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Organ Boundary Determination Algorithm for Detecting Internal Bleeding

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***Abstract*— The purpose of this paper is to propose an organ boundary determination method for detecting internal bleeding. Focused assessment with sonography for trauma (FAST) is important for patients who are sent into shock by internal bleeding. However, the FAST has a low sensitivity, approximately 42.7 %. This study aims, therefore, to construct an automatic internal bleeding detection robotic system on the basis of ultrasound (US) image processing to improve the sensitivity. We developed method for determining algorithms of organ boundaries by low-brightness set analysis, and we detected internal bleeding by the proposed method.**

Experimental results based on clinical US images of internal bleeding between Liver and Kidney showed that proposed algorithms had a sensitivity of 77.8% and specificity of 95.7%.

I. Introduction

Focused assessment with sonography for trauma (FAST) has become widespread as a first step for diagnosing traumatic shock patients [1]-[3]. FAST can narrow the diagnosis area down to four major parts, regardless of the field in which the doctor or medical staff specializes. It is therefore a quick and easy echography method for shock patients [4], [5].

However, the FAST has a low sensitivity, and delays in lifesaving treatment due to internal bleeding being missed have become a serious problem in emergency medical care. B. Natarajan et al. reported that the use of FAST in hemodynamically stable blunt trauma patients does not seem worthwhile, because the sensitivity of FAST was approximately 42.7% based on clinical research [6]. This means medical doctors cannot accurately detect internal bleeding in more than half the internal bleeding patients. Ultrasound (US) image processing technology with controlling the US probe, therefore, is needed to improve the sensitivity of the FAST.

In recent years, many US image processing systems and robotic systems have been developed [7]-[9]. G. Sumei et al. reported a gray-level image thresholding method by extracting the pixel that has big changes in the concentrations [10]. A. Takemura developed an adaptive filter for US images under High-Frequency Ultrasonic Equipment [11]. T. Deguchi et al. extracted liver regions from competed tomography images by using probability distributions [12]. R. Chan et al. and H. K. Chang et al. constructed US imaging processing and visual servoing for internal objects [13], [14]. These systems, however, cannot distinguish and identify unknown low-brightness areas in clinical images. Also, no study has focused on detecting accumulated internal bleeding in US images.

In this study, therefore, we aim to construct an automatic internal bleeding detection robotic system on the basis of US image processing to improve the sensitivity. In this paper, we focus on one of the FAST area (the area between the liver and kidney), and report a method for determination algorithms of organ boundary by low-brightness set analysis for detecting internal bleeding.

II. System Configuration and Requirements

A. Overview of the FASTele System

Fig.1 shows a robotic FAST system, "FASTele". The system is composed of a US imaging device, a manipulator holding a US probe and a PC for the manipulator control and image processing. An output image from the US imaging device is processed and sent to the PC in order to control the position and posture of the probe. The US imaging device (MicroMaxx (SonoSite Inc., Micro-convex probe (1-5 MHz)) outputs the image signal (30 fps), which is then captured by video grabber Epiphan's DVI2USB Solo into a PC (Core2Duo 2.0GHz). The image processing is implemented by Intel's OpenCV.

The FASTele has two functions: contacting the surface of the patient's body, and adapting to a wide variety of body types and body movements. Also, the FASTele has 4-DOF (Pitching (1DOF), Rolling (1DOF), Positioning (1DOF), and Contacting (1DOF)). The curvature rails and rotary motors (Harmonic drive; RSF-5A, 66g) are used to achieve the pitching and rolling of the probe.

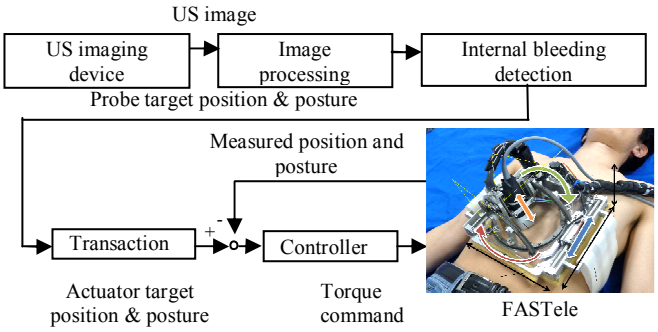

Fig.1 Block diagram of the FASTele

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B. Requirements for Internal Bleeding Detection

In each FAST area, internal bleeding has two key features on the B-mode image: it is extracted as low-brightness areas in US images and accumulates between organs [4], [5]. Blood differs from the other tissue in terms of acoustic impedance. Also, each organ is separated by a gap, and the internal bleeding accumulates in that gap. The following functions are required to develop an internal bleeding detection algorithm. In this paper, we focused on US image processing 1) and 2).

1) Extracting low-brightness areas for detecting blood:

Since blood is extracted as low-brightness areas, the echo image has to be binarized. The low-brightness areas caused by blood have larger brightness change that the surrounding tissue. Therefore, an algorithm is required to extract only the area enclosed by the boundary with a large brightness change.

2) Determining organ boundary (liver and kidney) to identify internal bleeding:

The low-brightness caused by internal bleeding must be distinguished from the low-brightness caused by blood in a vessel. Internal bleeding could be detected by using the fact the bleeding accumulates between organs. Therefore, an algorithm is required to extract the gap between organs (liver and kidney) in US images. This means that an algorithm is needed for determining the organ boundary.

3) Searching internal bleeding with controlling US probe:

Since the vision of US image depends on posture of a US probe, a method is required to search for internal bleeding by controlling the probe automatically for appropriate FAST.

III. Organ Boundary Determination Algorithm

Since the low-brightness area caused by blood has large brightness change, we binarize the US image by using a differential value between adjacent pixels.

To extract only low-brightness areas caused by internal bleeding, we detect a gap between organs (liver and kidney) on the basis of determining organ boundaries by proposing low-brightness set analysis.

1) Organ Area Segmentation: First, we obtain an edge enhancement image on the basis of smoothing by using the Mean-Shift method [15] and differential value between adjacent pixels, as in (1). Next, organ areas are segmented as follows;

(i) Marking of a unit circle

As shown in Fig.2 (a), a unit circle marks an organ in the edge enhancement image.

(ii) Expansion of the unit circle area

The unit circle is automatically expanded to the extracted edge adjacent pixels by adjacent pixels. Fig.2 (b) shows the example of expanding a unit circle area 10 times.

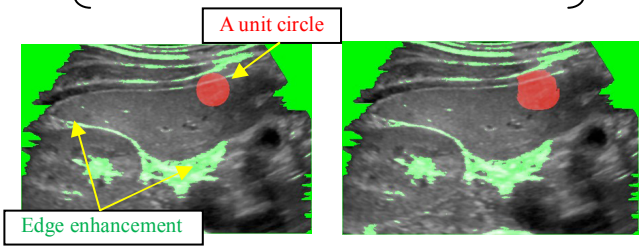
(iii) Settlement of the unit circle area

Since the extracted edge is often lost on an organ boundary, we cannot stop the expansion of the unit circle area just a condition that the area touches the extracted edge. In this paper, therefore, we set a limit of the expansion (5 times) up to nine pixels around one pixel that touches the extracted edge. This means that when a pixel touches the extracted edge, the expansion around the pixel can only performed 5 times. In the case of a vessel in an organ is touched, the expansion is maintained around the vessel by setting the limitation of expansion. When no pixel can expand, the expansion of the unit circle area and area segmentation are finished. Fig.2 (c) shows the results of area segmentation on liver.

$$\mathbf{y}_{j+1} = \frac{\sum g(\mathbf{y}_j - \mathbf{x}_i)\mathbf{x}_i}{\sum g(\mathbf{y}_j - \mathbf{x}_i)} \quad (1)$$

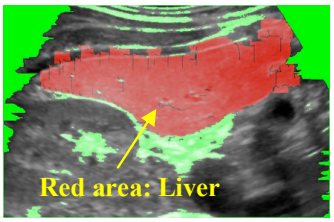
$$g(x) = \exp\left(\left\|\frac{\mathbf{x}_i^s}{h^s}\right\|^2\right) \times \exp\left(\left\|\frac{\mathbf{x}_i^r}{h^r}\right\|^2\right)$$

y: Feature space vector (Position(x, y), Color(L, u, v))
h^s: Bandwidth of position space (2D)
h^r: Bandwidth of color space (3D)
$\mathbf{x}_i^s$: Feature space vector in position space
$\mathbf{x}_i^r$: Feature space vector in color space



(a) Marking a unit circle

(b) Expansion of the unit circle (Example of 10 times)



(c) Settlement of the unit circle area (Liver)

【Organ Area Segmentation】
A medical doctor marks a unit circle on Liver (or Kidney). The circle automatically expands. When a pixel touches the extracted edge, the expansion around the pixel can only performed 5 times

Fig.2 Flow of organ area segmentation

2) Determination of Organ by Low-brightness Set Analysis: To extract the gap between liver and kidney by determining what the segmented organ areas are, we propose low-brightness set analysis as follows;

(i) Obtaining extremal value distributions in each segmented organ areas

First, each segmented organ area is differentiated with respect to brightness. Next, we obtain extremal values, which are the brightness values when the pixel brightness moves from a low value to a high one, as in (2). These processes are performed in horizontal and vertical directions in the image. Extremal value distribution is calculated as the area ratio of low-brightness to high brightness, as in (3). Fig.3 shows the extremal value distribution.

(ii) Analysis of the extremal value distributions

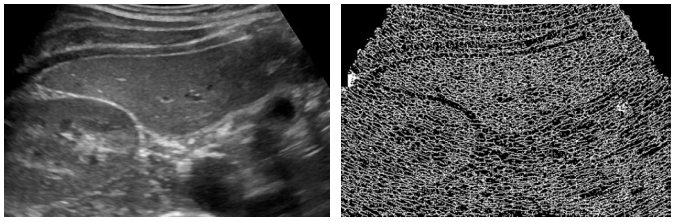
By comparing extremal value distribution of each organ, we found a distinction of the distribution between liver and kidney, as shown in Table I. Liver has a larger low-brightness area than kidney.

We defined occupancy of low-brightness areas in each organ as the low-brightness set. Liver and kidney are determined by the Low-brightness Set Analysis.

$$E(x,y) = \begin{cases} 1: & \dfrac{\Delta P}{\Delta x} = 0 \text{ AND } \dfrac{\Delta P^2}{(\Delta x)^2} > 0 \\ & \dfrac{\Delta P}{\Delta y} = 0 \text{ AND } \dfrac{\Delta P^2}{(\Delta y)^2} > 0 \\ 0: & \dfrac{\Delta P}{\Delta x} \neq 0 \text{ OR } \dfrac{\Delta P^2}{(\Delta x)^2} \leq 0 \text{ OR } \dfrac{\Delta P}{\Delta y} \neq 0 \text{ OR } \dfrac{\Delta P^2}{(\Delta y)^2} \leq 0 \end{cases} \quad (2)$$

[P: Brightness value of the pixel
E(x,y): Extreaml value]

$$\text{Extreaml value distributions} = \frac{\text{Area of low} - \text{brightness } (E(x,y) = 1)}{\text{Area of high brightness } (E(x,y) = 0)} \quad (3)$$



Original image [FAST 2]

Extracted extremal value [Black: High brightness
White: Low-brightness]

Fig.3 Extremal value distribution

Table I Results of low-brightness set analysis (N = 5)

Organ	Statistics	Low-brightness set value
Liver	Average	2.98
	Max	3.57
	Min	1.50
Kidney	Average	2.62
	Max	3.38
	Min	2.04

IV. Experiments and Results

A. *Experiment of Determination of Organ Boundary (Liver and Kidney)*

1) Methods: The purpose of this experiment was to evaluate determination of organs by low-brightness set analysis. US images vary depending on the posture of the US probe.

In this experiment, therefore, we used FASTele to obtain 213 US images of posture of the probe on FAST2 showing liver and kidney (seven types of each angle: rolling and pitching). Statistical analysis was performed by a rank test followed by Wilcoxon, and statistical significance was tested with a p value < 0.01.

2) Results and Discussion: Fig.4 shows the results of low-brightness set analysis. We confirmed that the low-brightness area of liver was significantly larger than that of kidney ($p < 0.01$). This means that liver and kidney could be determined by using the proposed low-brightness set analysis.

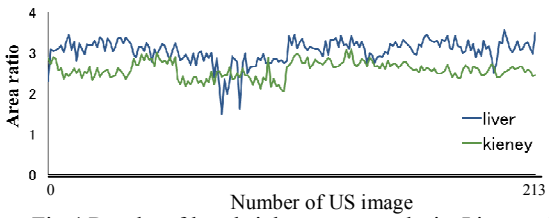


Fig.4 Results of low-brightness set analysis, Liver and Kidney

B. *Experiment of Internal Bleeding Detection*

1) Methods: The purpose of this experiment was to evaluate a proposed internal bleeding detection algorithm based on determination of organ boundaries by low-brightness set analysis.

We verified the number of the images in which internal bleeding could be detected by the proposed algorithm on the basis of clinical US images showing or not showing internal bleeding.

2) Results and Discussion: Table II shows the results of sensitivity and specificity of internal bleeding in the proposed algorithm. We confirmed that the sensitivity and specificity were 77.8%, 95.7%.

Also, the successful results of internal bleeding detection are shown in Fig.5.

Table II Sensitivity and specificity of the proposed algorithm

	FAST Positive	FAST Negative
Internal Bleeding	**21 (77.8%)**	6
Not Found	9	**204 (95.7%)**

$$\text{Sensitivity} = \frac{\text{Internal Bleeding (FAST Positive (21))}}{\text{Internal Bleeding (FAST Positive (21) + FAST Negative(6))}}$$

$$\text{Specificity} = \frac{\text{Not Found (FAST Positive (204))}}{\text{Not Found (FAST Positive (9) + FAST Negative(204))}}$$

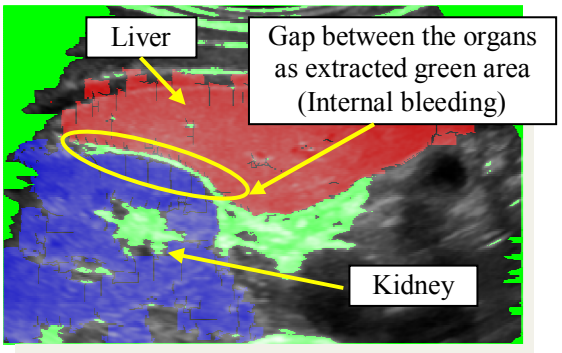


Fig.5 Example of internal bleeding detection (Success)

V. Discussion

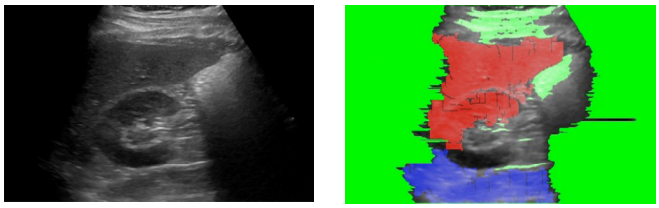
As shown in Fig.4, we confirmed that liver and kidney could be determined by using the proposed low-brightness set analysis. Liver has a lot more blood than kidney. This means that the in US images of liver contain more low-brightness areas than those of kidney. It is considered, therefore, that the proposed low-brightness set analysis that compares the ratio

of low-brightness area in each organ effectively determines liver and kidney.

However, there were some failures to extract the gap between liver and kidney, as shown in Fig.6. These cases are thought to be due to the failure of the organ area segmentation caused by the brightness change of the organ boundaries being small and that of the blood vessel in kidney being high. Therefore, boundary enhancement processing and automatic adjustment of contrast are required for these images. In addition, in case of organ disease, it is considered that the volume of blood in each organ would be different from normal status. A new method to adapt these situations is needed in clinical site in the future.

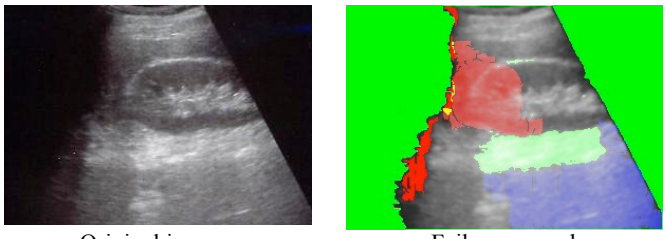
As shown in Table II, the proposed system is more sensitive to internal bleeding than medical doctors. Also, the specificity is maintained high standards. This means that quality of focused assessment with sonograpfy for trauma (FAST) was improved by proposed method. Therefore, we confirmed the effectiveness of the proposed internal bleeding detection algorithm.

Fig.7 shows an example of failure of the detection. Organ area segmentation failed due to the extracted liver area being very small in the image and internal bleeding existing on the left side of the image. In these cases, a US image is needed from which the organs can be extracted with a certain balance. It is considered, therefore, that this system is required to control position and posture of a US probe automatically for obtaining an optimal image to detect internal bleeding by the proposed algorithm.



Original image Failure example

Fig.6 Example of failure of extracting gap between organs



Original image Failure example

Fig.7 Example of failure of detecting internal bleeding

VI. Conclusions and Future Works

In emergency medical care, Focused Assessment with Sonography for Trauma (FAST) is performed to detect internal bleeding. However, FAST is not sensitive enough to internal bleeding, which is a critical problem. In this research, therefore, we aimed at developing a robotic system to improve the sensitivity. In this paper, we focused on the one of the FAST area (the area between liver and kidney), and proposed internal bleeding detection algorithm. With results of experiment of internal bleeding detection using clinical US images, we confirmed that the proposed algorithm could improve the sensitivity to internal bleeding. In addition, it was suggested that the proposed low-brightness set analysis could determine liver and kidney.

On the basis of the current study, we advance the research of automated US probe controlling algorithm by using the proposed detection algorithm. Moreover, the system will be extended to diagnosis of all FAST areas, and applicability to patients with internal bleeding will be evaluated. Also, we try to add the Doppler flow to confirm the vessel positions.

Acknowledgment

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