Experimental Study of Human Performance in High Precision Tracking Task Using Iterative Learning Technique

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In this paper, the ability of a human operator in tracking the desired trajectory with high precision using an iterative learning technique is studied. Experiments are designed to provide the best perception of data and fine control to the human operator. Results of the experiments show the ability of the human operator to perform the tracking tasks very precisely. The convergence of the human control input to the desired control input is observed to be fast. Furthermore the control strategy of the human operator is analyzed in this paper.

I. Introduction

Learning to perform many new tasks is an ongoing practice of human being in the daily life. Human beings are capable of performing the new tasks successfully after enough practice without having any prior knowledge. For instance, the task of a crane operator is a good example of manual control. A novice crane operator feels difficulty in maneuvering the crane but after enough practice, he can control the crane to follow the desired trajectory very smoothly. A juggler can juggle and an expert painter can draw pictures very precisely.

Many attempts to some aspects of the man-machine system (MMS) have been reported. An important class of MMS models may be referred to as the control system theoretic models. These models are based on the modeling principles such as, goal oriented modeling approach, human operator functions considering as the components of the total system and human operator modelling with the assumption that he behaves optimally but subjects to his inherent limitations and constraints. Historically much interests have been devoted to the manual control, especially in the context of aircraft control. Many researchers have studied the tracking performance of the human operator [1,2] using different techniques. Moreover, the ability of the human operator in performing control tasks and the control characteristics while working as an adaptive controller [3], an optimal controller [4] and telemanipulation [5] have been studied. R. Ikeura and H. Inooka [6] have presented an iterative modification method using the master slave manipulator.

In this paper, we are concerned with the behavior of the human operator while learning to track the specified reference trajectory and trying to minimize the error between the plant output and the reference input trajectory after each iteration. The plant dynamics are not known to the human operator. The human operator modifies his control strategy by identifying the dynamics of the process from his accumulated experience of the previous iterations.

Since the human operator performs the new task starting with some guess and then in each next trial, he recalls the previous control pattern and thus modifies it according to the task requirements. The repetitive task performed by the human operator can be described by the following equation.

$$u_i(t) = \gamma_i u_{i-1}(t) + \delta u_i(t) \quad (1)$$

In this equation, $\delta u_i(t)$ is the control input generated by the human operator through the joystick in i^{th} iteration. $u_{i-1}(t)$ is the previous control input used for $(i - 1)^{th}$ iteration and stored in the memory of computer. $u_i(t)$ is the control input comprising of the previous control input $u_{i-1}(t)$ and the modification to the control input done by the human operator in the i^{th} iteration. It will be used as the control input to the system in the i^{th} iteration and will also be stored in the memory of the computer. γ_i corresponds to the recalling factor. This recalling factor is introduced to incorporate the fact that the human operator finds difficulty to recall his previous control pattern precisely. As he performs the task many times, he improves his recalling factor. For an experienced human operator, this factor approaches to one. In this paper, we have provided the facility of a computer memory rather than human memory to recall the previous control patterns. It is done by storing the previous control actions in the computer memory. The human operator is not required to recall his previous control action, as it will be available to him from the computer memory. The only task left for the human operator is to generate the modifications to the previous control input in a way to minimize the error. Hence recalling factor is equal to 1.0 for all manual control experiments. By using such a technique, the authors believe that it is easy to study the learning process of the human operator for a specified task.

M. Arif and H. Inooka [7] have performed some experiments regarding the human performance in iterative learning control and found out that the human operator can perform the task quite intelligently. The important feature they have quoted is that the human operator can not improve his performance if the error spectrum shifts to the higher frequency range.

In this paper, a relatively simpler reference trajectory is chosen so that the error spectrum during the initial iterations may not shift to the high frequency range, unabling the human operator for further improvement. In this way, it is easier to study the control strategy adopted by the human operator in accomplishing the required task. The performance of the human operator for a high precision tracking task is analyzed for a specified tracking task using a single link pendulum.

This paper is organized as follows. In section 2, experimental setup is explained. In section 3, results of the experiments are discussed and analyzed in section 4. Finally conclusions are given in the last section.

II. Experimental Setup

A. Compensatory Manual Control Setup

The compensatory manual control setup as shown in the figure 1 is equivalent to a one dimensional servomechanism in which the human operator has only one input, the error, the difference between actual system response and the desired or reference trajectory. The majority of the research in manual control theory has dealt with single loop compensatory systems [8,9], where the human operator's problem is to observe and compensate the error between the system output and the desired trajectory. The human operator neither knows the desired trajectory nor the plant dynamics. The only information provided to him is the error signal.

To study the human performance in high precision tracking task, a nonlinear single link pendulum is used as the system. The dynamic equation of the nonlinear model of a single link pendulum is

$$I\ddot{\theta} + \zeta\dot{\theta} + \left(\frac{1}{2}m + M\right)gl \sin \theta = \tau. \quad (2)$$

Where $\theta(t)$ is the angular position of pendulum and $\tau(t)$ is the deriving torque. The variables m , M and l are the mass, tip load and length of the pendulum respectively. I is the moment of inertia with respect to the joint and defined as

$$I = Ml^2 + \frac{1}{3}ml^2. \quad (3)$$

Let $m = 0.5$ Kg, $M = 1.0$ Kg, $l = 1.0$ m, $g = 9.8$ m/s² and damping term $\zeta = 0.6$ be chosen as system parameters with the sampling period of 0.01 second. $\theta_d(t)$ is the desired trajectory.

Precision index J^{pi} of i^{th} iteration is defined as

$$J^{pi} = \max_{0 < t \leq T} |e_i(t)| = \max_{0 < j \leq N} |e_i(j)|. \quad (4)$$

An analog joystick is used as a human operator control device. Data from the joystick is transferred to the computer through an ADC board (12-bit resolution) at the rate of 100 samples/second.

To illustrate the difficulty of the human operator in performing high precision task, an experiment is performed for the tracking of a desired trajectory as shown in figure 2. The desired precision index J_d^p is set to be 2°. The desired final position is set to be 45°. The compensatory manual control setup as shown in figure 1 is used for the tracking experiment. The precision index J^{pi} is plotted at log scale in the figure 3.

The base-line set at 2° in the figure shows the goal of the human operator i.e. the desired precision index J_d^p . It can be observed from the figure that the human operator was unable to achieve the required precision in 200 trials. Based on this observation it is concluded that using such kind of experimental setup it is difficult to perform high precision tracking task by the human operator.

Fig. 1 Compensatory manual control setup.

Fig. 2 The desired trajectory.

Fig. 3 Precision index J^{pi} using compensatory manual control setup.

B. Proposed Experimental Setup for Iterative Learning

In our setup, we have designed a computer assisted experimental setup based on the iterative learning to study the human learning and performance in the high precision tracking tasks.

Figure 4 shows the block diagram of the experimental setup of computer assisted iterative learning control of a given plant by the human operator. A computer simulates the plant dynamics and the results in term of the error signal are displayed to the human operator. $\theta_d(t)$ is the desired trajectory which is required to be followed by the plant for a fixed time period of $[0, T]$. Error $e_i(t)$ at time t and $e_{i-1}(t)$ for $t \in [0, T]$ are displayed to the human operator on CRT screen and the human operator tries to correct the error using joystick actions. In the i^{th} iteration, observing the resulting error $e_i(t)$, the human operator generates the appropriate signal $\delta u_i(t)$ which is then added to the $u_{i-1}(t)$ stored previously in the memory to generate the control signal input $u_i(t)$. This control input $u_i(t)$ is applied to the controlled element or plant. The error $e_i(t)$ and the control input $u_i(t)$ are also stored in the computer memory to be used in the next i.e. $i + 1^{th}$ iteration. At the end of i^{th} iteration, the precision index J^{pi} is calculated using the data of the error of i^{th} iteration. If the precision index J^{pi} becomes equal or less than the desired precision index J_d^p then the iteration process is terminated. Otherwise the same above procedure is repeated for the next i.e. $i + 1^{th}$ iteration.

$e_i(t)$ is defined as

$$e_i(t) = \theta_d(t) - \theta_i(t) \quad (5)$$

where $\theta_i(t)$ is the plant output in i^{th} iteration and

$$u_i(t) = u_{i-1}(t) + \delta u_i(t). \quad (6)$$

$u_i(t)$ is used as the control input to the system for the i^{th} iteration and also stored in the memory as a modified

Fig. 4 Proposed experimental setup.

Fig. 5 Precision index J^{pi} using our proposed experimental setup.

control signal. Initial conditions remain the same for each iteration.

Furthermore the information display is also modified to overcome the difficulty of the human operator in performing high precision tracking task due to the visual information perception error. The ability of the human operator to generate minimum control steps is also improved by varying the gain of the joystick in the iterative learning process. Hence a multi-step approach is adopted which is illustrated as follows: The desired precision index J_d^p is defined prior to the experiment. The experiment is categorized into three steps. In each step, a sub desired precision index is defined, leading to the final desired precision index in the third step. In the first step, the subject is asked to attain a relatively relaxed precision index i.e. $20 \times J_d^p$, which is assumed to be comfortable for the subject. In the next step, the information displayed to the subject is magnified by a factor of five ($\times 5$) to increase the visual perception of the subject and the sensitivity of the joystick is reduced accordingly by five times to give the subject more precise control. Thus a relatively tough precision index $4 \times J_d^p$ is required to be attained. In the third step, display magnification is further increased by four times, resulting in the total magnification of $\times 20$ and the sensitivity of joystick is reduced accordingly. The subject has to attain the actual desired precision index J_d^p .

The effectiveness of the above proposed experimental setup is illustrated by repeating the same experiment as done in the section IIA using the compensatory manual control setup. The precision index J^{pi} is plotted in figure 5. It can be observed from the figure that the human operator has succeeded in performing the tracking task by the desired precision index of 2° in 26 iterations. Hence our proposed experimental setup gives us an opportunity to study the human learning and performance in high precision tracking tasks very efficiently.

III. Experimental Results

The task is defined as the controlled maneuvering of the pendulum to the desired final position θ_f with desired precision J_d^p defined in equation (4). To illustrate the advantage of the multi-step information display setup with variable joystick gain control another experiment is performed in which the desired trajectory is same as shown

Fig. 6 Precision index J^{pi} vs iteration for $J_d^p = 0.4^\circ$.

Fig. 7 Required iterations vs J_d^p in backward and forward sequences.

in figure 2 and the desired precision index J_d^p is set to 0.4° . In figure 6, the precision index J^{pi} is plotted on the log scale for the case when normal display is used for the perception of error data by the human operator and the case in which the proposed multi-step information display magnification technique is used. It is clear from the figure 6 that the human operator can achieve the desired precision index J_d^p very smoothly with fast convergence in about 15 iterations by using the specified technique, hence showing the effectiveness of the multi-step information display magnification technique. Further experiments are categorized into three categories.

A. Experiments for Different Desired Precision Indices J_d^p

In the first category, experiments are designed to track the desired trajectory $\theta_d(t)$ with the desired precision J_d^p (in degrees) = 0.8, 0.6, 0.4, 0.3, 0.2 and 0.1 respectively. The desired final position is set to 45° . Experiments are done in both backward and forward sequences. Firstly, in the backward sequence that is starting from the easiest J_d^p and going to the difficult one and then in the forward sequence. The number of iterations required to perform this task are plotted vs J_d^p in figure 7.

It can be observed from the figure 7 that from 0.8° to 0.4° the change in the number of iterations required are not so significant, but for more difficult desired precision indices J_d^p , the required number of iterations increase sharply. In the case of the forward sequence, the number of iterations required for the same difficult J_d^p are less, but there is no improvement for the relatively easier J_d^p . The reason may be due to the fact that the human operator, while performing the experiments in the forward sequence, relaxes for the easier J_d^p and does not improve. In figure 8, the precision index J^{pi} of the three subjects is plotted on the log scale for the case when the desired

Fig. 8 Precision index J_d^{pi} for $J_d^p = 0.1^\circ$.

Fig. 9 System's output and reference trajectory for $J_d^p = 0.1^\circ$.

precision index $J_d^p = 0.1^\circ$. The base-line at 0.1° in figure 8 shows the desired precision index J_d^{pi} . Although the number of iterations required to achieve the desired precision index is different for the three subjects but the important thing to be noted is that all the subjects have succeeded in attaining the desired accuracy. In figure 9, the output of the system and the desired trajectory θ_d are plotted for $J_d^p = 0.1^\circ$. It can be noted from the figure that the human operator can track the trajectory very accurately.

In figure 10, the desired control input $u_d(t)$ to track the trajectory and the control input generated by the human operator are plotted. $u_d(t)$ is obtained by using a standard D type iterative learning control technique [10] described as follows,

$$u_i(t) = u_{i-1}(t) + \delta u_i(t) \quad (7)$$

such that

$$\delta u_i(t) = \begin{cases} 2.5 & \text{if } \delta u_i(t) > 2.5 \\ -2.5 & \text{if } \delta u_i(t) < -2.5 \end{cases} \quad (8)$$

where $\delta u_i(t) = \Gamma \dot{e}_{i-1}(t)$. Γ is the learning gain matrix.

Despite very small oscillations, the human operator has reached to the desired control input $u_d(t)$ efficiently (figure 10).

Fig. 10 Human control input $u(t)$ and $u_d(t)$ for $J_d^p = 0.1^\circ$.

Fig. 11 Iterations required vs final desired angles.

B. Experiments for Different Final Desired Angles θ_f

In the next category, experiments are performed to track the trajectories to the final desired angle $\theta_f = 45, 70, 90, 110, 135$ and 155 for a fixed value of J_d^p that is 0.4° . In figure 11, number of iterations required to achieve the desired precision index is plotted vs final desired angle θ_f . In this figure, human control efforts are compared with the automatic control. D type iterative learning control (equation 7) is used for the tracking task. It can be observed from the figure that the human operator can perform the tracking very well by using the enhanced perception with fine control technique and the number of iterations required to perform the task are very close to the automatic control. For the $\theta_f = 45^\circ$ case, the human operator even can perform better as compared to the automatic control. The increasing trend of the number of iteration is also the same in both cases.

C. Controlled Swing Up of the Pendulum

In the last category, the experiment for swing up of the single link pendulum is performed. The swing up is controlled in the sense that the desired swing up trajectory is predefined. The desired trajectory is assumed to be achievable and continuously differentiable on the finite time interval $t \in [0, T]$, such that for the bounded desired trajectory $\theta_d(t)$, there exists a unique bounded input $u_d(t)$ for $t \in [0, T]$, for which system has unique bounded states. The controlled swing up problem is more difficult as compared to the free swing up problem. In controlled swing up, the human operator has to follow the desired trajectory on each point as compared to the

Fig. 12 The desired trajectory $\theta_d(t)$ and the output $\theta(t)$ of the pendulum after 70 iterations.

Fig. 13 The desired control input $u_d(t)$ and the control input $u_h(t)$ of the human operator after 70 iterations.

free swing up in which only final position is desired to be achieved. The desired precision index J_p^d is set to be 1° for this experiment. The desired precision index is achieved by the human operator in 70 iterations.

In figure 12, the output of the system $\theta(t)$ and the desired trajectory $\theta_d(t)$ are plotted. It is clear from the figure 12 that how well the human operator can track the trajectory with the required accuracy. The final human control $u_h(t)$ and the desired control input $u_d(t)$ generated by D type iterative learning control (equation 7) are plotted in figure 13. The human operator succeeded in approaching to the desired control input with some small oscillations (figure 13).

IV. Analysis of Experimental Results

A. Time Domain Analysis

The above experiments show the ability of the human operator in high precision tracking task. Since the human operator generates the control input based on the information of the perception of the error data displayed to him, therefore for each iteration, error $e_i(t)$, error rate $\dot{e}_i(t)$ and $\delta u_i(t)$ are analyzed to study the human control. It is found that the human operator generates $\delta u_i(t)$ depending on both the error and the error rate. $\delta u_i(t)$ can be represented as

Fig. 14 $\delta u(t)$, $e(t)$ and $\dot{e}(t)$ at iteration number 3. Fig. 15 $\delta u(t)$, $e(t)$ and $\dot{e}(t)$ at iteration number 11.

$$\delta u_i(t) = \Lambda_{i-1} e_{i-1}(t) + \Gamma_{i-1} \dot{e}_{i-1}(t) \quad (9)$$

where Λ_{i-1} and Γ_{i-1} are the learning gains relating to the error and error rate respectively.

One typical example is presented here in which the human operator has to achieve the desired precision index J_d^p equal to 0.4° in tracking the trajectory leading to the final desired angle of 90° . $\delta u_i(t)$, $e_{i-1}(t)$ and $\dot{e}_{i-1}(t)$ are plotted in figure 14 for iteration number 3 and plotted in figure 15 for iteration number 11.

It can be observed that the human operator gives more weight to the error $e_{i-1}(t)$ as compared to the error rate $\dot{e}_{i-1}(t)$ in iteration number 3 (figure 14), whereas he gives more weight to the error rate $\dot{e}_{i-1}(t)$ as compared to the error $e_{i-1}(t)$ (figure 15) in iteration number 11. In both cases, the control input is leading to the error $e_{i-1}(t)$ and the error rate $\dot{e}_{i-1}(t)$. It may be due to the fact that the full error data of the previous iteration is available to the human operator and he generates his control action a little earlier as he can perceive the whole data.

According to the observations, the correlation of the $\delta u_i(t)$ in each iteration is investigated with respect to the error $e_{i-1}(t)$ and the error rate $\dot{e}_{i-1}(t)$. In figure 16, the cross correlation coefficient between $\delta u_i(t)$ and $e_{i-1}(t)$ is plotted, whereas in figure 17, cross correlation coefficient between $\delta u_i(t)$ and $\dot{e}_{i-1}(t)$ is plotted. Results of three subjects are plotted as points and the average of the three data points is plotted as line. It can be observed from the figures 16 and 17 that the human operator assigns different weights to the error and the error rate data and modifies the gains in each iteration. In the beginning of the experiments when the error is large, the human operator's control is much more like Proportional type iterative learning control ($\delta u(t)$ is a function of the error $e(t)$ only), whereas towards the end of experiment when the error is small but the error rate is large, the human

Fig. 16 Correlation coefficient of $\delta u(t)$ and $e(t)$. Fig. 17 Correlation coefficient of $\delta u(t)$ and $\dot{e}(t)$.

Fig. 18 Rasmussen's decision making stages.

operator's control is similar to Derivative type iterative learning control ($\delta u(t)$ is a function of the error rate $\dot{e}(t)$ only). Moreover, based on the analysis of the data, it suggests that the human operator makes certain rules to handle the task. One simple rule that can be extracted from the above analysis is given as follows: The human operator generates $\delta u(t)$ using the error $e(t)$, when $e(t)$ is prominent, and generates $\delta u(t)$ using the error rate $\dot{e}(t)$ when $\dot{e}(t)$ is prominent.

Our analysis suggests that the human operator perform rule based control in the high precision tracking

Fig. 19 f_{half} of $e(t)$ for $J_d = 0.1^\circ$ and $\theta_d = 45^\circ$.

Fig. 20 f_{half} of $\dot{e}(t)$ for $J_d = 0.1^\circ$ and $\theta_d = 45^\circ$.

tasks. This observation also coincides with the well known results of the Rasmussen's work [11] which describes the multi-modality of the human operator's performance. The decision making stages of the human operator proposed by Rasmussen et al. [11] is shown in the figure 18. In this ladder type realization, Rasmussen et al. suggest that the human operator in the real life tasks prefer to define certain rules which can be recallable and simple. In our analysis of the experiments, we also found that the human operator follows a simple rule to generate his control actions.

B. Frequency Domain Analysis

To get some more insight, the error $e(t)$ and the error rate $\dot{e}(t)$ are analyzed for some typical cases in the frequency domain and f_{half} is defined as the parameter of interest as described below.

Let a signal $g(t)$ is transformed into the frequency domain by the Fast Fourier Transform method. G is the vector in frequency domain corresponding to $g(t)$. Let $P(k)$ is the power sum to some number k defined as

$$P(k) = \frac{1}{N} \sum_{i=1}^k |G(i)|^2. \quad (10)$$

Consider a number k_{half} which represents the number for which

$$P(k_{half}) \cong \frac{P(N/2)}{2} \quad (11)$$

Fig. 21 f_{half} of $e(t)$ for controlled swing up case.

Fig. 22 f_{half} of $\dot{e}(t)$ for controlled swing up case.

and the frequency value f_{half} corresponding to k_{half} is given as

$$f_{half} = \frac{k_{half}}{NT_s} \quad (12)$$

where T_s is the sampling period = 0.01 second.

f_{half} of $e(t)$ and $\dot{e}(t)$ are plotted in figures 19 and 20 respectively for the case of the trajectory tracking with the precision of 0.1° , leading to the final position of 45° . Data of three subjects are plotted. The number of iterations for all the subjects to achieve the desired accuracy is different. It can be observed from the figure that initially f_{half} increases with the iterations but the subjects 1 and 3 somehow managed to keep it under 1.5 Hz and succeeded to attain the required precision of 0.1° whereas for the subject 2, the f_{half} of $e(t)$ and $\dot{e}(t)$ goes beyond 2.0 Hz. It is given in [12] that studies of tracking performance in which the human operator must follow a continuously varying desired trajectory yields bandwidth estimate of about 1 Hz and humans are not very good at following signal components above 1 Hz. Hence it justifies the large number of iterations required by the subject 2 to achieve the desired precision index.

f_{half} of $e(t)$ and $\dot{e}(t)$ of subject 3 is plotted in figures 21 and 22 for the controlled swing-up case respectively. There is an increasing trend of f_{half} in the beginning of the iterations but after 30 iterations, f_{half} decreases and remains almost constant for the rest of iterations. It shows the human operator's ability to decrease the f_{half} of the error and the error rate, enabling him to achieve the required task.

V. Conclusion

Iterative learning is the common practice utilized by humans. While performing routine tasks, he improves his ability to perform certain task after each iteration according to his past experience. In this paper, the ability of the human operator in the tracking task with high precision is investigated. The experiments show the ability of the human operator to reduce the error and to improve the precision index efficiently despite of the unavailability of the plant information. The human operator tries to perform the required task based on his perception of the input-output data without analyzing exactly the plant dynamics. He can improve his performance based on the previous experience. It is concluded from the experiments that if the perception of the data by the human operator is improved and a better control sensitivity is provided, the human operator can perform the tracking tasks with higher precision. It is also concluded that the human operator performs simple rule based control and modifies the control input in each iteration giving different weights to the error and the error rate data. The human operator shows variable gain PD (Proportional and Derivative) type iterative learning control as given in equation (9) and modifies the weights in each iteration according to some simple rule. Furthermore, the frequency analysis shows that the human operator can control the f_{half} of the error and the error rate under a limit so that he can achieve the desired accuracy in the tracking task.

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