Application of two non-linear methods for the localization of artifacts on trend data

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Abstract This paper presents the application of two non-linear methods for the localization of transient artifacts on trend data. The first method is based on Matching Pursuit the second is a multidimensional technique which makes use of a particular neural network, namely the marginal median linear vector quantizer. The application concerns trend data issued from monitored Pulmunary Artery Pressure

Introduction

The term artifacts is often used to identify events occurring 'accidentally' during data recordings. For ECG and EEG signals, the artifacts may designate transients or burst events, for example those due to the electrodes (artifacts induced by acquisition system) or those due to other electrophysiological sources like muscular activity and eyes motion, or events with a long time support due to the patient motion (base line drift) or resulting from the intervention of the medical team (in ICU). The traditional way of handling artifacts in ECG and EEG data processing has been to exclude from the analysis the segments of the recording which are contaminated by artifacts. According to the type of artifacts and also the purpose of the data processing, different approaches can be considered. Classical schemes for transient detection and change are available under the assumption of stationarity or piece-wise stationarity. If these assumptions are not verified, methods based on time-frequency analysis or time-scale (wavelet) analysis can be considered for this purpose.

In this paper we will focus on the artifact (transient like) localization on trend data issued from the diastolic, systolic and mean Pulmonary Artery Pressure (respectively PAPd, PAPs, PAPm) of the IMPROVE Project Data Library [1] [2]. Each monitored signal is obtained by evaluating the mean value of the original data, over a sliding window of two minutes duration, of the continues signal.

Two methods for artifact localization are proposed. The first method is a monodimensional approach, called matching pursuit, which is based on the analysis of the signal over a redundant set of particular functions to identify the artifacts. The second method is a multidimensional technique which makes use of a particular neural network, namely the marginal median linear vector quantizer, to recognize the artifacts. In the next two paragraphs the methods are briefly described. Preliminary results are then reported and discussed.

Artifact localization using Matching Pursuit theory

The matching pursuit method has been found to be a very effective algorithm for extracting both time and frequency information from transient signals, since it decomposes a signal into a linear expansion of waveforms according to the local structure of the signal. Its remarkable adaptive property to nonstationary signal provides a wide spectrum of applications in signal processing.

The matching pursuit method is based on a dictionary which contains a family of functions called time-frequency atoms. The decomposition of a signal is performed by projecting the signal over the function dictionary and by selecting the atoms which can best match the local structure of the waveforms. A complete redundant dictionary of time-frequency atoms is generated by scaling, translating and modulating a normalized envelope function g(t). Theoretically, the matching pursuit method represents a signal f(t) as a combination of an infinite number of time frequency atoms and can be described by :

$$f(t) = \sum_{i=0}^{+\infty} a_i \cdot h_i(t) ; h_i(t) = \beta_i \cdot g_i(t) \cdot u_i(t)$$

$$g_i(t) = g\left(\frac{t - p_i}{s_i}\right) ; u_i(t) = Cos(2\pi f_i t + \phi_i)$$

where i is the index of the atoms and a_i are the expansion coefficients. The square of a_i is the energy of each atom $h_i(t)$. In the approach of Mallat and Zhang [3], the function g(t) is a gausssian function i.e. $g(t) = 2^{1/4} e^{-\pi \cdot t^2}$ and $g_i(t)$ is a translated and scaled form of g(t) by a time-translation p_i and a standard deviation s_i. The parameters s_i are also called the scale factors because they are used to control the width of the waveform envelope. The parameters β_i are normalizing constants to keep the norm of $h_i(t)$ equal to 1. The parameters f_i and ϕ_i are the frequency and the phase of the cosine function $u_i(t)$ respectively. Therefore, five parameters need to be extracted for each atom by the matching pursuit method in order to represent a signal. For simplicity, let λ_i represent the parameter set (a_i, s_i, p_i, f_i, ϕ_i).

The decomposition of a signal by the matching pursuit algorithm is a complex iterative process which was developed independently by Mallat and Zhang [3] and by Qian and Chen [4]. The basic idea is to search among all the atoms of the dictionary and for each iteration, the best matched time-frequency atom by looking for all the maximum inner product between the signal residue and each atom. The artifacts under consideration have a short support and often high amplitude. Their localization relies on the decomposition of the signal according to the dictionary. The procedure developed for this purpose is based on a non-linear processing of the parameters λ_i. Based on the prior informations regarding the frequency contents of both the signal and the artifacts, the time duration of significant isolated events, their energy,..., the parameters λ_i that do not match the signal specifications are then used to determine the time location of the artifacts (the time position of the artifact is p_i). These parameters λ_i are defined by comparing the frequency parameters f_i and the scaling s_i factors to two different thresholds.

Artifact localization using neural networks methods

A large variety of artificial neural networks has been developed based on a multitude of learning techniques and having different topologies [5]. One prominent example of neural networks is the Learning Vector Quantizer (LVQ). *Learning Vector Quantizer* is an autoassociative nearest-neighbor classifier which allocates arbitrary patterns into classes using an error correction encoding procedure related to competitive learning [6]. In the following, we will give a short description of the standard LVQ algorithm.

Let us assume a sequence of vector-valued observations $\mathbf{x}(n) \in \Re^p$ and a set of variable reference vectors or weights $\{\mathbf{w}_i(n)\,;\, \mathbf{w}_i \in \Re^p, i = 1,2,\ldots,K\}$. Let $\mathbf{w}_i(0)$ be randomly initialized. Competitive learning tries to find the best-matching reference vector $\mathbf{w}_c(n)$ to $\mathbf{x}(n)$ (i.e., the winner) where $c = \arg\min_i \|\mathbf{x} - \mathbf{w}_i\|$ with $\|.\|$ denoting the Euclidean distance between any two vectors. After a large number of iterations, the different reference vectors $\mathbf{w}_i$ tend to be placed into the input space $\Re^p$ in such a way that they approximate the probability density function $f(\mathbf{x})$ of the multivariate input data. Each reference vector is tuned to a different domain of the input data. By doing so, a clustering of the input multivariate data is achieved. The recall procedure of LVQ is used to determine the class C_g represented by $\overline{\mathbf{w}}_g$ to which the vector of input observations is most closely associated with, i.e.:

$$\mathbf{x}(n) \in C_g \text{ if } \|\mathbf{x} - \overline{\mathbf{w}}_g\| = \min\{\|\mathbf{x} - \overline{\mathbf{w}}_i\|\}$$

where $\overline{\mathbf{w}}_i$ denotes the weight vector of the i-th neuron after the convergence of the learning procedure.

It can easily be seen that the reference vector for each class $i = 1,\ldots,K$ at instant $n+1$ is a linear combination of the input vectors $\mathbf{x}(j), j = 0,\ldots,n$ that have been assigned to class i. As a consequence, standard LVQ suffers from the following drawbacks:

- It does not have robustness against erroneous choices for the winner vector, since it is well known that linear estimators have poor robustness properties [7].
- It does not have robustness against the outliers that may exist in the vector observations.

In order to overcome these problems, a new variation of the Learning Vector Quantizer that is based on order statistics [8], [9] has been proposed in [10], [11]. It is well known that operators based on order statistics have very good robustness properties. In the case of Learning Vector Quantizers we should rely on multivariate order statistics. For the derivation of the LVQ variant marginal ordering was used. For this paper we use the Marginal Median LVQ (MMLVQ) [10].

When dealing with multichannel signal which exhibits a significant degree of correlation, techniques which exploit interchannel correlations can lead to better results with respect to artifact detection. Therefore the MMLVQ learning procedure is performed on multidimensional or vectorial observations. Artifacts are samples that often deviate significantly from the local signal values and can be classified in distinct. The quantification of these deviations is required for this purpose. Here we generate, for each channel, a new signal by computing the absolute difference between the current sample and the corresponding local median, i.e. the median evaluated within a window centered at the current sample. When the learning procedure (based on the new multidimensional signal) reaches convergence, we reject the samples that have been classified to extreme classes and mark these classes as artifact classes. The above procedure can be applied on the data more than once, each time using the samples remaining from the previous iteration of the algorithm. When efficient artifact detection has been performed (usually after 2-3 iterations) we stop the learning procedure. At the end of the learning phase we are left with the reference vectors $\overline{\mathbf{w}}_i^{\,p}$ where p is the iteration number and i the class index. For a given patient, artifact detection is done by assigning vectors to the classes that have been established in the corresponding iteration of the learning phase and rejecting vectors assigned to classes marked as artifact classes.

Application to trend data

The example reported Figure 1 depicts the first 10 hours of the monitored signals associated to the Pulmonary

Artery Pressure (PAP) of patient N° 9 of the Improve Data Library. The signal contain two sharp transient artifacts with high amplitude resulting from the flushing of the sensor and some sharp transients of low amplitude. The superscripts 'o' and 'x' represent the time occurrences of the events detected by the first and the second method respectively.
The method based on the matching pursuit process is applied independently to each channel, that is the detection of an event in one channel does not imply its detection in the other ones. Transients of low amplitude as well as those of high amplitude can be detected if they have a short support. The application of the algorithm requires some inputs from the user i.e. the scale and frequency thresholds. In the example Figure 1, these parameters were set to 2 (points) and 0.5 (normalized frequency) respectively. In the implementation of the MMLVQ algorithm, the training set consisted of PAP data from 15 patients from the IMPROVE project data library (13000 vector-valued samples) and the number of iterations was set to 3.The main advantage of the algorithm is that it is an unsupervised one and it requires minimum human intervention (selection of the classes that correspond to artifacts during the learning phase of the algorithm). On the other hand, the main drawback of the method is that artifacts that are present in only one channel may pass undetected because the corresponding vector may not deviate significantly from the local signal value.

The main difficulty is the validation of the output of the algorithms in order to evaluate their performances especially when dealing with monitored data. In fact, during the time period over which the trend parameter is evaluated (here two minutes), different actions may take place and generate sharp variations on monitored data. For example, the first algorithm indicates that an 'artifact' occurs in PAPd data between the first and the second hour of the recording; during its time support, the Pulmonary Capillary Wedge Pressure (PCWP) is measured, momentary short lasting event (touch on patient) is conducted and the patient coughs. Such combination of actions make difficult the determination of the cause of the detected event. The change of the position and/or posture of the patient induces changes on the monitored data that are detected by the algorithms. An example of this kind of situation is happening just after the fourth hour.

Conclusion

The proposed procedures lead mainly to the same results in particular for events of high amplitude but their behavior is different for transient signals of low amplitude.

The methods are essentially transient event detection methods. The classification of the detected events is a very important issue if the elimination of the artifacts is needed. After artifacts have been identified they can be rejected by substituting them by the output of an appropriate interpolating filter.

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Ethical considerations

The monitoring, collection/storage of data and subsequent publication or public presentation of this information was granted Ethics Committee approval in Kuopio University Hospital, after informed assent was given by the patients' relative(s).

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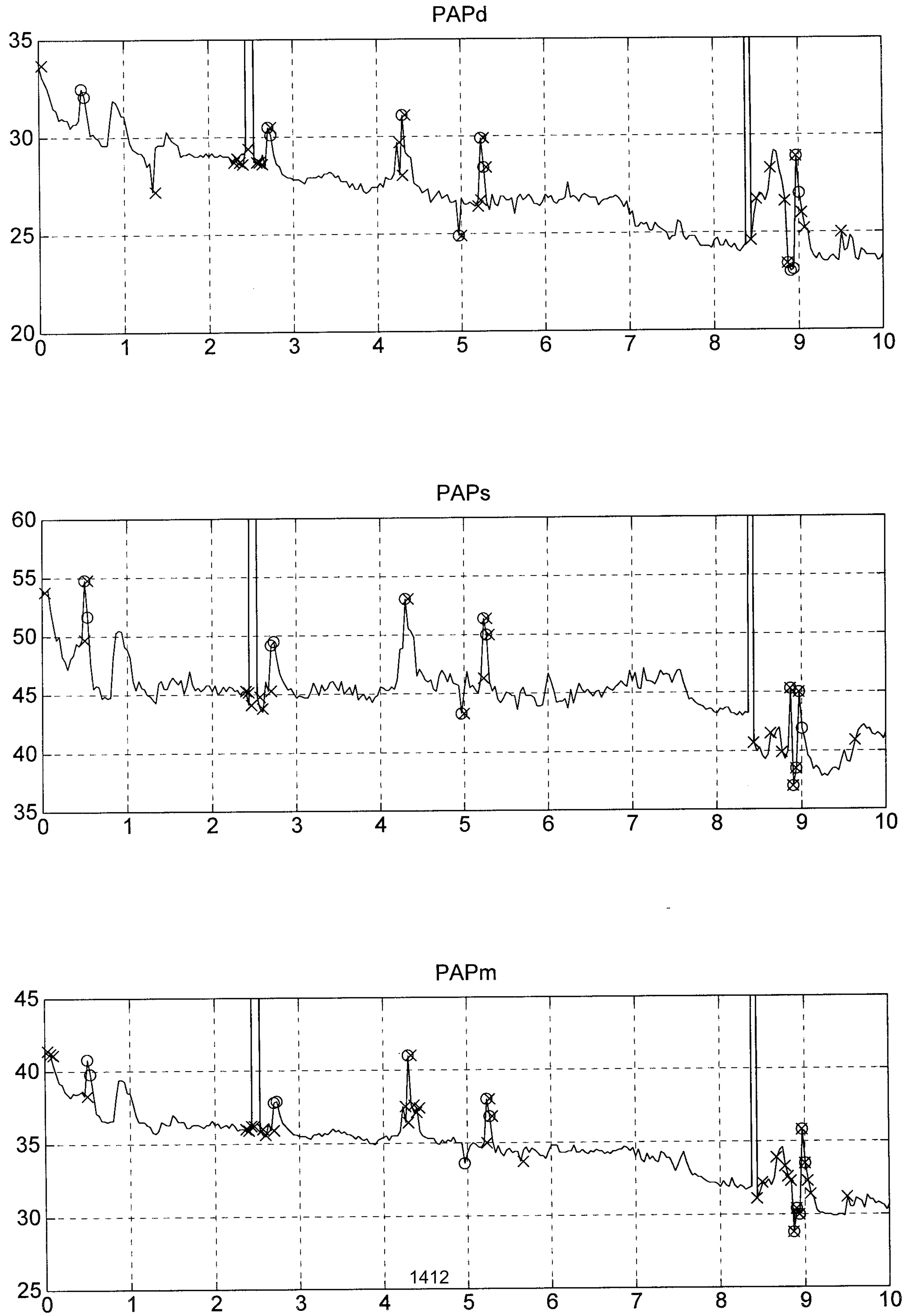

Figure 1 : Example of Artifact localization