

Classification of uterine fibroid from ultrasound images using wavelet transform

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Uterine myoma and adenomyoma are the most common benign tumors of the uterus. Ultrasound Imaging is the widely used method in the diagnosis of both the disease conditions; however the diagnosis strongly depends on the physician's expertise and ultrasound system quality. These drawbacks have motivated the development of computer aided applications for the quantitative analysis of ultrasound images to assist the physician in the accurate diagnosis. In this work, statistical texture based features of uterine myoma and adenomyoma of ultrasound images are extracted using wavelet transform and the effectiveness of the selected features are analysed using various classifiers. The energy feature proved to be the best feature in the classification of uterine myoma and adenomyoma with the classification accuracy of about 70%.

Keywords: Ultrasound, Myoma, Adenomyoma, Wavelet Transform.

Introduction

Uterine myoma and adenomyoma are the most common pelvic disorders that bring problems in the health of women during their reproductive age. Both the conditions are mostly asymptomatic and about 20–50% of women have symptoms such as menorrhagia, pelvic pain and infertility, or complications during pregnancy¹. The primary method involved in the diagnosis of uterine masses is ultrasonography. The ultrasonography is a non-ionizing imaging modality and also a cost-effective diagnostic method. The common ultrasonography characteristics considered by the physician in the differential diagnosis of uterine myoma and adenomyoma are position, number margin, echogenicity of the uterine masses and the presence or absence of hypoechoic spaces. Margin, echogenicity, mass number and hypoechoic space are significantly different for both the conditions. An adenomyoma is diagnosed, when there is an inhomogeneous circumscribed area in the myometrium, with an indistinct margin, containing hypoechoic spaces larger than 5 mm. A uterine myoma is diagnosed, when a well-circumscribed nodule with a distinct margin and heterogeneous structure is identified in the myometrium^{2,3}. An accurate preoperative diagnosis between the two

conditions is very essential in women who have planned for the preservation of fertility. However, until now, the accurate diagnosis of both the conditions depends on the samples of biopsies. The problem identified with ultrasonography in the diagnosis of the two conditions is to correctly distinguish between them because of their common symptoms & features^{2,3}. In this work, statistical texture based features are used to differentiate between the uterine myoma and adenomyoma from the ultrasound image.

Materials and Methods

Ultrasound tissue characterization has been proven to improve the sensitivity of diagnosis of disease conditions in breast, liver, prostate, retina, myocardium etc. Arivazhagan and Ganesan proposed wavelet statistical features and co-occurrence features for texture classification of an image in their work⁴. Texture analysis can be done by various methods. One of the methods is using the extracted statistical features. Usually lower order statistics, particularly first order and second order statistical features are exploited in texture analysis. First order statistics like mean, standard deviation and higher order moments of histograms deal with individual pixels of image. Second order statistics deals with co-occurrence of two pixels^{5,6,7}. Grey level differences, auto correlation function and local binary pattern operator are second order statistical features.

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Higher order statistical features can also be investigated, but with increase in order of statistics there is a corresponding increase in computational complexity. The literature on methods used to classify uterine myoma and adenomyoma from ultrasound image includes fractals and wavelet based texture features⁸. This work considers first order and second order statistical features to classify and characterize the tissue of uterine ultrasound. A total of 120 ultrasound images (70 uterine myoma and 50 adenomyoma) obtained from 50 subjects, from Department of Radiology, PSG Institute of Medical Science and Research were analyzed. Two sets of data were selected: one for training the system and another for evaluating its performance. For training the system, 50 uterine myoma and 35 adenomyoma images were used, whereas for evaluation of the system, the remaining 20 uterine myoma and 15 adenomyoma ultrasound images were used. The proposed method involves extraction of features using wavelet transform. From the features extracted, the characteristics of the images are described which helps in the classification of uterine myoma and adenomyoma. The steps involved in the proposed method is given in figure 1. Image preprocessing is an enhancement process which improves the subjective quality of the image. Prior to the extraction of a region of interest from the ultrasound image, two preprocessing techniques were performed on the original image using MATLAB. First, the ultrasound image is processed with a Gaussian Low Pass Filter to suppress the multiplicative noise. Speckle noise is a multiplicative noise which is difficult to remove than Gaussian noise. It is common to represent speckle noise as additive noise⁹. For converting the multiplicative noise into an additive noise, log transformation was applied on the ultrasound image. Thus, speckle noise can be removed from the ultrasound image using a Gaussian low pass filter.

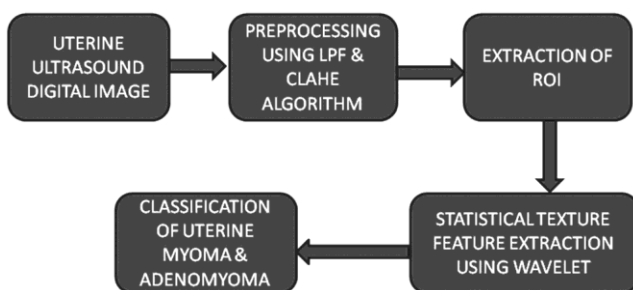


Fig. 1—Flow Chart of the Proposed Methodology

Then, the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique was applied on the filtered image to normalize the inhomogeneous brightness and contrast of the ultrasound image. Finally, the region of interest was manually extracted from the ground truth image. Statistical texture based features are extracted from the segmented ROI of the ultrasound images using the wavelet transform¹⁰. Texture is a repetitive pattern in an image, which is used to describe the characteristic of an image. The wavelet transforms work by decomposing a discrete signal into two subsignals each having equal lengths, whose pictorial representation is shown in the figure 2. One subsignal is called “approximation” and another is the “details”. The approximations of the subsignals are computed by taking the running average (referred as G in figure 2) and the details are computed by taking the running difference (referred as H in figure 2) on the second half of the subsignal. This results in the first level of decomposition of the image. The second level decomposition of the image is performed by computing the approximation and details on the first level approximation coefficients. The result of the second level decomposition includes 1 approximation coefficient and 2 detail coefficients. Similarly, third level decomposition includes 1 approximation coefficient (A1) and 3 detail coefficients (D1, D2, D3) which is shown as an example in figure 3. The figure 3 shows the original image of uterine myoma and adenomyoma of ultrasound image and the wavelet transform based 3-level decomposition of uterine myoma and adenomyoma. In this work, a 3-level Haar transform is considered to extract the features from the wavelet transform domain coefficients. The features extracted for each level of decompositions: Energy, Mean, Median, Mode, Standard Deviation, Maximum value, Minimum Value, Range, Median Abs Deviation, Mean Abs Deviation, L1 norm, L2

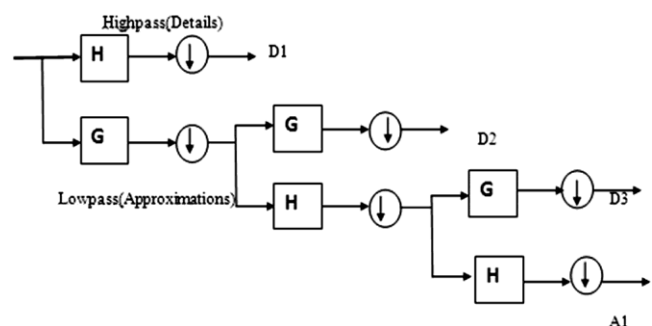


Fig. 2—Schematic of 3-level Wavelet Decomposition

norm, and Maximum norm. A total of 58 statistical features were extracted using wavelet transform domain technique.

The final sets of features used for classification were determined using the data clustering and analysis algorithms. Features which are redundant and

uncorrelated were removed to provide better classification accuracy. A total of 12 statistical texture based features were selected for tissue characterization using wavelet transform domain techniques among the 58 features extracted.

Results & Discussion

A total of 120 (70 uterine myoma and 50 adenomyoma) ultrasound images of uterine fibroid images were analyzed. The following are the definitions used to find the rank order of the selected features based on distance measures as a criterion.

$$\text{Mean: } m = \frac{\sum x_i}{n} \quad \dots (1)$$

$$\text{Standard Deviation: } \sigma = \sqrt{\frac{\sum (x_i - m)^2}{n - 1}} \quad \dots (2)$$

$$\text{Distance Measure: } \frac{|m_1 - m_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}} \quad \dots (3)$$

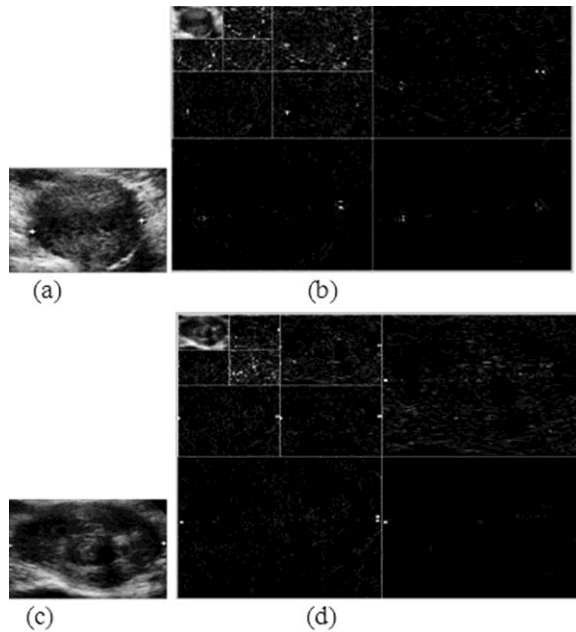


Fig. 3—Wavelet Decomposition of Uterine myoma and Adenomyosis: (a) & (b) Uterine Myoma and its 3-level decomposition, (c) & (d) Adenomyosis and its 3-level Decomposition

Table 1 summarizes the best statistical texture feature in the wavelet transform domain using the distance between classes as a criterion. The rank order of the features confirms that the tissue characteristics of the uterine myoma and adenomyoma have significant variations with respect to the statistical texture based features. Tissue characterisation of

Table 1—Rank order of the Selected Features

S.No	Texture Feature	Uterine Myoma		Adenomyoma		Distance $\frac{ m_1 - m_2 }{\sqrt{\sigma_1^2 + \sigma_2^2}}$	Rank Order
		Mean m_1	Standard Deviation σ_1	Mean m_2	Standard Deviation σ_2		
1	Energy-Vertical Details (2 nd level Decomposition)	1.7557	2.4052	0.5254	0.4339	0.5034	1
2	Energy-Diagonal Details (1 st level Decomposition)	0.8508	1.7533	0.2651	0.5473	0.3188	3
3	Energy-Diagonal Details (2 nd level Decomposition)	0.9032	1.5891	0.2003	0.2027	0.4387	2
4	Level 1 Median abs Deviation	1.5387	0.9898	1.5441	0.7136	0.0043	12
5	Level 1 Mean abs Deviation	2.5455	1.7512	2.2220	1.0837	0.1570	6
6	Level 1 L1 Norm	2309.38	1665.20	2136	1041.23	0.08828	9
7	Level 2 Median	0.0086	0.12848	0.00183	0.14226	0.03538	10
8	Level 2 Median abs Deviation	2.3589	1.6137	2.3145	1.19632	0.0221	4
9	Level 2 Mean abs Deviation	3.61662	2.58467	3.17646	1.8643	0.1381	7
10	Level 2 L1 Norm	3447.82	2515.66	3052.52	1791.77	0.1571	5
11	Level 3 Mean	0.0187	0.1904	0.0028	0.1246	0.03491	11
12	Level 3 Median	0.0196	0.4904	0.1360	0.6878	0.13780	8

Table 2—Cross Validation accuracy between classifiers

Feature Set	Feature Set Vector Size	Best Feature Vector set	SVM classifier		KNN classifier		Decision tree	
			Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Wavelet Transform Coefficient based Statistical Features	58	12	54.1	0.003	44.78	1.896	70.99	1.53

ultrasound image varies from simple gray level histogram based methods to various texture based statistical & structural methods. In this work, in order to classify the uterine myoma and adenomyoma of uterine ultrasound images, wavelet transform based statistical features are used, and the efficiency of the selected features are evaluated using different statistical classifiers. In order to verify the accuracy of the classifiers, 10 fold cross validation of the classifiers was performed and their results are tabulated in the Table 2. It is observed that, we are able to distinguish between uterine myoma and adenomyoma classes with the accuracy of 70% with respect to Decision Tree classifier when compared to SVM and KNN classifiers.

Conclusion

In this proposed work, a methodology using statistical texture based features and Decision tree classifier is used for the tissue characterization of uterine myoma and adenomyoma from ultrasound uterus images. The proposed methodology will help in improving the accuracy of ultrasonography in the diagnosis of uterine myoma and adenomyoma. The number of texture statistical features extracted using wavelet transform were 58 and selected features were 12. The results of this study indicate that it is possible to characterize the tissues of uterine myoma and adenomyoma using the texture based statistical features extracted from the ultrasound images of uterus. By extracting higher order texture statistical features from high quality ultrasound image it is possible to improve the performance of the classifier further.

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