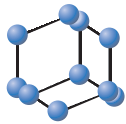


## RESEARCH ARTICLE

BENTHAM  
SCIENCE

# Semi-dynamic Control of FCM Initialization for Automatic Extraction of Inflamed Appendix from Ultrasonography



Kwang Baek Kim<sup>1,\*</sup>, Hyun Jun Park<sup>2</sup> and Doo Heon Song<sup>3</sup>

<sup>1</sup>Division of Computer Software Engineering, Silla University, Busan 46958, South Korea; <sup>2</sup>Division of Software Convergence, Cheongju University, Cheongju 28503, South Korea; <sup>3</sup>Department of Computer Games, Yong-In SongDam College, Yongin 17145, South Korea

**Abstract: Background:** Current naked-eye examination of the ultrasound images for inflamed appendix has limitations due to its intrinsic operator subjectivity problem.

**Objective:** In this paper, we propose a fully automatic intelligent method for extracting inflamed appendix from ultrasound images. Accurate and automatic extraction of inflamed appendix from ultrasonography is a major decision making resource of the diagnosis and management of suspected appendicitis.

**Methods:** The proposed method uses Fuzzy C-means learning algorithm in pixel clustering with semi-dynamic control of initializing the number of clusters based on the intensity contrast dispersion of the input image. Thirty percent of the prepared ultrasonography samples are classified into four different groups based on their intensity contrast distribution and then different number of clusters are assigned to the images in accordance with such groups in Fuzzy C-means learning process.

**Results:** In the experiment, the proposed system successfully extracts the target without human intervention in 82 of 85 cases (96.47% accuracy). The proposed method also shows that it can cover the false negative cases occurred previously that used self-organizing map as the learning engine.

**Conclusion:** Such high level reliable correct extraction of inflamed appendix encourages to use the automatic extraction software in the diagnosis procedure of suspected acute appendicitis.

## ARTICLE HISTORY

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## 1. INTRODUCTION

The appendix is a vestigial, tubular organ that arises from the inferior pole of the cecum, 2-2.5 cm inferior to the ileocecal junction. Appendicitis occurs from a gastrointestinal infection (viral, bacterial, or fungal) that has spread to the appendix [1], or an obstruction that blocks the opening of the appendix [2].

Among several types of the disease classified by its development stage [3], acute appendicitis is one of the most common general surgical emergencies worldwide, with an estimated lifetime risk reported at 7-8% [4]. Typically, the illness begins with vague mid-abdominal discomfort followed by nausea, anorexia, and indigestion and within several hours the pain migrates to the right lower quadrant [5]. 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 [6].

However, the diagnosis of acute appendicitis is difficult especially for women between ages 20 and 40 due to high false-positive diagnosis rate [7] and women in pregnancy because the nausea, vomiting, and abdominal pain of appendicitis can also be features of pregnancy and physical examination may not be reliable in such cases [8].

Medical imaging techniques such as ultrasonography (US), Computed Tomography (CT), and Magnetic Resonance Imaging (MRI), have been used for the diagnosis of acute appendicitis for decades [9] and among them, US examination should be the first imaging test performed, particularly among the pediatric and young adult populations [10], who represent the main targets for appendicitis, as well as in pregnant patients due to its non-invasive characteristics. The reliability of US in diagnosing acute appendicitis has been improved to be matched to that of CT or MRI [11]. However, current naked-eye examination of the US has limitations in accurate measurement in cases of unclear delineation of the appendix with thick abdomen, and in cases showing ill-defined borders of the appendix by surrounding tissues and its intrinsic operator subjectivity problem [6, 12].

Automatic extraction or segmentation of a human organ for the reliable diagnosis from US is a solution for the US

\*Address correspondence to this author at the Division of Computer Software Engineering, Silla University, Busan 46958, South Korea; Tel: +82-51-999-5052; Fax: +82-51-999-5657; E-mail: gbkim@silla.ac.kr

operator subjectivity problem. There have been several successful attempts of developing such automatic tools in soft tissue tumor extraction [13, 14], ganglion cyst detection [15], muscle extractions related to cervical vertebrae [16, 17], measuring carotid artery Intima-Media Thickness [18], and detecting breast cancer cells [19]. Like many other medical diagnosis, there are many known measurement indices to give a reliable diagnosis of acute appendicitis from sonographic findings such as outer appendiceal diameter, lack of compressibility, intraluminal fluid, visualization of appendicolith, increased color signals along its wall, cecal wall thickening, periileal lymph nodes, and peritoneal fluid [11, 20].

Acute appendicitis is usually associated with right lower abdominal pain, but there can be cases in the right upper abdomen or pelvis. It is not easy to find a normal appendix, but tubular structures could be found from the back of the appendix between the appendix and the distal ileum to the cecum. The normal diameter is 5 mm and it is pressed well and moves easily.

Unlike normal bowel, the inflamed appendix is fixed, non-compressible, and appears round on transverse images. Measurements of appendix are performed with full compression. Traditionally, the diagnosis of appendicitis is made when the diameter of the compressed appendix exceeds 6 mm [21].

Often the site of maximum tenderness is located at McBurney's point, which lies two-thirds along a line from the umbilicus to the anterior superior iliac spine [22]. However, the location of the appendix may vary thus we should test not only around the simple McBurney's point, but also test the inside of the right lower abdomen and even the pelvic cavity.

Thus, it is important to extract the inflamed appendix with sufficient size from US correctly with minimum human intervention for the reliable diagnosis of the acute appendicitis in order to avoid serious operator subjectivity. Nevertheless, this does not mean that such automatic extraction completes the automatic diagnosis. Rather, such automaticity can reduce human error in the diagnosis procedure.

Several systems that use relatively simple histogram analysis with thresholding in conjunction with edge detecting methods [23, 24] have been developed for the accurate extraction of inflamed appendix but those methods are weak when the brightness contrast is not very high. Furthermore, they have potential information loss in edge linking procedure.

Intelligent pixel clustering methods [6, 12, 25, 26] are designed to enhance the brightness contrast and form an appendix object from US. A method uses fascia as a predictor of the appendix location and uses fuzzy binarization techniques to determine the appendix boundaries with various image processing algorithms [25]. However, that method was not satisfactory in accuracy due to various sources of noises. Other effort uses K-means clustering with cubic spline interpolation to form the object [6] and showed better result but the extraction rate is still below satisfaction (reported as 67.5% [12]). Since patient's ascites of a significant size may mislead the system to extract it as a false positive

appendix or when the shape of appendix is not like ordinary patterns, the system could not catch the correct fascia line that is the main predictor of appendix location. While the recent effort [12] shows successful extraction rate (sensitivity over 81%) with fuzzy Adaptive Resonance Theory (ART) algorithm over other pixel clustering methods, the analysis of failed extraction cases suggests that there might be a close relationship between the shape of the appendix and the brightness distribution of the surrounding environments.

We further developed the automatic extraction of inflamed appendix with Self-organizing Map (SOM) learning [26]. And that approach is very successful in correct extraction rate except a long oval shape type appendix whose brightness contrast is very low compared with surroundings. In the quantization process, the hexagonal SOM structure takes single winner neuron while the radius was reduced thus the loss of intensity information in that repetitive learning process could cause the failed extraction of appendix.

In this paper, we propose a Fuzzy C-Means (FCM) based approach in automatic extraction of inflamed appendix to overcome the drawbacks found in [26]. FCM has been applied to medical imaging domain successfully [16, 27] but has static initialization problem like K-means [28]. Thus, we apply sampling strategy to determine the optimal number of clusters in FCM learning phase that is similar to the strategy used for K-Means [29]. We randomly take approximately 30% of the image as sample and then classify them as groups by standard deviation of the intensity distribution under fascia area where the target organ appendix would appear. Then, the number of clusters are assigned differently to the groups depending on the intensity standard deviation in that the number of clusters in a group is negatively proportional to the standard deviation. We call this as the semi-dynamic control of FCM initialization in this paper.

## 2. METHODOLOGY

As shown in Fig. (1), abdomen ultrasound image consists of image filming information on the above and measurement information on the right and the abdomen image at the center. In the abdomen image, there are fascia area including muscles and appendix area below the fascia. Appendix has the shape of a circle or flat oval.

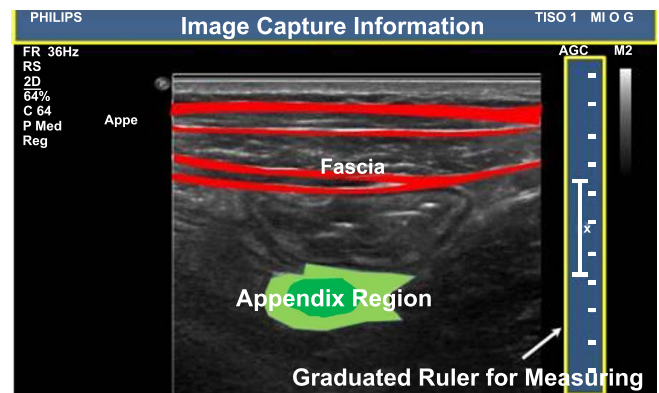
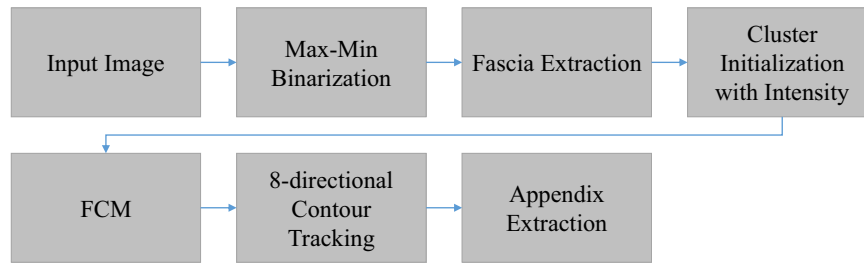


Fig. (1). Typical input ultrasound image and appendix location from [24].



**Fig. (2).** Overall processes of the proposed method.

The main procedure of the proposed method can be summarized as shown in Fig. (2). In this section, we explain the first three pre-processing steps to extract the region of inflamed appendix.

The grey-scale input ultrasound image may not have enough brightness contrast between the “bright” side and the “dark” side. Thus, we stretch 0’s and 1’s so that the bright contrast is effectively exaggerated. The first step is to enhance the brightness contrast by Ends-in Search Stretching that is a kind of normalization step and remove noises by Max-Min binarization and region labeling method [30].

In order to locate the target inflamed appendix area from input US after binarization, we seek the fascia region first since the appendix is below the lower boundary of the fascia. Usually in real world US filming, the fascia area is at least 1/3 of the input image based on radiologists’ suggestion. Thus, we search the fascia area with sufficient size as used in [31] by applying region labeling method [30] and locate the lower boundary. Smaller objects would be removed as noise during the process. Fig. (3) demonstrates the effect of this preprocessing steps.

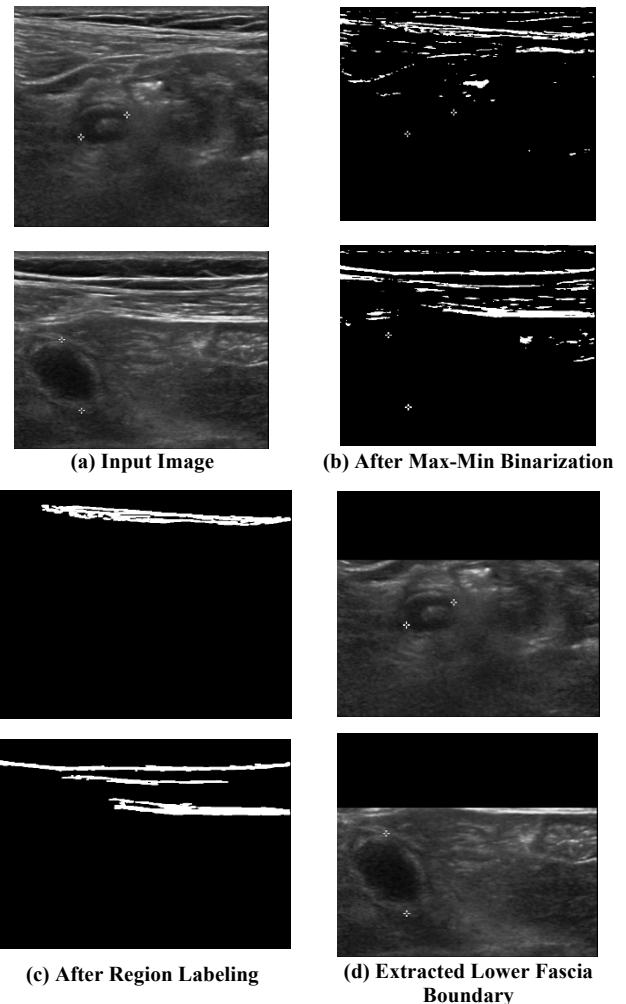
### 3. SEMI-DYNAMIC CONTROL OF FCM IN APPENDIX EXTRACTION

As stated in section 1, our previous approach using SOM [26] works nicely in most cases but we found that SOM based pixel clustering was subtle when there was a loss of intensity information during its repetitive learning process to select the single winning neuron. In failed extraction cases, it could not locate the inflamed appendix since the lost intensity information misguided the software to remove the appendix object as noise. In order to reduce such false negative cases, we should bring more noise-tolerant algorithm in appendix object formation.

Fuzzy C-Means (FCM) clustering is an unsupervised learning algorithm that classifies the image into groups having similar data points in the feature space. This clustering is achieved by iteratively minimizing the cost function that is dependent on the distance of the pixels to the cluster centers in the feature domain. FCM allows one piece of data to belong to two or more clusters depending on the degree of membership to each cluster. For  $n$  data vectors, we may have  $c$  fuzzy clusters ( $c < n$ ) and each vector is classified into the cluster whose membership degree is the highest.

However, FCM as its standard version has the static control of the number of cluster  $c$  like K-means and it can cause

other type of false positives and false negatives [6]. Thus, we adopt a semi-dynamic control of the crucial parameter  $c$ .



**Fig. (3).** Effect of preprocessing steps.

We would like to assign the number of clusters  $c$  based on the intensity contrast dispersion of the input image. If the intensity contrast is low, the number of clusters should be sufficiently large so that FCM can be sensitive to the intensity changes. Thus the parameter  $c$  is assigned differently in accordance with the standard deviation of the intensity distribution. Similar approach was successful with K-means in different domain [29].

Thus, we first select approximately 30% of the input image as training samples to determine the number of FCM

Table 1. Determination of # of clusters.

Intensity SD	< 0.06	0.06~0.07	0.07~0.1	> 0.1
# of Samples	4	4	8	9
# of Clusters	25	20	15	10

clusters. In this paper, we took 25 images as samples and classify them into four groups according to the standard deviation of the intensity in the target area. Then the parameter  $c$  is assigned as negatively proportional to the standard deviation as shown in Table 1.

Thus, the FCM used in this paper works as following;

**Step 1:** Compute the standard deviation of intensity among candidate region of the input image under lower boundary of fascia. Initialize the number of cluster  $c$  ( $2 \leq c < n$ ) according to Table 1, exponential weight  $m$  ( $1 \leq m < \infty$ ), and the membership degree  $u^{(0)}$ .

**Step 2 :** Compute the central vector  $v_{ij}$  as equation (1) for  $\{v_i | i = 1, 2, \dots, c\}$ .

$$v_{ij} = \frac{\sum_{k=1}^n (u_{ik})^m x_{kj}}{\sum_{k=1}^n (u_{ik})^m} \quad (1)$$

**Step 3 :** Compute the distance  $d_{ik}$  between the  $k^{\text{th}}$  pattern  $x_k$  and the central vector of the  $i^{\text{th}}$  cluster by the equation (2).

$$d_{ik} = d(x_k - v_i) = \left[ \sum_{j=1}^l (x_{kj} - v_{ij})^2 \right]^{1/2} \quad (2)$$

where  $l$  denotes the number of pattern nodes. Then,  $v_{ik}$ , the

new membership degree of  $k^{\text{th}}$  pattern in  $i^{\text{th}}$  cluster is computed as equation (3).

$$u_{ik}^{(r+1)} = \frac{1}{\sum_{j=1}^c (d_{ik}^r / d_{jk}^r)^{2/m-1}} \quad \text{for } I_k = \varphi \quad (3)$$

or  $u_{ik}^{(r+1)} = 0$  for all classes  $i, i \in \tilde{I}_k$

$$I_k = \{i | 2 \leq c < n; d_{ik}^{(r)} = 0\}, \tilde{I}_k = \{1, 2, \dots, c\} - I_k$$

$$\text{AND } \sum_{i \in I_k} u_{ik}^{(r+1)} = 1$$

**Step 4:** Compute the difference between the new and the previous membership degree as shown in equation (4). Also, in this step, accumulate the differences based on the number of clusters  $c$ . If the difference is larger than the error threshold ( $\epsilon$ ), then go to Step 2.

$$\Delta = \|U^{(r+1)} - U^{(r)}\| = \max_{ik} |u_{ik}^{(r+1)} - u_{ik}^{(r)}| \quad (4)$$

if  $(k > \epsilon_r) \quad k = \Delta + k$

The effect of FCM quantization with different number of cluster initialization is shown in Fig. (4).

After FCM quantization, we should extract the appendix object with labeling method. Grassfire labeling method [30] searches for pixels forming one object with  $3 \times 3$  mask and 8-directional contour search. First, it searches for a pixel whose brightness is 255 among its 8-directions from the pixel whose brightness is equal to the initial mask center. If

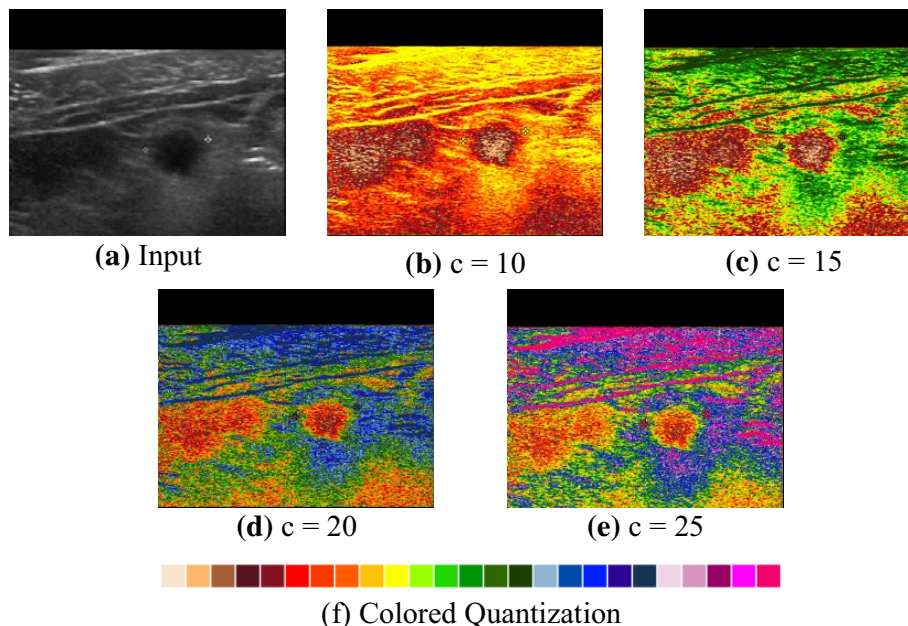
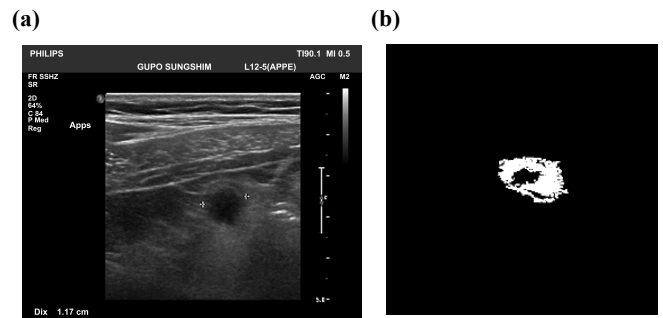


Fig. (4). Quantization by FCM with different number of clusters (parameter  $c$ ). (The color version of the figure is available in the electronic copy of the article).

the search succeeds, the center of the mask moves to that pixel and labels it, and then takes the 8-directional search. If the search fails, the center is moved to the previously labeled one. If the initial pixel fails to find pixels to form an object, the next pixel becomes the center. The tracing is done from top to bottom, left to right and we label each pixel such that the same object has the same valued pixels. Fig. (5) demonstrates an example of appendix extraction with such 8-directional tracking and labeling.

**4. RESULTS AND DISCUSSION**

The proposed method is implemented with C# under Microsoft Visual Studio 2010 on an IBM-compatible PC with Intel(R) Core(TM) i5-4210 CPU @ 2.80GHz and 8.0 GB RAM. The experiment uses eighty five DICOM format ultrasound images that contain the inflamed appendix. Abdominal ultrasonography is performed by Philips iU22 using 3 ~ 5MHz transducer. If the subject complains pain on a spe-



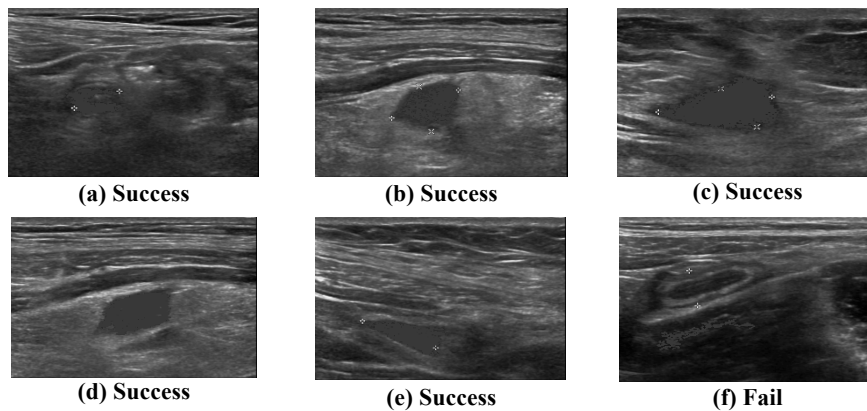
**Fig. (5).** Appendix extraction with 8-directional contour tracking. (a) Input image. (b) Appendix object formation.

**CONCLUSION**

In this paper, we propose a method to extract inflamed appendix from ultrasound image automatically with various image processing techniques and fuzzy C-means (FCM)

**Table 2.** Experiment result in extraction accuracy (85 images tested).

Methods	SOM	Ext. Rate	Proposed	Ext. Rate
Successes	74 Cases	87.06%	82 Cases	96.47%



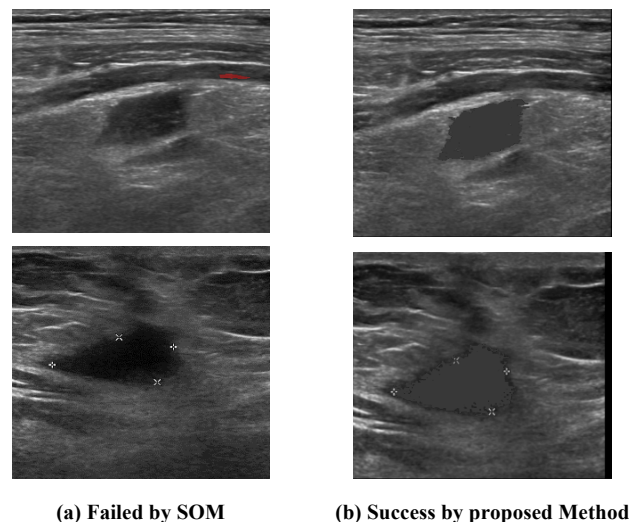
**Fig. (6).** Appendix extraction cases.

cific body part, 7.5Hz high frequency transducer is used to examine that part. All 85 images are from Gupo Sungsim Hospital, Pusan, Korea and there was no appendicolith case in this experiment.

In Table 2, we report the successful extraction rate of inflamed appendix by the proposed method and our previous attempt using SOM. The decision of “successful extraction” is made by field radiologist.

In Fig. (6), one can find various different shapes of successful appendix extractions by our proposed method except Fig. (6f). In that specific failed extraction, there exists exceptionally large appendix object that our object labeling was misled to remove. Other than that, the proposed method works nicely for many different size and shape of the appendix.

Furthermore, we report how this proposed method reacts to the failed cases of previous SOM based method as shown in Fig. (7).



**Fig. (7).** Appendix extraction improvements. (a) Failed by SOM (b) Success by proposed Method

learning algorithm. This work adopts FCM with semi-dynamic control of number of cluster initialization. What we have learned from previous attempts of using various pixel clustering and learning algorithms such as Fuzzy ART [12] and SOM [26] is that input US in this domain - abdomen ultrasonography - usually has low intensity contrast and sensitive to the environment. FCM is less sensitive to the environment since it does not take winner-takes-all strategy like SOM. However, it has the same static initialization problem as K-means has. Thus, we randomly take approximately 30% of the US image as training sample and then classify them as groups by standard deviation of the intensity distribution under fascia area where the target organ appendix would appear. This is based on the old machine learning school strategy of 30% vs. 70% training and test assignment. Then, the number of clusters are assigned differently to the groups depending on the intensity standard deviation. In this paper, the number of cluster assignment was given from 10 to 25 as shown in Table 1 as the number of the clusters is negatively proportional to the intensity contrast of the given US image.

The proposed method is successful in 82 out of 85 cases or 96.5% correct with respect to human experts' judgments for ground truth. Not only this high level successful extraction rate, our proposed approach shows a clear improvement from our previous SOM approach in that it seriously reduce the false negative cases SOM approach had due to its information loss during learning as shown in Fig. (7).

The limitation of this research is that the proposed method is only focused on automatic extractions of inflamed appendix accurately. The correct diagnosis of acute appendicitis needs more features to take into account than features considered in this paper.

#### ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

#### HUMAN AND ANIMAL RIGHTS

No Animals/Humans were used for studies that are the basis of this research.

#### CONSENT FOR PUBLICATION

Not applicable.

#### AVAILABILITY OF DATA AND MATERIALS

Due to confidentiality issues, it is not permitted to share the data.

#### FUNDING

None.

#### CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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Declared none.

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