

# Collision Detection of Manipulator Based on Adaptive Control Law

Taishi Matsumoto Kazuhiro Kosuge

Machine Intelligence and Systems Engineering  
Tohoku University  
Aoba-yama 01, Sendai 980-8579,  
JAPAN

matsumo@irs.mech.tohoku.ac.jp kosuge@irs.mech.tohoku.ac.jp  
<http://www.irs.mech.tohoku.ac.jp>

**Abstract**—In this paper, we propose a collision detection method of a manipulator based on the nonlinear adaptive control law proposed by Slotine and Li. The collision of a manipulator with its environment is detected by the difference between the actual input torques to the manipulator and the reference input torques calculated based on the manipulator dynamics. An adaptive control scheme is employed for the manipulator control and the parameter estimation of the manipulator. The reference input torques are calculated using the estimated manipulator parameters. The proposed collision detection scheme is applied to an industrial manipulator and the experimental results illustrate the validity of the proposed scheme.

## I. INTRODUCTION

Many robots have been used in industries for repetitive tasks with precise positioning. The robots are located in factories and their working spaces are isolated from humans for the safety of humans. Robots are expected to expand their application fields to our daily life, such as nursing, assistance of human workers [1][2] and so on. The safety of humans has to be guaranteed, even if the humans and the robots share their working space.

Much research has been done for obstacle avoidance of robots [3] [4], however it is not easy to avoid obstacles in unstructured real environments such as our living environments, where new robot applications are expected. If the robots, which are used in our living environments, have an ability to detect collisions with their obstacles, fatal accidents could be avoided. Yamada *et.al.* have proposed a collision detection scheme for a manipulator [5] based on comparison of the actual motor torques and the reference torques calculated from a dynamic model of the manipulator. The proposed contact detection scheme assumes that the dynamic parameters of the manipulator are known precisely, however, this assumption is not always satisfied for the robots used in our living environment.

We have proposed an alternative collision detection scheme for a manipulator based on an adaptive control of a manipulator and shown the validity of the method for one degree of freedom manipulator[6]. In the proposed scheme, we compare the actual input torques to the manipulator with the reference input torques calculated from the estimated dynamic parameters of the robot using adaptive control law[7]. The parameter convergence of the control scheme is also discussed for the adaptive control scheme. The method does not require a priori knowledge of the parameters of the robot dynamics, nor any hardware modifications or external sensors for the collision detection. In this paper, we apply the method to an industrial robot and show the validity of the method.

In the following part of this paper, we first briefly introduce the adaptive control algorithm proposed by Slotine et al. [7], and show that the parameter identification is possible based on the algorithm for most of manipulators. Then we develop a collision detection scheme for a robot based on the identified parameters by the adaptive control algorithm. The proposed collision detection scheme is implemented in an industrial manipulator and the experimental results illustrate the validity of the scheme.

## II. ADAPTIVE CONTROL LAW AND ITS PARAMETER CONVERGENCE

The dynamics of a  $n$ -link rigid manipulator is expressed as

$$\tau = H(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) \quad (1)$$

where  $q$  is a  $n \times 1$  vector of joint displacements,  $\tau$  is a  $n \times 1$  vector of joint torques,  $H(q)$  is a  $n \times n$  manipulator inertia matrix,  $C(q, \dot{q})\dot{q}$  is the  $n \times 1$  vector of centripetal and Coriolis torques, and  $G(q)$  is a  $n \times 1$  vector of gravitational torques.  $H(q)$ ,  $C(q, \dot{q})$  and  $G(q)$  includes unknown

parameters such as the inertia, the length, the weight of each link etc. These parameters are difficult to measure in practice.

In this section, we introduce the adaptive control law, which was proposed by Slotine et al [7]. Rewriting eq. (1), we have the following equation;

$$\begin{aligned}\tau &= \mathbf{H}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{G}(\mathbf{q}) \\ &= \mathbf{Y}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\mathbf{a}\end{aligned}\quad (2)$$

where  $\mathbf{a}$  is a  $m \times 1$  unknown parameter vector and  $\mathbf{Y}$  is a  $n \times m$  matrix. Eq. (2) means that eq. (1) is linear in terms of the manipulator parameters. Eqs. (3) and (4) show the adaptive control law for the manipulator.

$$\begin{aligned}\tau &= \hat{\mathbf{H}}(\mathbf{q})\ddot{\mathbf{q}}_r + \hat{\mathbf{C}}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}}_r + \hat{\mathbf{G}}(\mathbf{q}) - \mathbf{K}_D \mathbf{s} \\ &= \tilde{\mathbf{Y}}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}_r)\hat{\mathbf{a}} - \mathbf{K}_D \mathbf{s}\end{aligned}\quad (3)$$

$$\dot{\hat{\mathbf{a}}} = -\Gamma^{-1} \mathbf{Y}^T(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}_r) \mathbf{s} \quad (4)$$

where  $\mathbf{q}_d$  is a  $n \times 1$  vector of a desired trajectory,  $\tilde{\mathbf{q}} = \mathbf{q} - \mathbf{q}_d$  is a tracking error vector,  $\dot{\mathbf{q}}_r = \dot{\mathbf{q}}_d - \Lambda \tilde{\mathbf{q}}$ ,  $\ddot{\mathbf{q}}_r = \ddot{\mathbf{q}}_d - \Lambda \dot{\tilde{\mathbf{q}}}$  and  $\mathbf{s} = \dot{\mathbf{q}} - \dot{\mathbf{q}}_r$ . Where  $\Gamma$ ,  $\Lambda$  and  $\mathbf{K}_D$  are positive definite matrices. The unknown parameter vector  $\hat{\mathbf{a}}$  is updated by eq. (4). Slotine et al. proposed the above adaptive control law and showed that the position control for the manipulator was possible by the adaptive control without using the acceleration of the manipulator motion. Note that the parameter convergence is not always guaranteed, because the update of the parameter estimation stops if  $\mathbf{s} = 0$ .

Let us consider the parameter estimation error updated by eq. (4). If  $\mathbf{s} = 0$ , the parameter estimation stops by eq. (4). Therefore, the estimated parameter vector  $\hat{\mathbf{a}}$  does not necessarily converge to the actual parameters.

Consider the case of  $\mathbf{s} = 0$ . Substituting eq. (2) into eq. (3), we have

$$\mathbf{Y}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\mathbf{a} = \tilde{\mathbf{Y}}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}_r)\hat{\mathbf{a}} \quad (5)$$

Since  $\mathbf{s} = \dot{\mathbf{q}} - \dot{\mathbf{q}}_r = 0$ , we have  $\dot{\mathbf{q}} = \dot{\mathbf{q}}_r$ . Substituting this relation to eq. (5), we have

$$\mathbf{Y}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})(\mathbf{a} - \hat{\mathbf{a}}) = 0 \quad (6)$$

The solution of eq. (6) is,

$$\mathbf{a} - \hat{\mathbf{a}} = \boldsymbol{\xi} \quad (7)$$

where,

$$\mathbf{Y}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\boldsymbol{\xi} = 0 \quad (8)$$

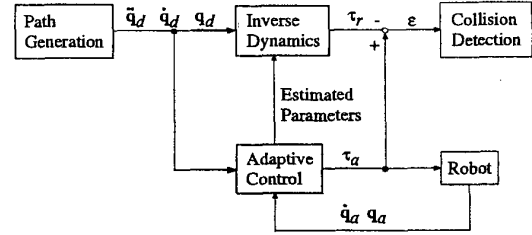


Fig. 1. Collision detection

Since the actual parameter vector  $\mathbf{a}$  is constant and  $\dot{\hat{\mathbf{a}}} = 0$  from eq. (4), the estimated parameter vector  $\hat{\mathbf{a}}$  is also constant. Thus,  $\boldsymbol{\xi}$  is a constant vector from eq. (7).  $\mathbf{Y}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$  in eq. (8) is a function of  $\tilde{\mathbf{q}}$ ,  $\dot{\tilde{\mathbf{q}}}$ ,  $\mathbf{q}$  and a time-varying matrix. In most of cases, a constant vector which satisfies eq. (8) is  $\boldsymbol{\xi} = 0$ . Therefore, we have

$$\hat{\mathbf{a}} = \mathbf{a} \quad (9)$$

This means that the estimated parameter vector  $\hat{\mathbf{a}}$  converges to the actual parameter vector  $\mathbf{a}$ .

### III. COLLISION DETECTION ALGORITHM

The dynamics of a manipulator is expressed as eq. (1). If the dynamic model is precise and there were no disturbances, the complete position tracking is realized by repeating the inverse dynamics calculation of eq. (1) in real time. However, it is not easy to realize the desired trajectory tracking, because of the impreciseness of the dynamic model and unexpected disturbances. Therefore, to correct the tracking error between the desired trajectory and the actual trajectory, we often use feedback controllers.

The outline of the model based collision detection algorithm, which we propose in this paper, is shown in Fig. 1. The reference input torques  $\tau_d$  and the actual input torques  $\tau_a$  are expressed by

$$\tau_d = \hat{\mathbf{H}}(\mathbf{q}_d)\ddot{\mathbf{q}}_d + \hat{\mathbf{C}}(\mathbf{q}_d, \dot{\mathbf{q}}_d)\dot{\mathbf{q}}_d + \hat{\mathbf{G}}(\mathbf{q}_d) \quad (10)$$

$$\tau_a = \hat{\mathbf{H}}(\mathbf{q})\ddot{\mathbf{q}}_r + \hat{\mathbf{C}}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}}_r + \hat{\mathbf{G}}(\mathbf{q}) - \mathbf{K}_D \mathbf{s} \quad (11)$$

where  $\tau_d$  is the reference torques and  $\tau_a$  is the actual input torques with feedback. Eq. (11) is calculated using the identified parameters by the adaptive control law.

The first three terms of the eq. (11) are feedforward terms and the last term is the feedback.  $\tau_a$  usually deviates from  $\tau_d$ , because of joint frictions and the disturbances from its

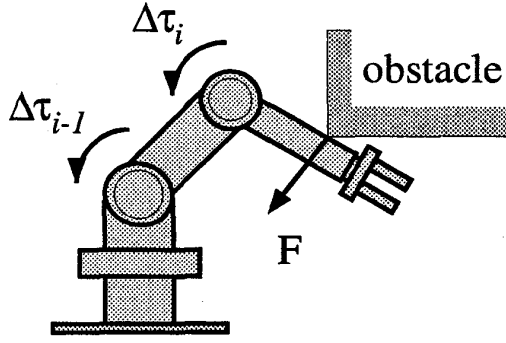


Fig. 2. Collision between robot and obstacle

environment. The feedback controller adjusts the actual input torque  $\tau_a$ , so that the tracking error is kept small.

Let us consider the torques generated by the collision of the  $n$ -th link of a manipulator and an obstacle as shown in Fig. 2. In this case, the disturbance force  $F$  is applied to the  $n$ -th link by the collision and increase the tracking error. The disturbance torques  $\Delta\tau$  shown in eq. (12) is applied to each joint.

$$\Delta\tau = J^T F \quad (12)$$

The controller adjusts the actual input torques so as to decrease the effect of  $\Delta\tau$ . As a result, the error of the actual input torque and the reference input torque becomes large. This deviation is used to detect the collision.

For the model based collision detection algorithm, it is important to consider the torque deviation  $\varepsilon = \tau_a - \tau_d$ . Let us assume that the error distribution is the normal distribution. Since the actual input torque corresponds to the reference input torque, we can assume that the mean of  $\varepsilon$  is zero. Based on the characteristic of the normal distribution, we have the following relations;

$$P(-3\sigma \leq \varepsilon \leq 3\sigma) = 0.997 \quad (13)$$

Assuming zero mean of  $\varepsilon$ , eq. (13) means that  $\varepsilon$  satisfies the condition  $|\varepsilon| \leq 3\sigma$ , with the probability of 99.7%. In other words, the probability of  $|\varepsilon| > 3\sigma$  is 0.3%. Since this probability is very small, this phenomenon rarely occurs when a robot moves without collision. The phenomenon that a robot collides with an obstacle rarely occurs in an ordinal condition.

As mentioned above, the actual input torques deviate from the reference torques by the effect of the feedback

when a robot collides with an obstacle. That is,  $|\varepsilon|$  increases.

We consider that a collision occurs when  $\varepsilon$  satisfies the following inequality for a certain period of time to reduce misdetection;

$$|\varepsilon| > 3\sigma \quad (14)$$

#### IV. EXPERIMENTS

In order to show the validity of the proposed system, we implemented the algorithm in the industrial manipulator shown in Fig. 3. In the experiments, we use only three degrees of freedom, although the manipulator has seven degrees of freedom. For illustrating the validity of the method, we executed two experiments. First, we compare the result of the adaptive controller with that of the PD controller with full dynamics feedforward. Then we executed the collision detection experiment using the proposed method.

##### A. Comparison with PD Controller

The dynamics of the experimental system is expressed by eq. (2). For the collision detection, the reference input torque vector  $\tau_d$  and the actual input torque vector  $\tau_a$  are defined by eq. (15) and eq. (16).

$$\tau_d = \hat{H}(q_d)\ddot{q}_d + \hat{C}(q_d, \dot{q}_d)\dot{q}_d + \hat{G}(q_d) \quad (15)$$

$$\tau_a = \hat{H}(q)\ddot{q}_r + \hat{C}(q, \dot{q})\dot{q}_r + \hat{G}(q) - K_D s \quad (16)$$

where  $\hat{\cdot}$  means that the term with  $\hat{\cdot}$  is calculated using the estimated parameters by the eq. (17);

$$\hat{a} = -\Gamma^{-1}Y^T(q, \dot{q}, \ddot{q}_r, \ddot{q}_r)s \quad (17)$$

To show the validity of the use of the adaptive control scheme, the PD controller with the full dynamic feedforward is considered. In the case of the PD controller, the reference input torque vector  $\tau_d$  and the actual input torque vector  $\tau_a$  are expressed as follows;

$$\tau_d = \bar{H}(q_d)\ddot{q}_d + \bar{C}(q_d, \dot{q}_d)\dot{q}_d + \bar{G}(q_d) \quad (18)$$

$$\tau_a = \bar{H}(q_d)(\ddot{q}_d - K_p \tilde{q} - K_d \dot{\tilde{q}}) + \bar{C}(q_d, \dot{q}_d)\dot{q}_d + \bar{G}(q_d) \quad (19)$$

where  $\bar{\cdot}$  means that the term with  $\bar{\cdot}$  is calculated using the constant parameters, which were identified through an experiment by the adaptive controller. eq. (19) is the combination of the PD feedback and the feedforward of the dynamics.

The frequency of the torque deviation  $\varepsilon = \tau_a - \tau_d$  for the adaptive control case is shown in Fig. 4, and their means



Fig. 3. Experimental System

and variances are shown in Table I. The actual input and the reference input are also shown in Fig. 5. You can see that  $\varepsilon$  is considered as a normal distribution. The frequency of torque deviation  $\varepsilon$  for the case of the PD control case is shown in Fig. 6, and their means and variances are shown in Table II.

In case of the adaptive control case, you can see that the mean of  $\varepsilon$  is almost zero. In case of the PD control case, however, the mean of  $\varepsilon$  is no more zero, although the PD controller was designed based on the estimated parameters through the experiment of Fig. 4. This means that some parameters, relating to frictions, may not be constant and precise detection of collision is not easy as long as we use constant parameters.

### B. Collision Detection

Based on the stochastic parameters obtained by the previous experiment of Fig. 4, we roughly defined the thresholds for the collision detection as follows;

$$\Delta\tau_1 = 13.9Nm (= 4\sigma) \quad (20)$$

$$\Delta\tau_2 = 8.25Nm (= 3\sigma) \quad (21)$$

$$\Delta\tau_3 = 2.79Nm (= 3\sigma) \quad (22)$$

Since the joint 1 shows wider distribution than joint 2 and 3,  $4\sigma$  was used for the threshold. Fig. 7 shows an example of torques when disturbance force was applied to the third link. Fig. 8 shows the experiment using a paper cup. The paper cup was crashed because no collision detection was implemented in this case. Fig. 9 shows the experiment when the proposed collision detection method was implemented. As soon as the collision was detected, the manipulator motion was stopped and the paper cup was not crashed.

TABLE I  
TORQUE MEAN AND VARIANCE OF PD CONTROLLER

	Joint1	Joint2	Joint3
Mean $\mu$ [Nm]	$-3.91 \times 10^{-2}$	$5.85 \times 10^{-2}$	$1.60 \times 10^{-2}$
Variance $\sigma^2$ [Nm]	$2.84^2$	$2.00^2$	$1.86^2$

TABLE II  
TORQUE MEAN AND VARIANCE OF PD CONTROLLER

	Joint1	Joint2	Joint3
Mean $\mu$ [Nm]	$1.80 \times 10^{-1}$	1.38	$2.00 \times 10^{-1}$
Variance $\sigma^2$ [Nm]	$2.60^2$	$1.98^2$	$1.83^2$

## V. CONCLUSIONS

In this paper, we proposed a collision detection method of a manipulator based on the adaptive control. The proposed method calculates the reference input torque based on the estimated dynamic parameters of the manipulator and detects collision properly. Since the method does not require a priori knowledge of dynamic parameters, the method works even if the robot carries unknown object. The proposed method was implemented to an industrial manipulator, and the experimental results using three degrees of freedom of the manipulator illustrated the validity of the proposed method.

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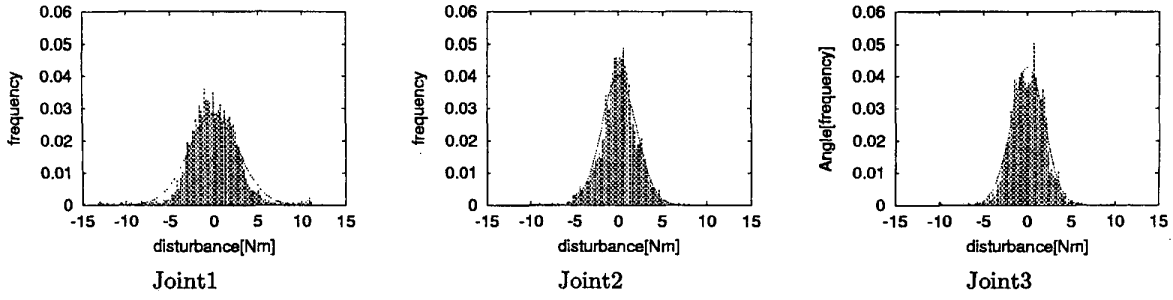


Fig. 4. Torque deviation of adaptive contrller

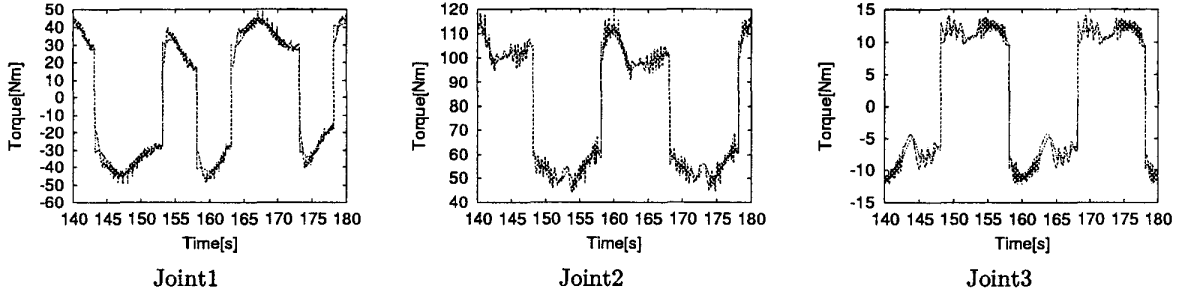


Fig. 5. Actual input torque and referenced input torque

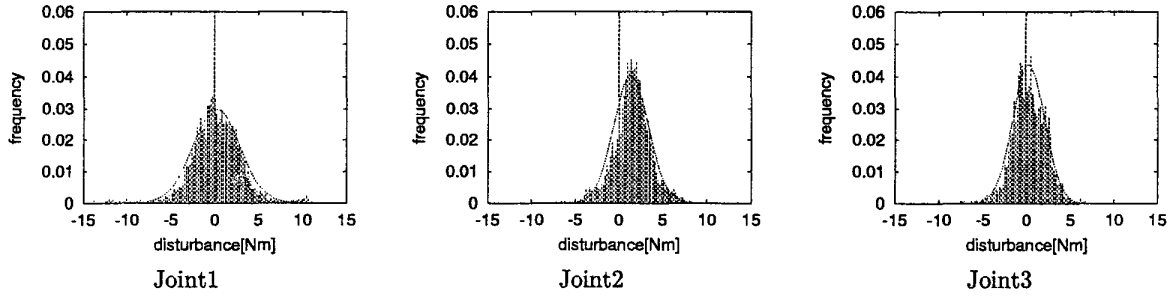


Fig. 6. Torque deviation of PD controller

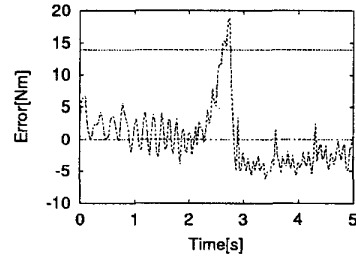


Fig. 7. Error between actual input torque and reference input torque when disturbance force was applied to 3rd link

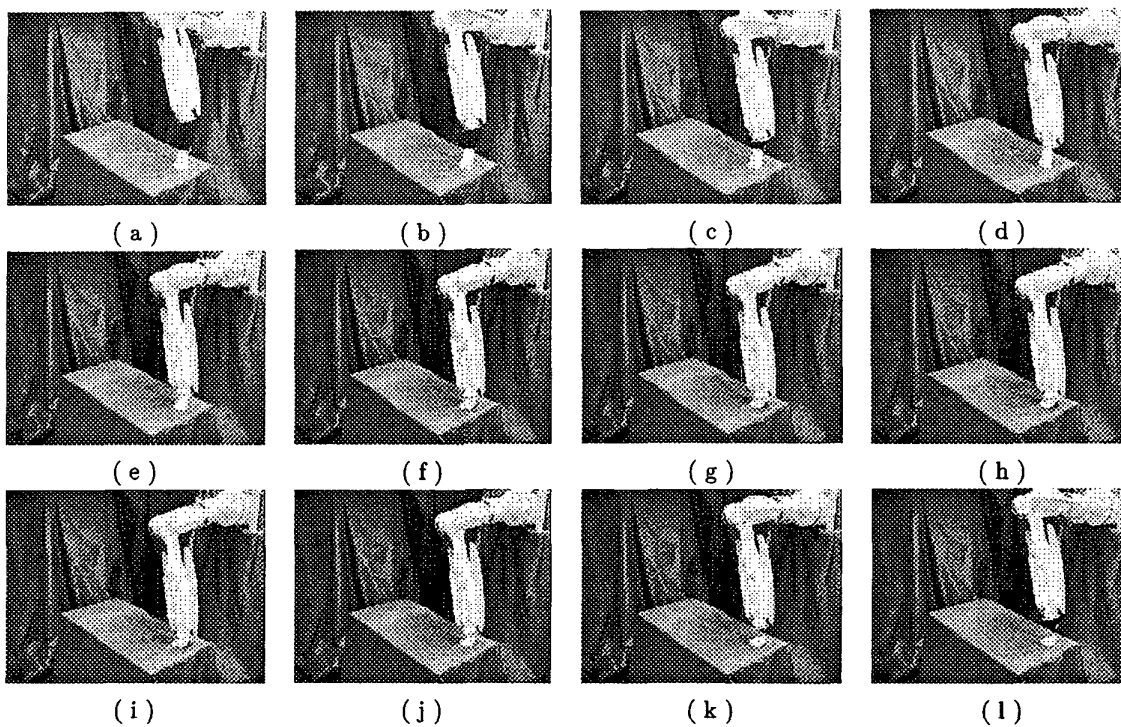


Fig. 8. Without Collision detection

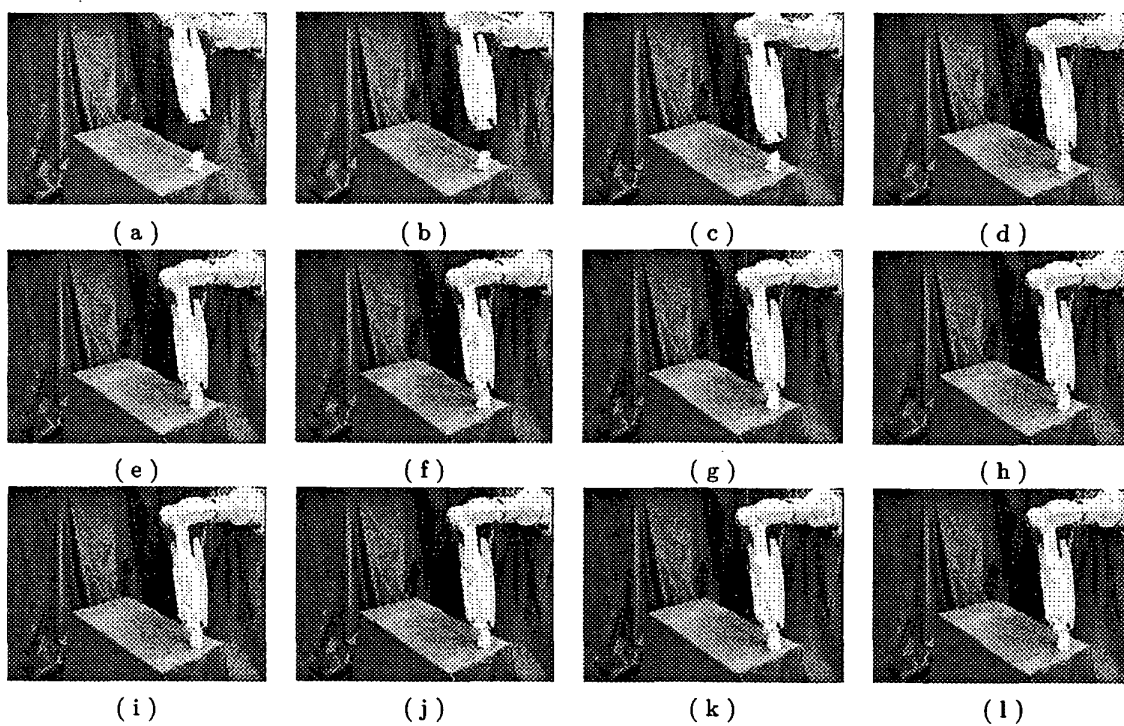


Fig. 9. Without Collision detection