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Classification of esophagitis grade by neural network and texture analysis †

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Abstract

Esophagitis is divided into four grades according to the progress degree of disease by the LA classification method. This research was carried out on image processing with endoscope images for quantifying the four grades under the LA Classification. In a previous paper, which presented our work, the algorithm for detecting abnormal parts from one image was developed. This paper was conducted to classify esophagitis grade of one image itself. Whole 30 images were used in an experiment and included normal images and abnormal images with four grades. GLCM (gray level co-occurrence matrices) factors were extracted. The distributions of the texture image histogram were analyzed from each image for texture images. The algorithm to determine esophagitis grade used BPN (Back propagation network) that was composed of the texture histogram distribution for input data. It learned 20 images and verified with 10 images to diagnose under the LA classification system. Recognition ratio of learning result was 93.0% and verification result 77.0%. With features of the neural network, the success rate could be improved with this result by learning the data which were errors. Consequently, the recognition success rate appeared at 96% by total re-learned 30 images in addition to 10 images.

Keywords: Back propagation network; Endoscopic image; Texture analysis

1. Introduction

The current clinical esophagitis diagnosis methods include 24-hour ambulatory esophagus pH-metry, bilious reflux test, gastro-esophageal reflux scintigraphy, esophagus pressure test and esophagus endoscopic test. Among these, 24-hour ambulatory esophagus pH-metry is currently the most reliable method to test the abnormal reflux condition of GERD (Gastro-esophageal reflux disease) (Na, et al., 1994). However, endoscopy is typically used to visually observe the condition, size or precise location of the lesion. Therefore, this study was undertaken to detect abnormalities using endoscopic images (Krishnan, et al, 2001; Zheng, et al, 2002). Wang et al. (2001) suggested that automatic abnormality detection would assist in a doctor's judgment of a lesion. Considering that the pixel value of the endoscopic image can serve as a statistical reference and that contrast, smoothness, roughness, homogeneity and directionality exist for each pixel, classification was performed according to these criteria. In addition, Seo et al. (2006) suggested use of the artificial neural network algorithm with color and texture parameters as entered values to detect abnormalities in the esophagus.

While the Savary Miller classification was used a great deal in the past for endoscopic diagnosis, the LA (Los Angeles) method is currently the main method being used. The LA method is widely used in clinical studies as it makes it easy for various testers

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to use coincident diagnostic criteria of esophagitis. In the LA classification method, esophagitis is classified as A~D according to the degree of mucosal break (Goh KL, et al., 2000).

Therefore, in this study, learning was conducted by using the BPN (Back propagation neural network) algorithm for esophagus images diagnosed by the LA classification method according to texture parameters acquired from the endoscopic images. The objective of this paper was not detecting some esophagitis regions within one image, but classifying the esophagitis grade of one image itself.

2. Materials and methods

2.1 Materials

The methods for classification of reflux esophagitis include many methods such as Modified Savary & Miller classification, LA classification, Japanese Esophagus Disease Society classification, etc. Nevertheless, the LA method is the preferred method recently as it provides a high degree of coincidence between testers and is well-matched with symptoms or seriousness of gastric acid reflux. The LA method classifies esophagitis as A~D according to the degree of mucosal break. Table 1 shows the criteria of LA classification.

For this study, endoscopic images of esophagitis were obtained. Six images each from normal esophagus and esophagitis (A~D) were used for a total of 30 images. All images were obtained from different patients. Fig. 1 shows endoscopic images of normal esophagus, and Fig. 2 shows images of esophagitis according to LA classification.

2.2 Methods

2.2.1 Texture parameters

The level of GERD is determined by the degree or pattern of mucosal damage rather than by the quantity of inflammation. Therefore, in order to determine the degree of esophagitis by LA classification, this study used texture patterns of the endoscopic images according to degree, rather than detection of inflammation.

The texture parameter used in this study was GLCM (Gray level co-occurrence matrices). GLCM provides information on pixel location, including

Table 1. LA Classification of esophagitis.

Grade	Classification
A	Mucosal breaks confined to the mucosal fold, each no longer than 5 mm.
B	At least one mucosal break longer than 5 mm confined to the mucosal fold but not continuous between two folds.
C	Mucosal breaks that are continuous between the tops of mucosal folds but not circumferential.
D	Extensive mucosal breaks engaging at least 75% of the esophageal circumference.

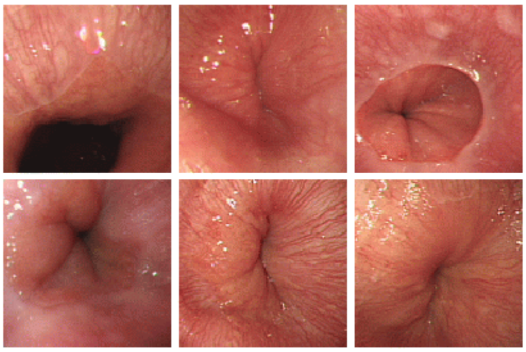

Fig. 1. Normal esophagus images.

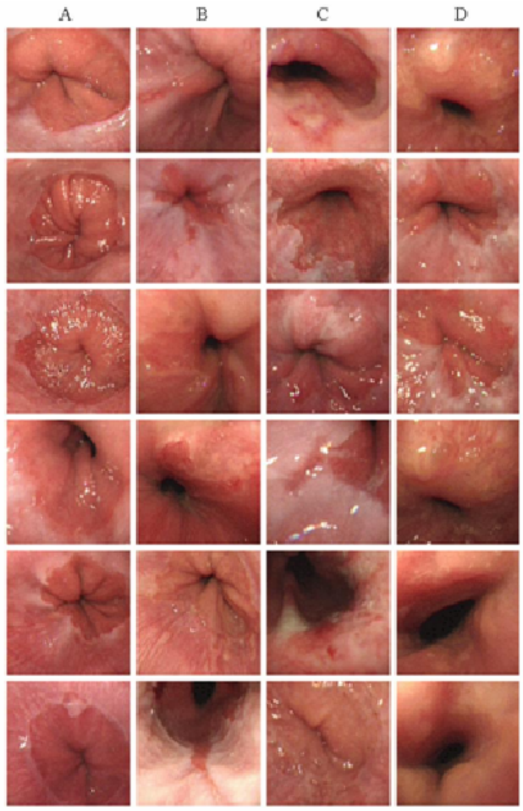

Fig. 2. Esophagitis images by LA classification.

similar grey levels. This is a statistical method of scanning the image and measuring the frequency of each pixel's grey level appearing a certain distance from the pixel in a specific location. Medically, there is an evaluation index in which redness reflects an inflammation, but the endoscope image appears generally with only the intensity of red ton. Therefore, this paper tried to classify grade of esophagitis by using GLCM factors in texture image.

While there is generally an issue of what kind of directionality is measured, this issue can be resolved through use of a matrix, a vector having various directionalities. As the matrix is created, the pixel appearance distribution can be measured by analyzing that matrix, and each space's characteristic is defined by values called descriptors.

By dividing the image into partial sections of 5×5 pixels that do not overlap, descriptors of each of six types of matrix were calculated. Each result value can be shown as the characteristic value of the corresponding partial section.

The six characteristics of each partial section are defined as "Maximum Probability" showing the greatest luminosity level pair, "Moments" showing the degree of continuous appearance of luminosity level pair, "Contrast" showing the expected value between pixels, "Homogeneity" showing the even distribution of luminosity level, "Entropy" showing whether a characteristic point exists in the image, and "Correlation" showing the image's directionality. If the $i \times j$ sized image data divided in partial sections is called M_{ij}, then the GLCM matrix descriptors are defined as follows (Parker, 1997; Tjoa, et al., 2001; Seo, et al., 2004):

Maximum Probability: $$Max(M_{ij}) \tag{1}$$

Moments: $$Mom = \sum_i \sum_j (1-j)^2 M_{ij} \tag{2}$$

Contrast: $$Con = \sum_i \sum_j |i-j|^2 M_{ij} \tag{3}$$

Homogeneity: $$G = \sum_i \sum_j \frac{M_{ij}}{1+|i-j|} \tag{4}$$

Entropy: $$H = -\sum_i \sum_j M_{ij} \log(M_{ij}) \tag{5}$$

Correlation: $$C = \frac{\sum \lfloor ijM_{ij} \rfloor - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{6}$$

where $\mu_x = \sum_i i \sum_j M_{ij}$, $\mu_y = \sum_j j \sum_i M_{ij}$,

$$\sigma_x = \sum_i (i-\mu_x)^2 \sum_j M_{ij},$$

$$\sigma_x = \sum_j (j-\mu_y)^2 \sum_i M_{ij}$$

Once the texture values of all partial sections of the test image are determined, they are normalized into values from 0 to 1. When these values are transformed into an image, a map expressing each texture parameter is drawn. Fig. 3 shows texture maps of all test images by "Maximum Probability."

2.2.2 Learning parameters

To quantify and judge lesion progress with texture parameters as input values, learning was conducted by using the BPN algorithm (Karkanis, et al., 2000; Nguyen, et al., 2001; Seo, et al., 2006). Fig. 4 is a flow chart of programming about BPN algorithm implementation.

The normalized histogram for each image by each texture parameter was classified by units of 0.1. Thus, one texture map holds total 2601 data points, and 10 data points by units of 0.1 were selected as input neurons for the artificial neural network. The number of neurons in the hidden layer was decided on 8 by random value and that of output neurons was 1; scalar

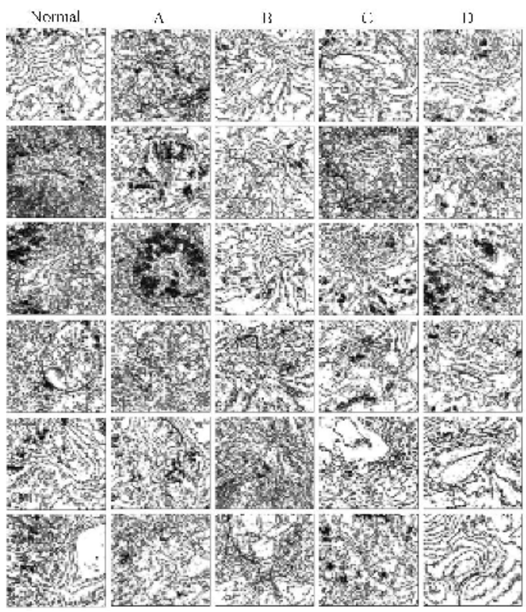

Fig. 3. Texture images of esophagitis about maximum probability.

Table 2. BPN learning factors for esophagitis grade classification.

Learning parameters	Value
Number of image data sets	30
Number of input data units	10
Number of target data units	1 (N:0.1, A:0.3, B:0.5, C:0.7, D:0.9)
Number of hidden-layer units	8
Learning rate	0.1
Momentum constant	0.9
Maximum system error	0.001

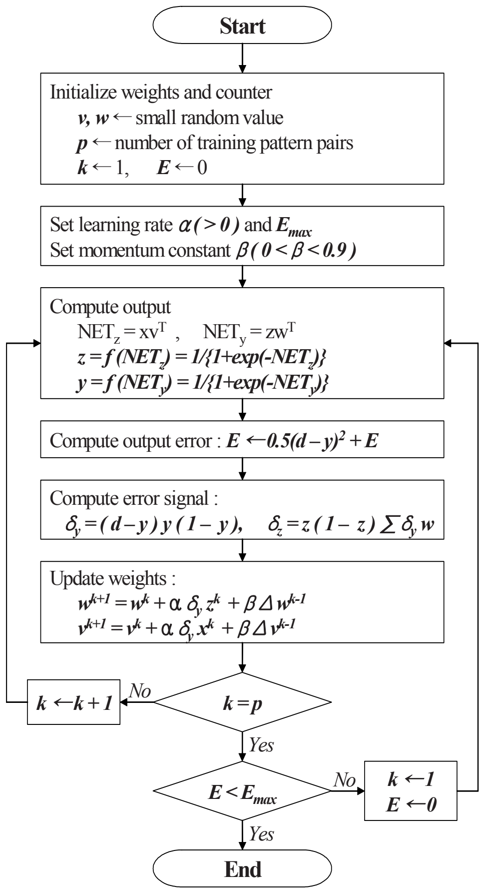

Fig. 4. Flow chart of BPN algorithm.

value was outputted. For result values, the learning target values were set so that Normal Grade was out putted as 0.1, Grade A as 0.3, Grade B as 0.5, Grade C as 0.7, and Grade D as 0.9. The learning rate was 0.1 and the convergence error was 0.001. Table 2 presents the learning parameters and Fig. 5 displays the designed neural network model.

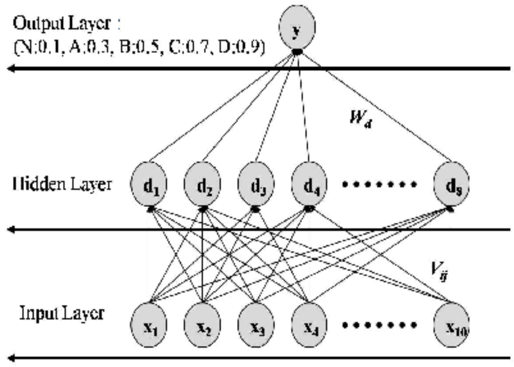

Fig. 5. BPN design for esophagitis grade classification.

3. Results and discussion

An algorithm for quantifying the four grades under LA classification was implemented for esophagitis images in order to determine the lesion progression. When the experiment was conducted per six texture parameters, learning did not occur for Contrast and Correlation. On the other hand, Maximum Probability, Moment, Homogeneity, and Entropy were successfully learned.

"Contrast" shows the expected value between pixels in local image, and "Correlation" shows the image's directionality. These descriptors express a property of a local image and visible patterns. Therefore, these do not reflect the characteristic of whole image for esophagitis classification, and also were not learned. But, four descriptors (Maximum Probability, Moment, Homogeneity, and Entropy) succeed in learning, because these distributions show characteristics of the whole image.

In Table 3, high recognition with a mean of 93.0% was observed if only the learned data were used. Learning was conducted with 20 images among a total of 30 images, and validation was performed with 10 images. Table 4 shows the results of 10 images of validated data. After this validation, a somewhat low validation rate was observed with a mean recognition rate of 77.0%. We deemed that the recognition rate would rise through relearning of all 30 images, including the 10 unlearned images for validation. Therefore, upon relearning with the 10 additional validation images, a mean recognition rate of 96.0% was obtained as shown in Table 5. With features of the neural network, the success rate could be improved for this result by learning the datum which was in error.

Table 3. The results of BPN learning.

Texture parameter	Repetition no.	Classification rate
Maximum probability	8249	95.0% (19/20)
Moment	5167	95.0% (19/20)
Homogeneity	56047	90.0% (18/20)
Entropy	9518	90.0% (18/20)
Average		93.0%

Table 4. The results of BPN validation.

Texture parameter	Total images	Success images	Classification rate
Maximum probability	10	1	90.0%
Moment	10	2	80.0%
Homogeneity	10	3	70.0%
Entropy	10	3	70.0%
Average			77.0%

Table 5. The result of BPN re-learning after adding 10 validation images.

Texture parameter	Epoch no.	Classification rate
Maximum probability	9184	96.7% (29/30)
Moment	7518	96.7% (29/30)
Homogeneity	46446	93.3% (28/30)
Entropy	10267	96.7% (29/30)
Average		96.0%

4. Summary and conclusion

Various endoscopic images of esophagitis were used in an experiment to quantify lesion progression. Esophagitis is diagnosed into four classifications of A~D under the LA the classification system, according to form and length of mucosal damage. This study was performed not to detect the esophagitis region in one image, but to classify the esophagitis grade of one image itself. In this experiment, six esophagitis images of each of the four classifications were used, as well as six normal esophagus images, for a total of 30 images. Since color parameters did not greatly influence the division of lesion phases, texture parameters were used. All texture data were normalized and the distribution was imaged. The normalized data for each image were recomposed, and units of 0.1 were set as the learning parameters of the artificial neural network; the experiment was conducted with six texture parameters. Maximum Probability, Moment, Homogeneity, and Entropy were successfully learned, but Contrast and Correlation were not. High recognition of 93.0% was observed as a result of learning with 20 images out of 30 total images. When the recognition rate was validated with the 10 images not included in learning, a low mean recognition rate of 77.0% was shown. Since relearning was possible with new additional data in the artificial neural network, all 30 images were relearned with the 10 additional images for validation. A mean recognition rate of 96.0% was observed, and we concluded that new data could be learned and high recognition rate could be maintained.

Acknowledgment

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