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THE EFFECTS OF SAMPLING RATE ON THE TEXTURE SEPARABILITY OF ULTRASOUND IMAGES

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ABSTRACT

Ultrasound machine has been a useful diagnosis tool for several decades, and many researches tried to use computerized algorithms to help physicians diagnose diseases according to the ultrasound texture patterns. However, the effects of sampling format and the sampling rate on the texture feature were not treated properly. In this paper, the authors try to evaluate the effects of the scan conversion done at imaging stage and the sampling rate used at the texture feature extraction stage. They demonstrate the indispensability of considering sampling format and sampling rate according to the feature used, and their proposed method would improve the separability of texture feature for coarse and homogeneous ultrasound images.

1. INTRODUCTION

In the past decades, medical ultrasound has been a useful clinical tool for diagnosing the diffuse parenchyma liver diseases, and the visual properties of ultrasonic textures usually used by the physicians are “homogeneity” and “coarseness”. Many literatures [1-2] about computer-aided diagnosis tried to help physicians discriminate the ultrasound images of abnormal tissue from those of normal tissue; however, because of the difficulty of transferring qualitative homogeneity and coarseness into quantitative measurement, the visual properties were not used by those literatures, and the proposed methods always suffer inaccuracy somehow. Most of the reasons leading to the inaccuracy are the effect of scan conversion, and without considering the sampling rate for each feature.

In order to get large area of field of view, curved-linear mode is the most common choice of the probes. It is the nature of the curved-linear scanning, which transforms the acoustic scan lines to a raster format, and the transforming procedure is called “scan-conversion”. It is well-known that scan-conversion distorts the structural information and the statistical distribution of the texture pattern in the ultrasound image [3-4], even without considering the diffraction effect of beam-forming. For computer-aided diagnosis, texture features are very susceptible to the change of characteristics of texture primitives, such as the shape and intensity contrast; consequently, the performances of the features of the same primitive vary with the depth and orientation relative to the intersection of scan lines. Fig 1 shows two regions in different depths of a homogeneous ultrasound image, in which the scan conversion distorts the textural pattern of speckle.

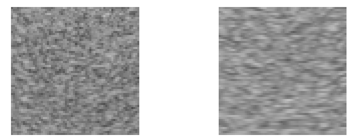

Fig 1: Textures in different depths of a homogeneous ultrasound image. The left has a shorter imaging distance than that of the right one.

Besides the effect of texture distortion by the scan conversion, texture features are also sensitive to the texture scale. For example, adjusting the setting of ultrasound far range (the maximal imaging distance) does not affect the visual judgment much; physicians could still classify the textures as coarse or homogeneous. But it influences the result of computed feature values very much. In Fig 1, the scan conversion enlarges the scale of speckle in deeper depth, and the computed texture features would take these two regions as different texture patterns; however, the two regions should have similar visual properties when they are in the original positions of the homogeneous ultrasound image.

In this article, the authors try to analyze the effects of scan conversion and the scale on texture features. They propose a method, called “back-scan conversion”, to adjust the sampling format as well as the sampling rate of ultra-sound images, and then use those images of homogeneous sponges and cirrhotic livers to compare the efficiency of back-scan conversion with considering the sampling rate. Based on clinical experience, the texture of cirrhotic livers should be coarser than that of the reference (sponge here) [5]. Fig 2 shows two typical experimental samples used in this study.

2. METHODOLOGY

To realize the effect of the sampling format on texture features, we converted ultrasound images in polar coordinates which has sampling points on polar grids only, and adjusted the sampling rate. The proposed method, back-

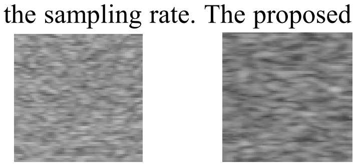

Fig 2: Typical experiment samples. The left is sponge, and the right is liver cirrhosis.

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scan conversion, first convert the raster format into the polar format with over-sampling, and next down-samples the polar format created previously for the desired sampling rate. After the back-scan conversion with different sampling rate of the ultrasound images of homogeneous sponges and cirrhotic livers, one computational feature for textural coarseness was used to analyze these images and the original images.

A. Back-scan conversion

Let $f(k,l)$ be the image value of any pixel at (k,l) in the raster grid, and $g(r,\theta)$ the image value at (r,θ) in the polar format corresponding to (k,l), where r and θ are the depth and angle from (k, l) to the intersection of scan lines (as O depicted in Fig 3). By geometrically transformation,

$$g(r,\theta) = f\left(\sqrt{(k+R)^2 + l^2}, \tan^{-1}\frac{l}{k+R}\right),$$

where R is the shortest distance between O and any location in the echo area, such as the length of $\overline{OA}$ in Fig 3.

However, as k, l, r, and θ are all integers in digital imaging system, it is impossible to calculate integral r and θ using integral k and l. So we used bilinear interpolation with the 4 pixels, in the raster format, nearest to (k', l') to calculate the image value at (r,θ), where

$$k' = r\cos\theta \text{ and } l' = r\sin\theta.$$

That is, (k', l') in the raster format according to integral (r,θ) in the polar format was calculated at first. Afterward, the 4 pixels nearest to (k', l') with integral coordinates in the raster format were used to interpolate the image value at (k', l'). In order to prevent the loss of information from converting the raster format into the polar format, the images were over-sampled during the conversion.

The method mentioned so far only removes the dependence of depth and orientation caused by scan conversion, but dose not solve the problems of feature sensitivity to scale. Besides, over-sampling should not affect the performance of the texture features. Therefore, it is necessary to deal with the sampling rate after the back-scan conversion.

B. The Sampling Rate

The number of samples per speckle is used to quantify the sampling rate, and the full width at half maximum (FWHM) of the autocovariance function of the ultrasound image is a statistical measure of mean speckle size. Homogeneous speckle is required for measuring the FWHM of an ultrasound scanner. Images of fine sponges immersed in water are chosen to serve as the source of homogeneous speckles. The FWHM can be measured using the axial and lateral autocovariance functions of the over-sampled ultrasound sponge images mentioned above, respectively. The axial FWHM might be treated as the axial speckle size, and the lateral FWHM as the lateral speckle size. Then the over-sampled ones were down-sampled with proper sampling spacing along the axial and lateral directions. The sampling spacing is in proportion to the reciprocal of the sampling rates; namely, the over-sampled images were down-sampled according to the axial sampling rates in the axial direction, and by the lateral sampling rates in the lateral direction, respectively. Consequently, the down-sampled images must meet the requirement that the axial resolution is equal to the lateral one in the processed ultrasound sponge images. These sampling rates used above were also used to down-sample the ultrasound cirrhotic liver images.

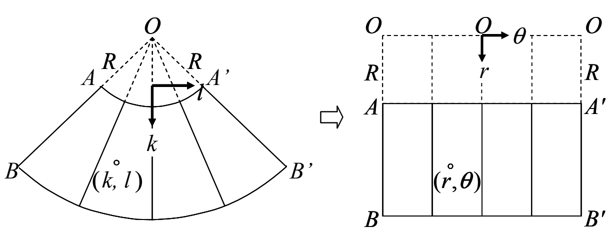

Fig 3: Back-scan conversion. The left is the raster format, and the right the polar format.

C. Feature of Coarseness

The textural features proposed by Amadasun are chosen for texture analysis [6], and these computational features relate highly to visual properties. One of the proposed measures is used for evaluating the effects of sampling format and sampling rate on the coarseness of ultrasound texture, which is

$$f_{\cos} = \left[\varepsilon + \sum_{i=0}^{G_h} p_i s(i)\right]^{-1}, \qquad \text{(Eq. A)}$$

where p_i is the probability of occurrence of gray level i, excluding those in the peripheral regions, G_h is the highest image value, and ε is a very small number to prevent $f_{\cos}$ being infinite.

These features in [6] are based on a vector $s(i)$, called neighborhood gray-tone difference matrix (NGTDM), which is composed of local variations. Let $f(k,l)$ be the image value at pixel (k,l), the average gray level over the neighborhood centered at the (k,l) but excluding (k,l), is defined as

$$\overline{A_{kl}} = \frac{1}{W-1}\left[\sum_{m=-d}^{d}\sum_{n=-d}^{d} f(k+m, l+n)\right], \qquad (m,n) \neq (0,0),$$

where d specifies the neighborhood size and $W = (2d+1)^2$.

Let $N_i = \{j\}_{j=1}^{J}$ be the set of all pixels at (k_j, l_j) with gray level i (except in the peripheral region), and J is the amount of entities in N_i. $\overline{A_j}$ is the average gray level over the neighborhood centered at the (k_j, l_j). The ith entry in the NGTDM is defined as

$$s(i) = \begin{cases} \sum_{j=1}^{J} \left| i - A_j \right|, & \\ 0, & \text{otherwise.} \end{cases}$$

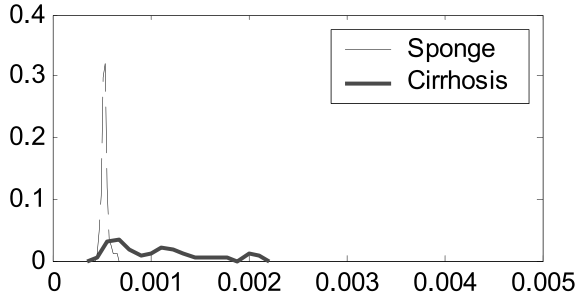

Fig 4: Histograms of feature coefficients of the raster format

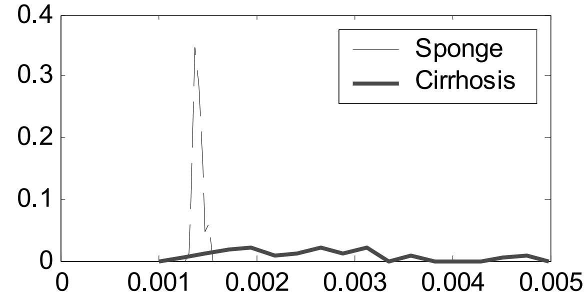

Fig 5: Histograms of the polar format. The sampling rate is 2 samples per speckle.

In an ultrasound image, speckle is inevitable and texture patterns with high spatial frequency are usually treated as speckle; therefore, other texture patterns are considered coarser and have primitives with larger areas. In a coarse textures, there would be small differences between the image value at (k,l) and the average intensity over the neighborhood, $\overline{A_{kl}}$, leading to the values of $s(i)$ in the NGTDM small. Hence the summation of NGTDM over all image pixels would give an index of coarseness. Moreover, as $s(i)$ is the mean deviation of pixel intensity from the neighborhood average intensity, it should be normalized with its occurrence probability. Small value of $f_{\cos}$, from Eq. A, means the significant spatial rate of change in intensity, and it resembles to the characteristics of speckle; while large value of $f_{\cos}$ corresponds other coarser texture patterns.

3. EXPERIMENT AND RESULTS

A Toshiba SSA-700 ultrasound scanner with a curved-linear transducer of 3.5 MHz was used. Three pieces of homogeneous sponges and 20 patients with liver cirrhosis were scanned with the same far range, and the TGC was adjusted to make the images visually comfortable. The sponges were scanned beneath the water level, and the air was squeezed out of the sponges as far as possible.

The regions of interest (ROIs) of each ultrasound images were selected by the following criteria: (1) the area contains no artifacts such as tissue boundary and TGC contrast; (2) the area size is as large as possible. All the images, including which in the raster format and which in the over-sampled polar format, of the sponges and liver cirrhosis, were tackled. Then the ROIs of the over-sampled polar format were down-sampled with three kinds of sampling rates: one sample per speckle, 2 samples per speckle, and 4 samples per speckle of the over-sampled sponge textures, along the axial and lateral directions. After the ROI selection and the down-sampling, the textural feature mentioned in the last section was used to measure the coarseness of the ultrasound sponge textures and the liver cirrhosis textures, in the polar format and the raster format.

The textural coarseness feature, $f_{\cos}$, was used to demonstrate the effect of sampling format, and its parameter d was set as 1 here. Fig 4 depicts the distributions of feature coefficients of the raster format. Let the threshold be $\mu_s + 3\sigma_s$, where μ_s and σ_s are the mean and standard deviation of the feature coefficient of sponge, respectively. The false negative to detect liver cirrhosis is about 15%, and the false positive is about 3%. However, if the down-sampling rate is adjusted to be 2 samples per speckle, it is observed that the separability between the homogeneous sponges and the cirrhotic livers is improved, as depicted in Fig 5. Let the threshold also be $\mu_s + 3\sigma_s$, the false negative to detect liver cirrhosis is about 8%, and the false positive is about 1%.

It is obvious that the separability of other sampling rates is not as good as that with 2 samples per speckle, even worse than that in the raster format. Mahalanobis distance is used to demonstrate the separability (dissimilarity) between the feature values of liver cirrhosis and that of the reference (sponge), and it may be treated as a standardized distance. The value of Mahalanobis distance being unity means that the test event locates at the position of one standard deviation from the mean of the reference cluster. The larger it is, the more far away from the reference. In the case of

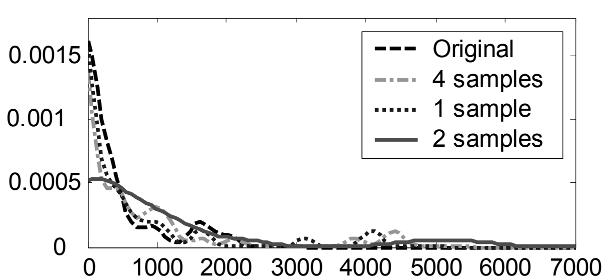

Fig 6: Histograms of Mahalanobis distances with respect to different sampling rates.

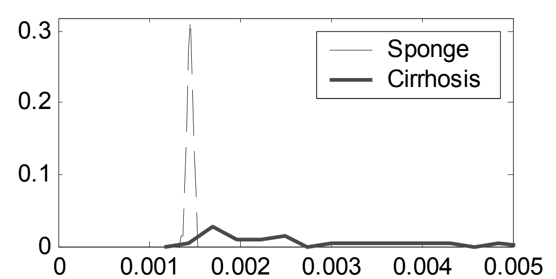

Fig 7: Histograms of the polar format. The sampling rate is 2 samples per speckle. The far range is 6 cm.

diagnosing liver cirrhosis, the feature value of cirrhotic liver should be much larger than one. Fig 6 depicts the histograms of Mahalanobis distance with respect to different sampling rates, and it is observed that the sampling rate of 2 samples per speckle has the best separability. Changing the scanning far range does not change the phenomena mentioned above. Fig 7 shows the histograms of the polar format, in another far range, with sampling rate of 2 samples per speckle. The far range in Fig 4 to 6 is 8 cm, while the one in Fig 7 is 6 cm.

The back-scan conversion and different sampling rates of course affects the characteristics of the sponge images used as the reference. The smaller intra-distance stands for the better performance of clustering a fixed texture pattern. The intra-distance here is defined as σ / μ, where σ and μ are the standard deviation and the mean of the feature coefficient. Table 1 shows the intra-distances of the feature coefficient of the sponges in the different sampling formats. It shows that the intra-distance with sampling rate of 2 samples per speckle has the almost smallest value, except that with sampling rate of one sample per speckle in 8 cm, which might be ignored for the under-sampled case.

	R	P_2	P_4	P_1
6 cm	0.0409	0.0216	0.0229	0.0335
8 cm	0.0658	0.0323	0.0339	0.0313

Table 1: The intra-distances of the feature coefficient of ultrasound sponge images with different far ranges, where R denotes the raster format, P_1, P_2, and $P_4$the polar format with sampling rate of one, 2, and 4 samples per speckle

4. DISCUSSION

From the result of the raster format, as shown in Fig 4, the feature of coarseness [6] is a good texture feature to discriminate the coarse ultrasound images from the relatively homogeneous ones. Yet there is about 18% of area overlaps, and this is due to the various resolutions in many directions caused by the scan conversion.

It is useless to transfer the raster format into the polar format without considering the scale, as shown in Fig 6. For the feature extractions in the ultrasound images, the axial and lateral resolution must be the same for the prominence of speckles. It is based on the hypothesis that making the axial and lateral resolutions the same would lead to the isotropy of features for speckles; in other words, considering with the optimal sampling rate for a texture feature, the proposed method would separate the isotropic characteristics of speckles from other textural patterns.

The optimal sampling rate should be considered with the characteristics of textural feature case by case, and is related to the speckle size. This is because that ultrasound images suffer from speckles severely such that speckle size might be treated as a reference standard. For the textural coarseness feature, as its window parameter W was set as 3, the optimal sampling spacing being half the speckle size means that the window would cover a speckle completely, and this is the Nyquist sampling rate. However, because of the randomness of speckle and discrete computation, higher sampling rate does not have better performance, as shown in Fig 6 and Table 1. Of course, if W is set by other values, the optimal sampling rate varies.

There are some other aspects should be considered concurrently in the proposed method here. One is the interpolation which might induce the distortion of the polar format and then causes the inaccuracy of sensitive texture features. The image processing used by the ultrasound machine also results in the same problem. If the far range is large, as the limitation of the number of the pixels on the screen, much of the locally detailed texture information is lost, which leads to the difficult of separating speckles from other visually coarse tissue patterns in computation.

5. CONCLUSION

Texture features are very susceptible to the textural characteristics, and their usage for ultrasound images, for the most part, is always affected by scan conversion and speckles. In this paper, the authors demonstrate that a method, called "back-scan conversion", can reduce the effect of texture distortion caused by scan conversion. They also discuss the importance of sampling rate, which is related to the speckle size, for the feature extraction.

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