IDENTIFICATION OF THE HUMAN BEHAVIOR IN VIRTUAL ENVIRONMENT TASKS AS A NON-LINEAR CONTROL BLOCK

Jorge A. Méndez-Iglesias [1] **Vicente Parra-Vega**
Francisco J. Ruiz-Sánchez

CINVESTAV-IPN, México.
Departamento de Ingeniería Eléctrica
A.P. 14-740, 07300 México D.F., México
{jamendez, vparra, fruiz}@cinvestav.mx

Abstract: First results on characterizing the human action as a controller are presented. The corresponding model of the human behavior as a control block is obtained by means of experimentation, and statistically validated. The identified human control mode corresponds to a nonlinear PID model. Using the methodology presented in this paper, it is possible to forecast parameter magnitude and therefore to implement a predictive system of the human behavior. The experimental platform consists of a 3D virtual space and a PHANToM haptic interface. A dual AMD Athlon-MP processor computer is used as real-time processing unit. RTLinux 3.1 operating system and PHANToM driver written by Zdenek Kabelac are used in order to achieve timing restrictions.

Keywords: Man/machine interaction, Parameter identification, Time-varying systems, Teleoperation, Human factors, Dynamic modeling, Control system analysis

1. INTRODUCTION

Modeling and characterization of human operator has been a long standing problem, studied by the diverse research community of man-machine-interface (MMI), such as neurophysiology, robotics, biomechanics, and recently teleoperation and haptics.

In this paper, new results on the identification of the human behavior as a control block in virtual environments are presented.

An approach to analyze human behavior is suggested by Fitts (Fitts, 1954), who considers the time to accomplish a task as an indicator of the performance. This idea was applied to study man performance in computer interaction by McKenzei (McKenzie, 1991) and, in a similar way, the work of Zhai, Accot and Woltjer in virtual reality (Zhai *et al.*, 2004).

Using the Fitts law as a performance indicator, in 1963, Sheridan and Ferrell studied time delayed teleoperation systems (Sheridan and Ferrell, 1963). In 1965, Ferrell continued his work (Ferrell, 1965); in 1966 introduced force feedback and observed instability when force feedback delay is present in the control system(Ferrell, 1966).

These studies provide qualitative results of the human performance. It means that based on those results, it is not possible to have a model of the human operator considered as a part of a physical

[1] This work is partially supported by CONACyT Fellowship Folio_174132 to J.A. Méndez-Iglesias

system and therefore, it is not possible to apply classical or modern control theory approaches to analyze the complete man-machine system.

A control systems approach has been considered in several ways, such as time-optimal control proposed by McRuer (McRuer, 1980). McRuer proposed a structural isomorphic model of man-machine system, considering three blocks in the man : sensory mechanisms, central elements and neuromuscular actuation system. In the central elements block, a visual channel equalization block, containing integral, proportional, rate and acceleration varying gains is included. This provides an idea of a nonlinear model.

Another systems approach using hidden Markov models is proposed by Nechyba and Xu (Nechyba and Xu, 1996) and in the same way, neural networks proposed by Song, Xu, Nechyba and Yam (Song *et al.*, 1998). The common aspect of them, is to use a virtual road as visual input to the man. This approach, provides a dynamic task, but studies only the response for a car-driving maneuver and therefore, does not consider small three dimensional movements of a limb.

Robles-De-La-Torre and Sekuler, observed that subjects performed as feed-forward, predictive controllers when practicing the task in virtual environments (Robles-De-La-Torre and Sekuler, n.d.).

In this paper, considering the dynamical behavior of the human, and the characteristics of current operation requirements, such as small movements and precise actions, it is intended to characterize the human action in the control loop in order to establish real stability criteria that assure good performance of the system.

The human responses are analyzed facing the task of positioning a cursor on a specified position, starting from a predetermined fixed point in a 3D environment. As a first approach, both points, initial and final, are placed on the rectangular axes of the scene in such a way that the six directions of motion are considered. The cursor is controlled using a PHANToM interface over RTLinux in a 3D environment developed in OpenGL.

An anisotropic response of the human operator is observed, resulting in a model that relates different degrees of PID actions according to the error and its dynamical changes -its temporal derivative and integral.- It is also observed that the movements on the z-axis, perpendicular to the screen, are affected by the difficulties to perceive depth in a flat representation of a 3D environment.

Key aspects of this work, will provide the basis to evaluate human behavior in regulation tasks, and possibly in tracking tasks.

2. PROBLEM FORMULATION

Modeling human behavior, as analyzed by Sekuler in 1980, requires to consider either environment and human decision. The human structure presents changes due to experience as well as sensory mechanisms. This last comment, indicates that it is not possible to have a fixed and general model of the human due to the different experiences acquirerd individualy. In this sense, it is required to measure both stimuli and response in order to have an input-output model of the man behavior.

Having established the need to measure the input/output behavior of the man, it will be required to have an accurate high resolution and fast measuring device. In this sense, such device should be specifically chosen to obtain the information generated by a specific task.

In order to have a simplified model, it is needed to reduce the ammount of freedom degrees, from both mechanical and statistical standpoints. For this reason, a three degrees of freedom haptic interface and a simple translational task are used. In this sense, a virtual reality space provides a simple and flexible experimental environment. As a result of using a virtual environment and a haptic interface, it is necessary to have a time delay robust computational system cappable to uniformly acquire position and speed measurements. Based on these considerations, a PHANToM interface (HD) is proposed, using only the final effector as position/velocity measuring device.

3. PRELIMINARIES

In order to determine a model of the human operator, considering only the input-output response, it is required to have at least the following conditions

- Constant sampling period.
- System behavior is continuous and changes are at least two times slower than sampling frequency.
- Due to the ammount of samples per experiment, the transfer function of the system is determined recursively.
- Considering the possibility of having a nonlinear system, continuous linearization of the system is performed at every sampling period.
- Direct measurement of position and speed.
- Provide a mechanism to specify either a numeric as a geometrically vissible setpoint or target position for the task execution.
- Simple task.

Continuity of the system model and recursiveness in modeling allows to forecast the behavior of

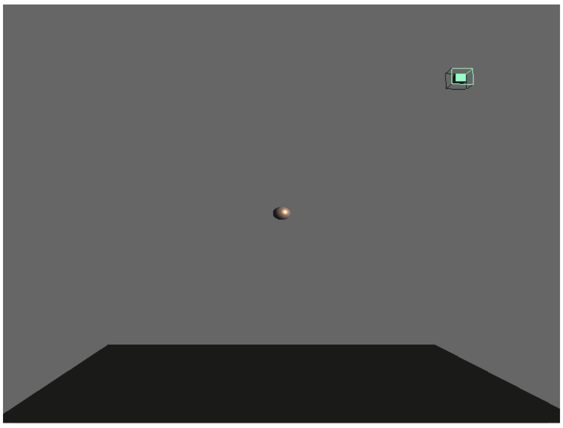

Figure 1. Virtual environment. A virtual tool is moving toward a final position.

the system coefficients. Linearization is used in order to deal with nonlinearities or time varying coefficients of the model. The measurement of the speed, instead of determining it numericaly, will give noiseless information. The selection of the task is of deterministic importance. Based on previous experience, it is abserved that man performs different between free movement and trajectory following tasks. In this case, it is prefered to apply a free movement task with a fixed setpoint or target position and analyze the convergence of the system either with lack of persistency of excitation with the phase portrait method as explained in (Slotine and Li, 1991) and (Wellstead and Zarrop, 1995).

4. MODEL OF THE MAN/MACHINE INTERACTION

The model estimation should be determined in a controlled environment in order to reduce possible sources of unknown information. As will be discussed, factors such as direction of movement for example will produce changes in the model parameters.

4.1 Virtual environment

As said previously, a 3D virtual environment is used as work space. It consists of a virtual cube, which contains a departing/arriving place located in each of its eight corners. In figure 1, a place is shown (top right position) and the spherical cursor at the center of the space. The orientation of the space corresponds to the OpenGL standard, x axis from left to right, y axis from bottom to top, and z axis perpendicular to the screen. The working space is of 20 cm x 20 cm x 20 cm. The video refresh rate is 10 ms.

Figure 2. Gripping the haptic device with three fingers in order to reduce degrees of freedom.

4.2 Experiment execution

It is known that human behavior presents an anisotropic response or different behavior for each different direction of the movement. I is important to reduce the amount of factors that could increase complexity. In order to reduce the amount of degrees of freedom, the man handles the HD employing three fingers instead of one inserted in the thimble as shown in figure 2. The task starts when the man activates the target position using the keyboard and finishes when the man feels that the task is completed. This mechanism provides freedom to the operator to start / finish when he realy feel confidence to execute the task and therefore avoid psycological factors such as stress or fear. Model identification is executed along the task, using the HD as a data acquisition device.

4.3 System model identification

In order to obtain the model of the man action, some identification alternatives were tested. A first approach was the recursive least squares algorithm (RLS), but this produced unacceptable identification errors. As a second approach, the recursive extended least squares method (RELS) was used, with covariance matrix instability. Therefore, a third approach was used, the U-D factorization of Bierman (variation of the Kalman filter). This last approach gave better results, but not perfect, due to the forgetting factor tunning. In this case, a combination of exponential and variable type of forgetting factor as described in (Wellstead and Zarrop, 1995) was used. This specific aspect is an open problem in the systems identification field. Specifically, the algorithm presents sensible identification errors when applied to the z axis (perpendicular to the video screen).

As a preliminary approach, a discrete single-input / single-output (SISO) linear second order model was proposed

$$y[k]+a_0y[k-1]+a_1y[k-2] = b_0u[k-1]+b_1u[k-2], \tag{1}$$

with the target position as input (u) and current position as output (y). Both target position and current position are considered as 3D rectangular components. The identification process is executed simultaneously for each rectangular component. This model will provide information about anisotropy and effects of other factors over the behavior of the model coefficients as will be described below.

4.4 Model validation

In order to validate the proposed model, it is required to validate either model order and other factors effects. The model order validation, as will be described next, is important in order to have confidence in the quality of the estimated values and therefore, in the dynamic correspondence with the reality. Other factors effects should be analyzed in order to determine if variation in the estimated coefficients is produced by noise or if it is caused by such factors.

4.4.1. Model order The order of this model was verified experimentally, varying the model order and analyzing the estimation error. This is required due to the fact of the time variation of the parameters, which eliminated conventional ways of estimation of the system order. The results obtained in this order validation are presented in table 1. The selection criteria consisted in selecting the model of minimum standard deviation and minimal estimation error. The models with type 1 and 2 are candidate to possible model order. Models type 4 and 5 could be candidates, but based on Söderström and Stoica recommendations (Söderström and Stoica, 1989) it is recommended to choose the lower possible order. This is important from the computational aspect, due to the time required to determine the magnitude of the coefficients for a larger model order.

Table 1. Order estimation error for different model orders of the identified system.

Type	model	mean	var
1	$\frac{b}{1+az^{-1}}$	-1.5x10^{-3}	8.3
2	$\frac{b}{1+a_0z^{-1}+a_1z^{-2}}$	-1.1x10^{-3}	1.1x10^{2}
3	$\frac{b_0+b_1z^{-1}}{1+a_0z^{-1}+a_1z^{-2}}$	-1.4x10^{-2}	1.6x10^{3}
4	$\frac{b}{1+a_0z^{-1}+a_1z^{-2}+a_2z^{-3}}$	-1.5x10^{-3}	5.8x10^{1}
5	$\frac{b_0+b_1z^{-1}}{1+a_0z^{-1}+a_1z^{-2}+a_2z^{-3}}$	-1.2x10^{-3}	7.0x10^{1}
6	$\frac{b_0+b_1z^{-1}+b_2z^{-2}}{1+a_0z^{-1}+a_1z^{-2}+a_2z^{-3}}$	2.9x10^{-4}	1.3x10^{2}

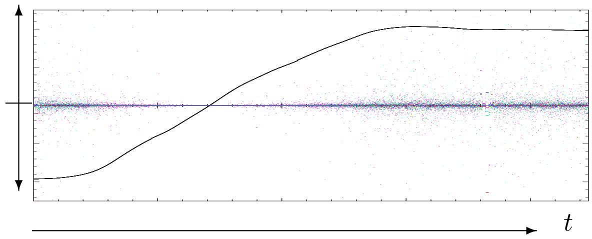

Figure 3. Identification error associated with model order. Continuous line represents the real position. Disperse points represent estimation error as function of different model order for each sampled position

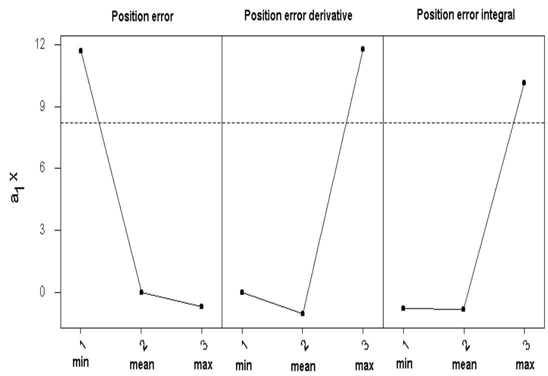

Figure 4. Main effects plot. Data means for a_1 factor as a function of e, $\dot{e}$ and $\int_0^{\tau} e(t)dt$

In figure 3, each dot corresponds to the estimation error, and each color corresponds to the model order. The continuous line represents the real position as function of time.

4.4.2. Main effects analysis A main effects analysis was done in order to determine which factors affect the model, wich resulted as an anisotropic performance of the system, which corresponds with (Zhai *et al.*, 1997). Considering the man-machine system as a physical structure, represented by a second order differential equation, it is required a main effects analysis of the model coefficients behavior as function of the position error and the time derivative and integral. This analysis provided a dependency between those factors as shown in figure 4.

4.5 Proposed PID model

Based on the results from the main effects analysis, it is proposed a new model of the transfer function of the operator when acting as controller of the system. This model includes the position error (e) and its time derivative and integral

$$\begin{aligned} &y[k] + a_0y[k-1] + a_1y[k-2] \\ &= \eta e[k-1] + \delta\dot{e}[k-1] + \iota \int_0^{(k-1)T} e(t)\ dt, \end{aligned} \tag{2}$$

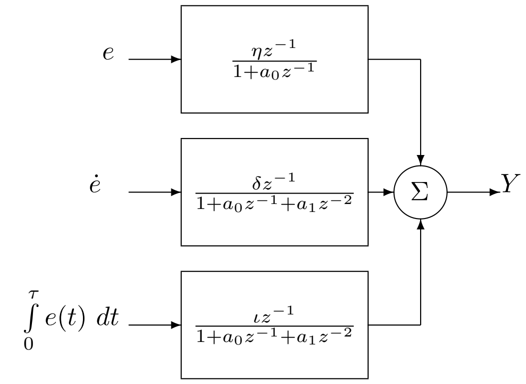

Figure 5. Identified time varying PID control scheme.

Table 2. Comparison of the identification error of the first two order models for e.

type	min	max	mean	var
1	0	2.02	1.31x10^{-4}	5.1x10^{-1}
2	0	3.99	6.99x10^{-4}	5.5

Table 3. Comparison of the identification error of the first two order models for $\dot{e}$.

type	min	max	mean	var
1	0	2.17	-3.08x10^{-4}	6.58
2	0	3.99	-3.15x10^{-5}	2.63

Table 4. Comparison of the identification error of the first two order models for $\int_0^{\tau} e(t)\ dt$.

type	min	max	mean	var
1	0	5x10^{1}	-1x10^{-2}	3x10^{3}
2	6x10^{-42}	4.2	-2x10^{-3}	4x10^{1}

where η, δ and ι are the identified time varying coefficients corresponding with the position error and its time derivative and integral.

This result, gives the possibility to systematically obtain a model of the human in the loop

$$G = \frac{\eta e}{1+a_0 z + a_1 z^2} + \frac{\delta \dot{e}}{1+a_0 z + a_1 z^2} + \frac{\iota \int_0^{\tau} e\ dt}{1+a_0 z + a_1 z^2}, \tag{3}$$

in order to have a real input-output dynamic model of the man-machine system. Figure 5 is a block representation of this model. With this representation it is easy to observe a PID control scheme.

The statistical analysis of the order of the model indicates that a better response is obtained with this second model approach as is showed in tables 2, 3 and 4

An important aspect to consider is to avoid numerical noise introduced by estimators when applied to derivative factors. For this reason, we used the measured velocity of the end effector of the HD and applying the derivative definition to obtain the derivative of the error (e)

$$\begin{aligned} e &:= Sp - X, && (4)\\ \frac{\delta e}{\delta t} &:= \frac{e_2 - e_1}{t_2 - t_1}, && (5)\\ &:= \frac{(Sp - X_2) - (Sp - X_1)}{t_2 - t_1}, && (6)\\ &:= \frac{-X_2 + X_1}{t_2 - t_1}, && (7)\\ \lim_{t_2 \to t_1} \frac{-X_2 + X_1}{t_2 - t_1} &:= \frac{-dX}{dt}, && (8)\\ &:= -V_x && (9) \end{aligned}$$

where Sp is the set point, X is the desired position, $e_2 - e_1$ is the magnitude difference, t_2 and t_1 are time instants. In this way, we determined the magnitude of the derivative of the position error as

$$\frac{de}{dt} = -V. \tag{10}$$

where V is the velocity of the end effector of the HD in the corresponding rectangular component.

In the case of the integral factor, we used a trapezoidal integration algorithm, considering a constant time difference ($\Delta t = 1$ ms)

$$\int_0^{kT} e(t)\ dt \approx \sum_{i=1}^{k} \frac{T}{2}(e[i-1] + e[i]) \tag{11}$$

It is important to remark that this model, even considering e, $\dot{e}$ and $\int e(t)\ dt$, presents an anisotropic behavior.

5. RESULTS ANALYSIS

When analyzing the behavior of the PID gains between x, y and z axes, it is possible to observe the anisotropic behavior of those coefficients. Comparing the x axis against the y axis, a high frequency and amplitude transient appears in the x axis and not in the y axis. The transient seen is observed during the first 500 ms. These observations are explained in a physical way as follows: The difference between the x axis and the y axis corresponds to the effect of the gravity force. This means, that the y axis is continuously controlled, compensating the gravity force. In the case of the x axis, there is no continuous force and it means, that it is required an initial force adjustment needed to start moving the arm. In Fig. 6, it is possible to observe the behavior of the PID gains for the x axis, while Fig. 7 show the corresponding signals for the y axis. It is no relevant in this case to know what is represented by each line, but the indicated differences are the real important aspects of these images. This fenomenon requires a more detailed study in order to have a scientific explanation.

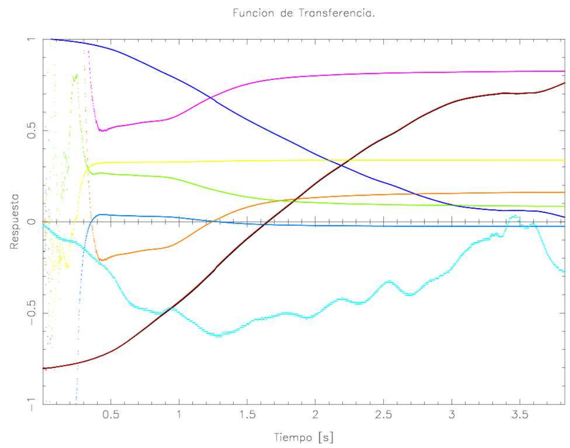

Figure 6. Human PID behavior on x axis.

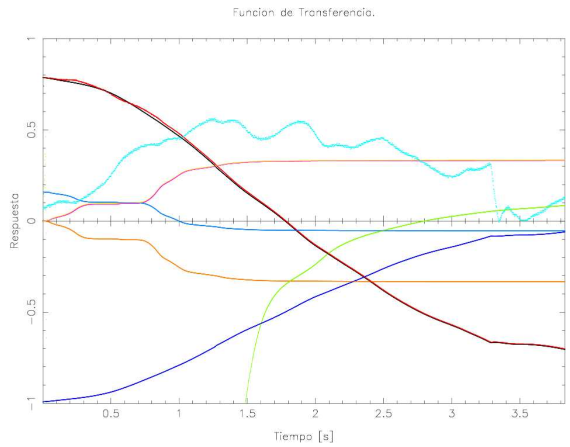

Figure 7. Human PID behavior on y axis.

6. CONCLUSIONS

Results on identification of the human operator behavior when performing as controller in a virtual 3D environment were shown. These results are grouped in two main aspects:

- Anisotropic behavior of the operator when freely moving in the work space.
- Effects of the position error and its time derivative and integral over the human action transfer function.

The observed anisotropic behavior of the operator corresponds with previous results found in the literature. The utilization of the main effects analysis methodology, has demonstrated to be an important decision tool in this dynamic system identification field. The anisotropic behavior of the identified human action model, reflects the unconsidered physical aspects of the human action. Finally, the estimated human action model, based on the explained considerations, presents new possibilities in the field of human machine interaction, mainly where a system stability analysis is required. With time series forecasting methodology, a predictive system could be implemented and therefore to better obtain human-machine systems.

REFERENCES

Ferrell, W.R. (1965). Remote manipulation with transmission delay. *IEEE Transactions on Human Factors in Electronics* **HFE6**, 24–32.

Ferrell, W.R. (1966). Delayed force feedback. *Human Factors* **8**, 449–455.

Fitts, P.M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology* **47**, 381–391.

McKenzie, I.S. (1991). Fitts' law as a performance model in human-computer interaction. PhD thesis. University of Toronto: Toronto.

McRuer, D. (1980). Human dynamics in man-machine systems. *Automatica* **16**, 237–253.

Nechyba, M.C. and Y. Xu (1996). On fidelity of human skill models. *Proceedings of the 1996 IEEE International Conference on Robotics and Automation* pp. 2688–2693.

Robles-De-La-Torre, G. and R. Sekuler (n.d.). Practice builds an internal model of virtual object dynamics.

Sheridan, T. and W.R. Ferrell (1963). Remote manipulative control with transmission delay. *IEEE Transactions on Human Factors in Electronics* **HFE6**, 25–29.

Slotine, J-J E. and W. Li (1991). *Applied Nonlinear Control.* Prentice-Hall International Editions.

Söderström, T. and P. Stoica (1989). *System Identification.* Prentice Hall International.

Song, J., Y. Xu, M.C. Nechyba and Y. Yam (1998). Two performance measures for evaluating human control strategy. *Proceedings of the 1998 IEEE International Conference on Robotics and Automation* pp. 2250–2255.

Wellstead, P.E. and M.B. Zarrop (1995). *Self-tuning Systems : Control and Signal Processing.* John Willey & Sons Ltd.

Zhai, S., J. Accot and R. Woltjer (2004). Human action laws in electronic virtual worlds: an empirical study of path steering performance in vr. *Presence* **13**, 113–127.

Zhai, S., P. Milgram and A. Rastogi (1997). Anisotropic human performance in six degree-of-freedom tracking: an evaluation of 3d display and control interfaces. *IEEE Transactions on Systems, Man and Cybernetics - Part A: Systems and Humans* **27**, 518–528.