An Iterative Learning Control Scheme for the Capsubot

Yang Liu*, Hongnian Yu* and Luige Vladareanu**

**Faulty of Computing, Engineering and Technology, Staffordshire University, Stafford, UK (e-mail: {y.liu, h.yu} @ staffs.ac.uk)*

*** Institute of Solid Mechanics, Romanian Academy, Bucharest, Romania*

Abstract: A Capsubot, which consists of three parts, the inner body, the capsule shell, and the driving mechanism, is a micro capsule robot with no legs and no wheels, and is driven by the interactive propulsion between the inner body and the capsule shell. The desired locomotion of the Capsubot is generated by making the inner body track a designed trajectory repeatedly. Due to the nature of repetitive motion, an iterative learning control scheme is proposed to improve the tracking performance of the inner body, in order to achieve the desired locomotion of the Capsubot. Extensive simulation studies are conducted to demonstrate the effectiveness of the scheme.

1. INTRODUCTION

Human adaptive mechatronics (HAM) is intelligent electrical-mechanical systems that are able to adapt themselves to the human's skill in various environments and providing assistance in improving the skill, and overall operation of the combined human machine system to achieve the improved performance (Harashima, 2005; Iwase etc 2005). The fundamental problem of HAM is to make the human-in-the-loop system adapt human operations based on the classification of human control actions. The Capsubot is considered as an alternative HAM mobile robot devise in medical applications: a novel endoscope technology that aims to diagnose disease inside the human body. It is more preponderant than traditional endoscope technology since traditional endoscope diagnosis causes patients pain due to the stiffness of the tube, and cannot reach all areas of the body. A Capsubot is the size of a vitamin pill, meaning it can be swallowed by patients, and is equipped with a video camera in front of the capsule (www.givenimaging.com; www.rfnorika.com). The internal driving mechanism makes the Capsubot move inside the human body, and the image data can be transmitted to a doctor for diagnosis.

In this paper, we study the tracking control issue of the Capsubot from the underactuated system point of view. The Capsubot consists of three parts: the inner body, the capsule shell, and the driving mechanism. The Capsubot can move in the desired direction by using the interactive propulsion between the inner body and the capsule shell generated by the driving mechanism. Initially, two motion stages, fast motion and slow motion, are proposed in (Liu 2008). In the fast motion, large propulsion is used to make the inner body and the capsule shell have reverse displacement. In the slow motion, small propulsion is used to pull the inner body back to its initial position, while the capsule shell remains stationary by using dry friction. By repeating the two stages, the Capsubot will have consecutive displacement in one direction. Based on the two stages, an optimum seven-step motion for the inner body is studied in (Liu 2008). The inner body will track the seven-step velocity profile to achieve the desired locomotion. From the underactuated system point of view, the original two-degree-of-freedom system with one actuator is reduced to a one-degree-of-freedom system with one actuator. A few control methods have been studied in (Liu 2008). The open-loop control method directly uses the mathematical models of the Capsubot and the desired velocity profile to compute the input signal per cycle. The closed-loop control method uses inverse dynamics control with a fixed gain PD controller to achieve good tracking performance. The drawback of this method is that the full Lagrangian dynamic model which includes the system parameters must be calculated in real-time. This makes the system sensitive to uncertainties. The simple switch control method is based on the sliding mode control and the aforementioned methods. The control input changes based on different switching conditions. This method is simple to implement in real experiments (Wane 2007), but the displacement and the energy consumption are uncontrollable.

Due to the limitations of the aforementioned three methods, we propose an iterative learning control (ILC) scheme in this paper to improve the tracking performance of the repetitive motion of the Capsubot. The notion of ILC is that the system repeatedly executes the same task and can improve its performance by using the knowledge of the previous task. The ILC can work even with limited a priori knowledge of the mathematical model of the system. Moreover, it allows the system dynamics to have small parametric uncertainties and repetitive external disturbances. For the past decade, extensive ILC schemes have been studied in the robotics field. Bristow (2006) fully reviewed ILC from theory to application. Luca (1992) implemented a frequency-domain approach to learning control on a robot manipulator. Two separate filters were used in the scheme to obtain rapid improvements in a specified bandwidth while cutting off possibly destabilizing dynamic effects that would bar learning convergence. Kuc (1991) proposed a similar learning scheme which consists of a unique feedforward learning controller and a linear feedback controller by using the Lyapunov approach. The feedback controller can provide a stable open neighbourhood along a desired trajectory, while the feedforward learning controller can reject unknown deterministic disturbances and adapt itself to unknown system parameters. Moon (1997) proposed an ILC scheme, which only utilizes locally-measured signals and does not require the computation of complicated nonlinear manipulator dynamics, on high-geared industrial manipulators that perform repeated tasks.

2. DYNAMIC MODELLING AND MOTION STRATEGY OF THE CAPSUBOT

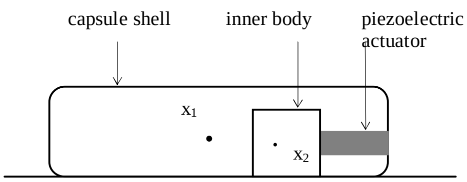

Figure 1 Capsubot

The Capsubot studied in this paper is shown in Figure 1. The system consists of three parts: the inner body, the capsule shell, and the piezoelectric actuator. The propulsion is generated by the piezoelectric actuator which interacts between the capsule shell and the inner body. M is the mass of the capsule shell, m is the mass of the inner body, u is the propulsion generated by the piezoelectric actuator, g is acceleration due to gravity. Considering the shell centre and the inner body centre as reference points, x_1 is the position of the capsule shell, and x_2 is the position of the inner body. To distinguish the static friction and the kinetic friction, we use μ_{1s} as the static friction coefficient, and μ_{1k} as the kinetic friction coefficient between the capsule shell and the environment. μ_{2s} is the static friction coefficient and μ_{2k} is the kinetic friction coefficient between the inner body and the capsule shell. The static friction coefficients are twice the kinetic friction coefficients, i.e. $\mu_{1s}=2\mu_{1k}$, $\mu_{2s}=2\mu_{2k}$.

Let the capsule shell centre be the origin of the coordinate. Then the dynamic model of the Capsubot is given (Liu 2008)

$$M\ddot{x}_1 + m\ddot{x}_2 + m_{1k}(M+m)g\,\mathrm{sgn}(\dot{x}_1) = 0 \qquad (1)$$

$$m\ddot{x}_2 + m_{2k}mg\,\mathrm{sgn}(\dot{x}_2 - \dot{x}_1) = -u \qquad (2)$$

Let $q_1=x_1$ and $q_2=x_2$. Equations (1) and (2) can be represented by the generic compact form of underactuated systems,

$$\begin{cases} D_{11}\ddot{q}_1 + D_{12}\ddot{q}_2 + h_1(q_1,\dot{q}_1,q_2,\dot{q}_2) = 0 \\ D_{21}\ddot{q}_1 + D_{22}\ddot{q}_2 + h_2(q_1,\dot{q}_1,q_2,\dot{q}_2) = u \end{cases} \qquad (3)$$

where D_{11}=M, D_{12}=m, D_{21}=0, D_{22}=m,
$h_1 = m_{1k}(M+m)g\,\mathrm{sgn}(\dot{x}_1)$, $h_2 = m_{2k}mg\,\mathrm{sgn}(\dot{x}_2 - \dot{x}_1)$, $\tau = -u$.

As shown in (3), the Capsubot is a two-degree-of-freedom system, which has one actuated input and two variables needing to be controlled. Due to the nature of underactuated systems, the piezoelectric actuator cannot directly control the locomotion of the Capsubot (i.e. the position of the capsule shell). So we control the inner body under certain constraints in order to indirectly control the locomotion of the Capsubot. Next, we will design a desired trajectory for the inner body based on the system constraints. The Capsubot will move in the desired direction by tracking the trajectory repetitively.

Article I. Motion generation analysis

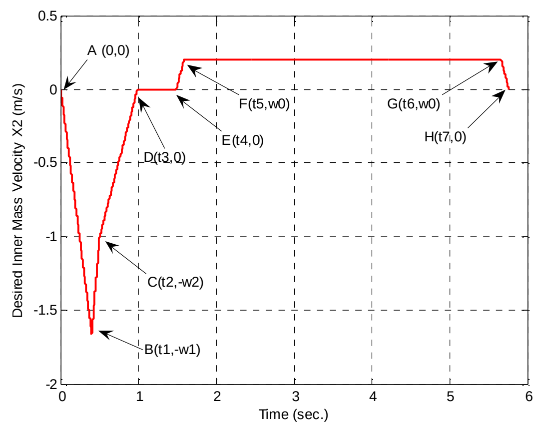

Figure 2 Desired inner body velocity profile

To move the Capsubot in one direction, a two-stage motion is studied in (Liu 2008). The trajectory profile of the inner body is shown in Figure 2. The motion is considered in two stages:

a) fast motion stage (A to C) – moving the inner mass fast using $|u|>>F_m$, where F_m is the maximum static friction between the capsule shell and the environment.
b) slow motion stage (D to H) – moving the inner mass slowly to its initial position using $|u|<F_m$.

From Figure 2, the formula of the desired inner body velocity profile is given as

$$\dot{x}_{2d}(t) = \begin{cases} -tw_1/t_1 & t\in[0,t_1) \\ -w_1+(w_1-w_2)(t-t_1)/(t_2-t_1) & t\in[t_1,t_2) \\ w_2(t-t_3)/(t_3-t_2) & t\in[t_2,t_3) \\ 0 & t\in[t_3,t_4) \\ w_0(t-t_4)/(t_5-t_4) & t\in[t_4,t_5) \\ w_0 & t\in[t_5,t_6) \\ w_0(t_7-t)/(t_7-t_6) & t\in[t_6,t_7] \end{cases} \qquad (4)$$

The optimum selections of the parameters w_1, w_2, w_0, and t_1~t_7 are given in (Liu 2008). The desired trajectory of the inner body shown in Figure 3 is given by integrating (4).

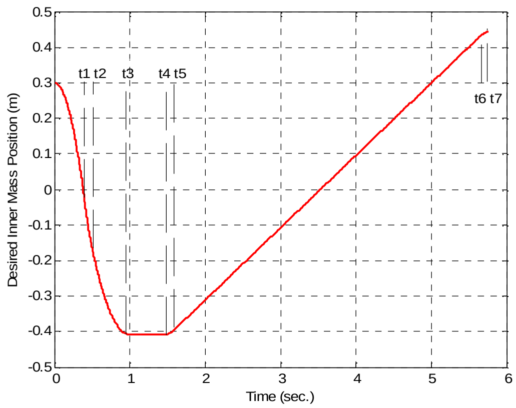

Figure 3 Desired inner body trajectory

3. ITERATIVE LEARNING CONTROL SCHEME

The control scheme consists of two parts: a feedback controller designed by using the approximated linear model and a feedforward learning controller to compensate parametric uncertainties and repetitive disturbances.

An approximated linear system model can be found by applying the control law

$$u = -[\hat{m}_{2k}\hat{m}g\,\mathrm{sgn}(\hat{\dot{x}}_2 - \hat{\dot{x}}_1) + v] \qquad (5)$$

to (2), where $\hat{m}_{2k}$, $\hat{m}$ $\hat{\dot{x}}_1$, and $\hat{\dot{x}}_2$ are observed parameters.

Consider the term

$$d(t) = \hat{m}_{2k}\hat{m}g\,\mathrm{sgn}(\hat{\dot{x}}_2 - \hat{\dot{x}}_1) - m_{2k}mg\,\mathrm{sgn}(\dot{x}_2 - \dot{x}_1) \qquad (6)$$

as system uncertainty, then the approximated linear transfer function of the Capsubot is given

$$p(s) = \frac{x_2(s)}{v(s)} = \frac{1}{ms^2} \qquad (7)$$

A fixed-gain PD controller is chosen as the feedback controller, which gives the transfer function

$$c(s) = k_p + k_d s \qquad (8)$$

where k_p is the proportional gain, k_d is the derivative gain.

The resulting scheme has the closed-loop transfer function w(s), given by

$$w(s) = \frac{x_2(s)}{r(s)} = \frac{p(s)c(s)}{1+p(s)c(s)} = \frac{k_d s + k_p}{ms^2 + k_d s + k_p} \qquad (9)$$

where r(s) is the reference input.

At iteration k, a learning control law $f_k(s)$ is added to the feedback controller output to yield

$$v_k(s) = e_k(s)c(s) + f_k(s) \qquad (10)$$

The learning algorithm is defined by an update law

$$f_{k+1}(s) = a(s)u(s) + b(s)f_k(s) \qquad (11)$$

where α(s) and β(s) are filters that are selected by the convergence criterion

$$|b(s) - a(s)w(s)| < 1 \qquad (12)$$

for all values of s=jw (Luca, 1992). Then the tracking error and the learning law have convergence such that

$$e_\infty(s) = \lim_{k\to\infty} e_k(s) = \frac{r(s)}{1+p(s)c(s)}\frac{1-b(s)}{1-b(s)+a(s)w(s)} \qquad (13)$$

and

$$v_\infty(s) = \lim_{k\to\infty} v_k(s) = \frac{r(s)}{p(s)}\frac{a(s)w(s)}{1-b(s)+a(s)w(s)} \qquad (14)$$

According to (12) and (13), it is easy to find that

$$a(s) = \frac{1}{w(s)},\; b(s) = 1$$

which gives the convergence criterion $|b(s) - a(s)w(s)| = 0$. Under this condition, the tracking error and the learning law are

$$e_\infty(s) = 0,\; v_\infty(s) = \frac{r(s)}{p(s)}$$

This provides the optimal theoretical choice for the learning filters which makes exact tracking achievable just after the first iteration. However, this optimal choice is not feasible unless w(s) is a stable minimum-phase system with relative degree 0 (Moon, 1997). Moreover, it leads to an extremely high gain in high frequencies which can make the overall system sensitive to high-frequency noise. So the learning filters should be properly chosen according to convergence criterion (12).

The block diagram of the proposed control scheme is shown in

Figure 4, where d(s) represents the system uncertainty, and n(s) represents the repetitive disturbance.

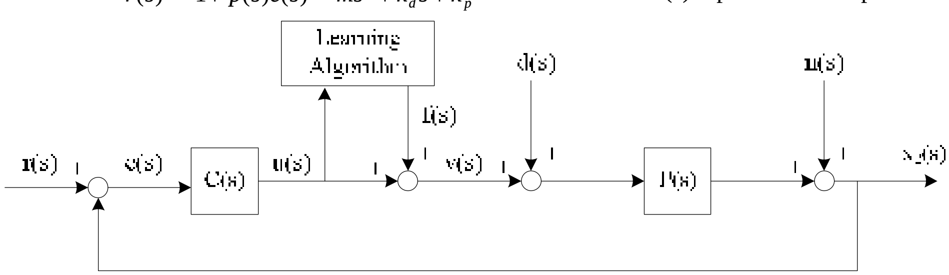

Figure 4 Block diagram of the learning control scheme

4. SIMULATION STUDY

The parameters of the Capsubot are given in Table 1. So we can find the desired trajectory for the inner body in (15), and its plots are shown in Figure 5.

Table 1 Parameters of the Capsubot

M (kg)	m (kg)	μ_{1s} (N/m/s)	M_{2s} (N/m/s)	g (m/s^2)	
0.9	0.6	0.166	0.016	9.81	
t_1 (s)	t_2 (s)	t_3 (s)	t_4 (s)	t_5 (s)	t_6 (s)
0.4	0.49	0.98	1.48	1.58	5.66
t_7 (s)	w_1 (m/s)	w_2 (m/s)	W_0 (m/s)	T_s (ms)	
5.76	1.66	1.0	0.2	1	

$$\dot{x}_{2d}(t)=\begin{cases}-4.15t & t\in[0,0.4)\\ 7.33t-4.59 & t\in[0.4,0.49)\\ 2.04t-2 & t\in[0.49,0.98)\\ 0 & t\in[0.98,1.48)\\ 2t-2.96 & t\in[1.48,1.58)\\ 0.2 & t\in[1.58,5.66)\\ -2t+11.52 & t\in[5.66,5.76]\end{cases} \tag{15}$$

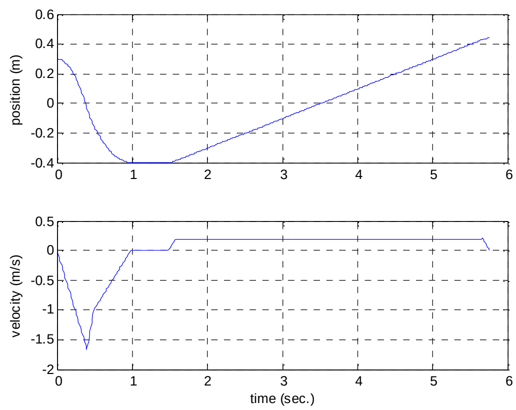

Figure 5 Desired Inner body trajectory

In the simulation, the relative position is initially set to 0.3m. Since the ILC requires that the system performs the same operation repeatedly under the same operating conditions (Bristow, 2006), we set the relative position at each iteration as $x_{2,k}(0)-x_{1,k}(0)=0.3$

4.1 Convergence criterion

We can test the convergence of the learning control scheme directly using the Nyquist frequency plot. The Nyquist diagrams of the system are reported in Figure 6. The Nyquist diagram of the system with only feedback controller (non-learning) is shown in case 1. The unstable behavior occurs due to the presence of $|w(jw)|>1$. In case 2, we select the filters as $a(s)=0.5$, $b(s)=\dfrac{1}{0.008s+1}$

The filter α(s) is selected as a constant value, so it will not take advantage of the knowledge about the closed-loop system. However, it can be considered as a weighting factor for the feedback control signal and the last learning control signal. The chosen β(s) is a low-pass filter which gives a cut-off frequency of 20 Hz. It works as a lag compensator which compensates the non-learning case with the resulting effect given in the second case shown in Figure 6. The bandwidth of β(s) should be sufficiently higher than the desired trajectory, since uncertain disturbances always contain higher harmonic components of the reference signal. With the introduction of β(s), the stability of the system will no longer be affected by the high-frequency content of the closed-loop signals.

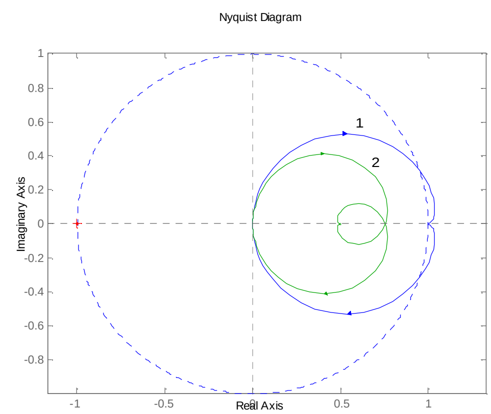

Figure 6 Nyquist plots: (1) non-learning (2) learning

4.2 Simulation results

The overall scheme is initially tested without disturbances. The tracking errors of the inner body are shown in Figure 7. The case 0 shows that the learning control input is initialized as $f_1(t)=0$, so the tracking errors are the result of only the PD control. The tracking errors are drastically reduced by the learning proceeds from iteration 1 to iteration 10. Figure 8 shows the root mean square (RMS) values of the tracking errors. The RMS errors show a fast convergence tendency to accurate tracking and decrease steadily to approach an acceptable error margin. At the beginning, without the learning control, the PD control performs the RMS value at 1.33cm. At iteration 10, the learning scheme gives the RMS value at 0.11cm.

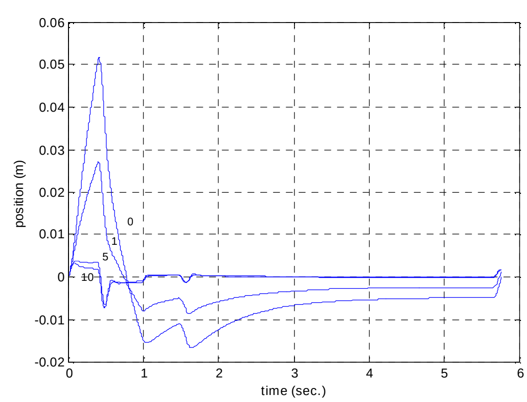

Figure 7 Tracking errors of the inner body

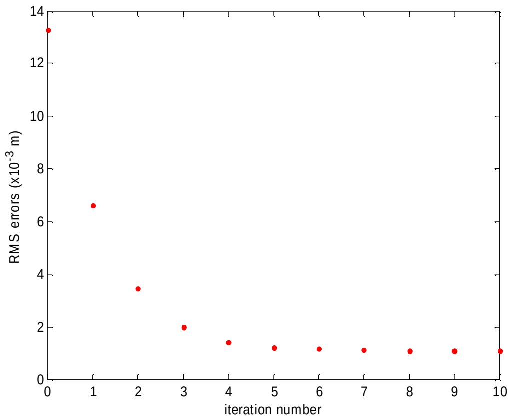

Figure 8 RMS values of tracking errors

Figure 9 shows the input signals generated by the piezoelectric actuator for trajectory tracking. The resulting locomotion of the Capsubot is shown in Figure 10. Due to the inaccurate tracking of the inner body using only the PD control, a backward movement results at the fast motion stage for the Capsubot in case 0. With the introduction of the learning control, the backward movement is shortened at each repetition. At iteration 10, the backward distance is sufficiently reduced to an acceptable value.

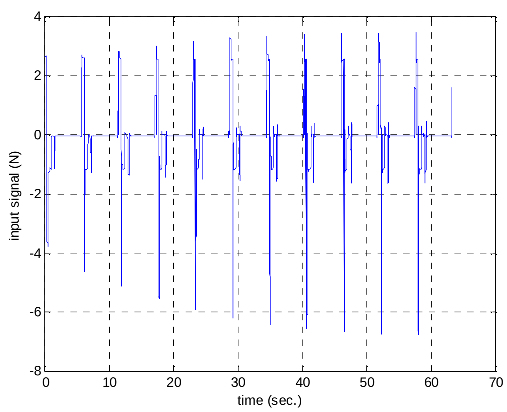

Figure 9 Input signals for the Capsubot

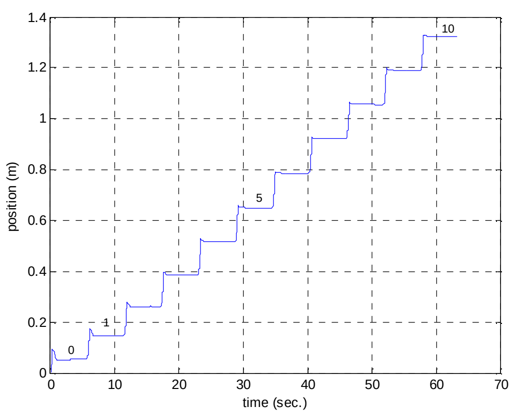

Figure 10 Trajectories of the Capsubot

4.3 Robust test

The robust test is implemented by introducing 10% less measure errors at the parameters of the capsule shell mass, the inner body mass, and the friction coefficients. The repetitive disturbance n(t) that affects the observation of the inner body position $x_2(t)$ is chosen as a sine function such that $n(t)=0.5\sin(2\pi t/t_6) \quad t\in[0,t_6]$

Figure 11 shows the inner body trajectory with only PD control compared with the desired trajectory. The figure shows that the PD control cannot eliminate the measure errors and the repetitive disturbance. The tracking errors of the inner body are shown in Figure 12. Case 0 gives large tracking errors without learning proceeds. Then the tracking errors are gradually reduced to an acceptable value until iteration 10. The performance of the learning scheme is shown in Figure 13, which demonstrates the RMS values of tracking errors. Initially, the RMS value is 1.79cm with only PD control. Then the RMS value is drastically reduced at iteration 4, and successfully decreases to an acceptable value, 0.12cm, at iteration 10.

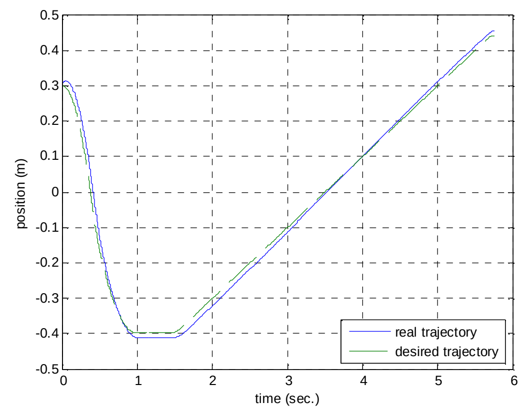

Figure 11 Inner body trajectory with repetitive disturbances using only PD control

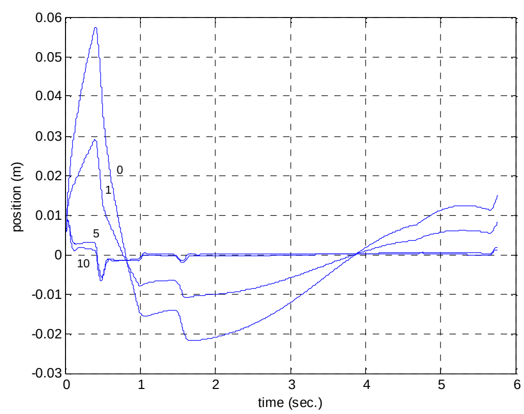

Figure 12 Tracking errors of the inner body with repetitive disturbances

The input signals with repetitive disturbances for the inner body to track the desired trajectory repeatedly are shown in Figure 14. Compared to Figure 9, the peak values of each repetition are extremely high. Due to the disturbance n(t), the observation of the inner body position $x_2(t)$ is disturbed. So higher input signals are required to compensate for the tracking errors of the inner body. This leads to the further movement of the Capsubot shown in Figure 15.

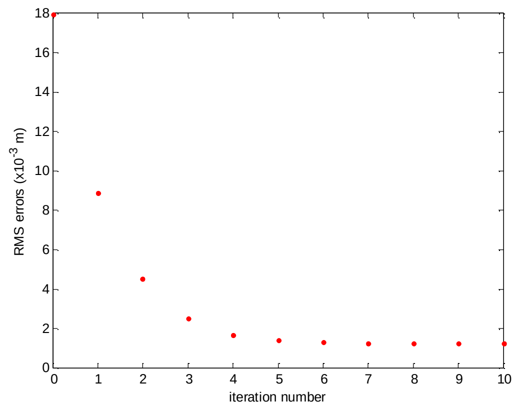

Figure 13 RMS values of tracking errors with repetitive disturbances

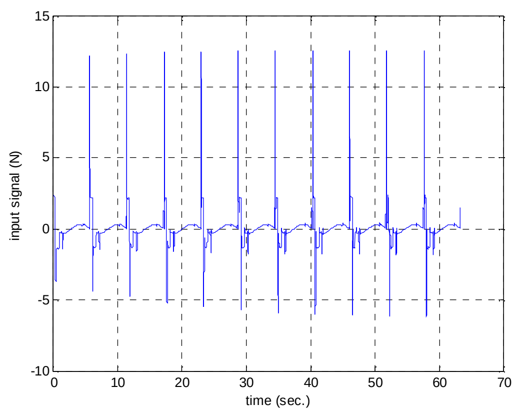

Figure 14 Input signals for the Capsubot with repetitive disturbances

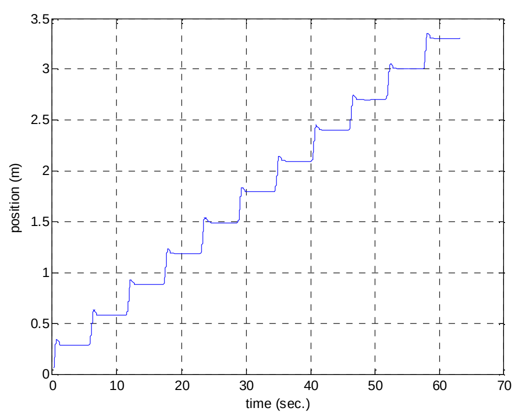

Figure 15 Trajectories of the Capsubot with repetitive disturbances

5. CONCLUSION

The tracking issue of the Capsubot system has been studied in this paper. To move the Capsubot in the desired direction, the repetitive motion for the inner body has been studied. Based on the nature of the repetitive motion, an ILC scheme has been studied. The convergence of the ILC scheme was demonstrated from the frequency domain by using the Nyquist plot. The effectiveness of the proposed scheme has been demonstrated from extensive simulations.

Acknowledgements: The authors would like to thank the EPSRC research council (research grant EP/E025250/1) for the support of this research.

REFERENCES

F. Harashima, "Human Adaptive Mechatronics – Interaction and Intelligence," Proceedings of the IEEE International Conference on Emerging Technologies and Factory Automation, Catania, Italy, September 2005

M. Iwase, H. Shoshiro, and K. Furuta, ''Analysis of Intermittent Control Systems by Human Operations,'' Proceedings of the 31st Annual Conference of the IEEE Industrial Electronics Society, Raleigh, North Carolina, USA, November 2005.

Y. Liu, H. Yu, and T. C. Yang, ''Analysis and Control of a Capsubot,'' accepted by the 17th IFAC world congress, Seoul, Korea, July 2008.

S. O. Wane, H. Yu, and Y. Liu, "Implementation of an Actuated Inverted Pendulum on a Real Time System," the 13th International Conference on Automation and Computing, Stafford, UK, September 2007.

D. A. Bristow, M. Tharayil, and A. G. Alleyne, A Survey of ILC, *IEEE Control Systems Magazine*, Vol.26, Issue 3, June 2006, pp.96-114.

D. Luca, G. Paesano, and G. Ulivi, A Frequency-Domain Approach to Learning Control: Implementation for a Robot Manipulator, *IEEE Transactions on Industrial Electronics*, vol.39, no.1, February 1992.

T. Kuc, K. Nam, and J. S. Lee, An ILC of Robot Mnipulators, *IEEE Transactions on Robotics and Automation*, vol.7, no.6, December 1991.

J. Moon, T. Doh, and M. J. Chung, ''An ILC Scheme for Manipulators,'' Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, Grenoble, France, September 1997.

K. L. Moore, M. Dahleh, S. P. Bhattacharyya, ILC: A Survey and New Results, *Journal of Robot Systems*, vol.9, no.5, p*netics*, Montreal, Canada.