IMPROVING THE RESOLUTION OF INFRARED IMAGES OF THE BREAST

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Abstract

An algorithm is described which performs a 2:1 zoom on a infrared image of the breast. The method takes into account processes of blur, noise, and image correlations, to make an optimal estimate of the missing pixels. The theory is briefly described and experiments are reported.

Introduction

Images of the breast taken with infrared sensors suffer from a lack of resolution compounded by rather high levels of noise. The objective of this project is threefold: to increase the resolution of the image by a novel type of zooming, to remove the noise, and simultaneously to preserve the detail of features including in particular the sharpness of edges.

A Maximum-a-posteriori (MAP) image restoration philosophy is followed to pose the problem. The image acquisition and restoration processes are modeled in the figure below. In this model, the image f (resolution 2N x 2N) is first blurred by the point spread function of the imaging system, and then noise is added. The resulting blurred, noisy image is then subsampling 2:1 to produce the measured NxN image, g. The algorithm described in this paper reverses this process to produce a new image $\hat{f}$ which is double the effective resolution of the measurement g.

Mathematical Approach

We define $\hat{f}$ to be the estimate of f which minimizes the following objective function: $H_n(f, g) + H_p(f)$, where H_n is referred to as the "noise term", and incorporates the effects of blur, subsampling, and noise. $H_p(f)$, referred to as the "prior term" incorporates knowledge of local statistics, including correlations, of f. The specific form chosen for H_n is $H_n(f, g) = \sum_{i=1}^{N} \frac{(g - (h \otimes f)_i)^2}{2\sigma_i^2}$

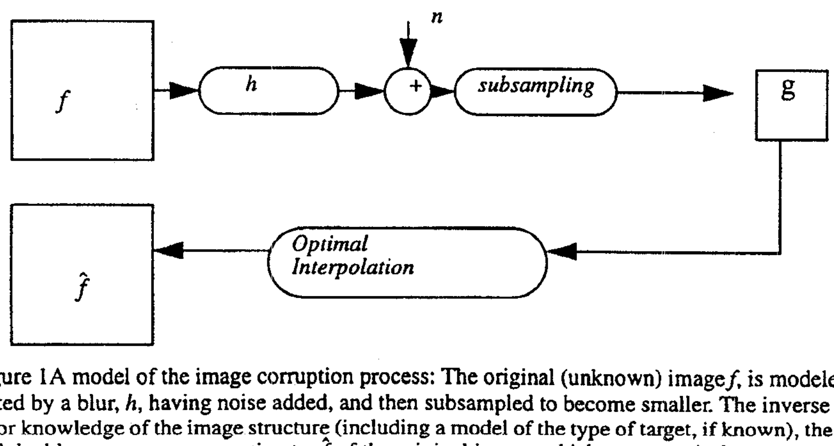

Figure 1A model of the image corruption process: The original (unknown) image f, is modeled as being distorted by a blur, h, having noise added, and then subsampled to become smaller. The inverse problem uses prior knowledge of the image structure (including a model of the type of target, if known), the noise process, and the blur, to compute an estimate, $\hat{f}$ of the original image, which most precisely represents the unknown larger image.

where $(h \otimes f)_i$ denotes a local convolution in the vicinity of pixel i of the unknown image f, with known blur h. Note that in this form, h may be space-variant. Likewise, the additive noise may be non-stationary.

The proper choice of a prior term is discussed at length in the literature [1,2,5]and may be referred to as a "regularization" term is the estimation problem is considered as a formal underdetermined inverse problem. We have found the following form to be particularly effective in removing noise while preserving edges.

$$H_p(f) = \sum_i \sum_{j \in \aleph_i} \exp\left(-\frac{(\nabla f)_i^2}{2\tau^2}\right)$$

where $\aleph_i$ denotes the neighborhood of pixel i, $(\nabla f)_i$ denotes some derivative operator at pixel i, and t is a problem-specific constant. More details are available in the literature. [3,4]

This formulation is implemented in sufficient generality to accommodate space-variant blur and nonstationary noise. The proper choice of forms for both the noise and prior terms is discussed in the full paper.

The optimal estimate of f is found by minimizing $H(f)$ with respect to f, using a nonlinear optimization method known as Mean Field Annealing[4], which smooths out noise while preserving the sharpness of edges.

The proposed algorithm does not claim to *exactly* restore the missing pixels (every other row and column) in the zoomed image, and thus does not violate the sampling theorem. Instead, the claim is made that these methods produce optimal estimates of the missing data. Although exact determination of the missing data is (in general) impossible, the proposed algorithm is, however, optimal in its ability to estimate those values, given the suitability of the blur, noise, and image models. The estimate can be surprisingly accurate. In the absence of noise, blur is exactly invertible by simple operators such as the inverse filter. Since each of the missing pixels in the image has, via the blur, contributed to a set of neighboring, measured pixels, the missing pixel can be optimally estimated.

Methods

Fifteen studies were acquired, with three breast IR images in each study, using an Inframetrics 600M scanner, (which utilizes a scanning mirror for image acquisition), including: 5 patients with normal IR breast images, 5 patients who were normal but had abnormal IR images of the breast (and are therefore at high risk for breast cancer), and 5 breast cancer patients confirmed positive by biopsy. All were zoomed using the proposed algorithm. Initial experiments have approximated the sensor point spread function with a uniform Gaussian blur, however, investigation of the device properties indicate that a space-variant, nonisotropic blur model would be more appropriate, such a model will be tested before the conference. Results are evaluated by expert clinicians, in comparison with images zoomed using linear interpolation, spectrum extrapolation, and pixel replication. Example images will be presented at the conference.

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3 G. Bilbro and W. Snyder, "Mean Field Annealing, an Application to Image Noise Removal", in *Journal of Neural Network Computing*, Fall, 1990

4 G. Bilbro, W. Snyder, S. Garnier, and G. Gault, "Mean Field Annealing: a formalism for Constructing GNC-like algorithms", *IEEE Transactions on Neural Networks*, 3(1), Jan, 1992.

5 S. J. Garnier, G. L. Bilbro, J. W. Gault, W. E. Snyder, "The Effects of Various Basis Image Priors on MR Image MAP Restorations", *Journal of Mathematical Imaging and Vision*-(1994)