# A Multi-Variable Modeling Approach for Improving Operator Proficiency

Rui Antunes, Fernando V. Coito, and Hermínio Duarte-Ramos

***Abstract*—**Nowadays there is a strong interest for improving the usability, ergonomics and safety in the assortment of human-assisted equipments and mechatronic gadgets that we all depend on in our modern way of life. This is due to the fact that the overall performance, in any human-machine process, in terms of productivity, energy cost, quality and safety depends both on the skills of the human operator and the machine technical conditions. Hence, for control purposes, and in order to enhance operator proficiency, the human complexity must be taken also into account. An effective strategy for developing new intelligent assisted-machines and human adaptive control schemes can be performed by first modeling the human-machine interface, which often takes place in multi-spatial dimensions. This work describes a simplified multi-variable modeling and control strategy for improving human operator performance on 2-D spatial environments, by combining state-space and frequency analysis identification methods with an optimal control approach.

***Keywords*—**Control system human factors, human-machine dynamics, human-in-the-loop control, manual tracking systems.

## I. Introduction

RECENT studies [1] reveal that in many industrial and productive activities which involve manual operations, the human impact factor on the overall machine performance, regarding productivity, safety, quality and energy cost, can reach over 40 %. This fact leads to recent developments on human-assisted-control projects and on the design of new intelligent human-machine devices, aiming to improve the operator proficiency. These machines should be able to adapt according to the skills of the human operator, by previously evaluating/estimating the skills of the operator.

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The Human Adaptive Mechatronics (HAM) concept [2]–[4] aims to intelligently assist the human operator in improving its skills. First HAM research projects were launched between 2003 and 2008 in Japan [4]–[6]. Recent advances on HAM research include human operated manufacturing, adaptive assistance for vehicles and mobile working machines, laparoscopic surgery and surgical support systems [7], teleoperation [8], [9], haptic and other human-machine interfaces [10], intelligent coaching systems [11], space and marine environments, aviation [16], etc.

It is clear that to conceive such a HAM device we need to model the whole system with the inclusion of the operator's systemic complexity. Since the 1940's that there have been extensive research on human modeling [4], [12], [13]–[15] and human-machine performance analysis [18]–[20], [25], [33] using pursuit and compensatory tracking experiences [18], [21], [25]. Although human-machine response do not always follow a linear behavior, there are studies [12]–[14], [17], [25]–[27] that have shown that linear systems theory can still be used to capture the most relevant characteristics of the overall human-machine system. Other complementary state of the art research for obtaining human operator characteristics covers also the use of Hidden Markov Models for recognizing actions in haptic devices [10], fuzzy-ARX, NARMAX, neuro-fuzzy modeling techniques [22], variable strategy control (VSM) models, modeling the operator by an intermittent approach, using particle swarm optimization and the MOCM (modified optimal control model) method [1], and also clustering methods with self-organizing maps for estimating operational intention and skill in human-machine operations [23], [32], [34].

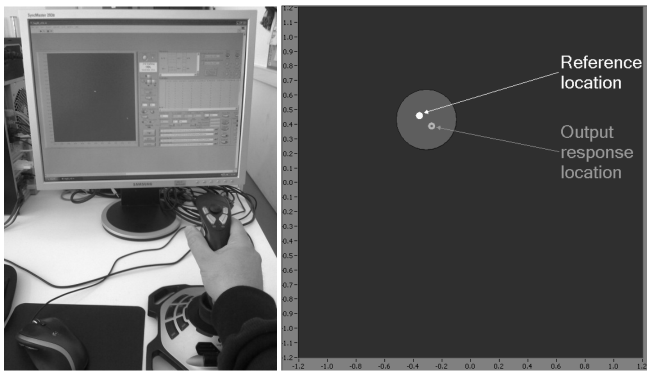


Fig. 1 (a) a 2-D pursuit manual tracking time-trial, using Logitech's Extreme 3D Pro. 8-bit analog Joystick as the Human-Machine Interface (HMI). (b) LabVIEW pursuit test window (right)

## II. Aim of The Work

The HAM project design and optimization may hold the following three steps:

1) Modeling the human-machine characteristics;
2) Quantify the overall skill;
3) Select an "assistant-controller".

The main goal of this work covers the first and second phases of the HAM design, i.e. the problem of obtaining the human-machine dynamics, and the quantification of skill. A real-time LabVIEW application was developed for the execution and evaluation of multi-dimensional manual tracking experiences, using an analog Joystick as the human-machine input device (Fig. 1). The platform allows performing any 2-D pursuit and point-to-point manual tracking tasks, over a predefined MIMO process. A future goal will be to design and select a MIMO HAM switching-controller device which, for each process, and task, assists the operator to improve its skills by performing the improved tracking task. Hence, the present project serves as a framework for the development of new human-machine intelligent devices, which will be able to enhance the operator's skills in many crucial areas involving manual operations.

## III. Human-Machine Modeling

The problem of the modeling approach is to obtain a state-space linear model, from several pursuit manual tracking experiences, that accurately captures the relevant human-machine dynamic characteristics. The proposed methodology uses previous frequency identification methods described in [24], [25], [28]–[29].

Consider an input normalized one-dimensional signal $x(t)$ to be tracked, of duration $T$, built from a sum of $N$ sinusoids at fixed multiple frequencies:

$$x(t)=x_0+\sum_{k=1}^{N} a_k \sin(\omega_k t) \quad \max\{|x(t)|\}=1 \quad x(t=0,T)=x_0. \quad (1)$$

Assuming an LTI system, and time $T$ as a multiple of the sinusoid period, the resulting human-machine output $y(t)$ is

$$y(t) = y_0 + \sum_{k=1}^{N} b_k \sin(\omega_k t+\varphi_k) \quad (2)$$

$$T=\frac{k2\pi}{\omega} \quad (3)$$

The I/O response for each of the frequencies may be obtained through the following scheme:

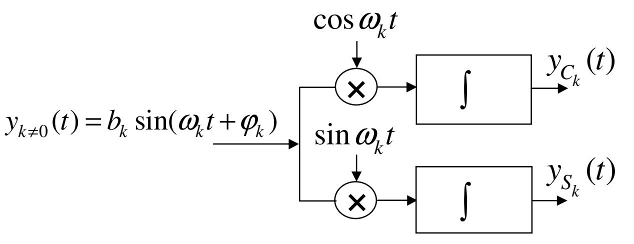


Fig. 2 frequency analysis block diagram for each multiple frequency

By performing the integration along time $T$, results in:

$$y_{C_k}(T)=\int_0^T b_k \sin(\omega_k t+\varphi_k)\cos\omega_k t\,dt \quad y_{C_k}(T)=\frac{b_k T}{2}\sin\varphi_k \quad (4)$$

$$y_{S_k}(T)=\int_0^T b_k \sin(\omega_k t+\varphi_k)\sin\omega_k t\,dt \quad y_{S_k}(T)=\frac{b_k T}{2}\cos\varphi_k \quad (5)$$

which corresponds to the resulting human-machine closed-loop frequency response and static gain:

$$b_k=\frac{2}{T}\sqrt{y_{C_k}{}^2(T)+y_{S_k}{}^2(T)} \qquad \varphi_k=\arctan\left(\frac{y_{C_k}(T)}{y_{S_k}(T)}\right). \quad (6, 7)$$

$$K_0=\frac{y_0}{x_0} \quad (8)$$

The static gain $K_0$ is obtained from the manual tracking average output, with the input offset ( $x_0$ ) known.

Voluntary motion affects machine movement because the operator and the machine form a closed-loop system. Hence, the resulting open-loop human-machine LTI models must be extracted from the closed-loop experimental data. Three multivariable modeling techniques are described below.

### A. *Modeling from independent 1-D input/output collected data*

The aim of obtaining open-human-in-the-loop models for 2-D spatial environments can be simplified by assuming that the output response in one axis does not influence the orthogonal direction. Therefore, a human-machine MIMO system may be modeled from two independent LTI transfer functions, which leads to a diagonal state-space dynamic matrix pattern, discarding the cross-terms:

$$\begin{bmatrix} P_x(s) \\ P_y(s) \end{bmatrix} = \begin{bmatrix} M_{xx}(s) & 0 \\ 0 & M_{yy}(s) \end{bmatrix} \cdot \begin{bmatrix} J_x(s) \\ J_y(s) \end{bmatrix} = \mathbf{M} \cdot \begin{bmatrix} J_x(s) \\ J_y(s) \end{bmatrix} \quad (9)$$

where $J_x(s)$ and $J_y(s)$ are the frequency-domain input targets, and $P_x(s)$ and $P_y(s)$ the frequency-domain output responses (for the $X$-axis and $Y$-axis, respectively). For each direction there are used separate sets of trials, and each axis input-output closed-loop transfer function is then obtained from the pursuit manual tracking data, by using the frequency analysis procedure. The two open-loop correspondent transfer functions are obtained, for each independent axis, through inverse manipulation.

### B. *Modeling from independent 1-D tracking input signals, and 2-D output collected data*

The second modeling approach uses the same independent one-dimensional input tracking target signals, but extends the output response to 2-D spatial dimensions. Collected multi-variable experimental data from the pursuit manual tracking experiments is now used for obtaining four transfer functions. Hence, the multivariable human-machine matrix representation (**M**), using at this phase the cross-terms, may be re-written as

$$\mathbf{M} = \begin{bmatrix} M_{xx}(s) & M_{xy}(s) \\ M_{yx}(s) & M_{yy}(s) \end{bmatrix} \tag{10}$$

### C. *Modeling from 2-D input/output collected data*

Previous work [25] revealed that the human-machine behavior may not be fully described with a single LTI model, and may also depend on the type of manual tasks involved. Hence, it seems more natural to use multi-variable input tracking target references, and collected multi-variable output responses, for obtaining the matrix representation, as defined in (10). Therefore, the resulting state-space model may also reflect full axis cross-dependency effects.

## IV. Experimental Procedures

In all the proposed three methods a same target normalized input signal $x(t)$, feasible for a human to track, was generated from a sum of $N$ different fixed frequencies.

The magnitude characteristics and shape of $x(t)$ are presented below:

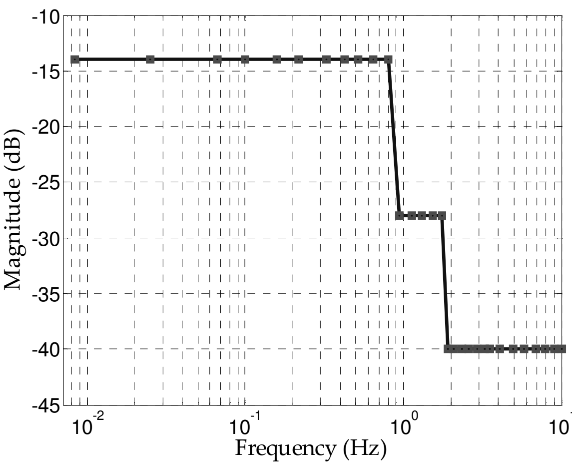


Fig. 3 input signal magnitude in the frequency domain for the one-dimensional pursuit manual tracking experiments, based on the $N$ = 30 frequencies sum, ranging from 0.0083 Hz to 10 Hz

For the state-space model development fifty pursuit tracking time-trials, with T = 120 seconds duration were evaluated for a same participant with no history of neurological disease. A minimum 5 minute rest (at least) between trials was given to avoid human fatigue or memorization.

The procedure of modeling from independent 1-D input/output collected data comprises the execution of two sets of twenty five 1-D pursuit manual tracking experiences, which are alternatively and independently performed for each axis. From the collected data, two amplitude independent open-loop nominal models were obtained by inverse manipulation:

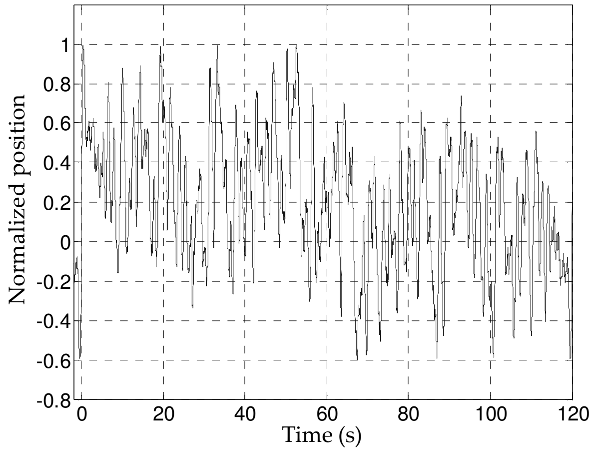


Fig. 4 input signal for the one-dimensional pursuit manual tracking experiments. The period $T$ is 120 seconds, and the input offset equals 0.2

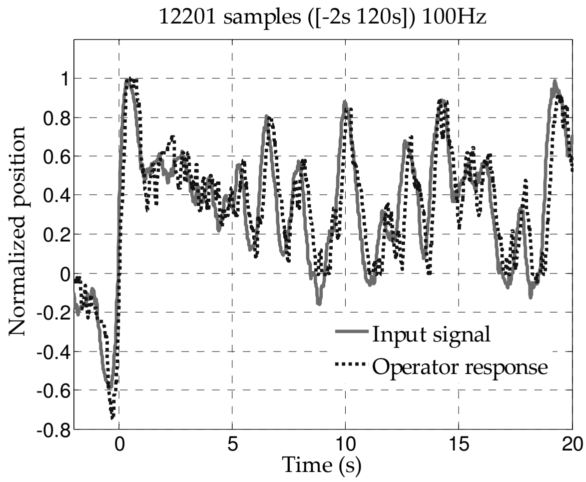


Fig. 5 time domain target input and response (first 20 seconds) of a pursuit manual tracking time-trial (for the $Y$ axis)

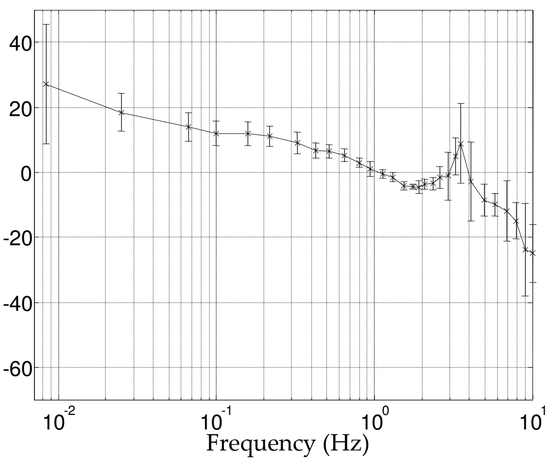


Fig. 6 open-loop magnitude Bode of uncertain data for the $Y$-axis, with confidence intervals for two standard deviation

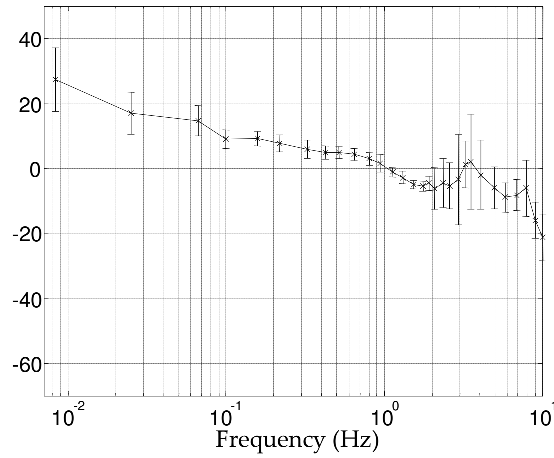


Fig. 7 open-loop magnitude Bode of uncertain data for the *X*-axis, with confidence intervals for two standard deviation

The error bars in Fig. 6 and Fig. 7 show the standard deviations between the dynamics frequency domain data clusters. Magnitude is assumed similar for both the axes, and a unique simplified open-loop model, representing the human-machine behavior was proposed through Matlab simulation. Hence, the state-space model will not reflect any axis cross-dependency:

$$M_{xx}(s) \approx M_{yy}(s) = \frac{3667}{s^3 + 4.5s^2 + 527s + 679} \tag{11}$$

The experimental procedure for the second modeling approach is now described in detail: two equal sets of twenty-five 1-D pursuit tracking time-trials, with $T$=120 seconds duration were alternatively evaluated as in the first modeling procedure, and with the same participant.

From the full 2-D collected data, four open-loop nominal models can now be obtained from the magnitude Bode plots, through inverse manipulation.

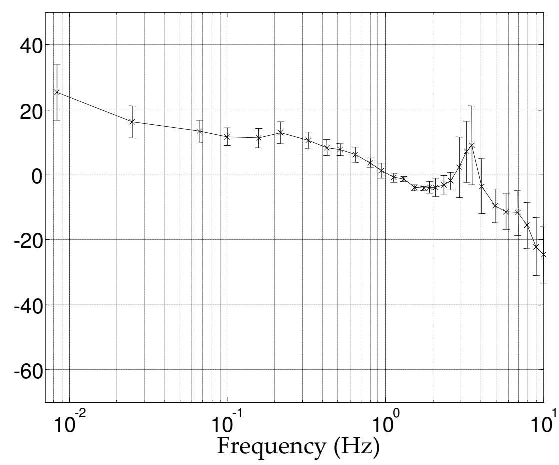


Fig. 8 open-loop magnitude Bode of uncertain data, representing *Myy*

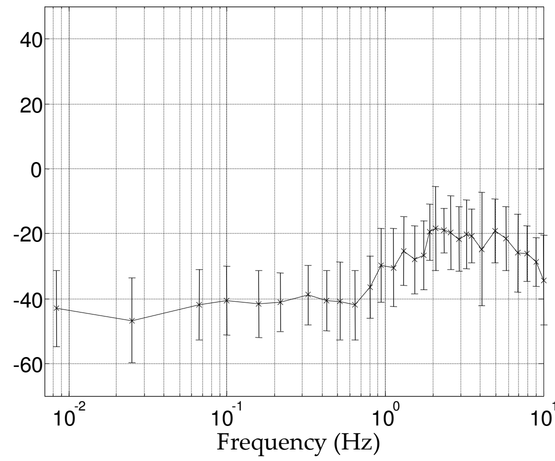


Fig. 9 open-loop magnitude Bode of uncertain data, representing *Myx*

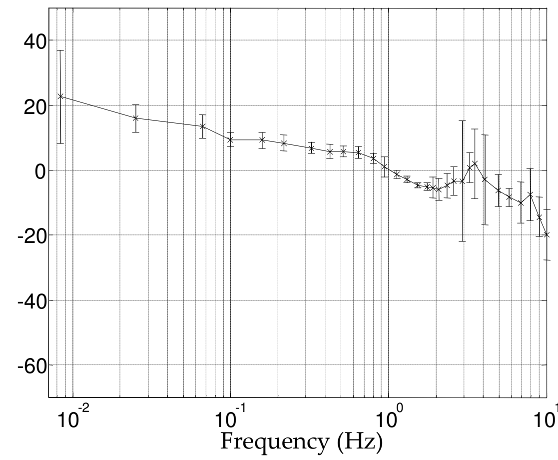


Fig. 10 open-loop magnitude Bode of uncertain data, representing *Mxx*

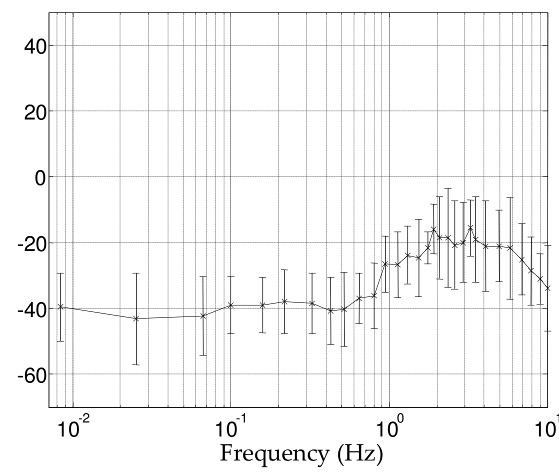


Fig. 11 open-loop magnitude Bode of uncertain data, representing *Mxy*

It can be confirmed that the magnitude behavior of $M_{xy}$ and $M_{yx}$ can be neglected when compared with $M_{xx}$ and $M_{yy}$.

For the third modeling procedure a set of twenty five 2-D pursuit tracking time-trials (with 140 seconds duration each) was evaluated. To ensure the *X* and *Y* axis responses are uncorrelated, the input generated target signals have different periods (*T1* = 120 seconds and *T2* = 140 seconds), and are built from a sum of different ( $w_k$ ) frequencies.

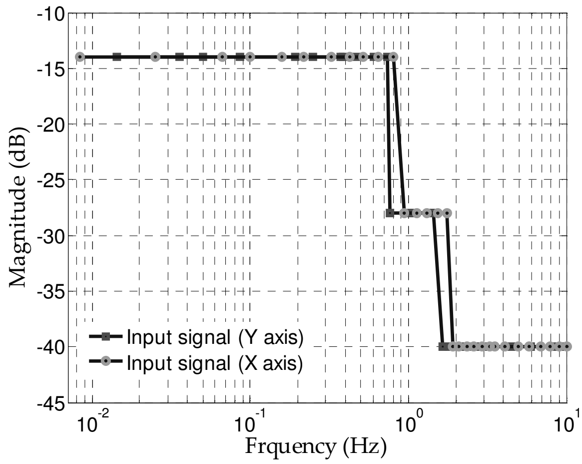


Fig. 12 input magnitude for the *Y* axis target signal (gray) and the *X* axis target signal (bold), based on the *N*=30 frequencies sum, ranging from 0.0083 Hz to 10 Hz

The resulting magnitude Bode plots are presented in Fig. 13 and Fig. 14:

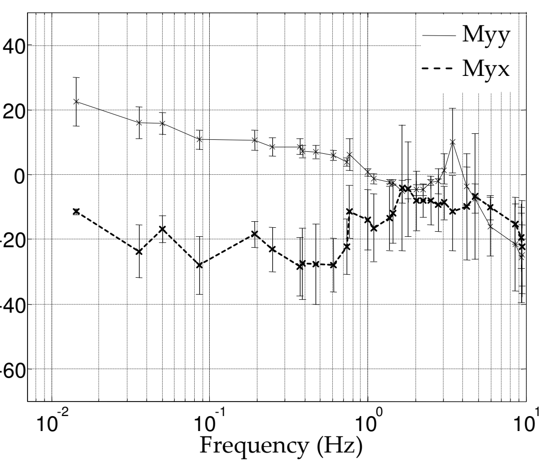


Fig. 13 open-loop magnitude Bode of uncertain data, representing *Myy* and *Myx*

The dynamics frequency response data obtained shows that the axis cross-dependency is higher than the one obtained from the second modeling method, but can still be considered negligible at most frequencies, except near the frequency range between 1.5Hz and 3Hz.

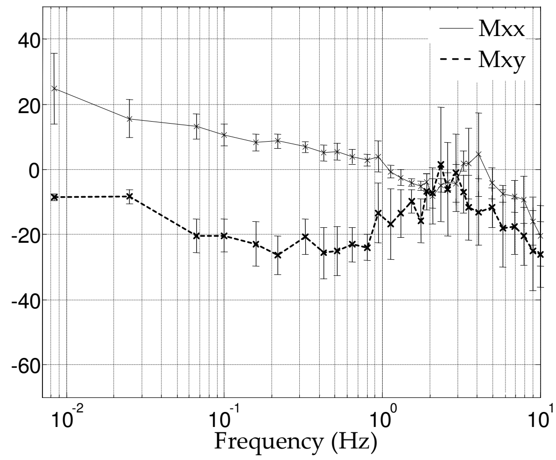


Fig. 14 open-loop magnitude Bode of uncertain data, representing *Mxx* and *Mxy*

The open-loop magnitude behavior for $M_{yy}$ and $M_{xx}$ is almost equal to the previous methods. Hence, the experimental results allows us to conclude that a simplified modeling procedure, based on the first method, may be used to model this human machine interface and applied to design an improved closed-loop multivariable control structure.

## V. Optimal Controller Design

The manual tracking human-machine interface was applied to a 2D double-integrator unstable process ( $P(s) = \frac{10}{s^2}$ ), implemented on both spatial dimensions (*X*, *Y*). In order to design an optimal MIMO controller to assist the human operator in conducting the pursuit tasks, a Linear Quadratic Gaussian (LQG) technique is proposed. This design combines an optimal regulator and an optimal estimator, representing a tradeoff between tracker performance and control effort, regardless any process disturbances and the measurement noise.

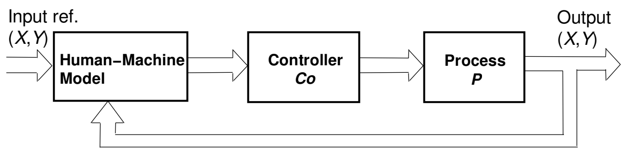


Fig. 15 conceptual block diagram of the closed-loop HMI system to be controlled (example: propelling a mass in a zero gravity environment)

An optimal LQG controller is formed from a linear-quadratic regulator (LQR) and a linear-quadratic estimator (LQE, or a Kalman state estimator). With the LQG synthesis, the stability of the resulting closed-loop system is achieved. An independent design for the regulator and the estimator is assured by the separation principle. For the LQ-optimal control pursuit tracking tasks, the following criterion was considered:

$$J(u)=\int_0^{\infty}\left(y^2(t)+\rho u^2(t)\right)\mathrm{d}t \tag{12}$$

where $\rho$ represents a weighting value to specify the tradeoff between control effort and regulation performance, with $y$ defined as the output response and $u$ as the input reference. For each axis, a controller $Co(s)$ was obtained from an optimal LQG regulator with $\rho = 1e+12$.

$$C_o(s)=\frac{-1.039e004s^4-4.683e004s^3-5.478e006s^2-7.086e006s-3.667e004}{s^5+417.1s^4+8.749e004s^3+1.137e007s^2+9.131e008s+3.668e010} \tag{13}$$

A complete state-space representation of the closed-loop controlled HMI system may be written as:

$$\begin{aligned}\begin{bmatrix}X_1\\X_2\end{bmatrix}&=\begin{bmatrix}A&[0]\\ [0]&A\end{bmatrix}\cdot\begin{bmatrix}X_1\\X_2\end{bmatrix}+\begin{bmatrix}B&[0]\\ [0]&B\end{bmatrix}\cdot\begin{bmatrix}u_x\\u_y\end{bmatrix}\\ y&=\begin{bmatrix}C&[0]\\ [0]&C\end{bmatrix}\cdot\begin{bmatrix}X_1\\X_2\end{bmatrix}+\begin{bmatrix}d&0\\0&d\end{bmatrix}\cdot\begin{bmatrix}u_x\\u_y\end{bmatrix}\end{aligned} \tag{14}$$

The MIMO control system is implemented using a Zero-Order-Hold discretization method, under a 10 ms sampling period.

## VI. Results and Critical View

A human-machine state-space linear model obtained from the first (simplified) method was successfully applied on the design of an improved closed-loop control structure. A real-time 2-D manual tracking twenty seconds experiment, using an analog joystick, was conducted for evaluating operator skill under an unstable process $P(s)$. Any proposed pursuit tracking operator skill index or task-performance criterion must take into account variables such as precision or acuity, and also human effort. Hence, for the performance quantification three metrics were introduced: to measure acuity, is was proposed the mean quadratic Cartesian error (*MQE*) between the input target and the output response, and for measuring the operator effort (force and movement) the mean quadratic Cartesian deformation (*MQD*) and the total absolute value of the Cartesian movement divided by the experiment duration (*TMD*) were also proposed.

The experiment used an origin centered irregular octagon polygon as moving target. A four second delay was given to allow the operator to move the target to the initial position. The obtained results confirm that with the proposed controller the task performance is enhanced while manual effort is considerably reduced, especially at low and medium frequencies.

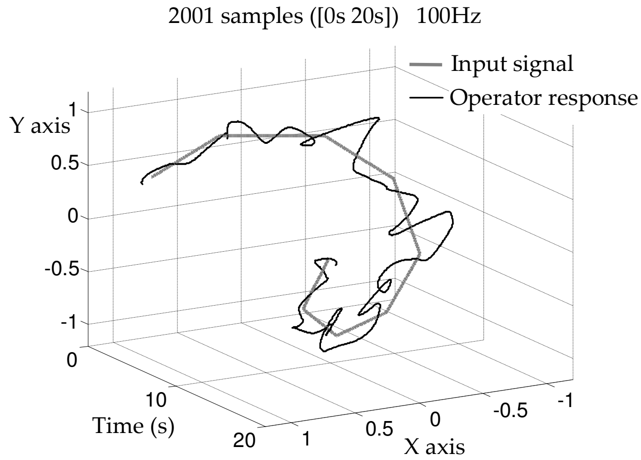


Fig. 16 time domain manual tracking response for an octagon polygon target reference, without any controller, over a double-integrator $P(s)$ unstable process

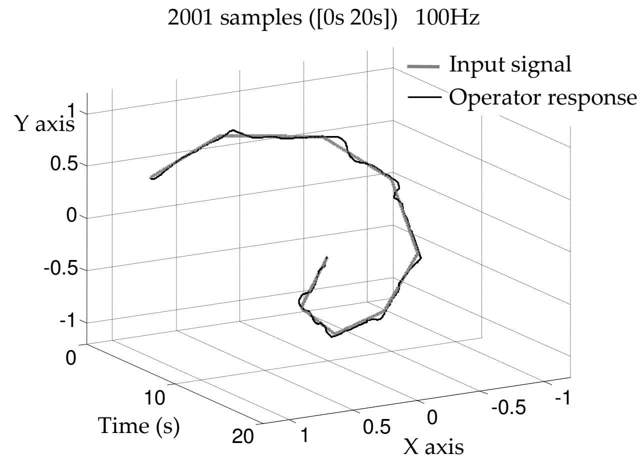


Fig. 17 time domain manual tracking response for an octagon polygon target reference, with the LQG controller $Co(s)$, over a double-integrator $P(s)$ unstable process

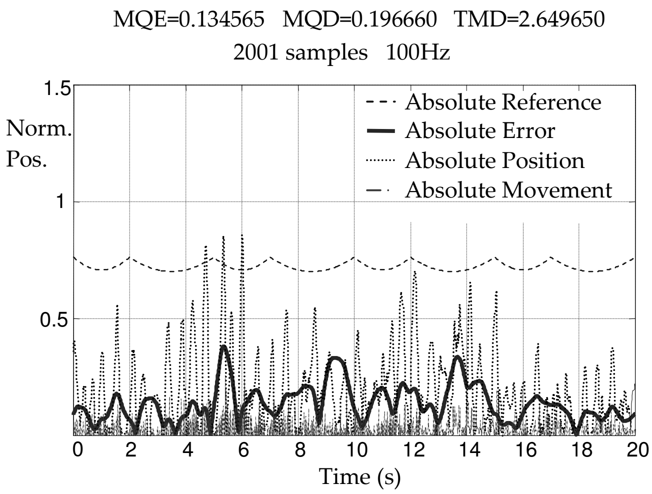


Fig. 18 acuity and effort for an octagon polygon reference, without any controller, over a double-integrator $P(s)$ unstable process

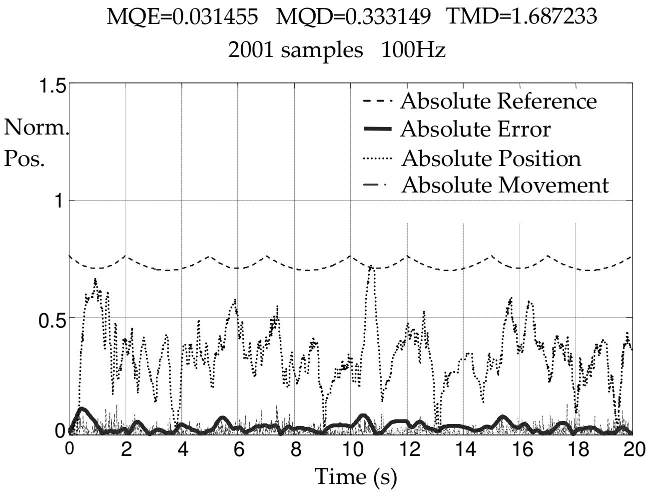


Fig. 19 acuity and effort for an octagon polygon reference, with the LQG controller $Co(s)$, over a double-integrator $P(s)$ unstable process

The time evolution of the mean quadratic Cartesian error *MQE* (over a two-second window) is presented in Fig. 20, to

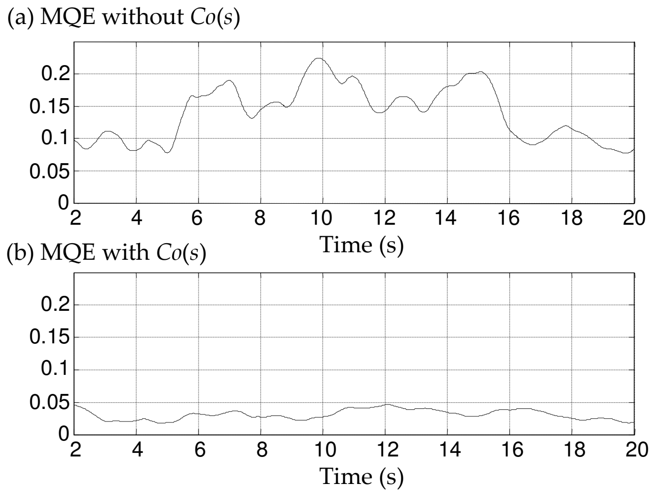


Fig. 20 (a) time evolution of the mean quadratic Cartesian error over a two-second window. without any controller, and (b) with the proposed LQG controller

analyze the operator's learning process in becoming skillful.

From the experimental data it can be concluded that with the inclusion of the *Co* controller the evaluated edge (polygon) transition human time responses (at $t$ = 2, 5, 7, 10, 12, 15, 17 and 20 seconds) are faster, and the human operator takes less time and effort to became expert in the pursuit tracking task, which validates the simplifying human machine modeling strategy used for the controller design. By combining the defined metrics, a task-performance *Tp* index (Appendix) may also be proposed, for quantifying the overall proficiency.

The robustness of the obtained closed-loop human-machine control system was also confirmed between 0.037 Hz to 10 Hz by the use of a bound for uncertainty model *B(s)*, assuming a closed-loop control system diagonal representation.

$$B(s)_{xx} = B(s)_{yy} = \frac{319s + 1540}{s + 400} \tag{15}$$

Nevertheless, it should be stated that at frequencies below 0.037 Hz, the open-loop amplitude experimental data has higher dispersion levels.

## VII. Conclusion

This work developed and validated a human machine multi-variable modeling methodology, based on a diagonal state-space dynamic approximation, for the HAM design philosophy. For that purpose it introduces also a multi-model LQG control design strategy to enhance the operator's proficiency. This human-machine simplified modeling approach takes only into account the amplitude dynamics frequency response.

Skill evaluation Cartesian metrics are also proposed for quantifying operator's proficiency in 2-D manually operated pursuit tasks. A real-time monitoring human-machine setup was developed, implemented and tested, to validate the effectiveness of the applied identification and control methods.

This modeling and control approach has proven to improve the overall human skills during manual tracking operations, which occur in many human-machine tasks, such as navigation, piloting, driving, etc.

A future promising work direction also covers manual point-to-point (PTP), path planning, and obstacle avoidance tasks, which often take place in operated manufacturing and mobile working machines. An evaluation criteria based on a pre-defined task-performance index, and using Fitts law can then be used for quantifying the operator's skill. In other words, the task-performance index of users fit to Fitts law [30]–[32] improves when skills increase.

## Appendix

The mean quadratic Cartesian error (*MQE*) is obtained from all the discrete input target instant values $X[k] \in \Re^2$, and the correspondent outputs $Y[k] \in \Re^2$.

$$MQE = \frac{1}{N} \sum_{k=1}^{N} \sqrt{\left(y_y[k] - x_y[k]\right)^2 + \left(y_x[k] - x_x[k]\right)^2} \tag{16}$$

$$X[k] = (x_x[k], x_y[k]) \tag{17}$$

$$Y[k] = (y_x[k], y_y[k]) \tag{18}$$

$$N = 1 + f \cdot T_{trial} \tag{19}$$

For a total of $N$ samples, trial duration $T_{trial}$, and sampling rate $f$.

The mean quadratic Cartesian deformation (*MQD*) is defined as:

$$MQD = \frac{1}{N} \cdot \sum_{k=1}^{N} \sqrt{\left(d_y[k]\right)^2 + \left(d_x[k]\right)^2} \tag{20}$$

With the instant joystick deformation values $D\left[k\right]\in\Re^2$ expressed as

$$D\left[k\right]=(d_x\left[k\right],d_y\left[k\right]) \tag{21}$$

The total absolute value of the Cartesian movement divided by the experiment duration (*TMD*) is defined as

$$TMD=\frac{f.\sum_{k=2}^{N}\left(\sqrt{\left(d_y\left[k\right]-d_y\left[k-1\right]\right)^2+\left(d_x\left[k\right]-d_x\left[k-1\right]\right)^2}\right)}{N-1} \tag{22}$$

A generically operator task-performance weight index *Tp* may be defined as

$$T_p=\alpha\cdot MQE+\beta\cdot MQD+\varphi\cdot TMD \tag{23}$$

with

$$\alpha+\beta+\varphi=1 \tag{24}$$

The optimal *K* gain matrix, for which the feedback law:

$$u=-Kx \tag{25}$$

minimizes the quadratic cost criteria *J*:

$$J(u)=\int_0^{\infty}\left(x^TQx+2x^TNu+u^TRu\right)\mathrm{d}t \tag{26}$$

is computed through solving the resulting Ricatti equation.

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