International Journal of Engineering & Technology
CENTRE OF PROFESSIONAL RESEARCH PUBLICATIONS
ISSN 2049-3444

International Journal of Engineering and Technology Volume 2 No. 5, May, 2012

Analysis and Classification of Ultrasound Kidney Images Using Texture Properties Based on Logical Operators

E.KOHILAVANI[1], E.THANGASELVI[2], O.REVATHY[3]
[1,2]Assistant.professor, Department of Electronics and Communication Engineering,
[3]Associate.professor, Department of Electronics and Communication Engineering,
P.S.N.A.College of Engineering and Technology, Dindigul.

ABSTRACT

In this paper, a novel method for classification of Ultrasound Kidney images using texture properties based on Logical operators is presented. Different regions of an image are identified based on texture properties. This algorithm mainly deals with operators and that are constructed from logical building blocks. The different classes of images are convolved by these operators and the resulting responses are converted to standard deviation matrices computed over a sliding window. Features for classification of images are extracted from these standard deviation matrices using zonal masks. Feature selection process is applied to these zonal sampling features and new set of features are used for classification. This work proposes an algorithm for classification of textures of three different categories namely Fine, Coarse and Rough. Based on this texture classification, this algorithm applied to medical images. Three kinds of Ultrasound kidney images namely Normal (NR), Medical Renal Diseases (MRD) and Cortical Cysts (CC) images are classified based on texture properties. This algorithm involves only convolution and simple arithmetic in various stages which leads faster implementation. The efficient feature space is created for textures as well as US kidney image classification. For classification, zonal mask sum features gives efficient classification for texture images. For kidney images difference features gives better results. This algorithm has higher classification accuracy and computational superiority.

Keywords: *Cortical Cysts, Medical Renal Diseases, Standard deviation matrices, logical operators.*

1. INTRODUCTION

The medical research has been quite receptive of image processing in application like X-ray, Computer Aided Tomography, Ultrasound and Magnetic Resonance. The output of these techniques, an image of the patient's body, allows the physician to examine and diagnose without the need of surgery. But the process of objective diagnosis is very much difficult with out any support. If any modern techniques are implemented on the medical images it will be very helpful for the objective diagnosis. One such technique is the development of an algorithm using logical operator method to classify the image using its texture properties. Different regions of an image are identified based on texture properties. Some of the applications that demonstrate the importance of texture analysis are found in medical images, remote sensing and industrial images. Textures are usually characterized by its features. Features are extracted based on logical operator to classify the image. This technique is usually applied for medical images to enhance the quality of representation and better understanding of hidden information for proper objective diagnosis. In this project, the texture properties are applied to the medical images to classify the three different categories of Ultrasound kidney images. By using this technique, it is also possible to extract some features that will be very helpful for the diagnosis of the medical images to make comparative study on images for better decision making. In this paper, we introduce a simple algorithm for classification of ultrasound kidney images based on logical operators. Logical operators have been used for Boolean analysis, image coding, cryptography and communication. Logical systems considered in this work are logical Hadamard transform, adding and arithmetic transforms and logical operators such as equivalence, conjunction, and disjunction. In this paper, totally six operators are used. Logical operators are applicable in compression also. Because of its simple arithmetic and convolution involves computationally attractive with excellent performance over a wide variety of images. This method gives an excellent performance on texture images. So it can be applied to the medical US kidney image classification and compare the performance with the texture result.

2. LOGICAL OPERATORS

All the operators are of size 2 x 2, which is adequate in generating an efficient feature space. Hence, the logical operator considered here are order-2 elementary matrices. The building blocks for defining these matrices are 0, 1,-1, matrices of order 1 x 1. The order-2 matrices are generated by using row-wise join (RWJ) and column-wise join (CWJ) on these basic building blocks.

When the RWJ operation is applied to the above order 1 x 1 matrices for all possible concatenation, there are nine different matrices of order 2 x 1, which are shown in Fig 1.

$$\begin{bmatrix}1\\1\end{bmatrix}\begin{bmatrix}1\\-1\end{bmatrix}\begin{bmatrix}-1\\1\end{bmatrix}\begin{bmatrix}-1\\-1\end{bmatrix}\begin{bmatrix}1\\0\end{bmatrix}\begin{bmatrix}0\\1\end{bmatrix}\begin{bmatrix}0\\-1\end{bmatrix}\begin{bmatrix}-1\\0\end{bmatrix}\begin{bmatrix}0\\0\end{bmatrix}$$

Fig 1: Basic operator generation matrices

Next, the CWJ operation is applied to the above order 2 x 1 matrices for all possible concatenation, 81 different matrices of order 2x2, basic core matrices are shown in Fig.2. Only 2 x 2 is sufficient in transforming the textures in to an effective feature space. The higher order matrices are obtained by successive application of the Kronecker product to the core matrices shown in Fig 2.

In this paper, six types of operators are used for texture classification. They are logical Hadamard, Arithmetic, Adding, Equivalence, conjunction, and disjunction operators.

1) Logical hadamard Operator

The logical Hadamard Operator is nothing but the Walsh Hadamard transform. Walsh functions and transforms are important analytical tools for signal processing and have wide applications in digital communications, digital image processing as well as digital logic design. To build this transform is very simple compare to other transforms.

Arithmetic Operator

In many applications of arithmetic operator, the values of only some spectral coefficients are needed. An efficient way has been developed for calculating the transform, which has the ability to evaluate only some chosen spectral coefficients.

2) Adding Operator

Just like Arithmetic operator, Adding operator can be chosen.

$$\begin{bmatrix}1 & 1\\1 & -1\end{bmatrix} \qquad \begin{bmatrix}1 & 0\\1 & 1\end{bmatrix} \qquad \begin{bmatrix}1 & 0\\-1 & 1\end{bmatrix}$$

O1: Hadamard O2: Adding O3: Arithmetic

$$\begin{bmatrix}1 & 0\\0 & 1\end{bmatrix} \qquad \begin{bmatrix}0 & 0\\0 & 1\end{bmatrix} \qquad \begin{bmatrix}0 & 1\\1 & 1\end{bmatrix}$$

O4: Equivalence O5: Conjunction O6: Disjunction

Fig.2: Basic core operators for texture classification

4) Equivalence Operator" $\Leftrightarrow$ ": The equivalence operator is true if x and y have identical values.

5) Conjunction Operator " $\wedge$ ": The conjunction of x and y, $x \wedge y$, is true if x and y are both true and is false otherwise. This operation same as the "AND" operation.

6) Disjunction Operator " $\vee$ ": The disjunction of x and y, $x \vee y$, is false if x and y are both false and is true otherwise. This operation same as the "OR" operation.

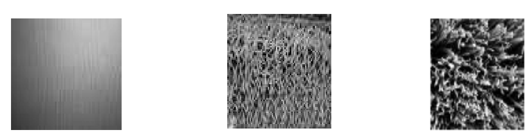
Table 1: Equivalence, Conjunction, and Disjunction Operations

x	y	$x \Leftrightarrow y$	$x \wedge y$	$x \vee y$
F	F	T	F	F
F	T	F	F	T
T	F	F	F	T
T	T	T	T	T

3. PROCESSING TECHNIQUES

* The input image sample is convolved with six different types of operators.
* The standard deviation matrix is computed on the convolution response.
* Zonal filtering masks are applied to the standard deviation matrices and features are computed.
* A classifier is used to identify the unknown sample from the reduced feature space.

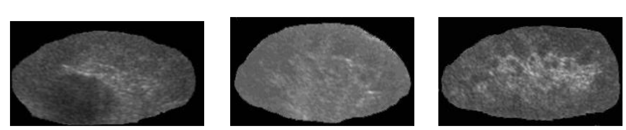
THREE KINDS OF TEXTURE IMAGES



fine coarse rough

Fig 3: The three kinds of texture images

THREE KINDS OF US KIDNEY IMAGES



CC MRD NR

Fig 4: The three kinds US kidney images

4. ALGORITHMS FOR ANALYSIS AND CLASSIFICATION

A. The first step in this paper describes analysis of an image. The analysis part contains two main functions.

I. Convolution response:

To extract the feature first, the input image is convolved with one of the set of logical operators.

$$G(u,v) = F(u,v) * O(u,v) \qquad \text{(Eq. 1)}$$

Where *F* is the image function and *O* is one of the logical operators.

II. Standard deviation matrices:

The response of the resulting images to the six operators given from (1) is used to compute the standard deviation matrix using sliding window.

$$SD(u,v) = \frac{1}{w^2}\left\{\sum_{m=-w}^{w}\sum_{n=-w}^{w}\left[G(u+m,v+n) - M(u+m,v+n)\right]^2\right\}^{1/2} \qquad \text{(Eq.2)}$$

Where W x W is the size of the scanning window which is 5 x 5 and it slides pixel by pixel. M is the mean value of the window. The center pixel is replaced by the standard deviation value. In order to avoid loosing boundary information the image is padded with zeros on all sides.

The convolution and standard deviation matrix for texture and US kidney images shown in Fig. 5 and Fig.6 respectively.

Image Analysis for Rough category

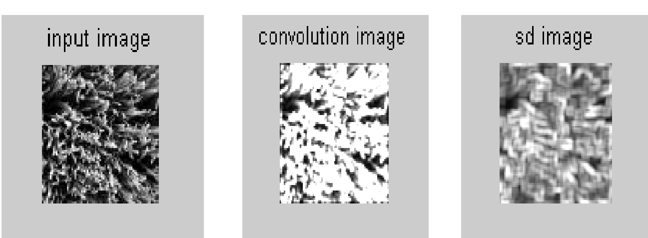


Fig 5: Input, Convolution and SD Images for Texture

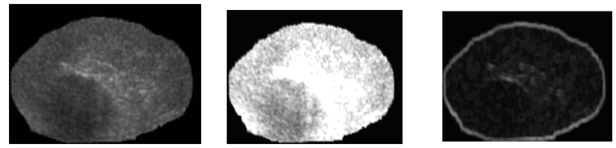


Fig 6: Input, Convolution and SD images for US CC Kidney Image

The operators in Fig 2 are convolved with texture and kidney images, which constitute filtering operation. The resulting standard deviation response can be seen as a smoothing operation.

B. The next step in this algorithm involves, classification phase. This part includes feature extraction, normalization, feature selection, and classification.

I. Feature Extraction

From the above resulting standard deviation matrices $SD(u,v)$, where $1 \le u \le N1$ and $1 \le v \le N2$, *N1* and *N2* are the number of rows and columns features are extracted by zonal filtering using zonal masks. The zonal mask, also called zonal filter, is a simple slit mask. Masks are sets of integers that are used to extract features from the standard deviation matrix. Here, four types of slits masks are used. They are Horizontal mask, Vertical mask, Ring mask, and Sector mask.

Horizontal slit feature:

$$Y_1 = \sum_{(u,v)\in Hm} SD(u,v) \qquad \text{(Eq. 3)}$$

Where the horizontal slit mask *Hm* = {(*u*, *v*): *u*, *v* integer, $U_1 \le u \le U_2; 1 \le v \le N2$}

For better performance, three horizontal slit masks can be chosen from three different places in an image. The position can be fixed at the top, center and bottom of an image. The three horizontal slit masks named as Top Slit (*Ts*), Center Slit (*Cs*) and Bottom Slit (*Bs*).

The horizontal sum feature can be computed from these three slit masks and defined as

$$H_{SUM} = T_S + C_S + B_S \qquad \text{(Eq. 4)}$$

The width of the horizontal slit is 15 for US kidney images.

Vertical slit feature:

$$Y_2 = \sum_{(u,v)\in Vm} SD(u,v)$$

Where the horizontal slit mask Vm = {(u, v): u, v integer, $1 \le u \le N1; V_1 \le v \le V_2$ }

The same way, vertical sum can be calculated by using three slit masks namely Right Slit (Rs), Center Slit (Cs) and Left Slit (Ls). The vertical sum can be defined

$$V_{SUM} = R_S + C_S + L_S \qquad \text{(Eq .5)}$$

The width of the horizontal slit is 20 for US kidney images.

Ring feature:

$$Y_3 = \sum_{(u,v)\in Rm} SD(u,v) \qquad \text{(Eq .6)}$$

Where the ring mask Rm = $\{(u, v)$: u, v integer, $\rho_1 \le \rho(u,v) \le \rho_2$ }

The ring sum can be calculated by the sum of ring pixel values. The radius of the ring can be taken as our wish according to the image but the radius should not exceed the image.

For texture images, the outer ring radius (r_1) is 300 and inner ring radius (r_2) is 200. Except the ring, all the pixel values are replaced by '0' and ring sum can be computed from sum of the pixels from ring (r_1) to (r_2). The ring can be defined by,

$$R^2 = (x-a)^2 + (y-b)^2 \qquad \text{(Eq. 7)}$$

$$R_{SUM} = SUM\ (r_1 \text{ to } r_2) \qquad \text{(Eq. 8)}$$

For US kidney images, the outer ring radius (r_1) is 500 and inner ring radius (r_2) is 300

Grid feature:

$$Y_4 = \sum_{(u,v)\in Gm} SD(u,v) \qquad \text{(Eq.9)}$$

Another type for feature extraction leads to formation of grids. Five grids are taking at various places in an image for further classification. Grid size is 15 x 15 for both texture and kidney images to extract the feature. Particular portion of an image is taken by using grid. Here center (gc), left (gl), right (gr), top (gt), and bottom (gb) are taken to get the features.

The sum of these grids are defined by,

$$G_{sum} = I_{gc} + I_{gl} + I_{gr} + I_{gt} + I_{gb} \qquad \text{(Eq.10)}$$

From the above four types of feature selection masks over six logical operators which give totally 24 features for classification which leads to better classification efficiency. The results are analyzed by using individual operator responses over US kidney image shown in Fig 7.

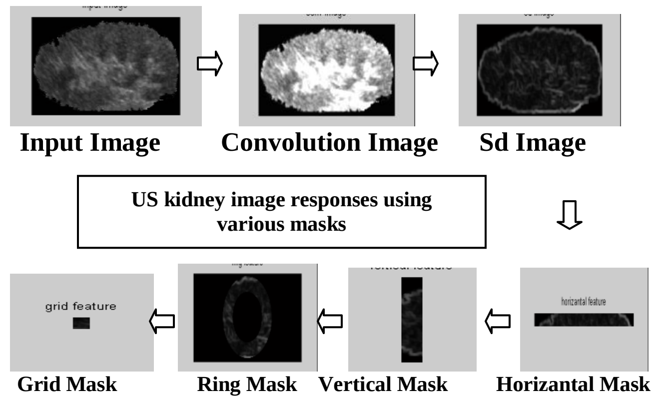


Fig 7: US Kidney Image Responses Using Various Masks

5. CLASSIFICATION

For classification of texture images ($H_{SUM,}$, V_{SUM})

Features and ($R_{SUM,}$,G_{SUM}) gives efficient classification for three kinds of texture images.

$$H_{SUM} = T_S + C_S + B_S$$

$$V_{SUM} = R_S + C_S + L_S$$

$$R_{SUM} = SUM\ (r_1 \text{ to } r_2)$$

$$G_{sum} = I_{gc} + I_{gl} + I_{gr} + I_{gt} + I_{gb}$$

By comparing the texture and US kidney image databases, we are easily come to conclude, the texture classes are predictable by using this sum features. The H_{SUM}, V_{SUM},, R_{SUM}, *and* G_{SUM} features give efficient response for classifying texture images. But for medical image application it's hard to predict the result. So new feature space has been computed by using this same sum features.

For US kidney images, new set of training features are created for efficient classification by using H_{SUM}, V_{SUM},, R_{SUM}, and G_{SUM} features. It can be defined by,

$$H_{DIFF} = G\ (u, v) - SD\ (u, v) - H_{SUM} \qquad \text{(Eq .11)}$$

$G\ (u, v)$ denotes the Convolution response defined in (Eq.1) and SD (u, v) denotes the Standard deviation response defined in (Eq.2). The new difference features are computed by using convolution, SD and sum feature responses. The Eq.11 gives the horizontal difference features. Similarly vertical, ring and grid difference features are defined by,

$$V_{DIFF} = G\ (u, v) - SD\ (u, v) - V_{SUM} \qquad \text{(Eq .12)}$$

$$R_{DIFF} = G\ (u, v) - SD\ (u, v) - R_{SUM} \qquad \text{(Eq. 13)}$$

$$G_{DIFF} = G\,(u, v) - SD\,(u, v) - G_{SUM} \quad \text{(Eq .14)}$$

The difference feature set and the corresponding graphs are shown in Fig 8a -8f. This new set of features gives required information to classify the US kidney images.

6. RESULTS AND DISCUSSION

In texture images, 25 Fine, 25 Coarse and 25 Rough images are taken as a training images. All these images are processed with six logical operators to extract the features for classification. Each operator gives unique responses over the images. Sum features are extracted for texture classification.

The US kidney images are obtained from Medical systems Private Ltd., Chennai. From each category, 8 CC, 8 MRD and 8 NOR images are used for creating training database. Difference features are extracted for classify the images. The difference feature for three kinds of US kidney images using six operators are shown in Fig 8

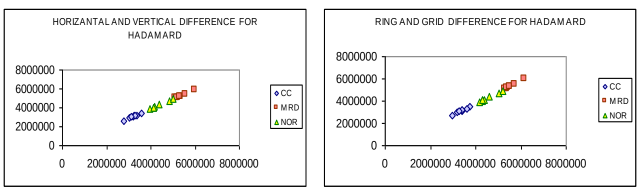


Fig 8a: Hadamard operator

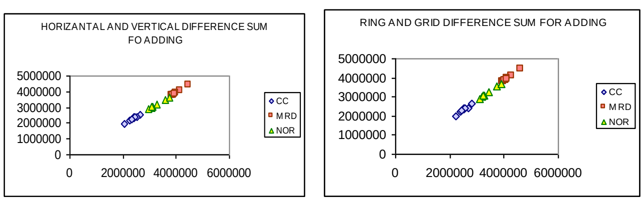


Fig 8b: Adding operator

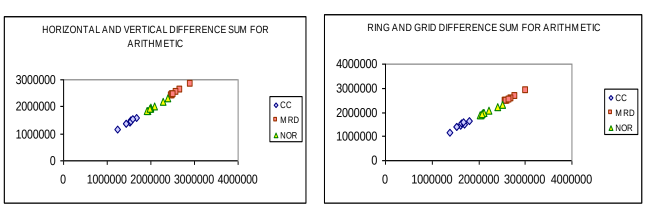


Fig 8c: Arithmetic operator

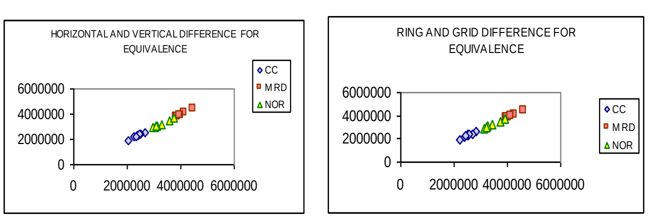


Fig 8d Equivalence operator

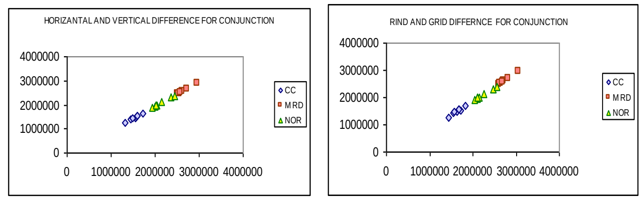


Fig 8e: **Conjunction operator**

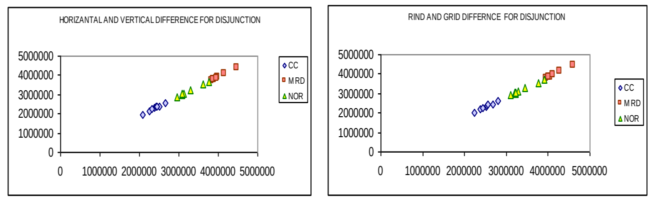


Fig 8f: Disjunction operator

Fig 8: Difference Feature for Three Kinds of US Kidney Images using Six Operators

7. CONCLUSION

The study was made on different texture and US kidney image categories using six logical operators. This work provides significant results in detection and classification of images for objective diagnosis. For texture image classification, the sum features are computed using various zonal masks. The sum features alone gives efficient classification result over texture images.

But for US kidney images new set of features are developed by using sum features. The new feature space can be computed from convolution, SD and sum feature responses. The differences between all three responses are taken as a new difference feature set. These features give much information to classify the US kidney images. Classification of US kidney images is very much valuable for objective diagnosis for physicians. By using the texture properties, an efficient algorithm is developed for classification of medical images using simple logical operators. And textures are base for many images and it is also applicable for remote sensing, textile, industry and compressed images. The algorithm involves convolution with 1, -1, and 0, which can be implemented efficiently and the feature extraction and classification stages involve only additions and comparisons which leads better computational efficiency. Hence it can be suitably implemented in VLSI.

REFERENCES

[1] Raja, K.B., Reddy, M.R., Swaranamani, S., Suresh, S., Madheswaran,M., Thyagarajah, K., Study on Ultrasound Kidney Images for Implementing Content Based Image Retrieval System using Regional Gray-Level Distribution, *Proc. International Conference on advances in*

infrastructures for electronic business, education, science, medicine,and mobile technologies on the internet, L-aquila, Italy, Paper No. 93,Jan 6 – 12, 2003.

[2] Xie, J., Jiang, Y., Tsui, H., Segmentation of Kidney From Ultrasound Images Based on Texture and Shape Priors, *IEEE Trans On MedicalImaging*, Vol. 24, No. 1, 2005.

[3] Raja, K.B., Madheswaran, M., Thyagarajah, K., Quantitative and Qualitative Evaluation of US Kidney Images for Disorder Classification using Multi-Scale Differential Features, *ICGST-BIME Journal*, Volume 7, Issue 1, May, 2007.

[4] Hafizah, W.M., Supriyanto, E., Comparative Evaluation of Ultrasound Kidney Image Enhancement Techniques, *International Journal of Computer Applications*, 2011, Volume 21, No. 7, pp.15-19.

[5] Yap, M.H., Ewe, H.T., Region of interest (ROI) detection in ultrasound breast images. In: *Proceedings of MMU International Symposium on Information and Communications Technologies (M2USIC).* Cyberjaya, Malaysia: Multimedia University; 2005: 5–8.

[6] Yap, M.H., Edirisinghe, E.A., Bez, H.E., A novel algorithm for initial lesion detection in ultrasound breast images, *Journal of Applied Clinical Medical Physics*, Volume 9, Number 4, 2008.

[7] Cheng, H.D., Shan, J., Ju, W., Guo, Y., and Zhang, L., Automated breast cancer detection and classification using ultrasound images: A survey, *Pattern Recognition 43*, 1 (2010), 299-317.

[8] Drukker, K., Giger, M.L., Horsch, K., Kupinski, M.A., Vyborny, C.J.,Mendelson, E.B., Computerized lesion detection on breast ultrasound,*Medical Physics 29*, 7 (2002), 1438-1446.

[9] Madabhushi, A. and Metaxas, D.N. Combining low-, high-level and empirical domain knowledge for automated segmentation of ultrasonic breast lesions. *IEEE Trans. on Medical Imaging 22*, 2 (2003), 155-169.

[10] Gupta, S., Chauhan, R. C., Saxena, S. C., Robust non-homomorphic approach for speckle reduction in medical ultrasound images, *Medical and Biological Engineering and Computing*, 2005, 43, 189–195.

[11] Shrimali, V., Anand, R. S., Kumar, V., Comparing the performance of ultrasonic liver image enhancement techniques: a preference study, *IETE Journal of Research*, Vol 56, Issue 1, 2010.

ISSN: 2049-3444