Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

An Adaptive Identification Test Monitoring Procedure for Nonlinear Behavioral Interventions

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Abstract: Different studies have established correlation between physical inactivity and the incidence of chronic diseases. Prior investigations have been developed around the topic of mobile physical activity interventions relying on Multiple Input Multiple Output (MIMO) dynamical models of Social Cognitive Theory (SCT) that have been obtained through control engineering and system identification approaches. Identification Test Monitoring (ITM) is a technique that yields to the estimation of an adequate model with the shortest possible duration of the experiment. In this context, Local Polynomial Method (LPM) has been applied to estimate the Frequency Response Function (FRF) and the power spectrum of the disturbing noise for linear models. However, the experimental setup of physical interventions considers a decision block that is nonlinear. This paper describes the redesign of an ITM procedure for nonlinear behavioral interventions, through new uncertainty computations and stopping criterion analysis.

Keywords: Behavioral interventions, local polynomial method, robust performance, identification test monitoring, uncertainty estimation, system identification

1. INTRODUCTION

Sedentarism is one of the main causes of diseases that lead to mortality worldwide. According to the World Health Organization (World Health Organization, 2013), around 31% of population aged 15 and over were insufficiently active in 2008. Furthermore, 3.2 million deaths per year are attributable to insufficient physical activity. Different organizations are trying to motivate people to engage more in physical activities and investigate how to do this effectively [(González et al., 2017), (Centers for Disease Control and Prevention, 2018), (American Council on Exercise, 2013), among others]. As part of the aforementioned investigation a Behavioral Intervention model has been developed based on Bandura's Social Cognitive Theory [(Bandura, 1989), (Martin et al., 2018)]. The theory takes into account an individuals' past experiences. This model has been tested on focus groups to study its potential effectiveness in behavioral interventions.

Control systems are used in diverse engineering fields like aeronautics, industrial, electric, among others. Controllers are used to obtain a desired behavior on a variable of interest. Many of the controller design methods require a priori knowledge of the system's model and its parameters. Thus, system identification is a critical process for the subsequent controller design being the duration of the identification experiment and data accessibility the biggest constraints.

In health topics, control system engineering has gained important significance due to its potential application in different medical fields. For example, they have the potential to help individuals improve their lifestyles through behavior change by monitoring individuals physical activities. Indeed, it could be used to customize "just in time" behavioral interventions in sedentary individuals (Martín et al., 2015).

Intensively adaptive identification test monitoring procedures for nonlinear behavioral interventions rely on real time measurements of variables of interest, which are used in the decision making procedure of dosages for intervention related to Social Cognitive Theory (SCT) (Rivera, 2012). The main idea for identification test monitoring is to assess the quality of the data in terms of its usefulness for identification purposes. Thus, three different types of actions are considered, i.e. additional periods, apply a signal with higher amplitude or different frequency content. However, due to the nonlinear behavior of the system, a major problem related to its identification arises. Applying a signal with higher amplitude or different frequency content to a nonlinear system yields to a system response that is considered valid only under certain circumstances.

In this research, a procedure is proposed so that it avoids the effect of the nonlinear components of the system for identification purposes.

Fortunately, to mitigate the problem of sedentary behavior, recent technologies have opened new ways for intervening upon behavior in context via mobile apps, and data to improve and test the model can be collected easily and using a "patient-friendly" concept (Rivera et al., 2003).

The paper is organized as follows. Section 2 presents an overview of the results obtained from previous researches regarding the Behavioral Intervention problematic and the challenges that arose during research. Section 3 describes the proposed procedure to overcome the challenges presented in the previous section. Section 4 details the results obtained from a simulation using the proposed procedure. Section 5 gives a summary of conclusions and future work.

2. OVERVIEW

Social Cognitive Theory (SCT) has been used as the conceptual basis of health behavior interventions for weight management, smoking cessation, sedentarism problems, and other health behaviors (Rivera et al., 2017). SCT describes a human agency model in which individuals proactively self regulate, self reflect and self organize (Bandura, 1989) . In the work of (Martín et al., 2014) a comprehensive and dynamical model of SCT based on a fluid analogy was proposed, which simplifies and allows customized models. Here, exogenous variables are represented by inflows, outputs are represented by inventory levels. The relationships between constructs are depicted as interconnection flows between inventories. This is illustrated in Fig. 1, where the components are generated as a consequence of variation of external and internal stimuli. The main constructs are:

- *Self-efficacy*, the self-perceived capability to perform a given behavior.
- *Outcome expectancies*, the perceived likelihood that performing a target behavior will result in outcome.
- *Behavioral outcomes*, resulting from behavior. These may include positive or negative results.
- *Self-management skills*, which involves a class of complex behaviors such as self-monitoring, self reinforcement, etc. Thus, the individual increases the potential success for a target behavior.
- *Behavior*, the action of interest. In our case, steps walked per day.

As mentioned in the introduction, a low physical activity model will be obtained through an adaptive identification test monitoring procedure for nonlinear behavioral interventions relying on real-time measurements of variables of interest. Therefore, a simplified version of the SCT model is utilized in this work. The intervention includes a daily goal-setting component, and a reward mechanism where points are given to individuals when they achieve the daily goal, this is, 10000 steps per day on a weekly average. Variables ξ_i represent inputs, η_i are outputs, γ_{ij} and β_{ij} represent interrelations among the different constructs, ζ_i is an external disturbance, and θ_i represents delay times. All these variables will be considered (assumed) in the modeling through first-order differential equations, so that a set of equations associated with the flow analogy is obtained. According to the new exogenous components referred to above, physical behavioral interventions include:

- *Expected points*, announced together with the daily goal.
- *Granted points*, given to individuals if they achieve the set goal. This feature is represented by the "If/Then" block, which incorporates a nonlinearity to the system.
- *Goal attainment*, a signal representing how much success/failure individuals had pursuing the set goal.

Identification experiments are designed to consider the nonlinearity of the system. The goal is to utilize the SCT model in the design of an adaptive identification test monitoring for nonlinear behavioral interventions. The purpose is to incorporate the possibility to perform additional modifications to the input signal content at each periodic evaluation beyond what was proposed in Martin et al. (2016).

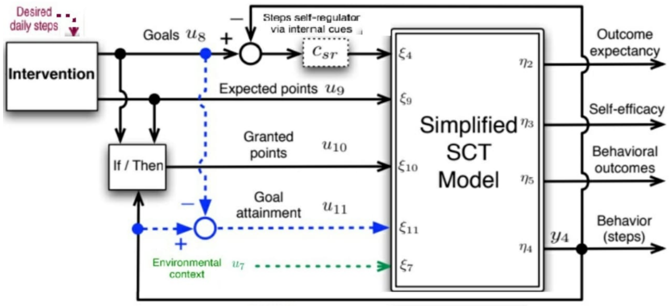

Fig. 1. Conceptual diagram relying on simplified SCT model (Martín, 2016)

The Local Polynomial Method (LPM) is a recently developed procedure for nonparametric estimation of the Frequency Response Function (FRF) of a linear system (Pintelon and Shoukens, 2012). A control oriented stopping criterion is defined relying on the computation of robust performance indexes. However, some considerations must be taken into account by the nonlinearities present in the design of the proposed intervention. Thus, a variation of the LPM method is explored. The fast LPM method is used to get an exact robust performance representation.

The proposed procedure is explained in detail below.

3. PROPOSED PROCEDURE

In general, LPM can be applied to obtain the frequency response of a certain system if the transient and the noise components of the system are assumed to be function of the frequency. The proposed procedure consists in using LPM to compute the frequency response matrix of the aforementioned system and then using these results to measure the uncertainty of the experimental data to determine if it can be used to obtain a valid model through the identification process, hence stopping the experiment. The stopping criterion will be defined in terms of Robust Performance index (RPi) which depends of the system's uncertainties.

Due to the nonlinear nature of the behavioral model described in the previous section, the monitoring procedure described in Martín et al. (2017) needs to be redesigned in order to overcome the aforementioned problem. The proposed methodology consists in excluding the nonlinear part of the model as part of the plant, incorporating its output as an input. The output of the nonlinear block is directly related to another input of the plant. Due to this, a zippered input design can not be developed and thus, the transient LPM can not be applied in this scenario. To overcome this situation, the use of fast LPM for the monitoring procedure is proposed. A brief summary of the fast LPM method for periodic signals is presented below. The methodology for arbitrary signals is presented in Martín (2016).

3.1 Fast LPM

If N samples of the system's output are obtained using a sampling time T_s when excited with an input $u(k)$ and white noise $v(k)$, its frequency response can be obtained following equation (1); where $Y(\omega_j)$ represents the Discrete Fourier Transform (DFT) of the N samples obtained from the system output, $G(\omega_j)$ represents the frequency response matrix of the system, $U(\omega_j)$ represents the DFT of the N input samples, $T(\omega_j)$ represents the frequency response of the transient component of the system and $V(\omega_j)$ is the spectral component of the system's noise. The transient component and the noise component affect all the frequency range.

$$Y(\omega_j) = G(\omega_j)U(\omega_j) + T(\omega_j) + V(\omega_j) \tag{1}$$

The frequency grid used for the DFT computation is determined following equation (2), where $j = 1, \ldots, N$. The transient component is approximated locally with a low degree polynomial following equation (3) where O_T is the remainder of the Taylor series expansions around j of order $R + 1$ for T.

$$\omega_j = \frac{2\pi j}{NT_s} \tag{2}$$

$$T(\omega_{j+r}) = T(\omega_j) + \sum_{s=1}^{R} t_s(j)r^s + O_T \tag{3}$$

To estimate $G(\omega_j)$, the system response at excited and non-excited frequencies is analyzed. According to Pintelon and Shoukens (2012), the system response at non-excited frequencies can be used to estimate the transient component of the system ($T(\omega_j)$). Then with the system response at excited frequencies and the transient component estimation, $G(\omega_j)$ can also be estimated.

A full input signal design is recommended as presented in Martín (2016). With the proposed method, the frequency response functions computed in the monitoring procedure are valid even if changes in the amplitude or spectral content of the signals are applied. Besides the type of signal recommended for transient and fast LPM, the main difference between them is that the fast LPM assumes that the frequency response functions obtained for periodic signals using the excited frequencies can be approximated locally with a low degree polynomial as shown in equation (4) whereas the transient LPM obtains the frequency response functions directly with the quotient between the Fourier Transform of the outputs and inputs. The term O_G in equation (4) is the remainder of the Taylor series expansions around j of order $R + 1$ for G.

$$G(\omega_{j+r}) = G(\omega_j) + \sum_{s=1}^{R} g_s(j)r^s + O_G \tag{4}$$

Non-excited frequencies If M periods of the input and output of the system are considered, and since $U(\omega_{jM+r}) = 0$, where ω_{jM+r} are the non-excited frequencies and $r = \pm 1, \ldots, \pm(M-1)$, equations (1) and (3) can be rewritten as:

$$Y(\omega_{jM+r}) = T(\omega_{jM+r}) + V(\omega_{jM+r}) \tag{5}$$

$$T(\omega_{jM+r}) = T(\omega_{jM}) + \sum_{s=1}^{R} t_s(j)r^s + O_T \tag{6}$$

It is desired to find the (R+1) coefficients of the equation (6). These coefficients are estimated using $2n_T$ frequencies around the excited frequency ω_{jM}. Equation (5) can be rewritten as equation (7) where $\Theta_{T,jM}$, $K_{T,jM}$ and $p(r)$ are defined in equations (8), (9) and (10) respectively.

$$Y_{T,jM} = \Theta_{T,jM}K_{T,jM} + V_{T,jM} \tag{7}$$

$$\Theta_{T,jM} = [T(\omega_{jM})\ t_1(jM)\ t_2(jM)\ \ldots\ t_R(jM)] \tag{8}$$

$$K_{T,jM} = \left[p(-n_T)^T\ \ldots\ p(n_T)^T\right] \tag{9}$$

$$p(r) = \left[1\ r^1 \ldots\ r^R\right] \tag{10}$$

Using a Linear Least Square approximation (LLS) $\Theta_{T,jM}$ can be estimated following equation (11) where $K^H_{T,jM}$ represents the Hermitian transpose of $K_{T,jM}$. Then the estimated transient component of the system $\hat{T}(\omega_{jM})$ is equal to the the first element of $\hat{\Theta}_{T,jM}$.

$$\hat{\Theta}_{T,jM} = Y_{T,jM}K^H_{T,jM}(K_{T,jM}K^H_{T,jM})^{-1} \tag{11}$$

From these results, $\hat{V_{T,jM}}$ can be estimated from equation (7) and its covariance matrix can be computed. Finally, a transient free frequency response can be defined as:

$$\hat{Y}(\omega_{jM}) = Y(\omega_{jM}) - \hat{T}(\omega_{jM}) \tag{12}$$

Excited frequencies Equation (12) can be rewritten as (13), where $\hat{Y}_{G,jM}$ represents the DFT of the system's outputs minus the transient components previously estimated, $\Theta_{G,jM}$ and $K_{G,jM}$ are associated with the Taylor series expansion of $G(\omega_j)U(\omega_j)$ and defined in (14) and (15) respectively, and $V_{G,jM}$ corresponds to the noise and disturbances component at excited frequencies $V(\omega_j)$.

$$\hat{Y}_{G,jM} = \Theta_{G,jM} K_{G,jM} + V_{G,jM} \tag{13}$$

$$\Theta_{G,jM} = [G(\omega_{jM}) \; g_1(jM) \; \cdots \; g_R(jM)] \tag{14}$$

$$K_{G,jM} = \left[p(-n_G)^T \otimes U(\omega_{(j-n_G)M}) \; \cdots \; p(n_G)^T \otimes U(\omega_{(j+n_G)M})\right] \tag{15}$$

To estimate $\Theta_{G,jM}$, $2n_G + 1$ frequencies around each excited frequency are used. In a similar way as described for the non-excited frequencies, $\Theta_{G,jM}$ can be estimated following an LLS approximation and hence (16) is obtained. Then, $\hat{G}(\omega_j)$ can be obtained from (17), where n_u is the number of inputs.

$$\hat{\Theta}_{G,jM} = \hat{Y}_{G,jM} K_{G,jM}^H (K_{G,jM} K_{G,jM}^H)^{-1} \tag{16}$$

$$\hat{G}(\omega_{jM}) = \hat{\Theta}_{G,jM} \begin{pmatrix} I_{n_u \times n_u} \\ 0_{Rn_u \times n_u} \end{pmatrix} \tag{17}$$

From these results, $\hat{V_{G,jM}}$ can be estimated from equation (13) and its covariance matrix can be computed.

3.2 Uncertainty

This parameter is a measure of the lack of knowledge about a certain process, variable or measurement. It is desired that this parameter be as low as possible. To estimate the uncertainty of the experimental data, the variance of the system must be known. Uncertainty can be computed per frequency and for each input-output combination.

When a change in amplitude or spectral content is applied to any of the inputs of the system, a new sequence of the signal l is considered and a new computation of uncertainty is necessary; also this input is considered as an arbitrary excitation. Then, the total uncertainty of the system is estimated with the uncertainties of each sequence. It will be considered that $l = 1, \cdots, L$ and that each sequence has M_l periods.

Variance Covariance matrices for the disturbance component for excited frequencies and for the frequency response function can be defined in terms of V_G and G estimated previously, as described in Martín (2016). Thus, these covariance matrices can be obtained following equations (18) and (19) respectively. In these equations df_G represents the degrees of freedom of $K_{G,jM}$ and is equal to $2n_G + 1 - (R+1)(n_u)$, and $\overline{S_G^H S_G}$ represents the conjugate transpose of $S_G^H S_G$ where S_G is defined in equation (20).

$$\hat{C}_{V_G}(\omega_{jM}) = \frac{1}{df_G} \hat{V}_{G,jM} \hat{V}_{G,jM}^H \tag{18}$$

$$\hat{C}_G(\omega_{jM}) = \overline{S_G^H S_G} \otimes \hat{C}_{V_G}(\omega_{jM}) \tag{19}$$

$$S_G = K_{G,jM}^H (K_{G,jM} K_{G,jM}^H)^{-1} \begin{pmatrix} I_{n_u \times n_u} \\ 0_{Rn_u \times n_u} \end{pmatrix} \tag{20}$$

For arbitrary excitations, the covariance for the frequency response function is defined as shown in equation (21) where S and $\hat{C}_{V_A}(\omega_j)$ are also defined in Martín (2016).

$$\hat{C}_{G_A}(\omega_j) = \overline{S^H S} \otimes \hat{C}_{V_A}(\omega_j) \tag{21}$$

From the covariance matrices, the variance of the system can be computed for periodic or arbitrary excitations following equations (22) and (23) respectively.

$$\hat{\sigma}^2_{\hat{G}_{[m,n]}}(\omega_{l,i}) = diag(|\hat{C}_{\hat{G}}(\omega_{l,i})|) \tag{22}$$

$$\hat{\sigma}^2_{\hat{G}_{A[m,n]}}(\omega_{l,i}) = diag(|\hat{C}_{\hat{G}_A}(\omega_{l,i})|) \tag{23}$$

Variance of a sequence To compute the variance of the L sequences of G, equation (24) is used. With this expression, the total frequency response matrix can be estimated using equation (25) where $w_{l[m,n]}(\omega_{l,i})$ represents the weight function presented in (26) and $\hat{G}_{[m,n]}(\omega_{l,i}, M_l)$ represents $\hat{G}(\omega_{jM})$ for the l sequence with $M = M_l$ periods and frequency $j = i$.

$$\hat{\sigma}^2_{\hat{G}_{[m,n]}}(\omega_i) = \left[\sum_{l=1}^{L} \frac{1}{\hat{\sigma}^2_{\hat{G}_{[m,n]}}(\omega_{l,i})}\right]^{-1} \tag{24}$$

$$\hat{G}_{[m,n]}(\omega_i, M) = \frac{\sum_{l=1}^{L} w_{l[m,n]}(\omega_{l,i}) \hat{G}_{[m,n]}(\omega_{l,i}, M_l)}{\sum_{l=1}^{L} w_{l[m,n]}(\omega_{l,i})} \tag{25}$$

$$w_{l[m,n]}(\omega_{l,i}) = \frac{1}{\hat{\sigma}^2_{\hat{G}_{[m,n]}}(\omega_{l,i})} \tag{26}$$

With all these results, circular trust regions of radius $\ell^{1-\rho}_{a[m,n]}(\omega_{l,i})$ and $(1-\rho) \times 100\%$ probability can be defined. The radius of these circular regions represent the uncertainty bound for each frequency and for each input-output combination of an l sequence; it is defined with equation (27)

$$\ell^{1-\rho}_{a[m,n]}(\omega_{l,i}) = (\sqrt{-ln\rho}) \hat{\sigma}_{\hat{G}_{[m,n]}}(\omega_{l,i}) \tag{27}$$

A more general MIMO uncertainty bound $\epsilon^{1-k}(\omega_{l,i})$ can be estimated considering the maximum singular value per frequency with a probability $1 - k$. This new bound is defined in terms of the Frobenius norm of the square of the maximum singular value $\overline{\sigma}$, which is computed using $\ell^{1-\rho}_{a[m,n]}$ as shown in the following equation:

$$\overline{\sigma}(\hat{G}(\omega_{l,i}) - G(\omega_{l,i}))^2 \leq [\epsilon^{1-k}(\omega_{l,i}, M_l)]^2 \tag{28}$$

$$[\epsilon^{1-k}(\omega_{l,i}, M_l)]^2 = \sum_{n=1}^{n_u} \sum_{n=1}^{n_y} [\ell^{1-\rho}_{a[m,n]}(\omega_{l,i}, M_l)]^2 \tag{29}$$

Considering the L sequences, the uncertainty bounds can be redefined as equations (30) and (31) respectively.

$$\ell^{1-\rho}_{a[m,n]}(\omega_i, M) = (\sqrt{-ln\rho})\hat{\sigma}_{\hat{G}_{[m,n]}}(\omega_i) \tag{30}$$

$$[\epsilon^{1-k}(\omega_i, M)]^2 = \sum_{n=1}^{n_u}\sum_{n=1}^{n_y}[\ell^{1-\rho}_{a[m,n]}(\omega_i, M)]^2 \tag{31}$$

3.3 Robust Performance Index and Stopping criterion

The objective of robust control is to allow the system to achieve robust performance or stability in the presence of uncertainty sources like modeling errors, sensors noise and disturbances. To achieve this goal, sensitivity and complementary sensitivity estimated functions are used. These functions are defined in (32) and (33) respectively.

$$\tilde{E} = (I + \tilde{G}C)^{-1} \tag{32}$$

$$\tilde{H} = \tilde{G}C(I + \tilde{G}C)^{-1} \tag{33}$$

It is desired to design a controller in order that in the worst case scenario, the normalized error be minimum when an arbitrary disturbance d is applied to the system. This can be achieved through the H_∞ norm of Ew_p; the objective is to design w_p so that it has a minimum bandwidth and lower amplitudes on low frequencies. This function allows the designer to limit the amplitude of the sensitivity function E and reshape it so disturbances are not amplified. To fulfill this requirement $\overline{\sigma}(Ew_p) < 1, \quad \forall\omega$ needs to be accomplished.

The sensitivity function E can be defined in terms of the estimated sensitivity function and the additive uncertainty L_A with equation (34) where $L_A(s)$ is equal to the product between the normalized additive disturbance $\Delta_a(s)$ and a scalar weight $\overline{l_a}$.

$$E = \tilde{E}(I + L_A\tilde{G}^{-1}\tilde{H})^{-1} \tag{34}$$

Then, the condition used to design w_p can be rewritten as (35). The estimated complementary sensitivity function $\tilde{H}$ requires the definition of a controller C that at the same time is defined in terms of the invertible and non invertible components of G and a low pass filter matrix F used to increase the robustness of the controller. Thus, the estimated sensitivity function can be redefined with equation (36) where G_+ represents the non invertible part of the system.

$$\overline{\sigma}(\tilde{E}w_p) + \overline{\sigma}(\tilde{G}^{-1}\tilde{H})\overline{\ell}_a < 1, \quad \forall\omega \tag{35}$$

$$\tilde{H} = G_+F \tag{36}$$

The filter matrix F can be expressed using v first order transfer functions on the matrix main diagonal. These transfer functions follow equation (37).

$$f_i(s) = \frac{1}{(\lambda_i s + 1)^n}, \quad i = 1, \dots, v \tag{37}$$

If $\tilde{G}$ and $\overline{\ell_a}$ are substituted in equation (35) with $\hat{G}$ and ϵ respectively; the resulting expression is named Robust Performance index (RP_i) which is shown below.

$$RP_i(\omega_i, M) = \overline{\sigma}(\tilde{E}w_p) + \overline{\sigma}(\hat{G}^{-1}G_+F)\epsilon^{1-k}(\omega_i, M) \tag{38}$$

Finally, the stopping criterion is to halt the experiment after M periods if $RP_i(\omega_i, M) \leq 1, \ \forall\omega_i$ during the last 3 consecutive iterations. To improve the results, λ_i are readjusted each iteration so that they minimize the maximum RP_i value among all frequencies.

4. RESULTS

Following the procedure described in the previous section, an identification monitoring procedure was developed using a hypothetical SCT simulation model. Initially two periods of the inputs signals are generated and the fast LPM is applied to determine the RP_i of the system. Then, an extra cycle of the inputs is generated, uncertainties are recalculated and a new RP_i is computed; this process is repeated until the stopping criterion is met. The total number of cycles used for this experiment was 10; during this experiment, there were no changes in amplitude or spectral content of the system's inputs. Also, a gray box identification is done after every cycle. Each cycle was generated using 18 samples and exciting 8 frequencies. The experiment starts with the generation of 2 consecutive cycles of the input signals.

The three input signals used for this experiment were: Desired step goal, Expected points, and Granted points. The latter is not a designed signal but the result of the if/then block of the system and a source of nonlinearity; for this reason, this block is excluded from the system and its output is considered one of the system's inputs. The output signals used for the RP_i computation were: Outcome Expectancy (y_2), Behavior (y_4) and Behavioral Outcomes (y_5).

The RP_i obtained each cycle is shown in Fig. 2. On the first two iterations $RP_i < 1$, however this is not valid as stopping criterion because the first three cycles of the system are considered as start-up cycles. The stopping criterion is met when $M = 7$ cycles because in this cycle, the third consecutive iteration present $RP_i < 1$.

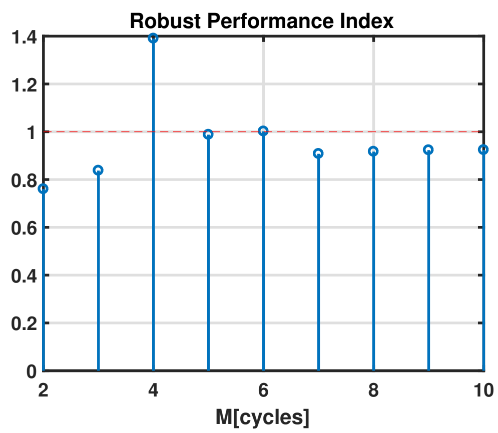

Fig. 2. Robust Performance index per cycle

After each cycle, a system identification was developed using the data obtained so far. Then, a different set of input signals is used to simulate the original system and the identified system. A comparison of the outputs of these systems is developed and a percentage fit is obtained. The percentage fit obtained after each cycle for each output is summarized on Table 1. It can be observed that the fits for the second cycle and partially for the third cycle are higher than the fit obtained after 10 cycles of the experiment. However, the first three cycles are considered part of the start-up stage so the fits obtained are not valid. Following the results obtained from the robust performance index, after the seventh cycle the experiment could be stopped. Analyzing the fits variation, it can be concluded that after the seventh cycle there is no significant fit change in any of the outputs. The same conclusion about the stopping cycle can be obtained using either the fit per cycle table or the robust performance index per cycle, being the latter more reliable.

M	y_2	y_4	y_5
2	87.0614	47.7118	48.2205
3	88.1505	43.1683	39.9319
4	87.9939	36.9043	39.7003
5	87.8575	38.9010	43.1016
6	88.1888	40.2961	45.1786
7	88.4197	41.4282	46.4382
8	88.4789	42.2203	47.2781
9	87.2018	33.1933	43.8522
10	88.3695	43.0504	48.0345

Table 1. Percentage fit obtained after each iteration

5. CONCLUSIONS AND FUTURE WORK

This work presents the results of an adaptive identification test monitoring procedure applied to nonlinear interventions for promoting physical activity in sedentary adults with the shortest possible duration. The experiment ended when a predefined criterion based on robust control was satisfied. The use of the fast LPM was necessary to overcome the nonlinearity of the system.

From results obtained from simulation, the potential of the proposed procedure was tested and the described stopping criterion can be considered valid. It could be observed that as the robust performance index decreases after each cycle, the percentage fit tends to increase. Also, the fit is highly affected by the system's noise, causing variations even after the stopping criterion is met.

As future work, a simulation experiment that includes amplitude change and a simulation experiment that includes spectral content modification are recommended. Also, a statistical validation using a Monte Carlo simulation is also recommended to further prove the proposed procedure and a result comparison between this method and the one presented in Martín (2016). Finally, to fully validate the identified model, an experiment with real data considering experiment limitations as signal amplitudes and frequencies, is highly recommended.

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