Identifying Sleep Disorder by Means of Chaos Control

VICTOR GRIGORAS[1] , CARMEN GRIGORAS [2]
[1] Faculty of Electronics and Telecommunications,
'Gh. Asachi' Technical University Iasi
1 Blvd. Carol I, 700506 Iasi
ROMANIA

[2] Faculty of Medical Bioengineering,
'Gr. T. Popa' Univerity of Medicine, Iasi
16 Universitatii, 700403 Iasi
ROMANIA

Abstract —The present contribution aims at identifying the nonlinear dynamic underlying sleep disorder for patients with high circulatory risk. The proposed approach is based on scalar adaptive chaos control, which allows not only the selection of unstable trajectories from chaotic regimes, but also estimating relevant parameters, within the limits of the low dimensional model chosen to demonstrate the principle.

Key words: nonlinear dynamics, chaos control, system modeling, sleep apnea.

1 Introduction

Recent research confirms the existence of chaotic regimes in many biomedical domains [1-3]. Joints, muscular, respiratory and brain diseases are just a few examples of situations when chaotic behavior might be dangerous to the health and life of a patient.

This paper deals with modeling and parameter identification of sleep disorder nonlinear dynamics especially for patients with high cardio-vascular risk.

Sleep disorders are common and obstructive sleep apnea (OSA) is the predominant type. OSA is the repetitive complete obstruction (apnea) or partial obstruction (hypopnea) of the collapsible part of the upper airway during sleep. The syndrome is associated with excessive daytime sleepiness or chronic fatigue. Several studies have shown that OSA is associated with hypertension, stroke and other cardiovascular disorders; some of them being associated with cardiovascular disease. As a consequence of OSA the cardiovascular disease may go worse, being even capable of determining the death of the patient during the sleep. This has generated increasing interest in recent years in sleep studies.

Our work aims to find some feasible solutions to the problem of early detection of cardiovascular disorder episodes with high risk.

The approach taken in our research is to start from a nonlinear chaotic prototype system, benefit from its rich oscillatory dynamics, and chose the desired trajectory by means of adaptive chaos control. Taking into account that the biomedical data is available in digital form, all systems are naturally discrete-time. The chaotic prototype system is chosen as an additive nonlinear discrete system (ANDS), due to their universality and ease of design [4-6]. Instead of using a feed-forward identifying scheme, such as the chaos synchronization approach [7], we use a feed-back adaptive control method.

The next section presents some aspects of ANDS and the method used throughout our research. Section three illustrates the obtained results by means of some of the simulation results performed. Conclusions, discussion and further research are briefly treated in the last section.

2 ANDS Chaos Control

The proposed control topology is based on applying linear control around a nonlinear prototype system. The linear gain is varied during time, using a gradient type learning algorithm that aims at minimizing the error between the output of the prototype system and the input signal. The resulting block diagram is presented in figure 4.

To achieve the desired modeling performance, we chose the particular prototype system in the form of state-space ANDS type. Such a system is built in a feedback loop, connecting a state transition matrix around the algebraic nonlinear function as shown in figure 2. Additivity is achieved by using a particular algebraic function, namely the symbolic residue function, $\mathbf{r}(x)$, depicted in figure 1 and given by the equation (1):

$$\mathrm{r}(x) = x - \mathrm{round}(x) \tag{1}$$

By denoting the symbolic quotient function by $\mathbf{k}(x)$, as given by equation (2):

$$\mathrm{k}(x) = \mathrm{round}(x) \tag{2}$$

We can conclude that any real number, x, can be decomposed as a sum of the two symbolic functions, as given in equation (3):

$$x = \mathrm{k}(x) + \mathrm{r}(x) \tag{3}$$

The highlighted additivity property is useful to easily build the blocks of the system, obtain some properties similar to linear systems (such as additive convolution [4] and additive Z transform [6]), while still allowing complex dynamics, such as chaos, as demonstrated in [5].

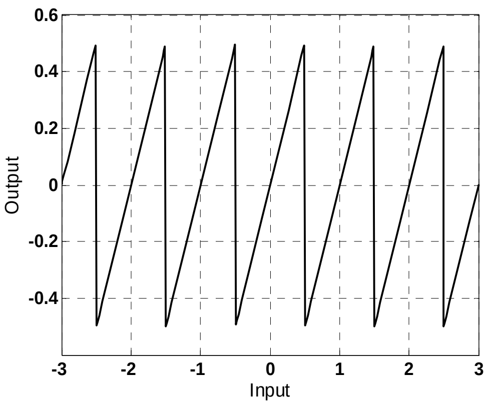


Fig. 1. The residue algebraic nonlinear function used in the chaotic system.

The chaotic prototype system is designed to have the state equations:

$$\mathbf{x}[k+1] = \mathrm{r}(\mathbf{A} \cdot \mathbf{x}[k+1] + \mathbf{e}[k]) \tag{4}$$

The state transition matrix, **A**, is chosen to have at least one eigenvalue outside the unit circle, to ensure chaotic behavior. The modulus of the largest eigenvalue is chosen only slightly larger than unit to have a positive but small Lyapounov exponent for the chaotic prototype system. The state vector and the input vector are of the same dimension to ensure matrix-vector operation compatibility in equation, without the need of a supplementary matrix coefficient for dimension adaptation.

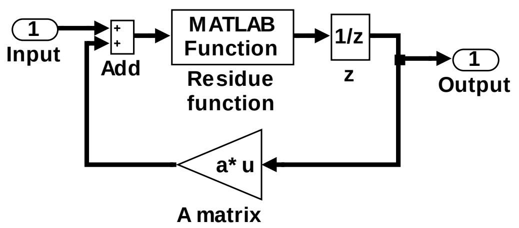


Fig. 2. Block diagram of the chaotic system.

The gradient type learning algorithm, that aims at minimizing the error between the output of the prototype system and the input signal, is developed as a vector LMS-type structure:

$$\begin{aligned} \mathbf{W}[k+1] &= \mathbf{W}[k] + 2\mu \cdot \boldsymbol{\varepsilon}[k] \cdot \mathbf{e}[k] \\ \boldsymbol{\varepsilon}[k] &= \mathbf{x}[k] - \mathbf{e}[k] \end{aligned} \tag{4}$$

This leads to the block diagram in figure 3, showing a nonlinear adaptive structure, performing in a vector-matrix environment.

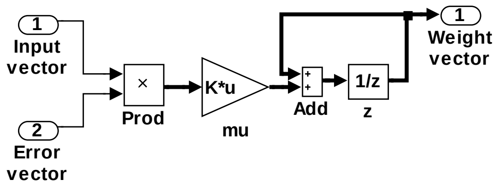


Fig. 3. Block diagram of the learning algorithm gradient type system.

The elementary blocks developed in the previous, must now be included in the global block diagram in figure 4.

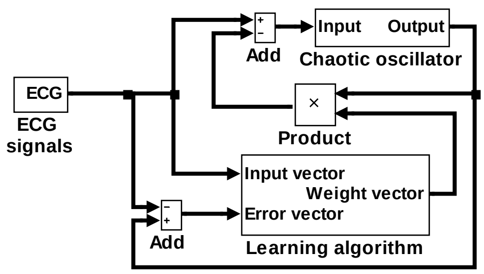


Fig. 4. Block diagram of the adaptive control system.

3 Simulation Results

In depth simulations were made to verify the desired behavior of the proposed system. Polysomnographic signals, taken from sleep apnea patients, were used in signal processing, up to four simultaneous traces. The results presented in the following, use two ECG signals, presented in figure 5.

The convergence of the proposed algorithm was verified for a large range of learning constants. Expectedly, the higher the value of the learning constant, the faster the convergence of the algorithm but the noisier the final weight traces. These phenomena are presented in the two examples in figure 6. The first graph is depicted for a large value of the learning constant (μ = 1000) while the second is obtained for a smaller one (μ = 100).

As presented in figure 7, convergence of the weight values, lead to smaller learning error. The results in fig. 7 are taken for large learning constant (μ = 1000) and the larger ripple in the weight value evolution lead to larger final error. Although most of the time, the average error value is smaller than 10^{-4}, when abrupt slopes are present in the input signal, short time spikes appear in the error trace too, with peak values of $5*10^{-3}$.

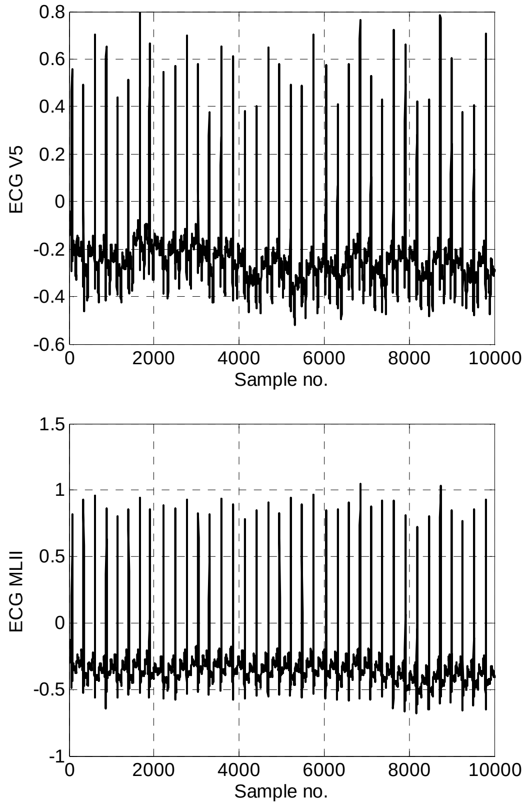
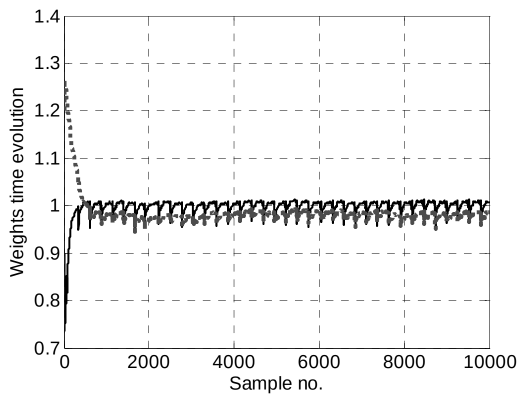


Fig. 5. Example of ECG signals for a patient with sleep apnea and cardiac arrhythmia.



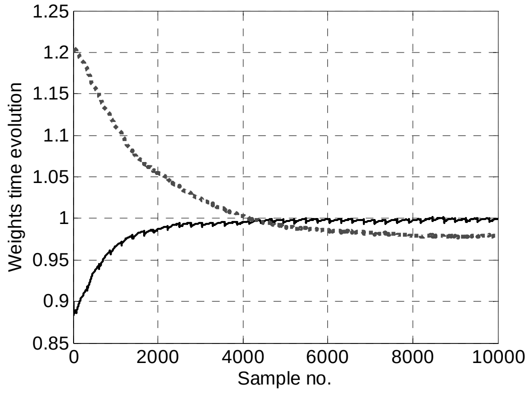


Fig. 6. Graphical representation of the time evolution of the adapted weights for large learning constant (up) and smaller one (down).

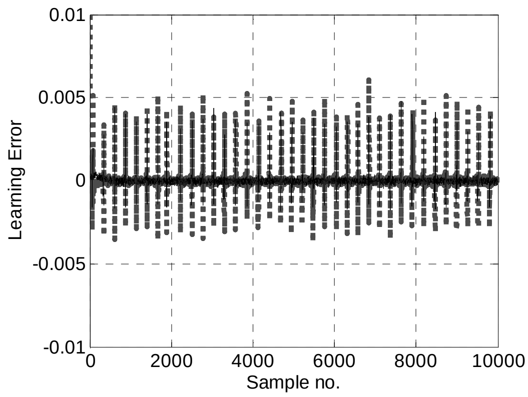


Fig. 7. Graphical representation of the time evolution of the learning error for large learning.

Unfortunately, the good results obtained till now are somewhat dependent on the weight initial conditions. Although for most initial condition values the algorithm converges, small domains can be found, where the starting point does not lead to convergence to the desired values. E.g. results in figure 8, show that for small, negative initial condition on both parameters, the algorithm diverges.

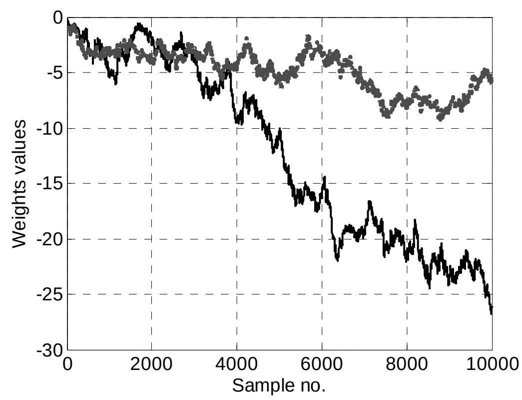


Fig. 8. Example of the time evolution of the adapted weights in the case of lack of convergence.

4 Conclusions

We proposed an adaptive feedback control approach for non-linear dynamics identification, parameter extraction and modeling for biomedical applications. The chaotic behavior of the prototype system allows the desired richness of periodic and quasi-periodic trajectories. The adaptive control loop selects the closest trajectory to the target bio-medical signal, also providing a parameter set based on the adapted weights.

We trained our system with selected ECG segments annotated by pulmonary and cardiovascular disease experts for cardiovascular disorders associated with sleep apnea. ECG traces were obtained from the Hospital of Pneumology of Iasi through polisomnography investigation. Arrhythmias are usually associated with the blood oxygen desaturation following the apnea or hypopnea episodes.

The obtained simulation results show good convergence control but some lack of flexibility towards spiky behavior and initial condition dependence due to local minima in the performance surface.

Further research is needed to extend the dimensionality of the proposed system to achieve higher dimension signal processing, as usually encountered in sleep apnea analysis. The linearization of the performance surface or some annealing technique is foreseeable solutions to the initial condition dependence of the convergence process. Identifying the normal/crisis situation of the patient under study by automatically tracking the adapted parameters is the final application of the reported research.

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