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Robot Collision Detection based on Fuzzy Identification and Time Series Modelling

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Abstract. Robots that share workspace with humans require safety capabilities to identify possible collisions and perform appropriate reactions in order to eliminate the potential injury of a human. For this purpose, an intelligent fuzzy identification method and a time series method are proposed and implemented in this paper. These systems are trained to the robot dynamics with and without collision to be able to detect contacts along the links of the robot. Since the speed of the detection is of critical importance to avoid injuries, attention is paid to recognise a collision as soon as possible. The proposed methods are evaluated in an experimental setup by using a KUKA LWR manipulator and their performance is compared with a model-based approach.

Keywords. collision detection, fuzzy identification, time series modeling

1. Introduction

When robots operate in unstructured environments and share the same workspace with humans, safety issues are of primary concern. Physical human-robot interaction (pHRI) can lead to unexpected collisions that can harm humans and to mitigate that risk, a sufficient method for avoidance or detection of the collision should be available.

In the relevant literature there is a variety of methods dealing with this problem either on pre-impact or during the impact phase. In the first case, a collision can be foreseen and avoided during motion planning by having knowledge of the environment. 3D vision techniques (Flacco et al., 2012) that allow the monitoring of the human pose can cope with this problem but these methods have high computational cost and blind spots can limit their reliability. Another approach is the use of proximity sensors in the robot body that are able to identify human through capacitive sensing (Lam et al., 2012). Although this method is able to identify the point of an imminent collision, a special treatment of the robot body is required for the sensor installation and the cost is quite high.

During a collision, a contact with the environment can cause high reaction forces that influence the dynamic behaviour of the robot. Passive safety features like compliant joints, actuators and lightweight manipulators cannot always guarantee harmless collisions and as a result an active safety system would be more reliable. For the identification of collisions in (Chen et al., 2010), the measured joint torques were compared with those determined by the robot model and sudden deviations were spotted. These methods either require a sufficient model of the system or are based on parameter estimation with adaptive control (Matsumoto and Kosuge, 2001). By using the generalised momentum of the robot, De Luca et al. (De Luca et al., 2006) developed an efficient collision detection method that is applicable in manipulators with rigid and elastic links. Lu et al. (Lu et al., 2005) trained a neural network to approximate the robot model and to overcome the problem of imprecise parameters of a dynamic model.

Fault detection methods that have been proven sufficient in rotating machinery, automation and aircraft systems can also be used in robotics. These methods were based on the following principle: small changes or faults in a structure can cause significant deviations in its dynamic behaviour. DeLuca and Mattone (De Luca and Mattone, 2005) detected faulty behaviours of the robot actuating system, which implied collisions, by measuring the position of the joints. Cho et al. (2012) continued their research and proposed a collision detection methods based on the generalised momentum and by using joint torque measurements.

Statistical time series methods have also been used for fault detection in systems (Sakellariou and Fassois, 2008). The main advantage of those methods lies to their ability to use data for building mathematical models that represent the true dynamical system, hence there is no need to interrupt the normal operation of the system.

In this paper, we study the collision detection problem of a robot with a human. Two novel methods for collision identification are proposed (section 2), that do not require the explicit dynamic model of the robot and are able to detect the occurrence of a collision throughout the robot link, very quickly and before the reaction forces become dangerous for the human. More specifically, a fuzzy inference system (FIS) is trained to approximate the collision force by using data with and without collision, while an external force sensor is used only for the training (section 3.1).

In addition, a time series model is trained to the robot dynamics without the need of an external force sensor and is able to identify collisions as a faulty behaviour of the robot by monitoring the error between the predicted and the actual joint torque (section 3.2). The performance of the proposed schemes is evaluated on a collision test-bed using a KUKA LWR robot and is compared with an explicit model-based approach (section 4).

2. Collision Identification Methods

In the development of a collision detection method it is necessary to identify the collision force as soon as possible and before large forces build up that can harm humans or the robot itself. The collision force can be calculated numerically from the analytic dynamic model using the position and torque sensors of the joint. The dynamics of a robot arm that interacts physically with the environment during a collision include the contact forces on the colliding link that are translated to joint torques. The dynamics of an n-link robot can be expressed as:

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = \tau_{mot} - \tau_{ext} \quad (1)$$

where $M(q)$ is the inertia matrix, $C(q,\dot{q})$ is the matrix that contains the Coriolis and centrifugal terms, $g(q)$ is the gravity vector, τ_{mot} is the actuator torque and τ_{ext} is the external torque from the collision. The external torque on each joint τ_{ext} can be calculated by using a torque sensor on the joints:

$$\tau_{ext} = \tau_{tot} - \tau_{mot} \quad (2)$$

where τ_{tot} is the measured joint torque and τ_{mot} is the expected motor torque that can calculated from the dynamic model (1) in the absence of τ_{ext}. Although this is a straightforward technique with many advantages, in order to be reliable, it requires a very accurate dynamic model of the system which is not so easy to obtain. Parameters like the weight and inertia of each link, the joint friction and the hysteresis effect are very difficult to calculate and as a result an estimation of the external torque that are exerted on a joint is not very accurate. Previous system identification methods approximate the robot dynamics only at normal operation of the robot and detect collisions from deviations between the identified model and the actual measurements (Lu et al., 2005).

In this paper, we propose two detection methods based on training systems using data of the robot dynamics with and without collision and can infer the occurrence and the magnitude of the collision torque along the robot link. Each detection system can be trained offline by using a small amount of data and can be implemented on the controller for online detection of collisions. Their main advantages are the sensitivity on detecting collisions because the training includes data of the robot dynamics with contact forces, the computational efficiency and finally the easy implementation on existing robots, which are designed for pHRI and have position and torque sensors.

The training process requires the provisioning of input-output associations. To achieve that the estimation error is as small as possible, the training set should contain enough information about the unknown system and we should choose a suitable signal q to excite the dynamics of the system so that we can see via the plant input-output data, what are the dynamics that generate the output.

The inputs that are used for the training should be available from the proprioceptive sensors of the robots, such as position encoders and torque sensors and the signals should include substantial information in order to identify the external torque τ_{ext}. However, the number of inputs should be kept as small as possible because otherwise the fitting would be computationally inefficient. Under those considerations, the main variables that are selected as inputs are the position error q_e of the position control system and the total joint torque τ_{tot} from the built-in sensor because they are greatly influenced by disturbances such as a collision. To verify this assumption we commanded a sinusoidal motion q on a single joint of a KUKA LWR robot and collisions were simulated by a human touching the robot with his hand. As it is illustrated in Fig. 1, the sudden peaks in the position error and in the measured torque signals can indicate collisions of the robot arm, but this is not always the case. Large alterations can also be observed under normal operation because of the high inertial forces that appear on the links during changes of the velocity direction. Since this phenomenon is related to the joint velocity, in order to distinguish the collision spikes, the signal of commanded joint velocity $\dot{q}$ can also be used as an input for the training.

To approximate the collision torque τ_{ext} that acts on the joint, an indication of the value of the collision torque is necessary to the training loop. For that purpose a force sensor is mounted on the robot end-effector and is used to measure the collision force f_{ext}. Since this force is applied by a user with his hand and perpendicular to the motion, it can be translated to the external torque τ_{ext}. It can be noted that during the evaluation, a collision can be detected throughout the robot link without using the external force sensor, which is only used for the comparison of the results.

2.1. Fuzzy Collision Identification

Fuzzy modelling is a powerful tool for non-linear system identification. A fuzzy system can be trained to identify complex systems by estimating the fuzzy parameters and rules. Fuzzy modelling is simple, flexible and can approximate complex non-linear functions even if inexact and incomplete data are available.

A Tagaki-Sugeno functional fuzzy system, which is computationally efficient and can work well with non-linear problems, has been selected. In this case, the rules have the following form:

$$R_i : If\ q_e\ is\ A^j_{q_e}\ and\ If\ \dot{q}\ is\ A^k_{\dot{q}}$$
$$and\ If\ \tau_{tot}\ is\ A^l_{\tau_{tot}}\ Then\ \tau'_{ext} = g_i$$

where R_i represents the i^{th} rule, $q_e, \dot{q}, \tau_{tot}$ are the linguistic variables that represent the inputs, A^n_m are the linguistic values and τ'_{ext} is the output of the fuzzy system that is a linear function of g_i and has the following form:

$$g_i = a_{i,0} + a_{i,1} q_e + a_{i,2} \dot{q} + a_{i,3} \tau_{tot}$$

where $a_{i,j}$ are real number parameters of each rule.

Given the function

$$\tau_{ext} : \tilde{X} \to \tilde{Y}$$

where $\tilde{X} \subset \Re^n$ and $\tilde{Y} \subset \Re$, we wish to construct a fuzzy system

$$\tau'_{ext} : X \to Y$$

so that

$$\tau'_{ext}(x) = \tau_{ext}(x) + e(x)$$

for all $x \in X$, where the approximation error $e(x)$ should be as small as possible.

For each of the three inputs $q_e, \dot{q}, \tau_{tot}$ of the fuzzy system (see Fig. 2a), three membership functions (MF) of triangular type are used that represent the linguistic values *small, medium, high*. With this relatively small number of MF and the number of inputs, grid partitioning is used to generate rules by enumerating all possible combinations of MF and creating a complete rule-base ($3^3 = 27$ rules).

The training of the FIS is a two-stage process that uses a combination of the least-squares method and the back-propagation gradient descent method to emulate a given training data set. During the forward pass the input signals are supplied and the consequence parameters are updated using the least square estimate method. In the backward pass, the error rates of the forward pass propagate towards the inputs and the premise parameters are updated using the gradient method. This learning process is continued until the change in output is zero and in comparison with the conventional gradient descent method, this hybrid process cuts down substantially the convergence time (Jang, 1993).

2.2. Statistical time series modelling

Statistical time series methods use scalar or vector random signals of the analysed structure that are capable of describing its dynamics (Sakellariou and Fassois, 2008). The principle of these methods for detecting collisions is based on the fact that the contact forces exerted to the robot arm cause changes in the dynamic system identified by the time series model. In order to achieve the best performance for this application, the time series model should be capable of describing the non-linear dependency of external joint torque with the position of the manipulator. Therefore, it is proposed to model the measured torque in the robot joint by means of an externally-dependent Auto

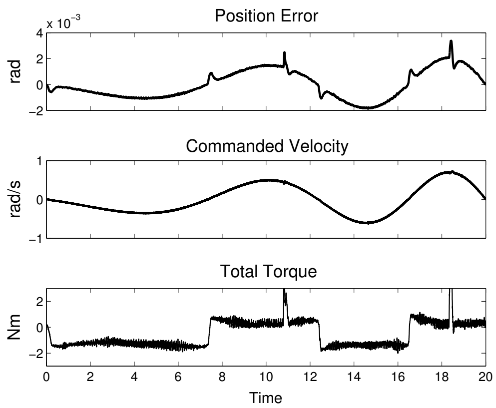

Fig. 1. Inputs of training that include collisions

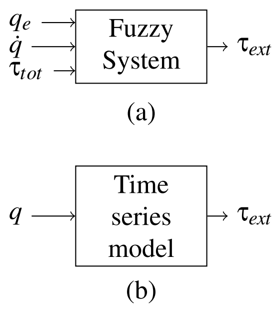

Fig. 2. Inputs and outputs of the (a) fuzzy inference system and (b) of the time series model

Regressive (AR) model of the following form:

$$\tau_{ext}[t] = -\sum_{i=1}^{n_a} a_i(q) \cdot \tau_{ext}[t-i] + w[t], \qquad (3)$$

$$w[t] \sim NID(0, \sigma_w^2)$$

where t is the normalised discrete time, $\tau_{ext}[t]$ is the signal to be modelled, $a_i(q)$ are the externally dependent model parameters, n_a the model order, and $w[t]$ is a Normally Independently Distributed (NID) random process with zero mean and variance σ_w^2. The proposed method differs from conventional AR models, because the model parameters $a_i(q)$ are a function of an external variable q, which for the current application, is the measured joint position (see Fig. 2b. In this way, the model is capable of describing the dependency of the dynamics of the robotic arm with the joint angle.

The model is completed by formulating explicitly the dependency of the model parameters $a_i(q)$ with the external variable q in the form of a Taylor series:

$$a_i(q) = \sum_{k=0}^{p_a} a_{i,k} \frac{q^k}{k!} \qquad (4)$$

where $q \in \mathbb{R}(0,1)$ is the normalised external variable within the specified range, $a_{i,k}$, $k = 0, \ldots, p_a$ are the projection parameters of the model, and p_a is the order of the power series. The identification of the externally dependent AR model consists of the selection of the model and power series orders, n_a and p_a, respectively, and the estimation of the projection parameters $a_{i,k}$. The estimation of the projection parameters is carried out by the minimisation of the one-step ahead prediction error $e[t]$ of the model, which is posed formally as:

$$\begin{aligned} \hat{\theta} &= \arg\min_{\theta} e^2[t] \qquad (5) \\ e[t] &= \tau_{ext}[t] + \sum_{i=1}^{n_a} a_i(q) \cdot \tau_{ext}[t-i] \end{aligned}$$

where $\hat{\theta}$ is the estimated parameter vector.

The model order selection is carried out heuristically by examining models with different orders and selecting the one that provides the best performance with the least number of parameters. To do so, performance measures such as the Residual Sum of Squares (RSS) or the Bayesian Information Criterion (BIC) are used (Sakellariou and Fassois, 2008).

The collision detection is performed by assessing the value of the prediction error of the externally dependent AR model. An increased prediction error indicates that there is a contact with the manipulator. Then, a threshold value σ_H can be selected, so that if $|e[t]| \geq \sigma_H$ then a collision is detected (Fassois and Sakellariou, 2009). The threshold σ_H is defined according to some probability value, namely, σ_H is the value for which $|e[t]|$ has a 90% of chance to be lower than. For example, the threshold values $\sigma_H = 2\sigma_w$ and $\sigma_H = 3\sigma_w$ cover a probability of 95% and 99.7% respectively.

3. Training

The training was conducted using data from the experimental setup that is based on a KUKA LWR IV manipulator, as it is shown in Fig. 3. The robot performed a single joint motion around the vertical axis. The selected excitation signal q was a sinusoidal profile of the joint position since it enables the sufficient dynamic excitation of the structure and the acquisition of rich signals. The sine amplitude was constant and the frequency was linearly increasing between 0.05Hz and 0.3Hz. This frequency produced an angular velocity of up to 2rad/s and linear velocity at the end-effector up to 1m/s.

The training data were divided in two sets: in the first set the robot joint performed the sine motion without any external force applied to the robot body and in the second set the same motion was performed with the user simulating collisions suddenly and stochastically with his hand. The forces were applied directly to a force sensor attached to the robot end, which was an ATI F/T Nano 25, and were translated into torques on the joint. During the experiments the robot was commanded to move with position control mode and no reaction strategy was implemented. The simulated collisions were applied momentarily on random time and the safety of the human during this experiment was succeeded by the ability of the arm to retreat before large forces rise.

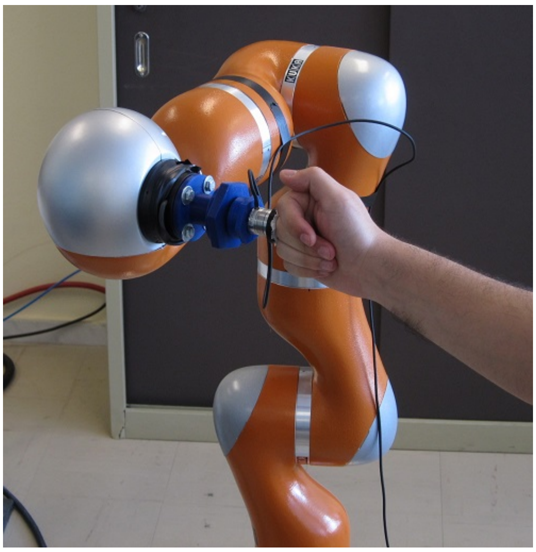

Fig. 3. Experimental setup with the KUKA LWR and an external force sensor attached to the end.

3.1. Fuzzy System Training

Using the data with and without contact, the fuzzy system was created and trained as it was described in section 2.1. A total number of 70.000 input-output pairs were used that were collected at a frequency of 500Hz and the training process lasted 10 seconds using a computing software on an average dual-core processor.

The trained fuzzy system is evaluated with the same data-set that was used for the training. The difference between the collision torque measured by the external sensor and the estimated output of the fuzzy system are illustrated in Fig. 4. It is clear that the approximation error of the collision torque is quite large (Fig. 4a). However, for the contact-free motion (Fig. 4b) the average error is very small (0.1Nm) and the maximum error value (0.4Nm) can be used as the threshold above which, a collision is assumed.

To examine more carefully the approximation error, the estimated collision torque from the fuzzy system and the actual collision torque that is measured from the external force sensor are compared as it is shown in Fig. 5. Even though the fuzzy system underestimates the collision torque, in conjunction with the small average error in contact-free motion, a collision can be identified very fast (14ms after its occurrence). The difference between the estimated torque and the small delay is caused by the non-collocation of the force and torque sensors.

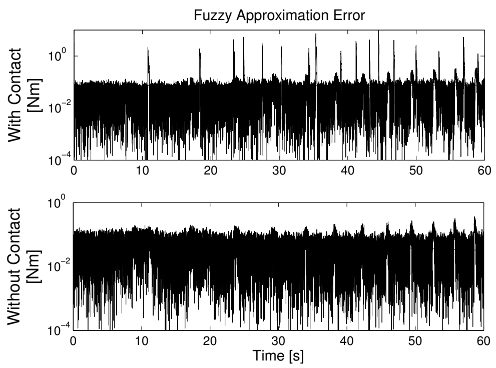

Fig. 4. Fuzzy approximation error on data with and without contact.

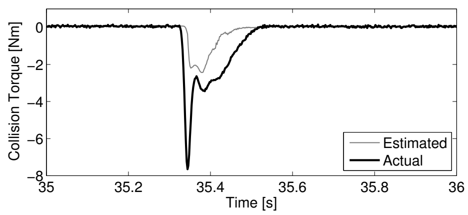

Fig. 5. Fuzzy approximated and actual measured collision torque.

3.2. Time Series Training

The externally dependent AR model presented in section 2.2, estimates the collision torque referenced to a joint using the time series with the measured joint angle as the external variable and the data-set with contact-free motion. The external force sensor is not used for the training in this method. The joint torque and angle time series are down-sampled at 100Hz and the order of the externally-dependent AR model is selected using the Bayesian information criterion (Fassois and Sakellariou, 2009). For that purpose, externally-dependent AR models are estimated using $n_a = \{1,\dots,20\}$ and $p_a = \{1,\dots,10\}$. The model with the lowest BIC is selected, leading to an externally-dependent $\mathrm{AR}(19)_5$ model. Figure 6 shows the estimation error of the model for the data-set of contact-free motion. The standard deviation of the prediction error during normal operation of the manipulator (without collision) is identified as $\sigma_w = 0.1463$ Nm.

Figure 7 illustrates a comparison between the actual external torque and the external torque predicted by the externally-dependent $\mathrm{AR}(19)_5$ model during a collision from the train data-set. The magnitude of the predicted collision torque is very close to the actual but with a small overshoot and a delay.

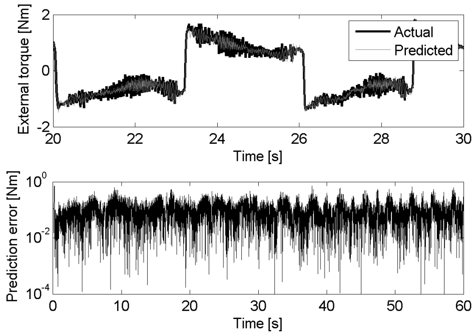

Fig. 6. Externally-dependent $\mathrm{AR}(19)_5$ approximation of the external torque in the training data. Top: Actual and predicted external torque. Bottom: Prediction error.

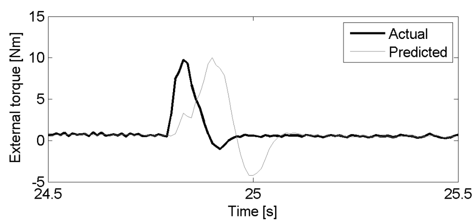

Fig. 7. Comparison of the actual and predicted external torque of the externally-dependent $\mathrm{AR}(19)_5$ model.

4. Evaluation

To verify that the proposed methods are able to identify collisions, we test them in the experimental setup by commanding the robot to perform a single joint motion around the vertical axis with steady velocity profiles. Since the training data were obtained only with variable velocity, by using a constant profile we can evaluate the methods considering their ability to generalised under a variety of conditions. Moreover, the collision detection systems are active during the acceleration phase and their realistic performance is demonstrated.

The contacts to the robot body are obtained by a human who touches the robot body with his hand. The forces are applied to the force sensor which is mounted on the robot end, in order to measure the actual contact force and compare it with the estimated one. A collision is identified from the fuzzy system as the external torque applied to the joint and from the time series method as a variation between the actual measured torque and the predicted one.

The evaluation of the collision detection is not implemented to the robot controller, since we are interested on identifying collisions and we are not investigating a reaction strategy. Consequently, we the record the data of the steady velocity experiment and we provide them to the trained systems. It should be noted that both methods can be easily implemented on the robot controller for real-time collision detection. In order to identify a collision, a threshold value has to be exceeded, that is selected equal to the maximum train error from contact-free motion training. The detection time is calculated as the elapsed time from the detection of a collision by the external force sensor to the moment when the estimated force exceeds the threshold.

To compare the proposed trained methods with an explicit model-based approach, the estimation of the external torque was obtained by the built-in model of the KUKA robot that uses a state feedback controller with inputs $q, \dot{q}, \tau_{tot}, \dot{\tau}_{tot}$ (Albu-Schäffer et al., 2007). The trained methods are evaluated with two different speeds, equal to 0.5rad/s and 1.0rad/s respectively, as it is shown in Fig. 8, 9 and with one collision occurrence on each. The evaluated collision torque from the estimation is illustrated along with the contact torque that is measured by the external force sensor and a model-based estimation of the external torque as it is provided from the robot controller.

More specifically, as it is shown in Fig. 8, the fuzzy inference system is able to identify the collision at a very fast rate with similar performance in both velocities. The estimated contact torque by the fuzzy system is very close to that of the model-based approach during the development of the collision and that verifies the success of the fuzzy collision detection system, assuming that the model is correct. However, during the acceleration of the robot link at the beginning of the motion, the model-based approach estimates an external torque equal to 1.2Nm while the fuzzy system estimates zero contact. The external sensor confirms that the contact force is equal to zero and consequently, the fuzzy system has greater sensitivity on identifying collisions as it is not limited by the problem of unmodelled dynamics as the model-based approach.

The results obtained by the time series approach are shown in Fig. 9, where a comparison is made between the actual external torque measured by the torque sensor, the predicted external torque and prediction error of the externally-dependent AR model. The prediction error is shown with the threshold σ_w for the detection of a collision that is equal to 1.3Nm.

Summarising the results from each method presented in Tab. 1, we come to the conclusion that the fuzzy inference system is able to achieve the smallest collision threshold value among the methods and as

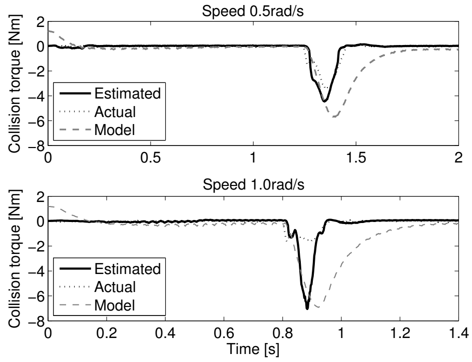

Fig. 8. Comparison of collision torque from fuzzy identification method, model-based method and measured.

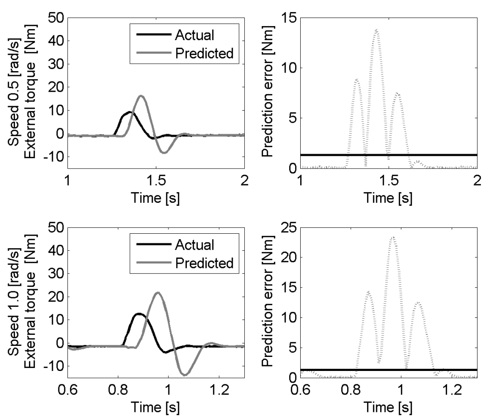

Fig. 9. Comparison of the actual external torque with the predicted external torque and prediction error of the externally-dependent AR model in the validation data.

Tab. 1. Comparison table between the collision detection methods for two different experimental velocities.

Detection Method	Threshold	Detection Time	
		0.5rad/s	1rad/s
Fuzzy	0.4Nm	28ms	16ms
Time series	1.3Nm	26ms	32ms
Model based	1.2Nm	42ms	28ms

a result the quickest detection times. The selected fuzzy inputs and the training with the two data-sets proved to be capable of identifying collisions without the problems of unmodelled parameters of the model based approach.

On the other hand, the time series method is the most efficient since it does requires one sensor less than the fuzzy and only contact-free data for the training that are more easy to acquire, but this is obtained to the expense of a largest threshold value that affects the detection time.

5. Conclusions

In this paper, two novel methods for robot collision detection are proposed based on fuzzy logic and times series modelling. Unlike previous methods that suffer from unmodelled parameters and low estimating accuracy, the proposed methods are able to detect the occurrence of a collision of the robot with a human hand very quickly and also the magnitude of the collision joint torque.

The fuzzy inference system is designed to evaluate directly the collision joint torque and is trained using data that are collected from the proprioceptive sensors of a KUKA LWR robot single joint. To enable better sensitivity of the fuzzy system on detecting collisions, the training data are derived from contacts of the robot body by a human hand. In that way, a richer signal is obtained and the train error becomes very small. On the other hand, the proposed time series method is more efficient since it is trained only with collision-free motion and by using one sensor less than the fuzzy system.

The evaluation of the proposed methods shows that the fuzzy system can detect collisions very fast and accurately by having the lowest threshold value. This is succeeded by the appropriate selection of the system inputs and by the ability of the fuzzy system to approximate the collision joint torque. The time series system after identifying the link dynamics through the recursive training, it can estimate a collision torque by only using the measured joint position signal. This efficiency is accomplished against the detection threshold, which is higher than the fuzzy system and similar to that of the model-based approach.

The results of this paper require further analysis and experimental evaluation in order to be used for the implementation of a collision detection system considering motion of all joints. Moreover, the accurate estimation of the collision magnitude can be used to develop an appropriate collision reaction strategy that mitigates the reaction forces.

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