Reducing False Alarms in Intensive Care Units Based on Wavelets Technology

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Abstract

Monitoring systems in intensive care units (ICU) generate a high rate of false alarms 80% [8, 14, 15, 16]. This has the effect of desensitizing the medical staff and extending the response time to these alarms. In this work we present a new method to reduce false alarms in intensive care units that is based on packet wavelet decomposition and alarms classification by SVM.

Keywords: Signal processing, wavelets, time series, Intensive care units

1. Introduction

Monitors in ICU record various physiological signals in continuous a way: heart rate (HR), Arterial Blood Pressure (ABP), Respiratory Frequency (RF), saturation of oxygen (SPO_2).

These parameters indicate the state of the patients and generate an alarm when they deviate from the threshold value.

Therefore, monitoring systems in ICU produce a high rate of false alarms. This can disturb the medical staff and delays taking the appropriate measures at the right time. So to improve the work in ICU, It is necessary to ameliorate the traditional monitoring system.

The physiological signals recorded by the ICU monitors are non-stationary, noisy and have high frequencies. So a time-frequency analysis presents the best tool to study these signals, because it provides a good localization in time and frequency.

The wavelet transform satisfies these conditions and presents a new and powerful tool for signal processing because it has the ability to detect singularities, to denoise and compress data.

In this work we choose this packet wavelet technique to extract trends. Indeed, the trend analysis provides a semi-qualitative or qualitative representation of signals that the medical staff is more interested in [2, 3]. Trend can also detect shapes with a defect in the signal.

Our objective is to make a tool for automatic detection of significant alarms from multiple signals in the ICU, to reduce false alarm rates and to improve monitoring systems.

2. Related Works

In the literature, several studies have been made to analyze the signals in the ICU. They can be classified in two types: statistical approaches and artificial intelligence approaches.

2.1 Statistical Approaches

The signal processing methods are increasingly used in the ICU, for their ability to analyze and interpret non-stationary signals. Among these methods, we mention the median filter, the Kalman filter, the autoregressive models, the cumulative sum (CUSUM) and wavelets.

Qiao and Gari in [10] presented a model in which they have applied the Kalman filter to track the heart rate signal and modify it using a new index of signal quality based on ABP to remove noise and artifacts. The model used arrhythmia alarms from the database MIMICII of physiobank, using the electrocardiogram (ECG) and ABP data. The algorithm has detected 149 false alarms from 201 and 504 true alarms from 506.

In [16], Van Loon et al studied the dynamic data of physiological signals in order to predict the stability of the patients in the ICU after coronary surgery. In the first step, they used five variables (HR, systolic blood pressure (BP), systolic pulmonary pressure (PP), temperature and (SPO_2)) and calculated the mean and standard deviation of each one. Then they applied the multivariate autoregressive model (MAR) and they have calculated the spectral coefficients. In the second step, they used these coefficients in the classification using Gaussian process. This classification gave two classes (Class 1: 9 hours before ICU admission and class 2: 9 hours after admission). These two classes determine the time required for each patient to achieve a stable condition after surgery. Finally, in the last step, they calculated the probability of each patient to belong to these two classes.

Charbonnier et al have studied the CUSUM in [2, 3], they presented a model to extract the trend of signal and represent it in a qualitative or semi-qualitative way. The objective of this model is to detect abnormal behavior in the signal. Charbonnier has developed a method for extracting trend online from univariate time series [2].

Several studies have used wavelets transform to deal with medical signals. In particular, the ECG and electroencephalogram (EEG). In [8], Kheder et al studied the variability of the HR and presented an approach to detect and classify heart defects in order to decrease mortality rates. The detection was made by the wavelet packet transform that decomposes the signal in high and low frequencies. The authors chose the Daubechies wavelet (db4) as a base. For classification, they used the method LS-SVM (Least Square Support Vector Machine). They obtained two classes (normal and abnormal). This model gave normal cases of ventricular tachycardia (VT), a sensitivity of 91% and a specificity of 92%, for normal cases of ventricular fibrillation (VF) a sensitivity 95% and a specificity of 97% and for abnormal cases a rate of sensitivity of 89% and a specificity of 90%.

In [6] Hazarika et al were interested in studying the EEG brain dysfunction. They used the Lemarie wavelet as mother wavelet for the decomposition to extract discrete characteristics of signal and neural networks (NN) for classification by identifying cases of schizophrenia and normal cases. This model was able to classify 71% of the cases with schizophrenia and 66% of the normal cases.

2.2 Artificial Intelligence Approaches

The artificial intelligence techniques (AI) have known an expansion in the field of medical monitoring. In [5, 7,9] were presented overviews of the different methods of AI used in ICU such as decision trees, random forests, neural networks, Bayesian networks, SVM.

Tsien et al in [15] used decision trees in the neonatal ICU containing 123 patients to detect artifacts and reduce the rate of false alarms. They studied five signals (ECG, HR, ABP, CO_2, SPO_2 and calculated several parameters (mean, median, slope, maximum value, minimum value, etc.) to build their decision tree. Each signal has its own tree that can

integrate other signals. This model was tested on these five signals, the results for the HR is 65.4% sensitivity and 99.8% specificity.

In [12] Silva et al have introduced a model of NN to evaluate the mortality rate in the ICU and they were compared with logistic regression (LR). This study was applied to 13 patients by measuring the following parameters: BP, HR, SPO_2 and Production of urine.
In [13], Silva et al presented an extension of the previous model [12] to assess the failure rate of an organ which is the main cause of mortality.

ICU-Bayes model proposed by Biagioli et al in [2], is based on Bayesian networks, in the aim to select the risk factors for preoperative, intraoperative and postoperative allowing a better prediction of morbidity after a transplant of a coronary artery. This model was applied to 1090 patients who have undergone transplantation.

3. Methodology

Wavelets have emerged in the 80 years due to the shortcomings of the Fourier transform. Yves Meyer [17, 19] introduced the wavelet as projected functions onto orthogonal bases. Stephane Mallat [19] in the 1989 used wavelets in the context of multiresolution analysis (MRA) of signals.

The Fourier transform (FT) is the most common technique in signal processing. It is used to represent the signal as a sum of exponential [17, 19].

$$X(\omega) = \int_{+\infty}^{-\infty} x(t).e^{-j\omega} dt$$

This transform provides a global frequency representation and not a local one and it cannot identify the frequency over time. Then, FT is only available for stationary signals whose frequency content does not change over time.

There are three types of wavelet transforms: the continuous transform (CWT), the discrete transform (DWT) and the wavelet packet transform (PWT).

3.1 Continuous Wavelets Transform CWT

The CWT is based on projecting the signal on a set of wavelets obtained by dilatation and contraction of a mother wavelet. The CWT of a function f is defined as the scalar product of f and the wavelet ψ:

$$CWT(a,b) = \frac{1}{\sqrt{|a|}} \int f(x)\psi\left(\frac{x-b}{a}\right) dx$$

with
a: is the dilatation factor corresponding to the frequency.
b: translation factor that corresponds to the time.
$\psi(t)$: is the mother wavelet.

CWT is redundant [17] because the windows of neighboring wavelet may contain information that is common. To overcome this problem, the solution was to discretize the factors a and b.

3.2 Discrete Wavelets Transform

An example of discretization is to take $a = 2^{-j}$ and $b = k2^{-j}$, where j represents the scale and n is the number of samples and $j, k \in Z$. This is called dyadic transform which the most used.

$$DWT(a,b) = 2^{-j/2} \int f(x)\psi(2^j t - k)\,dx$$

The discrete transform DWT can decompose the signal into approximation coefficients that indicate the low frequency (the shape of the signal) and detail coefficients that provide information on high frequencies. DWT is performed by two types of filters, a low-pass filter (low frequencies) and a high-pass filter (for high Frequencies).

3.3 Packet Wavelets Transform PWT

Indeed, the DWT has a problem in the decomposition of high frequencies [17] which results in the loss of data. The PWT, introduced by Coifman and Wickerhauser in 1992, is an extension of the DWT which further refines the decomposition of the signal. PWT is based on the decomposition of the signal in approximation (A) and detail (D) coefficients, and then the two types of coefficients will be decomposed again in approximations and details until the last level of decomposition. This decomposition form a symmetric tree as follow:
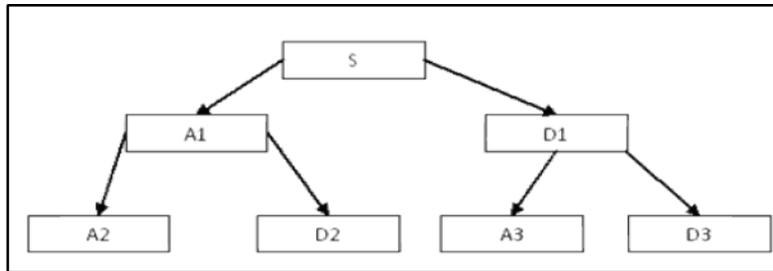

Figure 1. PWT Decomposition

4. Algorithm

To detect trends we choose the PWT because the CWT is redundant and the DWT doesn't have a good frequency resolution which can cause the lost of pertinent data in the signals. As we mentioned previously, that wavelets have been used with medical signals in many works, but most of them treat one kind of signals especially EEG. In our work we try to deal with multiple physiological signals.

Our solution contains five steps:

Step 1: choosing the analyzing wavelet (mother wavelet) by testing several wavelet mothers. We will study the mean squared error (MSE) between the original signal and the synthesized signal (signal after reconstruction). It is calculated as the difference between the original signal and the signal synthesis. The analyzing wavelet chosen is the one with the lowest reconstruction error. Indeed, we will study the characteristics of each signal (CO_2, SPO_2, ABP, HR, etc.) to determine the type of mother wavelet corresponding to it.

Step 2: Applying the PWT on the different physiological signals to denoise them and to eliminate the artifacts. This step requires the decomposition of the signal coefficients to approximations and details. The analyzing wavelet chosen in step 1 will act as a filter. This

calculation will be made by the fast algorithm of Mallat [19]. Approximation coefficients are calculated by applying successive filters as follow:

$$A_n^j = \sum_k \tilde{h}\,[2n - k]A_k^{j-1}$$

Details coefficients are calculated by applying filters on approximations coefficients of the previous level as follow:

$$D_n^j = \sum_k \tilde{g}\,[2n - K]A_k^{j-1}$$

Step 3: we determine the basis which well represents the signal according to the standard entropy algorithm by Donoho [4]. This algorithm calculates the entropy of all coefficients to form the entropy tree and next it compares the father's entropy with the sum of child's entropy and we select the minimum ones. After that we perform a soft thresholding [4] on the coefficients as follow:

$$x= \begin{cases} \text{Sign(x) (|x|-t)} & \text{if } |x| >= t \\ 0 & \text{if } |x| < t \end{cases}$$

Step 4: The trends are detected by the approximation coefficients and frequencies by the detail coefficients. We will use a multivariate time series composed by different physiological signals measured simultaneously.

Step 5: We calculate the statistical parameters of these coefficients (mean, standard deviation, etc.). And we will use them as input to a system of classification. We classify significant alarms in three classes:

1) Significant alarms order 1: representing a state with an urgent high risk.

2) Significant alarms order 2: To show that the patient is in an emergency.

3) Significant alarms order 3: This attracts the attention of the caregiver.

 In our work we will use data from the physiobank database MIMICII [18]. This database contains demographic data, laboratory results and the signals recorded by the monitors connected to beds in the ICU. These signals are HR, ABP, PAP (pulmonary arterial pressure), respiratory rate (RR) etc. We will use Matlab to develop our algorithm. In fact, Matlab offers a package to manipulate the different types of wavelets [20].

5. Illustrative Example

We will test our solution on an example. We took the RR signal of the database MIMICII. Then, we added noise as it is shown in Figure 2.
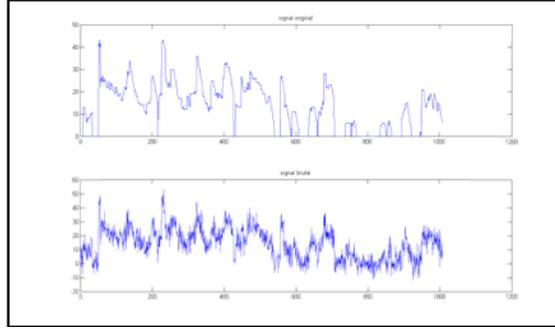
Figure 2. original Signal and Noising Signal

1) As a first step, we tested three types of mother wavelets which are: Haar wavelet, Daubechies wavelet with two vanishing moments and Symlet wavelet with eight vanishing moments. The Sumlet wavelet gave the lowest error rate because it had the largest number of vanishing moments and the most symmetrical wavelet. The MSE is calculated as follows:

$$\varepsilon = \frac{\sum_{i=1}^{N} |S_{oi} - S_{ri}|}{N}$$

S_{oi} : original signal and
S_{ri} : reconstructed signal

In table 1 we present the MSE for each mother wavelet tested on our RR signal.

Table 1. MSE

wavelet	Error
Haar	2.5629
Daubechies : db2	2.2806
Symlet : Sym8	0.0678

2) In the second step, we applied the PWT on the signal using the wavelet symlet8 chosen in the previous step and a decomposition level equal to 3. The approximation and detail coefficients are schematised in Figure 3.
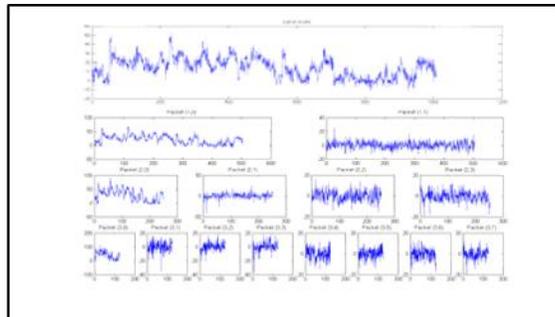
Figure 3. Coefficients

3) In the third step, we identify the best basis which represents the signal according to the algorithm of Donoho [4] by calculating the entropy of each coefficient and comparing the father's entropy to the sum of the child's entropy and we select the nodes that minimize this criterion. In Figure 4 we present the best basis for our RR signal:
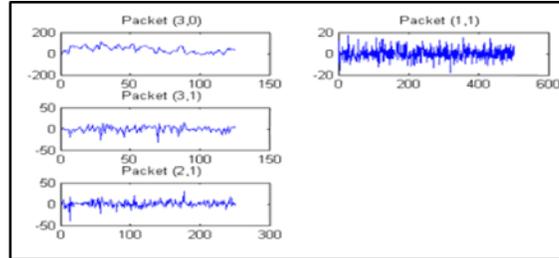
Figure 4. Best Basis

After that we applied soft thresholding on the coefficients of the best basis. Finally, we reconstructed the coefficients for denoising as shown in Figure 5.
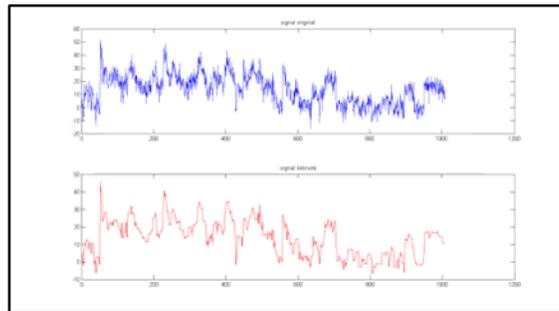

Figure 5. Reconstructed Signal

4) In the fourth step, we detected the trend of our signal. Indeed this trend is associated with the approximation coefficients. Figure 6 shows the trend of the RR signal.
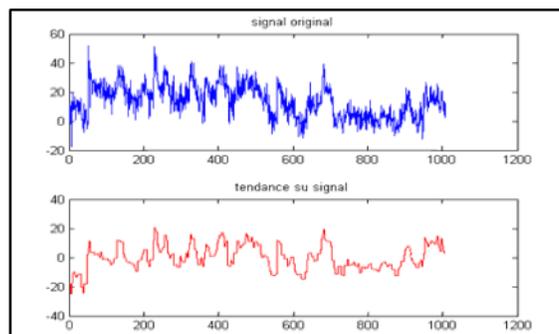

Figure 6. Trend of RR Signal

In this step, we study the multivariate time series. We will study the variation (stability and instability) of multiple parameters. Next, we calculate the statistical parameters (mean, standard deviation) for use in the stage of classification.

We will use these parameters as inputs in a classification model using the SVM model. We will classify the signals into three classes in order of emergency.

6. Conclusion

In this work, we used the wavelet packet transform for signal denoising and deriving trends. We looked for the suitable mother wavelet for each signal received by the ICU monitors, we applied the wavelet packet decomposition to calculate the coefficients of approximation and detail. That will inform us about the trends of the signals. Then we used these coefficients as input parameters to SVM to classify the alarms in alarm of order 1, order 2 and order 3.

Acknowledgements

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