Synthesis of biomedical tissue

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ABSTRACT

Image quality assessment in medical imaging requires realistic textured backgrounds that can be statistically characterized for the computation of model observers' performance. We present a modeling framework for the synthesis of texture as well as a statistical analysis of both sample and synthesized textures. The model employs a two-component image-decomposition consisting of a slowly, spatially varying mean-background and a residual texture image. Each component is synthesized independently. The technique is demonstrated using radiological breast tissue. For statistical characterization, we compute the two-point probability density functions for the real and synthesized breast tissue textures in order to provide a complete characterization and comparison of their second-order statistics. Similar computations for other textures yield further insight into the statistical properties of these types of random fields.

Keywords: textured backgrounds; random fields; medical backgrounds; texture synthesis; first and second order statistics.

1. INTRODUCTION

Medical and biomedical imaging research aims at developing better imaging systems, more accurate reconstructions, and methods of image processing and analysis that utilize the most important information present in an image for accurate and timely diagnosis of disease. Realistic numerical models of human tissue and medical imaging systems are key components to achieving this goal. This paper specifically addresses an approach to the modeling of biological tissue, where the technique is demonstrated for radiological breast tissue, also referred to as mammographic tissue.

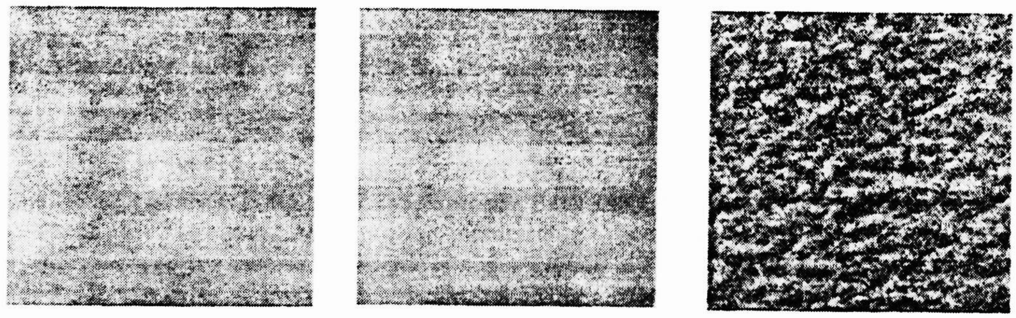
The method for synthesis decomposes an image into a slowly, spatially varying mean-background and a residual texture image.[1-3] We shall refer to the slowly, spatially varying mean-background as the mean background. The texture image can be successfully synthesized using a multi-scale multi-orientation framework based on the steerable pyramid transform. While we proposed in an earlier paper to model the mean background as a stochastic process known as the lumpy background,[3-6] we have encouraging results showing that those slowly, spatially varying backgrounds may also be synthesized with the framework used to synthesize the finer underlying texture.

A useful synthesis framework for medical imaging research is one that can yield images with known statistical properties. As a first step to characterize the statistical properties of textured backgrounds, we propose to estimate the first and second order statistics as the one-point and the two-point probability density functions that characterize completely their first and second-order statistics.

2. A COMPLEX BACKGROUND AS A TWO COMPONENT MODEL

Radiologic breast tissue samples appear as if they are formed as the superimposition of a slowly, spatially varying background and a finer texture image. Thus we propose to decompose them in these two components. A typical decomposition is shown in Fig. 1. The slowly, spatially varying background referred as the mean background is obtained by filtering the original mammogramm image with a Gaussian kernel with a standard deviation of six pixels. The residual texture image is the difference between the image and the mean background.

It can be noted from Fig.1 that the mean background resembles lumpy backgrounds.[5-6] In the literature on image quality assessment for medical imaging, lumpy backgrounds are considered to be useful models of anatomical variations because: 1. They account for background variability and 2. In one type of lumpy backgrounds the probability density is known to be multivariate Gaussian while in the other the covariance matrix is known to be Gaussian. Knowledge of the covariance matrix has made possible the computation of various predictive models of image quality assessment for the detection of lesions in such backgrounds.[4] Knowledge of the full probability density functions allows computation of the ideal observer.



(a) (b) (c)

Fig.1. Mammography breast image decomposition: (a) The original sample. (b) The slowly, spatially varying mean-background. (c) The residual texture image.

3. A FRAMEWORK FOR TEXTURE SYNTHESIS

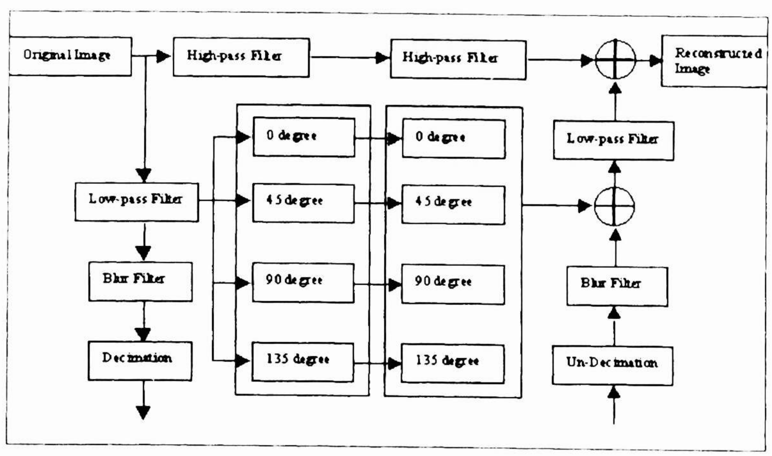


Fig.2. Illustration of one level of the steerable pyramid transform used in the texture synthesis algorithm. The input image in the upper left corner would be either the texture sample or the white noise image. A synthesis is obtained by recombination of the decomposed noise image through the right hand side of the pyramid.

The algorithm for texture synthesis we propose is based on a multiple scale decomposition of a sample texture image and the same decomposition of a realization of a uniformly distributed white noise image. The algorithm is composed of four essential components: the pyramid transform, the image decomposition, the histogram matching procedure, and the texture synthesis. The algorithm was implemented in IDL language and is best described by considering the four individual components:

The Pyramid Transform: The proposed algorithm for the synthesis of the residual texture is based on a four-layer steerable pyramid transform. One layer of the pyramid is depicted in Fig. 2. Layers are connected by a factor-of-two downsampling also known as decimation of the image.[7-8] Within each layer, the image is filtered by a set of bandpass filters and followed by a set of orientation filters that form a quadrature mirror filter bank.[7-10] A four (scales) by four (orientations: 0 degree, 45 degree, 90 degree and 135 degree) 17x17 size filters were adopted.

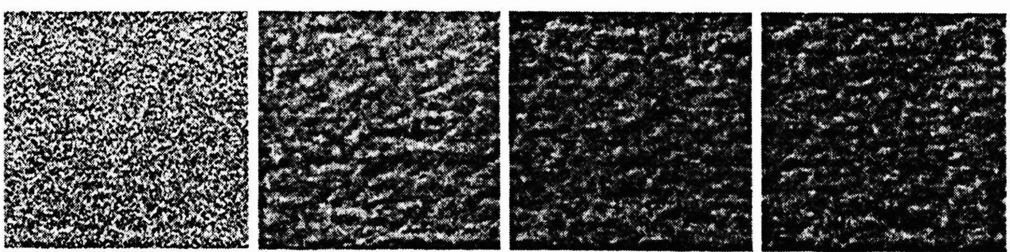
Image Decomposition: The texture image is processed through the left-hand side of the pyramid transform shown in Fig. 2. It is represented in Fig. 2 as an input to the pyramid in the upper left corner. In parallel, a realization of uniformly distributed white noise, referred thereafter as white noise, is also processed by the same pyramid transform, that is, it is also fed independently to the pyramid transform in the upper left corner. The role of the white noise image is to provide a starting point for the synthesis.

Histogram matching at multiple scales: After decomposition of a texture sample and a realization image of white noise, the histograms of the subband images (i.e. output images of the filters on the left hand side of the pyramid) of the texture image and of the noise image are matched.[11,12] Histogram matching is an image processing technique, specifically a point operation, which modifies a candidate image so that its histogram matches that of a model image.[13-14]

Texture Synthesis: The histogram-matched noise subband-images obtained at multiple scales are then recombined according to the right-hand side of the pyramid transform shown in Fig. 2. The synthesis operation is a blurring between scales. Moreover, the greylevels of the undecimated image must be multiplied by a factor of four at each stage of the synthesis to account for the loss in brightness the image did undergo upon decimation by a level of two. This process repeated at multiple scales yields a synthetic image. If another realization of white noise is processed instead, the synthesis yields another realization of the synthesized image.

4. SYNTHESIS OF MAMMOGRAPHIC BREAST TISSUE SAMPLES

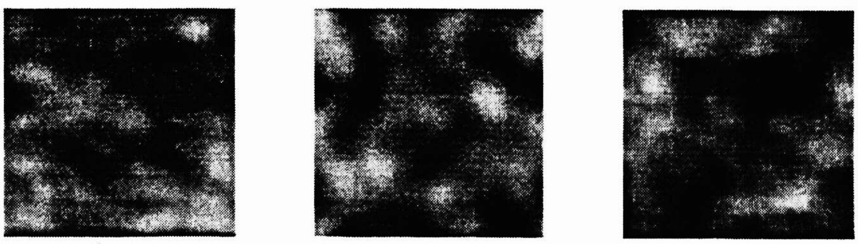
The framework described was applied to the synthesis of both the residual texture component and the mean background. Two synthesis realizations of the residue image are shown in the two rightmost images in Fig. 3. Each synthesis corresponds to a new realization of white noise as a starting point. On the left, a realization of the noise is shown which is followed to the right by the residual texture.



(a) (b) (c) (d)

Fig. 3. Syntheses of a residual mammographic texture image: (a) a typical sample of a uniformly distributed white noise image used as a starting point for one synthesis; (b) original mammographic residual texture; (c) synthesis1; (d) synthesis 2.

5. SYNTHESIS OF THE MEAN BACKGROUND



(a) **(b)** **(c)**

Fig. 4. Models of the mean background. (a) sample mean-background extracted from a mammogram; (b) a model using a lumpy background; (c) a model using the steerable pyramid transform to synthesize the background.

In an earlier paper, we proposed to model the mean background as the lumpy background, a wide-sense stationary random process established for image quality assessment in medical imaging.[3] In later investigations backgrounds synthesised with the steerable pyramid transform more closely matched the sample than those generated by the lumpy background process. The new synthesized backgrounds are shown in Fig. 4.

6. A PROPOSED MATHEMATICAL PHANTOM

The synthesis of an ensemble of images $M_i(x,y)$ according to the described mathematical phantom can be established using an adaptive linear combination of realizations from the two model components: a realization of the mean background component denoted as $L_i(x,y)$ and a realization of the synthesized texture component denoted as $T_i(x,y)$. The resulting synthesized image will then be given by

$$M_i(x,y) = \beta\ L_i(x,y) + (1-\beta)\ T_i(x,y)\ , \qquad (1)$$

where β ranges from 0 to 1. Such a combination will allow us to span a wide range of tissue types with relative amounts of mean and textured backgrounds. We hypothesize that by such a combination, various tissue types as described by Wolfe for example can be synthesized.[15] On a more theoretical basis, one can also study a wide range of combinations of such backgrounds by varying β and the texture samples associated with each component. Such a framework may naturally find application to a wide range of complex backgrounds.

7. FIRST AND SECOND-ORDER STATISTICS

While the original mammogram image and the mean background are non-stationary random processes, the extracted residual texture-image appears stationary. In fact, while we do not know whether it is stationary, we shall assume such property based on perceptual estimation. Furthermore, it is important to note that the proposed synthesis framework, that matches first-order statistics of subband images, would yield artifacts while synthesizing a non-stationary random process as a consequence of inhomogeneities in the texture.[11] Therefore, the success in synthesizing a given texture sample yields insight into the stationarity property of the sample texture.

By construction, a sample and its synthesis have equal first-order statistics. The next level of description of a random field is its second-order statistics. Second-order statistics are fully described by the two-point probability density function (2P-PDF). For a stationary random process, one component of the 2P-PDF can be estimated by the co-occurrence of two greylevels for any two pixels separated by a fixed vector **d** in the sample image. Computations of components of the 2P-PDF as **d** varies are shown in Fig. 5 and 6 for the mammographic texture and a granite texture. For the original residual texture sample, Fig 5 shows that its 2P-PDF is extremely similar to that of a synthesis of that sample. Quantification of the similarity between two PDFs can be estimated by the root mean-square distance between the two functions and is given in Table 1 for various textures.

It is critical to note that this distance measure is only meaningful between functions describing textures whose first-order statistics have been matched. Therefore, we chose to match the first-order statistics of all textures to that of the residue image. The 2P-PDFs were then computed and the measure of distance computed. Fig. 6 shows the 2P-PDFs for a granite-texture sample and the same texture after the first-order statistics have been matched to that of the residual texture image. We note that first-order statistics play a key role in the shape of the second order statistics. It is a question of investigation weather or not the measure of distance between two 2P-PDFs heavily depends on the first-order statistics. Future work will further explore properties of 2P-PDFs and investigate models of detection in textured backgrounds using such statistics.

8. CONCLUSION

We presented a framework for texture synthesis and application to mammographic breast tissue samples. A key component to the successful synthesis of such complex backgrounds was to decompose the radiologic tissue sample into a slowly, varying mean-background and a finer scale texture. Each component was successfully synthesized independently. Finally, we presented a complete analysis of the second order statistics of the residual texture image that prompted us with stimulating future work on texture characterization.

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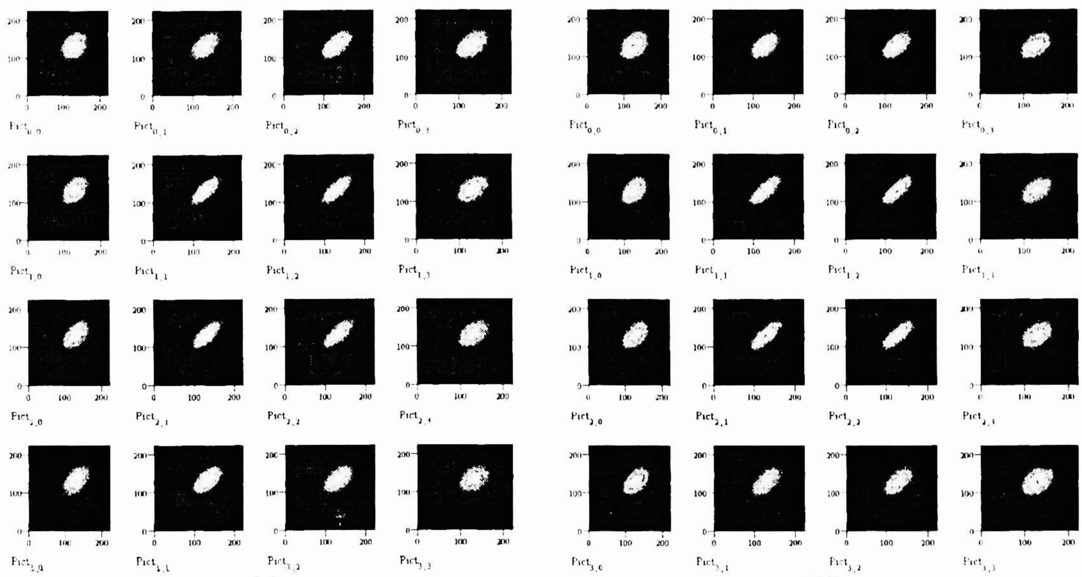
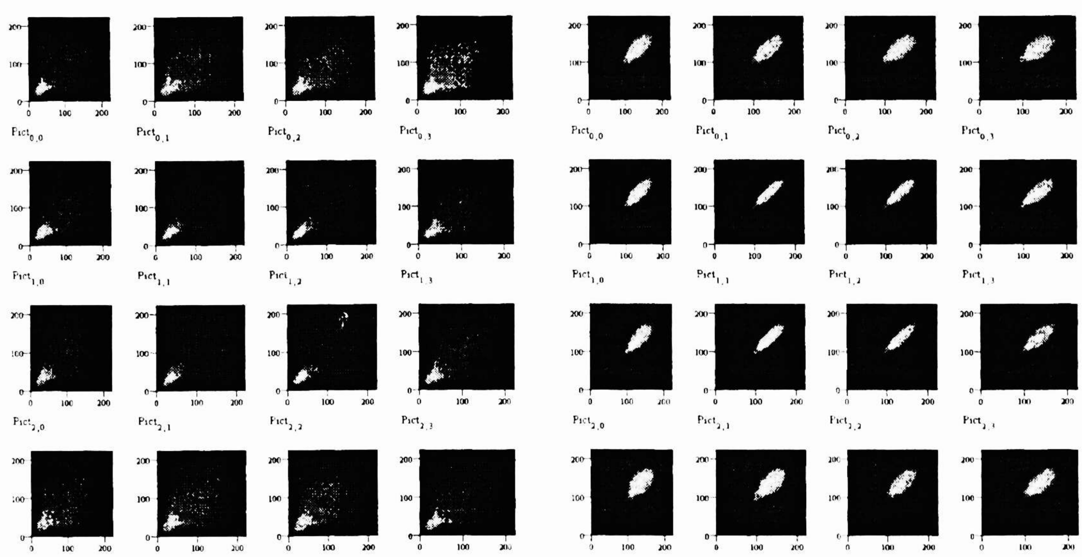


(a) (b)

Fig. 5. The two-point probability density functions for (a) the residue texture image; and (b) a synthesis of the residual image. Each function within an image corresponds to a different value of the vector **d**. From left to right, **d** equal (-5,5); (-3,5); (3,5); (5,5). From top to bottom **d** equal (-5,5);(-5;3);(-5,-3);(-5,5).



(a) (b)

Fig. 6. The two-point probability density functions for (a) a granite texture image before matching of the first-order statistics to that of the residue image; and (b) after matching of the first-order statistics to that of the residue image. The values of **d** are the same as described in Fig.5.

Textures	Distance
Mammo-syn1 to residue	0.618
Mammo-syn2 to residue	0.621
Mammo-syn3 to residue	0.623
Mammo-syn1 to Mammo-syn2	0.538
Granite1 to residue	2.370
Granite2 to residue	3.386
Granite3 to residue	2.487
Grass to residue	2.438

Table1. Values of the RMS distance between two 2P-PDFs.

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