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An Application of a Neuronal Method Used to Remove Artefacts

Dan Marius Dobrea, Monica Claudia Dobrea
"Gh. Asachi" Technical Uni., Faculty of Electronics and Telecommunication, Romania
mdobrea@etc.tuiasi.ro, qmonro@yahoo.com

Abstract

The aim of this paper is to present an adaptive artifact removing technique – used in a bio-instrumental system –, able to eliminate or reduce the artifacts from the respiratory signal. The non-contact bio-instrumental complex is used to determine the fatigued state of a person who is caring out activity under the stress conditions. The final aim is to discriminate/recognize the fatigue state, based on the information that is confined, simultaneously, in the respiratory signal, hand tremor and body torso movements. One of the major problems of this system is generated by the artifacts that disturb the signals. In this particular case, that will be present in this paper, the respiratory signal is one affected by the artifacts. In order to eliminate the respiratory artifacts two methods were used and the results are presented in this paper. A comparison between the methods is also presented.

1. Introduction

The problems generated by the sensor, the large amount of data, the artifacts, the complexity of the classification analysis and the large variability among the population of the physiological signals related with the same state are only few factors that determine the difficulty of using the user's states reflected through its physiological signals as an important indicator in the world of human computer interface and virtual reality.

One of the main directions of our research is to assess the bio-psychic state of a person using a computer. This assessment is based on the physiological data obtained from the user. One of the signals used in this system is the respiration signal. The respiratory activity is acquired by reography (impedancemetry) method [1], [2].

This research was undertaken by using healthy subjects and it is focused only on determining the best method able to remove or reduce the artifacts from the respiratory signal based on an adaptive technique.

The adaptive methods are more computational demanding than standard filtering techniques and in the last two-three decades they spread in almost all the fields of science and engineering applications like: medicine and biomedical application [3], physics, aviation [4], telecommunications [5], [6], home and industrial applications etc. In biomedical applications and human computer interaction systems, the adaptive filtering technique has been shown to be useful in a large class of problems [7], [8], [9], [10].

2. The acquisition system

The part of the bio-instrumental complex used to acquire respiratory signal consists in a chair with one sensor [11] incorporated in the back support, without direct contact with any parts of the subject's body, Figure 1.

The sensor consists in a coil. It is known that an element generating an external electromagnetic field changes its impedance due to the properties of the objects in its close vicinity.

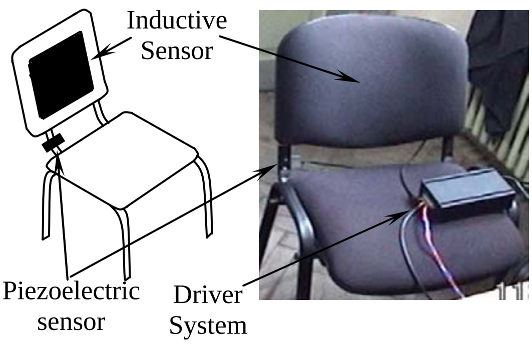

Figure 1. Embodiment of the system

The impedance change is due to the variation of the equivalent impedance (either reactive or resistive) viewed at the port of the measuring device. The idea is to determine the respiratory movements based on the change of impedance that these movements produce in the sensor.

The respiratory signals, acquired with the system (Figure 2(a)), also inherently include other components such as those derived from tremor movements, blood flow induced movements and small involuntary movements. These components are of small values and are easily removed with properly digital filters.

The most disturbing artifacts for this sensor are generated by the movement of the subject. This movement artifacts can be classified in two main subclasses (from the view point of artifacts life time versus respiratory signal periods): fast movements (like hand movements, Figure 2(b)) and slow movements (like slowly changes of the body position). Up to now, only the cancellation of the slow movement artifact is a solved problem [12].

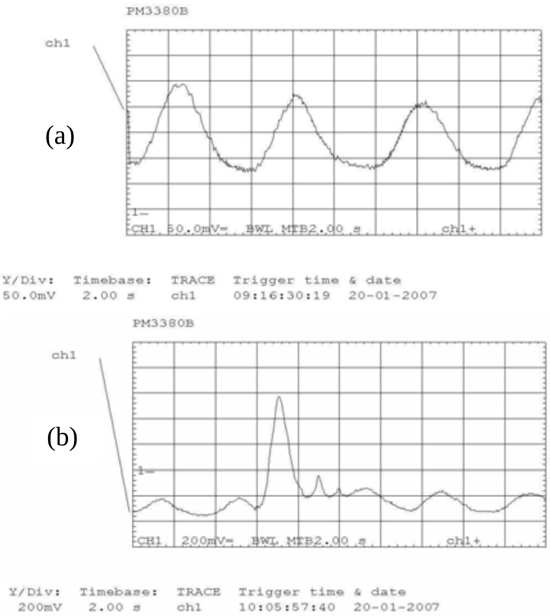

Figure 2. Respiratory signals

The user hand movement (**Figure 2(b)**) generates a special class of artefacts which appears and disturbs the respiratory signal. Classical filtering techniques can not eliminate these artefacts, first, because the amplitude of the artefact is a number of times larger than the respiratory signal and second, the artefacts overlap – in time and frequency domain – the respiratory signal. From these reasons another method must be found. Because the artefact cancellation requires different strategies for different sources of artefact signals, we tested two methods and, at the end, a comparison between them was made, in order to find the best solution.

The data acquisition hardware is divided into two blocks: a data acquisition-board plugged in a PC and an external signal conditioning hardware systems for all the sensors – the driver system presented in Figure 1.

The acquired signal is low-pass pre-filtered with analogue filters having the cut-off frequency 60 Hz. Then, the signal is sampled with a sampling frequency of 120 Hz and quantified on 12 bits using the AT-MIO16E-10™ (National Instruments™) acquisition board. The program (see Figure 3), which initializes the commands and starts the recording on the acquisition board, was developed in LabWindos™/CVI version 5.5.

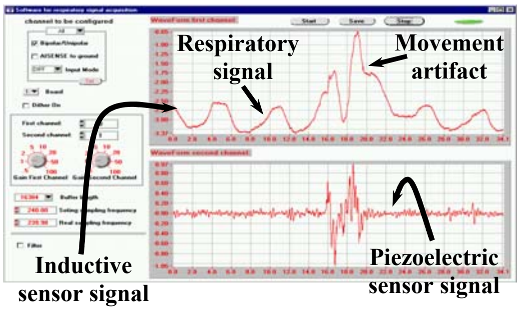

Figure 3. Screen snapshot of the basic program for signal acquisition

3. The adaptive methods used for artifacts removing

The first method used in order to remove the artefacts is based on a non-linear adaptive filtering, Figure 4. The second method belongs to the blind source separation class of algorithms, Figure 6.

Both methods require as a preliminary processing step another input path for signal, which in our case reflects mostly the hand movement signal contaminated by the respiratory signal. On this additionally acquiring channel the respiratory signal has amplitude several times lower than the amplitude of the movement signal. The respiratory signal is viewed, on this channel, like a noisy signal. A piezoelectric transducer, placed on the chair like in Figure 1, acquires this signal – Figure 3.

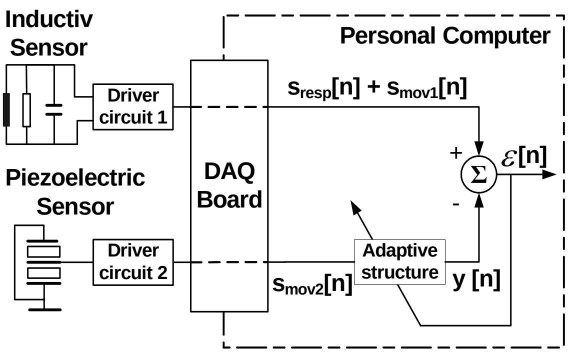

Figure 4. The general block scheme for the adaptive filtering method

3.1. Adaptive filtering method

The basic idea of the adaptive filter technique used here has been introduced by Windrow [13].

The adaptive filter, **Figure 4**, mainly minimises the mean-square error between the primary input – which consists in the respiratory signal and the movement signal, as artefact (s_{resp} and s_{mov1}) –, and a reference input that is mainly represented by the movement signal (s_{mov2}) captured by the piezoelectric sensor. The adaptive system error is:

$$\varepsilon = (s_{resp} + s_{mov1}) - y \tag{1}$$

From Eq. 1 we obtain:

$$\begin{aligned}\varepsilon^2 &= (s_{resp} + s_{mov1})^2 - 2y(s_{resp} + s_{mov1}) + y^2 = \\ &= (s_{mov1} - y)^2 + s_{resp}^2 + 2s_{resp}s_{mov1} - 2ys_{resp}\end{aligned} \tag{2}$$

The only assumption that this method requires is the fact that the movement signals (s_{mov1} and s_{mov2}) must be correlated. This is just the case for our problem. Because the movement and the respiratory signals are uncorrelated, the mean-squared error is:

$$E[\varepsilon^2] = E[(s_{mov1} - y)^2] + E[s_{resp}^2] \tag{3}$$

By minimizing the mean-squared error, the best least squares estimate of the respiratory signal, s_{resp}, will be obtained at the output of the adaptive structure.

In the first attempt to solve the problem, in the place of the adaptive structure from Figure 4 a linear adaptive filter (a FIR filter tuned by Least-Mean Squares algorithm) was used. The results were very poor in comparison with the second employed method, namely blind source separation method. This was mainly because the linear system is unable to model the non-linearity transfer function of the human body.

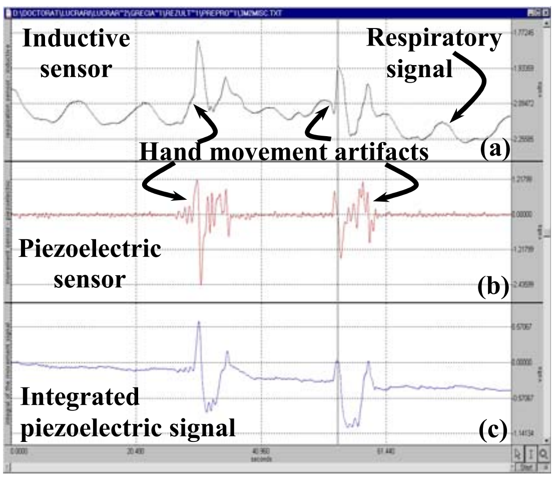

Figure 5. The signals from the respiratory monitoring system (a), (b) and the preprocessing result of the piezoelectric sensor signal (c)

Even if a two hidden layers feed-forward back-propagation artificial neural network has the ability to approximate, with any degree of accuracy, any continuous function [14], [15], in our particular case this approach gave poor results.

Only when the integral of the movement signal, supplied as an *a priory* information to the processing system – Figure 5, was used at the artificial neural networks input, the performances obtained on the test set started to improve. In Figure 5 one can observe the direct correspondence between the integral of the piezoelectric sensor signal and the signal delivered by the inductive sensor.

In order to further improve the performances, the maximum cross-correlation value between the signals, obtained from the both sensors, was computed; also, the time-delay between them, introduced by the chair transfer function, was removed.

In these new conditions, after the training process, we obtained not only the remove of the artifacts but also the respiratory signal was canceled too. This problem happened mainly because in the signal supplied by the piezoelectric sensor the respiratory signal is also present beside the hand movement signal. In this situation the artificial neural network naturally adapts in order to remove both, the movement artifact and the respiratory signal. To overcome this drawback, in the training stage each pair of time series was split into particular segments. Only the segments containing the artifacts were used in the adapting process, the rest of the time series being discarded.

The neural network was trained with the backpropagation algorithm [16].

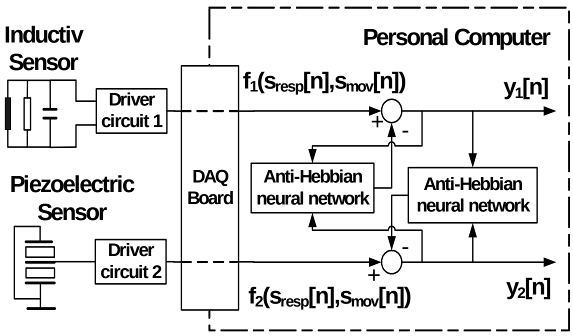

Figure 6. The block scheme of the blind source separation method

3.2. Blind Source Separation method

In the case of blind source separation method we use two types of signals: the movement and the respiratory signals. These signals are mixed by the human body system and they are passed, through the chair transfer function (this is only the case of the piezoelectric sensor), toward the sensors. The inductive sensor supplies the signal $f_1(s_{resp}, s_{mov})$, while the piezoelectric sensor provides the signal

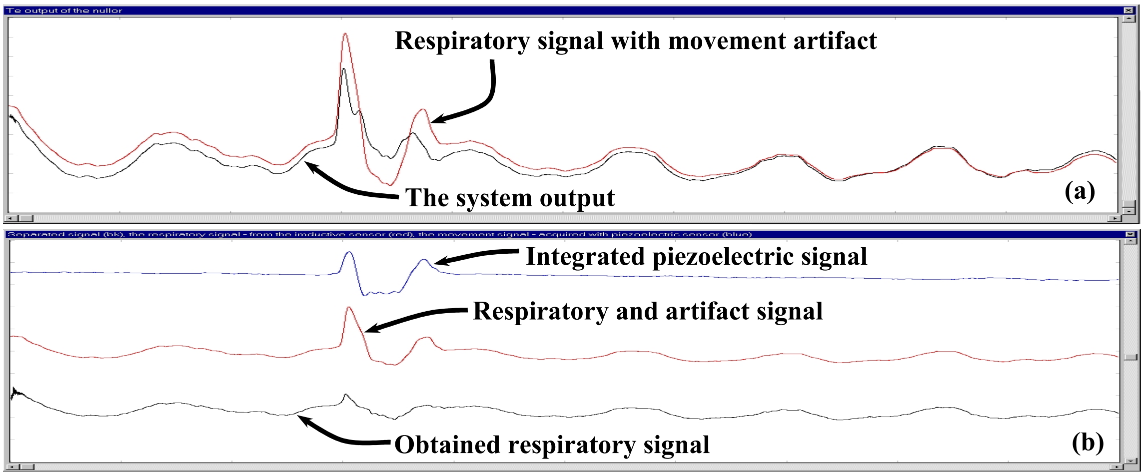

Figure 7. (a) One of the results obtained using a neural network as an adaptive filter and (b) The results obtained using the blind source separation method

$f_2(s_{resp}, s_{mov})$ to the adaptive structure (f_1 and f_2 are two different functions that combine the respiratory and the movement signals), see Figure 6.

The anti-Hebbian neural networks are finite impulse response filters trained with a learning forced anti-Hebbian rule. In this case, the adjustment applied to the weight is:

$$\Delta w_{k,\{1,2\}}[n+1] = -\eta \cdot y_{\{2,1\}}[n-k] \cdot y_{\{1,2\}}[n] \quad (4)$$

In the Eq. 4 the k index differentiates the number of the weights for the first, {1}, or second, {2}, anti-Hebbian neural networks; here, the brackets {·,·} represent a selection mechanism of one of the numbers placed on the same position inside the brackets on all the equation.

The outputs of the anti-Hebbian system are:

$$y_{\{1,2\}} = \sum_k \Delta w_{k,\{1,2\}}[n] \cdot y_{\{2,1\}}[n-k] \quad (5)$$

The singular requiring of the blind source separation method is that the two signals must be orthogonal (independent). This assumption is accomplished in our problem. In this case, the two anti-Hebbian networks will force the outputs of the network away from each other (because each network will try to find the null space). In other words, this will push the output signals y_1 and y_2 towards the original signals (that are independent). The weight vector of the anti-Hebbian network is normalised to the unit length as a caution necessary to avoid convergence of the network to the trivial solution (zero weights) [17].

4. Results and discussions

Some of the results, obtained for both adaptive methods, are presented in graphical form in Figure 7.

The linear adaptive filter (a FIR filter structure tuned by Least-Mean Squares algorithm) used with the first method (Figure 4) shows poor results in comparison with the blind source separation method. This is mainly because it cannot model the non-linearity characteristics of the human body.

At the moment when a neural network (with one hidden layer of 18 neurons, each of them using the tangent hyperbolic activation function) was used in place of the adaptive structure (see Figure 4), the performances started to increase but the direct replacement of the FIR structure with a neural network did not give the expected superior result in comparison to the results obtained with the blind source separation method.

The performance of the neural network method started drastically to improve when we embedded knowledge of our data into the neural network. The embedded knowledge are the following:

- the fact that the signal acquired with the piezoelectric sensor is a derivated form of the signal acquired with the inductive sensor,
- the time delay between the input signals, and
- the existence of the parasitic respiratory signal on the second signal path.

Even if an extensive increase of performances is observed in the training set after the knowledge is embedded in the neural network, the results achieved on the test set continue to be not so outstanding – Figure 7(a). The impossibility of the neural network to maintain the same degree of performances in the test set is generated by the nonstationarity characteristics of the hand movement artifacts.

In the second method, the procedure used to adapt the weights is very simple and, also, it is a faster one (anti-Hebbian rule); more, the decorrelation network is much simple then the multilayer perceptron approach of the first method.

Blind source separation system with the anti-Hebbian networks is able to compute the temporal cross-decorrelation function for either stationary or nonstationary signals; in this mode this method is more suitable for the nonstationary movement signals.

5. Conclusions

In this paper a complete solution (hard and soft) to acquire the respiratory signal is proposed, based on a new type of sensor configuration. Also, a procedure able to remove the artifacts generated by fast hand movements is presented.

It is very important to point out the ability of the blind source separation method, which is based on an anti-Hebbian rule, to operate and obtain superior results even with nonstationary signals.

Finally, if we add at this system another module able to remove the slow movements [12], we could get a complete independent intelligent system capable to record an accurate, artifact free respiratory signal.

Further, this global system could constitute the start point of a more complex system used to assess the user's state based on other additional physiological signals.

6. References

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