Regularized autoregressive model preserving spatial discontinuities for analysis of radio-frequency (RF) signals in echographic images.

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RÉSUMÉ

Cet article traite de l'estimation spectrale locale à partir de signaux radio-fréquence obtenus en imagerie medicale par échographie ultrasonore. Du fait de la nature particulière des signaux RF (signaux aléatoires fortement bruités et non-stationnaires et présence de plusieurs milieux tissulaires), l'objectif principal est de régulariser l'estimation paramétrique locale tout en préservant d'éventuelles discontinuités.
Nous proposons un shéma de régularisation 2D basé sur les modèles autorégressifs, introduit dans un cadre Bayesien où l'a-priori de continuité spatiale est exprimé par l'intermédiaire des champs de Markov. L'utilisation de fonctions non quadratiques (phi-fonctions) dans le terme d'a-priori permet de preserver les discontinuités.
Nous appliquons tout d'abord cette méthode sur des simulations où des discontinuités spectrales ont été générées par un décalage de la fréquence centrale entre 2 milieux. Nous montrons comment le shéma de régularisation permet d'améliorer considérablement l'estimation des coefficients AR. De plus, l'utilisation des Phi-fonctions s'avère très efficace pour préserver les discontinuités.
Enfin, nous appliquons cette méthode sur des signaux radio-fréquence acquis à l'Université de Leuven avec un système développé pour l'acqisition de tels signaux et adapté à un échographe conventionnel. Ces résultats montrent l'intérêt de cette méthode pour l'étude de signaux réels acquis in-vivo sur des tissus biologiques en conditions cliniques.

ABSTRACT

This paper deals with the local spectral estimation from radio-frequency signals in medical echographic ultrasound images. Due to the nature of the data (noisy signal and presence of different biological tissues in the image plane), the main problem is to regularize the estimation while preserving the discontinuities.
Based on autoregressive models, we propose a 2D regularization scheme in a Bayesian framework where the priors are expressed by means of MRF (Markovian random Fields) defined on the set of AR coefficients. The use of non quadratic functions, called Phi-functions allows to preserve discontinuities.
We applied first our method on simulated data where spectral discontinuities have been simulated by the way of a central-frequency shift. In particular, we show how the regularization scheme increases the performances of the AR estimation. On these simulations the use of Phi-functions to preserve the discontinuities is shown to be efficient.
We then apply our method on real RF echographic cardiac data obtained at the University of Leuven using system dedicated to RF acquisitions and adapted on a conventional echographic apparatus. These results show the interest of such method for real signals acquired in-vivo on biological tissues.

1 Introduction

Conventional B-scan echographic images correspond to the envelope of the ultrasonic signal (RF signal) delivered by the probe. This implies that much information is lost when using B-scan images. Indeed, the analysis of the frequency spectral content of the RF signal can deliver information related to the acoustic properties of the imaged tissues, such as frequency-dependent attenuation or backscatter. Such information can be very useful to characterize the state of a tissue when specific pathologies (i.e. ischemia or infarct) are present or to improve segmentation of the imaged organs (i.e. blood-myocardium interface). We propose to exploit this information by estimating the local spectrum of the RF signal at each point of the echographic images.

Methodologically, the local estimation of the spectral content of RF signals from echographic data is not a trivial task due to the following characteristics:

- the stochastic nature of the RF signal yields noisy estimates when using conventional spectral estimation approaches.
- the spectral content of the signal exhibits discontinuities at the interfaces of the different tissues present in the image (i.e. myocardium, blood, lungs...).

The first point implies to use some regularization scheme for robust spectral estimations. A conventional approach consists in performing several acquisitions and averaging the estimated spectra. Short Time Fourier transforms or classical AR models may be used for the characterization of an homogeneous medium either for attenuation or backscattering estimation ([1], [2]). These approaches have been shown to be efficient for the characterization of homogeneous media.

However the study of real 2D images containing at least two media implies the ability to take into account discontinuities in the estimation scheme. We propose to estimate the local spectrum of the RF signal by using an autoregressive (AR) model approach. In order to overcome the above mentioned difficulties, this estimation is performed in a Bayesian framework, where a priori information is included as a smoothness constraint on the spectral estimates. This constraint is modeled through a Markov random field, which allows to smooth the spectral estimation while preserving the discontinuities.

2 Method

In a framework of linear models, the local PSD (expected power spectral density) $P_{xy}(f)$ of the received signal may be expressed as a product between a spatially variant point spread function of the acquisition system and two terms (attenuation and backscatter) relatives to the tissue response, *i.e.*

$$P_{xy}(f)=H^2(f,x,y).A^2(f,x,y).\eta_{bs}(f,x,y) \qquad (2.1)$$

where H is the space-variant point spread function (PSF) of the acquisition system, A(.) reflects the attenuation effects of soft tissue and $\eta_{bs}(.)$ stands for the expected mean frequential response of the tissue at (x,y).

Our goal consists in the robust estimation of $P_{xy}(f)$ by the mean of AR regularized models.

Let us introduce the following notations :

-**y**(i,j) is a n-vector : the i^{th} n-points truncated segment of the j^{th} signal.

-$\mathbf{a}_p$(i,j) is the p-order ar-parameters vector for the (i,j) case in the image to be estimated.

-A is the set of the AR vectors in the image.

The PSD of an AR process is given by :

$$P(f)=\left|S(f)\right|^2=\frac{\sigma_b^2}{\left|1+\sum_{k=1}^{P} a_k \cdot e^{-j2\pi fk}\right|^2} \qquad (2.2)$$

where the a_k's are the AR coefficients to be estimated, contained in vector $\mathbf{a}_p$.

Assuming that **y** is a Gaussian process, the probability of **y** given $\mathbf{a}_p$ is expressed by:

$$\Pr\left(\mathbf{y}/\mathbf{a_p}\right)=\frac{\exp\left(-\frac{1}{2\sigma_\mathbf{b}^2}\left(\mathbf{y}+\mathrm{Y}.\mathbf{a_p}\right)^t\left(\mathbf{y}+\mathrm{Y}.\mathbf{a_p}\right)\right)}{\left(2\pi\sigma_\mathbf{b}^2\right)^{\frac{N}{2}}} \qquad (2.3)$$

where

$$\mathbf{y}=\begin{bmatrix} y(1)\\ y(2)\\ \dots\\ y(N)\\ 0\\ \dots\\ 0 \end{bmatrix}, \quad \text{and} \quad Y=\begin{bmatrix} 0 & 0 & .. & 0\\ y(1) & 0 & .. & \dots\\ \dots & y(1) & .. & \dots\\ y(N) & \dots & .. & 0\\ 0 & y(N) & .. & y(1)\\ \dots & 0 & .. & \dots\\ 0 & 0 & .. & y(N) \end{bmatrix}$$

Using the Bayesian formula the a-posteriori probability of $\mathbf{a}_p$ can be expressed as :

$$\Pr\left(\mathbf{a_p}/\mathbf{y}\right)\propto \Pr\left(\mathbf{y}/\mathbf{a_p}\right)\cdot \Pr\left(\mathbf{a_p}\right) \qquad (2.4)$$

Without a-priori knowledge (*i.e.* $\Pr(\mathbf{a}_p)$ is a uniform probability density function), the computation of the maximum a-posteriori (MAP) probability reduces to the maximization of (2.3) and leads to a maximum likelihood estimate (MLE).

Finding the MAP implies therefore the minimization of Q(A) defined as :

$$Q(A)=\sum_{(i,j)\in D} Q_o\left(\mathbf{a_p}(i,j)\right) \quad , \qquad (2.5)$$

where $$Q_o(\mathbf{a_p})=\left(\mathbf{y}+Y.\mathbf{a_p}\right)^t\left(\mathbf{y}+Y.\mathbf{a_p}\right) \qquad (2.6)$$

This minimization yields to the classical least square solution (Yule-Walker technique). In this case the estimation of each $\mathbf{a}_p$(i,j) from each **y**(i,j) may be done separately. As mentioned in the introduction, this scheme leads to noisy estimates when applied to US RF signals. In order to avoid this drawback, Giovannelli [3] proposed a regularization scheme based on the minimization of spectral-distance between two adjacent signals in a 1D framework. This can be made by the introduction of a-priori knowledge (by the mean of $\Pr(\mathbf{a}_p)$) yielding to a complementary quadratic term written by (2.7):

$$Q_{sm}(A)=\sum_{(i,j)\in D}\sum_{(k,l)\in V}\left\|\mathbf{a_p}(i,j)-\mathbf{a_p}(k,l)\right\|_k \qquad (2.7)$$

The MAP calculus leads to the minimization of Q_2(A) :

$$Q_2(A)=Q(A)+\lambda\cdot Q_{sm}(A) \qquad (2.8)$$

where λ is an hyperparameter balancing the proximity to the data and the smoothness of the solution.

The Q_2(.) term is also a quadratic form and the solution can thus be easily computed (by gradient descent types methods for instance). Nevertheless this last method leads to an oversmoothed solution for signals returned from more than one medium.

We propose to express the prior (*i.e.* $f(\mathbf{a}_p)$) in a Markov random field framework. This can be done by defining the appropriate associated neighborhood system and cliques. Such a framework allows to replace the quadratic form Q_{sm} by a modified penalty function, which allows to smooth small variations in the estimates while preserving significant discontinuities :

E. 1 $$Q_\varphi(A)=\sum_{(i,j)\in D}\sum_{(k,l)\in V}\Phi\left(\mathbf{a_p}(i,j)-\mathbf{a_p}(k,l)\right)$$

where Φ(u) is called a potential function, or simply phi-function, and is taken to be even and increasing in |u|.

Many Phi-functions have been proposed in the literature (see [4] and [5] for a review). Some of them lead almost surely to a non-convex optimization problem, thus providing motivation for the use of a simulated annealing algorithm

3 Results

3.1 Simulation

RF images were generated by simulating the propagation of a gaussian pulse through 3 media with different backscatter functions defined by gaussian shapes with different correlation length in the Fourier domain. In these simulation the attenuation was not taken into account. The theoretical influence of such backscatter functions on the RF signal corresponds to a shift of the Pulse Central Frequency (PCF).

We illustrate in the remaining the behavior of the proposed technique by using a 1rst order complex AR model to estimate the local PCF from the simulated signals.
Figure 1 shows the theoretical PCF image to be recovered in these simulations. Figure 2 to 4 show the results obtained :

- without regularization (i.e. classical AR method).
- with a regularization term using a quadratic function (i.e. without preservation of discontinuities).
- with a regularization term using an adapted phi-function preserving the discontinuities.

Figure 4 shows how the proposed method improves the results by avoiding to oversmooth the PCM estimation in the vicinity of the discontinuities.

3.2 Cardiac data

The method is then applied on real RF data acquired in-vivo. These data were obtained with a dedicated system for RF data acquisition developped at the Gasthuisberg Hospital in Leuven and connected to a commercial B-scan apparatus.

Figure 5 shows the conventional B-scan image reconstructed from these data where the left cavity of the heart and the cardiac walls can be observed.

Figure 6 shows the PCF images obtained from these data. It can be observed how the regularization scheme improves the estimation of the PCF. Indeed the difference between the PCF measured in the blood and the heart is clearly enhanced.

4 Perspectives

The obtained results show how the proposed approach allows to improve the spectral estimates from RF US signals. The next step of our work will consist in optimizing the choice of the Phi-function in order to improve the detection of the spectral discontinuities. The application of the method to cardiac sequences potentially provides a way to relate *in-vivo* the tissue state and the RF signal characteristics. This method thus can be considered as a step toward the estimation of parametric images of tissues from 2D echographic data.

5 Références

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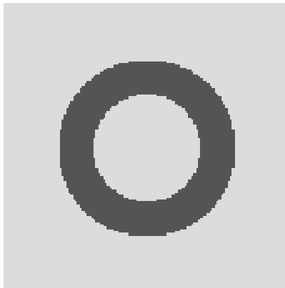
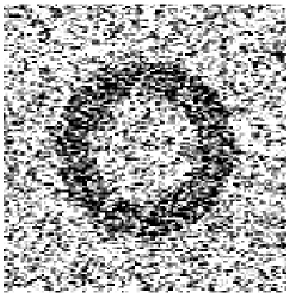
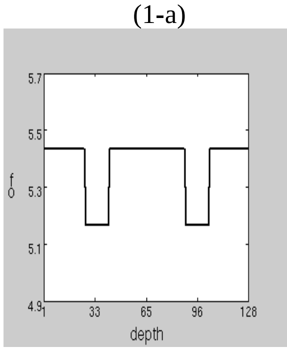


(1-a)



(2-a)



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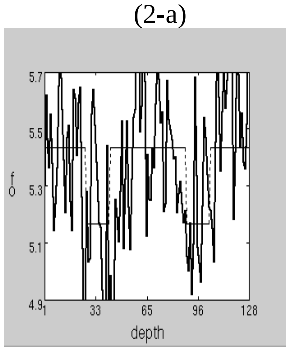
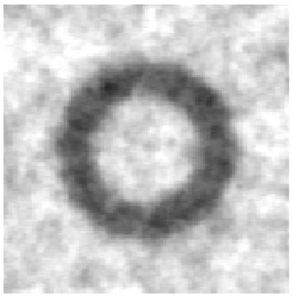
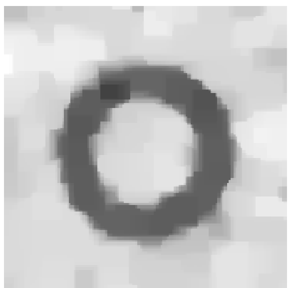


(2-b)

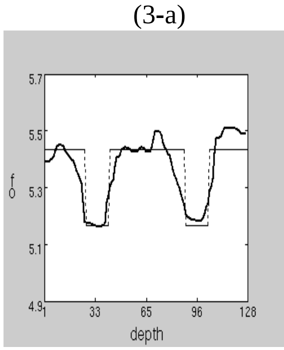
figures 1,2 : theoretical (1-a) and conventional AR-model estimation (2-a) of the PCF images for simulation data, and slices (1-b, 2-b) through the middle line.



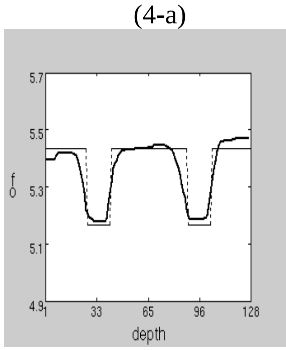
(3-a)



(4-a)

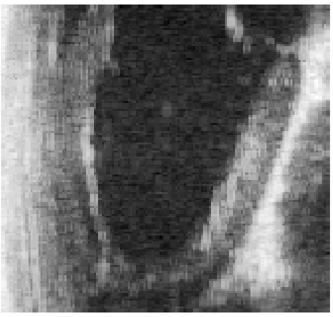


(3-b)



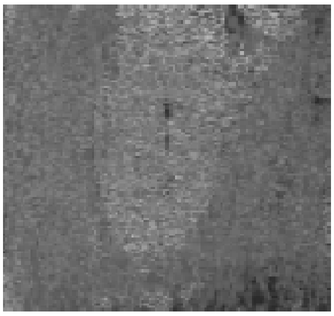
(4-a)

figures 3,4 : estimated PCF obtained with a regularization term using a quadratic function (3) and a phi-function (4).

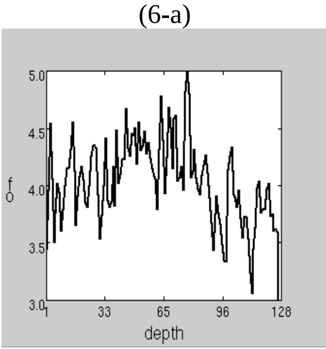


(5)

figure 5 : Conventional B-scan image reconstructed from RF data. The left ventricle and the cardiac wall can be observed.

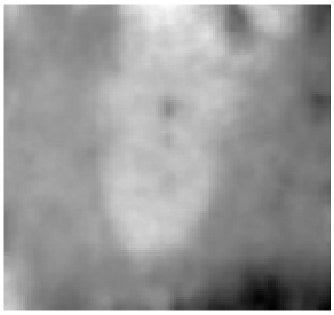


(6-a)

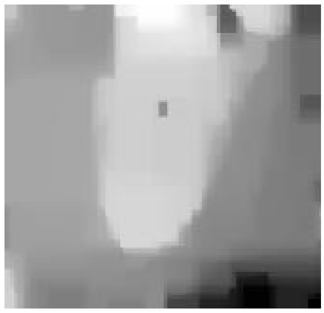


(6-b)

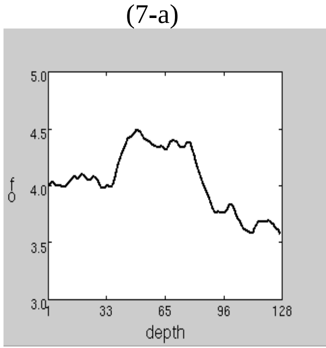
figure 6: PCF image obtained with a complex 1[rst] order AR model and without regularization.



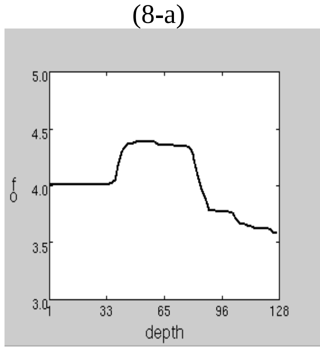
(7-a)



(8-a)



(7-b)



(8-b)

figure 7,8 : PCF images obtained with a complex 1[rst] order AR model with a regularization term using a quadratic function (7) or a phi-function (8).