Extraction of Appendix from Ultrasonographic Images with Fuzzy Binarization Technique

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Abstract

Accurate diagnosis of acute appendicitis is a difficult problem in practice especially if the patient is too young or pregnant women in that radiological test have high risk. Thus, ultrasonographic image analysis is a good way to reduce the difficulty. However, studies show that there are few reliable common predictors and the decision is usually made by medical expert's naked eye examination since there is yet a reliable software tools to use in decision making. In this paper, we propose a new intelligent method to extract appendix from abdomen ultrasonography as a basic building block of developing such intelligent tool for medical practitioners. Knowing that the appendix is located at the lower organ area below the bottom fascia line, we conduct a series of image processing techniques to find the fascia line correctly. And then we apply fuzzy binarization to the organ area in order to extract appendix accurately. The experiment verifies that this two-phase image analysis is effective in extracting appendix.

Keywords: *Appendix, Appendicitis, Fuzzy Reasoning, Binarization, Ultrasonography*

1. Introduction

As one of the most common surgical abdominal emergences, accurate diagnosing of acute appendicitis has been a topic among clinical researchers. Appendicitis is a disease having an inflammation of the appendix [1]. Typically, acute appendicitis leads the removal of the inflamed appendix, either by laparotomy or laparoscopy. Furthermore, although it is not acute, it may develop into complications such as appendiceal abscess, perforated appendicitis, peritonitis, pelvic inflammatory disease, and pelvic abscess and the mortality is relatively high if untreated [2]. A typical process of treating appendicitis is that after confirming the pain from lower-right abdomen, a blood test is required to observe the change of white blood cell rate followed by urinalysis to exclude the possibility of urolithiasis and nephropyelitis. Then the CT and/or ultrasonography finally verifies the state of appendix to diagnose the pain occurred by the appendicitis by naked eye examination of medical doctors. The findings of appendix on CT or ultrasonography are often classified into five categories - definite appendicitis, probably appendicitis, equivocal CT findings for diagnosis of appendicitis, probably not appendicitis, and normal looking appendix. Recent research showed that the diagnosis of appendicitis by CT and ultrasonography were correlated with clinical or pathologic diagnosis but not agree with all the time. Thus, the reevaluation of CT findings by ultrasonography could avoid misdiagnosis of appendicitis on CT and improve diagnostic accuracy of acute appendicitis [3]. Furthermore, there exists a high level of reluctance of using radiological test to young children or pregnant women. Thus, ultrasonography is often used in diagnosis of appendicitis in such cases. There have been many researches to find proper predictors of appendicitis [4]. For example, a study reports that the MR findings of appendicitis include a dilated, thick walled blind-ending tubular structure measuring >7 mm with periappendiceal stranding and inflammation [5]. However, recent research reevaluates many predictors reported on various literatures with a multivariate analysis and find that only the inflammation of the periappendiceal fat is statistically significant predictor of the acute appendicitis (OR = 68.93, P < .0001). Other criteria such as diameter, noncompressibility, hyperemia, the presence of an appendicolith, and loss of stratification of the appendiceal wall do not independently predict [6]. Such image analysis by experience is especially helpful in cases of patients presenting with atypical signs/symptoms for acute appendicitis and those presenting with a classic presentation where an alternative diagnosis is determined [7]. However, considering the seriousness of acute appendicitis diagnosis, current naked-eye examination of CT or ultrasonography by medical expert cannot avoid the risk of misdiagnosis. Thus, there are growing needs for an intelligent decision tool for more accurate diagnosis by artificial intelligence technology. Unfortunately, there are few tools for the practitioners to use with credibility up to date.

In this paper, we propose a method to extract appendix from ultrasonography with fuzzy binarization. This might be the first step of developing a reliable intelligent software tool for diagnosing acute appendicitis more accurately. An ultrasonographic image is represented by intensity levels from 0 to 255 in gray scale where the solid region as bright levels and the fluid region as dark levels [8]. With that characteristic, the image could be analyzed several times by a serious of image processing techniques to extract the goal area - appendix. Firstly, the image is standardized to avoid machine dependency [9]. All our discussion below is based on such standardized image. Our analysis starts with removing unnecessary part from the image such as the ruler area and then we apply Ends-in Search Stretching technique [10] to enhance the difference of brightness. Then the block binarization technique is used to extract candidate fascia area. Noise area is removed by Grassfire technique and the bottom fascia is extracted by applying expansion operation. Those processes will be explained in Section 2. Section 2 serves to find bottom fascia line successfully. Knowing that appendix is located below that line, our fuzzy binarization technique that will be explained in Section 3 will extract candidate appendix area without the affection of muscle area brightness distribution above the fascia line and then the area with a certain brightness and size will be decided as appendix as a result. The implementation result will be explained in Section 4 followed by discussion.

2. Extracting Fascia Line

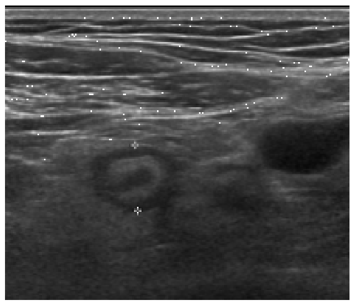
2.1. Enhancing Abdominal Fascia Area by Ends-in Search Stretching

In the preprocessing step, the main area including only components of ultrasonic waves and the ruler area indicating the size of muscle areas are removed from an original ultrasonographic image. Such information is only helpful for naked eye examination.

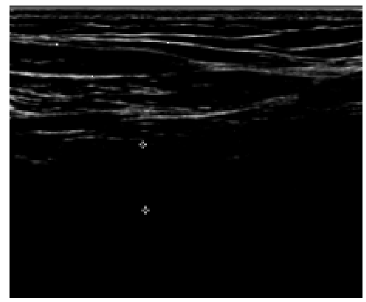
Ends-in Search Stretching technique is applied to enhance the difference of the brightness to emphasize fascia and muscle area by applying formula (1) for cells whose brightness is larger than 100.

$$outImg[x][y] = \begin{cases} 0, & for\ X \le Low \\ \frac{X-Low}{High-Low} \times 255, & for\ Low < X < High \\ 255, & for\ High \le X \end{cases} \tag{1}$$

where X denotes the brightness of the cell in the original image and Low and High denote the brightest and the darkest cell's brightness that are larger than 100 in respectively. By this technique, we can obtain more differentiable image from the original as shown in Figure 1.



(a) Original Ultrasonographic Image

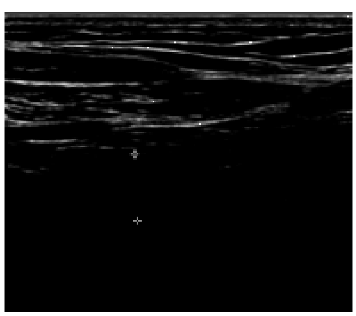


(b) After Applying Ends-in-Search Stretching

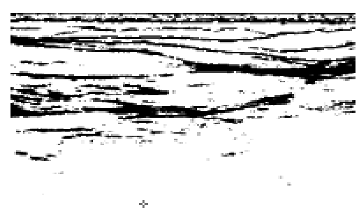
Figure 1. Applying Ends-in Search Stretching Technique

2.2. Extracting Fascia Area by Block Binarization

For each pixel in the input image, we need binarization procedure for efficient analysis. Usually the binarization process takes single threshold to make the image as black and white but it might mislead the analysis if some parts of the image have far different brightness distribution from overall average of the image which is our case. Thus, we apply block binarization among many available binarization algorithms since ultrasound images often shows several characteristically different parts in the image. Block binarization divide the image into several parts and use different threshold value to each part according to the brightness distribution for each block. Figure 2 shows the result of block binarization process.



(a) After Ends-in Search Stretching

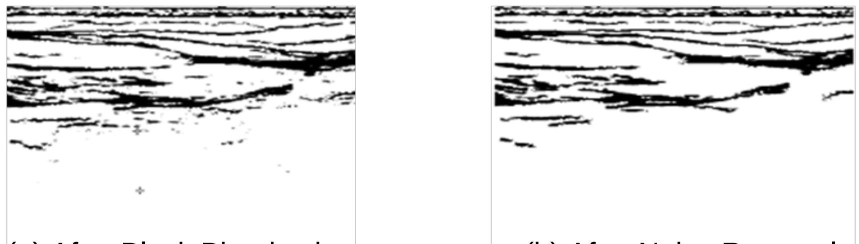


(b) After Block Binarization

Figure 2. Effect of Block Binarization

2.3. Noise Removal with Grassfire Algorithm

However, the binaries image contains noises in fascia and muscle area. In order to remove them, we apply labeling procedure by Grassfire algorithm and remove a small object which contains less than 200 pixels since those small objects are not likely to be a part of fascia or muscle area. Figure 3 shows the result of such noise removal.

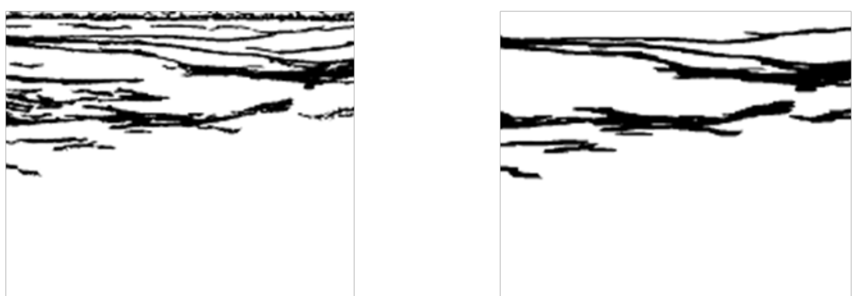


(a) After Block Binarization (b) After Noise Removal

Figure 3. Applying Grassfire Algorithm

2.4. Extracting Bottom Fascia and Fascia Line

Unfortunately, the binarized noise-removed image may have disconnected fascia area due to the brightness difference of that area. In order to reconnect them, we apply Grassfire again and search fascia objects from the bottom of the image. Since the shape of the fascia is horizontal, we apply expansion operation with 1x7 masks to reconnect them. Figure 4 shows the compensated Fascia lines after expansion operation.



(a) Noise Removed (b) After Applying Grassfire and Expansion

Figure 4. Compensation of Fascia Lines with Expansion

Our interest in this series of image processing is finding the bottom fascia line since the appendix is located below this line. Thus, the final fascia line is found by object search from the bottom as shown in Figure 5.

(a) After Grassfire and Expansion (b) Fascia Line found by Object Search

Figure 5. Extraction Fascia Line

3. Extracting the Appendix

3.1. Extracting Candidate Appendix Area by Fuzzy Binarization

Since the fascia line is found by the series of image processing explained in section 2, our next step is to extract candidate appendix below that fascia line. Here we need another binarization process but this organ area has no clear cut threshold thus we apply fuzzy binarization technique. The procedure of fuzzy binarization is as following;

Let RGB values of the original input image are X_i^{τ}, X_i^{Q}, X_i^{b} and the average brightness of a pixel X_m are defined as formula (2).

$$X_m = \sum_{i=1}^{255} \frac{\left(X_i^{\tau} + X_i^{Q} + X_i^{b}\right)}{3} \times \frac{1}{X \times N} \quad (2)$$

where M and N denote the height and the width of the input image.

Then the distance from the dark area (D_{min}) and bright area (D_{max}) can be defined as formula (3).

$$\begin{aligned} D_{max} &= |X_h - X_m| \\ D_{min} &= |X_m - X_l| \end{aligned} \quad (3)$$

where X_l and X_h be the darkest and the brightest value of input image. Then the brightness control rate α is computed as formula (4).

$$\begin{aligned} & if\,(X_m > 128)\; then\; X_m = 255 - X_m \\ & else\; X_m \\ & if\;(D_{min} > X_m)\; then\; \alpha = X_m \\ & else\; \alpha = D_{min} \\ & if\;(D_{max} > X_m)\; then\; \alpha = X_m \\ & else\; \alpha = D_{max} \end{aligned} \quad (4)$$

Brightness control rate α is used to compute maximum brightness (I_{max}) and minimum brightness (I_{min}) as shown in formula (5).

$$\begin{aligned} I_{max} &= X_m + a \\ I_{min} &= X_m - a \end{aligned} \quad (5)$$

The triangle type membership function of this binarization procedure is as shown in Figure 6 with interval$[I_{min}, I_{max}]$. I_{mid} whose membership degree is *1* is computed as fo rmula (6).

$$I_{mid} = \frac{I_{max} + I_{min}}{2} \quad (6)$$

Then the membership degree within interval $[I_{min}, I_{max}]$ is computed by formula (7).

$$\begin{aligned} & if\;(X_m \le I_{min})\; or\; (X_m \ge I_{max})\; then\; \mu(x) = 0 \\ & if\;(X_m > I_{mid})\; then\; \mu(x) = \frac{(I_{max} - X_m)}{(I_{mid} - I_{min})} \end{aligned}$$

$$if\ (X_m < I_{mid})\ then\ \mu(x) = \frac{(X_m - I_{min})}{(I_{mid} - I_{min})}$$
$$if\ (X_m = I_{mid})\ then\ \mu(x) = 1 \qquad (7)$$

The input image is then binaries by applying $\alpha - cut$ to the membership degree$(\mu(x))$. In this study, α is set to 0.4 meaning that if a pixel has membership degree greater than or equal to 0.4 then it is a member of candidate appendix and otherwise it is a noise.

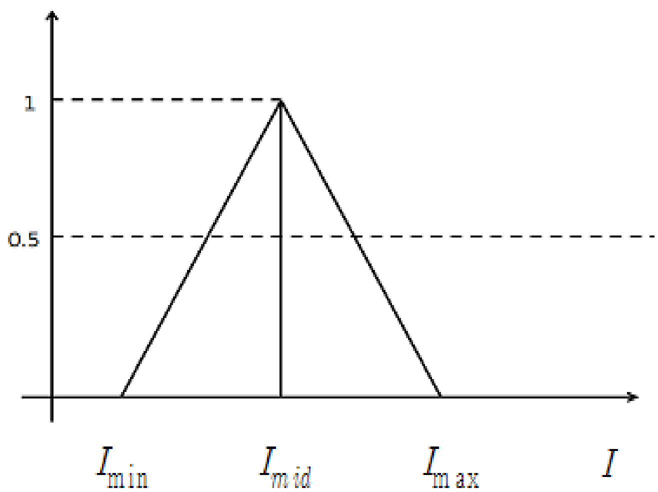
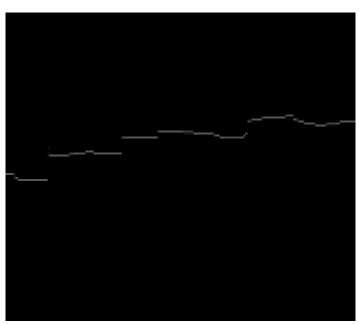


Figure 6. Triangle Type Membership Function

By applying such fuzzy binarization, we obtain candidate appendix as shown in Figure 7.



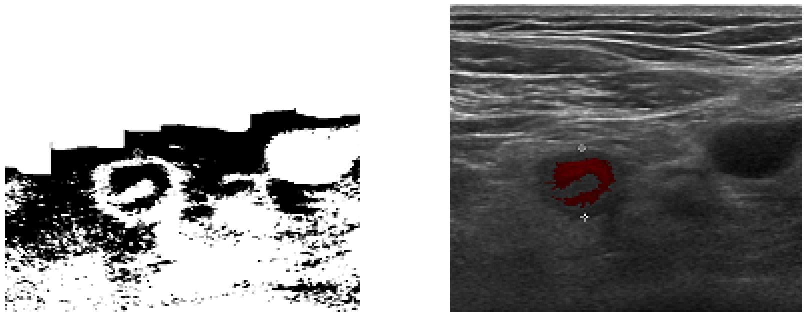
(a) Image with Fascia Line

(b) Applying Fuzzy Binarization

Figure 7. Extracting Candidate Appendix

3.2. Extract Appendix Area

Appendix resides in the internal organ area and has characteristics of relatively brighter than others with considerable size. Thus, we again apply Grassfire algorithm to label objects and find brighter area with significant size as a final appendix area. Figure 8 shows the resultant appendix extracted from the fuzzy-binarized image.

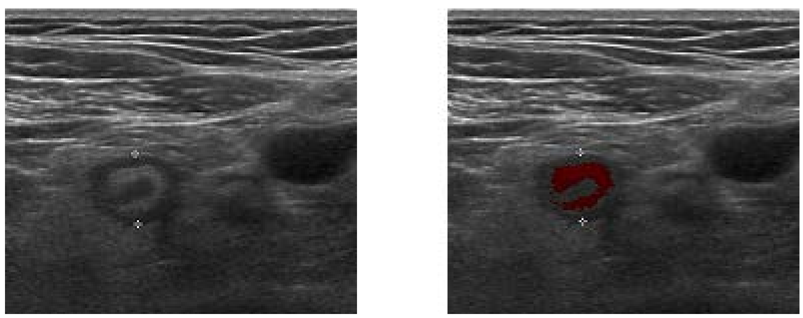


(a) After Fuzzy Binarization (b) Final Result

Figure 8. Extracted Appendixes

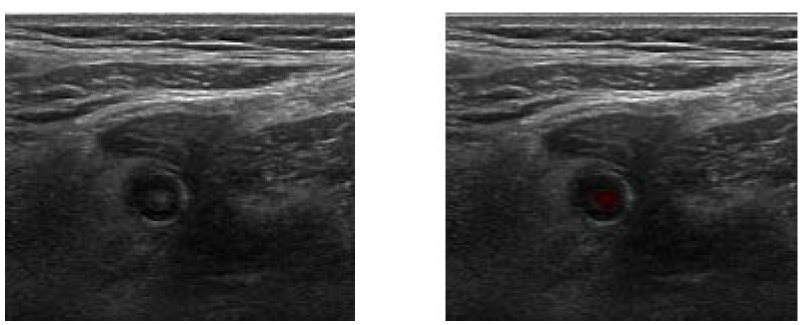
4. Experiment and Analysis

The system is implemented in Visual Studio 2008 C# with Intel(R) Core(TM) i7-2600 CPU @ 3.40GHz and 4GB RAM PC. Some example appendix extracted by proposed method is shown in Figure 9 and Figure 10.



(a) Original Image (b) Final Result

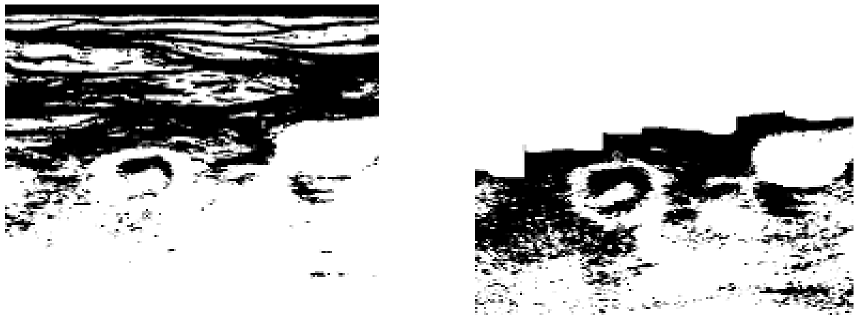
Figure 9. Extract Appendix Examples 1



(a) Original Image (b) Resultant Image

Figure 10. Extract Appendix Examples 2

In our method, we first extract bottom fascia line that divides muscle area and organ area and then extract appendix with fuzzy binarization. If we do not divide those areas, extracting appendix often fails because the brightness of muscle area affects the threshold value thus there is high possibility to have false positives. In order to verify the effect of this area division, we apply binarization from the original image without area division (Figure 11 (a)) and compare it with the proposed methods (Figure 11. (b)) and the effect is self- explanatory.



(a) Binarization from the Whole Image (b) Binarization within the Organ Area

Figure 11. Effect of Area Division in Extracting Appendix

5. Conclusion

In this paper, we develop a computerized method to extract appendix with area division. Appendix is located in organ area with relatively high brightness. Thus first we try to find the fascia line to divide the two areas. As explained in Section 2, a series of image processing - enhancing the brightness by applying Ends-in Search Stretching, extracting candidate fascia area by block binarization, noise removal by Grassfire algorithm, applying expansion operation to compensate disconnected fascia lines - are designed for that purpose. Then the target appendix is located below the fascia line and it can be successfully differentiated from muscle area above the fascia line which may have similar brightness distribution to the appendix area. Thus the target appendix could be extracted successfully by applying fuzzy binarization to the area below the line and the effect of that two-phase extraction is successfully verified by the experiment. However, the result obtained in this paper is only a starting point of developing reliable effective software tool to assist medical experts in acute appendicitis which is our final goal of the research.

Applying artificial intelligence technique in this research area may also help practitioners to decide the proper time to do laparotomies for acute appendicitis patients which is often very difficult decision. A recent study applying decision tree technique to improve the accuracy of the Alvarado scoring system (ASS) [11] is a good example. If our effort is extended to extract and analyze the inflamed part of the appendix and nearby organ status, we expect more intelligent decision making procedure can be designed effectively.

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