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Improved Kidney Stone Detection from Ultrasound Images Using GVF Active Contour

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ABSTRACT

Medical image segmentation is of large significance in supporting information about human body structures which assist physicians in correct diagnosis to determine doing radiotherapy or surgeries. Therefore, accurate interest region detection in ultrasound images represents a challenging function and hence needs to apply more trusted tools to gain the best segmentation and classification of kidney stones. This challenge in ultrasound images includes many factors like low contrast, occlusions, signal deviations, and noise made it difficult to determine these stone's boundaries. This paper applied gradient vector flow (GVF) model which has a large capture range to identify the image boundaries of kidney stones region and estimate variation in stone measurement to prepare a suitable treatment diagnosis.

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1. Introduction

Ultrasound imaging represents the safest and most inexpensive technique applied medical images to identify the correct diagnosis and helps in the broad field of diseases and conditions. The traditional segmentation methods failed to converge the concave regions and deep concavity boundaries of regions in addition to, noisy with speckle images made this mission is difficult to diagnose manually from surgeries and physicians [1]. Ultrasound scanning is commonly used to detect kidney stones although challenging to regard to the region of interest detection which makes this technique a difficult decision about the presence of kidney stones. Kidney ultrasound or renal ultrasound is a safe tool and unharmful test that create images of the kidney, ureters, and bladder using waves of sound. Sometimes obstacles have been made stone detection was difficult or fuzzy regarding gazes or unstable right position of the patient which led to an incorrect diagnosis. Researchers have participated to improve the vision of medical images [2]. Some researches explore the detection of kidney stones using different techniques to enhance the evaluation of correct decisions about the size and location of kidney stones.

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Monika Pathak et.al [3] developed a semiautomatic system to analyze the region of interest detection in ultrasound images which is manually selected, to overcome the presence of speckle noise and identify the stone region in the ultrasound images. They applied the feature extraction which included contrast, angular second moment, entropy, and correlation. The K-nearest neighbor classification (KNN) was applied to analyze the features for the detection of stone in the images.

Arpana Kop and Ravindra Hegadi [4] proposed a method to remove unwanted boundaries from the images using the GVF model. This method helps to segment and estimate kidney size from ultrasound images and identifies the presence of distortions like renal calculus, multicystic kidney, in these images.

Prema Akkasaligar and Savitri Unnibhavi [5] presented a method using GVF balloon snake to capture the possible boundaries of the kidney in ultrasound images and the K-nearest neighbor classification (KNN) which classifies the kidney ultrasound images to the normal or cystic kidney.

Goel and Jain [6] proposed a technique to detect kidney stones by adjusting the image density to enhance the image contrast, also applied the median filter to remove the noises.

Venkatasubramani.K et.al [7] proposed an image processing technique with backpropagation for kidney stone classification. Also, they applied the GLCM technique as a feature extraction method with fuzzy C-mean to detect kidney stones in the early stages.

Shruthi B et al. [8] presented a technique to enhance the equality of the ultrasound image for speckle reduction. K. Viswanath; R. Gunasundari [9] introduced a method to detect kidney stone location followed with steps, first enhanced the ultrasound images using image restoration is done to reduce speckle noise and smoothing using Gabor filter, Next to enhance the quality of resultant image using histogram equalization. Then the resultant image was segmented by level set segmentation. The classification is done using Multilayer Perceptron (MLP) with Back Propagation (BP) ANN to assign the kind of stone with an accuracy of more than 98%.

Shi Yin et al. [10] proposed segment kidneys in clinical ultrasound (US) images automatically. Experimental results have 28 demonstrated that our method could automatically segment the kidney with promising performance, 29 significantly better than deep learning-based pixel classification networks.

Veska M. et al. [11] presented active contour without edges to segment 2D ultrasound images after preprocessing including contrast enhancement with CLAHE and speckle noise reduction. This method made it easy to recognize object boundaries.

Mua'ad M et al. [12] proposed three segmentation techniques: threshold-based segmentation, watershedbased segmentation, and edge-based segmentation to check the area of the kidney and to improve kidney stone detection.

Stalina S, et-al.[13] presented a technique consisting of three steps, first is preprocessing using a type of filter and enhancing the resultant image, and removing noises. Dominik Vilimek et al. [14] presented a hybrid method to made identification and feature extraction of the kidney stone area using multiregional extraction with active contour. Also, applied median and Wiener filters in preprocessing.

Lin Sun et al. [15] proposed a new active contour model to segment inhomogeneous images based on two techniques, signed pressure force (SPF) and local image fitting (LIF) model. Fengjun Zhao et al. [16] proposed an effective kidney segmentation method with micro-CT- images based on multi-atlas registration (MAR) and random forests (RFs).

Vineela et al. [17] presented a technique to detect kidney stones from ultrasound images by an applied the median filter to remove speckle noise. Wei-Yen et al. [18] proposed an adaptive active contour model to evaluate the cancer size. They proposed a set of medical image processing applying images provided by the hospital and select the more obvious cases by the doctors.

A.Ishwarya et al. [19] proposed a technique to classify kidney stones using Convolution Neural Networks and simplify diagnosis using IoT. The IOR of the image is cropped out after is converted into a gray mode. After that

Active Contour was applied to segment textures features and classified using the Convolution Neural Networks model. Then, the data is sent to the Cloud using IoT in order to be accessed by doctors and patients.

Jie Lian et al. [20] proposed a kidney tissue image Features method based on ultrasound image segmentation by incorporating the brightness changing mode with a speckle tracking algorithm. Then verify the resultant method using the block-matching method.

Mohammad Talebi et al. [21] presented a segmental method by combing active contour with a genetic algorithm to overcome the restriction of initialization, local minima, and convergence to concave regions applied on medical ultrasound images.

2. The Active Contour

Active contour or snake introduced by Michael Kass et al. in 1988 and defined as the minimization of energy directed by external forces and affected by` image forces that led it to object boundaries and internal forces keep the slim contour. [22]. Active contours can be defined according to the following equations of external and internal energies. The position of AC snaxeles is assigned by the equation:

$$v(s) = (x(s), y(s)) \tag{1}$$

Also, the energy of AC defined as:

$$E_{snake} = \int_0^1 \left[E_{int} \left(v(s) \right) + E_{ext} \left(v(s) \right) \right] ds \quad (2)$$

Where:

$$E_{int} = \frac{1}{2} \left[\alpha(s) |v_s(s)|^2 + E_{ext}(v(s)) \right] ds \quad (3)$$

$$E_{ext} = -\gamma |\Delta I(v(s))|^2$$
(4)

Active contour suffers from some drawbacks like primary initialization of its snaxeles position; therefore, more times the primary location is away from the interesting position. Another drawback is poor convergence to concave or deep concave boundaries. These factors made active contours not activated to convergence the deep and narrow concave regions.

3. Proposed Method

The proposed method is based on Gradient vector flow (GVF) active contour. The method was tested (30) kidney images. These images are already enhanced with filters mentioned in the previous section. All steps of preprocessing were applied to each image to decrease drawbacks of segment or detect the interesting regions in the ultrasound image of kidney, these factors like low contrast, occlusions, signal deviations, and noise made the difficult to determine the kidney stones boundaries. Most of the previous segmentation methods had some disadvantages that led to inaccurate detection of kidney stone boundaries which made the diagnosis of size and region of stones is more difficult. Therefore, active contours have high convergence to concavity objects with different types of boundaries; specialist with Gradient Vector Flow (GVF) active contours can be convergence to deep and narrow concavity boundaries. Fig. 1 below represents the proposed method that enhanced the previous methods already applied to detect kidney stones.



Fig.1- Proposed Method

3.1 Preprocessing of image

The first step is to preprocess the ultrasound images to reduce speckle noise and smoothing, also better quality of contrast. Speckle noise on the ultrasound images is mainly led to corrupted images. The ROI was extracted after reading the image itself, then the area of interest in which kidney stones were located. Firstly, the images were converted from RGB to grayscale images using an edge map as s showed in Fig. 2.



Fig.2- images preprocessing using edge map.

Secondly, remove the noise like speckle, low contrast, occlusions, signal, and deviations using median filter, as well as applied for smoothing image as in Fig. 3.



Fig. 3- Images preprocessing, (a, b, c) original images, (c, d, e) median filter

Thirdly, we applied Otsu thresholding which represents a type of multiregional segmentation to distinguish among areas of the image by dividing into different segments according to region binarization technique as shown in Figure 4. This segmentation technique of kidney stones was inefficient because it was active with the high level of thresholding values, while inactive with fewer values. Fig. 4 below showed the Otsu threshold with different kidney stone images.



Fig. 4- Otsu thresholding

3.2 GVF segmentation

In the segmentation algorithm, we adopted different methods. Binarization represents the simplest method of segmentation. Although different threshold levels were applied; this method was not appropriate for more processing. The kidney stone could not be quite separated from the surrounding structures. So, calculating the threshold for each frame separately did not succeed.

Therefore; active contour represents the better alternative to segment and detect the kidney stone effectively. Although AC capability to segments kidney stones is limited except for deep narrow and concave boundaries.

GVF active contour has many priority factors that made it the better image segmentation method. GVF differs from classic active contours with the external force equation as shown below.

$$V(x, y) = (u(x, y), v(x, y))$$
 (4)

$$E_{external} = \iint \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 V - \nabla f|^2 \, dx \, dy \tag{5}$$

Where:

 μ : is an adapting variable

 ∇f : The gradient of the edge map.

The following equations applied to minimize the energy:

$$\mu \nabla^2 u - (u - f_x) \left(f_x^2 + f_y^2 \right) = 0 \tag{6}$$

$$\mu \nabla^2 v - (v - f_y) (f_x^2 + f_y^2) = 0$$
 (7)

Where:

 ∇^2 is the Laplacian operator

4. Result and Discussion

The ultrasound kidney stones images are preprocessed to remove noises. These tested images were converted and changed from RGB to Gray images already. Further, image noises were removed and contrast was enhanced using the median filter. The Median filter removes the speckle noise in an ultrasound image and detects stones in the kidney. The median filtering algorithm uses a neighborhood area as a filtering window, which changes the size of the filtering window according to certain setting conditions in the filtering process. For better formulation, GVF active contour applied with high convergence to object boundaries based on internal and external energies segmentation as explained previously. The kidney stone is detected by a red line. The number of iterations is important to assign a better board of active contours; therefore, lower number iterations will be better to object convergence with less computational complexity. Fig. 5 showed active contour initialized and converged by the number of iterations with a value between 50- 70.



Fig. 5- GVF segmentation

5. Conclusion

In this paper, a dataset with 20 ultrasound images was tested. For preprocessing ultrasound images were tested by three stages of preprocessing techniques including binarization technique and median filter to enhance and remove any noises from these images. In the second stage, we applied Otsu thresholding to detect and segment the ultrasound images. The third stage represents the resultant stage in which gain butter convergence to stone kidney boundaries with different sizes and shapes.

The initialization of active contour position is limited besides the kidney stone structures, which are assigned by a red curve. Convergence rate calculated upon the number of iterations which are rated by better value computed with different kidney stone shapes.

In this work, we faced limitations abstracted with the manual initialization of active contour position. In future work will be enhanced the manual to an auto position of active contour and to detect the deep concavity of kidney stone shape and size.

References

 Klibanov and Hossack, Ultrasound in Radiology: from Anatomic, Functional, Molecular Imaging to Drug Delivery and Image-Guided Therapy, HHS Public Access 2016.

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- [3] Monika Pathak, Harsh Sadawarti, Sukhdev Singh. Features extraction and classification for detection of kidney stone region in ultrasound images. International Journal of Multidisciplinary Research and Development. Vol. 3(5); 2016; pp. 81-83.
- [4] Arpana Kop and Ravindra Hegadi. Kidney Segmentation from Ultrasound Images using Gradient Vector Force. International Journal of Computer Application. IJCA Special Issue on "Recent Trends in Image Processing and Pattern Recognition" RTIPPR, 2010.
- [5] Prema T. Akkasaligar Savitri S. Unnibhavi. Identification of Kidney in Medical Ultrasound Images. 5th SARC-IRF International Conference, Bangalore, India, 2014.
- [6] Goel R., Jain A. Improved Detection of Kidney Stone in Ultrasound Images Using Segmentation Techniques. In: Kolhe M., Tiwari S., Trivedi M., Mishra K. (eds) Advances in Data and Information Sciences. Lecture Notes in Networks and Systems, vol 94, Springer, Singapore. 2020
- [7] Venkatasubramani.K, 2K. Chaitanya Nagu, 3P. Karthik, 4A. Lalith Vikas, Kidney Stone Detection Using Image Processing and Neural Networks. Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Pages. 13112 – 13119.
- [8] Shruthi B et al, Detection of Kidney Abnormalities in Noisy Ultrasound Images. International Journal of Computer Applications (0975 8887) Volume 120 – No.13, June 2015.
- [9] K. Viswanath; R. Gunasundari, Design and analysis performance of kidney stone detection from ultrasound image by level set segmentation and ANN classification. 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI), IEEE. 2014.
- [10] ShiYin et al, Automatic kidney segmentation in ultrasound images using subsequent boundary distance regression and pixelwise classification networks, Medical Image Analysis Volume 60, February 2020.
- [11] Veska M. Georgieva et al., Kidney Segmentation in Ultrasound Images Via Active Contours, M, .CEMA'16 conference, Athens, Greece 2016.
- [12] Mua'ad M et al., Analysis and implementation of kidney stones detection by applying segmentation techniques on computerized tomography scans, Italian Journal and Applied Mathematics - N. 43-2020 (590-602) 2020.
- [13] Stalina S, et al., Kidney Stone Detection Using Image Processing on CT Images, International Journal of Management, Technology and Engineering, Volume 8, Issue XI, November 2018.
- [14] Dominik Vilimek, et al., Modeling of Kidney Stones from Ultrasound Images based on Hybrid Regional Segmentation with Active Contour, Acta Mechanica Slovaca 23 (4): 38 - 45, December 2019.
- [15] Lin Sun, et al., An Image Segmentation Method Using an Active Contour Model Based on Improved SPF and LIF, Applied Sciences 2018.
- [16] Fengjun Zhao et al., Efficient Kidney Segmentation in Micro-CT Based on Multi-Atlas Registration and Random Forests, Volume 6, 2018. IEEE access.
- [17] Vineela et al., Kidney Stone Analysis Using Digital Image Processing, International Journal of Research in Engineering, Science and Management, Volume-3, Issue-3, March-2020.
- [18] Wei-Yen et al., Improving segmentation accuracy of CT kidney cancer images using adaptive active contour model.
- [19] A.Ishwarya et al., Kidney stone classification using Deep Neural Networks and facilitating diagnosis using IoT, International Research Journal of Engineering and Technology (IRJET), Volume: 06 Issue: 03 Mar 2019.
- [20] Jie Lian et al., Feature Extraction of Kidney Tissue Image Based on Ultrasound Image Segmentation, Hindawi, Journal of Healthcare Engineering, Volume 2021.
- [21] Mohammad Talebi, et al., Medical ultrasound image segmentation using genetic active contour, Journal of Biomedical Science and Engineering, 2011, 4, 105-109.
- [22] kass et al., Snakes: Active contour models, International Journal of Computer Vision volume 1, pages321–331 (1988).