Low Order Models for Human Controller – Mouse Interface

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***Abstract*—Modeling human operator's behavior as a controller in a closed-loop control system finds applications in different areas such as training of operators by expert operator's model, tele-operation or developing warning systems for drivers. In this paper, first, an experimental setup has been developed for collecting data from human operators as they controlled a process with a DC motor, using the mouse interface on the Matlab environment. Low-order ARX models are proposed for human operator modeling. Replacing the operator by a stand-alone human controller model was one of the validation methods. Experimental results are shown to evaluate the performance of the proposed approach for human low-order modeling.**

I. Introduction

Modeling human operator's dynamic characteristics in manual control has been an important research subject for several decades, at least after World War II.

Humans carry out many different monitoring and control tasks that range from simple manipulation to more complex tasks such as monitoring multivariable processes, operating machines, playing video games, driving vehicles or piloting airplanes.

Human operator models become an important tool when the goal is to design a system to be controlled by a human [15, 19, 21]. In the past, a lot of studies were motivated by the search of pilot models [5], nowadays the studies are more concentrated on obtaining models for drivers' control behavior [11, 12], and also for tele-operation applications [24, 25].

Manual controllers are very useful also in the training of controllers based on Principal Component Analysis [26, 27].

Human behavior as a dynamic controller is generally quite nonlinear [15, 30]. Human operators are able to gain experience and learn by repeating control tasks and, consequently, improve their dynamic behavior. Human operators can adjust themselves according to the changes in the dynamics of the system they control. So, the human is able to act as a nonlinear and time-varying controller. These features make the human modeling a complex and difficult task.

The different stages of information processing in human operators are described by Wickens [16], including attention, perception, memory (long-term, short-term and working), decision and response execution.

In this research area, the great challenge is to obtain a reliable and robust model able to replace the human in monitoring and control tasks.

In general terms, there are three main alternatives to obtain a dynamic model; either based on full knowledge of the system dynamics (white-box model), either based on partial knowledge of the system dynamics (gray-box model) or based on system identification techniques (black-box model). For some simple tasks the human control behavior can be accepted as quasi-linear.

If the aim is to develop a white-box or gray-box model for the human operator various human characteristics, both in terms of physical limitations as well as certain attributes, should be taken into account namely human time delay, threshold limitations, visual characteristics (perception of position and velocity), etc, [11]. Fitt's law should also be taken into account [23]. Fitt's law is an empirical formula known for encapsulating the speed/accuracy trade-off. Fitt's law describes the human's behavior on the input side of a control system. There is a trade off between the size of movement and required accuracy.

The research area of manual control is related to different fields such as discrete and continuous models, adaptive control, information theory, multivariable control, displays and interfaces, motion and stress, optimal control, and analysis and design methods [5].

In this work, black-box low-order linear models are proposed for human controller modeling. Under investigation is the application of nonlinear fuzzy models based on Sugeno inference using local linear ARX models.

The layout of the paper is the following. In section II is described the experimental system setup and the architectures. Low-order models for human controller and the proposed modeling approach are presented in section III. Experimental results appear in section IV. Finally, the conclusions are presented in section V.

II. Architectures and Experimental System Setup

The architectures and the setup used in the work are presented next.

A setup based on a DC motor has been the system to be controlled by a human operator in our laboratory. The operator uses a mouse interface to generate the control action using the Matlab environment, in order to control the motor speed, as described next.

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A. *High Level Manual Control Architecture*

The high-level manual control architecture used in the experiments is depicted in Fig. 1. The operator observes the reference "r" and the output "y" signals on the screen, estimates a perception of the real control error "e" and its derivative, and generates a control action "u".

The DL2125 DC motor setup can be observed in Fig. 2. The interface between the computer and the setup is done using a NI USB-6009 data acquisition board. The algorithms were implemented, in discrete-time, in the Matlab environment. A low pass first-order digital filter with unitary gain and a discrete pole located at 0.8 was used to filter the process output, in order to reduce the noise and the system bandwidth, and to be able to use a sampling time around $T_s = 0.2$ s.

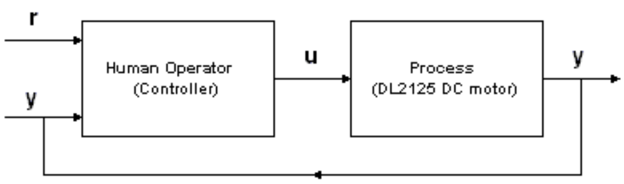

Figure 1. High-level manual control architecture.

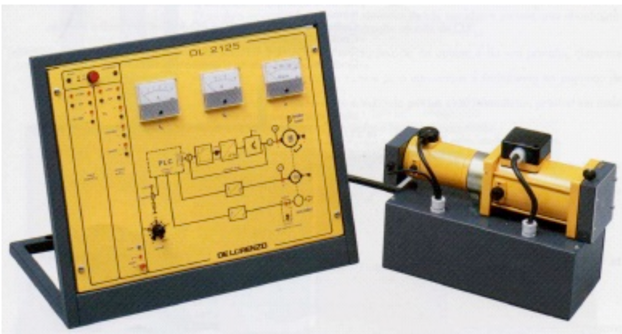

Figure 2. DC motor DL2125 setup (De Lorenzo group).

The low-level manual control architecture is depicted in Fig. 3. The algorithms work with normalized data **r**, **y**, **u** in a range between zero and one.

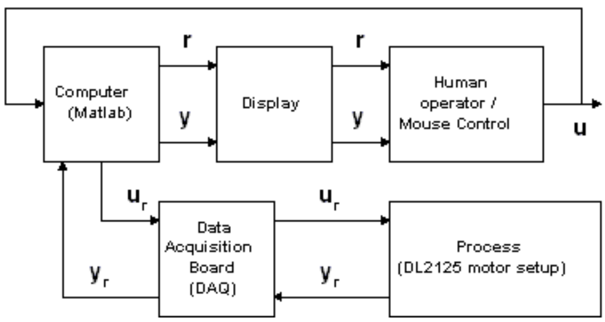

Figure 3. Low-level manual control architecture.

B. *Matlab Code for Reading Mouse Position*

In this work, the control action "u(k)" is given by the vertical coordinate of the mouse position "xmouse.y(k)", as described in the following Matlab code.

In off-line operation:

```
xdisplay.size = get(0,'ScreenSize');
xdisplay.ymax = xdisplay.size(4);
```

In on-line operation, for each discrete time k:

```
xmouse.coords = get(0,'PointerLocation');
xmouse.y0(k) = xmouse.coords(1,2);
xmouse.y(k) = xmouse.y0(k) / xdisplay.ymax;
u(k) = xmouse.y(k); % u(k): control action
```

III. LOW-ORDER MODELS FOR HUMAN CONTROLLER

A brief historical review of the most popular low-order models proposed for human operator modeling is presented. The proposed models for human controller using a mouse interface are also described in this section.

A. *Historical Review*

Here, an historical review of the most popular low-order models proposed for human operator modeling is presented.

In 1961 Ornstein [15] proposed the following transfer function, $H_1(s)$, model of the human operator for manual tracking tasks,

$$H_1(s) = \frac{U(s)}{E(s)} = \frac{\alpha_1 s + \alpha_0}{\beta_2 s^2 + \beta_1 s + \beta_0} e^{-s\tau} \tag{1}$$

and noted that the coefficient α_1 associated with the anticipatory behavior (velocity component) of the human operator, was adaptive to changing plant dynamics and methods of visual presentation. This is one of the pioneer works showing the adaptive nature of human operator and the use of prediction. The parameter τ was an effective transport time delay.

Some studies were also done to analyze the stability and performance of manual control systems [20].

Different models were proposed to capture the pilot dynamics. The human pilot is a multimode, adaptive, learning controller capable of exhibiting an enormous variety of behavior. In 1967 McRuer and Jex [19] proposed the following simplest pilot describing function form, based on frequency domain synthesis, which corresponds to the open-loop crossover model:

$$H_2(j\omega) = \frac{U(j\omega)}{E(j\omega)} = K_p \frac{T_L j\omega + 1}{T_I j\omega + 1} e^{-j\omega\tau} \tag{2}$$

In (2) K_p is the pilot static gain, T_L is the lead-time constant (relative rate-to-displacement sensitivity), T_I is the lag-time constant and τ is the effective time delay, including transport delays and high frequency neuromuscular lags. This model has been used as a basis for different modeling approaches including multi-loop control tasks [7].

Most of the proposed human operator models were formulated in the input/output form such as the models described in [2, 8, 9, 15, 19]. The experimental frequency response transfer function can be estimated by using periodograms [3]. State-space models were also investigated for human operator modeling [10].

In the paper written by Arif and Innoka [18] experiments have been done to study the human capability to perform tasks by learning iteratively. It is concluded that the human operator performs the repetitive task by modifying his control action using the perception of error and error rate, in each iteration.

The surge model for the human operator was proposed to deal with discontinuities in the tracking signal, applying a switching strategy between models [8]. Adaptive models were proposed to deal with sudden changes in plant dynamics and transient disturbances [6].

The role of a human operator in machine control varies with the level of automation. To compensate the insufficient human performance, human adaptive assist control should be developed [1, 4].

A third-order linearized model (3) was proposed by Antunes et. Al. [1] to model the human operator in assisted path following tasks in a two-dimensional space using a joystick interface:

$$H_3(s) = \frac{U(s)}{E(s)} = \frac{K}{s^3 + \gamma_2 s^2 + \gamma_1 s + \gamma_0} \quad (3)$$

The research studies done in the past concluded that low-order human operator models, typically of first, second or third orders are adequate for most control tasks.

B. *Proposed Models for Human Controller using a Mouse Interface*

This paper deals with a methodology that determines human operator linear models from input/output data using a mouse interface. Discrete-time ARX models are proposed to capture the operator dynamics on nominal control task execution.

In the control task under investigation, the operator observes the reference “r” and the output “y” signals on the screen and estimates a perception of the real control error (e = r - y) and its derivative.

Identification of the human operator’s transfer function from normal working data is a great challenge. This is because the control signal “u” should be rich enough, i.e., the persistent excitation conditions should be verified.

Two ARX models were investigated for human operator modeling in closed-loop control tasks. The first model (4), M_{ury}, relates the manual control action “u(k)” with the reference “r(k)” and the output “y(k)” signals.

$$u(k) = -a_1 u(k-1) - a_2 u(k-2) + b_1 r(k-1) + c_1 y(k-1) \quad (4)$$

The second model (5), M_{ue}, relates the manual control action “u(k)” with the control error “e(k) = r(k) – y(k)”.

$$u(k) = -d_1 u(k-1) - d_2 u(k-2) + - d_3 u(k-3) + f_1 e(k-1) \quad (5)$$

If the discrete-time model (5) is converted to continuous-time, it will be possible to map the obtained model into the model (3) proposed by Antunes et. Al. [1] and compute the parameters $\{K, \gamma_2, \gamma_1, \gamma_0\}$. In this mapping, sometimes it is necessary to neglect the zeros of the obtained transfer function.

In this work, for estimation of ARX model parameters the Principal Components Regression (PCR) algorithm was used, [22]. The parameter estimation problem can be formulated as follows (6), where ***Y*** is the output variable vector, **X** is the regression matrix and θ is the regression coefficients vector.

$$Y = X\theta \quad (6)$$

PCR can be understood as an extension of Principal Components Analysis (PCA) to the modeling of some **Y** data from the **X** data. The approach to defining this relationship is accomplished in two steps. The first is to perform PCA on the **X** data, and the second is to regress the scores onto the **Y** data. The main advantages of PCR over LS (least-square) for parameter estimation are: a) the noise remains in the residuals, since the eigenvectors with low eigenvalues represent only parts of the data with low variance; b) the regression coefficients θ are more stable, due to the fact that the eigenvectors are orthogonal to each other.

A challenge for future research is the development of approaches for human dynamics identification, based on pattern recognition approaches, in the presence of disturbances, faults and failure situations.

IV. Experimental Results

To capture the human behavior some experiments have been done on nominal task execution. One of the manual control experiments, using the right hand, is depicted in Fig. 4.

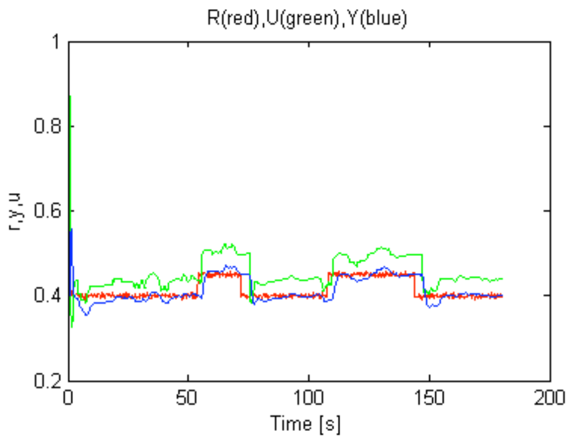

Figure 4. Manual control data used for ARX models identification.

The operator controls the process and also tries to guarantee good persistent excitation conditions, in order to perform well the model parameters estimation. A small dither signal was added to the reference signal "r". The color mapping for each signal is the following: reference ("red"), control action ("green") and output ("blue").

Replacing the operator by a stand-alone human controller model was one of the validation methods. Fig. 5 depicts the process controlled by the stand-alone human controller model (5) for a reference signal equal to the one used for training the controller model. The controller parameters obtained are the following:

$$\theta_{ue} = [d_1; d_2; d_3; f_1] = \\ = [-0.56301; -0.33265; -0.10025; 0.47958] \tag{7}$$

The conversion to a continuous time model using the ZOH method results in a model that is mapped into the structure (3), thus obtaining

$$H_a(s) = \frac{U(s)}{E(s)} = \frac{K}{s^3 + \gamma_2 s^2 + \gamma_1 s + \gamma_0} \tag{8}$$

where
$K = 263.1; \gamma_2 = 11.5; \gamma_1 = 168.3; \gamma_0 = 2.242$.

In fact, accordingly to the dominant poles approach, a model order reduction was performed, resulting in a first order model,

$$H_b(s) = \frac{U(s)}{E(s)} = \frac{K_1}{s + \alpha} \tag{9}$$

where $K_1 = 1.565; \alpha = 0.01333$, with a static gain of 117.4 and similar dynamic characteristics verified by the comparison of the step response of both models $H_a(s)$ and $H_b(s)$.

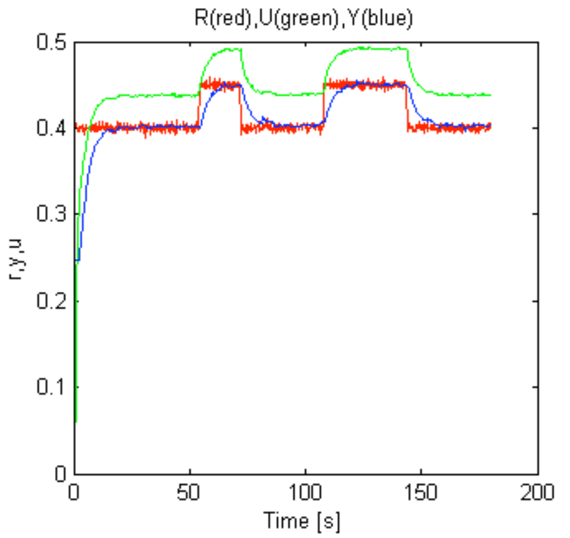

Figure 5. Stand-alone human controller model (5) in operation with reference signal equal to the training data.

Fig. 6 depicts the process controlled by the stand-alone human controller model (5) for a reference signal different from the one used for training the controller model. Both experiments present good performance showing the potential of the proposed approaches for human operator modeling, although having different rise-times and overshoots.

In the future the performance of the proposed human controller low-order models will be evaluated in terms of rise-time, overshot, robustness and stability.

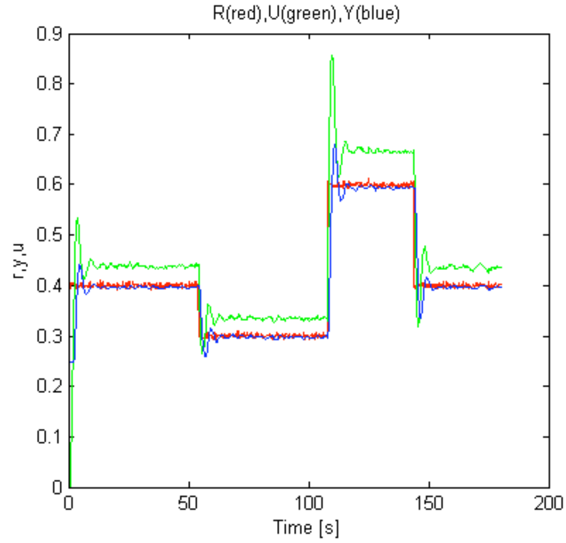

Figure 6. Stand-alone human controller model (5) in operation with reference signal different from the training data.

A good performance was obtained for the human controller model (5) has shown in the last experiments. For the human controller model (4) the performance is not so good in terms of control error as depicted in Fig. 7 and presented in Table 1.

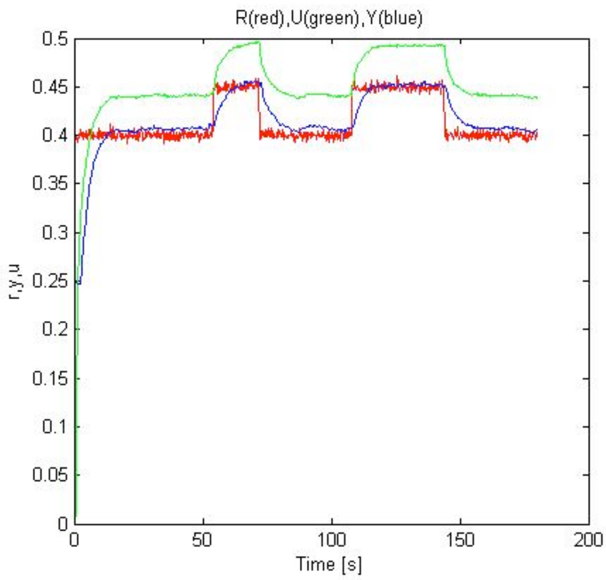

Figure 7. Stand-alone human controller model (4) in operation with reference signal equal to the training data.

The parameters of the controller model (4) are the following:

$$\theta_{ury} = [a_1; a_2; b_1; c_1] = \\ = [-0.33263; -0.34648; 0.16055; 0.18988] \quad (10)$$

Table 1 shows the controller's models performance, for models (4) and (5), in terms of mean squared control error (MSE) and variance of control action (VCA). The poles, in the "z-plane", for each controller are also presented. Both controllers present similar performance.

Table 1 – Controller's performance and poles.

	MSE(10^{-3})	VCA(10^{-3})	Poles ("z"-plane)
M_{ury}	0.69	1.86	0.7780 -0.4454
M_{ue}	0.44	2.17	0.9973 -0.2172 ± j 0.2310

Observing Fig. 5 and Fig 7 can be concluded that the dynamics of the closed-loop is faster for the case of the controller model (4), M_{ury}. This fact can be verified looking for the dominant poles of each controller (see Table 1). It is also expected that the controller model M_{ue} presents a pole near z = 1, i.e., an almost pure integrator; indeed, the pole is located at 0.9973.

Some experiments were done to analyze the human operator reaction time (human time delay) in terms of changes on the set-point (reference) signal, for a closed-loop control system. One of these experiments is depicted in Fig. 8. For the architecture considered in this work (Fig. 3), the estimated reaction time belongs to the range $[0.2; 0.8]$ s. This range includes the typical neuromotor lag [28, 29].

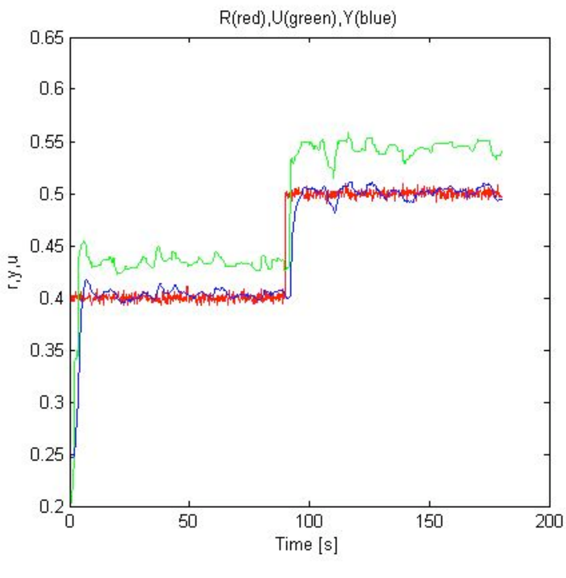

Figure 8. Experiment to analyze the reaction time for a set-point change (right-hand operation).

Remarks.

Human behavior as a dynamic controller is generally quite nonlinear. For some simple control tasks, quasi-linear models are enough for human modeling, as presented in these experimental results.

In industrial plants, a great challenge is the operator's identification, i.e., discover which operator is the active controller in a certain task. The solution for this problem is not a straightforward task. Nonlinear human models, signal processing methods and pattern recognition approaches are certainly needed to solve this complex problem, based on features such as variance of control action, human reaction time, closed-loop dynamics, etc. For the authors, this problem is a pointer for future research in the human-machine systems. The right-hand operation and left-hand operation should also be taken into account, since they are different in terms of the features mentioned, as depicted in Fig. 8 and in Fig. 9.

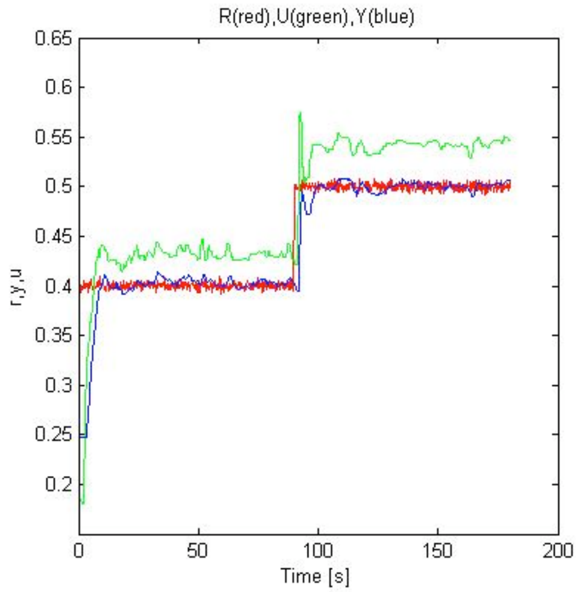

Figure 9. Experiment to analyze the reaction time for a set-point change (left-hand operation).

V. CONCLUSIONS

Low-order human operator models, typically of first, second or third orders are adequate for most simple control tasks, accordingly to the past research studies. The last statement was also confirmed in the research presented in this paper.

In this paper, low-order ARX models for human operator were proposed. In the work presented, the operator uses a mouse interface to generate the control action using the Matlab environment, in order to control the speed of a DC motor setup. The proposed models were validated and mapped into continuous time models. A good performance was obtained for two types of human operator models tested on a DC motor setup.

Each human operator observes the real facts but, in fact, assimilates in his brain only a perception of the reality. In control tasks the human operator computes on-line a perception of the control error and its derivative, acting accordingly to these variables.

Some pointers for future work are: a) the development of human operator models for teleoperation; b) the development of approaches for human dynamics identification, based on pattern recognition approaches, in the presence of disturbances, fault and failure situations; c) the validation of the modeling approaches using SVD/PCA methods; d) the application of nonlinear fuzzy models based on Sugeno inference using local linear ARX models.

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