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Designing Efficient Morphological Segmentation Methodology for Kidney Stone Detection

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Abstract*— The kidney Sstone (KS) is a serious problem in peoples beyond 45 years of age. Presence of stone may disturb urinary system and cause excruciating discomfort in abdomen. The major goal of this study is to use sequence of image processing algorithms to determine the presence of kidney stone within a digital ultrasonography images. However, because of a lack of contrast as well as the existence of speckle noise, the captured KS images by ultrasonography techniques is not appropriate for further processing. Thus paper initially proposed CLAHE enhancement for contrast improvement. In order to eliminate the speckle noise study proposed image de-noising approaches using median filter to achieve improved the visibility of the ultrasound scan. Finally morphological processing and thresholding sequence is used for the precise location of the stone is determined using the improved ultrasound imaging. The outcome of stone detection is qualitatively evaluated.

***Keywords*—Adaptive Filter, Neural Network, BPNN, ADALINE, Amplitude Modulation, AWGN Noise, Filter Design.**

I. INTRODUCTION

A variety of kidney disorders exist, including the growth of stones, cysts as well, urinary obstructions, genetic disorders, including malignant cells. As a solid fragment of material develops within the urinary system, the most common of these conditions is kidney stone disease [1].

The tiny stone fragment could pass with no creating any symptoms. When a stone is larger than 5 centimeters, it may clog the urinary bladder and cause excruciating discomfort in the lower abdomen or the belly. Therefore, in order to prevent from these conditions or from further health problems, it is required to design an efficient method to find the kidney stone in images [2].

The major goal of this study was to create a simple, uncomplicated method for locating kidney stones. Any normal person can check using ultrasound regarding a kidney stone as well as dissolve it at the early stages by performing this procedure is executed using the MATLAB software. According to the size and placement of the stone, these approaches primarily assist the doctor for further treating the patient

A typical example of the kidney stone image captured using ultrasonography is shown in the Figure 1. The presence of KS is not clearly visible and if then its size and shape is not clear form captured images. Therefore in this paper prime concern is to detect the KS using improved contrast and image morphology.

Pink, crimson, or brownish urine; cloudy or as foul-smelling urine; discomfort that extends across the lower abdomen as well as groyne; pain that occurs in waves and varies in severity; and pain when urinating are the major kidney stone symptoms. High-frequency sound waves used in ultrasound cause the body to reverberate. It does not involve radiation, generally non-invasive, as well as painless. The most common application of ultrasound usually to detect blood clots and also to detect kidney stones, a Baker's cyst behind the knee, or even a torn rotator cuff in the shoulder.

Fig.1. Typical Example of the Ultrasound image of kidney

II. KS DETECTION SYSTEM

The KS detection system diagram is shown in the Figure 2/ it can be seen that initially the KS image is load to the MATLAB environment then converted to gray image for further processing. The Contrast enhancement is achieved, than initial threshold estimation is formed. Based on the observation the morphological processing is applied to smoothen the connected regions and final segmentation is applied.

This process is common in any KS detection but methods are different. In this paper the combination of adaptive filter and opening and closing is proposed to segment the KS images. Various preprocessing stage may be used for improving the segmentation efficiency.

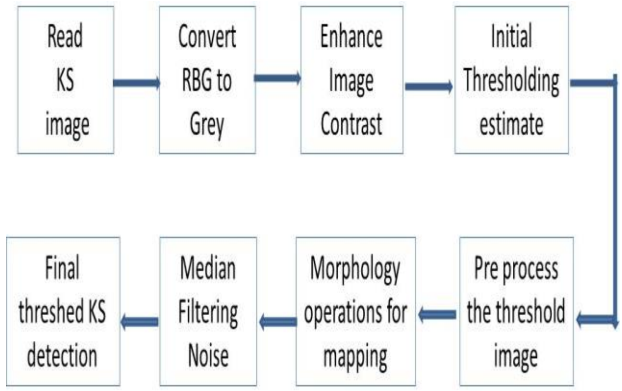


Fig.2. Example of Modulated data and noisy data generation

III. REVIEW OF RELATED WORK

Huge research has been already done to identify and detect the KS in the ultrasound images. Although, The KS detection may be performed in CT images and MEI images too. But ultrasound is preferable because of no radiations losses. Thus this section sequentially reviewed the contributions of the research in these domains Dominik Vilimek et al [1] studied to suggest a completely automated hybrids technique for identifying and extracting kidney stone features. The kidney's stone area is segmented and approximated using a multiregional approach in the model. Methods utilize the active contour idea, which is centered on the extraction of geometrical features. The technique impressively enables an impartial evaluation and categorization of the renal stones. These findings might help replace currently employed clinical techniques in which doctors manually designate kidney stones without receiving software feedback. The best course of action for treating kidney stones will mostly rely on the position, size, and makeup of the stones as well as the patient's overall health.

Rohith Annameti [2] have employing the median filters to detect kidney stones in ultrasound pictures will increase the detection rate's sensitivity and accuracy. The performance and sensitivity of the rank filter (n=114) and median filter (n=114) were tested. In ultrasound pictures, the median filter is used to find kidney stones. The sample size chosen with a p-value of 0.8 was 114, and it was utilized to increase the accuracy and sensitivity of the MATLAB simulation tool's kidney stone detection rate. Results are based on the results, the median filter has an accuracy of 86.4%, the rank filter has an accuracy of 82.2%, and both filters have a sensitivity of 87.7% and 82.5%, respectively. The Median filter outperforms the rank filter with regard to of detection rate.

Jyoti Verma and other [3] have studied to begin by using the median filter, Gaussian filter, and un-sharp masking to enhance the image. The examination of kidney stone pictures then employs morphological procedures including erosion and dilation, followed by entropy-based segmentation to identify the area of interest and KNN and SVM classification approaches. This operation's goal is to identify the best quality so that identification is made simpler. Because they are utilized in a more delicate field, namely the medical field, and because they must be correct, medical photography is one of the essential imaging disciplines.

Monika Pathak and others [4] proposed automated object detection in ultrasonic images is a hot one, and current research is moving in the same direction. We've created a tool that makes it easier for doctors to spot the stone location in an ultrasound image. It is a semiautomatic method in which the user must choose the area to be examined for the presence of stones by the suggested system. Application of the feature removal is made to cropped areas that may contain stone. Different features are used, including contrast to that, angular second moment, entropy, and correlation. The KNN classifier is employed to categories data sets of training images. Around 91% of the time, the classification system is accurate. The suggested system's complexity and accuracy are also examined using the confusion matrix.

Angshuman Khan et al [5] proposed a most prevalent condition affecting the urinary tract is kidney stones. Due to the nature of living, kidney stone problems affect every human being on a regular basis. A kidney stone, also known as a renal calculus, is a hard piece of substance that develops inside the kidney when elements usually discovered in the urine are concentrated to an abnormally high level. The main goal of segmenting medical images is to decrease the time a radiologist must spend reviewing an image in order to locate the areas of renal calculi.

Akkasaligar, Prema and others [6] describes an ultrasonic speckle suppression technique for locating kidney stones in humans. The first step in improving an image is to adjust its intensities using image enhancement techniques. Next, noise is removed and the image is smoothed using median filters. Segmenting preprocessed photos is done by holding the threshold. Impulsive noise is separated from salt-and-pepper noise via the median filter.

Wan Mahani Hafizah, among others [7] study and suggests a method for extracting features from renal ultrasound images based on 19 GLCM features (grey level co-occurrence matrix) and five intensity histogram features. Four different categories of kidney ultrasound images were created: normal (NR), bacterial infection (BI), cystic disease (CD), and kidney stones (KS). The photos were initially preprocessed in order to preserve interesting pixels before feature extraction. Techniques for preprocessing have been used, such as region of interest trimming, contour detection, image rotation, and background removal. According to the test's findings, cluster shades, cluster prominence, skewness, and kurtosis take precedence over other factors

Back Propagation Network (BPN) technology is used by Riya Mishr et al. [8] to classify kidney stones automatically using images and data process methods. It is not possible to generate results for big amounts of datasets using human inspection and operators. There is an excessive amount of noise produced by CT scans and MRIs, which causes errors. Neural network approaches used in artificial intelligence have shown to be quite important in this area. As a result, the Back-Propagation Network (BPN) is being used in this project. GLCM is used to extract the features, while BPN is used to classify them. In order to detect kidney stones in their early stages, this study provides a segmentation technique called the Fuzzy CMean (FCM) clustering algorithm for computing tomography images.

M. S. Uddin et al [9] have also preseted KS study on ultrasound images. Yingpu Cui and others [10] A deep learning and reinforcement learning-based model for automated stones in the kidney detection and scoring using stone nephrolithometry is being developed and validated. Procedures: From February 2018 to April 2019, abdominal non-contrast computed tomography (NCCT) images were back-archived for three sections: a segmentation dataset (n = 167), a Classification dataset for hydronephrosis (n = 282) and test data set (n = 117). The prototype included comprises four actions. The 3D

U-Nets for segmenting the kidneys and renal sinus came first. The development of deep 3D dual-path network for hydronephrsis grading came next. Third, stone in the kidney sinus area were found and segmented using thresholding approaches. The segmented stone region was used to calculate the stone size, CT attenuation, and tract length. The stone's location was discovered in the fourth step. Consequently, the algorithm for detecting stones achieved a sensitivity of 95.9% (236/246) and a PPV of 98.7% (236/239).

M. Kavitha and others [11] worked on production of physiochemical compounds in the urinary system is the primary cause of kidney stones. The primary cause of the stone is the highly concentrated urine that contains salts. When these salts are oversaturated, they precipitate and crystallize.

Because of the stone-promoting or stone-inhibiting chemicals, the crystals might be expelled or develop into stone. Proteins mixed with a variety of organic and inorganic compounds such calcium, uric acid, cysteine, struvite, and ammonium acid can result in kidney stones. Of these, calcium compounds such calcium oxalate and calcium phosphate make up 80% of the stones. Kidney stone development may occasionally be influenced by metabolic alterations, hyperparathyroidism, distal renal tubular acidosis, malabsorptive syndrome, obesity, and the severity of diabetes.

In other work of, kidney stone identification employing image processing methods using CT scans was thoroughly analyzed. Felix Alberto Caycho Valencia et al. [12] one of the most significant problems in the world is locating kidney stones in their right location. Two kidneys in the human body are crucial for filtering and recycling water. In this study, four stages—image preprocessing with a median filter, segment with a k-mean clustering technique, kidney stone detection, and classification—were all studied. Information was gathered from 40 hospital patients utilizing a CT scanner to diagnose kidney stone illnesses. This study investigates a cutting-edge method to identify boundaries, segmented areas, and improve kidney stone location identification. This study aids in pinpointing the location of a stone using pixels. It also counts the amount of patients who have stone-related issues. According to the investigation, this research has a 92.5% accuracy rate with a reliable stone identification method.

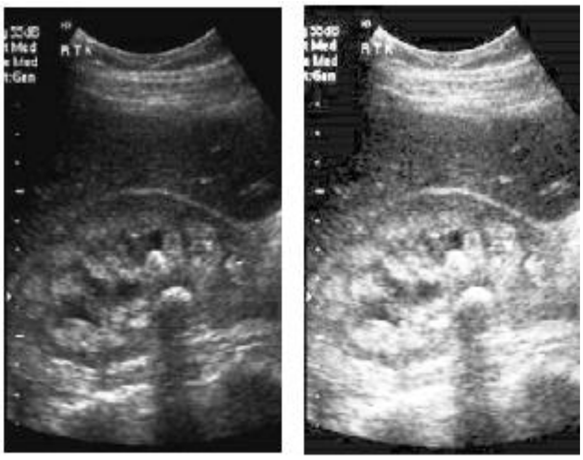
Cunitz, Bryan et al [recent years have proposed optimum Doppler imaging approach for detecting the KS in images. Overall very complex or versatile approaches are available and preprocessing has to be added.

IV. PROPOSED METHODOLOGY

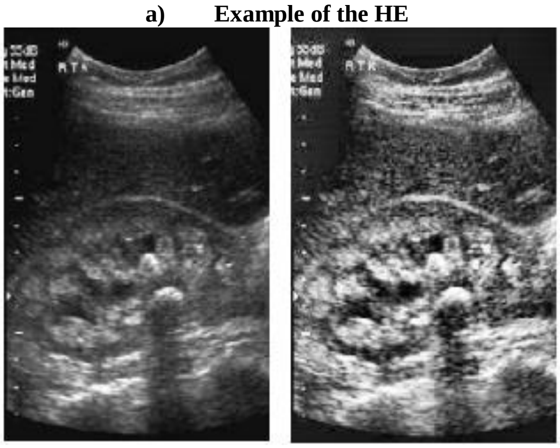
In the paper first CLAHE is proposed for contrast enhancement. Since it may sometimes makes it more difficult to segment the KS due to overlapping intensities. Thus it is required to design the morphological processing for further clearly segment the desired region. The morphological opening and closing is sequentially implemented for reducing the degree of closeness. The final stage of proposed stage is to use the thresholding to segment the desired kidney stone reigns. The system diagram representation was already shown in Figure 2.

A. Contrast Enhancements

In this paper standard contrast limiting adopted histograms equalization (CLAHE) method is used for preprocessing stage**.** The case of contrast enhancement is shown in the Figure 3. Figure 3 a) also compared the performance of Contras enhancement with the simples histogram equalization approach (HE) it can be observed that the CLAHE out perform in terms of enhancement over HE for KS images. The histogram is representation of the values of grey levels in terms of probability. It is required to stretch the histogram by any SDE method. The comparison of the histograms is shown in the Figure 4. a) to c). It is clear form Figure 4 that the CLAHE out performs over HE and has much closer brightness to original image also it is capable of enhancing the contrast too. HR may lose the information.

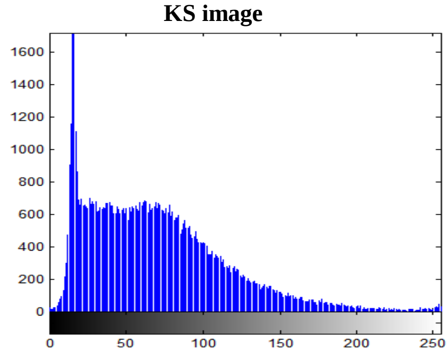


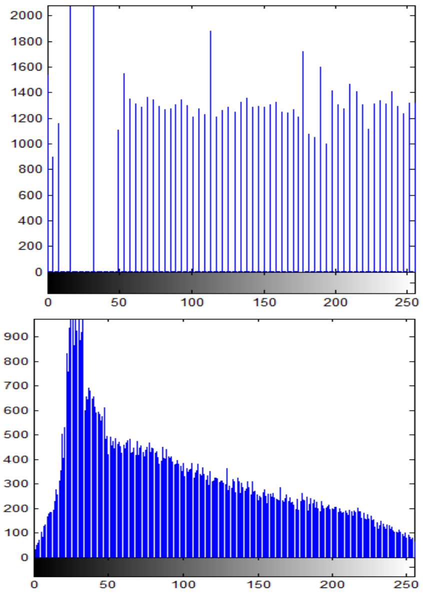
a) Example of the HE



b) With CLAHE enhancement

Fig.3 Example of the CLAHE contrast enhancement for KS image

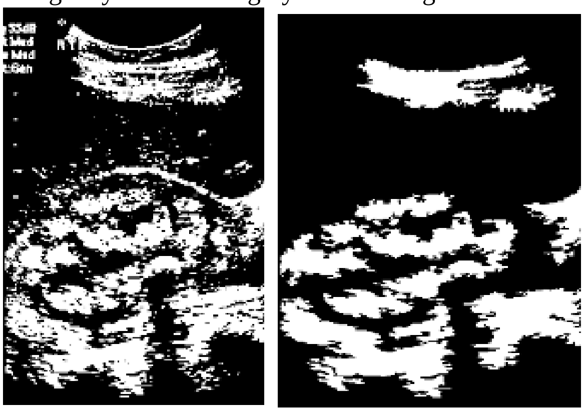




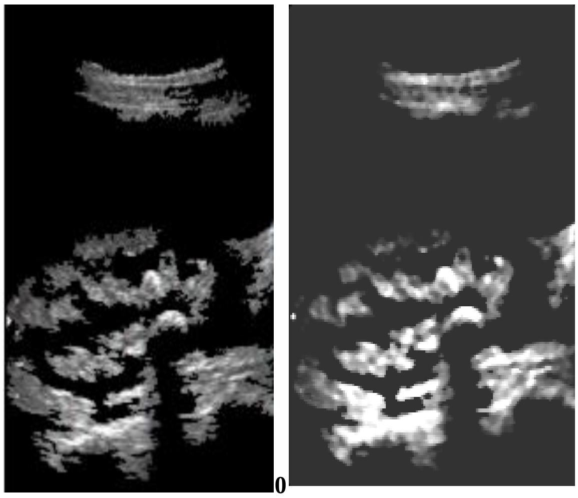
a) Original b) for HE c) for CLAHE
Fig.4. Comparisons of the histograms

B. Median Filter adoption

The median filter is used for the noise elimination from the KS images. This issue is related to the fact because the error signals detected at the multiplayer perceptron's output layer are partially caused by the hidden neurons [13]. Since such neurons are physically unattainable The results of the example for median filtering and the segmented and masked in morphological domain is shown in the Figure 5 for KS image1. It can e clearly observed that after the filtering significant object information is obtained. The may connected regions are rejected by the preprocessing of the images. Also masking may convert the gray outcomes again.



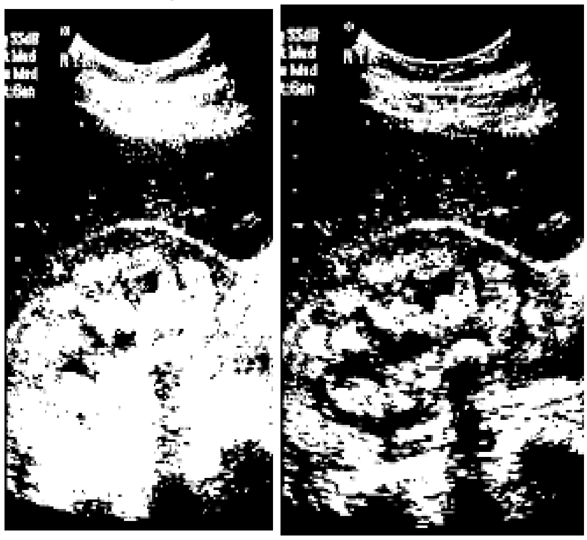
a) Threshold image b) morphological opened image



c) gray maped image f) median filtered region
Fig. 5 Median Filtered image with preprocessing

V. RESULTS AND EVALUATIONS

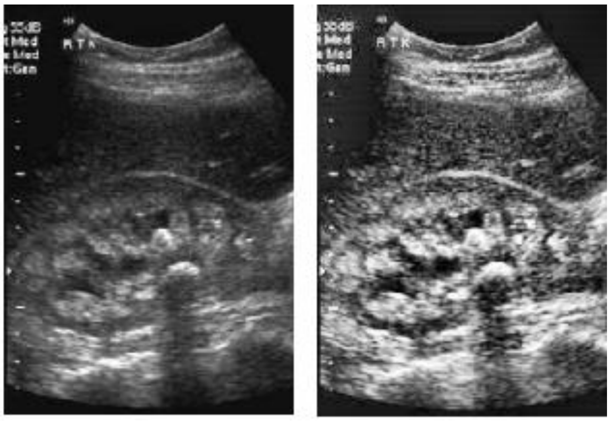
In this section outcomes of proposed KS detection and segmentation stages are presented. The most basic results of the KS detection with two contrast enhancement methods is shown in the Figure 6. It can be observed that he CLAHE enhancement at the front end may offer the less connected regions in the threshold images. This this paper has first conclusion to adopt CLAHE over HE for front end enhancing.



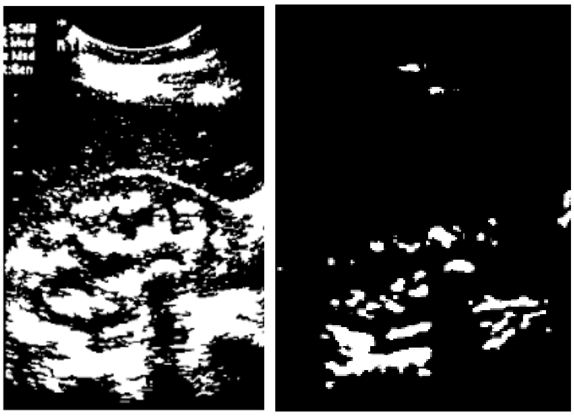
a) with HE segmented b) with CLAHE segmented
Fig.6 KS image segmentation using thresholding without morphology for HE and CLAHE methods

Sequential results of the proposed KS segmentation methodology are preseted and shown in the example of Figure 7 for the KS image1. These results offers the initial contrast enhancement using CLAHE image and then morphological thresholding is offered as combination of opening and closing followed by thresholding.

Figure 7 preseted the thresholding result with and without morphology processing.



a)) original KS image b) Enhanced processed image



c) Segmented without Morphology d) with Morphology

Fig.7. Sequential results of the proposed KS segmentation methodology.

Finally it can be concluded that the using the proposed essential combination may efficiently segment and detect the KS in the ultrasonography images. The

VI. CONCLUSION AND FUTURE WORK

The purpose of this work is to employ a series of image processing algorithms to detect the presence of kidney stones in digital ultrasound pictures. However, because to usually lack of contrast and the presence of speckle noise, the KS pictures acquired by ultrasonography techniques are not suitable for further processing. As a result, the study initially proposed CLAHE enhancement for contrast enhancement. To reduce speckle noise, the study offered picture de-noising algorithms based on the median filter to improve the visibility of the ultrasound scan. Finally, morphological processing and thresholding sequences are employed to detect the specific location of the stone utilizing enhanced ultrasound imaging. It is concluded that CLAHE out performs for KS detection. And morphology is required to eliminate the connected regions. In future optimization method may improve the performance.

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