the target points, the robotic manipulator is controlled to that point by the proposed intelligent motion planner. The proposed motion planner find several candidate motions with predefined target points with neural networks 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.

Acknowledgements

This work has been partially supported by EESRI 02-CHUNG-08, which is funded by MOCIE. This work is also partially supported by KOSEF under the Korea-Japan basic scientific promotion program.

References

[1] Z. A. Kerin and J. I. Aunon, "Man-Machine Communications Through Brain-Wave Processing," *IEEE Engineering in Medicine and Biology Magazine*, Vol. 9, pp. 27-36, 1990.

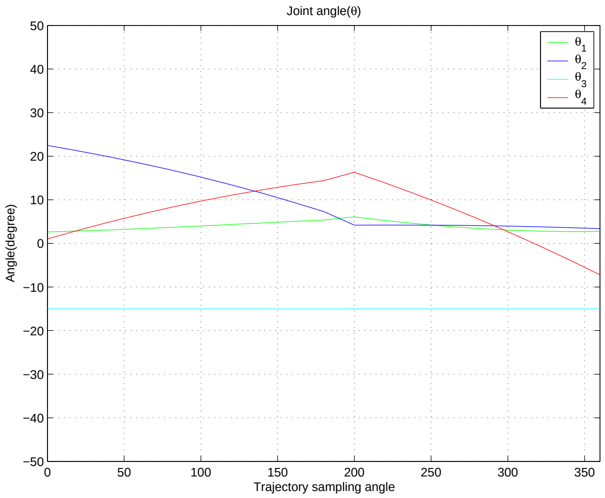

Fig. 8. Joint Angle with Difference Criteria

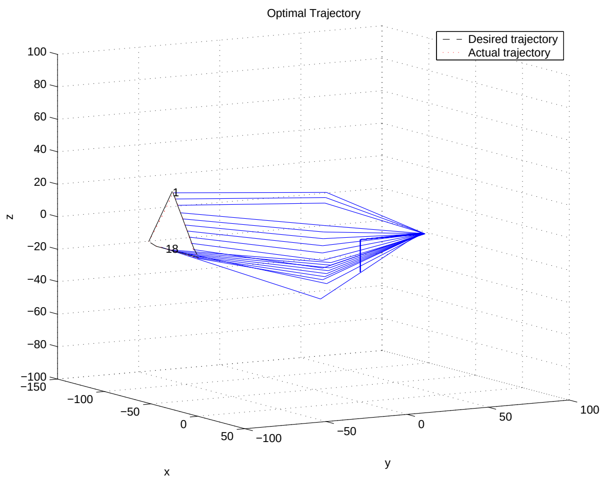

Fig. 9. Tracking Result with Both Criteria

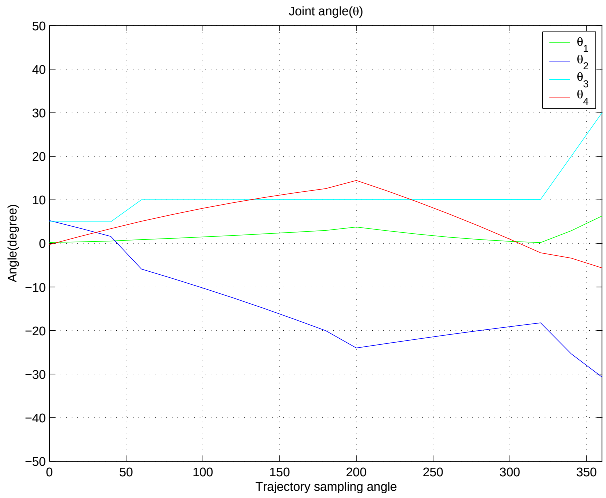

Fig. 10. Joint Angle with both criteria

[2] Y. Katsuki, T. Sugi, H. Shibasaki and M. Nakamura, "Extraction of Human Desire from EOG Signal for Meal," *7th Int. Joint Seminar between KAIST and SAGA University*, pp. 67-68, 2002.

[3] D. E. Whitney, "Resolved Motion Rate Control of Manipulators and Human Prostheses," *IEEE Trans. on Man-Machine Syst.*, Vol. 10, pp. 45-53, 1969.

[4] A. A. Maciejewski and C. A. Klein, "Obstacle Avoidance for Kinematically Redundant Manipulators in Dynamically Varying Environment," *Int. J. Robotics Research*, Vol. 4, pp. 109-117, 1985.

[5] T. Yoshikawa, "Manipulability of robotic mechanisms," *Int. J. Robotics Research*, Vol. 4, pp. 3-9, 1985.

[6] K. C. Suh and J. M. Hollerbach, "Local versus Global Torque Optimization of Redundant Manipulators," *IEEE Conf. on Robotics and Automation*, Vol. 2, pp. 619-624, 1987.

[7] C. L. Chen and C. J. Lin, "Motion Planning of Redundant Robots," *J. of Robotic Systems*, Vol. 14, No. 12, pp. 839-850, 1997.

[8] A. A. Goldenberg, B. Benhabib and R. G. Fenton, "A Complete Generalized Solution to the Inverse Kinematics of Robots," *IEEE J. of Robotics and Automation*, Vol. RA-1, pp. 14-20, 1985.

[9] M. W. Spong and M. Vidyasagar, *Robot Dynamics and Control*, John Wiley & Sons, 1989.

[10] P. J. McKerrow, *Introduction to Robotics*, Addison-Wesley, 1991.