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Speckle Noise Removal by SORAMA Segmentation in Digital Image Processing to Facilitate Precise Robotic Surgery

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ABSTRACT

Kidney stones are renal calculi that are formed due to the collection of calcium and uric acid. The major symptom for the existence of these renal calculi is severe pain, especially when it travels down the urethra. To detect these renal calculi, ultrasound images are preferable. But these images have speckle noise which makes the detection of stone challenging. To obtain better results, semantic object region and morphological analysis (SORAMA) is found to be productive. The first scanned image undergoes a noise removal process. Later the image is enhanced. Detection of region of interest (ROI) in the image is done. Later it undergoes dilation and erosion, a part of morphological analysis that produces a smoothening effect on the image. From the smoothened image, the stone is detected. If the stone is not detected, it again undergoes noise removal technique, and the whole process is repeated until the smoothened image with the stone is detected. This novel paper will be a boon to medical patients suffering from this disease, which needs to be detected and diagnosed at a very early stage.

KEYWORDS

Medical Image Processing, Morphological Analysis, Renal Calculi, Robotic Surgery, Segmentation, Speckle Noise

INTRODUCTION

Kidneys are a vital organ that is bean-shaped, about 12 centimeters (4.7 in) in length in the average human adult. They are located at the right and left in the retroperitoneal space. The kidney's primary function is to receive the blood from the paired renal arteries and purify it; later, the blood exits through

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paired veins. They also clean up the chemical waste, control and balance the pH of homeostasis fluids in the body. Finally, the waste removed from the blood is transformed into urine and is ejaculated. According to Tilahun Alelign and Beyene Petros's survey in 2018, kidney stone disease is an escalating urogenital disorder among various countries, impacting almost 15% of the global population. It is a common disorder, regardless of ages, sexes and races, but found to be more frequent in men than in women within 20-49 years. The study also says that it undergoes a prevalence of greater than 30% recurrence rate within ten years (Tanzila, Rahman and Shorif Uddin, 2013).

Renal calculi or kidney stones are hard solid particles or crystals that are deposits of acid salts and minerals that stick together in specific chemical concentrated enough in urine. The name nephrolithiasis also applies to these stones. The primary symptom for these renal calculi is severe pain, especially when it travels down the urethras, and this intense pain is called renal colic. Usually, this pain is experienced in one side, back or abdomen region. Therefore, it is essential to diagnose the problem at the initial stage, i.e. when the symptom starts appearing. There are various techniques available to detect kidney stone. In medical imaging practicalities, ultrasound is a therapeutic application as it is portable, versatile, and obsolete to radiations of ionizations and is relatively cost-effective and affordable. However, even though ultrasound is adaptable, comparatively safe and transferable, it has still much acoustic interference, i.e. speckle noise, a complex phenomenon. That decreases the ability to detect the targeted region or organ.

Moreover, these images are of low contrast and formed of the back-scattered wave due to diffused reflections. So, detection of nephrolithiasis in ultrasound images is a real-time challenge. Thus, to obtain specific and accurate results, noise (speckle) removal filtering is the foremost and crucial step that must be carried out. That will result in the removal of erroneous detection. Furthermore, preprocessing techniques are applied, and the image is segmented to delineate the boundaries of different tissues to characterize and differentiate between healthy (Pramanik et al., 2020) and weak tissues, followed by morphological analysis for automatic detection of renal calculi. There has been consequential and remarkable publicizing of robotic facilitate surgery in the province of upper tract oncology and urological pelvic. To accomplish the significant robotic-assisted surgery, the morphologically analyzed image is fed into the robot. It will recognize the exact location of the stone to carry out the procedure of surgery.

The effective speckle-noise reduction and segmentation process for nephrolithiasis identification for ultrasound images with less interference and decreased image perplex is proposed in this research paper. To combat speckle distortion or noise, the image is subjected to rigorous preprocessing processes, which results in a significant reduction in speckle noise and simplifies subsequent processing. For improved edge detection for irregular areas, image segmentation using the ROI model is used. Picture segmentation is followed by morphological regression to smooth out the image pixels. In addition, the position or coordination of the observed renal calculi is fed into the robot, making laparoscopic ureter-lithotomy easier. That has been discovered to be more effective than existing processes. This study will be combined with the robotic arm in the future for real-time deployment and observation.

BACKGROUND

Tanzila et al. (2013) dealt with ultrasound images to detect kidney disorders earliest to reduce End-stage Renal Disease (ESRD). Still, this proposal failed to achieve the precise stone location in terms of coordinate detection. Sheth et al. (2014) proposed two segmentation processes, i.e. cell segmentation and region-based segmentation. Out of that, two-method region-based segmentation yielded compelling results. But this method doesn't seem to be applicable for the images where the kidney boundaries are not clear (Sheth, Dhrumil and Shah, Saurin, 2014). Prema et al. and Brisbane et al. expedients THE Inner Outer Based Watershed Segmentation Approach (IOREWS) method, Region Indicator with Contour Segmentation (RICE) approach, renal calculi and its systematic examination using texture characteristics by logical operation and stone using squared Euclidean distance have been tested and discovered that not one single technique can be taken into consideration for all sorts of imagery as segmentation remains a challenging and perplexing in computer vision and image processing world (Akkasaligar et al. 2016).

Mobarakol Islam et al. (2020) proposed a technique with the development of robotics and imaging systems. Robot arms were applied to operate. In robot-enabled surgery, precise segmentation of the surgery scene helps detect instruments and facilitate information regarding various tissues and gadgets used in operation. The authors have designed a cascaded CNN to segment the surgical devices from videos through the robotic system. The feature maps of various measurements and channels from the auxiliary and main branch are fused using a multi-resolution feature fusion module (MFF). Also is presented a new method for regularizing the segmentation model by integrating additional loss and adversarial loss. Auxiliary loss aids in learning low-resolution features, while adversarial loss enhances segmentation prediction by learning higher-order structural details. The model also includes a lightweight spatial pyramid pooling (SPP) unit for aggregating rich contextual data at the intermediate level. In prediction accuracy and high-resolution video segmentation time, the authors prove that the model outperforms current algorithms (Alzubi, J., Nayyar, A., & Kumar, A. (2018) pixel-wise segmentation of surgical instruments. The experimental findings indicate that the suggested approach is well-suited to robotic instrument segmentation and can also segment tissues. As a result, the research differs significantly from previous results and serves as a foundation for potential research into real-time surgical guidance and robot-assisted surgery.

Pakhomov and Navab(2020) researched that surgical instrument segmentation is a critical step towards complete instrument pose estimation. In robot-assisted surgery is directly used for masking augmented reality overlays during surgical procedures. The majority of implementations focus on high-resolution surgical images being segmented accurately in real-time. Although previous studies mainly focused on methods that produce high-accuracy segmentation masks, the vast majority of them are too computationally expensive to be used in real-time applications. We propose a lightweight and highly effective deep residual architecture for real-time inference of high-resolution images in this paper. We conduct a differentiable check over dilation rates for residual units of our network to account for the decreased precision of the discovered lightweight deep residual network while avoiding any unnecessary computational burden. We validate that our model is state-of-the-art in terms of speed and accuracy tradeoff with a speed of up to 125 FPS on high-resolution images on the EndoVis 2017 Robotic Instruments dataset.

Arpit Singhal and Mandeep Singh (2011) researched that Mathematical morphology, a brand-new field founded on rigorous mathematical principles. For image recognition, analysis, and comprehension, mathematical morphology is used based on set theory. It's an effective instrument for analyzing and describing geometric morphology. Preprocessing steps such as noise reduction and edge detection are crucial. Nonlinear filtering techniques are superior to linear filtering techniques for removing speckle noise without compromising thin and tiny image characteristics in image processing applications. Mathematical morphology is a framework used to construct nonlinear filters. Edge detection is often used to locate depth discontinuities, surface orientation discontinuities, material property changes, and lighting variations in the scene. Edge identification and enhancement were made once again using statistical morphological operations. This paper explains how to strip speckle noise from images and then use mathematical morphology to extract useful edges from the output image.

Yifang Huang et al. (2020) showed that when propagating in water, acoustic waves are distorted by channel characteristics such as scattering and reverberation, resulting in speckle noise in sonar images. As a result, in sonar image implementations, denoising is a vital preprocessing technique. On the other hand, speckle noise is mainly caused by sediment echo signals, which are relevant to the history of seafloor sediment and can be predicted using the previous modeling. Even though deep learning-based denoising algorithms are currently a research hotspot, they are not suitable for such applications due to the high calculation number and essential requirements of original images, mainly because they are carried by autonomous underwater vehicles (AUVs) for collecting sonar images and performing calculations. The dictionary learning-based denoising approach, on the other hand, is more appropriate and straightforward to model. In addition, it can significantly reduce the number of calculations needed compared to deep learning and is easier to incorporate into AUV systems.

Furthermore, image denoising can be achieved successfully using a dictionary learning approach based on sparse image representation. The authors suggest a new adaptive dictionary learning approach based on multi-resolution characteristics that incorporate K-SVD dictionary learning and wavelet transform to address the issues raised above. The features of dictionary learning and wavelet analysis are also present in our system. The suggested approach reduces speckle noise and preserves edge information better than most classical methods. Simultaneously, the measurement time is drastically shortened, and reliability is dramatically increased.

Bo Chen et al. (2012) showed that speckle noise depends on the signal and is impossible to eliminate. Their research suggested a novel method for removing multiplicative noise from images based on a fourth-order PDE model. The noisy image is subjected to a Fourier transform and a logarithm technique to translate convolutional noise to additive noise, which can then be filtered using a frequency domain additive noise reduction algorithm. A new fourth-order PDE model for noise removal has been developed, which avoids the blocky effects caused by second-order PDE models while improving edge-preserve ability. On images of both additive and multiplicative noise, the proposed method's accuracy has been tested. Experiments reveal that the proposed approach outperforms specific conventional approaches on various PSNR values and visual consistency.

According to Yuhui Ma et al. (2018), optical coherence tomography (OCT) speckle-noise degrades visual clarity and automated analysis efficiency. When it comes to speckle removal, edge retention is vital. The conditional generative adversarial network is used in this paper to propose an end-to-end method for simultaneous speckle reduction and contrast enhancement for retinal OCT images (cGAN). An edge loss function is applied to the final target to make the model responsive to edge-related information. We also suggest a new approach for extracting clean training images from industrial OCT scanner outputs. The proposed approach outperforms other conventional and deep learning approaches in terms of overall denoising efficiency. The proposed model can also be capable of despecking various retinal OCT images and have a high generalization potential.

Sharavana Raju et al. (2013) showed that image noise is a significant element that lowers image quality. Digital image processing researchers face a challenge in reducing noise from satellite photographs, medical images, and other sources. Noise reduction can be made in a variety of ways. Speckle noise is prevalent in satellite images and medical images captured with Synthetic Aperture Radar (SAR). This study presented several filtering strategies for removing speckle noise from satellite photographs, thus improving image quality. While there are many filters for speckle reduction, others are better suited for SAR photographs. Statistical parameters are determined for the output images collected from all of the filters. SNR, PSNR, RMSE, and CoC are used to compare statistical measures. The output images corresponding to the best statistical values and the filters' names and the statistical measurements' corresponding values are shown.

Choi and Jeong (2020) showed that ultrasound (US) imaging could analyze human bodies of all ages; however, speckle noise is generated from acquiring US photographs. Since speckle noise makes it difficult for doctors to examine lesions correctly, a speckle noise reduction system is a critical technology. The authors suggest a novel algorithm based on speckle noise characteristics and filtering methods such as speckle minimizing anisotropic diffusion (SRAD) filtering, discrete wavelet transform (DWT) using symmetry characteristics, weighted directed image filtering (WGIF), and gradient-domain guided image filtering to improve speckle noise removal (GDGIF). Since it can be applied directly to a medical US image with speckle noise without requiring log-compression, the SRAD filter is used as a preprocessing filter. The drawback of using the wavelet domain is that it suppresses additive noise. As a result, the multiplicative noise is converted into additive noise using a homomorphic transformation. GDGIF and WGIF are used to minimize noise from seven high-frequency sub-band images and one low-frequency sub-band image, respectively, after two-level DWT decomposition remove residual noise of an SRAD filtered image. Finally, using the inverse DWT and an exponential transform, a noise-free image is achieved. As opposed to traditional denoising approaches, the proposed algorithm achieves excellent speckle noise removal and edge conservation.

Shruthi and Renukalatha (2015) showed that by its non-invasive nature, low cost, and potential to shape real-time imagery, ultrasound imaging is a commonly used and secure medical diagnostic procedure. Ultrasound imaging uses high-frequency sound to visualize internal structures by comparing the reflection signals generated when a beam of sound is reflected through the body and bounces back at structure interfaces. However, the presence of signal-dependent noise such as speckle reduces the utility of ultrasound imaging. The speckle pattern is determined by the image tissue's composition and different imaging parameters. Speckle noise in ultrasound images affects edges and fine points, limiting contrast resolution and complicating diagnosis. In medical ultrasound imaging, speckle reduction serves two purposes: (1) to increase human understanding of ultrasound images and (2) to enhance image quality. (2) Despeckling is a prerequisite for specific ultrasound images processing activities like segmentation and registration. In ultrasound imaging, a variety of techniques for speckle reduction have been suggested. This article aims to describe speckle reduction in ultrasound imaging.

According to Milindkumar and Deshmukh (2011), researchers in digital image processing face a challenge in reducing noise from medical photographs, satellite images, and other sources. Noise reduction can be accomplished in several ways. Speckle noise can be used in synthetic aperture radar photographs, satellite images, and medical images. Filtering methods for removing speckle noise from digital images are proposed in this article. The signal to noise ratio is used in quantitative measurements, and the standard deviation is used to determine the noise level.

Ren et al. (2019) suggested a new approach for eliminating the effect of speckle noise on image grey values based on porous silicon (PSi) microarray images, called the phagocytosis algorithm (PGY). Speckle noise of various intensities is applied to images in theoretical analysis, and an appropriate denoising technique is created to restore the image grey level. This technique can reduce the impact of speckle-noise on the grey values of PSi microarray images, improving detection sensitivity and precision. The technique is used to detect refractive index changes in PSi microcavity images in experiments, and a robust linear relationship between grey-level change and refractive index change is obtained. The algorithm is also applied to a PSi microarray graphic, with promising results.

The research of (Dass, 2018) shows that the elimination of speckle-noise is a critical problem of ultrasound image processing and provides vital medical information about the human body. The visual assessment of ultrasound images is harmed by speckle noise. The primary goal of despeckling is to keep all of the ultrasonographic images' fine details and margins. There is a kind of speckle removal process that uses the log transform to translate the multiplicative behavior of speckle-noise to addictive behavior. As compared to multiplicative noise, removing additive noise is easy. A new method for denoising extremely blurred images caused by speckle noise is proposed in this paper. The suggested approach is realized in a homomorphic setting by cascading bacterial foraging optimization (BFO) with wavelet transform and Wiener filter. The wavelet packet decomposition is used to classify and eliminate noise from the pixels that have been affected. For preprocessing, the Wiener filter is used. Following homomorphic framework processing, the BFO algorithm reduces the error between the speckled image and the Despeckled output image. It's used to keep track of the more refined data, and the error percentage is 0.0001. In terms of peak signal to noise ratio (PSNR), Mean Absolute Error (MAE), clarification, and retention of more refined data, the proposed technique outperforms other techniques.

According to Ahmed Zihni et al. (2018), robotic systems can give surgeons more skill and accuracy when conducting complex laparoscopic procedures, which is particularly beneficial for training. There have been few comparative comparisons of surgical task success between laparoscopic and robotic platforms among surgeons with differing experience levels. In novices and seasoned laparoscopic and robotic surgeons, we compared measurements of consistency and productivity of Fundamentals of Laparoscopic Surgery task success on these platforms. The Methods used was: Peg transfer (PT), pattern cutting (PC), and intra-corporeal suturing, which were conducted on both laparoscopic and robotic platforms by 14 novices, 12 expert laparoscopic surgeons (>100 laparoscopic procedures performed, no robotics experience), and five expert robotic surgeons (>25 robotic procedures performed). Each topic completed each task three times in a randomized order on each platform. In both platforms, mean completion times and mean errors per trial (EPT) were determined for each mission. The student's t-test was used to compare the results (statistically significant at P 0.05). The results obtained was: During laparoscopic PC, novices made more mistakes (Lap 2.21 versus Robot 0.88 EPT, P 0.001). According to expert laparoscopists, laparoscopic PT caused more mistakes than robotic PT (PT: Lap 0.14 vs Robot 0.00 EPT, P = 0.04). Laparoscopic PC was associated with more errors among expert robotic surgeons (Lap 0.80 versus Robot 0.13 EPT, P = 0.02) than robotic PC (Lap 0.80 versus Robot 0.13 EPT, P = 0.02). Task output on the robotic platform was slower than laparoscopy among expert laparoscopists. Expert robotic surgeons made fewer mistakes during the PC task to study expert laparoscopists and expert robotic surgeons conducting tasks on the robotic platform (P = 0.009). Conclusions: Robotic assistance reduced errors for certain laparoscopic procedures at all stages of expertise, but there was no gain in task speed. The use of robotic assistance can improve the precision with which surgical tasks are completed.

Basar et al. (2020) proposed a pixel-based image segmentation known as region-based segmentation, which gave many results as discussed earlier but does not find efficiency when the borders of the calculi are not clear. Stergiopoulos et al. detected bleeding in 3D abdominal ultrasound images based on a probabilistic model of kidney shape. Still, this technique lacked the detection of the axis of bleeding position due to the absence of an efficient preprocessing technique. To overcome the challenge of speckle interference in ultrasound images, specific initial preprocessing techniques must be performed. Loganayagi et al. (Loganayagi, 2015) discussed renal calculi detection. Still, due to unfiltered speckle noise in the image, the detection of the calculi axis is challenging with this existing method. More efficient segmentation methods like "SORAMA" should be implemented to overcome all the flip side of the current method.

EXISTING WORK

Different filtering methods like median filter, adaptive filter, and median adaptive filters are applied on ultrasound images for segmentation in the existing ways. Error filtering examination was done where morphological filtering methods were effective and efficient as they exhibit minor error comparatively (Pawar et al., 2020; Loganayagi et al., 2015). The database consisted of images with single or multiple calculi (Anitha et al., 2021.). The filters employed are bilateral, median, anisotropic, nonlocal mean filters to process the speckle noise and subsequent performance parameters. Performance measures like Root of Mean Square Error (RMSE) (Pramanik. and Bandyopadhyay, 2014), Peak Signal to Noise Ratio (PSNR) (Pramanik and Bandyopadhyay, 2013), Signal to Noise ratio (SNR), and Structural Similarity Index (SSIM) are graphically plotted for all the four methods, out of which bilateral filter gave efficient results (Priyankaa and Kumar, 2020). But still, the challenge of speckle-noise removal is not yet met to its fullest extent:

$$\text{Root Mean Square Error RMSE } (\theta) = \sqrt{MSE\left(\theta\right)} \tag{1}$$

where MSE is Mean Square Error.

$$\text{Signal to Noise Ratio (SNR)} = 10{*}log10\left(\frac{signal}{Noise}\right) \tag{2}$$

$$\text{Peak Signal to Noise Ratio (PSNR)} = \frac{10\log 10\left(Peak - Val^2\right)}{MSE} \tag{3}$$

where "Peak-Val" is the maximal amplitude of the image pixels.

$$\text{Structural Similarity Index SSIM (a, b)} = \left[l\left(a,b\right)^{\alpha} .c\left(a,b\right)^{\beta} .s\left(a,b\right)^{\Upsilon}\right] \tag{4}$$

where l (a, b) is luminance calculation between the two elements of a and b, similarly c (a, b) and s (a, b) are contrast and structure, respectively.

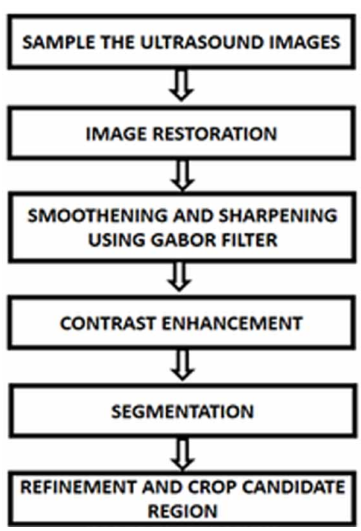
For the existing work sample, ultrasound data images are processed through image processing techniques. The operation is carried over the low-intensity image pixels with intense distortion, and these techniques are performed to improve the image's texture for a better outcome. The following block diagram is shown in Figure 1. It gives a glimpse of how the algorithm works using the Gabor filter (Hafizah, Supriyanto and Yunus, 2012). This filter is used primarily to analyze ultrasound images with a kidney stone. It's a linear filter that extracts the textural features related to the frequency content present in the image:

$$G(a, b, \lambda, \theta, \psi, \sigma, \gamma) = \mathrm{Exp}\left(-\frac{a^2 + \gamma^2 b^2}{2\sigma^2}\right)\cos(2\pi\frac{a'}{\lambda} + \psi) \tag{5}$$

where a' is Gaussian filter and b' is a sinusoidal filter, and the following are filter harmonics λ, θ, ψ, σ, γ.

Contrast enhancement is achieved after smoothing and sharpening processing techniques. Then, sequentially segmentation methods which are mentioned in the literature survey, are implemented and processed.

Figure 1. Flow chart for kidney stone detection in the existing method using image processing



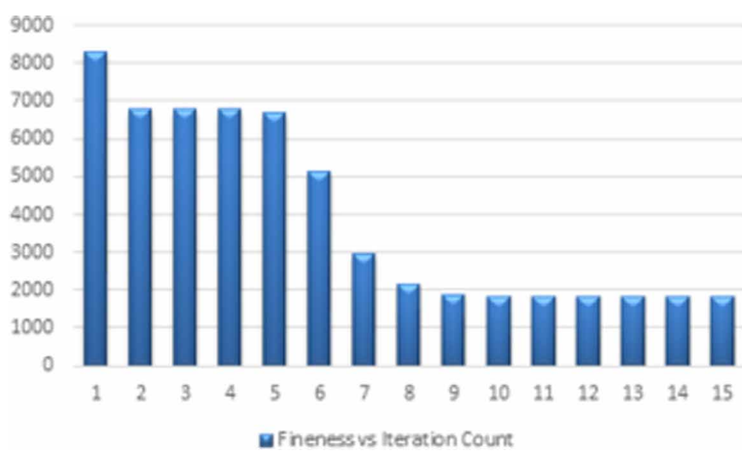
PROPOSED METHODOLOGY

The technique shows the SORAMA method for calculi detection and Robotic Facilitate Surgery. Speckle Noise Removal is the most critical initial step to be carried for ultrasound images. To accomplish effective results, Semantic Object Region and Morphological Analysis (SORAMA) algorithm, as depicted in Figure 2., is implemented where primarily the image undergoes preprocessing techniques in which bilateral filter is applied to remove the speckle distortions. As it has better edge persevering capacity and gives an efficient performance, this facilitates the segmentation process and helps in intensifying or reducing specific image information. That also involves image enhancement and edge filtering techniques.

A few of the intensity histogram and Gray Level Co-Occurrence Matrix (GLCM) features are extracted for texture analysis of the preprocessed image, followed by preprocessing techniques. This applies to calculate the gray level intensity for pixels composed in the image. To achieve intensity, histogram analysis skewness and kurtosis are considered (Vinoth et al., 2018; Sharma and Irmani, 2017). Furthermore, Gray Level Co-Occurrence Matrix (GLCM) is statistically calculated to obtain the pixels of the image with spatial relation, otherwise called the matrix of Gray Level Spatial Dependence. Also, this approach is used to exact textural statistics of the second-order picture. This paper includes GLCM features of three groups: Contrast group, Orderliness group, Statistics group. In contrast, group homogeneity, contrast, and dissimilarity are considered, whereas in orderliness and statistics groups consist: Entropy; Energy; Angular Second Moment; Max Probability and Mean; Variance; Correlation respectively after that image segmentation is done, which is a process of splitting up the digital image into pixel sets to form superpixels.

This proposed method can Region of Interest (ROI) model is implemented. It specifies the shape or volume of the calculi to successfully rule out the ROI boundaries in computer graphics and natural scenes. Depending upon the inherent distance, the input data sets are clustered using a clustering algorithm. Thus, it contains a plausible area. To exact the invisible region affected, it is found to be a much efficient method. After segmentation, morphological analysis is carried out based on the shape obtained from the previous step. In this step, the image undergoes irregularity feature exaction and determines the stone shape. These morphological operations, including dilation and image erosion, smoothen the image by removing unwanted pixels (Martínez et al., 2020; Choi et al., 2021). If the stone is not detected, then the algorithm undergoes multiple iterations. Ultimately the recognized nephrolith’s (scientific term of kidney stone) coordinated are fed into the assisted robot that does the surgical operation for urinary tract calculi (Duarte-Salazar et al., 2020).

Figure 2. SORAMA algorithm for kidney stone detection using image processing



RESULTS FOR PROPOSED SEMANTIC OBJECT REGION AND MORPHOLOGICAL ANALYSIS (SORAMA)

The raw input Figure 3 portrays the abnormality of intravascular ultrasound images because of the inconsistent angular velocity of the perfunctory type, which is to be processed using digital image processing techniques. This image is taken from the hospital database of a male patient aged 45 to 50. Unfortunately, this image is corrupted with distortions or disturbances known as Speckle Noise (Kumar, D. 2020). In addition, it degrades the excellent details and information of edges and contrast resolution.

Figure 4 displays the grayscaled image (Pramanik and Bandyopadhyay, 2014), where the value of each pixel is a simple representation and are arranged in a grid of 2-dimensions. The contrast ranges from black as weakest to white as most robust (Batool et al., 2020). According to the original contrast and intensity, the color image is represented in monochromatic gray shades (Lazar et al., 2020).

Skewness and kurtosis are calculated under the category of intensity histogram analysis as depicted in Figure 5 with the mathematical formula mentioned in Equation 6 and 7. Skewness is defined as the deviation of the bell curve from the symmetrical curve or normal distribution. At the same time, kurtosis measures data distribution based on heavily tailed or lightly tailed or maybe moderately tailed on an asymmetric bell curve. These are applied on the discrete image as v(p,q), and the total no of pixels is considered NM:

$$\text{Skewness } S(a,b) = \frac{1}{NM}\sum_{p}^{q}\sum_{p}^{q}\left[\mathrm{v}\left(\mathrm{p}-\mathrm{a},\mathrm{q}-\mathrm{b}\right)-\mathrm{M}\left(\mathrm{a},\mathrm{b}\right)\right]^{3} \tag{6}$$

$$\text{Kurtosis } K(a,b) = \frac{1}{NM}\sum_{p}^{q}\sum_{p}^{q}\left[\mathrm{v}\left(\mathrm{p}-\mathrm{a},\mathrm{q}-\mathrm{b}\right)-\mathrm{M}\left(\mathrm{a},\mathrm{b}\right)\right]^{4}-3 \tag{7}$$

Figure 3. Real-time ultrasound image with distortions

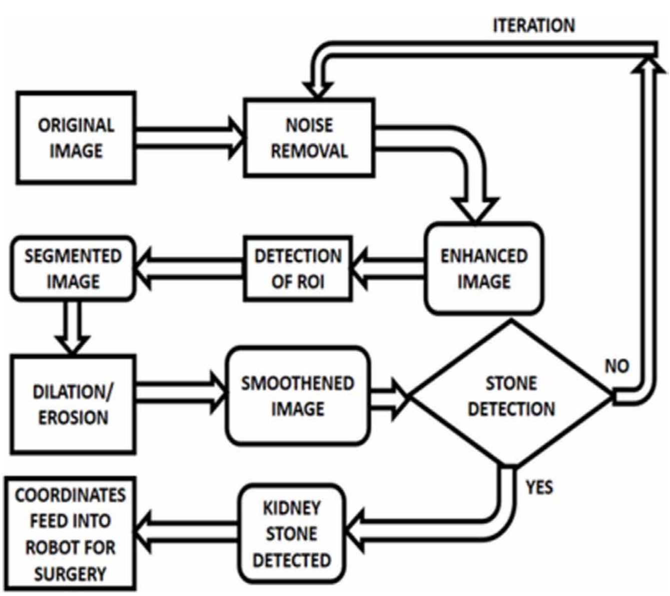


Figure 4. Computer-generated imagery or grayscaled image

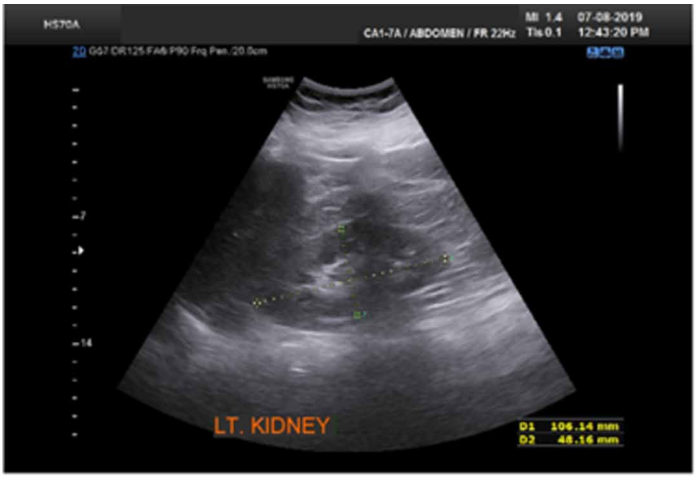


Figure 5. Skewness and Kurtosis image under SORAMA technique

Table 1 depicts the values obtained by extracting Skewness and Kurtosis statistics. Skewness measures symmetry, and kurtosis measures terminal tail characteristics on par with the normal distribution curve. Kurtosis value is found to be 3.0123, which are efficient enough for an ultrasound image as the optimum range varies between negative 3.5 to positive 3.5. On the other hand, the skewness results are 2.403, which are again considered suitable for texture analysis of ultrasound image containing renal calculi.

Table 1. Intensity Histogram Analyses – SORAMA

S. No.	Intensity Parameter	Values
1	Skewness	2.4031
2	Kurtosis	3.0123

In addition to the previous parameters, Gray Level Co-Occurrence Matrix textural features are also exacted to clarify the processed ultrasound image.

Figure 6 portrays the comparison of the GLCM parameters between existing and proposed work. The graph clearly shows the decreasing value of contrast from existing to proposed work which implies the edges and the noise interference has decreased significantly. Also, GLCM means that variance and correlation have improved optimal values, resulting in effective preprocessing on the ultrasound image.

Figure 7 portrays a multiplied version of all intensities by a scalar value. It is the modified adaptation of pixel values. Scaling is done automatically to force the scale on massive peaks to obtain more minor features imperceptible (Matsumoto, 2018). Contrast stretching is known as normalization of the image, where it undergoes enhancement techniques to improve the contrast by operating 'stretching' over the range of intensities.

A bilateral filter balances the intensity values from nearby pixels. These weights are based on Gaussian distribution (continuous function for the binomial distribution with remarkable properties such as edge-preserving. That is used for smoothening (Pramanik and Singh, 2017) of the image and decomposing the noise distortions. Figure 8 depicts the bilateral filtered version with preserved edges and smoothened noise-reduced image.

The automatic SORAMA algorithm for morphological analysis is presented in Figure 9. The stone is segmented by the assistance of the Region of Interest (RoI) modal. Hence, it implies Advanced Imaging Technology (AIT) for practical implementation as the results are drawn with the evidence of reduced perplexed image segmentation method (Chang, 2021).

As the iteration count increases, the fineness of the image decreases, Table 2 implies or depicts the handling of image processing (Pramanik and Raja, 2020) in taking a path of simplification, less distorted or perplexed.

The graph depicted in Figure 10 represents the variation between iteration count and corresponding fineness. The iteration count varies from 1 to 15 on the x-axis, and the fineness scale ranges from 0 to 9000 on the y-axis. The decreasing fineness for each iteration depicts the speckle noise that has been removed. Thus, it is evident that the increase in iteration count decreases the fineness of the medical image, thereby making the image - speckle noise-free, to determine the exact Region of Interest (ROI) effectively, i.e., Renal Calculi (Kurian and John, 2014).

Figure 6. GLCM Parameters comparison between Existing and Proposed Work

Figure 7. Intensity Scaled and contrast Stretching Image

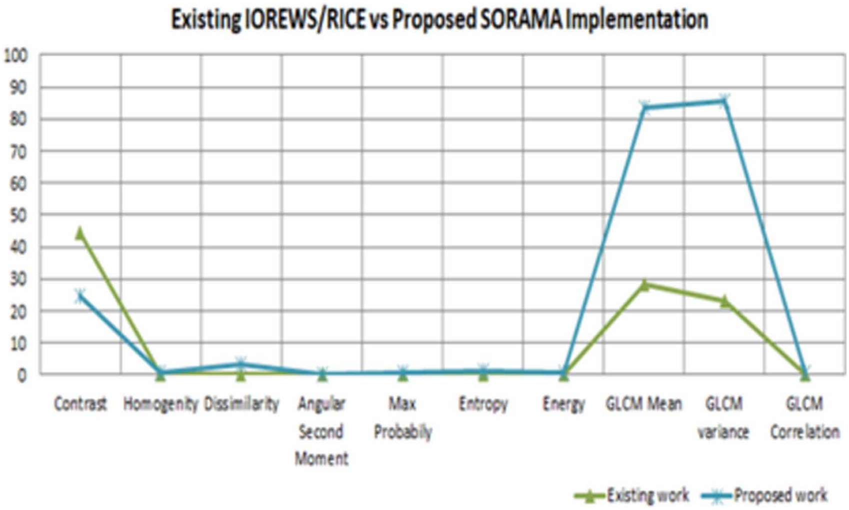


Figure 8. Bilateral filter: nonlinear, edge-preserving smoothing filter

Adopting robotic facilitation techniques will be maintained by the cost incurred on health (Mahapatra and Nayyar, 2019), maintenance and medical management. Coordinate delineates the location of the stone pixels, i.e. [1,1,1366,395], which represents the corresponding position of the stone in matrix format of x1, x2, y1, y2 of the image which is fed into the robotic system which is used for the surgical operation procedure for renal calculi patient to locate the precise location of calculi effectively using SORAMA segmentation.

COMPARISON TECHNIQUE

Statistical features are extracted in the proposed method, and these features are mainly classified into three groups: contrast, orderliness, and statistics. As mentioned in Table 3, they are measured efficiently compared to the existing work that uses Gabor filter with IOREWS, RICE algorithm.

Figure 9. Perfectly Segmented and Morphological Renal Calculi Medical Image

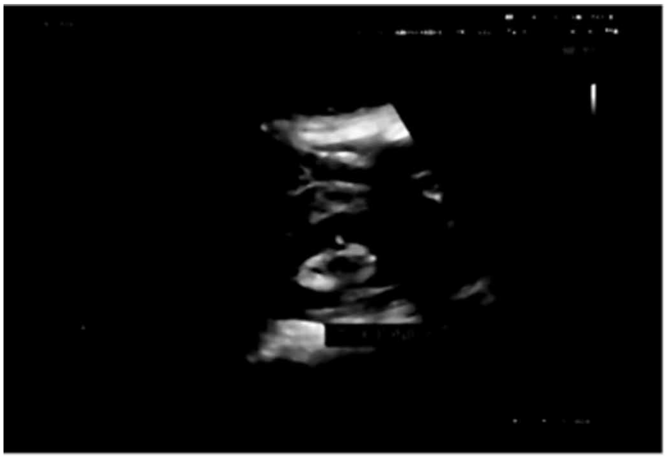


Table 2. Iteration count vs Fineness for SORAMA implementation

Iteration Count	Fineness
1	8308.2855
2	6775.5142
3	6775.1775
4	6769.7681
5	6677.6264
6	5137.3532
7	2944.9799
8	2132.7600
9	1884.5748
10	1821.8977
11	1807.5743
12	1804.4630
13	1803.6657
14	1803.6310
15	1803.6294

Researchers have tried improving the image quality using IOREWS, RICE algorithm (Kamiran and Toon, 2012) for speckle noise removal. Still, they fail to yield good contrast for object identification at extreme conditions. Contrast is calculated to locally obtain a gray level variance or inertia on a processed image under the SORAMA segmentation technique. A very high value of this indicated the presence of edges and wrinkles in the image. Homogeneity measures gray-level distribution all over the image, and it's inversely proportional to contrast. Dissimilarity measure plays a vital role to obtain content based on an image, where data sets are represented as vectors. Angular Second Moment is the test for uniformity in the image. Max probably is used to finding the random distribution of the data or pixels. Entropy defines the corresponding intensity value, and pixel can adjust or adapt

Figure 10. Decreasing graph of fineness for each incremental Iteration count for SORAMA implementation

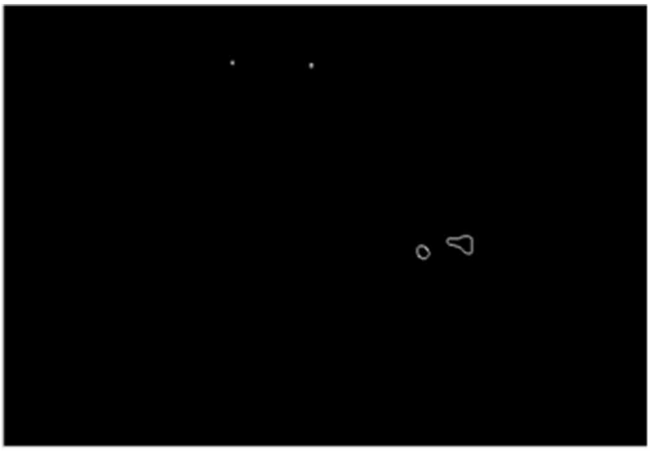


Table 3. GLCM feature extraction and texture analysis

GLCM Groups	Texture Features	Existing Work	Proposed Work
Contrast Group	Contrast	88.4928	24.4563
	Homogeneity	0.2738	0.7238
	Dissimilarity	0.041	3.4021
Orderliness Group	Angular Second Moment	0.2859	0.2859
	Max Probably	0.5347	0.7465
	Entropy	0.9589	1.51602
	Energy	0.2861	0.53473
Statistics Group	GLCM Mean	56.7895	83.4562
	GLCM variance	6.7198	85.7303
	GLCM Correlation	0.0048	0.9021

according to adjacent pixels (Pramanik, Singh and Ghosh, 2020). Energy emphasizes the steadiness of intensity of the pixels. GLCM mean is the average of all the pixels present in the image, especially considering intensity levels. GLCM variance measure the dispersion found around the mean of the pixels, and correlation calculates the dependency of each pixel on the neighboring pixel.

CONCLUSION

Semantic Object Region and Morphological Analysis (SORAMA) and Robotic facilitated laparoscopic ureter-lithotomy are implemented to investigate and realize urolithiasis (renal calculi) using digital image processing on ultrasound images. This research paper proposes an efficient speckle noise removal and segmentation method for nephrolithiasis detection for ultrasound images with less distortion and reduced image perplex. To overcome speckle distortion or noise issues, the image undergoes preprocessing techniques, which results in effective reduction of speckle noise and simplifies for further processing. Furthermore, image segmentation using the ROI model is done for better edge detection for abnormal regions. Followed by image segmentation, morphological analysis is done to smoothen the image pixels.

Finally, the location or coordinated renal calculi is fed into the robot facilitated for laparoscopic ureter-lithotomy. That is found to be efficient than the existing methods. In the future, this research work will be integrated with the robotic arm for real-time implementation and practical observation.

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