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Prediction-Based Reactive Control Strategy for Human-Robot Interactions

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Abstract— **In this paper a reactive control strategy intended for human-robot interactions (HRI) is presented. A conventional reactive control scheme is reviewed first. This is followed by the introduction of a new prediction-based reactive control strategy. The new control strategy considers foreseeable dangerous events by predicting human motion using artificial neural networks, based on the previous pattern of the motion. This approach enables a robot to foresee an upcoming danger in order to take preventive actions before the danger is immanent. Experimental results for a CRS-F3 robot manipulator are presented in order to demonstrate and validate the effectiveness of this method.**

I. Introduction

SINCE THEIR inception, robot manipulators have been an integral part of industrial automation resulting in much higher productivity while relieving humans from laborious tasks. In recent years, the integration of robotic systems into human environments has become one of the most prominent milestone of the robotic community [1]. Although, motivated by in-depth research, it is not difficult to imagine the socio-economic benefits of an interactive environment in which robots and humans can share their space [2]. At the same time, the prospect of introducing robots into human environments has illuminated a universe of safety concerns among standardization bodies, robotic manufacturers, and the researchers. This is simply due to the fact that all existing safety norms are founded based on isolating robots from their surroundings and consequently are at odds with the requirements of an interactive environment [3]. Thus, much research has focused on developing a new breed of safe and intelligent robots that can share a common workspace with humans to perform common tasks either collaboratively or individual tasks amicably [4]. In this regard, a significant body of the work has focused on mechanical design of such robots. These studies mainly pursue a mechanical design that reduces manipulator link inertia and weight by using lightweight but stiff materials, complemented by the presence of compliant components in the structure in order to reduce the instantaneous severity of an impact [4][5][6].

Controlling robots intended to interact with humans constitute another important aspect of the introduction of robots into the human environments [7]. In order to develop effective and dependable control strategies for HRI, the concept of safety (or equivalently the lack of it, defined as danger) needs to be clearly addressed. The application of such methods as artificial potential fields [8], elastic strip framework [9], and linear impedance control [10] can partially address the issue when the distance of the robot to the obstacle (e.g., human) is used as a criteria for safety evaluation. Although these methods are highly successful, a more effective collision avoidance algorithm can be obtained by considering other factors affecting the risk of collision. In order to identify the risk involved in the current operation a danger index can be defined such that it characterizes the impact force not only based on the distance of the robot to the obstacle, but also the relative velocity, the inertia, etc., [11]. Such indexes can be used for path planning of an interactive robot, commonly referred to as safe planning [12]. In our previous work [13], an optimal safe planning method was developed by taking advantage of one such danger evaluation method. In order to enhance the previous method in responding to unanticipated dangerous situations arising in interactive environments, it seems natural to consider a sensor-based online reactive component that can assess and predict the value of the danger not only for the present moment but also for the near future. The information from the sensor can be used as a means of modifying the current robot path to avoid possible (predicted) risks. The success of this method hinges upon an accurate and high speed prediction of future dangers. The current study addresses this issue using a prediction-based danger evaluation method. By taking advantage of artificial neural networks (ANN), a technique is developed that allows prediction of the future trajectory of a human close to a robot. Using this technique, a safety strategy for detecting and reacting to upcoming dangers is proposed. In this way, a preventive action is taken prior to the occurrence of a danger. This will allow to compensate for the delay results from the modification of the path and danger evaluations. To illustrate the effectiveness of the proposed method, several simulation and experimental results are presented and compared with a conventional reactive control strategy.

II. Prediction of the Human Trajectory

A. Motivation

Generally speaking, humans tend to react differently toward their robot counterparts than other humans. It is therefore, expected that a more natural robot motion will assist to change the acceptance of robots into the human environment [2]. Emulating human-like behaviors by a robot results in a more effective integration of man and machine. For instance, when the concept of perspective-taking that occurs in collaborative environments (e.g., a team of astronauts)

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was applied to a robotic system, it resulted in an improved collaboration between the robot and the human [7]. Also, other studies suggest the importance of touch [14] and body language [15] in approving an action or conveying an expectation in human-robot interactions. In this section a technique for predicting expected motion of a human (when walking in the vicinity of a robot) is developed. The approach is motivated by ordinary human-human interactions. As the awareness of a person of another person's motion allows for a mental prediction of the future motion and preventive action, including such an ability in the control strategy of an interactive robot can significantly improve its effectiveness toward safety. The application of human motion prediction, through weighted averaging of previous human velocities, in HRI is reported previously [16]. However, this approach suffers from large prediction errors. In this section, we will introduce the architecture of an ANN for accurate human motion prediction and use its results in a danger evaluation scheme to assess the risk involved in the motion. This will be then used in a new reactive control strategy.

B. Motion Prediction

The human motion follows a complex pattern that cannot be presented with a simple dynamic model. The proposed solution is to observe the pattern of the human motion and predict his motion in the near future using an ANN. In our previous work, we reported on a new sensory system that measured the $x - y$ location of fixed and mobile obstacles and accompanied a firmware specifically designed for the identification of human obstacles and their orientations [17]. The prediction becomes possible thanks to the information obtained from this sensory system. To simplify the prediction process, human trajectories in x and y directions are treated separately. Fig. 1 shows an *empirical* architecture of a feed-forward ANN for x direction that comprises 5 input neurons, 8 hidden neurons, and 3 output neurons. The hidden layer has a tan-sigmoid transfer function, while the output layer uses a linear transfer function. The inputs of the network are the relative displacements of the human in the last four steps (i.e., $\Delta x(n-i) = x(n-i+1) - x(n-i)$, $i = 1, \ldots, 4$) as well as the body orientation $\alpha(n)$ (the direction of human heading, see [17]). The outputs are the next three relative displacements (i.e., $\Delta x(n+i) = x(n+in_s) - x(n+(i-1)n_s)$, $i = 1, \ldots, 3$), where n_s is equal to the number of steps during which the displacement occurs. A similar ANN is used for the motion in y direction.

As part of the architecture of an ANN, the number of inputs can have a significant effect on the accuracy of the prediction. While a large number of inputs (history of motion) may result in more accurate and further prediction of the future steps, it places the prediction process at disadvantages, since a large number of inputs (i) adds to the computational complexity of the network, (ii) makes the network reluctant (sluggish) to predict sudden changes in human motion, and (iii) entails more time (sufficient number of steps) for learning the pattern of the motion of each new human obstacle as they appear on the sensory system. Another notable point is the use of the body orientation as an input. This input considerably decreases the prediction error since the body orientation is a good metric to predict the future direction of the motion. The ANN requires to learn the pattern of the human motion using a combination of both off-line (batch) and online (incremental) training. None of these training methods are individually sufficient. To this effect, an energy function of the network error, introduced next, is used for switching between the two training methods.

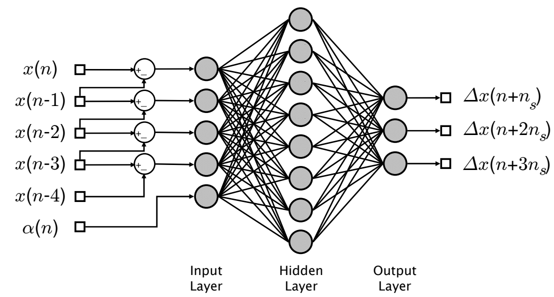


Fig. 1. The architecture of ANN used for human motion prediction in x direction (similar structure is used for the y direction).

C. Training of the Network

In order to obtain a training data set, a typical robot workspace (Fig. 2) with several pre-determined obstacles is considered. A set of randomly selected points visited by the human are also considered. By selecting a different order in which the points are visited, different training data sets are generated. Each data set includes the relative displacement along x and y axes as well as the body orientation.

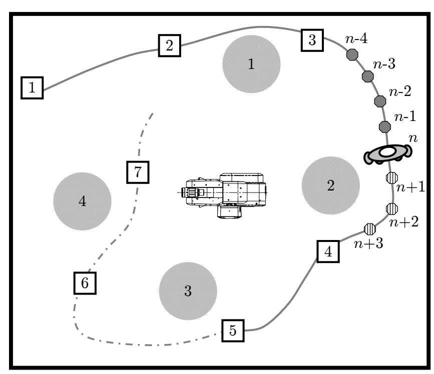
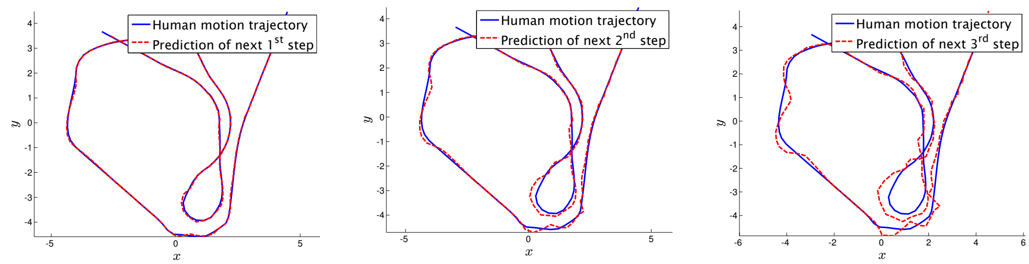


Fig. 2. Top view of the robot workspace. The gray areas are the pre-defined obstacles, numbered rectangles present random points visited by the human, and the hexagons present the preceding and future human's steps following instant n.

The network is then trained using the obtained data set and the Levenberg-Marquardt algorithm [18]. In this algorithm, the energy function of the error is used as an indicator of the performance. The energy function is defined as,

$$E_j = \Big(\frac{1}{m}\sum_{i=0}^{m}(\Delta x(i+jn_s) - \Delta x_d(i+jn_s))^2\Big)^{0.5} \quad (1)$$



(a) (b) (c)

Fig. 3. Trajectory prediction for (a) one, (b) two, and (c) three steps for a motion pattern (this pattern was not encountered during the training).

where $\Delta x(i+jn_s)$ and $\Delta x_d(i+jn_s)$ $(j = 1, \ldots, 3)$ are the predicted and the actual values of the next j^{th} displacement, respectively. Moreover, m is the number of samples in the training set. To study the effect of the number of inputs and the use of body orientation as an input, 6 different ANNs are considered. Table I compares the values of the error energy function. Clearly, the larger the number of inputs is, the more accurate prediction can be obtained. Furthermore, it is evident that including the body orientation input can significantly decrease the error energy. Based on the results summarized in Table I, the network architecture depicted in Fig. 1 (i.e., network No. 2 in the table) was adapted to meet the accuracy and speed requirements for the problem at hand. The performance of the adapted network was further evaluated for different motions with various complexities. One of these tests is shown in Fig. 3 which compares the output of the ANN with the actual motion. The motion is predicted for the next one, two, and three steps. The values of the error energy for these cases are equal to $E_1 = 1.7$ cm, $E_2 = 3.6$ cm, and $E_3 = 5.8$ cm, respectively. In all cases there is a good match between the actual and predicted motions. This indicates the suitability of the method for our purpose (foreseeing the upcoming dangers).

TABLE I

COMPARING MOTION PREDICTION PERFORMANCE OF 6 ANNS

Network Number	1	2	3	4	5	6
No. of inputs	4	4	4	6	6	6
Body orientation used		✓	✓		✓	✓
n_s	1	1	2	1	1	2
E_1 (cm)	4.5	3.0	8.4	3.2	1.5	4.9
E_2 (cm)	5.4	3.7	10.9	4.4	2.1	7.3
E_3 (cm)	6.5	4.8	17.4	5.2	3.0	11.0

III. PREDICTION-BASED REACTIVE CONTROL FOR HUMAN-ROBOT INTERACTION

In this section, a new control strategy that combines motion prediction and danger evaluation results is introduced. Existing reactive strategies are mainly impedance based in which the motion is modified in response to a virtual force representing the danger. The motion is modified through a series of danger-reaction steps. It is clear that the prediction of the future dangers can significantly contribute to the safety of the motion. This should not come as a surprise if one remembers how naturally the notion of anticipatory motion adjustments is integrated in the normal human movements [19].

A. Formulation of the Danger Index

The evaluation of the level of danger is one of the key elements in the systems intended for interaction with humans. Due to special shape of the human body, an accurate model of the body is essential for defining a danger index. In our previous work [20], an accurate, yet simple model for the human body was developed using superquadric shapes [21]. The main advantage of this model is its simplicity and accuracy in obtaining the distance of an arbitrary point in 3D space to the surface of the body. This model provides a pseudo-distance, κ [20] that is used in the definition of a danger index. Such indices are normally defined as a product of several factors affecting the level of danger, e.g., distance factor f_D and velocity factor f_V, etc. One such definition is as follows,

$$DI(\kappa_d, \kappa_v) = f_D(\kappa_d) f_V(\kappa_v) \tag{2}$$

where κ_d and κ_v are the pseudo-distance of the critical point (*closest point*) to the obstacle (e.g., human) and its rate of change, respectively. Also, f_D and f_V (the distance and velocity factors) are defined as,

$$f_D(\kappa_d) = k_D\left(\frac{e^{-\kappa_d}}{\kappa_d} - \frac{e^{-\kappa_{d_{\max}}}}{\kappa_{d_{\max}}}\right)^2 \mathbb{S}(\kappa_{d_{\max}} - \kappa_d) \tag{3}$$
$$f_V(\kappa_v) = k_V(\kappa_v - \kappa_{v_{\min}})^2 \mathbb{S}(\kappa_v - \kappa_{v_{\min}})$$

in which, $k_D = \left(\frac{e^{-\kappa_{d_{\min}}}}{\kappa_{d_{\min}}} - \frac{e^{-\kappa_{d_{\max}}}}{\kappa_{d_{\max}}}\right)^{-2}$, $k_V = (\kappa_{v_{\max}} - \kappa_{v_{\min}})^{-2}$, $\kappa_{d_{\min}}$ is the minimum allowable distance to the obstacle, $\kappa_{v_{\max}}$ is the maximum allowable velocity, $\kappa_{d_{\max}}$ and $\kappa_{v_{\min}}$ are the effective ranges for the distance and velocity factors, respectively, and $\mathbb{S}(.)$ is the unit step (heaviside) function (for more details see [20]).

B. An Impedance-Based Reactive Control Strategy

In the following, the notion of impedance-based reactive control strategy using danger index is briefly reviewed [22]. Given a threshold for the value of the danger index $DI_{\max}$, the results of the danger evaluation for the critical points (closest points on the robot links to the obstacle) can be utilized to trigger a corrective control action in the robot motion. Here, exceeding the threshold $DI_{\max}$ results in a virtual repulsive force F_c, at the location of the critical point that is given by,

$$F_c = k_{c_1} DI(\kappa_d, \kappa_v)\mathbf{u_c} \quad (4)$$

where k_{c_1} is a proportionality constant and $\mathbf{u_c}$ is a unit vector along the line connecting the critical point to the closest point of the body. The force moves the robot away from the danger through a series of steps as the danger is encountered. In case of multiple links exceeding the threshold value, a repulsive force is calculated for each link separately. Following successful reduction of the danger index below the threshold, a virtual damping torque (e.g., $\tau_d = -b\dot{q}$ with b as the damping factor and $\dot{q}$ as the joint velocity) is applied to stop the robot.

C. Prediction-Based Reactive Control Strategy

In this section, a new prediction-based reactive control strategy for human-safe robots is proposed. The new method utilizes the future human motion predicted by the ANN in order to obtain a value of the danger index. The predicted values of the danger index will then be used in conjunction with the impedance-based control scheme in order to maintain the danger index consistently below its threshold values.

Previously, we introduced the architecture of an ANN that could predict the human motion for the next three steps. By fitting a curve of a proper order to these steps, one can obtain a future motion trajectory of the human. The prediction-based reactive control method utilizes this trajectory in its entirety to obtain a modified path for the robot. To be more specific, let us assume a case in which one or more robot links crosses the predicted human trajectory. The impedance reactive control scheme simply pushes the robot away to a location whose corresponding danger index is less than $DI_{\max}$. Since such reactions are only due to the present value of the danger index, the new location of the robot may or may not cross the future human trajectory. Thus, as the human continues to move along his trajectory, another dangerous situation may arise which in turn will call for further reaction. Clearly, this method suffers from an inefficient way of dealing with current dangerous situations and forestalling future ones. To address this issue, we introduce a new approach that not only can guarantee the safety of the human at present, but it also avoids any interference with future motions of the human. The new approach utilizes the predicted human trajectory in the definition of a new *path danger index* PDI that for an arbitrary point along the link of a robot is defined as,

$$PDI(n_0, d_p) = C_p(e^{\lambda(\hat{d}_p + \hat{\kappa}_{d_{\max}})} - 1)\mathbb{S}(\hat{\kappa}_{d_{\max}} + \hat{d}_p) \quad (5)$$

where $\hat{d}_p = (-1)^{n_0+1} d_p$, $C_p = (e^{\lambda \hat{\kappa}_{d_{\max}}} - 1)^{-1}$, d_p is the shortest distance of the considered point to the path of the human, λ is the rate at which the danger index increases near the human path, $\hat{\kappa}_{d_{\max}} = \kappa_{d_{\max}} + \frac{w_T}{2}$, w_T is the average width of the human trunk, and n_0 is the number of times that the portion of the link, starting from the base of the robot to the considered point, crosses the human path. The value of n_0 plays a key role in evaluating the *path danger index*. To exemplify the new danger index, let us consider the 3-DOF planar manipulator depicted in Fig. 4 and an arbitrary human path. In this example, the human path is shown using a dashed-line in xy plane. In general, the human path in three dimensional space can be represented using a manifold that passes through all human steps and has an infinite height along the z axis. The figure plots the value of PDI for the assumed configuration with respect to the human path. Starting from the base and moving along the links, it is clear that as the link and the human path cross (future interference - high risk), the value of PDI will exceed 1, and once the link crosses the path for the second time (no interference - low risk region) this value will become less than 1 again. In this way, more emphasis is given to the part of the robot which causes future obstructions in the human path.

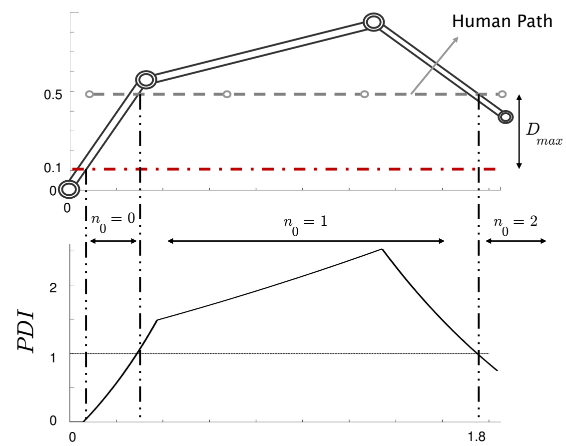
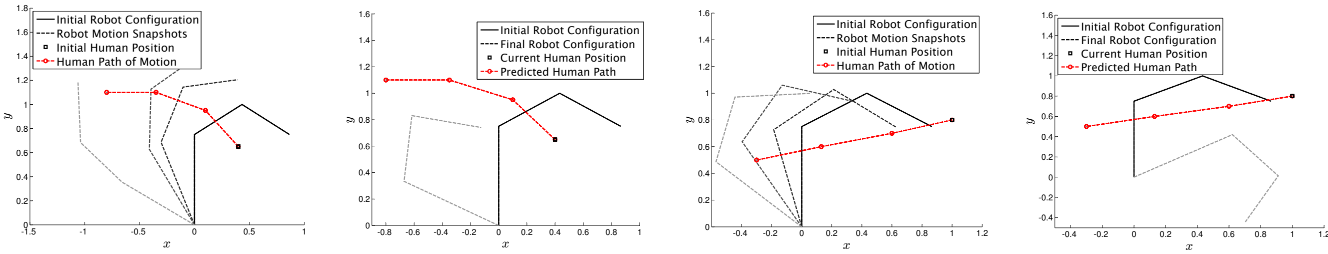


Fig. 4. Top: a 3-DOF planar manipulator and an arbitrary human path; Bottom: the value of *path danger index* for each point along the links ($\hat{\kappa}_{d_{\max}} = 0.4$m, $\lambda = 1$, and the robot base is assumed at $(0, 0)$).

Combining the *path danger index* with the danger index defined in (2) and applying the repulsive force of each index to the robot yields a new prediction-based reactive control strategy that meets all performance and safety requirements. The new scheme uses the values of the danger index acquired for the critical point on each link and apply a virtual force F_c, when these values exceed the predefined threshold of the danger index. This will guarantee the safety of the human at present time. Additionally, the new scheme uses the maximum value of the *path danger index* of a point on each link and apply another virtual force F_p in order to clear the future path of the human and avoid any danger in the future. The value of the virtual force is a function of *path danger index* and is given by,

$$F_p = k_{c_2} PDI(n_0, d_p)\mathbf{u_p} \quad (6)$$

where k_{c_2} is a proportionality constant and $\mathbf{u_p}$ is a unit vector connecting the point on the link with maximum PDI to the closest point on the human path. The application of this virtual force will push the links in a direction that does not interfere with the human path.



(a_1) (b_1) (a_2) (b_2)

Fig. 5. Simulation Results for case study 1 (a_1 and b_1) and case study 2 (a_2 and b_2). These figures compare the performance of (a_1,a_2) Impedance- and (b_1,b_2) prediction-based reactive control strategies.

IV. Results

This section summarizes simulation and experimental results for the prediction-based reactive control scheme. Simulation results for a 3-DOF planar robot are compared to those obtained from the impedance-based reactive control scheme. Furthermore, experimental results for a 6-DOF CRS-F3 robot manipulator are presented to validate the effectiveness of the proposed method.

A. Simulation Results

A 3-DOF planar robot (see Fig 4) is considered in order to study the feasibility and effectiveness of the proposed method. The parameters used throughout the simulations are listed in Table II. Note that the simulation results are for the sake of demonstrations and the dimensions of the human body may not be a true representative of an actual human. Each method (impedance- or prediction-based method) is evaluated for two different cases.

TABLE II
Parameters of Simulation Studies

Parameter	Description	Value
l_1, l_2, l_3	Length of links 1, 2, and 3	0.75,0.5,0.5 m
λ, b	Slope and damping factors	1, 0.1
k_{c_1}, k_{c_2}	Proportionality constant in (4) and (6)	1,1
w_T, l_T	Torso width and thickness	0.2, 0.07m
$\kappa_{d_{\min}}$	Minimum allowable distance to obstacle	0.2 m
$\kappa_{d_{\max}}$	Maximum effective range for f_D	0.2 m
$\kappa_{v_{\min}}$	Minimum effective range for f_V	-0.1 $\frac{\mathrm{m}}{\mathrm{s}}$
$\kappa_{v_{\max}}$	Maximum allowable relative velocity	0.1 $\frac{\mathrm{m}}{\mathrm{s}}$
$DI_{\max}$	Maximum acceptable DI and PDI	0

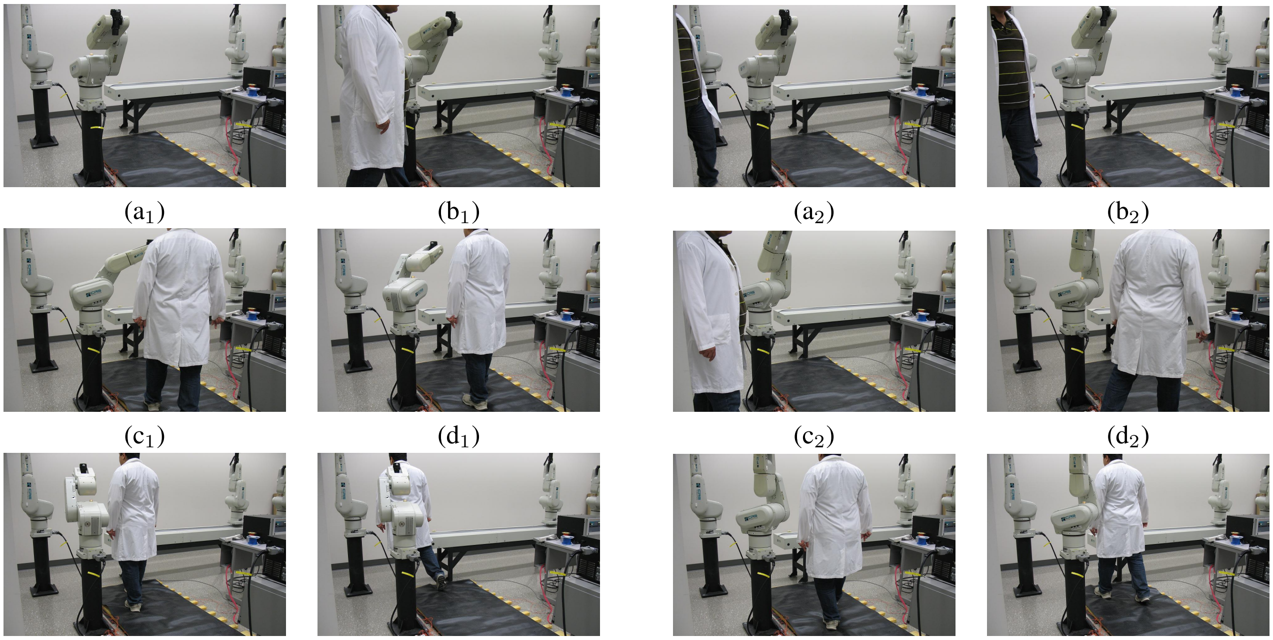
In the first case, a human is considered to be surrounded by all three links of the robot while approaching the robot, while, in the second case, it is assumed that a human is approaching the robot from the right-hand side. The results are presented in Fig. 5. As observed both methods are successful in moving the manipulator away from the present location of the human and avoiding arising dangerous situations. However as it can be seen in Figs. 5(a_1 and a_2), using the impedance-based method, the robot finds itself blocking the human path in each step, as the human walks along the path. This procedure eventually leads to a situation (local minimum) in which neither the human nor the robot can continue their motions without encountering a danger. However, the predication-based reactive control as shown in Fig. 5(b_1 and b_2) pushes the robot in such a way that it clears the current and future path of the human. The proposed method successfully and intelligently forestalls and clears the future dangerous situations.

B. Experimental Results

This section presents experimental results for impedance- and prediction-based method on a 6-DOF CRS-F3 robot manipulators. A real-time control platform consisting of a P4, 2.8GHz computer, a C500C CRS controller, and ActiveRobot software were used [23]. The required information about the human were obtained using a new sensory system called safety mat [17]. The motion prediction ANN and reactive control algorithms were coded in C++ classes to be added to ActiveRobot software. In this section, average values for the width and thickness of human torso were considered ($w_T = 0.4\ m$, $l_T = 0.25\ m$). Also, the minimum allowable distance and maximum allowable velocity to the obstacle were $\kappa_{d_{\min}} = 0.1\ m$ and $\kappa_{v_{\max}} = 1\ \frac{\mathrm{m}}{\mathrm{s}}$, respectively. In addition, effective ranges considered for distance and velocity factors were $\kappa_{d_{\max}} = 0.2\ m$ and $\kappa_{v_{\min}} = -0.1\ \frac{\mathrm{m}}{\mathrm{s}}$, respectively. The rest of the parameters were the same as the ones in Table II. The performance of the impedance- versus prediction-based methods for a case in which a human walks around the robot on a curved path (close to the base of the robot) are compared. Figs. 6 (a_1-f_1) presents the snapshots of the robot for impedance-based method. The robot moves on a step by step basis to temporarily clear the path of the human without considering the future path of the human. Thus, the first joint of the robot rotates about 180°. This clearly presents the shortcoming of the impedance-based method. On the other hand, the prediction-based reactive control method, as presented in Figs. 6 (a_2-f_2), efficiently pushes the second and third links of the robot to an upright direction in order to clear the path of human. The first joint of the robot moves much less than that in the impedance-based method. As a result, the danger is eliminated faster and the human can pass the robot with no obstruction. This shows the advantages of the prediction-based method.

V. Conclusion

This paper presented the results of a study on a reactive control strategy for HRI applications. It was shown that by



(a_1) (b_1) (a_2) (b_2)
(c_1) (d_1) (c_2) (d_2)
(e_1) (f_1) (e_2) (f_2)

Fig. 6. Experimental results for (a_1-f_1) impedance-based strategy (step by step retraction - high danger) and (a_2-f_2) prediction-based strategy (path clearance - fast elimination of danger).

using a feed-forward ANN the future motion trajectory of the human can be integrated in a reactive control safety strategy in order to foresee and react to an upcoming dangerous situation prior to its occurrence. It was shown that applying a prediction-based reactive control strategy can compensate for the delay due to danger evaluations and the modification of the path and can significantly improve the performance of the safety strategy. As for the prediction-based method, simulation as well as experimental results for a 3-DOF planar manipulator and a CRS-F3 manipulator were presented. The results showed high efficiency and intelligence of the presented safety strategy in ensuring human safety during human robot interactions. It was shown that prediction-based method are more successful in fast elimination of the current and future potential hazards in comparison to conventional reactive control methods.

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