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Dynamic switched non-parametric identification of the human physiological response under virtual reality stimuli ⋆

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Abstract: In this work, it is proposed a Switched Differential Neural Networks structure (SDNN) to model the human physiological response in a virtual stimuli scenario. Two physiological variables are assessed: electrocardiography and electrodermal activity, which provide a reflex response after stimuli. The proposed approach is focused on the representation of two discrete primary states, relaxation and stress as the response of the virtual stimuli. A switched dynamic approach is set, in which the trigger of an stimuli generates a change in the heartbeat rate as well as in the skin conductivity, constructing the switch between the mentioned states. The SDNN allows to obtain a model structure whose dynamics corresponds to the rate of change of the physiological variables, given as result a particular class of uncertain switched systems. The proposed non-parametric identification in this switched structure is implemented and experimentally assessed showing appropriate convergence rates in, both, switching regions and the continuous states.

Keywords: Uncertain dynamic systems, switching systems, non-parametric identification, virtual reality, physiological signals.

1. INTRODUCTION

The emergent applications of virtual reality systems have allowed studying multiple aspects of the human-machine interaction. One of the most studied is the detection of user emotions through the Autonomic Nervous System (ANS) responses when the subject is under provoked external stimuli [Picard et al. (2001)]. Here, the term stimuli refers to any combination of stimulus with visual, auditive, and haptic components. Physiological signals allow to measure these responses, among the available options, the electrocardiography (ECG) and electrodermal activity (EDA) have shown the possibility to identify states like relaxation, stress, joy, anger, or anxiety. There is a wide variety of works that deal with the identification of discrete emotional states showing fair results in areas like multimedia systems [Kroupi et al. (2016)], rehabilitation systems [Koenig et al. (2011)], human-robot interaction [Swangnetr and Kaber (2013)], and certainly virtual reality [Felnhofer et al. (2015)]. However, the mathematical modeling of those scenarios is a hard task since physiological systems are nonlinear, and highly uncertain; their structure depends on complex interactions, their parameters depend on the subject conditions and they are, in most of the cases, time-varying, or not measurable in real-time [Cobelli and Carson (2019)].

The aforementioned problem becomes much more challenging when the response of the human is changing according to external stimuli. It is common that when a system changes between different conditions, this is usually modeled as a hybrid system, where the stimuli can be seen as a discrete input, and the changes are time-continuous. Hybrid Dynamic Systems (HDS) arise whenever one mixes logical decision-making with a continuous-time process [Ye et al. (1998)]. The continuous/discrete-time subsystems are represented as a set of differential/difference equations whereas the logical/decision-making subsystem (supervisor) can be represented through a set of approaches as in [Henzinger et al. (1998)], for instance: Petri nets, Fuzzy logic decision system, static neural networks, and commonly by automata [Li et al. (2002)], [Branicky (1998)]. Recently, Dynamic Hybrid Systems have been used to model physiological systems, particularly linear and nonlinear Switching Systems [Lee and Galiana (2005)], [Huang et al. (2019)], as an alternative to deal with complexity behavior [Quinn et al. (2008)]. Nonetheless, the particular problem is still the modeling of the physiological behavior due to the high uncertainty and the lack of mathematical structures to represent it. In this sense, it is possible to take advantage of the so-called Differential Neural Networks (DNNs) [Poznyak et al. (2001b)]. The DNNs provide a nonlinear system identification technique

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to approximate the behavior of a system, obtaining an adaptive model structure of the uncertain system where the convergence approximation is guaranteed by means of Lyapunov techniques.Such method has shown appropriate results on identifying uncertain system which are difficult to model. For instance, chemical degradation processes is a highly uncertain system where the degradation kinetics are modeled via DNN [Poznyak et al. (2019)]. This allows to design and implement a control strategy for the regulation of some chemical agents during the process. Furthermore, another example is the modeling of distributed parameters systems governed by partial differential equations [Aguilar-Leal et al. (2016)]. In this case the technique is used along with Finite Element Methods to model the dynamic behavior of two and three dimensions objects.

In this paper, it is implemented a class of non-parametric adaptive identifier, a Switching Differential Neural Network Identifier (SDNN) for a class of uncertain HDS [García et al. (2009)]. Our work considers ECG, and EDA as two continuous uncertain switched states between two discrete states: relaxation and stress. An approach of ECG dynamic identification, as a switching system, has been presented by [Oster et al. (2015)]; it is tackled the case when mathematical models of the continuous-time subsystem (of HDS) are unknown, and only some data collections are available. ECG and EDA can be measured and collected in time. It is also assumed that the logical/decision-making subsystem is well established and known, which includes knowing the time when the stimuli are applied. From this information, a set of DNNs is adjusted to obtain a representation of each continuous-time subsystem component. Therefore, the main contribution of this work is the application of the SDNN to obtain a model structure that captures the dynamics of the physiological response under input stimuli, which is an open problem in the literature. Moreover, the obtained model will provide a continuous-time alternative to the current static classification schemes, which usually require several data sets per class during the learning process. Besides, getting such a continuous model will allow exploring the possibility of implement control strategies for the regulation of the physiological condition of a subject according to multi-modal input stimuli in a wide variety of multimedia systems.

The remainder of this paper is organized as follows. Section 2 introduces basic concepts and the nomenclature about hybrid (switching) systems as well as the notion of uncertain switching systems. Next, section 3 states the Switching Differential Neural Network Identifier (SDNN) along with stability methods based on Lyapunov theory for hybrid systems, and for the convergence of the identifier. The physiological uncertain system including the ECG and EDA models is presented in section 4, including the experimental setup for the virtual reality test. The results of the proposed approach are presented in section 5, showing the performance of the HDNN for the identification of the ECG and EDA signals. Last section includes the conclusions and future considerations for using the proposed model on human-in-the-loop control systems.

2. PRELIMINARIES

2.1 Hybrid systems (Switching systems)

Switching systems are continuous-time hybrid systems where the particular differential equation that governs the evolution of the state at any given time/instant is determined by a switching rule/signal [Goedel et al. (2012)]. Let us consider the following switching system consisting of nonlinear subsystems [Xu and Zhai (2005)]:

$$\begin{gathered} \dot{x}(t) = f_i(x,t) \\ x \in \mathbb{R}^n,\ f_i : \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}^n,\ i \in I \triangleq \{1 \ldots M\} \end{gathered} \tag{1}$$

For the system (1) the active subsystem at each instant is specified by switching sequences. Given $x(t_0)$, a switching sequence is of the form $\varpi = ((t_0, i_0), (t_1, i_1), \ldots, (t_M, i_M))$, where: $(t_0 \leq t_1 \leq \ldots \leq t_M, i_k \in I)$, and specifies that subsystem i_k is active in $[t_k, t_{k+1})$. All of them, non zero sequences. In general, it is also assumed that a hybrid system has a discontinuous state jump governed by

$$x(t) := g_{i,j}\left(x\left(t_k^-\right), t\right) \tag{2}$$

when it switches from subsystem i_{k-1} to $i_k(x\left(t_k^-\right), t_k)$ at time t_k. Each function $g_{i,j}$ $(i, j\epsilon I, i \neq j)$ characterizes the jump from subsystem i to j. Behavior study of switching system (1)-(2), usually specifies some infinite time interval $T = [t_0, \infty)$, or finite time interval $T = [t_0, t_f]$ in which a trajectory is generated. Switching sequences are generated by a switching law defined as in [Xu and Zhai (2005)].

Definition 2.1. Given a time interval T, a switching law S over T is a mapping $S : \mathbb{R}^n \to \Sigma_T$ which specifies a nonzero switching sequence $\varpi\epsilon\Sigma_T$ for any initial state $x(t_0)$. Here $\Sigma_T \triangleq$ {switching sequence Σ over T}.

S over a given T is often determined by some rules or algorithms, which describe how to generate a switching sequence for a given $x(t_0)$, rather than mathematical equations. As defined before, a hybrid system without state jump at switching instants is called switched system, which can be denoted as the system defined in equation (1). It will be assumed that for every $x(t_0)$ and Σ_T, the hybrid/switched system possesses a unique solution over T.

2.2 Uncertain Switching Systems

If each $i-$*component* of the right hand side of equation (1) is unknown or uncertain, a Hybrid Differential Neural Network Identifier (HDNN) [García et al. (2009)], [Garcia-Solares et al. (2016)] can be implemented. Such structures consider the capacity of Differential Neural Networks to approximate the dynamic behavior of the continuous-time process (incomplete or partially known). Compared to Static Neural Networks (NN), Dynamic Neural Networks as DNN approach permit to avoid problems related to global extreme search converting the learning process to an adequate feedback design [Poznyak et al. (2001a)], [Lewis et al. (1996)]. Thus, each $i-$*component* of equation (1) can be approximated by a set of nonlinear functions $\bar{f}_i(x(t), u(t) \mid W_i(t))$ where $\bar{f}_i \in \mathbb{R}^n$ defines the approximate mapping depending on the time-varying parameters $W_i(t)$. These parameters should be adjusted by a concrete *adaptation law*. That adaptive algorithm is derived by stability analysis based on Lyapunov theory. According to the DNN-approach of [Poznyak et al. (2001a)], a nonlinear function $\bar{f}_i(x(t), u(t) \mid W_i(t))$ may be decomposed into two parts: the former approximates the linear dynamic part by a *Hurwitz* fixed matrix $A_i \in \mathbb{R}^{n\times n}$ and the nonlinear part is approximated by time-varying parameters $W_i(t)$ with *sigmoid* multipliers, that is:

$$\begin{gathered}\bar{f}_i\left(x(t), u(t) \mid W_i(t)\right)\\ := A_i x(t) + W_{1i}(t)\sigma_i\left(x(t)\right) + W_{2i}(t)\varphi_i\left(x(t)\right)u(t)\end{gathered} \tag{3}$$

where: $A_i \in \mathbb{R}^{n\times n}$, $W_{(1,2)i}(t) \in \mathbb{R}^{n\times p}$,$\sigma(\cdot) \in \mathbb{R}^{p\times 1}$,$\varphi(\cdot) \in \mathbb{R}^{p\times r}$ and $u(t) \in \mathbb{R}^{r\times 1}$ is an external bounded input but not a control, i.e. $U^{adm} := \{u(t) : \|u(t)\| \leq \Upsilon_u < \infty\}$, this approximation considers the general situation including such where $u(t) \equiv 0$. The activation vector-functions $\sigma(\cdot)$ and $\varphi(\cdot)$ are usually selected as a function with sigmoid-type components, i.e.,

$$\begin{gathered}\sigma_r\left(x(t)\right) := a_r\left(1 + b_r \exp\left(-\sum_{s=1}^{n} c_s x_s(t)\right)\right)^{-1}\\ \varphi_{s,s}\left(x(t)\right) := a_{r,s}\left(1 + b_{r,s}\exp\left(-\sum_{e=1}^{n} c_e x_e(t)\right)\right)^{-1},\end{gathered} \tag{4}$$

Activation functions satisfy the following sector conditions

$$\begin{gathered}\left\|\sigma\left(x(t)\right) - \sigma\left(x'(t)\right)\right\|^2_{\Lambda_\sigma} \leq L_\sigma \left\|x(t) - x'(t)\right\|^2_{\Lambda'_\sigma}\\ \left\|\varphi\left(x(t)\right) - \varphi\left(x'(t)\right)\right\|^2_{\Lambda_\varphi} \leq L_\varphi \left\|x(t) - x'(t)\right\|^2_{\Lambda'_\varphi}\end{gathered} \tag{5}$$

and are globally bounded on $\mathbb{R}^n$. In system (3), the constant parameters A_i as well as the time-varying parameters $W_i(t)$ should be properly adjusted to guarantee the state approximation. For any fixed matrices $W_{1i}(t) = \hat{W}_{1i}$, $W_{2i}(t) = \hat{W}_{2i}$ the dynamics (1) can be represented as:

$$\dot{x}(t) = A_i x(t) + \hat{W}_{1i}\sigma\left(x(t)\right) + \hat{W}_{2i}\varphi_i\left(x(t)\right)u(t) + \tilde{f}_i(t) + \xi(t) \tag{6}$$

where: $\tilde{f}_i(t) := f_i\left(x(t)\right) - \bar{f}_i\left(x(t) \mid \hat{W}_i\right)$ is referred to the modelling error vector-field and the vector ξ_t represents the noises and disturbances affecting the state vector. This approximation remains valid inside each region $Z_i \subset \mathbb{R}^n$. In view of the corresponding boundedness, the following upper bound for the unmodelled dynamics $\tilde{f}_i(t)$ takes place:

$$\begin{gathered}\left\|\tilde{f}_i(t)\right\|^2_{\Lambda_f} \leq \tilde{f}_0 \ \forall i \in [1, M]\\ \tilde{f}_0 > 0;\ \Lambda_f > 0,\ \Lambda_f = \Lambda_f^\top\end{gathered} \tag{7}$$

3. SWITCHED DIFFERENTIAL NEURAL NETWORK IDENTIFIER

Without loss of generality, from here on the HDNN will be denoted as a Switched-DNN. In [García et al. (2009)] it is found the general stability proof for Uncertain Hybrid Systems Identification. Let us introduce the following Switched-DNN Identifier:

$$f_i(x, \hat{x}, t) := A_i\hat{x}(t) + W_{1i}(t)\sigma_i\left(\hat{x}(t)\right) + W_{2i}(t)\varphi_i\left(\hat{x}(t)\right)u(t) \tag{8}$$

working inside the region $Z_i \subset \mathbb{R}^n$. Here, the weights matrices $W_{1i}(t)$ and $W_{2i}(t)$ supply the adaptive behavior and accurate representation of the uncertain nonlinear system if they are adjusted by an adequate manner. It is suggested the following nonlinear weight *updating* law derived from the practical stability analysis described in [García et al. (2009)]:

$$\begin{gathered}\dot{W}_{1i}(t) = -\alpha_{Q_i}\tilde{W}_{1i}(t) - \tilde{k}_{1i}2k_{1i}P_i\Delta_t\sigma_i^\intercal\left(\hat{x}(t)\right)\\ \dot{W}_{2i}(t) = -\alpha_{Q_i}\tilde{W}_{2i}(t) - \tilde{k}_{2i}P_i\Delta_t u^\intercal(t)\varphi_i^\intercal\left(\hat{x}(t)\right)\end{gathered} \tag{9}$$

where: $\alpha_{Q_i} = 2^{-1}\lambda\min(P_i^{-\frac{1}{2}}Q_iP_i^{-\frac{1}{2}})$, $Q_i, P_i \in \mathbb{R}^{n\times n}$,$Q_i$, $P_i > 0$; $\tilde{W}_{ji}(t) := W_{ji}(t) - \hat{W}_{ji}$; $\tilde{k}_{ji} \in \mathbb{R}$, $k_{ji} > 0, j = 1, 2$ $\Delta(t) := \hat{x}(t) - x(t)$ with P_i positive definite solution of the following set of Riccati algebraic equations:

$$\begin{gathered}P_iA_i + A_i^\intercal P_i + P_iR_iP_i + \tilde{Q}_i = 0\\ R_i = \hat{W}_{1i}\Lambda_{1i}\hat{W}_{1i}^T + \Lambda_{4i},\ i = 1, .., M\\ \tilde{Q}_i = L_\sigma\Lambda_{1i}^{-1} + L_\varphi\Upsilon_u\Lambda_{5i}^{-1} + Q\end{gathered} \tag{10}$$

where Λ_{1i}, Λ_{4i} and Λ_{5i} are positive definite matrices ($\Lambda_{1i}, \Lambda_{4i}, \Lambda_{5i} \in \mathbb{R}^{n\times n}$). To improve the behavior of these adaptive laws, the matrix $\hat{W}_{1i}$ can be *provided* by one of the, so-called, training algorithms [Stepanyan and Hovakimyan (2007)]. For detailed concepts, methods, and proofs on the practical stability of hybrid systems, the reader is referred to [Xu and Zhai (2005)]. In the next section, it will be described the setup of the physiological switched system, which involves the ECG and EDA signals. This will be associated with the previously stated Neural identifier.

4. PHYSIOLOGICAL UNCERTAIN SWITCHED SYSTEM SET-UP

Currently there are multiple approaches to the identification of discrete states of the human (e.g. stress, anxiety, joy, boredom) through classification techniques using particular conditions of their physiological signals. There are two important considerations for the classification of these states, first the activity or type of stimulus a person is exposed to, and second their baseline physiological condition. The first refers to the fact that incorrect states can be identified due to the execution of physical tasks and not by the stimulus of interest. For example, in [Katsigiannis et al. (2019)], there was an incorrect assessment of the user status using a bicycle simulator due to the levels of sweating produced during the physical activity of the task. On the other hand, the baseline conditions of the subject are important since a normalization is necessary to see the changes in percentage form. For example Diemer et al. [Diemer et al. (2016)] recorded an average increase of 15 beats per minute with respect to the baseline state on test subject when they were exposed to an acrophobia scenario. Therefore, the switching conditions can be extended depending on the case study, the number of states to be identified, and the physiological conditions of each subject.

Particularly in this work, two discrete states are considered to model the switched physiological response under stimuli: relaxation and stress/anxiety. Such states are examined by means of two time-continuous states, the electrical heart activity ECG, and the electrodermal activity EDA. These signals are widely used in emotion assessment studies, showing accurate results to identify the mentioned discrete states.

The switch between the discrete states will be determined by the increment or detriment respecting a threshold fixed over the heart rate obtained from the ECG signal. The good health condition of the subject is assumed in this study, but it is possible to extend the transition rule to an abnormality condition, as considered in [Oster et al. (2015)] where switched Kalman Filters are proposed. Then, the general physiological uncertain switched system structure is presented below

$$
\begin{aligned}
Q_1 &= \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = [\, f_1(x,t) \,],\ \omega_{HR} \leq \omega^*_{HR} \\
Q_2 &= \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = [\, f_2(x,t) \,],\ \omega_{HR} > \omega^*_{HR}
\end{aligned}
\tag{11}
$$

where: Q_1 is the discrete state relaxation and Q_2 is the discrete state stress/anxiety. $x_1(t)$ is the ECG and $x_2(t)$ is the EDA, ω_{HR} is the current heart rate frequency, ω^*_{HR} is the threshold heart rate switching condition. Two scenarios were considered to implement the SDNN. First, using artificial signals generated by two mathematical models from the literature, and second, with real acquired signals from an experiment using Virtual Reality. The aim was to assess the behavior of the SDNN in the case of "ideal" signals (waveform), against the result with real subject's signals, usually including noise and artifacts. We describe the setup for both tests in the following section.

4.1 ECG and EDA Simulations

To generate artificial signals of ECG and EDA, the mathematical models of [McSharry et al. (2003)] and [Amin and Faghih (2019)] have been considered. Particularly the ECG signal is modeled using the set of differential equations proposed by [McSharry et al. (2003)]. These equations are adapted to a hybrid systems approach and reflects a quasi periodic movement around an attracting limit cycle of unit radius in the (x, y) plane, and where each revolution corresponds to a heartbeat. Subsequently, the human state changes can be represented as

$$
\begin{aligned}
\dot{\zeta}_1 &= \alpha\zeta_1 - \omega_j\zeta_2 \\
\dot{\zeta}_2 &= \alpha\zeta_2 + \omega_j\zeta_1 \\
\dot{\zeta}_3 &= -\sum_{j\in P,Q,R,S,T} a_{j,1}\Delta\theta_{j,1}\exp\left(\frac{\Delta\theta^2_{j,1}}{2b^2_{j,1}}\right) - (\zeta_3 - \varrho_0)
\end{aligned}
\tag{12}
$$

where the index j represents the $j-th$ discrete state, $\alpha = 1 - \sqrt{\zeta_1^2 + \zeta_2^2}$, $\theta = \arctan 2(\zeta_2, \zeta_1)$, $\Delta\theta_{j,i} = (\theta - \theta_j)$, and ω is the angular velocity of the trajectory which defines the variations in the length of the RR-intervals. Moreover, $\varrho_0 = Asin(2\pi f_2 t)$ with $A = 0.15mv$ which represents the coupling of the baseline value to the respiratory frequency f_2. In addition, the values of a, b, θ_j are defined according to the PQRST points of a normal subject (see [McSharry et al. (2003)] for details). The principal disadvantage of this model is that it is oriented to represent the electrical trace (waveform) without relation to the physiological conditions of a subject; this is, the system has no variables associated with stimuli inputs, and only the frequency of the signal can be modified.

In the case of the EDA, the Skin Conductance (SC) provides information about different eccrine sweat gland activities and can be represented by the summation of two signals, a tonic component (slowly varying) and a phasic component (fast varying) [Amin and Faghih (2019)]. Specifically the phasic component describes changes in SC, and it can be modeled by the following differential equations

$$
\begin{aligned}
\dot{\xi}_1(t) &= -\frac{1}{\tau_1}\xi_1(t) + \frac{1}{\tau_1}u(t) \\
\dot{\xi}_2(t) &= -\frac{1}{\tau_2}\xi_1(t) - \frac{1}{\tau_2}\xi_2(t)
\end{aligned}
\tag{13}
$$

where ξ_1 is a non-observed state variable (neural states), τ_1, τ_2 are SC time constants corresponding to rise and fall times, ξ_2 is the phasic component, and $u(t)$ is the input stimulation which corresponds to a set of neural impulses that according to different amplitude and length properties allow to quantify an emotional state (see [Amin and Faghih (2019)] for details about the deconvolution process of the input stimuli). The problem with such EDA model is that is related to non measurable inputs (the neural system control) which can not be physically generated without invasive techniques (invasive electrodes). Here, the models were used to create a simulation of the proposed system (11). A timeline of 35 seconds where the HR frequency of the ECG signal was modified such that changes from baseline state to a higher frequency that represents a stress shock. Later this returns to the baseline state. This process was repeated one more time during the considered interval. In the case of the EDA a set of stimuli were recreated using two pulse signals with amplitudes 6 and 7 according to the configuration described in [Amin and Faghih (2019)]. Both pulses were associated with the time instants were the ECG signal change the frequency. In this case, the exact moment of the "switch" between states was known due to the preprogrammed frequency and pulse signals.

4.2 ECG and EDA Experimental Measurements

The virtual reality experiment was based on a Mood Induction Procedure [Serrano et al. (2016)], which is commonly used to study the effects of stimuli on emotional states and cognitive functions. The ECG and EDA activity signals were recorded using a development board, Bitalino Revolution Kit. Both signals were sampled at 1 KHz using Ag/AgCl electrodes. For the ECG signal an Einthoven triangle configuration was used. In the case of the EDA, two disposal electrodes were placed on the medial phalanges of the index and middle finger of the right hand. Moreover, the signals were processed using MATLAB. The ECG and EDA signals were recorded from a healthy subject to determine the corresponding relaxed or stress states. The user signed an informed consent letter. To implement a virtual environment it was considered the Unity 3D game engine platform and the Oculus Rift display system which includes an immersive audio subsystem. The environment consists on a core scene that depicts a park scenario while the user remains in a park bench located on a structure that places it at a height equivalent to 30m (acrophobia scenario). This kind of Virtual Reality exposure has shown good results to elicit stress and anxiety on users even when they report to not have fear of heights [Diemer et al. (2016)].

The baseline or "relaxed" state considers the user seated on the bench while observing the three-dimensional environment; this was the start position and remained there for three minutes. Such an environment with their corresponding colors, sounds, and without movements was considered as the stimuli number one. The bench begins to rotate until it generates a free fall of the user within the virtual environment to provoke a change in the user's state, this is also complemented by a prototype movement platform where the user is sitting, allowing to feel the movements of rotation before the fall. Therefore, the stimuli number two is considered as this fall within the scenario which generates a rapid change in the alert state of the user, increasing their heart rate frequency as well as their skin conductance level. Besides, to obtain the time instant where Heart Rate HR frequency ω_{HR} increments or "switch", an R-peak detection algorithm (see [Sadhukhan and Mitra (2012)]) was used to compute HR of the subject. The selected algorithm posses low computing requirements; however, more sophisticated algorithms can be used according to the raw state of the ECG signal (for instance, consider the well-known Pan & Tompkins algorithm). Figure 1 depicts the prototype with the subject during the test.

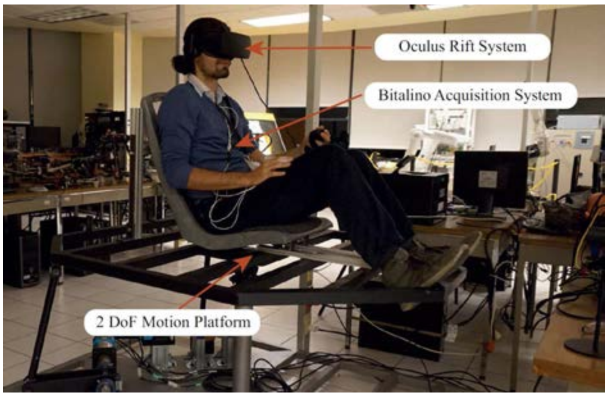

Figure 1. Experimental platform and subject connected to the Bitalino acquisition board.

5. RESULTS

The proposed SDNN identifier structure is:

$$\begin{aligned} f_1(x,\hat{x},t) &= A_1x(t) + W_{11}(t)\sigma_i(x(t)) \\ f_2(x,\hat{x},t) &= A_2x(t) + W_{12}(t)\sigma_i(x(t)) \end{aligned} \tag{14}$$

For the ECG and EDA simulation, the parameters of the SDNN were selected as $A_1 = [-1\ 0; 0\ \ -2] * 0.1$, $P_1 = [100\ 0; 0100] * 10000$, $A_2 = [-1\ 0; 0\ \ -2] * 0.1$, $P_2 = [350\ 0; 0\ 350] * 10000$. The states of the SDNN were defined as x_1 (ECG signal) and x_2 EDA. Figures 2 and 3 show the comparison between the states x_1, x_2 and their estimations $\hat{x}_1, \hat{x}_2$ generated by the DNN. The switching between states is represented by the gray coloured zones in the Figures. Notice that there is an asymptotic convergence of the states to the original generated by the models (12), (13), which is also reflected on the mean quadratic errors shown in Figures 4 and 5. Last Figures exhibit an error increase close to the switching zones which eventually decreases after a short time period (close to 500 ms). A simplified process to train the SDNN Identifier with the artificial signals can be seen in Algorithm 1.

For the identification test with the experimental signals, similar results were achieved. The same parameters for the SDNN were considered as the identifier was trained with the simulated signals. The results of identification are shown in Figures 6 and 7. The convergence of the states presents even shorter times in the case of artificial signals. In the case of artifacts in the ECG signal the convergence was appropriate. However, more signals subject to artifacts and noise due to physical activity must be analysed to study the robustness of the strategy. The corresponding error signals for the experimental tests are presented in figures 8, 9. Unlike the simulated error signals, the experimental ones does not exhibit the error increase in the switching zones, showing an appropiate validation of the identifier. This validation process of SDDN identifier is described by Algorithm 2.

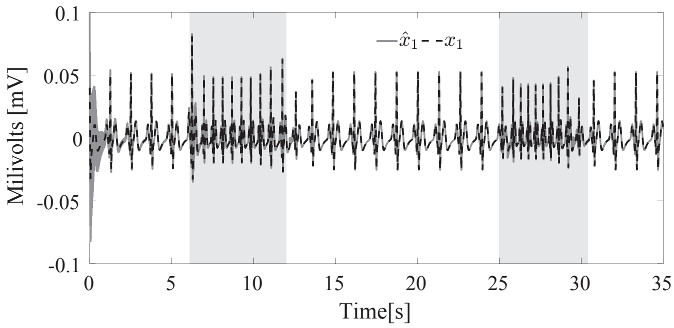

Figure 2. Comparison between the state x_1 and its estimation $\hat{x}_1$ for the simulated ECG signal. The gray coloured zones indicate the switching zones.

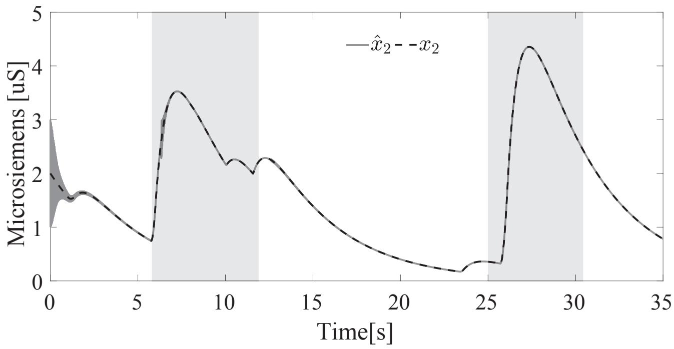

Figure 3. Identification of the state $\hat{x}_2$ and its comparison with the simulated skin conductance level x_2.

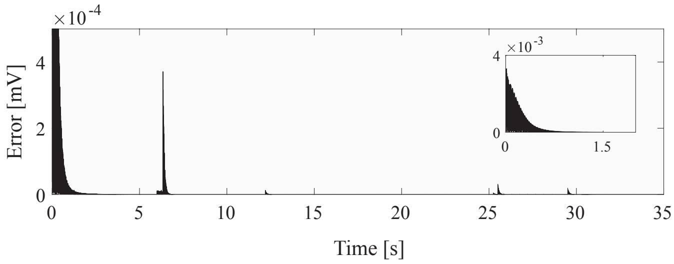

Figure 4. Identification error for x_1.

6. CONCLUSION

The suggested SDNN identifier has demonstrated good response in the face of variability of the physiological signals. This is an important feature since each person presents different physiological conditions, including variable baseline levels (which can be seen as initial conditions), distinct

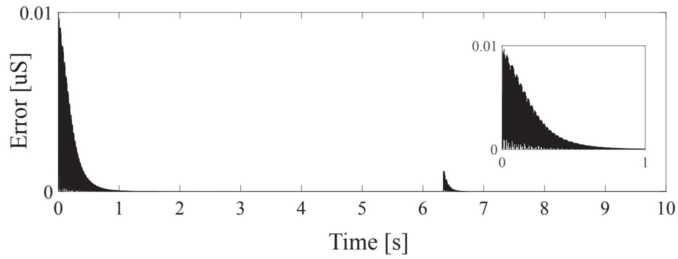

Figure 5. Identification error for x_2.

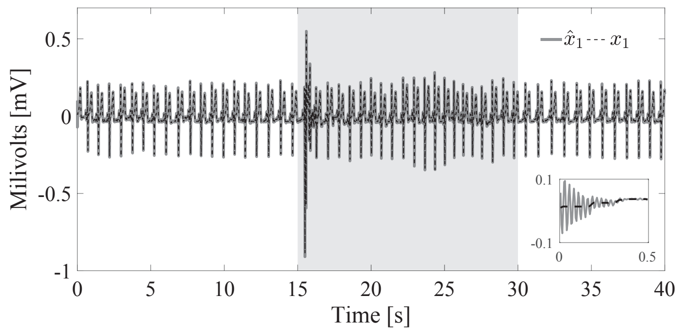

Figure 6. Comparison between recorded ECG x_1 and its estimation $\hat{x}_1$. The initial convergence is achieved in about 500 ms.

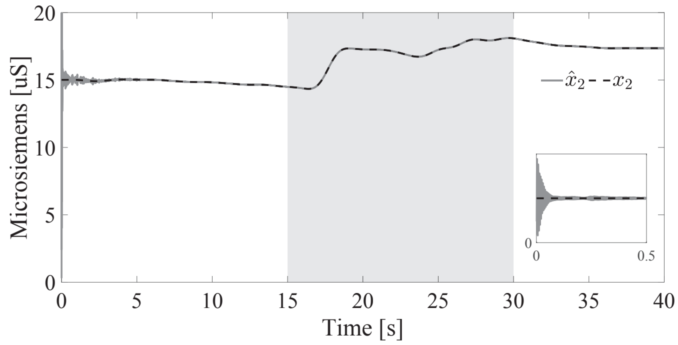

Figure 7. Identification of the $\hat{x}_2$ signal for the real skin conductance level.

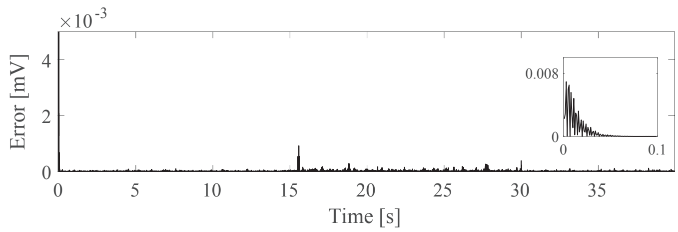

Figure 8. Experimental identification error for x_1.

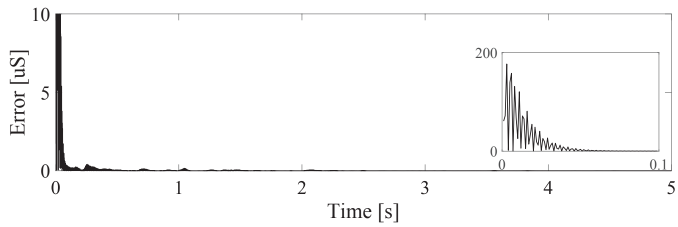

Figure 9. Experimental identification error for x_2.

Algorithm 1 DNN Identifier Training

Input: Use models 12, 13.
Output: $\hat{x}_1, \hat{x}_2, \Delta$, and matrix P_i.

Initialization : Set A_i, k_{1i}, α, select $f_1(x, \hat{x}, t)$
while $\Delta > \epsilon$ **do**
    Set P_i
    Execute Identification
    Compute ω_{HR}
    if $\omega_{HR} > \omega^*_{HR}$ **then**
        Switch to $f_2(x, \hat{x}, t)$
    else
        Remain with $f_1(x, \hat{x}, t)$
    end if
end while

Algorithm 2 DNN Identifier Validation

Input: Registered physiological signals.
Output: $\hat{x}_1, \hat{x}_2, \Delta$, W_1, W_2.

Initialization : Set A_i, k_{1i}, α, as previous, P_i obtained in Algorithm 5, and select $f_1(x, \hat{x}, t)$.
Execute Identification
Compute ω_{HR}
if $\omega_{HR} > \omega^*_{HR}$ **then**
    Switch to $f_2(x, \hat{x}, t)$
else
    Remain with $f_1(x, \hat{x}, t)$
end if

response times, and even change in the waveforms due to the measuring instruments and conditions of the experiments. So, the neuroidentifier is a suitable alternative to the problem of modeling for this class of systems. Despite the good performance of the identifier, the authors consider improving the study on future research, including the problem of partial measurements, which represents a real issue during the biosignal acquisition process. Additionally, future work includes the identification of multiple subjects that may require the individual training of the identifier; this could lead to characterize certain types of population or the effective/ineffective stimuli used in virtual reality. About the convergence analysis, it was realized considering the practical stability of identification error for a class of hybrid systems. As can be seen, this algorithm was easily implemented for real acquired signals. In this sense, the adaptive modeling strategy of the continuous subsystems represents an initial methodology to be used in the human-in-the-loop control implementation. The presented technique will allow studying the design of control strategies to regulate the state of a subject adapting the stimuli associated with the task in real-time, which is an open problem in the virtual reality systems.

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