International Journal of Multidisciplinary Research and Development
Online ISSN: 2349-4182 Print ISSN: 2349-5979, Impact Factor: RJIF 5.72
www.allsubjectjournal.com
Volume 3; Issue 5; May 2016; Page No. 81-83

Features extraction and classification for detection of kidney stone region in ultrasound images

[1] Monika Pathak, [2] Harsh Sadawarti, [3] Sukhdev Singh
[1] Research Scholar, I. K. Gujral Punjab Technical University, Jalandhar, Punjab, India.
[2] Director, Department of Computer Science, RIMT, Mandi Gobindgarh, Punjab, India
[3] Assistant Professor, Computer Science Department Multani Mal Modi College, Patiala, Punjab

Abstract
Region of interest detection in ultrasound image is a challenging task due to heterogeneous texture and presence of speckle noise. The ultrasound scanning is most frequently used tool to examine the patient for abnormities, especially presence of stone, in the kidney. Automatic object detection in ultrasound images is burning research areas and the present research work is in the same direction. We have developed an application, which helps the medical practitioner to identify the stone region in the ultrasound image. It is a semiautomatic system in which practitioner need to select the region, which is analyzed, by the proposed system for presence of stone. The feature extraction is applied on cropped regions, which may contain stone. The various features such as Contrast, Angular second moment, Entropy and Correlation are used. The KNN classifier is used to classification based on training image dataset. The overall accuracy of classification system is around 91%. The confusion matrix is also prepared to analyze the complexity and accuracy of the proposed system.

Keywords: feature extraction, KNN classifier, Kidney stone, confusion matrix, statistical features

1. Introduction
Kidney ultrasound imaging is an economical, non-invasive, real time diagnosis system, which is used to measure abnormalities in the shape, size and location of the kidneys in the body [1].

Fig 1: Ultrasound Images show Kidney stone and shadow

As shown in the figure1, the ultrasound B-mode image shows oval shape kidney with well-defined boundary. On the lower right side of the kidney, there is round object, which is expected to be a stone. The visual characteristic of a stone in ultrasound image is the presence of shadow. The black shade immediately after the round object confirms the presence of stone. However, in case of machine learning, we look for features like shade, contrast; correlation etc. to identify the region contains the stone.
The present research work is focused on object (stone) identification in ultrasound images based on feature extraction and classification.

2. Features extraction
The objective of the features extraction is to capture important characteristics of region under investigation in the kidney image [2]. The features of the region should be able to identify region uniquely. The present research has used statistical features to identify the region of interest. The concept of gray level co-occurrence matrix (GLCM) used to extract the following features [3].

Table1: Description of statistical features

S. No.	Feature	Description
1.	Contrast	It defines the difference between the lightest and darkest areas on an image $$\boldsymbol{contrast} = \sum_i \sum_j (\boldsymbol{i}-\boldsymbol{j})^2\ \boldsymbol{X}(\boldsymbol{i},\boldsymbol{j})$$ Where i and j are the pixel values.

2.	Angular second moment (ASM, Energy)	It is the state or quality of being homogeneous. It is calculated as sum of square of angular entries in GLCM moments. The higher value of ASM indicates textural uniformity. $ASM = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \boldsymbol{p}(\boldsymbol{i},\boldsymbol{j})^{2}$ Where, Ng is gray tone image in GLCM form.
3.	Entropy	Entropy measures the randomness of the image texture (intensity distribution). $Entropy = -\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \boldsymbol{p}(\boldsymbol{i},\boldsymbol{j})\boldsymbol{log}(\boldsymbol{p}(\boldsymbol{i},\boldsymbol{j}))$ The homogeneous image shows lower entropy value, whereas, heterogeneous region results in a higher entropy value
4.	Correlation	Correlation is a measure of the strongest of the relationship between two variables. $Correlation = \frac{Cov(x,y)}{\sigma_x \sigma_y}$

The following features are extracted from the GLCM of the ROI kidney images using MATLAB [4, 5, 6, 7]. Energy, Entropy, Contrast, Homogeneity, Maximum probability and correlation.

Table 2: Sample of Features Extracted from Ultrasound Kidney stone Images

Feature	Image 1		Image 2	
	Min Value	**Max Value**	**Min Value**	**Max Value**
Contrast	0.8842	1.3792	0.8991	1.2290
ASM, (Energy)	0.1902	2.0127	0.2811	2.7654
Entropy	2.3754	2.5419	1.9251	2.4019
Correlation	0.5452	0.7172	0.3912	0.4138

3. Classification

The k-Nearest Neighbors algorithm (or k-NN) is a nonparametric algorithm, which is used to classify different cases based on some similarity measures such as Euclidean distance. The Euclidean distance is measured using following equation [8].

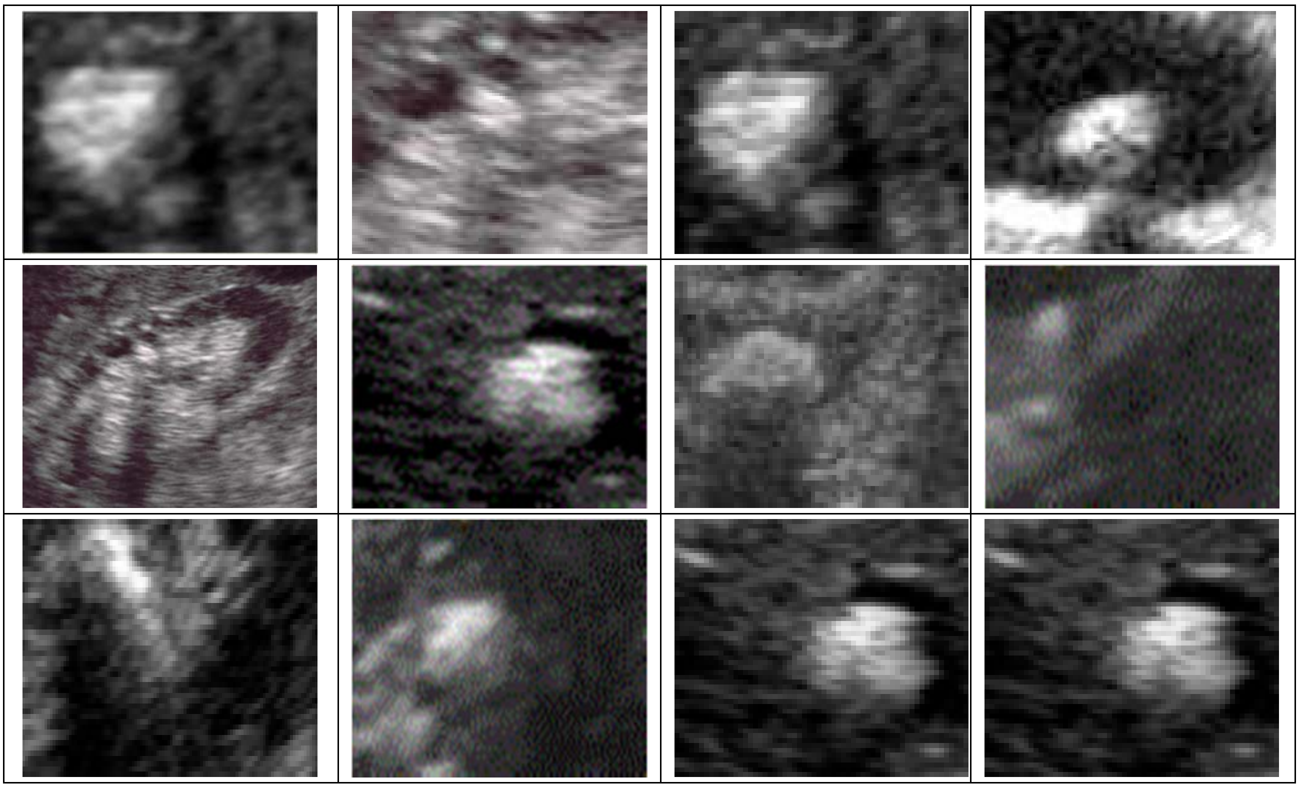
$$Euclidean = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$

The KNN machine-learning program takes decision based on previously stoned decisions. The basic principle of KNN is based on the rule to majority vote to its neighbors [9]. The present research used it to classify the kidney stone images by comparing the features extracted from training dataset.

Training Phase

The kidney Ultrasound images are collected and stone regions cropped to create training dataset. The training dataset contains nearly 250-cropped images, which contain stone. The feature extraction is applied on the training image dataset and features are stored as knowledge base. Table3 shows few images from training dataset.

Table 3: Sample images of training image dataset



The features extracted in the feature extraction phase are stored for classification analysis. The KNN classifier analyses the new feature set with the previously stored features set. If the features are close to the previous set of features then the image is well classified otherwise the image is rejected for stone images. The training image set show significant results and well classifies the stone images.

4. Result and Analysis

The statistical analysis of the present algorithm carried out on kidney ultrasound images. The following statistical parameters are used for analysis:

- **Confusion Matrix:** It contains information about actual and predicted classifications done by a KNN classifier [10]. The performance of the proposed region of interest detection system evaluated using the analysis of the confusion matrix. Table4 shows the confusion matrix for a two-class classifier.

Table 4: Confusion Matrix

		Predicted	
		Negative	**Positive**
Actual	Negative	TN	FN
	Positive	FP	TP

- **Accuracy:** The accuracy of classification process is based on correct and incorrect predictions. Following formula used to calculate the accuracy of the classification process [11].

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

Where,
TP (True Positive) – number of correct positive prediction,
TN (True Negative) – number of correct negative Prediction,
FN (False Negative) – Number of incorrect negative predictions.
FP (False Positive) – number of incorrect positive prediction.

5. Conclusion

The present research work is an attempt to automate the Ultrasound analysis process for detection of stone. The system aimed to identify the ultrasound image region, which may contain the stone. The stone region identification based on analysis of stone region features. The system consists of feature extraction and classification where the feature extraction carried out on the ultrasound image data and testing image dataset. The KNN classifier used to analyze the features for detection of stone in the images. The overall accuracy of the system is 91% which is satisfactory at the time. The accuracy may be enhance by considering more suitable features which can define stone region and multiple classifiers can also be added into the system.

6. Acknowledgement

Authors acknowledge the opportunity and support provided by I. K. Gujral Punjab Technical University, Jalandhar to conduct the present research work.

7. References

1. Loganayagi T, Kashwan KR. A Robust Edge Preserving Bilateral Filter for Ultrasound Kidney Image. Indian Journal of Science and Technology. 2015; 8(23).
2. Bojunga J, Dauth N, Berner C, Meyer G, Holzer K, Voelkl L. *et al*. Friedrich-Rust, Acoustic Radiation Force Impulse Imaging for Differentiation of Thyroid Nodules, Plos One, 2012; 7(8).
3. Tamilselvi, Thangaraj. Computer Aided Diagnosis System for Stone Detection and Early Detection of Kidney Stones, Journal of Computer Science, 2011; 7(2):250-254.
4. Jenho Tsao, Li-Hsin Chang, Chia-Hung Lin. Ultrasonic Renal-Stone Detection and Identification for Extracorporeal Lithotripsy, in the proceedings of the IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, 2005, 1-4.
5. Chalekar P, Shroff S, Pise S, Panicker S. Use of k-Nearest Neighbor in Thyroid disease Classification. Technical Research Organization India. 2014; 1(2):36-41.
6. Grigorescu SN, Petkov N, Kruizinga P. Comparison of Texture Features Based on Gabor Filters, IEEE Transactions on Image processing, 2002; 11(10).
7. Pal M, Mather PM. A Comparison of Decision Tree and Backpropagation Neural Network Classifiers for Land Use Classification IEEE International Symposium on Geoscience and Remote Sensing, 2002, 503-506.
8. Selvathi D, Sharnitha VS. Thyroid classification and segmentation in ultrasound imaging using machine learning algorithm international conference on signal processing, communication, computing and network techniques (ICSCCN), 2011.
9. Suganya R, Rajaram S. Content Based Image Retrieval of Ultrasound Liver Diseases Based on Hybrid Approach. American Journal of Applied Sciences. 2012; 9(6):938-945, ISSN 1546-9239.
10. Sridhar S. Segmentation of Ureteric and Bladder Calculi in Ultrasound Images. Journal of Computer Science. 2012; 8(5):716-720.
11. Maanasa NAS, Gowri V. Segmentation of mammogram using Tumour cut algorithm International Journal of Engineering and Innovative Technology (IJEIT), 2013; 2(10).