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Speckle Detection in Ultrasonic Images Using Unsupervised Clustering Techniques

Arezou Akbarian Azar, Hasan Rivaz, and Emad Boctor

Abstract— **In ultrasonic images, identification of speckled regions helps to estimate probe movement as well as improve performance of algorithms for adaptive speckle suppression and the elevational separation of B-scans by speckle decorrelation. By tracking FDS patch displacements over time we can calculate strain and detect tumor location. Previous studies for speckle detection were based on classification techniques which estimated parameters of the statistical distribution which were based on observation data and ultrasound echo envelope signal. However, in this study, we proposed a new combination of statistical features which were extracted from the ultrasound images and explored their properties for the speckle detection. These features were used as inputs to the unsupervised clustering algorithms for the speckle classification. We used five different types of unsupervised techniques and compared their performance by feeding different combinations of the statistical features. In order to quantitatively compare statistical features and classification methods, as ground truth, we used simulations of cyst and fetus ultrasound images which were generated using Field II ultrasound simulation program[1]. Initial results showed that by combining two statistical models (K and Rayleigh distributions) we can get best speck detection signatures to feed unsupervised classifiers and maximize speckle detection performance.**

Index Terms— **Ultrasound, Speckle detection, speckle tracking, pattern classification, unsupervised clustering, segmentation.**

I. INTRODUCTION

B-SCAN ultrasonic images unlikely carry unlikely images by scattering of ultrasound beams backed from structures within the body organ that is being scanned. Two major types of scatterings are diffused and coherent scatterings. Diffuse scatterings are caused when there are a large number of scatterers is with random phase within the resolution cell of the ultrasound beam and causes speckles in the reconstructed image; whereas the e coherent scattering arises when the scatterers in the resolution cell are in phase and causes light or dark spots in the image. Rayleigh distribution is the most common statistical model for the envelope signal and assumes that a large number of scatterers per resolution cell exist. However in some ultrasonic imaging fields such as echocardiography, Rayleigh distribution fits to reflect properties of reflections from blood but fails with complex structures such as myocardial tissue [2].

The K distribution , on the other hand, was initially designed for the envelope signal [3] and have been proposed to model different kinds of tissue in ultrasound envelope imaging [2, 4-6]. This distribution also has the advantage to model both fully and partially developed speckle. The first-order envelope statistics have been thought to follow a Rayleigh distribution, but recent work has shown that more general models, such as the Nakagami, K, and homodyned K distributions better describe envelope statistics [7-9].

With the current digital ultrasound imaging, the radio-frequency (RF) signal has gained more interest as it may contain more information than the envelope echo. When there are a large number of scatterers per range cell it yields Gaussian statistics for the RF signal, but the statistics of the RF signal in the case of partially developed speckle don't follow the Gaussian distribution. Therefore, , In this study to model statistical behavior of the RF data, we used K distribution framework as they provide a reasonable tradeoff between the complexity and model accuracy, described in [6] and for such statistics applied them to the RF data. By splitting the ultrasound image to image patches, statistical features for image patches can be extracted using the statistical modeling of the RF signal. These features could overlap for some tissues and the pattern classification approaches should be utilized to classify tissues based on the extracted statistical features.

Over past decades, several supervised and unsupervised classification and segmentation algorithms have been proposed to analyze the medical images. Some of these techniques are listed in [10-12]. Because of above mentioned problems (overlap between statistical features of tissues) and the fact that in our application (speckle classification), we cannot have enough training material and the data size (=number of image patches) is finite and small, we only focused on the unsupervised clustering techniques in this study.

Manuscript received June 20, 2011. Arezou Akbarian Azar, and Emad Boctor are from The Russell H. Morgan Department of Radiology and Radiological Science, Johns Hopkins University, 3400 North Charles Street, Baltimore MD 21218 USA; E-mails: {arezou, eboctor1}@jhmi.edu; Hasan Rivaz is a Jeanne Timmins Costello Post-Doctoral at McGill University, Montreal QC; E-mail: hassan.rivaz@mcgill.ca

II. METHODS

Our proposed speckle detection scheme is shown in Figure 2 and in this section we explain each step as following:

A. Speckles artifact

One of inherent characteristics of coherent imaging techniques including ultrasound imaging is the presence of speckle-type- noise. Speckle is a random and deterministic pattern in the image formed by the use of the coherent radiation of a medium containing many scatterers. Although the texture of the speckle pattern does not correspond to under-scanning structure, the local brightness of the speckle pattern reflects the local echogenicity of the under-scanning scatterers. As can be seen in figure 1, each pixel in an ultrasound image is formed by the back scattered echoes from an approximately ellipsoid called the resolution cell. If each resolution cell in an image patch has many scatterers, the corresponding patch is called fully developed speckle (FDS). Speckle has a negative impact on ultrasound imaging. It has been shown that the detectability of lesion reduced approximately by a factor of eight due to the presence of speckle in the image [13]. To track speckles as well as to estimate probe movement and improve performance of algorithms for adaptive speckle suppression and the elevational separation of B-scans by speckle decorrelation, we needed to model both fully speckle (blood pool) and partially developed speckle (tissue area). To this end, in the next subsections we investigated the ability of various statistical modeling of the RF signal and different unsupervised clustering techniques.

B. Statistical Features for Speckle Classification

The coherent signal to the diffuse signal energy ratio for a patch in an ultrasound image and the effective number of scatterers per resolution cell could be used as statistical features to identify speckles and characterize tissues. To find r and μ, we need to model envelope (RF) signal behavior. The K distribution has been developed for the envelope signal[3]. The interest of such distribution in ultrasonic and echocardiographic images relies on its ability to model both fully speckle (blood pool) and partially developed speckle (tissue area) situations. Based on K-distribution, previous studies [5, 14] suggested calculation of following statistics on arbitrary powers v of the image patch A.

$$R = \frac{mean}{Std} = \frac{\langle A^v \rangle}{\sqrt{\langle A^{2v} \rangle - \langle A^v \rangle^2}}, \quad Skewness = \frac{(A^v - \langle A^v \rangle)^3}{(\langle A^{2v} \rangle - \langle A^v \rangle^2)^{3/2}}, \quad (1)$$

$$Kurtosis = \frac{(A^v - \langle A^v \rangle)^4}{(\langle A^{2v} \rangle - \langle A^v \rangle^2)^{4/2}}$$

Where Std means standard deviation, <. > =mean. Based on the results in [15], values of v more than one is suggested to perform well.

Another statistical model is Rayleigh distribution. Given the assumption of fully developed speckle, the envelope RF image patch, R = {$r_{i,j}$}, is modeled by Rayleigh statistics, where the probability density function (pdf) is given by:

$$p(r_{i,j}) = \frac{r_{i,j}}{\sigma_{i,j}^2} e^{-\frac{r_{i,j}^2}{2\sigma_{i,j}^2}} \quad (2)$$

Each statistical models for the RF signal has some advantages and some disadvantages. This suggests that we must consider both statistical models (Rayleigh and K distributions) to better characterize statistical behavior of the RF signal. Therefore for each image patch A, we propose to compute statistical features in (1) and maximum likelihood (ML) estimation of the patch A following the Rayleigh distribution (2). After extracting features for each image patch A, we can use the classification scheme shown in figure 1 to classify each image patch to FDS and non-FDS.

C. Unsupervised Clustering for Speckle Classification

Data clustering means partitioning data to fuzzy or crisp (hard) subsets. Hard clustering in a data set X means partitioning the data into a specified number of subsets of X with such a condition that an object either does or does not belong to a cluster. The number of subsets (clusters) is denoted by K. The hard partitioning is the simplest approach for data clustering, though its results are not always reliable and has numerical problems as well. However, fuzzy clustering allows objects to belong to multiple clusters in the same time, with different degrees of membership. In many real applications fuzzy clustering is more realistic than hard clustering, as objects on the boundaries between several classes are not forced to fully belong to one of the classes. In this study we used both hard (K-means and K-mediod) [16] and fuzzy partitioning (Fuzzy C-Means, Gustafson-Kessel and Gath-Geva techniques)[17, 18] for speckle detection in a competitive manner.

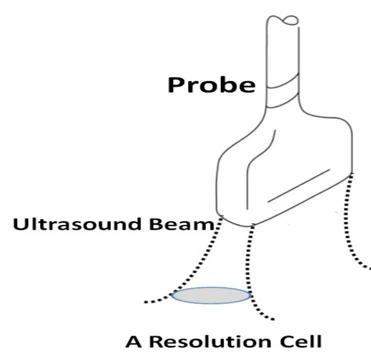

Fig. 1. Ultrasound beam and resolution cell.

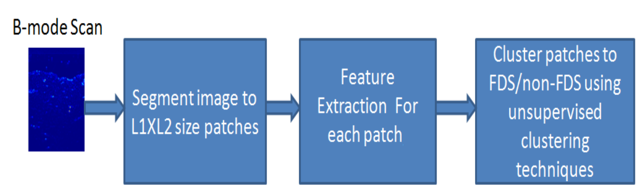

Fig. 2. Pipeline for Speckle detection.

To evaluate our proposed speckle classification scheme (Figure 2) We will use Dice similarity for quantitative metrics[19]. Where the measure is defined as:

$$DS = 2\frac{A \cap B}{A + B} = 2\frac{TP}{2TP + FP + FN} \quad (3)$$

where A=tissue 1,B=tissue 2, TP=true positive, FP=false positive and FN=false negative.

D. Ultrasonic Images Simulation

In order to quantitatively compare statistical features and classification methods, as ground truth, we used two different ultrasound image simulations: fetus and cyst phantoms generated Field II simulator [1].

III. Results

To evaluate our proposed speckle classification scheme and calculate performance of each unsupervised classification technique, as the ground truth, we used B-mode images (cyst phantom and fetus image) simulated by FieldII simulation program with 100,000 scatterers and 128 RF lines (see Figures 3 and 4)[1]. To calculate statistical feature, these ultrasound images were segmented to 12x8 image patches, where each image patch had size of 100x100 pixels. To have a comparative analysis on the speckle detection performance we used the same image patch sizes for both simulations. K-distribution is able to model image patches with low scattering, however, the image patch size should have a reasonable size (not be not very small or very large). We then calculated following statistical features for image patch: R, Skewness and Kurtosis features for the k-distribution and Maximum Likelihood (ML) for the Rayleigh distribution. After calculating statistical features

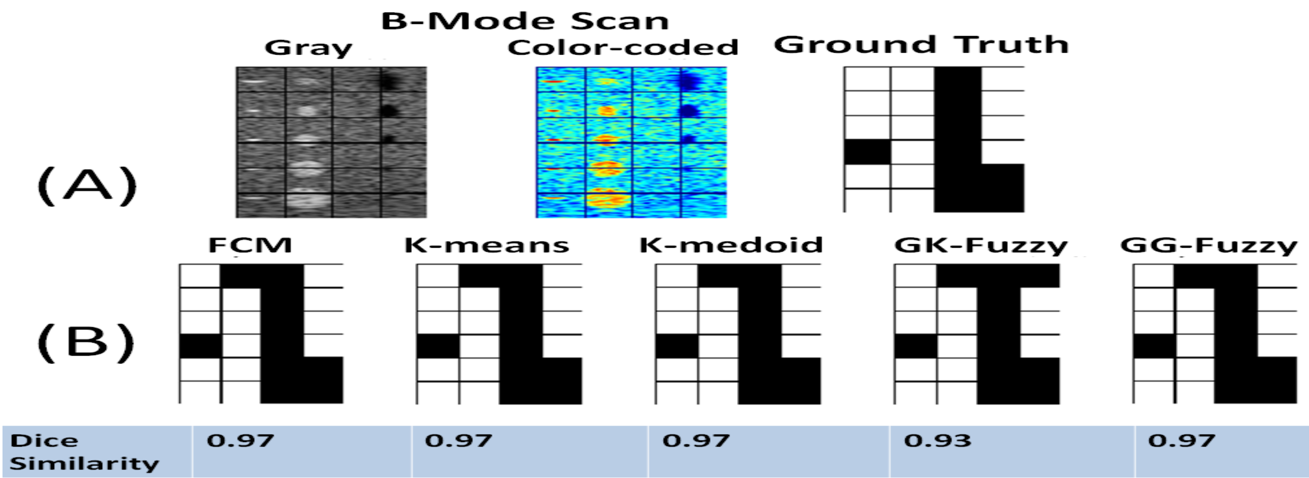

Fig. 3. Simulated ultrasound image of a cyst phantom (A) and speckle detection results for five different unsupervised classifiers. Total number of 100x100 patches for the phantom image was 24. Patches classified as fully developed speckles (FDS) are shown as black. All methods except GK-fuzzy classifier performed the same. Orders for K-distribution based features (Eq. 1) respectively was 1,1 and 0.5.

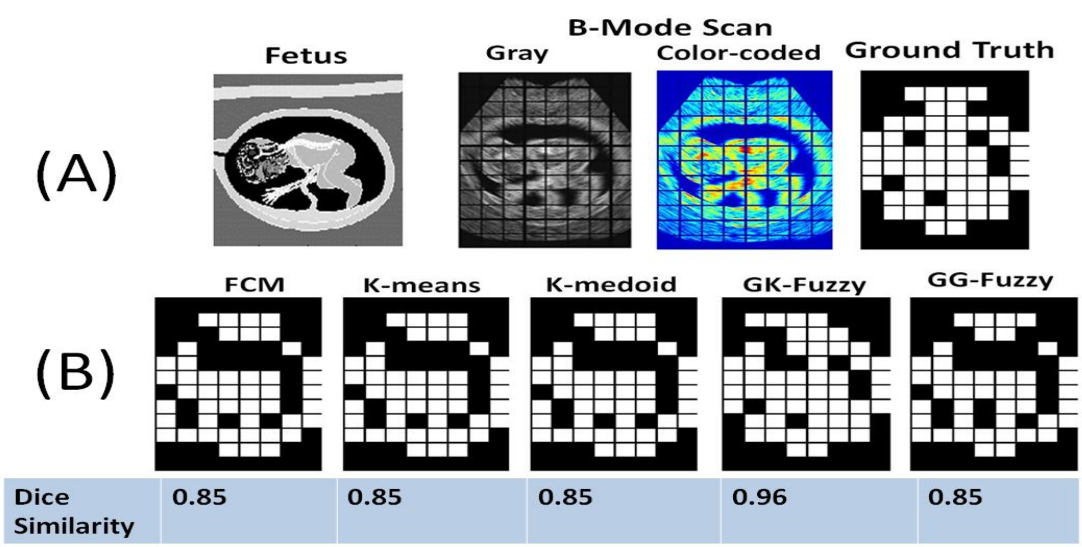

Fig. 4. Simulated ultrasound image of a fetus in 12th week (A) and speckle detection results for five different unsupervised classifiers. Patches classified as fully developed speckles (FDS) are shown as black. As can be seen, FCM,K-means and K-mediod performed the same. GK and GG fuzzy classifiers were able to decrease false positives and improve accuracy of the speckle detection. Total number of patches (100x100 pixels) for the phantom image was 96. Orders for K-distribution based features (Eq. 1) respectively was 10,1 and 0.01.

for each image patch, we will have 4 dimensional features for each image patch and we can classify them to FDS and non-FDS using unsupervised clustering techniques. For this purpose in this study we applied five pattern classification techniques: K-means, K-medoid, Fuzzy C-means, Gustafson-Kessel fuzzy classifier and Gath-Geva fuzzy classifier. Bottom of Figures 3 and 4 show performance of the classification methods for speckle detection.

IV. Conclusion

In this study we reviewed the present statistical models to predict behavior of the RF signal for different tissue types. In some ultrasonic imaging fields such as echocardiography Rayleigh distribution fits to reflect properties of reflections from blood but fails with complex structures such as myocardial tissue. However, another statistical model named K distribution have been proposed to model different kinds of tissue in ultrasound envelope imaging.

To consider both statistical properties of the ultrasonic images we applied both Rayleigh and K-distributions and for each image patch A, we computed statistical features for K-distribution and Maximum Likelihood (ML) estimation of the image patch following the Rayleigh distribution. After extracting features for each image patch, we applied the unsupervised clustering techniques to classify each image patch to FDS and non-FDS. Based on our observation, we found when we use all statistical features (R-S-K- ML) together classifiers was able to separate classes in data space better than with other combinations out of R-S-K- ML features. Based on the results, ranking of the classification methods is: 1) Gustafson-Kessel fuzzy; 2) Gath-Geva fuzzy; 3) Fuzzy c-means; 4 and 5) K-means and K-mediod.

In the future work we will apply above mentioned statistical models and unsupervised classification techniques to detect and track speckles in real ultrasonic image sequences. To improve specificity and sensitivity of our machine-learning speckle detection scheme as well, we will focus on feature whitening and mapping techniques such as Sammon mapping [20] to increase distance between features before applying unsupervised classification techniques. In this pilot study we only used rectangular patches with the uniform patch sizes. Another investigation should be done to test the sensitivity of our proposed speckle detection scheme to the image patch sizes and their shape. Using cone-shape image patches may improve the speckle detection performance.

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