DETECTION AND TRACKING OF NON-STATIONARY TRANSIENT SIGNALS BASED ON THE INNOVATIONS FILTER

Maciej Lopatka[1,2]*, IEEE student member, Olivier Adam*[1]*, Christophe Laplanche*[1]*,*

Jean-François Motsch and Jan Zarzycki[2]

[1]LISSI-iSNS, Université Paris XII
61 av de Gaulle, 94010, Créteil, France
phone: + (33) 1 45171774, fax: + (33) 1 45171754, email: maciej.lopatka@ieee.org
web: www.liia-paris12.net
[2]ITA Signal Theory Section, Wroclaw University of Technology, Poland

ABSTRACT

The paper shows an efficient detection and tracking algorithm that is based on the adaptive optimal orthogonal parameterisation. The model parameters, being a solution to second-order signal prediction, are updated at every time-instant, thus making this approach well adapted to detection and tracking problems. The proposed approach is robust in the sense of resistance to the continuously present noise. The innovations filter proposed as the transient signal detector is a lattice structure optimal orthogonal filter that is characterized by an extremely fast start-up performance and excellent convergence behaviour. At every sample the proposed method calculates recursively a set of reflection coefficients, which we propose to use in detection and second-order signal description. We demonstrate performances of the proposed approach by introducing the Receiver-Operating Characteristics curves in different algorithm aspects and for different SNR. The algorithm is well suited to the real-time application.

1. INTRODUCTION

Signal detection is one of the applications used in signal processing. In our case, the characteristics of the signal to be detected are in general unknown. By the signal we mean a non-stationary broadband or band limited transient signal with unknown amplitude and unknown time of arrival. We are placed in the situation where the probability of signal appearance is difficult to estimate and thus we propose to use the Neyman-Pearson criterion to deduce the presence of the signal [1].

One possible approach is to model the given signal in order to extract its intrinsic characteristics, namely the parametric linear filters (autoregressive, moving average autoregressive). The method proposed by Schur and in signal processing literature known as the innovations filter falls into this approach [2][3]. Based on the principle of this filter, the algorithm serves to calculate the model parameters: i.e. reflection coefficients, forward and backward prediction errors using each new signal sample (see eq. 4-6) [4].

For the detection task we define a likelihood ratio test (LR) based on the reflection coefficients. The LR test is performed at each time-instant thus giving the detector excellent time-reaction properties. Moreover, the reflection coefficients describe efficiently and entirely the second order signal. Regarding values of the coefficients from different sections of the innovations filter we can deduce not only the presence of the transient signal and thus segment the signal (transient signal present, transient signal absent), but try to describe these different parts by reflection coefficients which could be used later in defining patterns of different events (identification of the signal).

The objective of our research is justified by the fact that our laboratory works in collaboration with biologists and is interested in the detection and identification of transient non-stationary acoustic signals emitted by whales which spend most of the time under water. The aim is to propose the passive real-time tracking system to detect, identify and track certain species of marine mammals.

2. METHOD

The innovations filter is presented in fig.1. The filter consists of P equal sections ($\Theta(k,t)$; $k=1 \dots P$); P is the order of the filter representing the number of sections. Each filter's section is described entirely by the reflection coefficient ρ . For each new signal sample, the entirety of the coefficients is calculated.

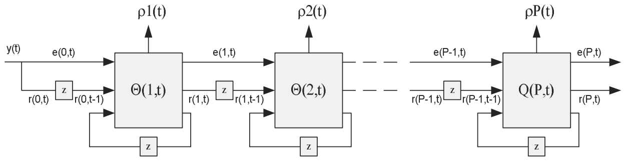

Fig. 1 Scheme of the innovations filter

The requisite number of sections P depends on the type of the signal. In fact the estimation quality is a function of the decreasing rapidity of covariance function $c(k)$ where k is a time-lag:

- if the rapidity is high (for broadband signals), estimation quality adjusts slowly and as a result we need to use the Schur filter of high order *P*,
- if the rapidity is low (for narrowband signals), estimation quality adjusts quickly – lower *P* order filters.

To reduce the number of steps, the reflection coefficients are updated based on their previous values (see eq. 4-6). In fact, the innovations filter is the time-order recursive algorithm that causes algorithm complexity reduction (diminution of needed time computation). Also, using available processors, this method can be used for real-time application such as for example a real-time underwater tracking system. This is one reason this technique has recently regained interest [5].

2.1 Algorithm

The innovations filter is in fact an optimal orthogonal linear prediction filter. At every time-instant the filter calculates an optimal value of the signal at instant t regarding all its past values. The solution of the prediction is founded by the orthogonal projection of the actual signal value on its past manifestation. The importance of the signal's past manifestation is steered by the forgetting factor λ [4][8].

The steps of the algorithm:

1. Initialization:
   - Signal normalization for t=0:

$$c_0 = y_0^2 + \varepsilon \,,\; y_0 = \frac{y_0}{\sqrt{c_0}} \tag{1}$$

   - Errors initializations for t=0:

$$e(0,0) = r(0,0) = y_0 \,,\; r(n,-1) = 0 \text{ for } n = 0 \ldots N-1 \tag{2}$$

   - Coefficients initializations:

$$\rho(n,-1) = 0 \text{ for } n = 1 \ldots N$$

2. Algorithm - signal normalization for t=1…T:

$$c_t = \lambda_t c_{t-1} + y_t^2 \,,\; y_t = \frac{y_t}{\sqrt{c_t}} \tag{3}$$

   - model parameters calculations (eq. 4-6)

where c denotes the estimated value of the signal's variance, y is the signal, ε is a small positive value to avoid division by 0 in case when $y_0 = 0$ and $\lambda \in [0;1]$ is the forgetting factor. The variance is used in the algorithm's normalisation step, guarantying numerical stability of the algorithm (all the filter's quantities are within 0 and 1).

Each section of the filter is defined by a set of three recursive equations:

$$\rho(n+1,t) = \rho(n+1,t-1)\left(1-e^2(n,t)\right)^{\frac{1}{2}}\left(1-r^2(n,t-1)\right)^{\frac{1}{2}} - e(n,t)r(n,t-1) \tag{4}$$

$$e(n+1,t) = \left(1-\rho^2(n+1,t)\right)^{-\frac{1}{2}}\left(1-r^2(n,t-1)\right)^{-\frac{1}{2}}\left[e(n,t)+\rho(n+1,t)r(n,t-1)\right] \tag{5}$$

$$r(n+1,t) = \left(1-\rho^2(n+1,t)\right)^{-\frac{1}{2}}\left(1-e^2(n,t)\right)^{-\frac{1}{2}}\left[\rho\;(n+1,t)e(n,t)+r(n,t-1)\right] \tag{6}$$

where $\rho(n+1,t)$, $e(n+1,t)$ and $r(n+1,t)$ denote respectively reflection coefficient, forward and backward prediction errors on the *(n+1)th* section at the time *t*.

We propose to analyze the energy of the reflection coefficients from all the filter's sections to choose the number of required sections. Moreover, this number, once fixed, can be updated with some periodicity. The important characteristic of the proposed filter is that it is not needed to change the structure of the filter, but only to eliminate or add new sections without recalculating previously calculated values of the reflection coefficients.

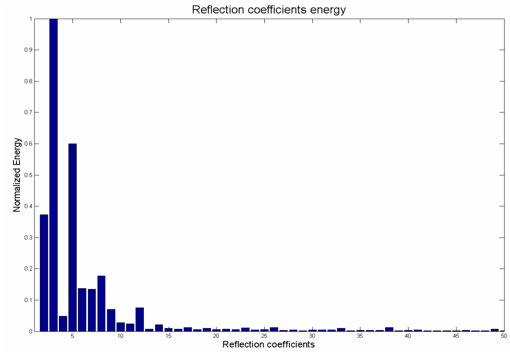

Fig.2 Proposition of the innovations filter order's choice

2.2 Adaptive approach

The updating of the reflection coefficients makes this technique an adaptive approach and, consequently allows us to work on non-stationary signals. The forgetting factor λ mentioned in section 2.1 was introduced much like those found in the other algorithms (LMS, RLS) [6]. The role of this factor is to minimize the weight of previous values as compared to the new signal samples. The value of this factor could either be fixed *a priori* or calculated adaptively in relation to the signal statistics and particularly the energy of the forward prediction error from the last section of the filter: a relatively constant weak value is proof of the signal's (quasi) stationariness and on the other hand, relatively strong and violent changes denote variations in the signal in the sense of second order statistics: i.e. the signal represents non stationary variations.

In [8] an adaptive method of calculation of the forgetting factor $\lambda(t)$ was proposed:

$$\lambda(t) = \mu\lambda(t-1) + (1-\mu)(1-R_e(t-1)) \tag{7}$$

$$R_e(t-1) = e(P,t-1).e(P,t-1) \tag{8}$$

where μ serves to set the convergence speed of the adaptation of the forgetting factor and $R_e(t-1)$ is the output energy error (on the section *P-th*). In practice, we initialize with a value of the forgetting factor close to unity i.e. $\lambda(1)=1$ (to speed up the estimation of the variance of the filtered signal) and after observing the signal's characteristics we diminish and adapt this value to changes of the signal's statistics (*via* $R_e(t-1)$).

In fig.3 we presented an example of the signal composed of 4 different stationary sine modes (see subplot 1). The adaptation scheme of λ, which takes into consideration the value of the output error (see subplot 3), calculates the appropriate value of the forgetting factor and thus we can mark out two different situations:

a) during quasi-stationary parts of the signal we have a long-term estimator of the variance (λ close to 1);

b) during non stationary parts of the signal i.e. appearance/disappearance of the sine modes we have a short-term estimator of the variance ($\lambda < 1$);

In fact, the influence of the forgetting factor on the algorithm performances is of great importance. We can distinguish two different situations:

- for small values of λ (i.e. in practise $\lambda < 0.8$) one finds a high variance of the model parameters estimators, but the algorithm adapts quickly to the second-order signal variations;
- for large values of λ (i.e. in practise $\lambda \geq 0.8$) one finds a low variance of the model parameters estimators, but the algorithm adapts slowly to the second-order signal variations;

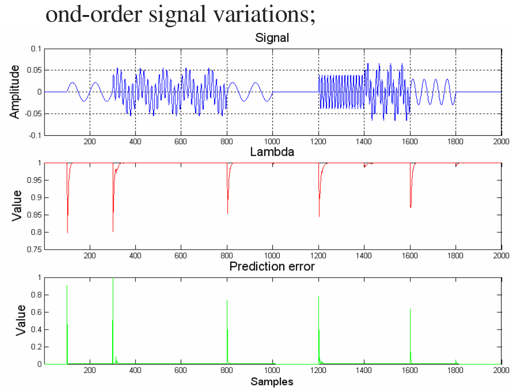

Fig.3 Use of the adaptive forgetting factor λ

One has to make a compromise between the speed of algorithm reaction and the estimators' variance (we call it the "stability/plasticity" compromise).

We can easily track the signal statistics by analysing the matrix of the reflection coefficients $\Theta(k,t) = \{\rho(k,t); k \in [1;P]\}$ where P is a number of the innovations filter sections and t is the time instant (see fig.1). The reflection coefficients tend to gravitate towards their optimal values when the signal is (quasi) stationary. When the intrinsic characteristics of the signal change, the reflection coefficients change as well. These variations allow us to carry out two important steps:

- The analysis of the reflection coefficients variations leads to a signal detection/segmentation. All new variations of the reflection coefficients (defined by their derivative), having a value bigger than a fixed threshold, give a new segment of the signal;
- It is possible, through analysis of the reflection coefficient, to characterize the signal, or carry out an advanced detection. We observe and save the reflection coefficients from all or selected sections and can envisage further classification of segmented signal regions (signal identification).

2.3 Detection and tracking algorithm

We decided to base our detector on the innovations filter as a consequence of its aforementioned characteristics and the results obtained during the simulations phase.

In contrast to the energy detectors working on the samples of the signal, our detector takes into account changes in the reflection coefficients meaning variations of the signal's covariance. The analysis of the reflection coefficients from different filter sections allows us find if the signal under question is present or absent.

In order to deduce the presence of the signal we defined a likelihood ratio (LR) test as:

$$LR(t) = \sum_{n=1}^{n=P} (\rho(n,t) - \rho(n,t-1))^4 \underset{H_0}{\overset{H_1}{\gtrless}} \eta \qquad (9)$$

where P is the filter order, ρ_n denotes the Schur time-varying coefficient on the n -th section and η denotes comparison threshold. H_0 is a null hypothesis: i.e. absence of the signal, and H_1 is an alternative hypothesis: i.e. presence of the signal.

The detector calculates at every time-instant the LR and compares this value with the value of the threshold η :

a. If $LR > \eta$ then signal is present,

b. If $LR < \eta$ then signal is absent.

The advantage of our approach is that the innovations filter based detector is sensitive for the signal's statistics changes and not changes in the signal's shape (energy). This algorithm has the capability of detecting every non-stationary event in the analysed signal even if the power ratio is substantially weak (fig.4).

As mentioned before, the innovations filter tracks all changes in the second-order signal. In fact, the reflection coefficients reflect the signal's covariance changes. In our application it means that at the moment of the non-stationary transient signal's existence, reflection coefficients change their values drastically. Therefore, in analyzing these changes and particularly their derivatives we are able to detect and segment different events in the time-series.

We illustrate here our approach with simulated signals. The detection process is made by transient estimation *via* the reflection coefficients analysis. The results presented below demonstrate the performances of the proposed method. The results obtained on real underwater acoustic signals are presented in [9].

The simulated signal is composed of the continuously present noise and present or absent transient signal. In fact, the resulting signal-to-noise ratio (SNR) calculated on the support of the transient signal depends on the amplitude and bandwidth ratios of the signal and the noise. The signal-to-noise amplitude and bandwidth ratios were chosen as follows: Amplitude ratios:

$$AR = \frac{\sqrt{\sigma_1^2}}{\sqrt{\sigma_2^2}} \qquad (10)$$

Bandwidth ratios: $$BR = \frac{B_1}{B_2} \quad (11)$$

where $\sigma^2{}_{1(2)}$ denotes the variance of the transient signal (and respectively noise) and $B_{1(2)}$ denotes the bandwidth of the transient signal (and respectively noise).

The influence of these two ratios is not the same. The analysis demonstrated that this importance for the amplitude ratio is of the linear-type (match respectively "A","B","C","D","E" points together) and for the bandwidth ratio is of the exponential-type (fig.5).

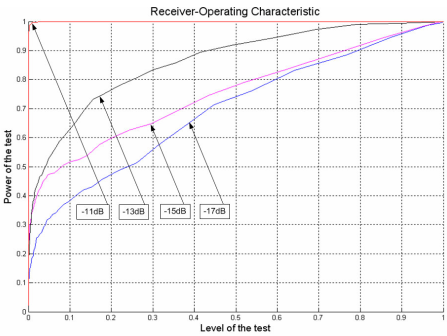

Fig.4 Receiver-Operating Characteristics of the innovations filter based detector for different values of SNR

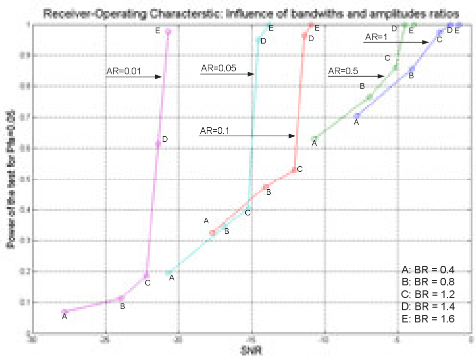

Fig.5 Power of the detector (false alarm probability=0.05) as a function of SNR for different values of amplitude (AR) and bandwidth (BR) ratios

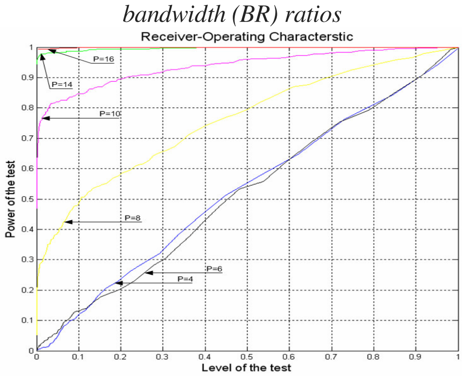

Fig.6 Receiver-Operating Characteristics of the innovations filter based detector for different values of the filter's order P (example for SNR= -13dB)

The performances of the detector depend on the filter's order as well. The choice of the filter order depends on the filtered signal and was described in section 2. One has to take into consideration the real-time aspect as primordial in our application and thus find a compromise between the performances of the detector and the required computation time which linearly depends on the number of filter's sections.

3. CONCLUSION

In this paper, we have demonstrated a new perspective on the innovations filter dedicated to the signal processing application, particularly for signal detection and characteristics tracking. We provided a short description of the innovations algorithm and discussed the influence of the model parameters. We have introduced different criteria in order to determine the filter order and to guarantee a satisfactory algorithm convergence. The results we obtained on simulated signals have enabled us to detect and segment different events in a time-series and particularly to segment transient non-stationary events. The results that we obtained on simulated signals are promising for future real-world applications.

4. AKNOWLEDGMENT

We wish to thank the Association DIRAC (France) and the Region 8 IEEE VCF for the support of our participation at the Eusipco 2005.

REFERENCES

[1] C.W. Helstrom, *Statistical theory of signal detection*, Pergamonn Press, 1975

[2] I. Schur, "On Power Series Which Are Bounded in the Interior of the Unit Circle I", *in I. Schur Methods in Operator Theory and Signal Processing*, Ed. I. Gohberg, Operator Theory: Advances and Applications, vol. 18, Birkhäuser-Verlag, pp. 31-60, 1986

[3] I. Schur, "On Power Series Which Are Bounded in the Interior of the Unit Circle II", *in I. Schur Methods in Operator Theory and Signal Processing*, Ed. I. Gohberg, Operator Theory: Advances and Applications, vol. 18, Birkhäuser-Verlag, pp. 61-88, 1986

[4] D.T.L. Lee, M. Morf, B. Friedlander, "Recursive Least Squares Ladder Estimation Algorithms", *IEEE Transactions on Circuits and Systems*, Vol. CAS-28, No. 6, June 1981

[5] J. Zarzycki, "Multidimensional Nonlinear Schur Parameterization of NonGaussian Stochastic Signals. Part Two: Generalised Schur Algorithm", *MDSSP Journal*, 15, 243-275, 2004

[6] ID. Landau, *Identification et commandes des systèmes,* Paris: Ed. Hermes, 1988

[7] S. Haykin, *Signal Processing*, Ed. IEEE Press, 1994

[8] B. Szlachetko, „Joint Time-Frequency Analysis of Telecommunications Signals Based on the AR model", *KKTOiUE*, Poznan-Kiekrz, 1999

[9] M. Lopatka, O. Adam, C. Laplanche, JF. Motsch, J. Zarzycki, *New Effective Analytic Representation based on the Time-Varying Schur Coefficients for Underwater Signals Analysis*, IEEE International Conference Oceans'05 Europe, Brest, France, 2005