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Unified Approach to the Detection and Classification of Speckle Texture in Diagnostic Ultrasound

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Abstract

Second order statistics have been derived for the speckle in diagnostic ultrasound that arises from diffuse (incoherent) scattering in the presence of distributed and organized specular (coherent) scattering. They serve as the basis for a three-dimensional feature space in which tissue textures can be classified. The covariance matrix of the measurements in this space is a generalization of the speckle spot number or sampling concept that arises in the study of signal or lesion detectability.

Introduction

The statistics of the texture of certain classes of back-scattered ultrasonic images (1-3) have been found to be similar to those that characterize the texture of laser speckle (4,5). In the laser case where the intensity is read out, exponential and modified Rician distributions describe the fully developed speckle pattern and its modification in the presence of a carrier or distributed specular signal. In the ultrasound case where the envelope (or square root of intensity) is read out, Rayleigh and Rician distributions describe the analogous textures. In this paper we present second order statistics of the imaged texture that can be used in these cases as a three-dimensional signature of the object or tissue texture. We then use the variability in these measures to derive the covariance matrix in the 3D feature space and show how it can be used to test for the significance of a change in these measures within a region of interest (ROI) that can roam through an image. In the following paper we shall present the diagnostic context for this analysis and describe its clinical implementation.

Second Order Properties of Detected Intensity

The second order measures that we have found fruitful for analyzing speckle texture are the autocorrelation function and its Fourier transform, the speckle power spectrum. We have derived them, using the analytical apparatus of Middleton (6), for the case of either envelope detected or intensity detected signals; however, we have found that the straight-forward study of the intensity signal can lead to the same results (7). We shall therefore review the results for intensity in this section.

When the speckle pattern arises from the interference of many statistically independent phasors, whose amplitude and phase are themselves statistically independent, and whose phases are uniformly distributed over $0 - 2\pi$, then the real and imaginary parts of the

resultant interference pattern, g_r and g_i , are also independent and follow a joint, zero mean, Gaussian probability distribution with equal variances (4). This distribution is commonly known as a circular Gaussian distribution, and the underlying scattering is referred to as diffuse scattering. If we designate the phasor at position 1 as $g_1 = g_{1r} + i g_{1i}$ with intensity $I_1 = |g_1|^2$, etc., then we may use the Gaussian moment theorem (8) to reduce quartic forms to quadratic forms and show that

$$\langle I_1 I_2 \rangle = \langle (g_{1r}^2 + g_{1i}^2)(g_{2r}^2 + g_{2i}^2) \rangle = I_1 I_2 [1 + |\rho|^2] \quad (1)$$

where ρ , the complex coherence factor, is

$$\rho = \langle g_1 g_2^* \rangle / (\langle I_1 \rangle \langle I_2 \rangle)^{1/2}$$

In particular, when $I_1 = I_2 = I_d$, i.e., the diffuse scattering intensity is independent of position, we have simply

$$\langle I_1 I_2 \rangle = I_d^2 [1 + |\rho|^2] \quad (2)$$

By setting $\rho = 1$ and $\rho = 0$ we find the mean square and the squared mean respectively, $\langle I^2 \rangle = 2I_d^2$, $\langle I^2 \rangle = I_d^2$ and take the difference to find the variance, I_d^2 . The ratio of the mean to the root of the variance is designated SNR_0 and has the value unity in this case. From the nature of the assumptions we refer to this as the diffuse or Rayleigh scattering condition.

The next level of complexity is achieved by adding a constant level of spatially distributed specular scattering I_s to the previous diffuse scattering intensity I_d . This can be treated without loss of generality by writing

$$g_1 = (g_{1r} + \mathcal{R}) + i g_{1i}, \quad g_2 = (g_{2r} + \mathcal{R}) + i g_{2i}$$

where $\mathcal{R} = \sqrt{I_s}$. Again, using the moment theorem and some algebra we obtain

$$\langle I_1 I_2 \rangle = I_d^2 [1 + |\rho|^2] + 2I_d I_s + I_s^2 + 2I_d I_s \rho \quad (3)$$

As before the mean square and the squared mean may be obtained by setting $\rho = 1$ and $\rho = 0$ respectively,

$$\begin{aligned} I^2 &= (I_d + I_s)^2 + I_d^2 + 2I_d I_s \\ I^2 &= (I_d + I_s)^2 \end{aligned} \quad (4)$$

and from the difference the variance i.e, the Rician variance, is

$$\sigma_R^2 = I_d^2 + 2I_d I_s = \text{var}_R \quad (5)$$

In this case the value of SNR_o , the mean to standard deviation, may be written in terms of $r = I_s/I_d$ as

$$\text{SNR}_o^2 = (1+r)^2 / (1+2r) \geq 1 \quad (6)$$

We refer to this case as Rician, after S.O. Rice who first considered the appropriate probability density function (9). The same function was also derived independently by D.O. North at about the same time (10).

Finally, if the distributed specular scattering is a function of position, we may obtain the general case by letting

$$g_1 = (g_{1r} + \mathcal{R}_1) + i(g_{1i} + \mathcal{I}_1), \text{ etc.}$$

where (g_{1r}, g_{1i}) represents the diffuse scattering, constant with position, and $(\mathcal{R}_1, \mathcal{I}_1)$ the specular scattering, now a, function of position. Again as above we obtain

$$\langle I_1 I_2 \rangle = I_d^2 [1 + |\rho|^2] + 2I_d I_s + \langle I_{s1} \otimes I_{s2} \rangle + 2I_d \langle \mathcal{R}_1 \otimes \mathcal{R}_2 + \mathcal{I}_1 \otimes \mathcal{I}_2 \rangle \rho = [I + II] + III + IV + V \quad (7)$$

If we set position $x_2 = x_1 + x$, and average over x_1 then terms IV and V can be interpreted as average autocorrelations, i.e., the average over x_1 of the autocorrelation of lag x . This result, like Eq.(3), contains a cross-term coupling diffuse and specular scattering contributions. This cross term in ρ effectively broadens the correlation cell of Eqs. (1) and (2) which has only the narrow shape $|\rho|^2$. We refer to this as the generalized Rician case.

The case of structure in the diffuse scattering strength has been treated by Lowenthal and Arsenault (11) and can be directly incorporated into the present analysis by considering I_d as the average diffuse scattering strength. The structure in I_d will show up as an additional term requiring a slight modification of the interpretation given above.

The starting point for the classification of tissue texture from the ultrasonic speckle texture is the recognition that this equation for the autocorrelation of detected intensities can be used

to derive estimates of I_d , I_s , and $\text{var}(I_s)$ from measured autocorrelation functions. This is most easily appreciated by taking the Fourier transformation of Eq (7) to obtain the power spectrum:

$$W(f) = \delta(f) [I_d + \tilde{I}_s]^2 + I_d^2 P \otimes P + \langle \Delta \tilde{I}_s^2(f) \rangle + 2I_d P [\overline{\mathcal{R}}^2 + \overline{\mathcal{J}}^2] + 2I_d P \otimes \langle [|\Delta \tilde{\mathcal{R}}(f)|^2 + |\Delta \tilde{I}(f)|^2] \rangle \quad (8)$$

Where

$$\begin{aligned} \rho \langle \rangle P \\ I_s \langle \rangle_s + I_s \\ \mathcal{R} \langle \rangle \mathcal{R} + \tilde{\mathcal{R}}, \text{ etc.} \end{aligned}$$

and

$$\otimes \langle \rangle \text{ correlation}$$

The tilde mark over a symbol means the Fourier transform of the corresponding spatial domain function. The first three terms are common to this result and the Rician result discussed above. The fourth term is the power spectrum of the variable component of the specular scattering strength. Its integral over frequency is the variance of I_s , $\text{var}(I_s)$. The fifth and sixth terms are the cross terms between the diffuse scattering intensity and the steady and variable components respectively of the specular scattering amplitude. Their total integral over frequency is the complete Rician cross term, which when lumped with the integrated third term is the Rician variance introduced earlier.

If the specular structure in the scanned object is relatively narrow band, i.e., more or less regularly spaced architecture, then its variance can be readily identified with $\text{var}(I_s)$ of the previous expression and it will be manifested as peaks in the frequency domain. This is demonstrated in the simulation of Fig. 1. When this contribution of the narrow band structure to the speckle noise power is removed, the remaining noise cloud is the Rician variance $I_d^2 + 2I_d I_s = \text{var}_R$. We have achieved this separation by a stripping technique discussed in the next paper. By simply measuring, finally, the square of the mean scattering intensity $(I_d + I_s)^2$, a pair of simple quadratic equations become available for solving for I_d and I_s . These values, together with $\text{var}(I_s)$ constitute a three component description of the sample under study. A fourth component, d , is frequently available as the characteristic dimension of the organized specular scattering.

If the specular scattering structure is broad band, on the other hand (isolated blood vessels, for example), the stripping technique will not work since the broad spectrum is indistinguishable in shape from the Rician noise cloud. However, it is frequently possible to remove such structures by matched filtering or cross-correlation techniques in a preprocessing stage. This is also exemplified in the next paper.

From Lesion Detection to Tissue Characterization

In principle, then, for quasi-regular structure it is possible from measurements of the signal power spectrum and its subsequent partitioning to estimate the values of I_d , I_s , and $\text{var}(I_s)$ in a region of interest (ROI). We now discuss the precision of such estimates and its effect on the discriminability of two such ROIs.

The discriminability of two ROIs based on texture measures is a generalization of the problem of the intrinsic detectability of a suspected lesion within an ROI against a speckle background. We begin, therefore, by considering the task of detecting a lesion that represents a small change $I_d = I_{d1} - I_{d2}$ in the diffuse scattering strength over an area A compared to a background with uniform scattering strength I_{d2} . In reference (12) we review some treatments of this problem in the literature (see, e.g., 1, 13) and present a derivation from signal detection theory that the signal-to-noise ratio (SNR) for this detection task is given by

$$\text{SNR}^2 = \frac{(\Delta I_d)^2}{I_{d1}^2 + I_{d2}^2} M, \quad (9)$$

where

$$M = A/S_C$$

and

$$S_C = \int \frac{C_I(\Delta x)}{C_I(0)} d(\Delta x).$$

M is the effective number of speckle cells over the area A , and the effective size of the speckle cell is the area under the normalized autocovariance function of the speckle intensity C_I . This relation indicates, for example, that to detect a 10 percent change in diffuse scattering intensity an area embracing several hundred expected speckle cells is required. This qualitative statement is refined in the reference.

If the scattering strength is made up of two components, namely a diffuse scattering component and a specular scattering component, then the SNR is

$$\text{SNR}^2 = \frac{(\Delta I)^2}{\text{var}_{R1} + \text{var}_{R2}} M, \quad (10)$$

where the Rician variances $\text{var}_{Ri} = I_{di}^2 + 2I_{di}I_{si}$. The number of cells over the test area, M' , is similar in concept to the value M just introduced; the actual value will generally be smaller since the Rician cell size is larger than the Rayleigh cell size, as mentioned above. This result reduces to the previous expression when $I_{si} = 0$.

In the previous examples we wished to discriminate a lesion, or any region of interest (ROI), from the surround based on the total scattering intensity. It may be of even more interest to discriminate two ROIs based not on their total scattering strengths but on a signature made up of their separate, components of scattering strength I_d , I_s , in two dimensions, say, or I_d , I_s , and $\text{var}^{1/2}(I_s)$ in the more general three dimensional case introduced above. The solution to this problem is based on the three piece partitioning of the noise variance discussed at that point. Then the problem is intrinsically three-dimensional, the estimates become coupled, and a 3D covariance matrix W is required. This matrix is a generalization of the concept of speckle number that arose in the one dimensional tasks just presented. The SNR for distinguishing the feature difference s between two ROIs can then be written

$$\text{SNR}^2 = \Delta s^t W^{-1} \Delta s.$$

Here

$$\begin{aligned} s^t &= (s_1, s_2, s_3), \\ s^t &= (t - b, p - b, b), \\ \text{and } W &= \langle \Delta s \Delta s^t \rangle \end{aligned}$$

and we use the measured parameters

$$\begin{aligned} t - b &= \text{var}_R + \text{var}(I_s) \\ p - b &= \text{var}_R \\ b &= (I_d + I_s)^2. \end{aligned}$$

Although $(t-b)$, $(p-b)$, b are usually taken from the speckle power spectrum (see following paper), in principle they may be identified as ordinates on the measured autocorrelation function (see Fig 1). The expected covariance matrix of the measurements may then be estimated from various covariances of points on the autocorrelation function. These covariances are immediately related to fourth order moments estimated for the ROI. For example, we would have for $\text{cov}((t-b), (t-b))$

$$\text{cov}(s_1, s_1) = \langle \sum x_i^2 \sum x_j^2 \rangle / n^2,$$

where x_i is the value at position i in the image, less the mean value over the ROI, and the region of interest contains n points down range. The estimation must be carried out first along the range direction, and then across the range direction.

Such expressions are generalizations of the speckle cell size mentioned above. In both cases the number of degrees of freedom available for estimating means, variances, etc., is the number of sample points degraded by a correlation cell size; i.e., the number of correlation cells contained in the sample area is only equal to the number of sample points in the case of

uncorrelated, i.e., delta function, speckles. For the case of estimating or discriminating means, considered earlier, the cell size is obtained from integrating the second moment, or autocorrelation function. For the case of discriminating variances, considered here, the cell size is obtained from averaging, or integrating, products of autocorrelation functions.

These products of autocorrelation functions are fourth order moments. It is tempting to reduce these fourth order moments to more transparent second order moments using the well-known Gaussian moment theorem. However, extensive numerical investigations of this question demonstrated the inadequacy of this theorem in the case of Rician statistics for intensity. In the latter case the fourth central moment (kurtosis, for short) was close to seven whereas in the Gaussian case it is equal to three, and the direct computation of the covariance led to results about three times the results obtained using the moment theorem. In fact, we often obtained results for the covariance in this case in the order of unity; this may be compared with results using the moment theorem in the order of the speckle cell size (2 - 10 pixels) divided by the number of sample points or pixels used (100). This was due to non-stationarity as well as to the non-Gaussian statistics. In practice, we settled on using the direct computation of the fourth order moment along the range direction, or data vector direction; we found it reasonable to use the moment theorem to estimate the covariance in the cross range direction, that is, the direction perpendicular to the data vectors. We are continuing our investigations of this issue using simulated images.

Practical estimates of the parameters (t-b), (p-b), b are approximately Gaussian distributed/so the distribution of SNR^2 is chi square with three degrees of freedom (14), even though (t-b), (p-b), b are not independent. From this probability distribution, then, we may express the confidence that two regions of interest represent populations with different average scattering properties.

Examples

We now present examples from our simulation studies and from a clinical study.

We simulated images for which $I_d = 1$, I_s ranged in roughly equal steps between 1 and 2, and $\text{var}(I_s) = 0$. They are shown in Figure 2. (The images are shown from upper left to lower right, in the order in which the simulations were generated, with increasing values of I_s .) We then estimated the values for the 3D feature vector s by partitioning the measured power spectrum, and calculated the covariance matrix using the basic technique outlined above. (Although this seems to be a two-dimensional problem, it was carried out in three dimensions since it was necessary in practice to remove low frequency trends from the images and to test for the significance of the residual non-Rician variance. The chi square value was obtained from the SNR^2 calculated from Eq. (10); the corresponding probability p that a given texture pattern came from the same population as the prototype given in the upper left of the figure is given under each of the patterns. It can be seen that the statistical ranking of the patterns by this algorithmic method is much more sensitive than the ranking any human observer might be capable of. (The limitations of the human observer for such tasks are discussed in ref. 15).

Finally, we present a clinical example. We analyzed an ultrasound scan of a liver which was known from a CT scan to contain a lesion that could not be called from the clinical examination of the ultrasound scan. Two “normal” regions of the liver were also analyzed using the methods given above. One of the normal regions was designated as a baseline or prototype normal. The other one then gave a high probability or p value of being from the same population, as shown in Table 1. On the other hand, a scan of the lesion region gave the probability as given under region 2 in the table, that is, significantly different from the normal texture.

Two scans of another region, known from a small encapsulating border also to be a lesion, gave p values as given under region 1 in the table, that is, not significantly different from the normal texture. This latter region is thought to have histological structure similar to normal tissue, and to be distinguishable principally from the border or boundary of the lesion.

Conclusion

We have presented a brief outline of a technique based on a generalization of Rician statistics that permits the estimation of two, three, or four parameters in a feature space based on underlying physical scattering properties, and have indicated how signal detection theoretic techniques may be generalized to address the problem of grading, or classifying with confidence, differences in measured values of these 3D features. A schematic summary is given as Fig. 3. The next paper exemplifies all of these principles in the context of clinical ultrasound images. We are currently integrating the approach into statistical pattern recognition algorithms for automatically clustering tissues on clinical scans.

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Fig 1.

(Left) Autocorrelation function for simulated Rician speckle with single frequency structured specularity. Labels are value at the origin (t), asymptotic value or squared mean (b), maximum structured correlation (p), and characteristic dimension (d). (Right) Corresponding speckle power spectrum showing Gaussian fit to Rician “noise cloud” which integrates to the Rician variance, and peak corresponding to structured specularity ($f \cong 0.06$) which integrates to $\text{var}(I_s)$. Low frequency peak is due to long range trends in the data which must be removed by pre-processing.

Fig. 2. Simulated Rician images for which $I_d = 1$ and I_s ranges in roughly equal steps between 1 and 2, upper left to lower right. Value of p is chi square probability that the given sample comes from the same population distribution as the prototype at upper left.

Fig. 3. Schematic summary of stages leading from digitization through partitioning of the spectrum, labeling ROIs as points in a 2, 3, or 4D space, to diagnosis (Dx) by detecting differences in ROI features from background features, or by natural clustering to segment the image.

Table 1
Texture discrimination in clinical B-scans

ROI		P
non-lesion (background)	1	reference
	2	0.93
Lesion 1	3	0.80
	4	0.65
Lesion 2	5	<0.001