Complaint Manipulation for Peg-in-Hole: Is Passive Compliance a Key to the Contact Motion?

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I. Introduction

Peg in Hole has been extensively researched because it represents a contact task of manipulation that requires both position and force control. Most of the approaches assume a manipulator of serially connected rigid links, therefore, they highly depend on excellent resolution of a force/torque sensor that is normally very expensive and quite noisy, a precise model of a dynamic system, and a very fast control time that is generally smaller than 1msec. Even if all these conditions are fulfilled, only a little unexpected uncertainty would be able to make the system very unstable and cause a failure. When looking at the above statements, the peg-in-hole seems to require extremely careful consideration to perform well even with a good manipulator hardware. However, think of that human babies play with LEGO blocks. A two-year-old baby can easily assemble large blocks even with his tiny arm and limited capacity for manipulation. When he becomes three years, assembling LEGO would not matter at all. What makes the difference? We seek the answer from two aspects of human manipulation: passive compliance and learning. While a robot manipulator pursues high speed and precision relying on high stiffness and good sensory measurements, a human depends on one's experience and passiv nature of muscles.

The goal of this research is to incorporate passive compliance and reinforcement learning for the peg-in-hole as the representative of the contact motion, and to show the importance of the passive compliance in learning of the contact motion. We show it enables a faster learning rate, robustness to noise and a slow control sampling time.

This paper is constructed as following. Section II talks about the various approaches to the peg-in-hole. Section III examines the differences between a robot manipulator and a human arm, and let a robot imitate a human. Section IV constructs the control scheme by reinforcement learning, and shows the results. We describes usefulness of the passive compliance in Section V. Section VI conclude research and address some future works.

II. Related Work

There have been numerous research on *peg-in-hole*. The milestone paper on the control strategy was given by Perez, Mason and Taylor [1]. They described how to synthesize compliant motion strategies from geometric constraints including uncertainty. Many researchers solveded the problem by hybrid of position and force control. By various methods, they reduce uncertainty in position and force [2]–[5].

Several works have been done about learning on peg-in-hole. Hovland, Sikka and McCarragher [6] proposed skill learning by human-demonstration. They implemented a hidden markov model to find out the relations among the motions. Ogawara and etc. [7] also suggested to learn a skill from visually learning a human demonstration. Lee and Kim [8] used reinforcement learning on 2D peg-in-hole simulation to develop an expert system. Gullapalli, Barto and Grupen [9] set up an associative reinforcement learning system based on the neural network. They let a 6-DOF manipulator learn to insert a peg by relationship between position and force sensing values, and output velocities.

Some research have been done on exploiting passive compliance in peg-in-hole, and they focus on special devices to help a robot with insertion. Southern and Lyons [10] analyzed usefulness of a passive accommodation device in robotic insertion processes. Haskiya W., Maycock K. and Knight J. [11] developed a hardware frame attached to a peg, in order to ensure good insertion.

Normally, research on a passively compliant robot deals with safety. Zinn and etc [12] developed DM^2 with a passive spring in a joint to ensure safety and good force control behavior. They used two actuators per a joint for a manipulator to have a flat force-control bandwidth over the entire range. Morita and Sugano [13] proposed MIA which has 7 passive compliant joints with variable stiffness springs and dampers. They used this arm to develop safety strategies. Yun and etc. [14] proposed a safe robot arm based on a torsional spring, a variable viscosity damper and soft skin.

Our approach is to let a robot manipulator, which has passive compliant joints, learn the contact motion by reinforcement learning.

III. How to Imitate Human's Contact Motion?

In this research, we let a robot manipulator have passive compliance and learning like a human by adding torsional springs and dampers to joints, and training it by a simple form of reinforcement learning.

While robot manipulators have a precise and quick movement in free space and they are clearly better than those of a human, contact motion of a human outperforms that of a robot even though a robot manipulator generally has a much faster sampling time and preciser sensors. A human never

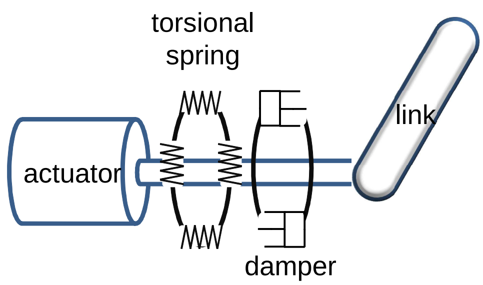


Fig. 1. a rotational passive compliant robot joint with a torsional spring and a damper

decides one's motion thousands times per second. As for peg-in-hole, tons of research proves that a human is much better at this kind of contact motions, because no human has a trouble in such a simple job. We believe this difference comes from two aspects of human manipulation: passive compliance and learning.

A. Passive compliance

Nature of muscles gives a human passive compliance in one's arm. Instead of reacting quickly at contact by accurate force sensing and high powered actuators, the muscles make an arm adapt to the external shape(hole in case of peg-in-hole) or force so that it can have high stability and a slow sampling time. Research on a series elastic actuator [15] have shown that passive compliance can greatly enhance stability of force control.

A torsional spring serially connected to an acuator provides our manipulator with passive compliance as shown in Fig 1. A damper is also added in order to reduce high frequency vibration and to dissipate some energy. Values of the spring constants and the damping ratios will be shown in Section IV-A, which are selected for a manipulator to have less than 10mm deflection by gravity when it is fully stretched horizontally. Note that springs can be deflected not only by gravity but also by dynamics of a manipulator. Therefore, this amount of the deflection appears huge in a view of traditional approaches in which extreme precision and high speed are the virtues of manipulation. However, we will show that a flexible arm can be better at the contact motion even with this deflection.

B. Learning

Learning is another big challenging problem for a robot. Whereas most robots make a decision only based on the current states, accumulated experience shapes manipulation skills of a human. We use reinforcement learning, because it resembles a way a human learns. A simple structure of reinforcement learning is developed to prove our hypothesis. Details are shown in Section IV-B.

IV. Peg-in-Hole by Reinforcement Learning

We solve a 2D peg-in-hole problem by the passive compliant joints and reinforcement learning. A square peg and a hole are implemented in the environment where contact model is a virtual spring, while a 3DOF manipulator is modeled with passive compliance. A robot will learn its control policy by a simple $TD(1)$ reinforcement learning [16].

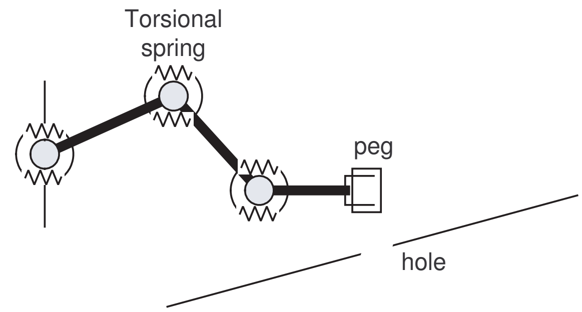


Fig. 2. A system is composed of a 3-DOF manipulator with passive compliant joints and the environment including a hole

parameters	1st joint	2nd joint	3rd joint
Point mass(kg)	0.5	0.5	0.1
link length(m)	0.3	0.3	0.05
inertia of actuators(kgm^2)	0.1	0.1	0.01
stiffness(Nm/rad)	50	20	5
damping constant(Nm/rad^2)	1.0	1.0	0.2

TABLE I
Parameters of a manipulator

A. System description

A system diagram including a manipulator and the environment is shown in Fig 2. Dynamic equations of a 3DOF manipulator with passive joints are obtained and implemented in a MATLAB graphical environment. We assume a point mass at the end of each link. We use only a square peg, and the size of a hole can be given arbitrary. For simplification, we assume no gravity in the system.

Considered parameters in the dynamic equations are following:

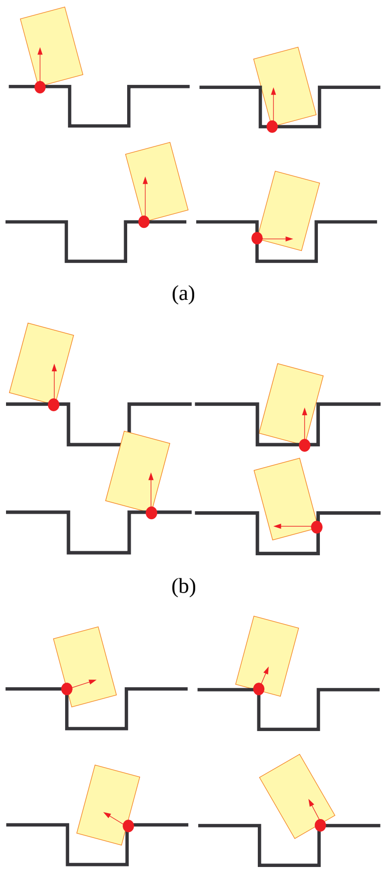
- state $x = [\theta_1, \theta_2, \theta_3, \varphi_1, \varphi_2, \varphi_3,]$, where θ is a joint angle and φ is a spring displacement
- J, M: inertia of actuators and mass of links
- L: length of links
- K, b: spring constant and damping of the passive joints

Lengths and Inertia are given by considering the size of an adult human. The parameter values used in the simulation are shown in Table I.

Contact between a peg and a hole is simply modeled as spring reaction without friction:

$$\Delta F = -K_e \Delta X$$

where K_e is a spring constant of the surface, ΔX is peg's penetration vector into the surface, and ΔF is a force vector reacted from the surface. Every possible case of the contact and corresponding force vectors are shown in Fig 3, and it



(a)

(b)

(c)

Fig. 3. Possible contacts and corresponding force vectors at (a)lower left corner of a peg (b)lower right corner of a peg (c)upper corners of a hole

shows contact happens at only four points: The left and right lower-corner of a peg, and the left and right upper-corner of a hole, if a peg is rectangle and so is a hole.

Simulation runs by a 4th order of Runge-Kunta with a $1kHz$ sampling time.

B. Control by learning

In order to find the optimal control policy, we implement *TD(1)* gradient descending method [16] with a slow control sampling time. Methodology of the learning is following. Firstly, a gaussian noise is added to the control input which is constructed from the current policy.

$$u = w + Z$$

$$Z \backsim \mathcal{N}(\vec{0}, \vec{\sigma}^2)$$

where w is the policy and u is the control input. This perturbation occurs every control sampling time - 0.01 sec in our simulation. Note that the sampling is very slow considering the contact motion, since, in general, it is known that manipulation for the contact motion requires over 1kHz sampling rate to ensure stability.

The policy is updated by the gradient descending method:

$$\Delta w = -\eta(E(w+Z) - E(w))e_N$$

where η is a matrix of learning rates, $E(\cdot)$ is a value function defined as the sum of the cost function:

$$E(w) = \sum_{n=1}^{N} g(x,u)$$

and e_N is an eligibility vector, updated by:

$$e_{k+1} = e_k + \frac{Z}{\sigma^2}$$

In this research, we select the cost function as the sum of the position and the force error.

$$g(x,u) = C_1\|x - x_D\|^2$$

when

$$|k_1\varphi_1| + |k_2\varphi_2| + |k_3\varphi_3| < \Gamma$$

otherwise,

$$g(x,u) = C_1\|x - x_D\|^2 + C_2(|k_1\varphi_1| + |k_2\varphi_2| + |k_3\varphi_3|)$$

where Γ is a threshold for the force error, and C_1 and C_2 are constants. Note that we do not use explicit force but measured torque by spring displacements.

We use the tilling method [16], [17] in which we divide the state space into grids that have parameters of the policy. In general, we have to make the grids for every state. However, the system have 6 states of the joint angles and the joint velocities and covering the entire workspace of a manipulator requires a huge size of dimensions. To reduce them, we propose two methods. Firstly, we assume that a manipulator always starts inserting a peg from the estimated starting position which is nearby the hole so that we focus only around that position. We narrow down the space for the tiles to $150mm \times 150mm \times 60^\circ$ in Cartesian space. Each state has 11 bins which covers $-75 \sim +75mm$, $-30 \sim +120mm$ and $-30^\circ \sim +30^\circ$ for x, y and θ from the desired position(a hole). The bins in 3-dimensional space and x and y grids overlayed on the workspace are shown in Fig 4.

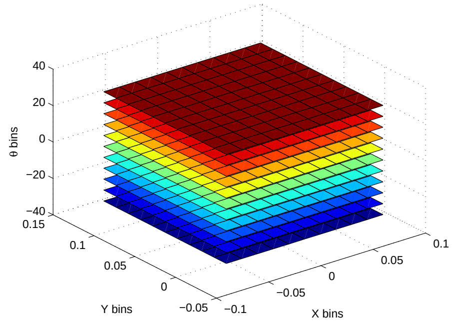
Each bin has three parameters: w_x, w_y and w_θ denoting two forces and one torque. With the parameters, control inputs are given by projecting them on Jacobian of the manipulator.

$$\tau = J^T \begin{bmatrix} w_x \\ w_y \\ w_\theta \end{bmatrix}$$

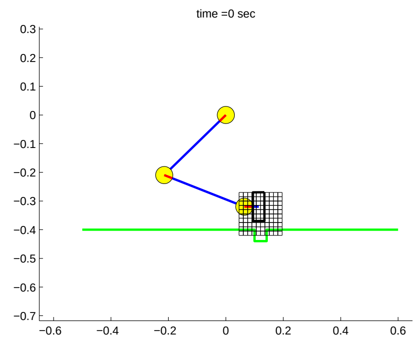
Since the system has a continuous domain of the states, parameters of a policy at a given point is interpolated by 8 neighborhood grid points. This is trilinear interpolation that interpolates a point within a 3D box [18], and convergence of the reinforcement learning parameters is proven when we use this method [19].

C. Simulation Result

We assume the completely deterministic system with no noise. Each trial is done by 2 sec and a robot tries to find the optimal policy by 300 trials. The value function is obtained by simulation without the random perturbation from the same starting position. We use a 40mm width peg and a 50mm



(a)



(b)

Fig. 4. Proposed tiling: (a) tiles for x, y and θ around the estimated starting position (b) overlayed x and y grids on the workspace of the manipulator

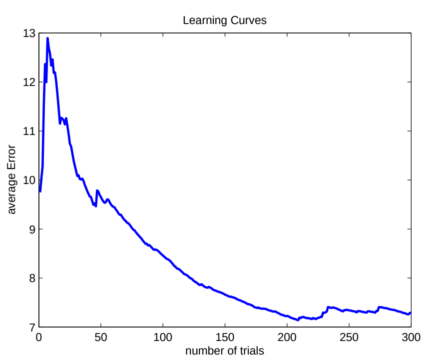
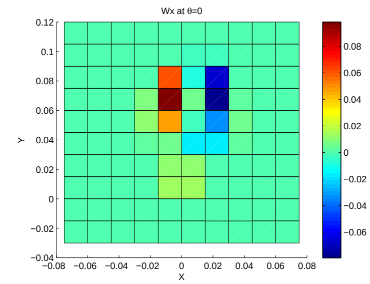


Fig. 5. Learning curve of reinforcement *Peg-in-hole* learning

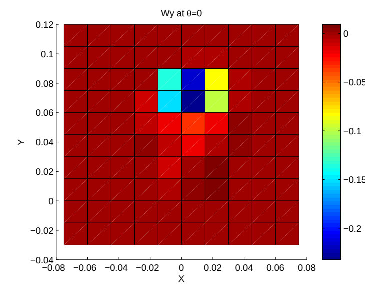
hole for training. The manipulator starts from around the randomly estimated starting position.

The resultant learning curve is shown in Fig 5. After 300 trials, the robot can successfully insert the peg with 100% ratio. Learned paramters of the policy at $\theta = 0$ are visualized in Fig 6. These patterns can be understood intuitively: w_x pushes a manipulator to the goal position, w_y always pulls it down to the goal and w_theta rotates it a little bit to give a better insertion.

After learning, the robot has learned two patterns according to which side it approaches from: it rotates a peg clockwise a little when it comes from the right side of the hole while it just slides over the surface when approaching from the left side. The patterns are shown in Fig 7



(a)



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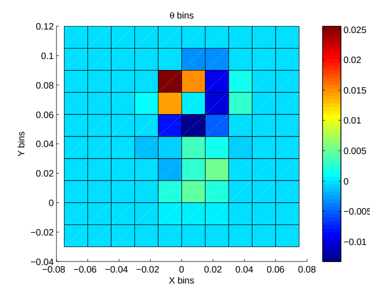

(c)

Fig. 6. Learned parameters at $\theta = 0$: (a)w_x (b)w_y (c)w_θ

V. Does Passive Compliance Really Help?

It appears that our manipulator can learn peg-in-hole by the simple form of reinforcement learning. What we has achieved is a perfect motion in the environment with no noise. However, it is not clear that how much amount of this success relies on the passive compliance. Now we want to see whether it really helps a robot with the contact motion. We compare simulation results from various stiffness range of a torsional spring, and also address that the passive compliance may give high robustness to noise.

A. *Performance of stiffer springs*

Simulations are implemented in a way that they have the same condition except for the spring constants. Manipulators with $2\times$, $3\times$, $4\times$, $8\times$, and $100\times$ stiffness of the original one learn peg-in-hole with 300 trials, and the learning curves are shown in Fig 8. Using the learned parameters, they try peg-in-hole 50 times, and success ratios are noted in Tabletab:SuccessRatios.

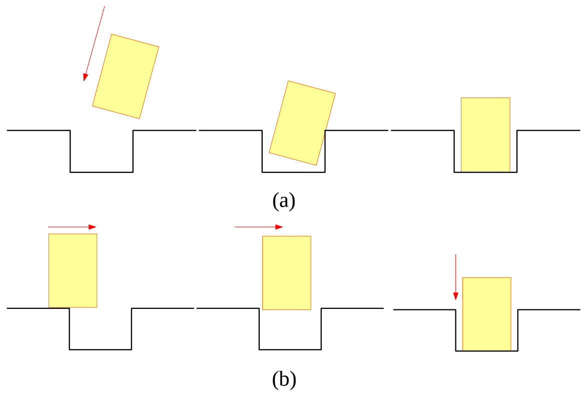

Fig. 7. Learned patterns (a)a peg comes from the right side (b) from the left side

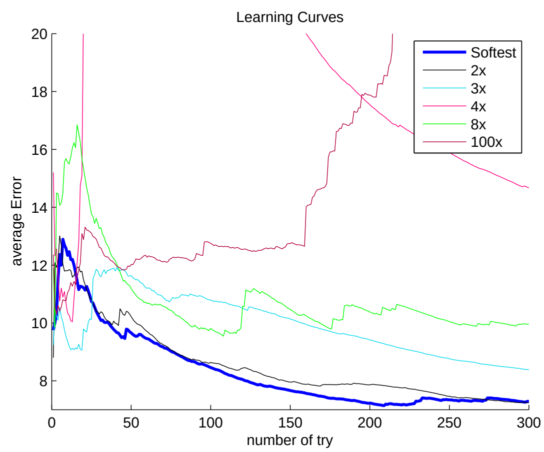

Fig. 8. Learning curves of manipulators with various spring constants

The result decribes that we have a slower learning rate as the stiffness increases. With almost rigid links (100× stiffness), the learning curve does not even converge. This does not directly mean a robot with rigid links cannot learn peg-in-hole by the proposed learning structure. However, at least we can say that we need to be more careful and a learning rate may be slower when we use a stiffer manipulator. With the proper stiffness of the passive compliant joint, a robot appears like being able to learn the contact motion more aggressively and efficiently.

Stiffness	Success ratio
original	100%
2×	90%
3×	50%
4×	0%
8×	0%

TABLE II
SUCCESS RATIOS OF THE MANIPULATORS WITH THE VARIOUS SPRING CONSTANTS

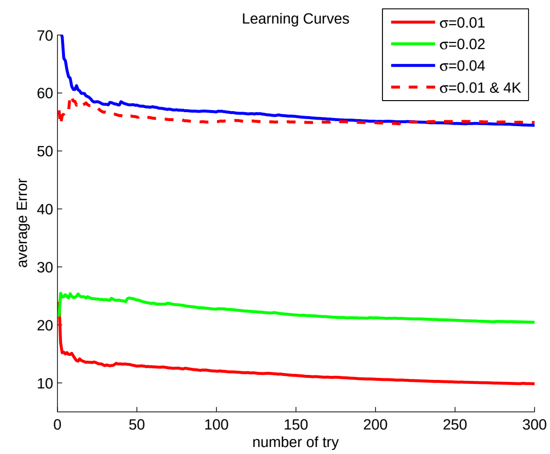

Fig. 9. Learning curves with three sizes of the noises and the smallest noise with 4× stiffer torsional springs

B. Robustness to noise

While we have trained our manipulator in the noise-free environment, difficulties of the contact motion normally emerges from uncertainty. We may not know the exact relative position of a hole from a coordinate of a robot, or a robot may not perfectly follow the control command even if we know the right position. Furthermore, signal from a force sensor is quite noisy.

In order to incorporate the uncertainty and to find out a role of the passive compliance in this case, we add gaussian noises in all the encoders so that a robot has force errors as well as position ones. Note that it senses forces by the angular displacements of the torsional springs. The noises are given:

$$\xi \backsim \mathcal{N}(\vec{0}, \vec{\sigma_n}^2)$$

where three kinds of σ_n are chosen as following:

$$\sigma_n = \{0.01, 0.02, 0.04\}$$

The maximum value of the nosies is bounded by $2\sigma_n$.

By experiments, we find out that the smallest size of the noise $\sigma_n = 0.01$ causes maximum ±17mm and ±3.5° error of a peg position and ±1.5Nm force error. Considering the width of the peg(40mm) in the simulations, this noise is quite large. Note that the previous research on reinforcement learning deal with much smaller noise [8], [9]. The larger noises will yield more errors in a proportional way.

Three simulations of reinforcement learning are implemented according to each size of ξ. In order to look at the effect of the stiffness, we also implement a simulation with the smallest noise and 4× stiffer torsional springs. Each simulation has 300 trials, and the learned policies are evaluated in 50 tests as the previous chapter. The learning curves and the success ratios are shown in Fig 9 and Table III.

The result describes that the robot has more than 50% chance to succeed in insertion even with the largest noise. We have still 100% success with the smallest noise, while 4× stiffness drops to nothing. That implies passive compliance

Conditions	Success ratio
$\sigma_n = 0.01$	100%
$\sigma_n = 0.02$	60%
$\sigma_n = 0.04$	60%
$\sigma_n = 0.01$ & $4\times$ stiffness	0%

TABLE III

SUCCESS RATIOS OF THE MANIPULATORS WITH THE NOISES

also provides with more robustness to noise. The learning curves of the largest noise only and the $4\times$ stiffness have the almost the same value after learning.

In addition, the same policy learned in the previous section works for 0.5mm gap between a peg and a hole even though we trained a manipulator with 10mm gap. Not surprisngly, this appears like coming from adatation of the passivity.

VI. CONCLUSION

We propose a new solution of 2D *peg-in-hole* by a compliant manipulator and reinforcement learningas imitating the contact motion of human's manipulation. We design a manipulator with a torsional spring and a damper in every joint, in order to passively adapt a peg to the environment in the contact motion. The gradient descending method is implemented for learning. To reduce dimensions, we assume a small area of peg-in-hole motion and a slow movement. They turns out to be reasonable in our case. The cost function reflects both of the position and force error. We see 300 trials allows the perfect peg-in-hole motion. By comparison among various stiffness and noises, we show that the passive compliance greatly helps with the contact motion and it yields more stability and a slower sampling time. We think that is what a human does.

In future, we want to include a more noble model of the contact. Also more efficient and realistic estimation of the value function is required to use the proposed method in the real world. Dynamic insertion is another challenging issue although we need to incorporate more dimensions.

VII. ACKNOWLEDGMENTS

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