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Neural Optimization networks with Fuzzy Weighting for Collision Free motions of Redundant Robot Manipulators

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ABSTRACT

A neural optimization network is designed to solve the collision-free inverse kinematics problem for redundant robot manipulators under the constraints of joint limits, maximum velocities and maximum accelerations. And the fuzzy rules are proposed to determine the weightings of neural optimization networks to avoid the collision between robot manipulator and obstacles. The inputs of fuzzy rules are the resultant distance , change of the distance and sum of the changes. And the output of fuzzy rules is defined as the capability of collision avoidance of joint differential motion. The weightings of neural optimization networks are adjusted according to the capability of collision avoidance of each joint.

To show the validities of the proposed method, computer simulation results are illustrated for the redundant robot with three degrees of freedom.

1. INTRODUCTION

Redundancy is a key element of designing more versatile robot. Recently, many researchers have devoted considerable efforts to studying redundant robots[1,2,3] because redundant manipulators are capable of not only following the desired trajectory, but also increasing dexterity[4], avoiding singularities[5], and achieving collision-free motion by making use of redundancy. Thus it has been a major interest to find out the best way how to use the redundancy in treating such robots. Among many a application area of redundant robots, the problem of collision avoidance with obstacle in the workspace has been regarded as an important issue[6,7,8]. Solving this problem usually includes the tasks of modelling obstacle and obtaining the proximity such as distance and artificial potential of the objects[9]. And there is often involved extremization of an objective function designed for increasing the proximity between the links and an obstacle. But the methods are very difficult to use due to their complex obstacle modelling as well as computational complexity.

In this paper, a new approach is proposed to overcome such difficulties by extending the neural optimization network in [10], where weightings of the network are adjusted by fuzzy rules. Specifically, end effector movement resulting from each joint differential motion is first separated into orthogonal and tangential components with respect to a given desired trajectory. Then the resolved motion is obtained by neural optimization networks in such a way that 1) linear combination of the orthogonal component should be null, 2) linear combination of the tangential components should be the differential length of the desired trajectory, 3) differential joint motion limit is not violated, and 4) a performance index, which is given by weighted sum of the square of the difference between each joint differential motion and a constant to be given for the control purpose, is minimized. Here, each weighting factor is adjusted by considering the joint dexterity measure defined as the ratio of the tangential and orthogonal components and by considering how much each joint differential motion can contribute for the collision avoidance between the links and the obstacle. Specifically, the distance between each link and the obstacle and its change due to the joint differential motion are firstly obtained to search for the links with danger of collision. And then some fuzzy rules are proposed to determine the capability of collision avoidance of each joint. Finally, each weighting factor is adjusted by the capability of collision avoidance of each joint.

The organization of the paper is as follows ; in section 2, is designed a neural optimization network for collision avoidance of redundant robot manipulators. In section 3, an approach is proposed by incorporating fuzzy reasonings to detemine the weightings of the neural network. In section 4, some numerical examples are illustrated to show the validities of our proposed approach. And in final section, serveral concluding remarks are given.

2. A NEURAL OPTIMIZATION NETWORK FOR COLLISION AVOIDANCE OF REDUNDANT ROBOT.

In controlling redundant robot manipulators, neural networks can be effectively utilized as in [10,11,12]. Among them, Hyun, Suh and Lim[10] proposed a neural optimization network to resolve the motion of redundant manipulators. And also they proposed a new model for the description of differential motion not to explicitly use the pseudo inverse of the Jacobian. In this section, the neural optimization network for the control of redundant manipulators in [10] is shown to be extended to solve the collision avoidance problem.

For this, the modelling technique in [10] is briefly reviewed as follows ; Suppose that the i-th joint moves with some velocity and the other joints locked up. Then end-effector moves with a velocity. Let the velocity of end effector resulting from the i-th joint motion be denoted by 6x1 vector $Z_i = [\ V_i^T \mid W_i^T\ ]$, where V_i and W_i represent the translational and rotational velocities. Let 6x1 vector $Z_d = [\ V_d^T \mid W_d^T\ ]$ be the desired velocity of end effector. The resultant translational velocity V_i of end effector by the movement of i-th joint can be decomposed into orthogonal component V_{ni} and tangential component V_{ti} to a given desired velocity V_d. In a similar way, the resultant rotational velocity W_i

of end-effector by the movement of i-th joint can be decomposed into orthogonal component W_{si} and tangential component W_{ci} to a given W_d. It is noted that if linear combinations of V_{ci} and W_{ci}, i = 1,2,...,n are equal to V_d and W_d, respectively, then the robot can follow the desired trajectory. This can be mathematically written as

$$g_1(U_1, U_2, \ldots, U_n) \triangle \sum_{i=1}^{n} U_i V_{ci} - V_d = 0 , \tag{1}$$

$$g_2(U_1, U_2, \ldots, U_n) \triangle \sum_{i=1}^{n} U_i V_{si} = 0 , \tag{2}$$

$$g_3(U_1, U_2, \ldots, U_n) \triangle \sum_{i=1}^{n} U_i W_{ci} - W_d = 0, \tag{3}$$

and

$$g_4(U_1, U_2, \ldots, U_n) \triangle \sum_{i=1}^{n} U_i W_{si} = 0 , \tag{4}$$

where U_i is a scalar which is to be mutiplied by a joint differential motion. Here it is remarked that the differential joint motion should be chosen as small as possible to guarantee the movement of end-effector to be linearized.

The resolved motion of the redundant robot manipulators is here shown to be obtained by solving an optimization problem with equality and inequality constraints. For this, let U be defined as $U = [U_1, U_2, \ldots, U_n]^T$, and let $f(U)$ be given by

$$f(U) = \sum_{i=1}^{n} G_i (U_i - \hat{U}_i)^2 \tag{5}$$

where G_i and $\hat{U}_i$ are the constants to be determined according to our control purpose. Also let $h_m(U)$ be given by

$$h_m(U) = \begin{cases} U_i - U_{imax}, & \text{for } m = 2i-1 \text{ and } i = 1,2,\ldots,n, \\ -U_{imin} + U_i, & \text{for } m = 2i \text{ and } i = 1,2,\ldots,n, \end{cases} \tag{6}$$

where U_{imax} and U_{imin} are the U_i's maximum and minimum quantities, respectively. Then the optimization problem can be formulated to resolve the motion of redundant robot manipulators as follows;

(Problem 1) Suppose that G_i and $\hat{U}_i$ are given for all i = 1,2,..,n. Then find U_i for i = 1,2,...,n such that $f(U)$ in Eq.(5) is minimized , while satisfying the equality constraints given by Eqs.(1) - (4) and the inequality constraints given as $h_m(U_i) \le 0$, m = 1,2,...,2n.

A neural optimization network with anti-symmetry connections among the neurons can be easily obtained to solve Problem 1 by applying the Platt and Rarr's approach[13] as follows; for i = 1,2,...,n, j = 1,2,...,2n, and k = 1,2,3,4,

$$\dot{U}_i = -2G_i(U_i - \hat{U}_i) - \sum_{k=1}^{4} \beta_k \frac{\partial g_k(U)}{\partial U_i} - \sum_{j=1}^{2n} \gamma_j \frac{\partial h_j(U)}{\partial U_i} \tag{7}$$

$$\dot{z}_j = -2 \sum_{m=1}^{2n} \gamma_m z_j , \tag{8}$$

$$\dot{\beta}_k = g_k(U) , \tag{9}$$

and

$$\gamma_j = h_j(U) + z_j^2, \tag{10}$$

where β_k's and γ_j's imply the neurons corresponding to the Lagrange multipliers for the equality constraints, and the z_j's imply the neurons for the slack variables to convert the inequality contraints to the equality constraints.

It is remarked that if U_i's are obtained to satisfy the inequality constraints given as $h_m(U) \le 0$, m = 1,2,...,2n, the joint velocity limit is not violated. It is also remarked that in [10], the joint dexterity measure Q_{pi} and Q_{si} defined as $\| V_{si} \| / \| V_{ci} \|$ and $\| W_{si} \| / \| W_{ci} \|$, respectively, are proposed as an alternative for the manipulability index [4] by showing that Q_{pi} and Q_{si} imply the degrees of capability for i-th joint motion to make the end-effector follow to the desired differential motion V_d and W_d, and then $\hat{U}_i$ is chosen as nullity for all i and G_i is determined to increase the Q_{pi} and Q_{si}. Thus the networks with such weightings cannot be guaranteed to avoid the obstacles.

Now, observe that collision avoidance can be additionally achieved by adjusting the weightings G_i and $\hat{U}_i$ of the neural networks given by Eq.(7), if n is greater than the number of degrees of freedom required to follow the given desired trajectory. To be specific, let the j-th joint be the redundant degree of freedom. Then the direction of the j-th joint can be controlled by letting $\hat{U}_j$ be equal to $U_{jmax} > 0$, or $U_{jmin} < 0$. And the magnitude of the j-th joint motion can be controlled by adjusting the magnitude of G_j. Thus, for example , if the j-th joint is known as the most effective one among all the joint motions to let the link with danger of collision move away from the obstacles, then the collision can be avoided by adjusting the $\hat{U}_j$ and G_j. In next section, some fuzzy rules will be proposed to determine such $\hat{U}_j$'s and G_j's.

3. DETERMINATION OF WEIGHTINGS FOR THE COLLISION AVOIDANCE

Let d_i be the minimum distance between the i-th link L_i and the obstacle. And let d_{mr} be the prespecified distance margin. Let the i-th link be regarded as the link with danger of collision if $d_i \le d_{mr}$, and specially denote it and its minimum distance as $L_i{*}$ and d_i^*, respectively. And define $d^+_{i,j}$, $d^-_{i,j}$ and $Cd_{i,j}$ as

$d^+_{i,j}$ $\triangle$ minimum distance between L_i and obstacle at the robot configuration after the positive (counter clockwise) differential motion of the j-th joint is completed,

$d^-_{i,j}$ $\triangle$ minimum distance between L_i and obstacle at the robot configuration after the negative (clockwise) differential motion of the j-th joint is completed,

and

$Cd_{i,j}$ $\triangle$ max { $d^+_{i,j} - d_i$, $d^-_{i,j} - d_i$ }.

Among all the $Cd_{i,j}$'s, change of d_i^* for the j-th joint differential motion is also specially denoted as $Cd^*_{i,j}$. Let SCd_j be defined by

$$SCd_j \triangle \sum_{i=1}^{n} Cd_{i,j} \tag{11}$$

and let $Y_{i,j}$ and Y_j^*, respectively, be defined as the capability of the j-th joint motion to let the L_i^* avoid the collision with the obstacle, and the total capability of the j-th joint motion for collision avoidance. Then the following approaches are employed to determine the weightings for the collision avoidance; For all i = 1,2,...,n and j = 1,2,...,n, 1) find d_i and L_i^*. If there is no $L_i{*}$ at all, the weightings of the network G_j's are determined by dexterity measures as in [10] and $\hat{U}_j$'s are chosen to be equal to zero. 2) Find $Cd^*_{i,j}$ and SCd_j. If $Cd^*_{i,j}$ is found to be zero for some j, G_j is determined by the dexterity measures since null $Cd^*_{i,j}$ implies that the j-th joint motion cannot entitly affect the motion of $L_i{*}$. 3) Find $Y_{i,j}$'s by applying fuzzy rules to be proposed, where the input variables of the fuzzy rules are given as $Cd^*_{i,j}$ and SCd_j. In case that there are S links with danger of collision, such links are simultaneously affected by a joint differential motion. For example, consider the case when L_i^* can be moved away from the obstacle, but L_k^* rather moves to the obstacle. In such a case, the i-th joint motion cannot devote itself to the collision avoidance. Thus it is needed to compute Y_i^* by taking such a case into consideration. Here, Y_j^* is given by

$$Y_j^* = (1/s) \sum_{i=1}^{S} Y_{i,j} . \tag{12}$$

4) Choose the redundant joints to be utilized for the obstacle avoidance in such a way that the redundant joints have Y_i^*'s as

large as possible. If some joints have the same Y_j^*'s, the joint with smaller dexterity measure is chosen as the redundant joint for the effective trajectory tracking and obstacle avoidance. 5) Find G_j by using Y_j^* and the dexterity measures. Here, if j-th joint is chosen as the redundant joint, G_j is obtained by

$$G_j = \begin{cases} 1, & Y_j^* \le 0, \\ \dfrac{G_{min} - 1}{Y_{max}} Y_j^* + 1, & 0 < Y_j^* \le Y_{max} . \end{cases} \qquad (13)$$

In Eq.(13) G_{min} and Y_{max} are the design constants implying the minimum value of G_j's and maximum value of Y_j^*'s, respectively. Otherwise G_j is determined by the dexterity measures as in [10].

Now fuzzy rules are proposed to determine the $Y_{i,j}$'s. For this, observe that '*positive large*' $Cd^*_{i,j}$ implies the j-th joint motion to be '*much capable*' of letting the L_i^* move away from the obstacle. And observe that '*positive large*' $SCd_{i,j}$ implies the j-th joint motion to be '*much capable*' of letting all the joints move away from the obstacle in the averaged sense. From these observations, a fuzzy rule for such a case can be set up to determine $Y_{i,j}$'s in the following; *if* $Cd^*_{i,j}$ *is "positive large" and* SCd_j *is "positive large", then* $y_{i,j}$ *is 'very positive large'*. In a similar way, the other fuzzy rules can be set up as in Table I, where PL(positive large), PS(positive small), Z(zero), NS(negative small), and NL(negative large) are the linguistic values for $Cd^*_{i,j}$'s and $SCd^*_{i,j}$'s, and VPL(very positive large), PL, PM(positive medium), PS, VPS(very positive small), Z, NS, NM(negative medium), and NL are nine linguistic values for $Y_{i,j}$'s. In Fig.1 and 2, the membership functions of linguistic values for $Cd^*_{i,j}$'s, SCd_j's and $Y_{i,j}$'s are shown, respectively. As a means of fuzzy reasoning, max-min approach by Zadeh[14] is employed, and center of gravity is utilized for the defuzzification[15].

4. SIMULATION RESULTS

For digital computer simulations, a redundant robot manipulator of the plannar type with three degrees of freedom is considered as shown in Fig.3, where the lengths of the links L_1, L_2 and L_3 are given as 400(mm), 400(mm) and 250(mm), respectively. And G_{min} and Y_{max} in Eq.(13) are chosen as 0.001 and 16, respectively. Also d_{mr} is given by 40(mm). To show the validities of our proposed method, the following two cases are considered; (i) the case when the obstacle is surounded by the robot manipulator, and (ii) the case when the obstacle lies in the right side of the robot manipulator. The start position of the end-effector is A in both cases.

CASE (i) : The initial joint angles q1(0), q2(0), and q3(0) are given as 80°, -80° and -80°, respectively. The desired trajectory is given by

$$y(t) = 0, \ x(t) = -20.557t + 210.0, \ 0 \le t \le 16.0 \qquad (14)$$

Fig.4(a) and Fig.4(b) show the resulting motions of the robot manipulator when applying the proposed network to the cases (a) without obstacle and (b) with obstacle, respectively. L_2 and L_3 become dangerous links to collide with obstacle after about 8 seconds elapsed as shown in Fig. 4(b) and Fig. 5(b). The collision can be avoided by letting L2 and L3 move away from the obstacle. The motion of 2nd joint can make move these links away from the obstacle in this case. It is observed from Fig. 5(b) that the robot succefully avoid the collision by increasing the velocity of 2nd joint with possitive direction. After 13 seconds elapsed, the links with danger of collision are changed to L1 and L2. In this case, the moion of 1st joint with counterclockwise can make avoid the collision . Fig.5(b) shows that the velocity of 1st joint increase to avoid the collision by proposed method.

CASE (ii): The initial joint angles q1(0), q2(0), and q3(0) are given as 120°, -110°, and -100°, respectively. The desired trajectory is given by

$$y(t) = 30., \ x(t) = 29.72t + 124.464, \ 0 \le t \le 16.0 \qquad (15)$$

It is observed from Fig.6(b) that L_3 is the most dangeous link to collide with obstacle, and L_3 never collides with the obstacle over the whole motion period. The collision is avoided by motion of 1st joint with counterclockwise. It is also observed from Fig. 7(b) that the velocity of 1st joint increase with positive direction. After 6 seconds elapsed, L2 also becomes dangerous link to collide with obstacle. From that time , the 2nd joint decrease its velocity to avoid the collision between L_1 , L_2 and obstacle and follow the given trajectory.

From these simulation results, it can be concluded that the proposed neural optimization networks with variable weighting by fuzzy rules can be successfully applied to the trajectory following control of redundant manipulators in an environment with obstacle or without obstacle.

5. CONCLUSIONS

A neural opimization network was proposed to control the redundant robot manipulators in an environment with the obstacle. The weightings of the network were adjusted by considering both the joint dexterity and the capability of collision avoidance of joint differential motion. The fuzzy rules were proposed to determine the capability of collision avoidance of each joint.

It is believed that in controlling the redundant robot manipulators in an environment with obstacle, our method is superior to the methods of [7,8,9] in the sense that our method never requires complex obstacle modelling as well as computational complexity.

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Table 1 Fuzzy Rules Table

$Cd^*_{i,j}$ \ scd_j	PL	PS	Z	NS	NL	d^*_i: S / L
PL	PVL / PM	PL / PS	PL / PVS	PM / PVS	PS / PVS	
PS	PM / PM	PS / PS	PVS / PS	PVS / PS	PVS / PVS	
Z	PVS / Z	Z / Z	Z / Z	Z / Z	Z / Z	

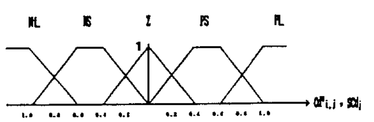

Fig. 1 Membership functions of fuzzy values for $Cd^*_{i,j}$ and SCd_j, where $Cd^*_{i,j}$ and SCd_j are normalized to unity.

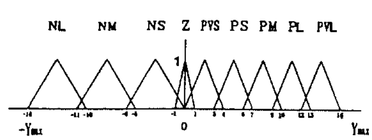

Fig. 2 Membership functions of fuzzy values for $Y_{i,j}$

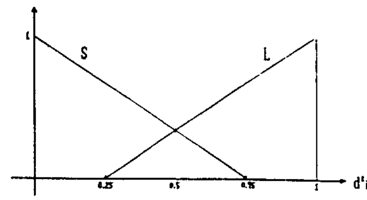

Fig. 8 Membership functions of fuzzy values for d^*_i

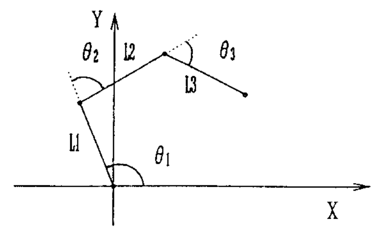

Fig. 3 Plannar Type Redundant Robot Manipulator with 3 DOF's

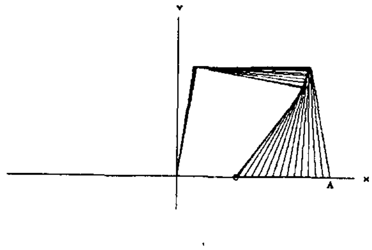

Fig. 4(a) The Robot Motion for the CASE (i).
(without Obstacle)

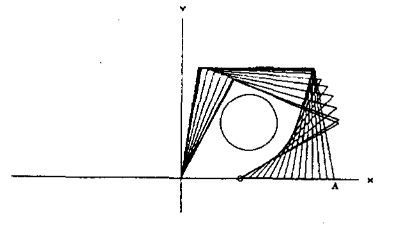

Fig. 4(b) The Robot Motion for the CASE (i).
(with Obstacle)

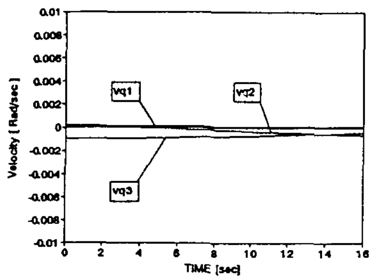

Fig. 5(a) Joint Velocities for the CASE (i)
(without Obstacle)

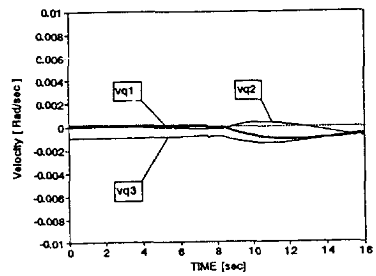

Fig. 5(b) Joint Velocities for the CASE (i)
(with Obstacle)

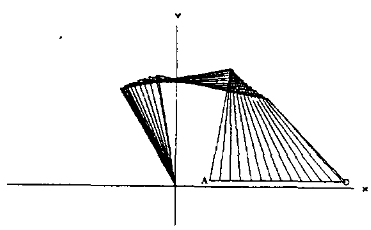

Fig. 6(a) The Robot Motion for the CASE (ii).
(without Obstacle)

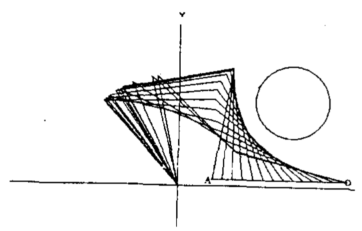

Fig. 6(b) The Robot Motion for the CASE (ii).
(with Obstacle)

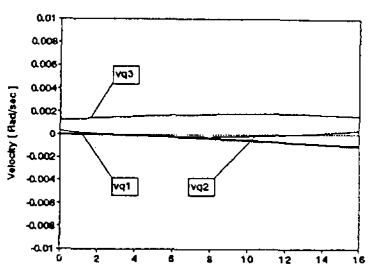

Fig. 7(a) Joint Velocities for the CASE (ii)
(without Obstacle)

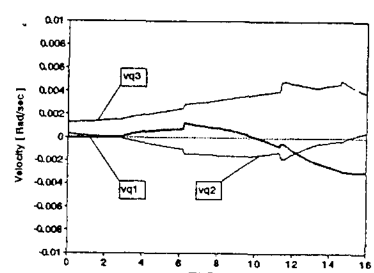

Fig. 7(b) Joint Velocities for the CASE (ii)
(with Obstacle)