### **Original Research Article**

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### Development of detection method for automatic hemostasis using machine learning with abdominal cavity irrigation

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#### ABSTRACT

**Background:** Abdominal cavity irrigation is a more minimally invasive surgery than that using a gas. Minimally invasive surgery improves the quality of life of patients; however, it demands higher skills from the doctors. Therefore, the study aimed to reduce the burden by assisting and automating the hemostatic procedure a highly frequent procedure by taking advantage of the clearness of the endoscopic images and continuous bleeding point observations in the liquid. We aimed to construct a method for detecting organs, bleeding sites, and hemostasis regions.

**Methods:** We developed a method to perform real-time detection based on machine learning using laparoscopic videos. Our training dataset was prepared from three experiments in pigs. Linear support vector machine was applied using new color feature descriptors. In the verification of the accuracy of the classifier, we performed five-part cross-validation. Classification processing time was measured to verify the real-time property. Furthermore, we visualized the time series class change of the surgical field during the hemostatic procedure.

**Results:** The accuracy of our classifier was 98.3% and the processing cost to perform real-time was enough. Furthermore, it was conceivable to quantitatively indicate the completion of the hemostatic procedure based on the changes in the bleeding region by ablation and the hemostasis regions by tissue coagulation.

**Conclusions:** The organs, bleeding sites, and hemostasis regions classification was useful for assisting and automating the hemostatic procedure in the liquid. Our method can be adapted to more hemostatic procedures.

Keywords: Endoscopic image processing, Support vector machine, Urology, WaFLES

#### **INTRODUCTION**

Minimally invasive surgery performed by inserting an endoscope and surgical instruments into the body cavity through small incisions to improve a patient's quality of life is commonly used in many surgical fields. This procedure provides several benefits to patients by shortening both the degree of postoperative pain and the period of recovery. However, skills of doctors should be very high, which increases the burden on doctors. To reduce the burden on doctors, assistance is provided by medical robots and navigation systems using medical images.<sup>1,2</sup> Furthermore, there is great interest in assisting and automating surgical procedures. We focused on assisting and automating hemostatic procedures frequently performed in surgical procedures.<sup>3</sup> The and assisting automating hemostatic procedures contribute to the safety of surgery. It is difficult for doctors to find all bleeding and hemostatic regions. There are multiple studies on reducing the invasiveness of tissue coagulation by energy devices because tissue coagulation by energy devices often causes loss of normal tissue.<sup>4-6</sup>

Many studies have attempted to minimize the invasiveness of tissue coagulation by controlling the output of the device. We considered that it is possible to provide feedback to the coagulation device and reduce invasiveness by monitoring the bleeding region and quantitatively judging that hemostasis is complete. Moreover, real-time detection of bleeding and hemostatic regions would assist doctors and reduce the burden on doctors. Therefore, we aimed to develop a method for assisting and automating hemostatic procedures. We began by hypothesizing that it is important to identify the bleeding region at the beginning of surgery to assist and automate the hemostatic procedure. At the end of the procedure, it may be necessary to detect the regions of hemostasis because of the application of an energy device such as holmium lasers and bipolar devices to an organ. The purpose of study was to devise a means for detecting organs, bleeding sites, and hemostatic regions in the endoscopic view.

In this paper, we focused on a new technique performed in liquid (water-filled laparoendoscopic surgery, WaFLES), because endoscopic images using liquid are clearer than those using gas.<sup>7</sup> This liquid surgical technique is majorly used in the field of urology owing to its high safety and low invasiveness.<sup>8</sup> Using the irrigation liquid, the region was cleaned, so it was possible to monitor the organs, bleeding sites, and hemostatic regions.<sup>9</sup> In addition, we considered that clear endoscopic images were effective for detecting organs, bleeding sites, and hemostatic regions.

By developing a new detection method using the improved endoscopic view provided by the WaFLES, we aimed to propose a surgical system that was minimally invasive and that reduced the burden on doctors.

#### **METHODS**

#### Our system design and plan of the detection method

The hemostatic procedure consists of detection of bleeding within the surgical area and coagulation of the bleeding tissue with the application of an energy device. Based on this workflow of hemostasis using an energy device, a part of the system necessary for assisting and automating the hemostasis procedure has been depicted in (Figure 1). We focused on constructing a method of detecting the bleeding and hemostasis regions, which is the most important factor in our system. The bleeding and hemostatic regions have various shapes and edges on the images. Therefore, we developed a detection method using machine learning with a focus on the change in color information due to the energy device. Studies on the detection of bleeding in endoscopic images have been based on the color feature descriptor, texture feature descriptor, and edge feature descript to in the field of diagnosing using wireless capsule endoscopy.7-13 In a previous study aimed at assisting the hemostasis procedure, the authors used a bleeding region detection method in endoscopic surgery with a focus on detection accuracy and calculation cost of a linear support vector machine (SVM) based on the color feature descriptor.<sup>14,15</sup> However, previous studies did not attempt to detect the hemostatic region. Therefore, in order to develop our system, we constructed a method of detecting three regions: the organ region, bleeding region, and hemostatic region. We adopted region detection using linear SVM with multiple color feature descriptors, while maintaining the real time property and detection accuracy.



#### Figure 1: Proposed surgical robotics system design and workflow of our proposed hemostatic system using WaFLES technique.

#### The linear SVM and the multi-classification

The SVM method is a statistical classification method using machine learning. The focus point was that the higher accuracy classification was possible using a few feature descriptors than the other method using machine learning so it was could reduce the calculation cost. It was considered to be a suitable method for us aiming at real time classification. The SVM classifiers were applied by calculating the best hyperplane using data points.<sup>15</sup> In general, hyperplanes are treated as optimization problems, as shown in equation.

$$\label{eq:stars} \begin{split} \arg\min_w \frac{1}{2}|w|^2 + C\sum_{n=1}^N \xi_n\\ \text{s.t. } t_n(w^T\phi(x_n)+w_0)-\xi_n \geq 1 \end{split}$$

where w is the gradient of the hyperplane,  $w_0$  is the intercept,  $t_n$  is the label corresponding to data point  $x_n$ , C is the parameter that determines the trade-off between the penalty and the margin,  $\xi_n$  is the slack variable, given as.<sup>15</sup>

$$\xi_n = |t_n - (w^T \varphi(x_n) + w_0)|$$

And  $\varphi(\cdot)$  is the kernel function. In the linear SVM, the kernel function is applied to equation.

$$\varphi(\mathbf{x}_n) = \mathbf{x}_n$$

In general, Lagrange's undetermined multiplier method is used to solve the minimization problem of equation (1). In this study, we used the sequential minimal optimization (SMO) algorithm.<sup>16</sup> When a new  $x_n$  is given, y is obtained as follows by solving the optimization problem.

$$y = w^T x_n + w_0$$

In above equation, linear SVM classification was performed according to the sign of y when a new  $x_n$  was given. In our study, we tried multiclass classification, which has not been done in previous studies. We used the multiclass model that does binary classifications as necessary of number.<sup>16</sup>

#### The selecting the color feature descriptors

Based on previous research, we began by selecting the color feature descriptors. Then, we focused on the sharpness of the endoscopic images in the liquid because the contrast between S value and V value in the hue, saturation, value (HSV) model which was the hexcone model.<sup>17</sup> These values were the better in liquid than in gas. Previous studies have demonstrated the usefulness of the S value in the detection of bleeding regions. Furthermore, the color information of the hemostatic region in the endoscopic image in liquid was investigated, and the color information of the organ region that was believed to be incorrectly identified as the hemostatic region was randomly extracted at 256 pixels. Subsequently, the contrast in the V value tended to be different between the organ and hemostatic regions. Furthermore, it was found that by adding the S value used in previous studies, each value demonstrated a high value in the hemostatic region (Table 1 and Figure 2).

#### Table 1: S and V values (n=256).

	Organ	Hemostasis
S (mean ±SD)	0.18±0.05	0.19±0.02
V (mean ±SD)	0.69±0.19	$0.88 \pm 0.07$

From the viewpoint of calculation cost, it was considered that up to three color feature descriptors would be good; therefore, we used a new descriptor  $F_3$  equation (5) that

was obtained by adding the V value to the color feature descriptors proposed in the conventional method in order to improve the detection accuracy of the hemostatic regions.<sup>14</sup> Below equation summarizes the color feature descriptors proposed in this paper.

$$F_{1} = R_{(i)}/(R_{(i)}+G_{(i)}+B_{(i)})$$

$$F_{2} = G_{(i)}/R_{(i)}$$

$$F_{3} = S_{(i)}V_{(i)}$$

where,  $R_{(i)}$ ,  $G_{(i)}$ , and  $B_{(i)}$  were the RGB values and  $S_{(i)}$  and  $V_{(i)}$  were the saturation and lightness at the i<sup>th</sup> pixel. In equation 5, the descriptors  $F_1$  and  $F_2$  were adopted from previous studies because we thought they would contribute to the detection of bleeding region. The descriptor  $F_3$  was a newly proposed descriptor in this paper because we thought it was effective in detecting the hemostasis region.





#### The create dataset and verification of SVM classifier

Our training database was created. The objects were endoscopic images of partial non-cancerous nephrectomy specimens in three animal experiments specific pathogenfree pigs weighing about 30kg performed by urologists using WaFLES with the approval of the local ethics committee for animal experiments. In the experiment, the endoscope was manually fixed. Our dataset was recorded with an endoscope (Karl Storz<sup>TM</sup> camera system; 30 fps, 1920×1080). From three animal experiments with different lighting, we obtained a total of three hemostatic procedures, for example one of the hemostatic procedures shown in (Figure 3).

Under the guidance of a urologist, we obtained the ground-truth label from 90 images, 30 images from each hemostatic procedure. From these endoscopic images, pixels of organs, bleeding, and hemostatic regions were randomly extracted at 106496 pixels, totaling 319488 pixels (Figure 3).



## Figure 3: For example, target pixels (white triangles) obtained from the endoscopic videos in WaFLES..

Then, the linear SVM classifier was learned by our training database and verified by five-part cross-validation using MATLAB® R2018a (Mathworks, Inc., Natick, MA, USA). In cross-validation, we used the K fold method.<sup>21</sup> Cross-validation is used to evaluate the generalization performance of the learning model. In this paper, the SVM classifier was sufficiently generalized with five-part cross-validation; then, the prediction accuracy was evaluated. In verification, true positive (TP), false positive (FP), true negative (TN), and false negative (FN) rates were calculated from the rate of the pixels classified in each region. Accuracy was obtained according to equation.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

By comparing the SVM classifier using our descriptors with the conventional descriptors, the accuracy level of the SVM classifier was guaranteed using our training database.<sup>14</sup> We applied the SVM classifier to images not

included in our dataset and confirmed detection accuracy based on the ground-truth label created by a urologist.

# Evaluation of the calculation cost and our detection method

In order to calculate the cost of our SVM classifier, the processing time was measured by adapting to endoscopic images of  $720 \times 480$  pixels. Our classification was implemented using a computer with intel core i7-6700K (4.00 GHz 4-core/8-thread CPU) and 16.0GB RAM. Open MP was introduced to run in multi-thread mode based on the CPU. The programming language used was C/C++.

As part of the verification of the effectiveness of our method, we set the region of interest (ROI) manually in the endoscopic images of non-ischemic partial nephrectomy using WaFLES in an animal experiment. Subsequently, areas of bleeding by ablation and hemostasis by coagulation using the energy device were detected, and changes in each region size and effects of the procedure on the endoscopic image were compared.

#### RESULTS

The evaluation of the prediction accuracy of the classifier using our descriptors revealed that the classification accuracy was 98.3%, which was better than that with the conventional descriptors 95.6%.<sup>17</sup> Figure 4 demonstrates the confusion matrices and TP and FP rates of each region in the classifier using our descriptors and the conventional descriptors.

Figure (5 and 6) summarize the frames of visualized images of the classification results based on our method, with green indicating the bleeding region and blue indicating the hemostatic region. Figure 5 summarizes the organ and bleeding regions alone and the organ and hemostatic regions alone.





Figure 6 summarizes the results with coexisting organ, bleeding, and hemostatic regions. The detection accuracy of the bleeding area in Figure 5(a) was 98.8%. The detection accuracy of the hemostatic region in Figure 5(b) was 94.1%.



#### Figure 5: Detection and visualization of (a) the organ and green indicating the bleeding region and (b) the organ and blue indicating the hemostatic region.

Regarding calculation costs, the processing time was  $21.6\pm0.6$ ms (mean  $\pm$ SD) (N=30). Verification results on the effectiveness of our method (Figure 7) demonstrated manually ROI (400×400 pixels) used for verification; then, the hemostasis procedure proceeded in time series from label 0 to 7 in the image.

At this time, our method was applied and the change in the size of each region in the image was evaluated (Figure 8). In the Figure 8, the green line shown that the change in the bleeding region, the blue line shown that the change in the hemostasis region.



Figure 6 (a-d): Detection and visualization of coexisting organ, bleeding, and hemostatic regions.



Figure 7: Procedure events on endoscopic images between time series 0 and 7.



Figure 8: Changes in the size of each region using images of Figure 7 time series from 0 to 7.

#### DISCUSSION

#### Detection using our descriptors

Previous studies have proposed region detection using linear SVM based on the calculation cost and detection accuracy of the bleeding region.<sup>10-17</sup> A new color feature descriptor was proposed using S and V values in the HSV model of identifying the bleeding region in liquid because in addition to characteristic color features in the hemostatic region, the higher clarity of endoscopic images in the liquid would have an effect as well. An endoscope has a very strong light source at its tip. Therefore, when gas is used, the light is reflected more frequently over organs and tissues, and halation is likely to occur, thereby, decreasing image contrast. Compared with gas, there is a tendency for light to diffuse more in liquid; thus, high contrast can be achieved. The contrast between the S and V values in liquid becomes high since the saturation and lightness in the HSV model are susceptible to the lighting environment; we believe that the proposed color feature descriptor contributed to the classifier in the hemostatic regions. In comparisons

between the conventional color feature descriptors and the matrices of our color feature descriptors in the results of the evaluation of prediction accuracy, our classifier's distinction between the organ and hemostatic regions was better. Therefore, we believe that that the three-region classification using our color feature descriptors is useful and has sufficient accuracy.

#### Measurement of calculation cost

It was possible to process approximately 21ms of an endoscopic image of 720x480 pixels; therefore, our classifiers are adaptable to the general 30fps endoscopic videos. In the present study, parallel processing on the CPU was performed, which was feasible with a generalpurpose computer. To further improve the processing time, various possibilities such as image processing based on the GPU were considered. Ultimately, verification of the processing time when running the workflow, as shown in Figure 1, was considered necessary.

#### Evaluating our detection method

In the verification results of the effectiveness of our method (Figure 7), we picked the same area on which the procedure was performed using the manually set ROI. Figure 7 (0) demonstrates the initial state of the organ, and the bleeding and hemostatic regions were not detected in Figure 7 (0). Figure 7 (1) demonstrates that the surface of the organ was coagulated with an energy device, and the hemostatic region was detected in Figure 8 (1). In Figure 7 (2), organ ablation was performed using forceps, and it was understood that bleeding was occurring; subsequently, the detection of the bleeding region is shown in Figure 8 (2). Furthermore, the size of the hemostatic region decreased since bleeding was flowing on the anterior surface of the coagulated organ. In Figure 7 (3-7), we confirmed that the hemostatic procedure had started. The peak size of the bleeding region was confirmed in Figure 8 (4) in comparison to Figure 8 (3) since multiple episodes of bleeding occurred at the beginning. Bleeding stopped as time passed after the hemostatic procedure was performed Figure 7 (5-7). The workflow of the hemostasis procedure using energy devices, by which the size of the hemostatic region increases was quantitatively defined by the change in the value in Figure 8. Therefore, it was demonstrated that the detection of bleeding and hemostasis by the energy device could be performed using our method by monitoring ablation and coagulation regions.

#### Benefits of minimal invasiveness and burden reduction

In WaFLES, by gentle irrigation, the distribution of blood was not diffuse and bleeding points could be stably observed. Furthermore, it was easy to detect the change in the state of organs by the hemostatic technique since it was easy to observe the hemostatic regions. Even when gas is used, the surgical field is cleaned often; therefore, it is possible to apply our method in environments similar to that in WaFLES.<sup>22-24</sup> Furthermore, the detection of the hemostatic region can result in the possibility of making the procedure less invasive.

#### Limitations

In our method, we detected the bleeding region on endoscopic images in real time and quantified the size of the region. Furthermore, processing the data while excluding the motion of the endoscope and organ was required for tracking the ROI setting. The solutions included adapting the self-position estimation method of the endoscope, detection of endoscope motion by the three-dimensional position measuring device, and calculating optical flow using landmarks in the image.<sup>25,26</sup> Therefore, our future work will be focused on guiding surgical robots to the detected bleeding region based on the feedback from the hemostatic procedure and alert from the bleeding region and hemostatic region quantitative evaluation shown. These advancements can help automate the assistance and evaluation of the method. Furthermore, we will develop robot hardware and integrate our method to automate the procedure and evaluate its performance.

#### CONCLUSION

We proposed a method for automation and assistance in hemostatic procedures. Real-time region detection of the hemostatic procedure by linear SVM was realized by newly adding identification of the hemostatic region. In our method, we used the new color feature descriptor and focused on the change in color information in endoscopic images owing to bleeding from organs and tissue coagulation owing to the use of energy devices. The accuracy of the classifier was 98.3% and the processing time was approximately 21 ms in images of 720×480 pixels; therefore, it was possible to detect three regions on endoscopic images of the hemostatic procedure using our method in real-time. Additionally, by measuring the bleeding and hemostatic regions during the hemostatic procedure in time series, assistance can be provided to the doctor by annotating the end of the hemostatic procedure. Moreover, the procedure can reduce the invasiveness by reducing the coagulation of normal tissues using energy devices. In our future studies, we will demonstrate that a medical robot that automates the hemostatic procedure by controlling the detection of the hemostatic region as a trigger can become a reality based on our method.

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