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Manipulating Deformable Linear Objects: Fuzzy-Based Active Vibration Damping Skill

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Abstract Human can handle a deformable object and damp its vibration with recognized skill. However, for an industrial robot, handling a deformable object with acute vibration is often a difficult task. This paper addresses the problem of active damping skill for handling deformable linear objects (DLOs) by using a strategy inspired from human manipulation skills. The strategy is illustrated by several rules, which are explained by a fuzzy and a P controller. A proportional-integral-derivative (PID) controller is also employed to explain the rules as a comparison. The interpretations from controllers are translated into high level commands in a robotic language V+. A standard industrial robot with a force/torque sensor mounted on the wrist was employed to demonstrate the skill. Experimental results showed the fuzzy based damping skill is quite effective and stable even without any previous acknowledge of the deformable linear objects.

Key words deformable object · force/torque sensor · fuzzy control · manipulation skill · robot · vibration reduction

Category (5)

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1. Introduction

Deformable objects such as cables, wires, ropes, cloths, rubber tubes, sheet metals, paper sheets and leather products can be found almost everywhere in the real world of industry and human life. In most cases, deformable objects and parts are still handled and assembled by humans. Fortunately, manipulating deformable objects using robots has gradually attracted more and more researchers from different research areas, such as manufacturing, robotics and artificial intelligence etc as reviewed by Henrich and Wörn [1] and Nakazawa [2].

Compared to rigid work pieces, the shape of deformable objects to be assembled is typically neither exactly known nor constant for the assembly process. This causes high uncertainties that have to be dealt with. In this paper, we concentrate on deformable linear objects (DLOs), such as ropes, hoses, electric wires or leaf springs. To cope with the uncertainties of the DLOs, either a model [3–5] or information from a sensor [6–9] must be used to predict/compensate for the uncertainties while performing the assembly. All of those approaches are used for solving clearly specified tasks, but it is not clear how they may be re-used in other, similar situations.

When a robot executes a manipulation task, its motion can be divided into several motion primitives, each of which has a particular target state to be achieved in the task context. These primitives are called 'skills.' Skills only involve high-level tasks and do not need to redesign low-level motion controllers. An adequately defined skill can have generality to be applied to various similar tasks. Different skills organized together may improve the manipulation ability of a robot very much. Until now, most of the research work on skill-based manipulation deals with rigid objects [10–12].

Skill-based manipulation for handling deformable linear materials has been touched upon recently, for example, [13–15]. However, the effects of vibration are not taken into account in the skill-related work described above. The dynamic effects of deformable objects cannot be neglected, especially when a robot arm moves the objects quickly. As shown in Figure 1, the uncertainty resulting from oscillation may cause failure during the insert-into-hole operation. Therefore, to maintain or speed

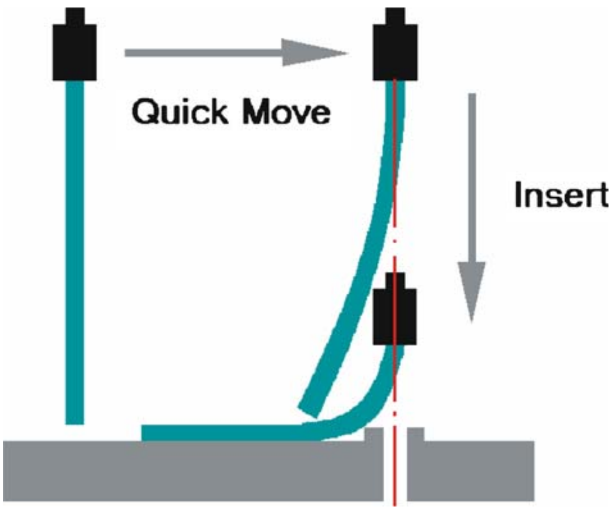


Figure 1 Quick-handled by a robot causes acute vibration and may result in failure when insert the DLO into a hole. It might be better to eliminate or reduce this unwanted vibration to an acceptable level before insert.

up efficiency, the inertia caused vibration should be depressed during the motion or eliminated as soon as possible after the motion.

Vibration reduction of flexible structures has been a research topic for some robotic researchers. Chen et al. [16] have reviewed the previous works and presented a passive approach based on open-loop concept for vibration-free handling of deformable beams; similar ideas can be found in [17, 18], which deal only with rigid bodies. However, application of the method presented by [16] is limited due to its stable start condition of the robot motion and a relatively simple trajectory of the previous motion. Considering the complex manipulations involved in practical situations, such as avoiding obstacles, picking-up and insert-into-hole etc., stable start condition cannot be satisfied easily.

With respect to manipulation, only the vibration that may cause failure of the next operation must be eliminated. Therefore, we prefer to remove as much as possible of the unwanted vibration immediately after the previous motion. Previous motion here refers to motions of robot end-effector that are completed before the next operation starts and result in vibration in the DLO. In recent papers, an off-line model-based method [19] and an on-line sensor-based method [20] to reduce the vibration of DLOs using attachable adjustment motions have been discussed. Although both of the methods have proved the effectiveness of the adjustment motion, they depend on previous knowledge of the DLO. For example, the physical parameters (width and height of cross-section, length, density and elastic modulus, etc) of the DLO are needed for model-based method, and frequency and stiffness for sensor-based method. In many cases, robot arm should deal with different DLOs with different physical parameters; some of the physical parameters may be unknown or difficult to be known in a limited time. Therefore, develop a new skill to cope with these difficult situations is badly needed.

As a good example, human can handle DLO and damp its vibration easily but with little or even without any previous knowledge of the DLO. Observing the skill of human, we try to present a new method to damp the acute vibration of a DLO without any known information about the DLO in advance. The only information, which may help sensing the states of the DLO, comes from a force/torque sensor which is mounted on the wrist of a robot. The robot will react according to the real-time data interpretation.

With the new method, the strength and scope of the robot's reaction are interpreted separately. The strength of the reaction here is defined by the speed of the jaws. The speed of the jaws is controlled by a fuzzy logic based interpreter or controller. PID method also used here to control the speed of the jaw as a comparison. The scope of the reaction is represented by the distance of the jaw's immediate motion and is interpreted by a simple P controller. Final decision on act right now or wait for next opportunity is made purely depends on how far the jaw is now from its original position. Once the strength and scope of the reaction together with the final act decision are made, they will be executed in real-time. Effect of each reaction will be evaluated immediately and reaction will continue until the vibration is weak enough and satisfy the terminating conditions. Experiments will be carried out to test the new method presented in the paper.

The rest of this paper consists of four parts. The skill is specified in details in Section 2. The approach to acquire data from sensor is described in Section 3. Implementation and experiments for testing and validating the proposed manipulating skill are illustrated in Section 4. Finally, conclusions and future work are related.

2. Method

As mentioned above, human can handle a DLO and damp its vibration with easy even without any previous knowledge of the DLO, for example, the material, the stiffness and frequency etc. It is observed that to damp the vibration of a DLO, human usually depends on information of the forces/torques sensed with fingers and/or wrist, sometimes, complemented by vision. However, we still can damp the DLO's vibration effectively even without visual feedback. What is the strategy for human to damp vibration without visual information and can an industrial robot do it in a similar way? We will address the problem in the following sections.

2.1. Rules for Reactions

There are at least two kinds of important information can be extracted from the force/torque signals: one is the direction of the forces/torques which can be used to control the hand to move along; another one is the strength of the forces/torques which is probably used to determine the precise motion of the hand. It is noticed that to damp vibration, we tend to let our hands follow the direction of the sensed force/torques if lack of visual information, and the speeds and scopes of these motions can be different according to the environments or demands. To develop a robust robot skill that can deal with the vibration of a DLO no matter what kind of material it may be or what physical characters it may have, the following four rules can be applied (also see Figure 2 for the manipulation skill diagram),

Rule 1. Robot should always follow the sensed direction of the force from the DLO.
Rule 2. The speed of the reaction motion depends on the strength of the sensed force/torque.
Rule 3. The distance of the motion also depends on the strength of the force/torque.
Rule 4. Stop if the strength of the force/torque is weak enough.

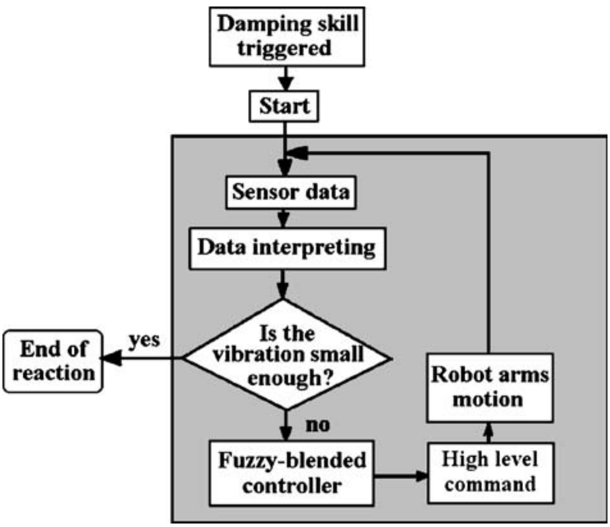


Figure 2 The diagram of the active vibration damping skill. The data from sensor are interpreted to check if the vibration is weak enough to stop the reaction; if not, the data are passed to a fuzzy-blended controller; the speed of the reaction is decided by a fuzzy controller and its distance is governed by a P controller. The output of the controller is translated into high level robot command which can be executed directly by the robot. No sensor data was read during a reaction period.

With these rules, once the skill is triggered, the robot arm will follow the direction of the forces it sensed. The speed and the distance of the robot arm's motion are controlled by a feedback loop. In other words, the robot arm will try to satisfy the demands from the DLO when the skill is triggered. These demands are sensed by the robot arm via the force/torque sensor. The robot arm reacts as soon as it receives the interpreted message from controllers. The effect of these reactions or adjustments is: the vibration will be dying out quickly since the elastic energy of the DLO is consumed or counteracted by these small scale reactions.

Unlike model-based [19] and previous sensor-based [20] methods, these closed-loop reaction motions can deal with a general DLO without any previous knowledge of the DLO and its previous motion. It should be mentioned here that, all our efforts is limited on high-level control and there is no need to touch upon the lower level motion control of the robot. For example, to tune the speed of the reaction, we only need to change the type of its acceleration profiles and program speed of the robot [25].

Now, the question is how to explain the above rules to a robot. In the following part, a closed-loop fuzzy logic method is used to explain Rule 2 and a P controller is used to explain Rule 3. The so-called *fuzzy-blended controller* (shown in Figure 2) in fact consists of one fuzzy and one P controller. A PID controller is also used here to explain Rule 2 but only as a comparison.

2.2. Fuzzy-blended Controller

Fuzzy logic was first introduced by Zadeh [24, 25] in 1960s. Fuzzy logic is proposed as an effort to model the uncertainty of natural language that often deals with the concept of partial truth, i.e., truth-values between 'completely true' and 'completely false.' In fuzzy set theory, an object can be allowed to have partial membership in more than one set through the introduction of the membership function. The fuzzy logic control method can make use of the human linguistic experiences [23] and has been used successfully in robotics, for example [26–28], so it is one of the best tools for us to implement the human skill inspired manipulating method.

Therefore, we use fuzzy controller to control the speed of the robot jaws, which are holding the DLO in the experiments, and the distance of the adjustment motion is controlled by a P controller. The Fuzzy and P blended control diagram can be found in Figure 3. The robot arm has its own control system to control the position and speed and acceleration etc but in lower level. Our control strategy only involves high-level robotic commands in V+, for example, *tool speed* and *ACCEL* [25].

The fuzzy controller used in the experiments is shown in Figure 4. The crisp input (error and change-in-error for example) will be converted to fuzzy value through

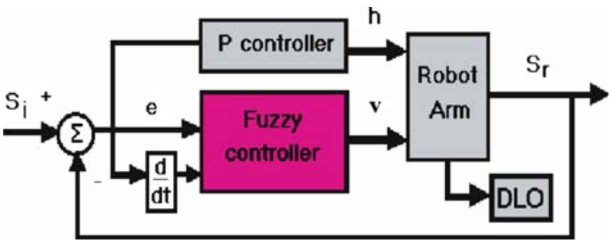


Figure 3 The fuzzy- and P-blended controller to interpret the sensor data and control the robot arm to damp the DLO's vibration. Fuzzy controller controls the speed of the adjustment motion v and P controller controls the moving distance h.

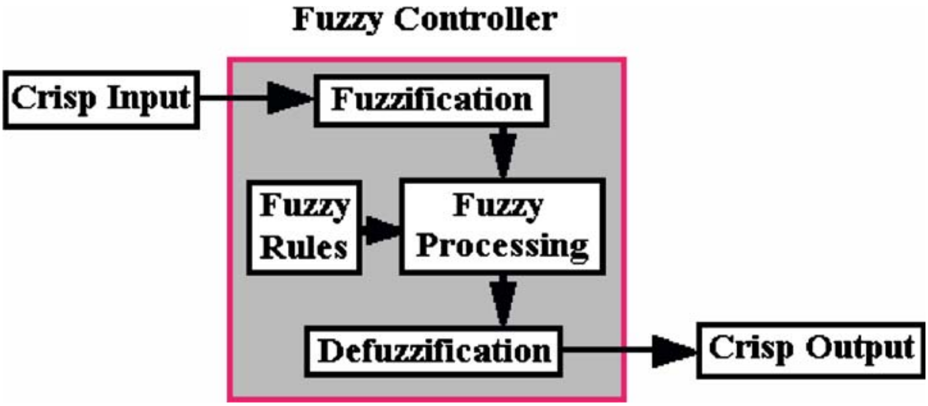


Figure 4 The Fuzzy controller with crisp input and crisp output. The crisp input is translated into fuzzy set value with membership functions via fuzzification; decisions are made in the Fuzzy processing by applying the fuzzy rules. The decisions are then translated back into real value via defuzzification as output.

fuzzification, and then processed according to fuzzy rules. Fuzzy conclusions can be draw after that, and crisp output can be obtained by using defuzzification. Here, the crisp output is the value of speed that will be given to robot arm as instruction. We will explain these procedures in details in the following parts.

2.2.1. *Fuzzification*

In Fuzzification process, real value input will be translated into fuzzy set array. In this paper, the input is highly depends on data (signal) from sensor. If e is the error between the real signal and the ideal signal defined as

$$e = S_r - S_i \tag{1}$$

where S_{r} is the real current signal, S_{i} is the ideal signal when the DLO has no vibration at all, we will use e as one of the input to the controller. Another input is the change-in-error $\dot{e}$, i.e., the difference of the two sequential e. Please note that error e controls the direction of the reaction motion according to Rule 1 (Section 2.1).

For all the error e, the change-in-error $\dot{e}$ and the output speed, we use the same kind of triangular membership functions (Figure 5) but with different name, i.e., the membership functions for the error is $u_e(e)$, the membership functions for the change-in-error is $u_{\dot{e}}(\dot{e})$ and the membership functions for the output speed is $u_v(v)$.

Here we use the membership function for the error e as an example (Figure 5a), a is a scale, e represents crisp input; five membership sets were used to describe the input, they are negative big NBig, negative small NSmall, zero, positive small PSmall and positive big PBig; for example, if the error input is 0.5a, then its value described with membership functions should be like this:

$$u_e^{ZERO}(0.5a) = 0.5 \tag{2a}$$

$$u_e^{PSmall}(0.5a) = 0.5 \tag{2b}$$

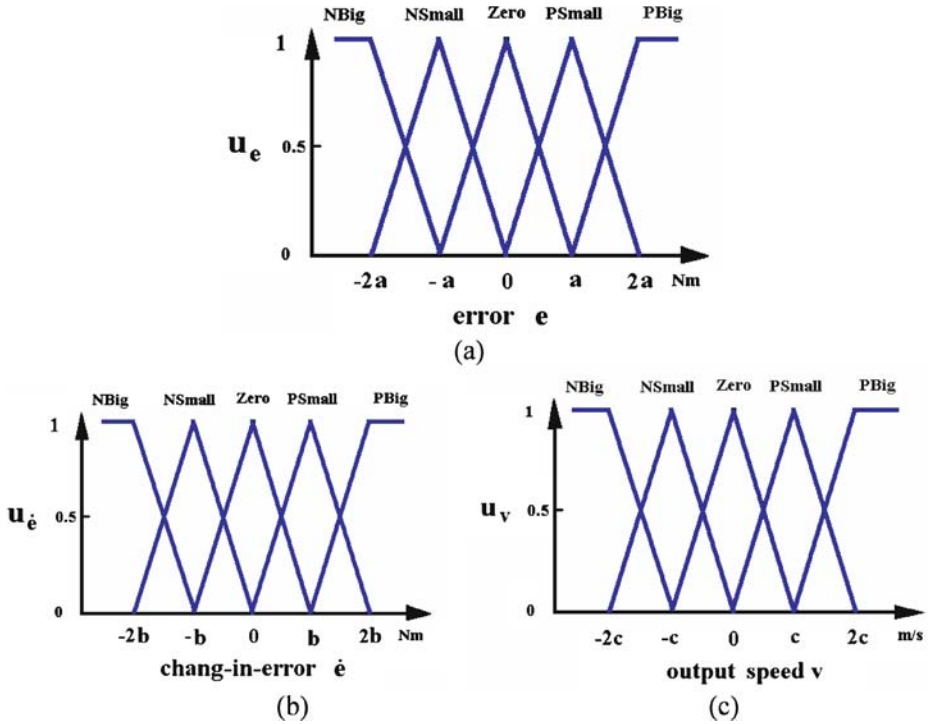


Figure 5 Membership functions used to translate crisp input into fuzzy memberships. **a** error; **b** change-in-error; and **c** output speed. Note, since we will use moment sensed by sensor, the error and the change-in-error are in Nm; units for output speed is m/s. NBig is negative big, NSmall is negative small, PSmall is positive small, and PBig is positive big.

In the implementation, these membership functions are described by several segments of functions and an input is automatically translated into value belongs to different sets like Equations (2a) and (2b). The membership functions for the change-in-error and the output speed can be expressed and operated in the similar way. In Figures 5b and c, the membership functions for change-in-error and output speed are also illustrated in details.

2.2.2. *Fuzzy Processing*

To meet the demands of our case, totally 25 fuzzy rules were introduced and listed in Table I. Fuzzy rules were expressed in if–then form in the fuzzy controller. Where NB means negative big, NS means negative small, PS means positive small and PB means positive big.

Next, we consider how to determine which conclusions should be reached when the rules that are on are applied to deciding what the speed instruction should be given to the robot arm to reduce the DLO's vibration. For our two inputs problem, there are at most four rules can be applied. Using the minimum to represent the premise, we have

$$u_{(j)} = \min\{u_e(e), u_{\dot{e}}(\dot{e})\} \qquad (j = 1, \ldots, 4) \tag{3}$$

Table I Rules for fuzzy controller to generate speed of reactions

Output speed		Change-in-error $\dot{e}$				
		NB	NS	Zero	PS	PB
Position error e	NB	NB	NB	NB	NS	Zero
	NS	NB	NS	NS	NS	Zero
	Zero	NS	Zero	Zero	Zero	PS
	PS	Zero	PS	PS	PS	PB
	PB	Zero	PS	PB	PB	PB

where as indicated in the above, $u_e(e)$ is the membership function value of error, $u_{\dot{e}}(\dot{e})$ is the one of change-in-error, $u_{(j)}$ is the correspond value of speed membership function with rule j of the total applicable rules applied.

2.2.3. *Defuzzification Method*

There are lots of defuzzification methods [23]. We will choose the 'center of gravity' (COG) defuzzification method (Figure 6) for combining the recommendations represented by the implied fuzzy sets from all the rules. Let b_i denote the center of the speed membership function (i.e., where it reaches its peak) of the consequent of rule (i). The defuzzificated crisp output u^{crisp} can be given as

$$v^{crisp} = \frac{\sum_i b_i \int u_v(i)}{\sum_i \int u_v(i)} \tag{4}$$

where $\int u_v(i)$ denote the area under the speed membership function $u_v(i)$, as shown in Figure 6. The final crisp output speed can be then obtained,

$$v^{out} = \lambda v^{crisp} \tag{5a}$$

where v^{out} is the speed value that could execute directly by the robot, λ is a constant scale. However, sometimes the output speed value is extremely small made it impossible for the robot covers the distance within a certain period of time. To

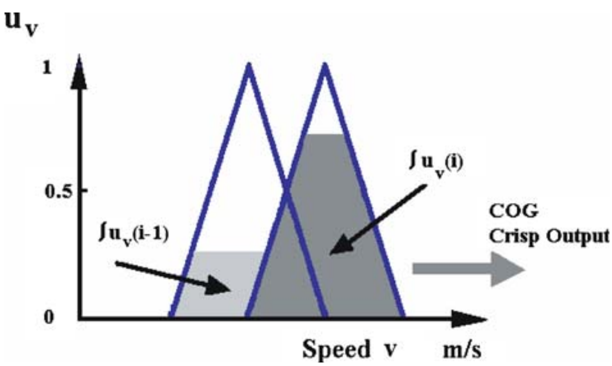


Figure 6 Centre-of-gravitiy (COG) defuzzification method used in the fuzzy controller.

avoid this embarrassing situation, the executable speed is modified from the crisp output speed,

$$v^{exe} = \begin{cases} abs(v^{out}) \ if \ v^{out} > v^{\min} \\ v^{\min} \qquad otherwise \end{cases} \tag{5b}$$

where v^{exe} is the final executable speed, v^{min} is the minimum speed allowed. Note here we take the absolute value of the crisp output speed because the direction of the reaction motion is decided by the sensed moment/force as stated in Rule 1 (Section 2.1).

2.2.4. *Graphic Example of the Fuzzy Controller*

In this subsection, a graphic example with crisp input and output will show how the fuzzy controller works in Figure 7. The input is supposed to be error 0.5a Nm and change-in-error −1.75b Nm. There are four rules could be applied at the same time according to Table I. They are:

(1) IF error is Zero and change-in-error is NBig, Then output speed is NSmall;
(2) IF error is PSmall and change-in-error is NSmall, Then output speed is PSmall;

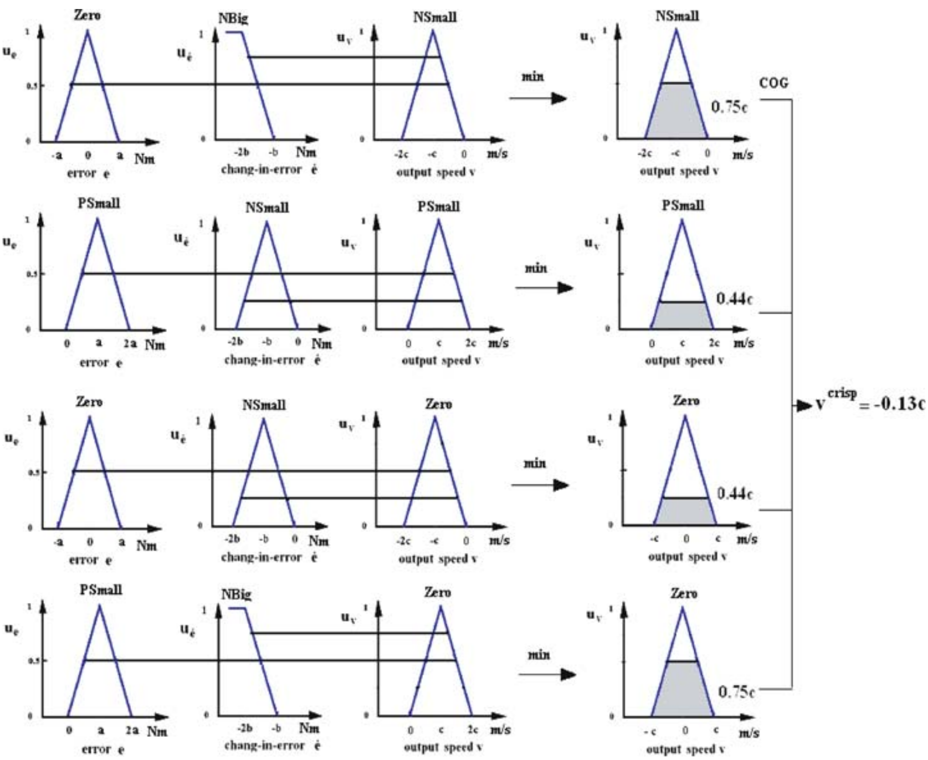


Figure 7 Graphic illustration of the fuzzy controller. In this example, four rules are on at the same time with the input: error is 0.5a Nm and change-in-error is −1.75b Nm. The output speed is finally determined as −0.13 cm/s with COG method.

(3) IF error is Zero and change-in-error is NSmall, Then output speed is Zero;
(4) IF error is PSmall and change-in-error is NBig, Then output speed is Zero.

Each of the four rules will generate an output speed membership set with two different values, as shown in the first to third columns of the Figure 7. The minimum (fourth column in Figure 7) will represent the value for each rule applied according to Equation (3). Therefore, totally there are four output sets with their own values need to be integrated into one crisp output. The final crisp speed value is computed with COG method and it equals: −0.13 cm/s.

2.2.5. *P Controller*

As shown in the Figure 3, a P controller explains the Rule 3 (Section 2.1), i.e., controls the scope of the robot arm reaction motions. We have a simple P control law to govern the distance of the reaction motions

$$h = K_d e \tag{6}$$

where K_d is the gain of the P controller. To balance the scope of the series of adjustment motions, we set a limit,

$$h^l \leq \sum h_i \leq h^r \tag{7}$$

where h^l and h^r are the left and right maximum allowed distance respectively, distance is measured from the original point where the skill is triggered, h_i is a real represents the moving distance of the i^{th} reaction motion, $\sum h_i$ represents the distance from the original point where the skill is triggered to the finish point of the i^{th} reaction motion. For example, if $h^l = -5$ cm, $h^r = 5$ cm, the whole series of reaction motions would be limited within a 10 cm small area; if $\sum h_i = -6$ cm, it exceeded the limitation, the i^{th} reaction motion could not be executed and the robot has to wait for the next opportunity.

2.3. PID Control Method

PID is a widely used effective control method [21]. It is reasonable to employ PID controller to calculate the speed of robot arm as a comparison. As illustrated in Figure 8, a PID controller gives the speed u and a P controller governs the moving distance h. We have the PID control law at time t as

$$v = K_c \left(e + \frac{1}{T_i} \int edt + T_d \frac{de}{dt} \right) \tag{8}$$

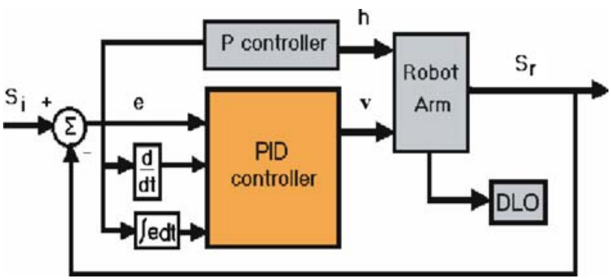


Figure 8 The closed-loop PID and P control of robot jaw's motion for vibration damping, where v is the speed and h is the distance of the jaw's motion.

where v is the speed of the robot's jaws, K_c is the gain of the PID controller, T_i is the integral time of the controller, T_d is the derivative time of the controller. The first term in Equation (8) is the proportional P part of the controller, the second term is the integral I part, and the third term is the D part which is proportional to the predicted error at time $t + T_d$. The PID output speed is also modified in the same way as described in Equation (5b) for Fuzzy crisp output speed.

A P controller as described in the above chapter controls the distance h of each reaction motion in the same way as described in Fuzzy-blended controller.

3. Sensor Data Processing

As we may have known, the signal coming from sensor is quite noisy. For a force/torque sensor that is mounted on the wrist of the robot arm, the inertia effect resulted from movements is also merged into the signal. Therefore, the first thing to do is try to eliminate the inertia effects. To achieve this goal, one successful method is to move the measurement center to the center of the gravity of the sensor; this will eliminate the inertia problem from the signal of moments [22]. We will use this method in this paper to eliminate the noise caused by inertia during or immediately after reaction motion. However, force signal is still affected by inertia.

On the other hand, to get more reliable signal, we average the value of the signals within a narrow sampling window, as shown in Figure 9. The data got within the sampling window is averaged and used as the sampling value corresponds to the latest time of the sampling window.

We have

$$g = \sum_{i=1}^{p} g(i) \frac{1}{p} \tag{9}$$

where g is the final signal used in our experiment, $g(i)$ is the direct output signal from sensor. The sampling rate of the force sensor we use is fixed at 100 Hz, means each sample needs 10 ms. Since in the experiments we set $p = 3$, the width of the sample window is actual 30 ms.

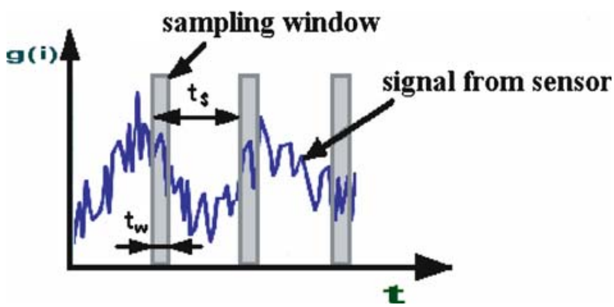


Figure 9 Force/torque signal sampling. Samples within a sampling window are averaged, where t_w is the width of the sampling window, t_s is the time interval between two samples, $g(i)$ is the signal from sensor and t is the time axis.

4. Experiments

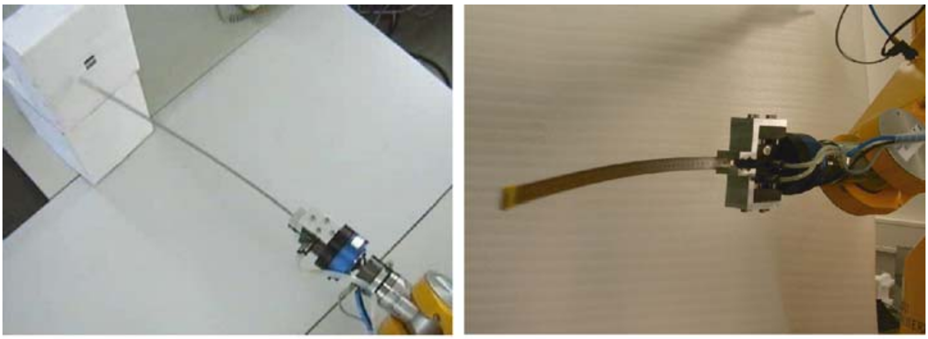
In this section, several experiments will be carried out to test the presented damping skill with Fuzzy or PID controller. Each experiment will be repeated for several times to got the averaged data.

4.1. Implementation

To build up the sensor-based damping skill experiment, a Stäubli RX130 industrial robot with a force/torque sensor was used. In the experiment, the DLO is a standard 500 mm stainless steel ruler with a cross-section of 0.5 × 18 mm. A 5-pfenig coin (about 5 g) is fixed to the DLO with yellow sticking tape at 2 cm from its free end. One end of the ruler was tightly grasped by pneumatic jaws, as shown in Figure 10, and the force/torque sensor was mounted on the wrist of the robot. The sensor used was an AdaptForce 50/100. The sensor weighs 0.35 kg and its relative accuracy is 2% of full scale, the resolution (standard deviation of force sensor readings with filter 2) is F_x: 0.027N, F_y: 0.027N, F_z: 0.16N, M_x, M_y, and M_z : 0.0023 Nm.

As related above, the speed of the reaction motion is either given by the Fuzzy control or the PID controller. The speed is implemented with high level command by define tool speed in MMPS (millimeter per second, [25]). However, there are still several types of acceleration profiles that mainly determines the time consumed to accelerate to the expected speed. In our experiments, we choose one of the fastest acceleration profiles with the same strength in acceleration and deceleration; in V+, it is $ACCEL(0)$ 100, 100 [25]. The monitor speed and program speed are all set to 100 [25].

The moment sensed by sensor is used as the signal that reflects the vibration of DLO. The ideal signal is zero because the DLO should not vibrate at all. Therefore, S_i is assumed to be zero in the experiments. The distance limit for the skill are set to be $h^l = -10$ cm and $h^r = 10$ cm in the experiments. The reaction motion is thus restricted to a 20-cm-long line. The maximum distance allowed is 14 cm and no minimum



(a) (b)

Figure 10 Experiment setup. The robot is handling a long DLO to access the hole and is going to insert the DLO into the hole. The fast moving operation causes acute vibration and this vibration is expected to be reduced to an acceptable level before try to insert. The DLO is a standard 500-mm stainless steel ruler with a 5-g coin fixed to it at 2 cm from its free end. **a** Above view, **b** side view.

limit. If the absolute value of the sensed error e is lower than 0.07 Nm and the absolute value of the change-in-error is less than 0.06 Nm, then, the reaction will be terminated. The damping reaction will also be terminated if the total number of reaction motions is more than 18 times in the experiments if without different statement. The minimum speed allowed v^{min} is set to be 60 mm/s in all the following experiments.

All the experiments start with the same previous motion and the same DLO if without different statement, which stimulates acute vibration with the amplitude of 310 mm at the free-end. The strength of vibration in amplitude in the following experiments is measured at the free-end if without statement.

4.2. Experiment with Fuzzy and P Controller

In this subsection's experiments, the speed of the reaction motion is explained by a Fuzzy controller. The distance is controlled by a P controller. The gains of P controller are set to be $K_d = 125$. In the experiments, sampling time interval t_s is 500 ms, means a group of three samples will be taken within the 30 ms sampling window at every 500 ms. The 500 ms time interval will allow the robot to fulfill

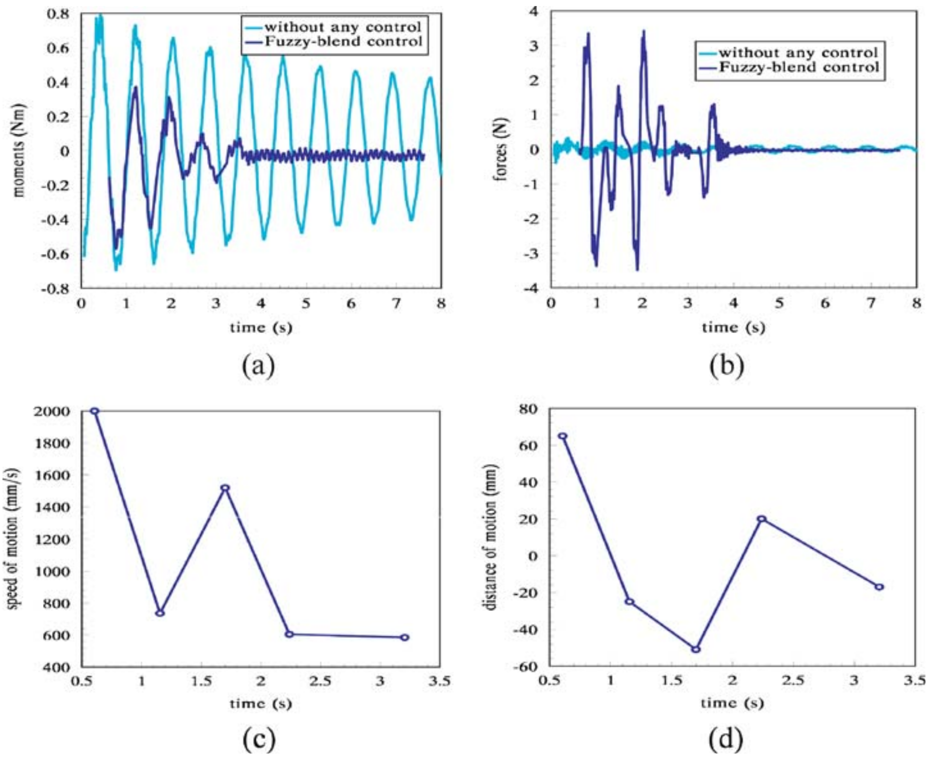


Figure 11 A trial of the Fuzzy- and P-controlled experiments. The reaction motions started from about 0.6 s as shown in the figures. **a** Moment M_X , without reaction motion caused noise [22]; **b** force Fx, reflects each reaction motion with pairs of symmetric impulses; **c** speed, controlled by the Fuzzy controller; **d** distance, given by the P controller.

one reaction motion completely. Other parameters used in the fuzzy controller are $a = 0.093$, $b = 0.093$, $c = 600$, and fuzzy scale $\lambda = 1{,}200$.

Ten times of the experiments indicated that Fuzzy logic method can help to reduce the vibration at the endpoint of the DLO from 310 to 8.8 mm (averaged from 10 times of experiments, mean is 8.8 mm, standard deviation is 2.2 mm^2) within about 3.38 s (averaged from 10 times of experiments, mean is 3.38 s, standard deviation is 0.23 s^2), almost 97% of the vibration was cut down. If without any active damping, vibration declines to this level will cost about 100 s.

One trial of the Fuzzy and P controlled experiment is shown in detail in Figure 11. The moment in Figure 11a showed clearly that vibration was reduced not by one but several times of reaction motions. From the quite symmetric force curve in Figure 11b, we can find that each of the reaction motion was completed within the 500 ms sampling interval. Each reaction's speed and distance are shown in Figure 11c and Figure 11d, respectively. The speed, the distance and the reaction caused force are correlated as shown in Figure 11. For example, the first reaction motion's speed was quite high, 2,000 mm/s, and its distance was more than 60 mm; reflected in the force, there were two strong symmetric impulses in the Figure 11(b); as a comparison,

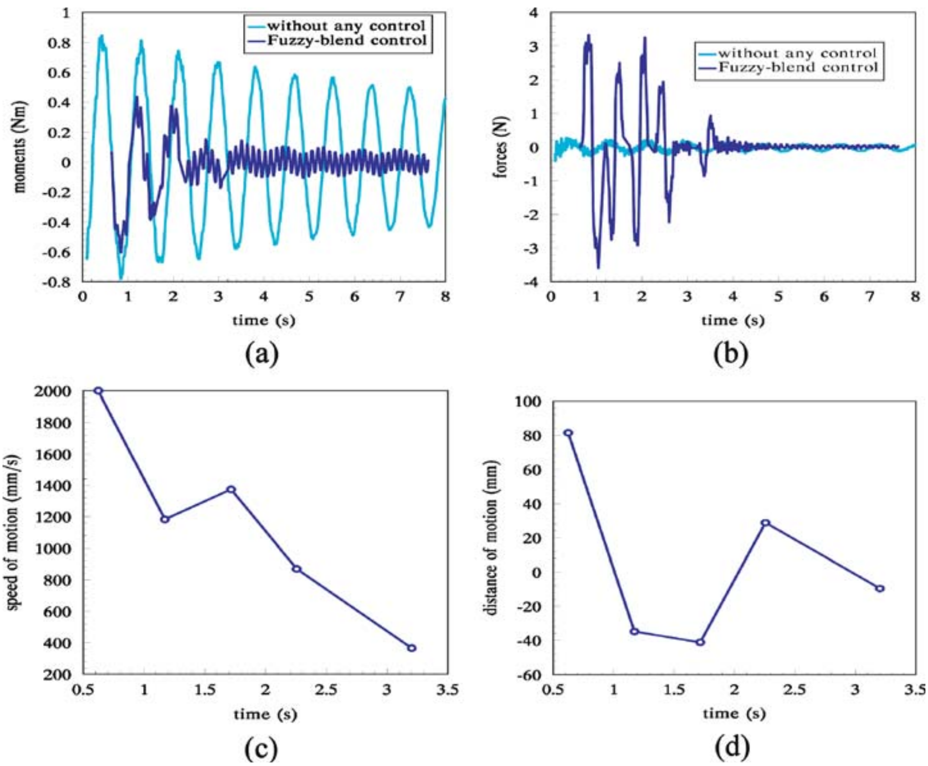


Figure 12 A trial of the Fuzzy- and P-controlled experiments but with a changed DLO. The reaction motions start from about 0.6 s as shown in the figures. **a** Moment M_x ; **b** force F_x; **c** speed given by the Fuzzy controller; **d** distance given by the P controller.

the last reaction motion was with smaller speed and smaller distance as well, so reflected in the force curve, there were two small impulses.

Additional experiment has also been done to find if this method could be used to different DLO. We added another 5pfennig to the DLO, fixed it to the DLO at the 20 cm from the free end with a piece of yellow sticking tape. With this new coin, the vibration amplitude caused by previous motion is 320 mm. Five experiments showed that it can still reduce the vibration amplitude dramatically, from 320 to 14.4 mm (averaged from five times of experiments, mean is 14.4 mm, standard deviation is 3.36 mm^2). The details of one trial is shown in Figure 12. After about 4 s, vibration amplitude reduced significantly.

It is also found that high frequency vibration may be stimulated or remain unreduced using the active damping skill (Figures 11a and 12a). Try to reduced these high frequency is probably beyond the robots ability since its acceleration and speed are quite limited and the robot jaws are made of metal without any passive damping effect. In fact, the vibration damping skill is only designed to reduced the low frquency vibraiton which is thought to be the main source of vibration that may cause failure in the forthcoming operations.

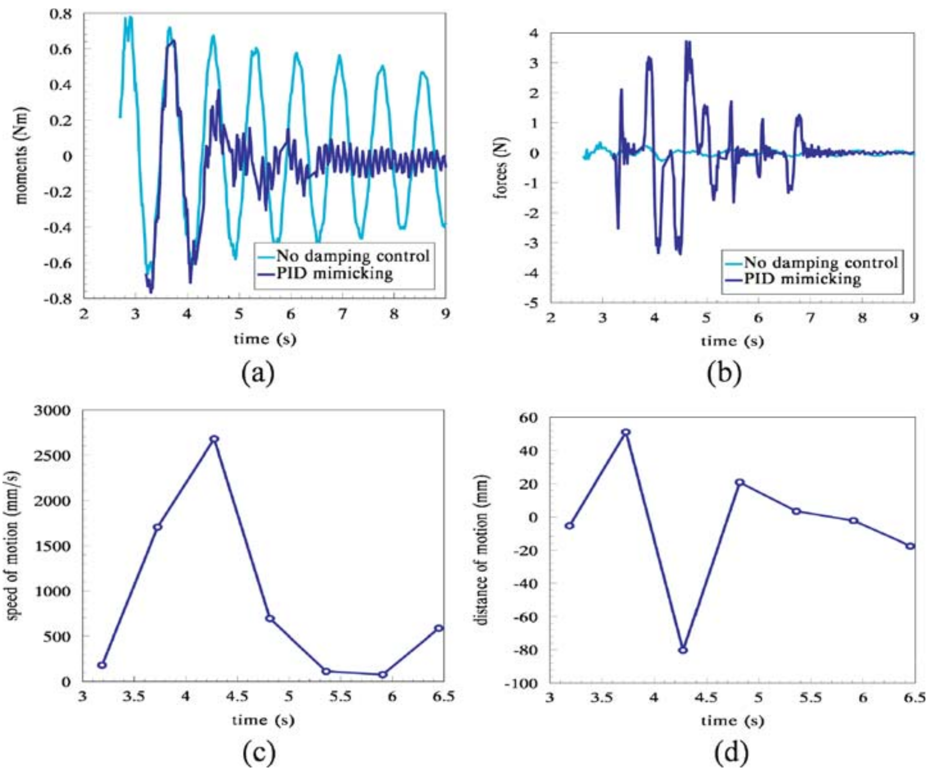


Figure 13 A trial of PID and P-controlled experiment. The PID controlled damping skill started from about 3.2 s as shown in the figures. **a** Moment M_x; **b** force F_x; **c** speed defined by PID controller; **d** distance defined by P controller during the experiment.

4.3. Experiments with PID and P Controller

In the following experiments, the speed of the reaction motion is explained by a PID controller. The distance is controlled by a P controller. The gains of the PID is set to be as high as $K_c = 8{,}000$ to get stable control effect. The gain of the P controller is $K_d = 125$ as before. The integral time of the controller T_i is set to be the sampling interval time, the derivative time T_d is set to be 0.01 sec. The sampling interval is 500 ms if without different statement.

It was found that the PID method can decrease the vibration amplitude quickly too from 310 to 25 mm (averaged from 10 times of experiments, mean is 25 mm, standard deviation is 13.6 mm^2), that is to say, about 92% vibration was cut down within a bit more than 3.7 s (averaged from 10 times of experiments, mean is 3.7 s and standard deviation is 0.6 s^2). The moment, force, speed and distance *versus* time in one trial of the experiment are shown in Figure 13. The distance of the whole series of reaction motions were quite balanced (close to its original position) too in this experiment.

Experiment has also been done with a changed sampling time interval, i.e., from 500 to 180 ms. As shown in the Figure 14 (one trial of the experiment), with

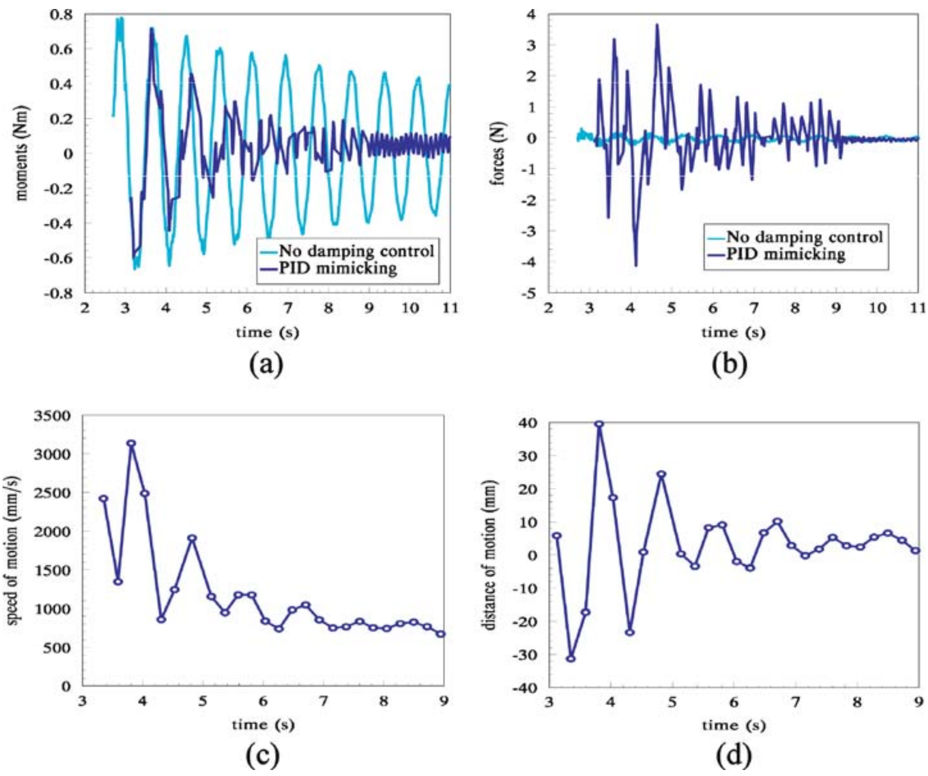


Figure 14 A trial of PID and P controlled experiments with sampling time interval 180 ms. The total number of reaction motions is limited to 40 times. The damping reaction starts from about 3.0 s as shown in the figures. The first reaction motion's speed was so small that has to be replaced by $v^{\min}$. **a** Moment M_X; **b** force F_X; **c** speed defined by the PID controller; **d** distance defined by the P controller.

180 ms sampling time interval, the PID method can decrease the vibration amplitude from 310 to 17.3 mm (averaged from 10 times experiments, mean is 17.3 mm, standard deviation is 6.65 mm^2), that is to say, about 94% vibration was cut down. However, more time was consumed in this case. It cost 4.9 s (averaged from 10 times experiments, mean is 4.9 s, standard deviation is 1.1 s^2) for the PID controller to finish its job. As shown in Figure 14, in this trial, it finished with total 26 times of reaction motions.

As one may have already found from Figure 14b, with the short sampling time interval 180 ms, not all the reaction motions demanded by the controller can be fully finished. They are often overlapped or disturbed. This is apparently because of the limited capability of the robot arm. If the sampling time interval is too short, the robot arm cannot fulfill each task that defined by the controllers.

4.4. Discussions

A summary of the above experimental results with different methods and conditions is shown in Table II. The presented manipulation skills based on both Fuzzy-P and PID-P controllers are quite effective. As revealed above, in most of the experiments (except PID-P with 180 ms sampling interval), the damping skill could satisfy termination conditions within 4 s. The results also showed that with the Fuzzy-blended method, both the mean and the standard deviation are smaller than those with PID controller. This means the Fuzzy controller is more effective and stable with the sets of parameters used in the experiments.

Both of the methods can be improved further in the future. For example, some of the parameters (gains, scales, and sampling interval etc) in both of the controllers can be tuned with optimization techniques; different rules in the Fuzzy controller can be introduced and compared; and different fuzzy membership functions that may affect the Fuzzy controller need to be compared and optimized [27].

In similar situation, human can reduce the vibration amplitude to millimeter level (less than 10 mm) within about one second. Fuzzy controller seems very promising since in one of the experiments it reached 8.8 mm level though cost more than 3 s with five reaction motions. It is possible to cut the time cost further by carefully select

Table II Summary of the experimental results with different methods and conditions

Methods	Sampling time interval and coins on DLO	Amplitude before (mm)	Mean amplitude after (mm)	Averages of experi-ments	STD (mm2)	Reduction in amplitude (%)
Fuzzy-P	500 ms, 1 coin	310	8.8	10	2.2	97
Fuzzy-P	500 ms, 2 coins	320	14.4	5	3.4	95.5
PID-P	500 ms, 1 coin	310	25.0	10	13.6	92
PID-P	180 ms, 1 coin	310	17.3	10	6.7	94

each reaction motion, for example, tiny reaction motions may be ruled out without execution.

5. Conclusions

In this article, a manipulation skill for robot arm to eliminate acute vibration when handling DLOs was presented based on rules extracted from human skill observation. Experiments to demonstrate the presented methods have been carried out and experimental results showed that vibration was reduced dramatically with Fuzzy-P or PID-P controller. The fuzzy method, which takes advantages of expert's linguistic rules, is proved to be more effective and stable than the PID method according to the averaged experimental results. With the Fuzzy-P controller, DLO's vibration was reduced to 8.8 mm within 3.38 s without any knowledge of the DLO in advance.

In the future, the presented manipulation skill can be improved further to the millimeter level in one second by optimizing the controllers and carefully selecting reaction motions.

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