A Mutual Control Method for a Multi-layered Non-contact Impedance Model-based Mobile Robots

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Abstract

In this paper, a mutual control method is proposed for multi-layered non-contact impedance model-based mobile robots. In the proposed system, the motion priority is set to the robot, and the stiffness, viscosity, and inertia parameters of the non-contact impedance model are changed appropriately according to the priority value allowing the robots to avoid collisions with each other and obstacles at the same time. In the experiment, two mobile robots one controlled by electromyogram signals were prepared and operated to intersect. The other mobile robot automatically stopped and resumed its movement in response to the EMG-controlled robot with high priority, indicating that the proposed method can be used to control multiple robots.

Keywords: electromyogram (EMG), collision avoidance, noncontact impedance control, recurrent probabilistic neural network

1. Introduction

To support and enable the physically disabled to live independently, it is essential to operate various types of equipment and support mobility. Several studies have proposed biological signal-based interfaces for mobility support[1-5]. However, collision accidents caused by the use of these systems depend on the skills of the user.

Several conventional techniques have been proposed for obstacle avoidance[6-8]. These methods can avoid obstacles and other robots by planning the paths using artificial potential fields[9]. The author's research group has also developed a natural obstacle-avoidance method for an EMG-controlled mobile robot that generates a multi-layered virtual wall based on the mechanical impedance model[10]. However, this system does not consider simultaneous control of multiple mobile robots. Therefore, in an environment where multiple mobile robots are present, the robots may recognize each other as an obstacle and an unintended movement may occur, such as repulsion caused by virtual forces.

In this paper, a multi-layered non-contact impedance (MLNCI) model is proposed that can automatically adjust the parameters according to the priority of each robot and apply them to the mobile robot control. Mobile robots within a specific region communicate with each other and adjust their parameters according to their control priority, enabling voluntary control even in an environment with multiple MLNCI model-based robots.

2. An EMG-controlled Mobile Robot Based on a Multi-layered Non-contact Impedance Model

In this section, an EMG-controlled mobile robot is described based on a multi-layered non-contact impedance model. EMG signals measured from L pairs of electrodes at a sampling frequency of f_s [Hz] are rectified and filtered using a second-order low-pass Butterworth filter (cut-off frequency: f_c [Hz]) and the values are then normalized such that the maximum value for each channel is 1 ($E_l(t)(l = 1, \ldots, L)$). the feature vector used to estimate the movement direction of the robot is extracted from the normalized signals such that the sum of the channels is 1. The force information $F_{\mathrm{EMG}}(t)$, which is the average of $E_l(t)$, is assigned to the robot velocity $V_{\mathrm{EMG}} = V_{\max} F_{\mathrm{EMG}}(t)$.

The direction of movement of the robot is discriminated using a recurrent log-linearized Gaussian mixture network to enter the extracted features. It is possible to learn the motions corresponding to the reference directions in advance and output the posterior probabilities of the new input feature vectors for each reference direction arranged in a clockwise direction from $\pi/2$, and the movement direction vector $\boldsymbol{e}(t)$ at time t is extracted [11]. The moving direction $\theta(t)$ of the robot is determined from $\boldsymbol{e}(t)$, and the velocity [w_l, w_r] of both wheels of the robot is controlled.

In addition, I virtual walls are deployed around the mobile robot, which can generate virtual external forces according to the mechanical impedance. When an obstacle o enters the i_{th} virtual wall, the virtual external force $\boldsymbol{F}_o^i$ is defined by the following equation using the distance $\boldsymbol{X}_o$ from the virtual wall to obstacle o.

$$\boldsymbol{F}_o^i = \boldsymbol{M}_i \Delta \ddot{\boldsymbol{X}}_o^i + \boldsymbol{B}_i \Delta \dot{\boldsymbol{X}}_o^i + \boldsymbol{K}_i \Delta \boldsymbol{X}_o^i, \qquad (1)$$

where $\boldsymbol{M}_i, \boldsymbol{B}_i,$ and $\boldsymbol{K}_i$ represent the inertia, viscosity, and stiffness parameters, respectively, and $\boldsymbol{F}_O^i$ is zero if the obstacle is outside the i_{th} virtual wall ($|\boldsymbol{X}_o| > q_i$) or inside the $(i+1)_{\mathrm{th}}$ virtual wall ($|\boldsymbol{X}_o| \leq q_{i+1}$). The virtual force ${}^{(p)}\boldsymbol{F}_o$ received by all virtual walls $q_i(i = 1,2,\ldots,I)$ from all obstacles $o(o = 1,2,\ldots,O)$ is expressed as the sum of ${}^{(p)}\boldsymbol{F}_o^i$. The equations of motion of the robot are defined as:

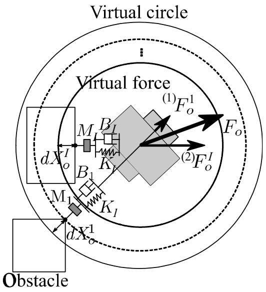

Fig. 1 Multi-layered non-contact impedance model [10].

$${}^{(p)}\boldsymbol{M}\Delta\ddot{\boldsymbol{X}} + {}^{(p)}\boldsymbol{B}\Delta\dot{\boldsymbol{X}} + {}^{(p)}\boldsymbol{K}\Delta\boldsymbol{X} = {}^{(p)}\boldsymbol{F} + \boldsymbol{F}_o. \qquad (2)$$

By solving the equation, the velocity of the robot $\Delta\dot{\boldsymbol{X}} = \left[{}^{(p)}\dot{x}, {}^{(p)}\dot{y}\right]^{\mathrm{T}}$ is obtained, the velocities of both wheels of the robot based on the MLNCI model are calculated, and the velocity of the robot is adjusted ($\left[{}^{(p)}\dot{x} + V_{\mathrm{EMG}}, {}^{(p)}\dot{y}\right]^{\mathrm{T}}$)[10].

3. A Mutual Control Method for a Multi-layered Non-contact Impedance Model-based Mobile Robots

For example, when two robots with the same parameters collide, the virtual repulsive force causes them to move backward. In an environment with multiple robots, it is necessary to determine the robot that takes priority allowing the other robots to automatically stop or take evasive action. In such cases, to give priority to other robots, it is necessary to change each parameter of the virtual non-contact impedance model shown in Equation (1) to achieve appropriate control, such as automatic stopping. In this study, the priority n for each robot is set, and the coefficient vectors m_i^n, b_i^n, k_i^n required to adjust each parameter of the MLNCI model and adjust the virtual repulsive force according to the priority are as follows.

$$\boldsymbol{F}_o^i = m_i^n \boldsymbol{M}_i \Delta\ddot{\boldsymbol{X}}_o^i + b_i^n \boldsymbol{B}_i \Delta\dot{\boldsymbol{X}}_o^i + k_i^n \boldsymbol{K}_i \Delta\boldsymbol{X}_o^i. \qquad (3)$$

To achieve this priority-based control in a real environment, robots must be able to communicate with

Table 1 Parameters used in the experiment.

	$\boldsymbol{M}_1$[kg]	$\boldsymbol{B}_1$[Nm]	$\boldsymbol{K}_1$[N/m]
Robot 1	(0.21,0.21)	(0.8,0.8)	(1.0,1.0)
Robot 2	(2.0,2.0)	(2.0,2.0)	(2.0,2.0)

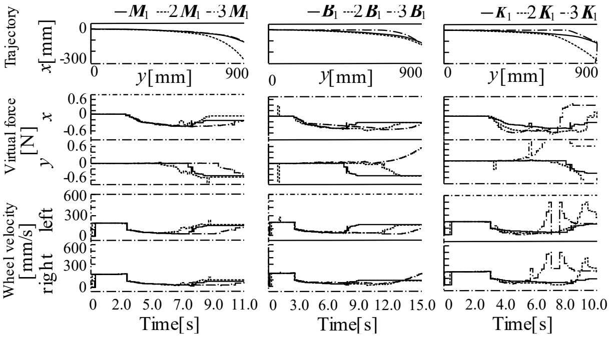

Fig. 2 Relationship between MLNCI parameters and virtual forces and velocities

each other and set their priorities. In this study, a server PC with a video camera that recognizes the robots by discriminating the markers attached to the robots is prepared, and the priorities are communicated through the server. Based on this priority, each parameter of the multi-layer non-contact impedance model is automatically adjusted, and the voluntary control of multiple robots can be realized.

4. Experiments

A validation experiment was conducted to identify the coefficient of varying for the MLNCI model. Two robots ($p = \{1, 2\}$) with one virtual wall ($I = 1$, see Table 1) were placed facing each other 900 [mm] apart. In the experiment, Robot 2 was moved forward at a speed of 200 [mm/s], and the parameters of inertia, viscosity, and stiffness were multiplied by 1, 2, and 3, respectively. RPLiDAR A1 (SLAMTEC) was used to measure the distances between robots (sampling frequency: 10 [Hz]).

The experiment results are shown in Fig. 2. The scatter plot at the top shows the trajectory of Robot 2, and the line graphs at the bottom show the results of varying the (a) inertia, (b) viscosity, and (c) stiffness of Robot 2.

The results show that the trajectory of Robot 2 until it starts to avoid Robot 1 is steeper when the stiffness parameter is varied compared to the viscosity and inertia parameters. The trajectory is also steeped in the second half when the inertia parameter is doubled. However, the velocities of both wheels change more slowly than when the stiffness parameter is varied. In addition, focusing on the change in velocity, the velocity slowly approached zero when the viscosity parameter increased, and the change in velocity was small when the inertia parameter increased. From these results, it can be observed that the robot can be stopped naturally by adjusting the inertia and viscosity parameters. In addition, the stiffness parameter can be used to rapidly move the robots away from each other. Based on the results, the next section shows that the proposed method can be used to preferentially control a mobile robot.

Table 2 Parameters used in the EMG-control experiment.

	$\boldsymbol{M}_1$[kg]	$\boldsymbol{B}_1$[Nm]	$\boldsymbol{K}_1$[N/m]
Robot 1	(0.21,0.21)	(0.8,0.8)	(1.0,1.0)
Robot 2	(6.0,6.0)	(6.0,6.0)	(2.0,2.0)
	$\boldsymbol{M}_2$[kg]	$\boldsymbol{B}_2$[Nm]	$\boldsymbol{K}_2$[N/m]
Robot 1	(2.1,2.1)	(8.0,8.0)	(10.0,10.0)
Robot 2	(6.0,6.0)	(6.0,6.0)	(4.0,4.0)

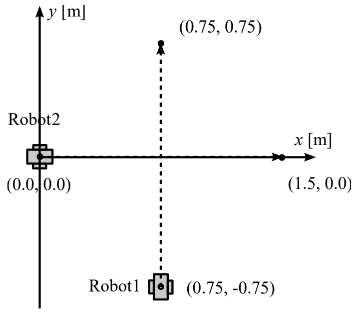

Fig. 3 Experimental setup

5. An example of EMG-based control

Based on the results presented in Section 4, mobile robot control was conducted in a real environment. Robot 1, which headed in the direction of the participant, was controlled using EMG signals measured from eight pairs of electrodes (Myo, Thalmic Labs, Inc.), and Robot 2 automatically moved toward $(x, y) = (1500, 0)$ [mm] (see Fig. 3). Two virtual walls ($I = 2$) were surrounded by each robot, and the parameters of the virtual walls were set as listed in Table 2.

Figure 4 shows the experimental scenes and trajectory of Robot 2. Figure 5 shows an example of the experiment results (from the top: virtual forces, wheel velocities, distance and angle to Robot 1, and the priority of Robot 2). The results show that from 0.5 [s], the parameters of Robot 2 were changed because of its lower priority, and it stopped to give priority to the myoelectric-controlled robot (Robot 1) between 1.5 to 11 [s]. At this time, the virtual repulsive force to Robot 2 was greater than that of Robot 1, and the velocity of each wheel was gradually decreasing. After Robot 1 passed, Robot 2 resumed its

(a) t = 4.0 [s] (b) t = 10.0 [s] (c) Trajectory

Fig. 4 Experimental scene and trajectory of Robot 1,2

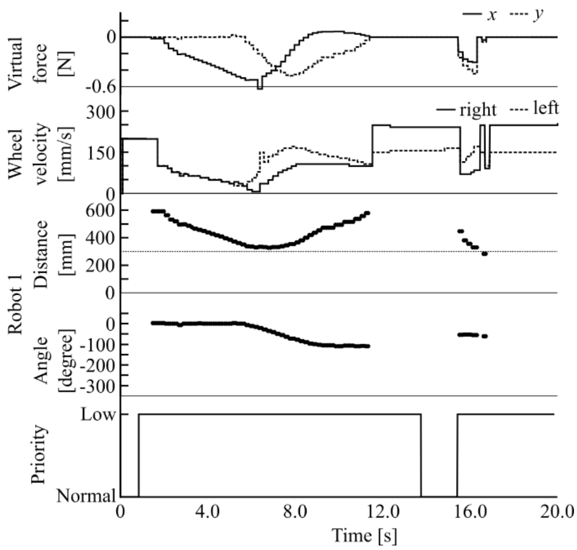

Fig. 5 An example of experimental results (Robot 2)

movement toward the position 1.5 [m] from the initial position.

These results show that the proposed method can be used for the mutual control of mobile robots based on a multi-layered non-contact impedance model.

6. Conclusion

In this paper, a mutual control method for mobile robots based on a multi-layered non-contact impedance model is proposed. The proposed method can simultaneously avoid collisions between robots and obstacles at the same time by changing the parameters of the model according to the motion priority of the robots. In the experiment, the myoelectric-controlled robot and automatic-controlled robot were manipulated such that they crossed each other. The experiment results showed that the automatically controlled robot was able to stop and resume its motion on its own in response to a myoelectric-controlled robot with higher priority.

In future research, we will consider the implementation of the model on aerial and undersea drones as well as the determination of priority using the movement direction and velocity of the robot and the surrounding environment through object recognition.

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