NUCLEAR MAGNETIC RESONNANCE IMAGERY RESTORATION BY MARKOV MODELIZATION AND ANNEALING

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RESUME

Des images R.M.N. bruitées sont "nettoyées" tout en préservant la complexité des structures non linéaires locales. La méthode, basée sur la modélisation markovienne et le recuit simulé, introduit plusieurs innovations: dynamiques ajustées efficacement, non homogénéité des champ markovien, estimation sophistiquée des parametres, adaptativité automatique complète de l'algorithme.

SUMMARY

Noisy N.R.M. images are cleaned up while preserving complex non linear detailed features. The method, based on Markov fields modelization, and simulated annealing introduces several innovations: efficient adjusted dynamics, non homogeneity of the fields, sophisticated estimation of the parameters, complete automatic adaptativity of the algorithm.

1. N.M.R. IMAGERY

The images we have worked on are obtained by N.M.R. techniques at the I.E.F., Univ. Paris-Sud. The magnetic fields used there by Prof. Sauzade's team have middle range energies (0.1 Tesla). This greatly lowers the cost of the machinary, but increases the noise level of the images. Whence the practical interest of an effective numerical restoration, preserving the complexity of medical images while cleaning up the noise. Let us point out that standart linear filtering is out of question due to the highly non linear features to be preserved such as narrow edges, numerous curved contours, etc...

Our choice of method has thus been Markov field modelization followed by annealing, in the spirit of D. and S. Geman [1].

2. THE RESTORATION METHOD

Call x the original (not observed image), w the noise, and y = x+w the degraded image actually observed. The noise is assumed to be gaussian, completely decorrelated and independent of x. The Markov field model considers that the probability of observing x is:

$$P(x) = Z^{-1} \exp[-H(x)]$$

where $Z = \sum_{z \in \Omega} \exp[-H(z)]$ is a normalizing constant, Ω is the set of all possible images, H(x) is an energy function capturing local statistical structures of the image.

Once H is completely specified standart probability reduces the estimation of x to the following problem:

$$\left[\begin{array}{l}\text{Find } z \text{ minimizing } U(z) \text{ given by} \\ U(z) = H(z) + \sigma^{-2}||y-z||^2\end{array}\right.$$

where σ^2 is the noise variance and $||.||$ is euclidian distance.

This minimization is carried out through a stochastic algorithm: simulated annealing.

3. THE ENERGY STRUCTURE AND ITS ESTIMATION

As suggested by Geman [1] we use simultaneous description by pixel and edge elements. Every pair of adjacent pixels is assigned an edge site s (the mid-point of the pair), carrying an edge orientation ξ_s. The energy H(x) is then structured as $H(x) = H_1(x) + H_2(\xi) + H_3(x,\xi)$ where H_1 is a quadratic form in pixel intensities, H_2 has a "logistic" structure, and H_3 relates local desirability of edges to discontinuities of pixel intensities. An early version of H is given in Chalmond [2], but we have since refined the structure of H to eliminate artefacts to preserve narrow lines and to maintain the dynamics.

The crucial problem, since the energy is parametrized (8 parameters in our case), is to estimate these parameters as well as the noise variance σ^2. In [2], pseudo maximum likehood techniques were given, and used. But in order to estimate new more complex energy forms, we now use more sophisticated techniques due to Younes [3].

4. EARLY EDGE DETECTION AND NON HOMOGENEOUS MARKOV FIELD

Another improvment since [2] is the automatic and adaptative choice of an appropriate edge detection to initialize the search for ξ in (x,ξ). Also, adaptative adjustments for the dynamics of the image actually handled by our algorithm, have increased its efficiency. Finally, the choice of a non homogeneous energy form, where the parameters actually vary over the whole image is a new and unusual feature in this context.

The images we handle have 128 by 128 pixels and (reduced) coding on 256 gray-levels. The computation time for restoration of one typical image is currently of 40 minutes on a VAX 750, and should be seriously reduced by optimization of the algorithm.

REFERENCES

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[3] L. Younes, Annealing and estimation of parametrized Gibbs fields. (to appear, Ann. Institut H. Poincarré, 1987).