Shannon and Non-Shannon Measures of Entropy for Statistical Texture Feature Extraction in Digitized Mammograms

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Abstract— **This paper deals with the problem of texture feature extraction in digital mammogram. For texture feature extraction, gray level histogram moments statistical texture analysis method is normally used. Entropy is an important texture feature, which is computed based on this method, to build a robust descriptor towards correctly classifying abnormal and normal regions of mammograms. Entropy measures the randomness of intensity distribution. In most feature descriptors, Shannon's measure is used to measure entropy. In this paper non-Shannon measures are used to measure entropy. Non-Shannon entropies have a higher dynamic range than Shannon entropy over a range of scattering conditions, and are therefore useful in estimating scatter density and regularity. Experiments have been conducted on images of mini-MIAS database (Mammogram Image Analysis Society database (UK)). The Results of this study are quite promising. This work is a part of developing a computer aided decision (CAD) system for early detection of breast cancer.**

Index Terms— **Breast cancer, Computer aided decision system, Digital mammogram, Non-Shannon entropies, Shannon entropy, Texture feature extraction.**

I. Introduction

As one of the leading deadly diseases, cancer is one of the most common diseases which affect men and women around the world. Among the cancer diseases, breast cancer is especially a concern in women. According to the statistics, breast cancer is one of the major causes for the increase in mortality among middle-aged women in both developed and developing countries. However, the etiologies of breast cancer are unknown and no single dominant cause has emerged. Still, there is no known way of preventing breast cancer but early detection allows treatment before it is spread to other parts of the body. However, it is evident that the earlier breast cancer is found, the better chance a women gets for a full recovery. Moreover, the early detection of breast cancer can play a very important role in reducing the morbidity and mortality rates.

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Mammography [1], [2] is the single most effective, reliable, low cost and highly sensitive method for early detection of breast cancerous. Mammography offers high-quality images at low radiation doses and is the only widely accepted imaging method for routine breast cancer screening. It is recommended that women at the ages of 40 or above should have a mammogram every one to two years. Although mammography is widely used around the world for breast cancer detection, there are some difficulties when mammograms are searched for signs of abnormality by expert radiologists. Such difficulties are that mammograms generally have low contrast compared with normal breast structure and sign of early disease are often small or subtle. This is the main cause of many missed diagnoses that can be mainly attributed to human factors such as subjective or varying decision criteria, distraction by other image features, or simple oversight. As the consequences of errors in detection or classification are costly and since mammography alone can not prove that a suspicious area is tumorous, malignant or benign the tissue has to be removed for closer examination using breast biopsy techniques. Nevertheless, a false- positive detection causes unnecessary biopsy. On the other hand, in a false- negative detection an actual tumor remains undetected. Thus, there is a significant necessity for developing methods for automatic classification of suspicious areas in mammograms, as a means of aiding radiologists to improve the efficacy of screening programs and avoid unnecessary biopsies.

A typical mammogram contains a vast amount of heterogeneous information that depicts different tissues, vessel, ducts, chest skin, breast edge, the film, and the x-ray machine characteristics [3]-[5]. In order to build a robust diagnostic system towards correctly classifying abnormal and normal regions of mammograms, present all the available information that exits in mammograms to the diagnostic system so that it can easily discriminate between the abnormal and normal tissue. However, the use of all the heterogeneous information, results to high dimensioned features vectors that degrade the diagnostic accuracy of utilized systems significantly as well as increase their computational complexity, Therefore, reliable feature vectors should be considered the reduce the amount of irrelevant information thus producing robust mammographic descriptors of compact size[6]-[8].

Texture is one of the important characteristics used in classifying abnormal and normal regions in mammogram. The texture of images refers to the appearance, structural and arrangement of the parts of an object within the image [9], [10]. Images used for diagnostic purposes in clinical practice are digital. A two dimensional digital image is made up of little rectangular blocks or pixels (picture elements). Each is represented by a set of coordinates in space, and each has a value, representing the gray-level intensity of that picture element in space. A feature value is a real number, which encodes some discriminatory information about a property of an object. Generally speaking, texture feature extraction methods can be classified into three major categories, namely, statistical, structural and spectral. In statistical approaches, texture statistics such as the moments of the gray level histogram, or statistics based on gray level co-occurrence matrix are computed to discriminate different textures [11]. For structural approaches, texture primitive, the basic element of texture, is used to form more complex texture pattern by grammar rules which specify the generation of texture pattern. Finally, in spectral approaches, the textured image is transformed into frequency domain. Then, the extraction of texture features can be done by analyzing the power spectrum. Various texture descriptors have been proposed in the past. In addition to the aforementioned methods, Law's texture energy measures, Markov random field models, texture spectrum etc. are some other texture descriptors [12]-[14].

This paper deals with the problem of statistical approaches to extract texture features in digital mammogram. Gray level histogram moments method is normally used for this purpose. Entropy [15]-[17] is an important texture feature, which is computed based on this method, to build a robust descriptor towards correctly classifying abnormal and normal regions of mammograms. Entropy measures the randomness of intensity distribution. In most feature descriptors, Shannon's measure is used to measure entropy. In this paper non-Shannon measures are used to measure entropy. Non-Shannon entropies have a higher dynamic range than Shannon entropy over a range of scattering conditions, and are therefore useful in estimating scatter density and regularity [18].

II. GRAY LEVEL HISTOGRAM MOMENTS

Regarding the statistical approach for describing texture, one of the simplest computational approaches is to use statistical moments of the gray level histogram of the image. The image histogram carries important information about the content of an image and can be used for discriminating the abnormal tissue from the local healthy background. Considering the gray level histogram $\{h_i,\ i = 0, 1, 2, \ldots, N_{g-1}\}$, where N_g is the number of distinct gray levels in the ROI (region of interest). If n is the total number of pixels in the region, then the normalized histogram of the ROI is the set $\{H_i,\ i=0, 1, 2, \ldots, N_{g-1}\}$, where $H_i=h_i/n$. Texture measures based on histograms

Shannon-Entropy: It is a measure of randomness.

$$S = -\sum_{i=0}^{N_g-1} H_i \log_2(H_i)$$

Non-Shannon measures of Entropy

a) Renyi's entropy is defined as

$$R = \frac{1}{1-\alpha}\log_2\left(\sum_{i=0}^{N_g-1} H_i^{\ \alpha}\right)$$

$$\alpha \neq 1, \alpha > 0$$

b) Havrda and Charvat gave the measure of entropy

$$HC = \frac{1}{1-\alpha}\left(\sum_{i=0}^{N_g-1} H_i^{\ \alpha} - 1\right)$$

$$\alpha \neq 1, \alpha > 0$$

c) Kapur's entropy

$$K_{\alpha,\beta} = \frac{1}{\beta-\alpha}\log_2 \frac{\sum_{i=0}^{N_g-1} H_i^{\ \alpha}}{\sum_{i=0}^{N_g-1} H_i^{\ \beta}}$$

$$\alpha \neq \beta, \alpha > 0, \beta > 0$$

III. EXPERIMENTAL RESULTS

Experiments have been conducted on images of mini-MIAS database (Mammogram Image Analysis Society database (UK)). For implementation, MATLAB 7.0 has been used. The mammograms of about 200 images have been considered for simulating the proposed work. For the completeness of description several experimental results have been depicted in Table I and Table II at different values of α , β .The exact values of parameters are of less significant and hence the range values have been considered for true or best classification

The basic classification of normal, benign and malignant mammogram images based on the values of the texture parameters are shown in Table III, Table IV. The original images and their corresponding histograms for basic classification are shown in Fig.1, Fig.2 and Fig.3. Graphical representation of these classifications is shown in Fig.4 and Fig.5. In order to validate the results, uncompressed fatty, fatty and non-uniform breast mammogram images are considered to examine the versatility of the proposed feature descriptor. These images and their corresponding histograms are shown in Fig.6, Fig.7 and Fig.8.These classification results are shown in Table V and Table VI. Graphical representation of these classifications is shown in Fig.9 and Fig.10.

From the above results it can be inferred that non-Shannon's entropies (Renyi, Havrda & Charvat and Kapur) are useful parameters for normal and abnormal mammogram images classification. Specially, Havrda & Charvat is most suitable for this purpose. Experimental results indicate that, in non-Shannon entropies, the values of constants α , β play important role for classification. So, selection of suitable values of these constants is necessary. Havrda & Charvat entropy at $\alpha = 0.5$ give the best suitable results for classification. This in turn also helps in the diagnosis of palpable or microcalcifications or tumors in the breast. This work may be employed to develop a computer aided decision (CAD) system for early detection of breast cancer.

TABLE I

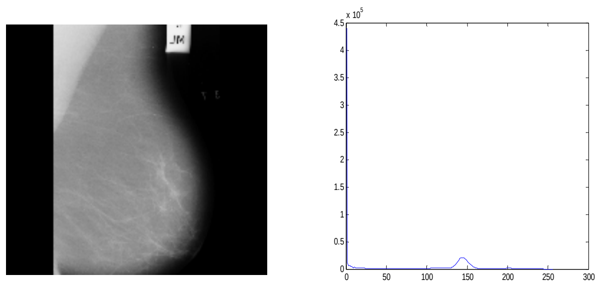
ENTROPY MEASURE OF MAMMOGRAM IMAGES BASED ON GRAY LEVEL HISTOGRAM MOMENTS AT α =0.5 FOR RENYI, α =0.7 FOR HAVRDA & CHARVAT AND $\alpha = 0.5, \beta = 0.7$ FOR KAPUR

Image samples	**S**	**R** α **=0.5**	**HC** α **=0.7**	$K_{\alpha,\beta}$ $\alpha = 0.5$ $\beta = 0.7$
Mam1	4.7658	6.9242	8.7940	7.9945
Mam2	5.1761	6.9060	9.0540	7.7959
Mam3	5.2400	7.0073	9.3439	7.8821
Mam4	5.1644	6.7166	8.6331	7.5718
Mam5	4.8436	6.7857	8.5198	7.8131
Mam6	5.1044	6.7977	8.7193	7.7227
Mam7	5.5805	7.0348	9.7094	7.7459
Mam8	4.2316	6.6505	7.8027	7.9252
Mam9	2.9738	6.1737	6.0264	7.9867
Mam10	4.1991	6.4753	7.3892	7.7603
Mam11	4.5951	6.7681	8.2881	7.9115
Mam12	4.9022	6.8990	8.8035	7.9257
Mam13	4.9559	6.8047	8.6226	7.7983
Mam14	4.4958	6.7285	8.1625	7.8909
Mam15	4.9878	6.9086	8.9161	7.8832

TABLE II

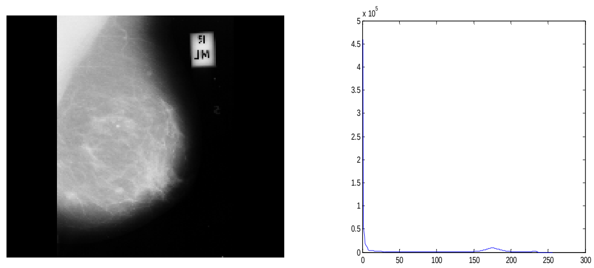
ENTROPY MEASURE OF MAMMOGRAM IMAGES BASED ON GRAY LEVEL HISTOGRAM MOMENTS AT α =0.1 FOR RENYI, α =0.5 FOR HAVRDA & CHARVAT AND $\alpha = 0.1, \beta = 0.9$ FOR KAPUR

Image samples	**S**	**R** α **=0.1**	**HC** α **=0.5**	$K_{\alpha,\beta}$ $\alpha = 0.1,$ $\beta = 0.9$
Mam1	4.7658	7.7796	20.0410	8.0925
Mam2	5.1761	7.7505	19.9023	8.0219
Mam3	5.2400	7.7346	20.6845	7.9934
Mam4	5.1644	7.6608	18.5109	7.9306
Mam5	4.8436	7.7167	19.0077	8.0217
Mam6	5.1044	7.7035	19.0954	7.9825
Mam7	5.5805	7.6587	20.9020	7.8736
Mam8	4.2316	7.7460	18.0460	8.1189
Mam9	2.9738	7.6251	14.9927	8.1298
Mam10	4.1991	7.7053	16.8654	8.0857
Mam11	4.5951	7.7552	18.800	8.0900
Mam12	4.9022	7.7795	19.8491	8.0820
Mam13	4.9559	7.7529	19.1466	8.0516
Mam14	4.4958	7.7473	18.5954	8.0910
Mam15	4.9878	7.7747	19.9222	8.0668



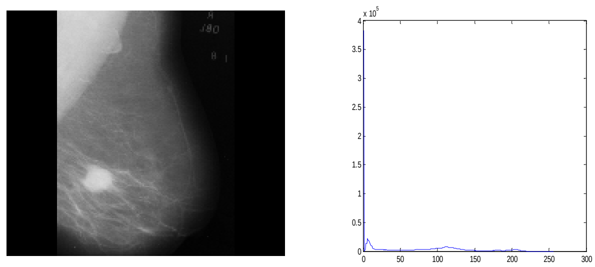
(a) mdb006 (b)

Fig.1. (a) Normal mammogram (b) Its histogram



(a) mdb312 (b)

Fig.2. (a) Benign mammogram (b) Its histogram



(a) mdb028 (b)

Fig.3. (a) Malignant mammogram (b) Its histogram

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TABLE III
CLASSIFICATION OF MAMMOGRAM IMAGES BASED ON SHANNON ENTROPY, RENYI'S ENTROPY AT α =0.5, HAVRDA & CHAR VAT'S ENTROPY AT α =0.7 AND KAPUR'S ENTROPY AT $\alpha = 0.5, \beta = 0.7$

Mammogram Images categories	**Average S**	**Average R α =0.5**	**Average HC α =0.7**	**Average $K_{\alpha,\beta}$ $\alpha = 0.5$ $\beta = 0.7$**
Normal	4.2315	6.4321	7.6275	7.6789
Benign	4.4236	6.7543	8.235	7.7678
Malignant	4.9875	7.0024	8.9678	7.8123

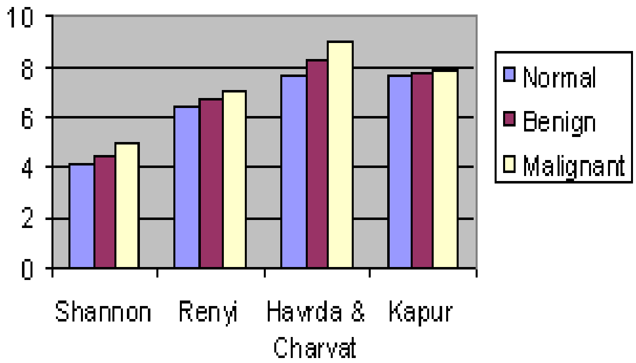


Fig.4. Graphical representation of classification of mammogram images based on Shannon entropy, Renyi's entropy at α =0.5, Havrda & Char vat's entropy at α =0.7 and Kapur's entropy at $\alpha = 0.5, \beta = 0.7$

TABLE IV
CLASSIFICATION OF MAMMOGRAM IMAGES BASED ON SHANNON ENTROPY, RENYI'S ENTROPY AT α =0.1, HAVRDA & CHAR VAT'S ENTROPY AT α =0.5 AND KAPUR'S ENTROPY AT $\alpha = 0.1, \beta = 0.9$

Mammogram Images categories	**Average S**	**Average R α =0.1**	**Average HC α =0.5**	**Average $K_{\alpha,\beta}$ $\alpha = 0.1$ $\beta = 0.9$**
Normal	4.2315	7.6975	18.2013	7.8020
Benign	4.4236	7.7204	19.5750	7.9652
Malignant	4.9875	7.7824	20.2542	8.0125

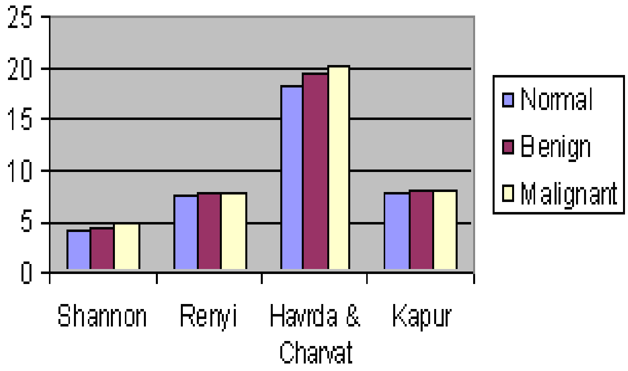
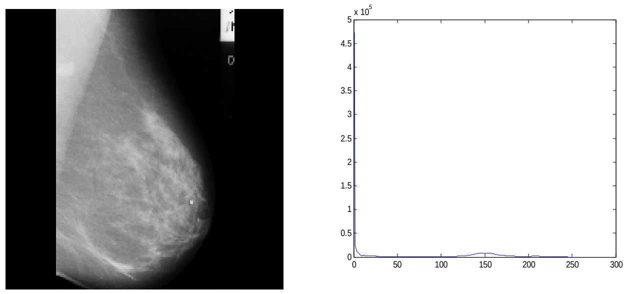
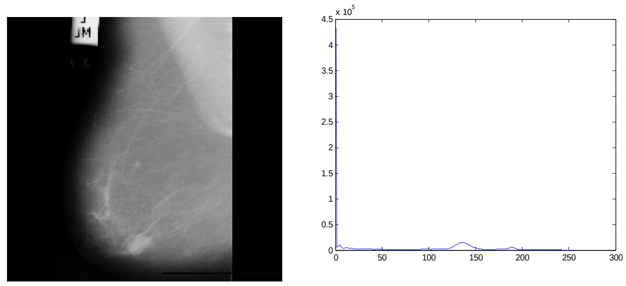


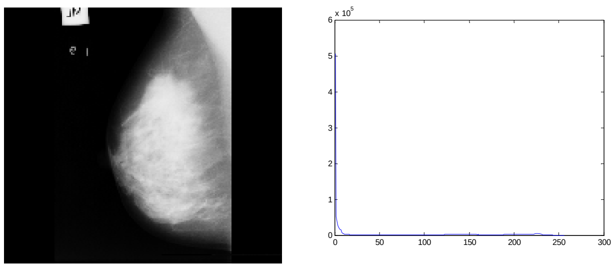
Fig.5. Graphical representation of classification of mammogram images based on Shannon entropy, Renyi's entropy at α =0.1, Havrda & Char vat's entropy at α =0.5 and Kapur's entropy at $\alpha = 0.1, \beta = 0.9$



(a) mdb008 (b)
Fig.6. (a) Uncompressed fatty image (b) Its histogram



(a) mdb005 (b)
Fig.7. (a) Fatty image (b) Its histogram



(a) mdb003 (b)
Fig.8. (a) Non-uniform fatty image (b) Its histogram

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TABLE V

CLASSIFICATION OF UNCOMPRESSED FATTY, FATTY BREAST AND NON-UNIFORM FATTY BREAST BASED ON SHANNON ENTROPY, RENYI'S ENTROPY AT α =0.5, HAVRDA & CHAR VAT'S ENTROPY AT α =0.7 AND KAPUR'S ENTROPY AT $\alpha = 0.5, \beta = 0.7$

Mammo-gram Images categories	**S**	**R** α **=0.5**	**HC** α **=0.7**	$K_{\alpha,\beta}$ $\alpha = 0.5$ $\beta = 0.7$
Uncompressed fatty	4.9878	6.9086	8.9161	7.8832
Fatty breast	5.1761	6.9060	9.2540	7.7959
Non-uniform fatty breast	4.5951	6.7681	8.2881	7.9115

TABLE VI

CLASSIFICATION OF UNCOMPRESSED FATTY, FATTY BREAST AND NON-UNIFORM FATTY BREAST BASED ON SHANNON ENTROPY, RENYI'S ENTROPY AT α =0.1, HAVRDA & CHAR VAT'S ENTROPY AT α =0.5 AND KAPUR'S ENTROPY AT $\alpha = 0.1, \beta = 0.9$

Mammo-gram Images categories	**S**	**R** α **=0.1**	**HC** α **=0.5**	$K_{\alpha,\beta}$ $\alpha = 0.1$ $\beta = 0.9$
Uncompressed fatty	4.9878	7.7747	19.9222	8.0668
Fatty breast	5.1761	7.7505	20.2023	8.0219
Non-uniform fatty breast	4.5951	7.7552	18.8800	8.0900

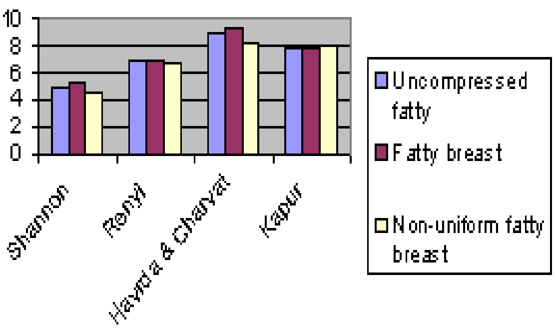

Fig.9. Graphical representation of classification of uncompressed fatty, fatty breast and non-uniform fatty breast based on Shannon entropy, Renyi's entropy at α =0.5, Havrda & Char vat's entropy at α =0.7 and Kapur's entropy at $\alpha = 0.5, \beta = 0.7$

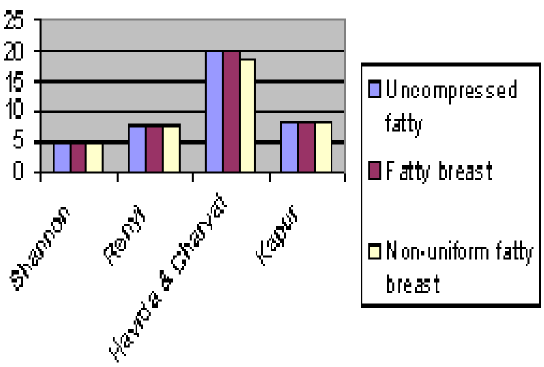

Fig.10. Graphical representation of classification of uncompressed fatty, fatty breast and non-uniform fatty breast based on Shannon entropy, Renyi's entropy at α =0.1, Havrda & Char vat's entropy at α =0.5 and Kapur's entropy at $\alpha = 0.1, \beta = 0.9$

IV. CONCLUSIONS AND FUTURE WORK

In this paper, an attempt is made to develop a new features descriptor based on non-Shannon's entropies (Renyi, Havrda & Charvat and Kapur) for classifying normal and abnormal mammogram images. Experiment results have demonstrated that Havrda & Charvat entropy based feature for classifying normal and abnormal mammogram images works satisfactorily for normal, benign and malignant digital mammograms images and also for uncompressed fatty, fatty breast and non-uniform fatty breast mammogram images.

In future work, Havrda & Charvat entropy based feature will be included with other existing statistical features to build a robust features descriptor for developing a CAD for early detection of breast cancer.

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