Human-Robot Collision Detection and Identification Based on Wrist and Base Force/Torque Sensors

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Abstract - In this paper, a collision detection and identification method of a manipulator, using base and wrist force/torque sensors, is presented. An impact model is used to simulate the interaction between the manipulator and the human or environment. A neural network approach and a model based method are developed to detect the collision forces and disturbance torques on the joints of the manipulator. The experimental results illustrate the validity of the developed collision detection and identification scheme.

Index Terms - Collision; Detection; Identification; Base and Wrist Force/torque sensor; Human; Manipulator

1. Introduction

Conventional industrial robots from the late 70's, which usually perform repeated movements with enormous speed and precision in a structured environment separated from human operators, are currently of practical use on the production level only [1]. In the future, robots are expected to expand their application field to our daily life, such as to services in homes and offices and for social welfare [2-4]. In contrast to industrial robots, service robots will "live" among humans, have the ability to maneuver in human-oriented environments, and are expected to have substantial autonomy in performing the required tasks in such complex environments [5]. Those robots, while operating in varying and unstructured environments, must cooperate and coexist with humans who are not trained to cooperate with robots and who are not necessarily interested in them. The safety of humans has to be guaranteed with these robots coexisting with human in the same working space.

Much research has focused on the efficient execution of tasks when they involved the interaction between robots and their environments including constraints on the environment. However, little research has been done with the human safety issue in mind. Some research has proposed collision free planning methods based on prior knowledge of the environment [6,7]. However, this method is not applicable in the unstructured situations. Others have studied non-contact obstacle avoidance approaches based on such sensors as optical sensors, ultrasonic sensors, and proximity sensors, to improve human safety [8-11]. Although these approaches have the potential advantage of no physical damage to humans, these sensors may be saddled with inherent problems involving dead angles, disturbances, as well as poor image processing capabilities in addition to the ambiguity of detectable volume in proximity sensing techniques. When the highest reliability is required, the use of these sensors

for practical human detection is unreliable.

Substantial research has been devoted to the safety based design of robots. Those approaches include the passive impedance control methods using viscoelastic material which covers the robot body [12,13], the mechanical impedance adjuster equipped robot with linear springs and brake systems [14], robots with flexible joints [15], compliant shoulders [16], and viscoelastic passive trunks [17]. Some research has also proposed safety requirements [13] as well as safety optimizing design methods [18]. The noted methods are a way of making the robot hardware itself compliant. In the case when a manipulator hits a person who is unable to flee to a safe space because of the constraints of the workspace or a lack of mobility of the person, the contact force may become large enough to cause injury to the person. If the robot is made very compliant for consideration of human safety, the result may be a lack of precision of the end-effector and thus low reliability of the task execution.

Some authors have proposed active compliance control approaches using a force/torque sensor mounted on the wrist of the robot's arm [19]. Using these control methods, human safety may be realized by compliance of the robot's arm when the end-effector collides with a human. Others used an adaptive control law [20] or a Kalman filter [21] to detect collisions. However, when the collision is caused by parts of the arm other than the end-effector, the methods fail to guarantee human safety unless the force/torque sensors are installed at appropriate locations on the arm. Other researchers proposed collision detection schemes based on the comparison of the actual motor torques and the reference torques calculated from a dynamic model of the manipulator [22,23]. However, these methods need torque sensors installed at the joints and it is not practical to obtain models that accurately account for the nonlinear joint viscous friction and Coulomb friction. When a collision occurs at the arm of the manipulator, none of the above approaches is able to estimate the collision force and/or position that are very important for a human-friendly robot to have the ability to control the collision force below the human pain tolerance limit.

When a collision is detected, an emergency stop command is issued to protect the human [13,22]. However, stopping the robot irrespective of the contact force level is not necessarily an optimal method for human safety and risk avoidance. If the collision can be detected, it becomes possible to control the contact force below the human pain tolerance limit, so that the robot does not require an emergency stop, and can continue its task after the human

responds to the collision and moves back to safe areas for example.

Based on the shortcomings of the existing methods, this paper proposes collision detection and identification methods which are then verified through experiment. The efficacies of the methods are discussed as are suggestions for future work.

2. BASE AND WRIST FORCE/TORQUE SENSORS-BASED COLLISION DETECTION

In the development of a human-friendly robot, the safety of the interacting human is of critical importance. The use of robots in a human-oriented environment will inevitably result in some sort of interaction between the robots and both humans and the environment. Such interaction will typically be a collision resulting in an induced force at the contact surfaces. In order to control the contact force below a safe level so that the human is not injured, a collision detection module is necessary to check whether collisions occur and to identify the possible contact force and position if possible.

Some researchers use a wrist force/torque sensor to measure the force/torque between the tip of a manipulator and the environment to realize collision detection. However, this method is unable to detect the contact that occurs at parts of the arm other than the end-effector.

When the end-effector of a manipulator follows a desired trajectory under the constraints of the environment, external tip forces from the environment can be measured by the wrist force/torque sensor. If the robot arm collides with a human or the environment, additional contact forces are exerted at the contact point.

The dynamic model of an n-joint serial manipulator can be written as

$$H_{qq}\ddot{q}+C_{qq}\dot{q}+G_q+F_q= au+J_cF_c-J_wF_w$$
 (1) where q is an $n\times 1$ vector of joint displacements, au is an $n\times 1$ vector of joint torques applied by the control means, H_{qq} is an $n\times n$ matrix of the centrifugal and Coriollis torques, G_q is an $n\times n$ matrix of the gravitational torques, F_q is an $n\times 1$ vector of the gravitational torques, F_q is an $n\times 1$ vector of the transmission and joint friction forces, F_w is the wrench measured by the end-effector force/torque sensor, F_c is the contact force vector on the robot arm, J_c is the Jacobian matrix relating to the contact force, and J_w is the Jacobian matrix of the position of the wrist force/torque sensor.

Equation (1) can be easily rewritten as

$$J_c F_c = H_{qq} \ddot{q} + C_{qq} \dot{q} + G_q + F_q - \tau + J_w F_w.$$
 (2)

If the torques on the links can be measured and a perfect model is used to compensate the friction, the contact force and disturbance torques can be calculated from Eq. (2). However, typical industrial manipulators do not have torque sensors at the joints and therefore, it is not practical to model and calculate the joint and transmission

friction.

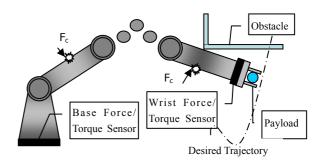


Fig. 1 Manipulator with two Force/Torque Sensors

To overcome the noted problem, a manipulator with two six-axis force/torque sensors is proposed as shown in Fig. 1. The first one is mounted on the wrist of the robot, and the second is located at the base of the manipulator. The dynamic model of the whole system is thus written as

$$H_{bq}\ddot{q} + C_{bq}\dot{q} + G_b = F_b + Ad_{g_{b_b}}^T F_c - Ad_{g_{b_b}}^T F_w$$
 (3)

where H_{bq} and C_{bq} are two $6 \times n$ matrices that express the dynamic forces applied by the joint displacement of the manipulator on the base, G_b is a 6×1 vector of the gravitational effect of the manipulator on the base, F_b is the wrench applied by the environment on the robot's base, $Ad_{g_{bw}^{-1}}$ is the adjoint transformation associated with the

inverse of g_{bw} , and $Ad_{g_{bc}^{-1}}$ is the adjoint transformation

associated with the inverse of g_{bc} [24]. Since the friction forces are internal forces, the base force/torque sensor does not include transmission and joint friction forces, and it only measures the gravity wrenches, dynamic wrenches due to the motion of the manipulator, and the wrenches due to the contact at the end-effector and the collision on the arm.

Based on the BWFTS (Base and Wrist Force/Torque Sensor), two approaches, a model based method and a neural network approach, are proposed to detect the collision and to identify the contact force as well as the disturbance torques on the joints caused by the collision.

2.1 Neural Network Approach $q(k)
q(k-1)
\vdots
q(k-h)
F_b
F_w$ Input
Hidden Layer
Output Layer
Output

Fig. 2 Neural Network

An artificial neural network approach is proposed to detect and identify the collision, since it can learn the characteristics of a non-linear, non-modeled system through training. Since a back-propagation network with biases, a sigmoid layer, and a linear output layer is capable of approximating any function with a finite number of discontinuities, a two-layer feed-forward neural network (shown in Fig. 2) is used to simulate (3), so that the collision force, contact position and its effect on the joints can be calculated.

The neural network is composed of an input layer, one non-linear hidden layer, and an output layer. According to (3), the dynamics of the robot and base and the wrist wrenches are required to detect the collision force and find the contact position. A short history of joint angles, $q(k), q(k-1), \ldots, q(k-h)$, is used as inputs to the neural network, so that the velocities and accelerations of the joints and all the transform matrixes can be derived. The readings from the wrist and base force/torque sensors, F_b, F_w are also chosen as the inputs of the neural network. The outputs of the neural network are the collision forces $(\hat{f}_{c1}, \hat{f}_{c2}, \ldots, \hat{f}_{cn})$ and contact positions $(\hat{p}_{c1}, \hat{p}_{c2}, \ldots, \hat{p}_{cn})$, where $(\hat{f}_{ci}, \hat{p}_{ci})$ are the collision force and contact position on Link i.

It is assumed that there are m inputs $X = [x_1, x_2, \cdots, x_m]$ and n outputs $Y = [y_1, y_2, \cdots, y_n]$, and they are related by a nonlinear unknown function Y = F(X). In this network, the function Y can be expressed as

$$Y = F_O(W_O * (F_I(W_I * X) + B_I) + B_O$$
 (4)

where F_O is the output activation function, F_I is the input activation function, W_O is the weight for the output layer, W_I is the weight for the input layer, and B_O and B_I are the weights for the output neurons and input neurons, respectively.

The neural network based collision detection and identification method does not require a priori knowledge of the dynamic parameters of the manipulator nor the parameters of the contacting object, and it is robust to noise. However, this method needs adequate experimental data to train the neural network.

2.2 Model-Based Method

Equation (3) is rewritten to calculate the contact force as

$$Ad_{g_{bc}^{-1}}^{T}F_{c}=H_{bq}\ddot{q}+C_{bq}\dot{q}+G_{b}-F_{b}+Ad_{g_{bw}^{-1}}^{T}F_{w}~.(5)$$

In addition, (5) is rewritten as

$$Ad_{g_{bc}^{-1}}^{T}F_{c} = H_{bq}\ddot{q} + C_{bq}\dot{q} + G_{b} - F_{b} + Ad_{g_{bc}^{-1}}^{T}F_{w} = F_{bc}$$
 (6)

where F_{bc} is the wrench, F_c is expressed in the base frame, and

$$Ad_{g_{bc}}^{T} = \begin{bmatrix} R_{bc}^{T} & 0\\ -R_{bc}^{T} \hat{p}_{bc} & R_{bc}^{T} \end{bmatrix} \tag{7}$$

$$F_c = \begin{bmatrix} f_c & \tau_c \end{bmatrix}^T, \qquad F_{bc} = \begin{bmatrix} f_{bc} & \tau_{bc} \end{bmatrix}^T. \tag{8}$$

Also, it is reasonable to assume that there is no torque present when the robot arm contacts the obstacle and only the contact force is induced, so that $\tau_c = 0$. From the above equations, the contact force \hat{f}_c and position can be estimated. Since uncertainties always exist in the robot dynamic model and the readings from force sensors are noisy, it is usually not practical to calculate the contact force directly from (5).

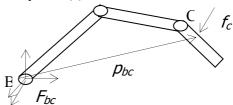


Fig. 3 Contact Wrench on the Base Force Torque Sensor

In Fig. 3, f_c is exerted onto the contact point C, and F_{bc} is the equivalent wrench in the base frame. To simplify the description of the model based approach, f_c is also expressed in a frame which has the same orientation as the base frame and the origin at Point C. Since $\tau_c = 0$, then

$$f_c = f_{bc} \tag{9}$$

and
$$\tau_{bc} = p_{bc} \times f_c. \tag{10}$$

It is reasonable to assume that no friction results from the collision between the robot manipulator and the object, so that the collision force is perpendicular to the link. With consideration of the configuration of the manipulator, a better estimation of \hat{f}_c can be obtained.

The model based method thus has the following steps:

- (1) From (6-8), get the first estimation of the contact force \hat{f}_c .
- (2) Due to the assumption of non-friction $(\hat{f}_c \perp \hat{n}_i)$ and (10), find the most possible link where contact occurs (where \hat{n}_i is the normal vector of the i-th link).
- (3) Using $\hat{f}_c \perp \hat{n}_i$, get a better estimation of \hat{f}_c .
- (4) Find the contact point vector \hat{p}_{bc} .

A threshold of the contact force $f_{\it th}$ is used to check if collision occurs; i.e., contact occurs when

$$\left| \hat{f}_c \right| > f_{th} \,. \tag{11}$$

Only when the above condition (11) is satisfied for a certain period of time Δt , then a collision is considered to occur so that the false detection rate can be reduced. However, the miss-detection rate may increase if f_{th} is

set to be too high and/or Δt is too large. Yamada, et al conducted an experiment to measure the static/dynamic threshold of the human pain tolerance limit [22]. Twelve points of a human body were chosen for measurement. Those points, which include hand, arm, leg, forehead, abdomen, chest, buttocks and back, are considered to have a high possibility to collide with robots. A unified pain tolerance limit of a human is parameterized by a contact force of 50N. To control the contact force under the human pain tolerance limit, it is desired that the collision is detected while the contact force is well below 50N. f_{th} is set to 10N and Δt is set to 15ms, which is three times the control interval.

3. COLLISION DETECTION EXPERIMENT

The developed contact detection methods were implemented on a Mitsubishi PA-10 robot, which has an open control architecture. The original motion control computer was bypassed and an Intel Pentium III 866 MHz PC was connected directly to the robot's servo drivers through an ARCNET card (5Mbps). The control program was implemented with Visual C++ in a RTX real time environment. The system architecture is shown in Fig. 4.

The computed velocities, from a finite difference approximation of the sensed angles, are fed to a Butterworth filter with a cutoff frequency of 30 Hz. The wrenches measured at the wrist and base force/torque sensors are also fed into low pass filters with a cutoff frequency of 20 Hz.

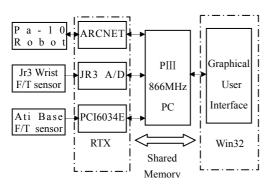


Fig. 4 System Architecture of PA-10 Contact Detection Experiment

3.1 Virtual Collision

Due to modeling error and uncertainties of the manipulator, a dynamic model of a robot arm is not suitable for data generation for training a neural network and the validation of the model based method.

A virtual collision approach is introduced to solve this problem. A collision model is used to get the collision force. Combined with the contact position on the manipulator, the virtual disturbance torque on relevant joints and the resulting wrench on the base force/torque sensor are calculated. These virtual disturbance torques are added to the torque commands and the readings of the base force/torque sensor, so that the robot runs in the same manner as if there is a real collision.

To model the collision between the environment and

the robot arm, the following assumptions are made:

- (1) There is no torque present when the robot arm contacts the obstacle and only one link collides with a human or the environment. In case there is more than one contact point on the link or there is an area contact, the composition of the contact forces is considered.
- (2) The surface of the robot manipulator and the contacting object are both deformable. The contact force is caused by local geometric deformation of the link of the robot and the contacting object.
- (3) No friction results from the collision between the robot manipulator and the object so that the collision force is perpendicular to the link.

The force applied to the contact point of the arm can be described as

$$F = K_0 \Delta x + B_0 \Delta \dot{x} \tag{12}$$

where F is the contact force, K_0 and B_0 are the effective stiffness and the damping matrices of the contact respectively, combining those of the manipulator and the human or the environment; Δx denotes the combined deformation of the surface of the robot arm and the contacting object; and $\Delta \dot{x}$ denotes the speed of the deformation.

3.2 Experiment Results

To verify the proposed scheme, single- and two-link contact experiments using the PA-10 manipulator were conducted for collision detection and identification. The reference contact force is generated by the virtual collision method. The virtual contact is removed after it has been applied for 4 seconds, which is long enough to exert forces larger than the human-tolerable limit of 50N. The contact point moves on the arm in a sinusoidal manner with the start point at the center of the link under collision. The reference contact position is defined as the distance from the collision point to the axis of the link at which the virtual contact force is applied. The contact force error is defined as the difference between the reference contact force applied and the one estimated by the neural network or model based approach. The contact position error is defined as the difference between the reference contact position and the one estimated by the neural network or model based approach.

In the first set of experiments, all of the links other than Link 4 of the PA-10 manipulator are locked. The desired trajectories of Joint 4 are sinusoidal joint space trajectories with a period ranging from 5 seconds to 10 seconds and amplitude ranging from 10 degrees to 40 degrees.

Figs. 5 and 6 show the results of a single link collision detection based on both the neural network and the model based approaches. Fig. 5 (a) illustrates the contact force error. Fig. 5 (b) is the result of the contact position error. Fig. 5 (c) shows the reference contact force, where the collision occurs at t=1.75s, and ends at t=5.5s. Fig. 5 (d) is the reference contact position, and it shows that the contact point moves on the link following a sinusoidal path.

In the second set of experiments, all of the links other than Links 2 and 4 of the PA-10 manipulator are locked. The desired trajectories for Joints 2 and 4 are sinusoidal joint space trajectories with a period ranging from 5

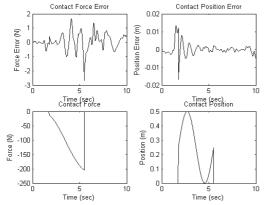


Fig. 5 Single Link Collision Detection using neural network

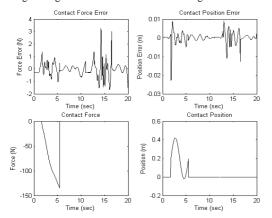


Fig. 7 Two-Link Collision Detection using neural network (Link2)

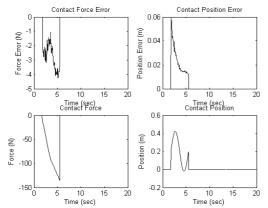


Fig. 9 Two-Link Collision Detection using Model-Based Method (Link2)

Fig. 7 shows the results of two link collision detection using a neural network when the collision is on Link 2 while Fig. 8 shows the results of link collision detection using a neural network when the collision is on Link 4. Fig. 9 shows the results of two link collision detection using the model based approach for the collision on Link 2. Fig. 10 shows the same for a collision on Link 4.

As shown in Figs. (5)-(10), both of the two proposed approaches work well to detect the collision and identify

seconds to 10 seconds, and amplitude from 10 degrees to 40 degrees. A collision occurs on Link 2 first, and then another collision occurs on Link 4.

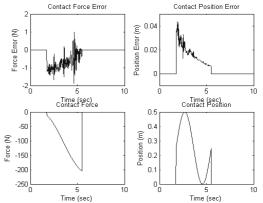


Fig 6. Single Link Collision Detection using Model-Based Approach

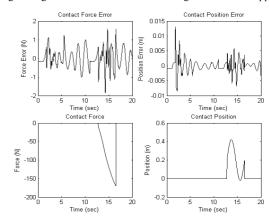


Fig. 8 Two-Link Collision Detection using neural network (Link4)

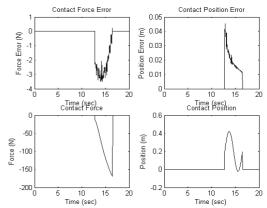


Fig. 10 Two-Link Collision Detection using Model-Based Method (Link4)

the contact force and position. The contact force errors are less than 4N, which means that the collision can be detected even when the collision force is very small and well before the contact force exceeds the human pain tolerance limit. In addition, the maximum position error is approximate 0.022m in the neural network approach, and 0.06m in the model based method. Large contact position errors occur at the early stage of the collision, while the contact forces are smaller than 20N. In the model-based method, while the contact force is relatively small, the

contact position error is larger than that of a large collision force because the contact position is estimated from Eq. (10). The experimental results show that, it is possible to detect the collision force and pinpoint the contact position at the early stages of a collision, so that the right response can be taken to control the collision force, and to ensure that the safety of the human is guaranteed.

The neural network based approach is noise free and outperforms the model based approach. However, it requires a large amount of data for training. The model based method does not need training, but it is difficult to derive a precise model because of the inherent complexity of the robot dynamics. Due to the use of the base force/torque sensor, the dynamic model is friction free. With the implementation of a more precise dynamic model of the robot, the performance of the model based approach may be improved.

4. CONCLUSIONS AND FUTURE WORK

In this paper, two new approaches based on the use of base and wrist force/torque sensors were developed to detect and identify collision between a manipulator and human or environment. The developed methods do not require modification of the existing designs of industrial robots, such as covering the robot with tactile sensors or elastic materials. The wrist and base force/torque sensors configuration has the friction free benefit, since the friction forces are internal forces. The efficacy of the method was validated by experiments through virtual collisions between the PA-10 manipulator and objects. Future work includes an extension of the methods to develop collision control algorithms with the human safety as the top priority.

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