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Automatic Polyp Recognition from Colonoscopy Images Based on Bag of Visual Words

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Abstract: Colorectal cancer (CRC) is one of the most popular cancer in the world. Adenoma and sessile serrated polyp precursor lesions claim over 95% of CRC. The incidence of CRC is reduced 76-90% through the early diagnosis and removal of colorectal polyps. Colonoscopy is the golden standard for the detection of colorectal polyps but about 25% of polyps were missed during colonoscopy examinations. In this study, we proposed a novel method to recognize polyps from colonoscopy images based on bag-of-visual-words (BoW) with extracted regions of interest. The proposed method generates a histogram of visual word occurrences to represent an image, and uses support vector machine (SVM) with error correcting output codes (ECOC) for the detection of polyps. A dataset composed of 131 cases' clinical data were used to train and test the proposed method. Validation demonstrates an average specificity of 97.8±1.5%, an average sensitivity of 97.2±1.7%, and an average accuracy of 97.5±1.0%.

Keywords: Bag of visual words; colorectal cancer; colonoscopy; region of interest.

1. Introduction

Cancer is a leading cause of death worldwide and accounts for 8.2 million deaths in 2012 [1]. The number of cases with colorectal cancer (CRC) has been increasing rapidly and is more than that of lung cancer recently especially in developed countries [2]. However, the number of subjects suffered from CRC in developing countries was actually more than that in developed countries based on data from 1990s or a specific year [3]. The discrepancy might attribute to the fact that CRC is usually not screened by colonoscopy in developing countries, and the stool-based testing, the traditional CRC screening method is less sensitive than colonoscopy examinations [4]. In Japan, CRC was the first-leading cancer in 2012, and the second-leading cause of cancer death in 2014 [5]. The incidence and mortality rates of CRC are expected to steadily increase in the future nevertheless ages and genders [5]. The incident rate of CRC is also rising in young generations, although they account for a relatively low proportion of overall incidences [6, 7].

The adenoma-carcinoma and sessile serrated adenoma-carcinoma sequences are the main pathways in the development of CRC. Evidence indicates and suggests that early removal of polyps is important for the prevention and early therapy of CRC [1, 5]. Hyperplasia (HP) polyps are non-neoplastic but should be removed in case of large sizes. Tubular adenoma (TA) polyps are more likely to develop to cancer following a so-called adenoma-carcinoma sequence [8].

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Laterally spreading tumor (LST), belongs to TA, is a colorectal pre-cancerous lesion. The definition of LST has already accepted in the world, and previous researches have confirmed that LST diagnosed as an early CRC with a high risk. Carcinomas with intracoastal invasion to scanty submucosal invasion (M/SM-s) are of microsatellite instability and regarded as a putative precursor of colorectal cancer. More, sessile serrated adenoma/polyps (SSA/P) were treated as mild lesion but have been targets for removal recently.

Colonoscopy examinations are the golden standard for the detection and screening of polyps and CRC [2, 9]. According to the statistical data in Fig.1 from Japanese Association of Clinical Cancer Centers, the relative 10 years survival rate of CRC is up to 92.4% after the screening and therapy using colonoscopy [10]. However, the CRC detection accuracy of the colonoscopy depends on physicians's experiences [11]. Generally, the complication of colonoscopy leads to wide difference in examination results and causes adenoma miss rate of 20%–30% [11, 12]. Missed polyps cause late diagnosis of CRC with a survival rate less than 10% [13].

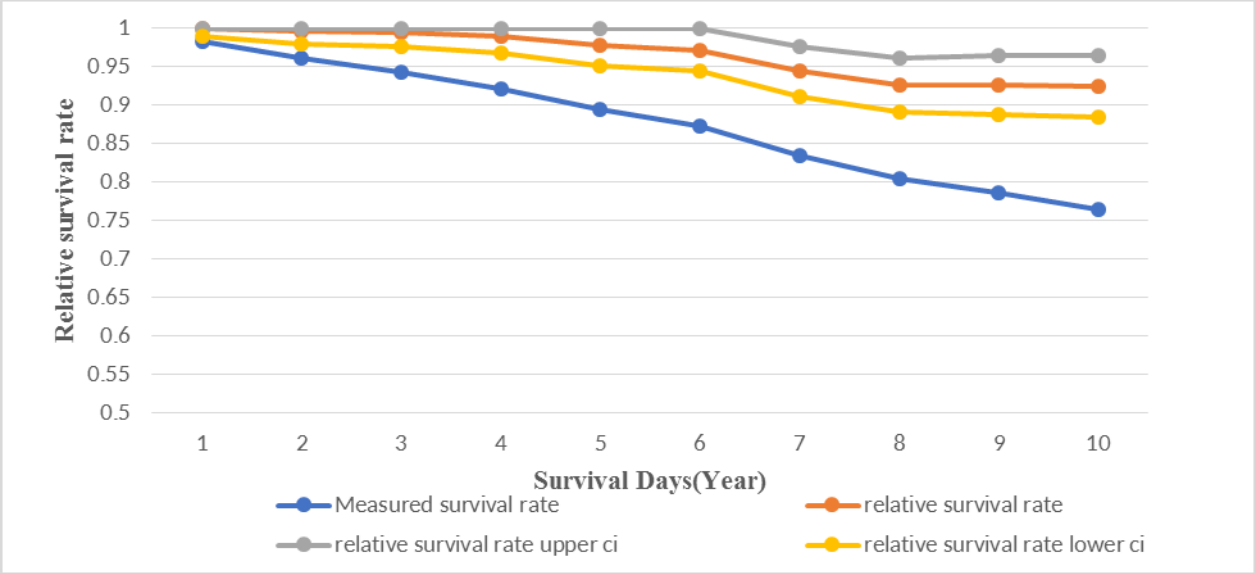

Figure 1. Relative survival rate (Large bowel (Colon/Rectum)/1997year-2019year). The 10-year relative survival data after colonoscopy examinations and treatment (Japanese Association of Clinical Cancer Centers). The curves are drawn based on the data in [10].

Fig. 2 shows typical colonoscopy images. Figs. 2(a)-(d) illustrate typical adenoma polyps (≥10 mm in diameter) easier to be found visually. Figs. 2(e)-(h) are narrow band imaging (NBI) endoscopy images of adenoma polyps. NBIs are usually used for identifying polyps through microvessels [14]. In contrast, small polyps and flat lesions in Figs. 2(i)-(q) are difficult to detect because of small sizes (≤5 mm in diameter), low resolution in white light, or similarities to background [15]. Figs. 2(r)-(t) show the normal colorectal images. Therefore, a computer-aided diagnosis (CAD) system for supporting visual inspection of polyps is desired to reduce misdetection and the workload of physicians.

In this paper, section 2 introduces the related works and contribution, section 3 describes data and the proposed method, and section 4 explains the result and experiences about the characteristics of polyps in endoscopy images. Finally, discussion of the method and result were in section 5.

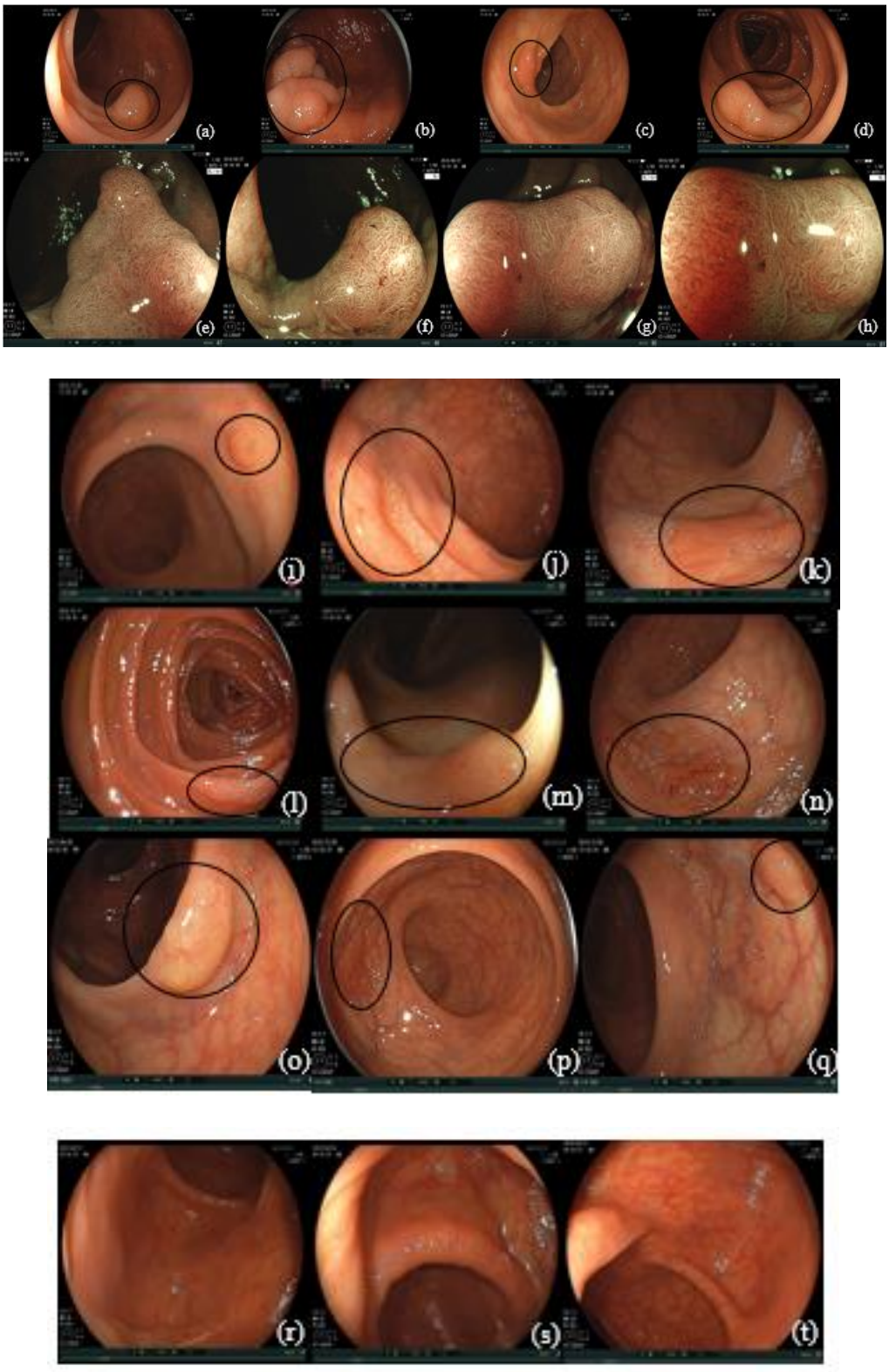

Figure 2. The colonoscopy images (the black elliptical curves show polyps' locations). (a)-(d) contain polyps easier to detect due to their bulge bodies and large sizes. (e)-(h) are magnifying BLI (blue laser imaging) images used to identify polyps' types. (i)-(q) are difficult to detect because of flatness and small sizes. (r)-(t) are normal colorectal endoscopy images.

2. Related works and contributions

To date, many studies have been performed to develop computer-aided diagnosis (CAD) systems for the automatic detection and recognition of polyps from colonoscopy images or video. Traditional research on CAD systems was mainly performed on the detection of polyps from white light endoscopy images [16]-[22]. However, narrow-band images (NBI) became more and more popular recently because NBIs provide more detailed features of vessels and grains. Kominami *et al*. used bag-of-feature with scale-invariant feature transform (SIFT) descriptors and support vector machine (SVM) for the classification of polyps using NBIs [23]. Tamaki *et al*. proposed a recognition system to classify polyps in NBIs based on a local feature-based recognition method [14]. Takemura *et al*. developed a Computer-aided system for predicting the histology of colorectal tumors by using narrow-band imaging magnifying colonoscopy [24].

Compared with NBIs, white highlight images are more important in the detection of polyps. Previous studies were reported by utilizing shape, color, context, and texture information to detect polyps [16]-[20]. For instance, Tajbakhsh *et al*. used context information to remove non-polyp structures and shape information to reliably localized polyps as structures with curvy boundaries [20]. Yu *et al*. proposed an offline and online 3D deep learning integration framework leveraging 3D fully convolutional network for the detection of polyps [25]. This method fully exploited spatiotemporal features, and integrated offline and online learning to effectively reduce false positives.

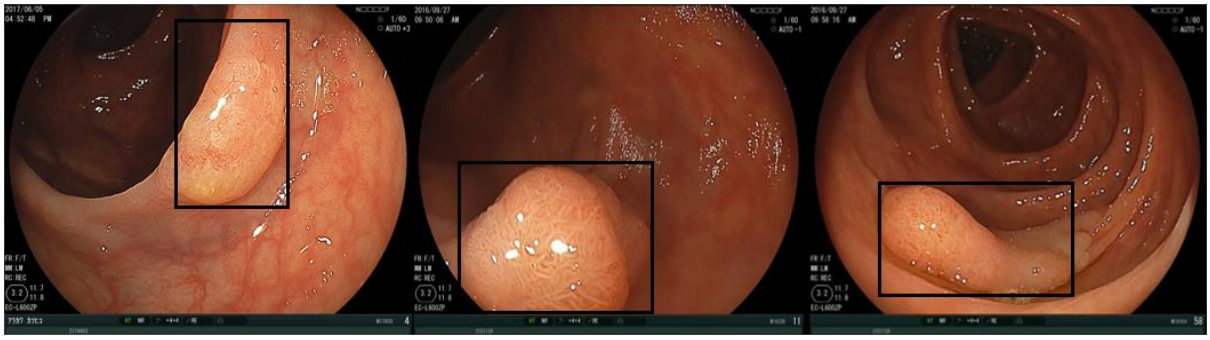

Figure 3. Three examples of ROI (region of interest).

In this paper, we propose an effective method using target extraction based region of interest (TEBROI) and bag-of-visual-words (BoW) for automatic recognition of polyps [26]. Since BoW has been successfully applied to different kinds of recognition problems, including generic object recognition and texture analysis, it is natural to expect that BoW would perform well for white light images. They have a wide range of variation in the texture of colorectal polyps. The proposed method differed from previous methods. The proposed method mainly employs color and texture information of polyps by assigning region of interest (ROI) to train an SVM classifier. The information to be learned from ROI was much less than full images because the region of training was assigned in advance as shown in Fig. 3. Hence, we may further accelerate the recognition by significantly reducing redundant information and achieving high performance simultaneously. The validation based on clinical colonoscopy images demonstrated that our method has a satisfying recognition accuracy.

The main contributions are summarized as follows.

(1) We proposed an effective method to automatically recognize polyps using BoW with TEBROI to efficiently learn color and texture information, and greatly reduced training time simultaneously.

(2) Our method achieved a satisfying polyp recognition accuracy.

In the following section, we outline the process of recognition with BoW, and address some technical aspects to be considered. The research of this study has been significantly extended from our prior work by introducing more clinical data and significantly improving the recognition accuracy.

3. Materials and methods

3.1. Data and methods

We collected 131 subjects' colonoscopy image data from Division of Proctology, Aizu Medical Center, Fukushima Medical University in 2016-2018. The image dataset was acquired using Fujinon 4450 HD (Fujifilm Medical Systems Inc., Tokyo, Japan) processors and adapted colonoscopes. Locations of polyps were marked by board certified gastroenterologists during colonoscopy examinations and confirmed by pathological examinations. We selected total 3,076 colorectal endoscopy images (1,747 with polyps and 1,329 normal) from the dataset. Examples are shown in Fig. 2. Some of the images contain the same polyps but include the polyp's appearances from different views. The sizes of sub-images with polyps are not fixed and vary from 224×224 to 359×220 pixels. This study was approved by the Ethic Committee of Aizu Medical Center, Fukushima Medical University.

3.2. Bag-of-visual-words

The algorithms were developed with Matlab R2018a (The Mathworks, Inc. US) and the Statistics and Machine Learning Toolbox™. We mainly used a BoW model to realize the computer-aided system.

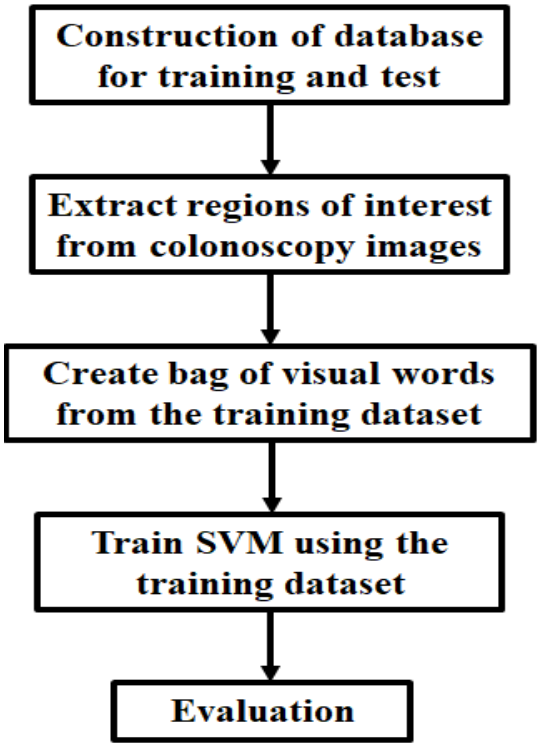

Figure 4. The flowchart of training and evaluating for automatic polyp recognition from colonoscopy images.

BoW was proposed by Sivic *et al*. and used in object and scene retrieval to localize an object in a video. BoW was motivated by text classification, where a document or text is represented by a histogram of words regardless of word order [27]. Similarly, BoW represents an image as a histogram of representative local features extracted from the image regardless of their location. Each representative local feature, called a visual word (or codeword, visual texton, keypoint), is the center of a specific feature cluster. A set of visual words is often called a visual vocabulary. BoW has been widely used in image characterizations because of BoW's simplicity and good performance. BoW has been applied to generic visual categorization to identify objects in natural images. BoW is one of the main methods for web image search and image semantic modeling. In this study, the vocabulary feature representation was based on speeded up robust features (SURF) descriptor, and the codebook was generated by a hierarchical k-means clustering over feature vectors [28]. Each cluster center corresponds to a visual word, and all of the visual words compose a codebook for images to be processed. All of the features are mapped to visual words. We proposed a training model based on bag of visual words extracted from ROI in colonoscopy images. Fig. 4 illustrates the flowchart to build image datasets, create the bag of visual words, train SVM, and evaluate. The details of the whole procedure are as follows.

(1) construct a database of colonoscopy images;
(2) build a training dataset by manually selecting ROIs from colonoscopy images in the database;
(3) extract features from the training dataset using the SURF descriptor;
(4) compute feature vectors from SURF features;
(5) cluster feature vectors to generate visual words;
(6) calculate a histogram of visual words for the training dataset;
(7) train the SVM classifier with histograms of visual words.

Fig. 5 illustrates the details of the procedure about creating BoW. The evaluation of CAD is based on 10-fold cross-validation, and sensitivity, specificity and accuracy are defined as follows:

$$\textbf{Sensitivity} = \frac{\boldsymbol{a}}{\boldsymbol{a}+\boldsymbol{b}} \cdot \mathbf{100}\ (\%) \tag{1}$$

$$\textbf{Specificity} = \frac{\boldsymbol{c}}{\boldsymbol{c}+\boldsymbol{d}} \cdot \mathbf{100}\ (\%) \tag{2}$$

$$\textbf{Accuracy} = \frac{\boldsymbol{a}+\boldsymbol{c}}{\boldsymbol{a}+\boldsymbol{b}+\boldsymbol{c}+\boldsymbol{d}} \cdot \mathbf{100}\ (\%) \tag{3}$$

where *a* is the number of true positive, *b* is the number of false negative, *c* is the number of true negative, *d* is the number of false positive. F-measure (F1) can be described as followed:

$$\mathbf{F1} = \frac{\mathbf{2}\boldsymbol{a}}{\mathbf{2}\boldsymbol{a}+\boldsymbol{b}+\boldsymbol{d}} \cdot \mathbf{100}\ (\%) \tag{4}$$

3.2.1. Tebroi

We proposed a novel method employing color and texture information of polyps by assigning region of interest (ROI). The information to be learned from ROI was much less than that of full images because ROIs for training were assigned in advance as shown in Fig. 3, where the green rectangle contains the useful information what we needed, and the other areas usually to be consider useless. To achieve the high performance and accelerate the recognition progress by significantly, through ROI to reducing useless information is very important.

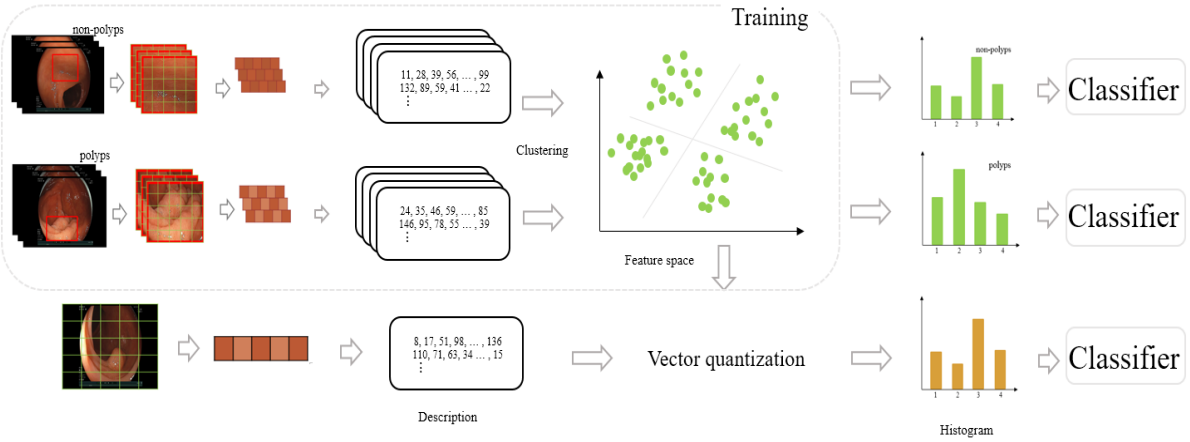

Figure 5. Details of CAD system based on BoW.

3.2.2. SURF

We construct a "vocabulary" of SURF features to representative of polyp and non-polyp categories accuracy because images do not actually contain discrete words. SURF is a scale-invariant and rotation-invariant detector and descriptor, and it is widely used in computer vision for extracting local features [29]. SURF has been used in image registration, classification, object recognition and etc. SURF is partly inspired by SIFT descriptors to describe the distribution of the intensity content within the interest point's neighborhood [28]. SURF is faster and more robust in different image transformations than SIFT [30]. We give a brief introduction on SURF for the self-containment of this paper. The SURF algorithm consists of three main steps: interest point detection, local neighborhood description, and matching.

Interest point detection uses integral images calculated as follows for fast computation of convolution filters.

$$\boldsymbol{S(x,y)} = \sum_{\boldsymbol{i=0}}^{\boldsymbol{x}} \sum_{\boldsymbol{j=0}}^{\boldsymbol{y}} \boldsymbol{I(i,j)} \tag{5}$$

The Hessian matrix determinant is used to measure the maximum determinant of local changes around points. Given a point $p = (x, y)$ in an image I, the Hessian matrix $H(p, \sigma)$ at point p and scale σ, is:

$$\boldsymbol{H(p,\sigma)} = \begin{pmatrix} \boldsymbol{Lxx(p,\sigma)} & \boldsymbol{Lxy(p,\sigma)} \\ \boldsymbol{Lyx(p,\sigma)} & \boldsymbol{Lyy(p,\sigma)} \end{pmatrix} \tag{6}$$

where $L..(p,\sigma)$ is the second-order derivative of gaussian at the point p, and σ is the scale of Gaussian function. Interest points are searched using features at different scales. The scale space is usually represented as an image pyramid. Images are repeatedly smoothed with a Gaussian filter, and then are down-sampled to get the next higher level of the pyramid. Therefore, several floors or stairs with various measures of the masks are calculated as follows,

$$\boldsymbol{\sigma = current\ filter\ size \times \begin{pmatrix} BaseFilterscale \\ BaseFilterSize \end{pmatrix}} \tag{7}$$

In SURF, the lowest level of the scale space is obtained from the output of the 9×9 filters. This process is accomplished with a single call to Matlab Bag of Features function, which select location of feature point using a Grid method [31], the grid step is 8 pixels, and the block width is 32, 64, 96, and 128. Further details of SURF can be found in [28, 30].

3.2.3. Overcome the unbalance of clinical data

As the training set contains an unequal number of images per category (polyp and non-polyp), we adjusted the image numbers to balance the number of images in each category. We separated the data to the training dataset (2,392 images) and test dataset (266 images). We further separated the training dataset into training and validation data. 90% of images in the training dataset were used for training and the other 10% images for validation. Randomly splitting training data is also important to avoid biasing.

3.2.4. Selection of features

In addition, the visual vocabulary is constructed by extracting SURF features from the image in all image categories, and then we use K-means clustering to create a 500-word visual vocabulary from 3,061,760 features to balance the number of features across all image categories. Additionally, we use an encoding method for counting occurrences of the visual word in an image. This method generates a histogram as a reduced representation of an image. An example of word histogram is illustrated in Fig. 6. These histograms are used for training a classifier and classifying images.

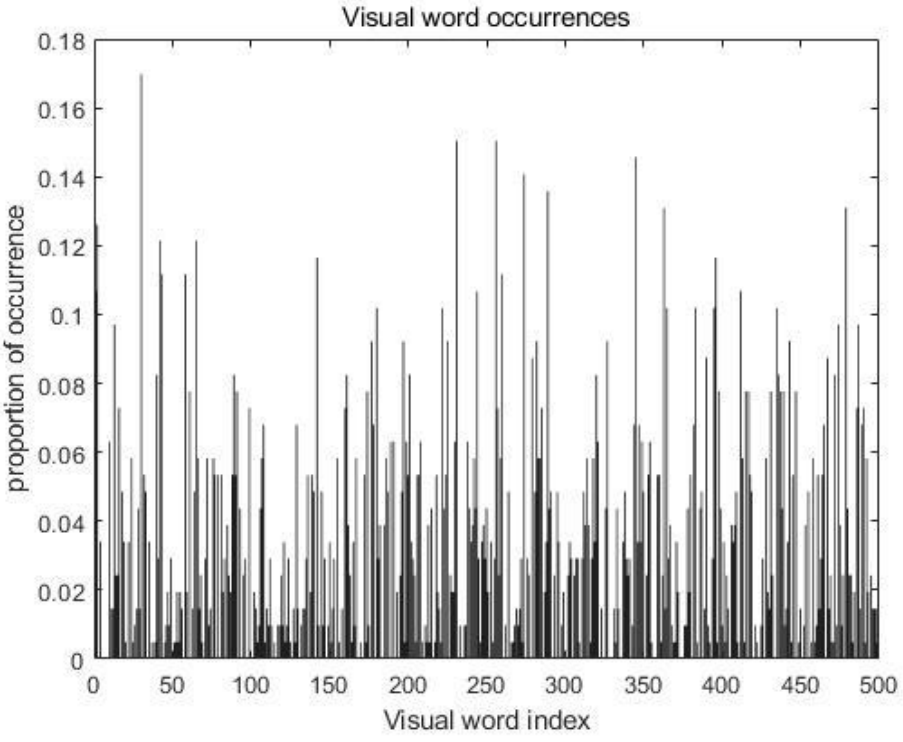

Figure 6. An example of word histogram.

3.3. Classifier

The classifier was developed using Statistics and Machine Learning of Matlab R2018a. Training images are randomly selected from each category and fed to a classifier training procedure. To handle the two-class problem, a linear SVM classifier using error correcting output codes (ECOC) strategy is employed. ECOC is an ensemble method designed for classification problems [32]. We utilize the encode method to formulate feature vectors from the training dataset for representing each image category. Tests were performed using the validation dataset. The validation dataset was not used during the training process. The evaluate function returns the confusion matrix to indicate the classifier's performance.

4. Results

Table.1 lists the evaluation results of the performance. The average sensitivity, specificity and F1 were 97.2±1.7%, 97.8±1.5% and 97.5±1.0%, respectively. Fig. 7 shows four wrongly classified examples, where black circles indicate the locations of ROI. Fig. 7(a) and (c) show the normal colon walls, where folds caused by the large intestine wiggled lead to false positive. The false positive case in Fig. 7(b) was caused by mucus left in the large intestine. The uplift intestinal wall caused the false positive in Fig. 7(d). Fig. 8 shows four false negative patterns, where black circles indicate the locations of ROIs. Our system is insensitive flat lesions because their color and shape are similar to the background as shown in Figs. 8(a) and 8(d). Moreover, small lesions on the dim corner were missed by our system as shown in Figs. 8(b) and 8(c).

Table .1 Evaluation of polyp diagnosis system.

KNOWN	Histologic classification (%)		
	non-polyps	polyps	total
non-polyps	97.8%	2.2%	100%
polyps	2.8%	97.2%	100%

5. Discussion and conclusion

In this paper, we proposed a framework based on a bag-of-visual-words representation of local features followed by support vector machine (SVM) to automatically diagnose polyps. We performed validation based on clinical colorectal images of white light from 131 cases. This method can effectively recognize the polyp from background and has a satisfying accuracy. Comparing with previous studies, the proposed method is much better than traditional methods using appearance model, shape, context information, etc. For example, a study using a model of polyp appearance achieved precision and recall of 47.14% and 71.66%, respectively [33]. Another study using shape and context information achieved sensitivity up to 88.0% [20].

Our study demonstrated that the proposed method is an easy and effective method for the classification of polyps from background. The detection of polyps from white light colorectal images is essential for colorectal examinations. Further analysis on the characterization of polyps can be performed by successive narrow-band imaging, indigo carmine dye, and pathological analysis. The main challenge for polyp recognition in colonoscopy video is to detect polyps in Fig. 2 (i), (j), (k), (l), (m), (n), (o), (p) and (q) where the polyps are difficult to be detected because of locations and colors. Especially, there are polyps with some characteristics like flat and pale. When the size of polyp in images is relatively small or similar with the wall of colon compared with background, the polyps are usually missed. These seriously reduce the polyp recognition sensitivity. In this research, we manually selected ROI with polyps under the physicians' direction to raise the recognition accuracy.

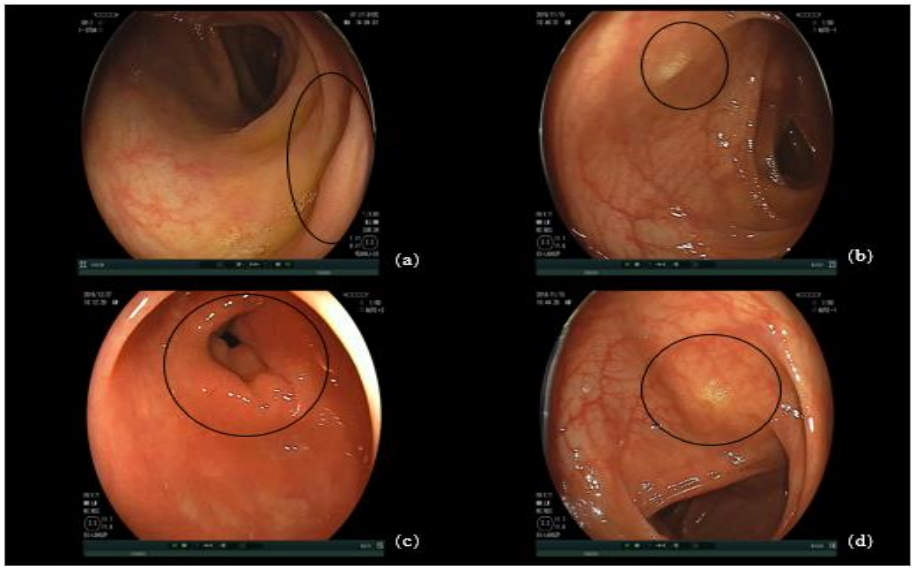

Figure 7. Four false positive patterns.

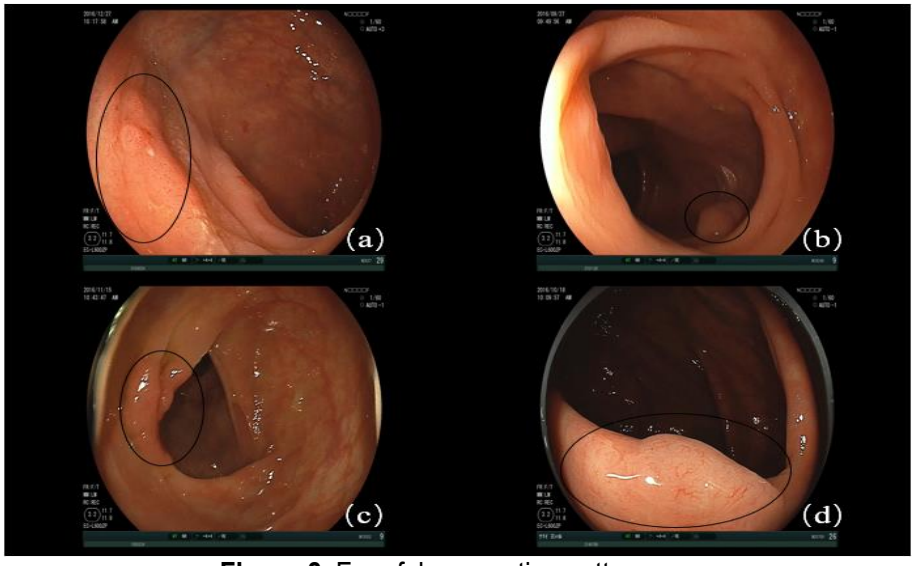

Figure 8. Four false negative patterns.

The limitations of the proposed method are as follows.

(1) The method proposed in this research can only classify whether ROIs contains polyps or not. In the future, we will perform the study on the automatic detection of polyps, i.e., the confirmation and localization of polyps in colonoscopy images.
(2) The number of images for training and testing should be increased to improve the performance and generalization of the proposed method.
(3) The proposed method is only for batch processing and will be improved for real-time detection of polyps in the future.

In this paper, we focus our study on the recognition of polyps from white light colonoscopy images for supporting visual inspection of polyps. Extending this method to a real-time detection system decreases misdetections in CRC screening; therefore, improves patients' survival rate accordingly. On the other hand, the classification of mild and malignant polyps is also important in clinical practice. For example, sessile serrated adenoma/polyps (SSA/P) previously regarded as mild lesions have been treated as a target lesion for colorectal cancer screening. SSA/Ps have flat and pale characteristics in conventional colonoscopy images and hard to be classified from adenoma polyps. In the future, we plan to employ convolutional neural networks to classify SSA/P, conventional adenoma polyps, and normal mucosa.

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