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Preliminary Study toward Anomaly Detection in Capsule Endoscopy Images based on Higher-order Local Auto Correlation

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Abstract: The aim of this research project is to develop the system automatically detecting anomaly (lesion, residue, blood etc.) in capsule endoscopy based on Higher-order Local Auto Correlation (HLAC). Toward this goal, this paper focuses on the extraction of HLAC feature and image preprocessing. The computational experiment shows the results of some methods for HLAC feature extraction, and their effects on the performance of anomaly detection are examined.

1. Introduction

Capsule Endoscopy is a new way to help doctors diagnose diseases in small and large intestine [1]. However, the average time required for visual inspection of a full 8-hour Capsule Endoscopy video ranges from 45 to 120 min, depending on the experience of the examiner [2]. If an automatic detection method could distinguish enteric lesions from normal organs, it will greatly lighten the workload of the examiners.

The previous studies are mainly based on inspecting the color component and combination directly [3]. However, as the images usually contain various kinds of objects which are multiform and mutable (e.g. dark lumen, bubbles), it is difficult to find out all types of diseases by this means.

In this paper, a preliminary study toward detection of anomaly for Capsule Endoscopy images utilizing statistical method is proposed based on HLAC feature and a subspace method using PCA (Principal component analysis). The computational experiment shows the results and their effects on the performance of anomaly detection are examined.

2. The process of abnormality detection

The whole process includes two phases as shown in Fig.1: learning phase and testing phase.

In learning phase, the proposed method employs samples in which only completely bright and clear wall of small intestine is included so that the features corresponding to normal intestinal images could be learned by our recognizer. In testing phase, the deviation distance between feature vectors extracted from testing samples and the learned subspace is calculated. Anomaly could be detected in this way that larger distance corresponds to higher anomaly degree.

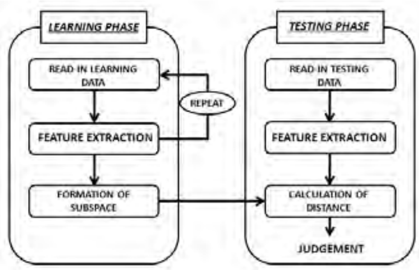

Fig.1 Flow of proposed method

3. Rotation and inversion invariant Higher-order Local Auto Correlation

The feature extraction methods based on Higher-order Local Auto Correlation (HLAC) [4] is employed in this paper. The *N*-th order HLAC is calculated by following autocorrelations:

$$R_N(a_1, \cdots a_N) = \sum_r I(r)I(r + a_1) \cdots I(r + a_N),$$

where I is the gray-scale image, $\boldsymbol{r} = (x,\ y)'$ (the apostrophe denotes the transpose) is a position vector, and $\boldsymbol{a}_i$ are the displacement vectors. For two-dimension HLAC feature, N is restricted to 0, 1, and 2. The configuration of gray-scale HLAC is comprised of 35 (local mask) patterns.

Furthermore, to eliminate the impact of rotation and inversion caused by spin of Capsule Endoscopy in gastrointestinal tract, pattern masks in same shape are treated equivalently, so that 35 pattern masks for gray-scale image are classified into 8 groups as shown in Fig.2 and 35-dimensional vectors are reconstructed to 8-dimensional vectors (Rotation and inversion invariant gray-scale HLAC).

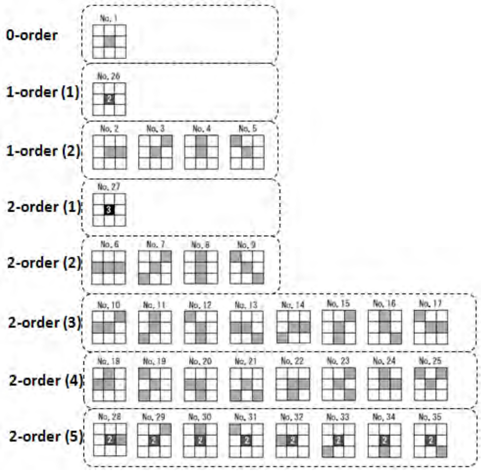

Fig.2 Rotation and inversion invariant HLAC masks in 8 groups

Before feature's extraction, original images are divided into R, G and B channels. Afterwards, the HLAC features above are extracted respectively from the three channels and in total 24-dimensional feature vector is adopted for each image.

4. Experiment

This paper employs 270 samples that almost occupied by bright and clear intestinal wall as learning samples. To evaluate the performances of the proposed method, unlearned testing samples are selected and classified into 5 types (groups (1) ~ (5), Fig.3). Respectively, Group (1) contains bright and clear intestinal wall; Group (2) contains clear intestinal wall and small area of darkness without residue; Group (3) contains clear intestinal wall and small area of darkness with residue; Group (4) contains clear intestinal wall with bubbles. Group (5) contains clear intestinal wall and small area of darkness with lesion.

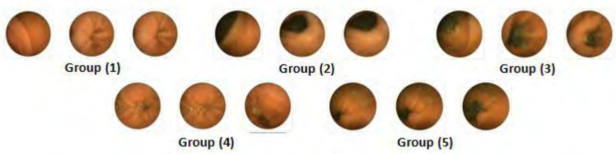

Fig.3 Unlearned testing samples in 5 groups

	Testing sample group 1	Testing sample group 2	Testing sample group 3	Testing sample group 4	Testing sample group 5
Relevance ratio	17/21	20/21	12/13	8/11	8/8
	80.95%	95.24%	92.31%	72.72%	100%

Table 1 Relevance ratio for unlearned testing samples

Anomaly degree is determined by the mean and standard deviation of the distances between learning samples and subspace. The result is shown as Table 1.

In gross, according to the relevance ratio, most of the anomaly in Group (2) (3) (4) (5) are discriminated. However, though images in Group (5) with lesion are all detected without missing, bubble samples in group (4) had the worst performance. One explanation is that the background in bubble samples is very close to learning samples, and the amounts of bubbles likely have limited the contribution to the extracted features. Meanwhile, false positive error occurred in Group (1). By viewing these samples we found that, in spite of no anomaly included, the hue of intestinal wall seems like ischemia and not so reddish enough as those in normal learning samples.

5. Conclusion

In this paper, we introduced a preliminary study on the method of anomaly detection for Capsule Endoscopy images. The proposed method comprises rotation and inversion invariant HLAC image features and subspace method by PCA.

To demonstrate the performance of proposed method, we implemented experiment by using 5 groups of testing samples, and most abnormal objects were detected in the experiment. By improving the performance in the future, this method will suggest detection for more complicated types of images and practical use in Capsule Endoscopy diagnosis.

References

1. G.Iddan, Gavriel Meron et al., Wireless capsule endoscopy. Nature, 405:417, May 2000.

2. M. Delvaux, Capsule endoscopy: techniques and indications. Best Practice & Research Clinical Gastroenterology, 22 (5) (2008), pp. 813-837.

3. Tao Gan, Jun-Chao Wu et al., A feasibility trial of computer-aided diagnosis for enteric lesions in capsule endoscopy, World Journal of Gastroenterology, 2008 December 7, 14(45), 6929-6935.

4. N. Otsu and T. Kurita, A new scheme for practical flexible and intelligent vision systems, Proc. IAPR Workshop on Computer Vision, pp. 431-435 (1988)