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TriZ-a rotation-tolerant image feature and its application in endoscope-based disease diagnosis

Ruixue Zhao[a,1], Ruochi Zhang[a,1], Tongyu Tang[c], Xin Feng[a], Jialiang Li[b], Yue Liu[d], Renxiang Zhu[a], Guangze Wang[a], Kangning Li[a], Wenyang Zhou[a], Yunfei Yang[b], Yuzhao Wang[b], Yuanjie Ba[a], Jiaojiao Zhang[b], Yang Liu[a], Fengfeng Zhou[a,*]

[a] College of Computer Science and Technology, Key Laboratory of Symbolic Computation and Knowledge Engineering of Ministry of Education, Jilin University, Changchun, Jilin, 130012, China
[b] College of Software, Jilin University, Changchun, Jilin, 130012, China
[c] First Hospital, Jilin University, Changchun, Jilin, 130012, China
[d] College of Communication Engineering, Jilin University, Changchun, Jilin, 130012, China

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ABSTRACT

Endoscopy is becoming one of the widely-used technologies to screen the gastric diseases, and it heavily relies on the experiences of the clinical endoscopists. The location, shape, and size are the typical patterns for the endoscopists to make the diagnosis decisions. The contrasting texture patterns also suggest the potential lesions. This study designed a novel rotation-tolerant image feature, TriZ, and demonstrated the effectiveness on both the rotation invariance and the lesion detection of three gastric lesion types, *i.e.*, gastric polyp, gastric ulcer, and gastritis. TriZ achieved 87.0% in the four-class classification problem of the three gastric lesion types and the healthy controls, averaged over the twenty random runs of 10-fold cross-validations. Due to that biomedical imaging technologies may capture the lesion sites from different angles, the symmetric image feature extraction algorithm TriZ may facilitate the biomedical image based disease diagnosis modeling. Compared with the 378,434 features of the HOG algorithm, TriZ achieved a better accuracy using only 126 image features.

1. Introduction

Stomach disease has become one of the most common cases in China and ranks only after lung cancer in the rates of both new cases and deaths in China [1]. Endoscopic imaging is an effective and widely used clinical technology to detect and diagnose the lesion sites in the esophagus and stomach [2–4]. Inexperienced endoscopists may miss the gastric lesions due to various reasons, and this may lead to severe results to the patients [5]. Computational technologies can detect subtle changes in the endoscopic images and may facilitate the efficient and accurate diagnosis of digestion tract diseases [6–10].

Endoscopists usually determine the disease types and severities based on image patterns, *i.e.*, the location, shape, and diameter of the target lesion area. For instance, gastric ulcers are mostly localized on the less curved regions of the stomach with a round to oval parietal hole, with a diameter 2–4 cm and perpendicular borders [11,12]. While gastric polyp mainly locates as a circle and oval upheaval under the endoscope. The majority of the gastric lesion areas have diameters ranging from 0.5 to 1.0 cm [13,14].

Computational calculations of various image features have been introduced for the disease diagnosis based on the endoscopic images. The feature extraction algorithms demonstrate different disease diagnosis performances for the lesion patterns mentioned above. The Local Binary Pattern (LBP) algorithm performs very well on the clinical images captured from different angles since LBP was designed for the property of rotation invariance [15,16]. The Local Configuration Pattern (LCP) algorithm was modified from the LBP features, and also achieved well in such cases [17]. The Histogram of Oriented Gradients (HOG) is another classical image feature extraction algorithm and is specialized for the detection of the contour of the target lesion sites [18]. An intermediate step of feature selection may be applied, integrating the features selected by the feature selection algorithms, including filters [19,20], wrappers [8,21] and hybrid ones [22–24]. The top-ranked features screened by the filter feature selection algorithms

* Corresponding author.
E-mail addresses: ffzhou@jlu.edu.cn, FengfengZhou@gmail.com (F. Zhou).
URL: http://www.healthinformaticslab.org/ (F. Zhou).
[1] The first two authors contributed equally to this work.

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may not achieve the best classification performance [25], and different solutions may perform similarly well [26].

Classification algorithms were applied after the features were extracted, including convolutional neural network [27] and transferring learning [28] based on the clinical image-based diagnosis modeling. Deep learning is a new machine learning technology, which performs very well on image analysis problems like [29]. But it usually requires a tremendous amount of training data to converge the model [30], which is difficult to meet in the biomedical area. The ensemble classifiers often performed very well on biomedical classification problems [31,32], and may achieve as large as 82.46% in the three-class prediction accuracy of the colonoscopy-based diagnosis modeling [33]. Colon polyps may be detected by the deep learning models transferred from the pre-trained models based on the colonoscopy images [34,35]. Other predictive strategies including threshold-based [36] and engineered features [37,38] also achieved satisfying prediction accuracies.

Deep neural network was recently demonstrated to achieve very good classification performances over the biomedical images. A deep convolutional neural network (DCNN) was integrated with the traditional features to predict the prognosis of lung adenocarcinoma patients and achieved 0.90 in accuracy of discriminating long-term from short-term survivors [39]. A DCNN was also trained over the magnetic resonance images (MRI) to predict the grades of canine meningiomas with an accuracy 0.80 [40]. Other DNNs were proven to have accurate image segmentation capability (U-Net) [41] or blurred image sharpening [42], *etc*.

We observed that endoscopic images may be captured from different angles of a given lesion, and many of the endoscopic lesions have a round shape. So we proposed a rotation-tolerant symmetric image feature type, TriZ. We carried out evaluation experiments to confirm that TriZ is rotation-tolerant and performs well on the endoscope-based disease diagnosis.

2. Material and methods

2.1. Two datasets for evaluating TriZ

The rotation-tolerant pattern of TriZ was evaluated on the 16 classes of texture images from Contrib_TC_00000 of the Outex Texture Database [43]. The images are in 256 × 256 pixels and belong to the sixteen classes, *i.e.*, canvas, cloth, cotton, grass, leather, matting, paper, pigskin, raffia, rattan, reptile, sand, straw, weave, wood, and wool.

TriZ was also evaluated for its disease diagnosis performance on the El Salvador Atlas of Gastrointestinal Video Endoscopy [44]. The database consists of endoscopic videos, including 16 healthy patients' videos, 17 gastric polyp videos, 26 gastric ulcer videos and 10 gastritis videos. Firstly, images were randomly retrieved from the gastrointestinal endoscopic videos, as similar in Refs. [45–49]. Capsule endoscopic images have different imaging settings [48,49], and this study focused on the regular endoscopic image analysis. A senior endoscopist, Dr. Tongyu Tang, vice director of the endoscopy center of the First Hospital of the Jilin University, manually screened the images and confirmed 574 gastrointestinal endoscopy images with a correct diagnosis, including 243 healthy, 158 gastric polyp, 98 gastric ulcer, and 74 gastritis. Fig. 1 illustrates one example for each of the four disease types. All the images are 352 × 240 pixels in sizes.

Since all the images were publicly available for the research purposes, no ethics approval or patients' informed consent forms were sought.

2.2. TriZ algorithm

This section provides an overview of the proposed TriZ algorithm, as summarized in Fig. 2. TriZ was developed based on the classical image feature Histogram of Gradient (HOG) [50]. HOG does not focus on the characteristic of rotation-invariance and round-shaped objects. But these are an essential characteristic of endoscopic images, which inspired us to develop a rotation-tolerant image feature. The basic idea of TriZ is to start extracting multiple features from the center of a given image, instead of the top left corner as in HOG. The detailed procedure was described in the following sections.

2.2.1. Image pre-processing and slicing

The images were preprocessed by gray scaling, gamma normalization, and then being sliced into equal-width layers. Endoscopic images may have different light conditions and capturing devices and need a preprocessing step to ensure the images have comparable baseline characteristics. So firstly a gamma normalization was utilized to adjust the image contrast [51].

Let an endoscopic image be in the size of m × n pixels, as shown in Fig. 3. It is sliced into layers by the solid lines. The center rectangle has p × q pixels in size, and m/n = p/q. So the original image is sliced into *nLayer* = 3 non-overlapping layers. From inside out, the layers are numbered as layer 1, 2, and 3, respectively. The original image is also sliced into p × q-pixel rectangle by both solid and dashed lines, as shown in Fig. 3. The p × q-pixel rectangle is called a cell.

2.2.2. Pixel gradient computation

After the preprocessing and image slicing, we calculated the following measurements of a pixel (x, y) in the image. These measurements include the level gradient Gx(x, y), the upright gradient Gy(x, y) and the pixel value H(x, y), as defined in the following.

$$Gx(x,\ \ y) = H(x+1,\ \ y) - H(x-1,\ \ y) \tag{1}$$

$$Gy(x,\ \ y) = H(x,\ \ y+1) - H(x,\ \ y-1) \tag{2}$$

The gradient magnitude was defined as:

$$G(x,\ \ y) = \sqrt{Gx(x,\ \ y)^2 + Gy(x,\ \ y)^2} \tag{3}$$

And the orientation angle was defined as:

$$\theta = \tan^{-1}\frac{Gy(x,\ \ y)}{Gx(x,\ \ y)} \tag{4}$$

2.2.3. Orientation binning and summarization

Each cell is summarized as a histogram. Each of the pixels in a cell in Fig. 3 has an orientation angle θ∈[0°, 360°). The angle range [0°, 360°) is split into *nBin* equally-sized bins, and the percentage of pixels in the cell with the orientation angle in each of these equally-sized bins is summarized. For example, when nBin = 18, the first bin gives the percentage of pixels in the cell with the orientation angle∈[0°, 20°).

The average value and standard deviation of each bin in a given layer are designated as the features of this layer. And the features of the layers are combined in the order from inside out. Each layer consists of 2 × *nBin* features except for the layer 1, which has only one cell and has only *nBin* features. So the total number of TriZ features extracted from a given image is (2 × *nBin* × *nLayer-nBin*). For example, if *nBin* = 18 and *nLayer* = 4, TriZ extracts 2 × 18 × 4–18 = 126 features from each endoscopic image.

2.3. Experimental settings

Images in size 352 × 240 were captured from the original endoscopic videos using the screenshot software HyperSnap. 574 images were captured for each disease class. An experienced endoscopist in this study excluded the blurred and unclear images. After the manual screening, there were 243, 158, 99 and 74 images left for the disease classes healthy, gastric polyp, gastric ulcer, and gastritis, respectively. TriZ extracted (2 × *nBin* × *nLayer-nBin*) features from each image, where nBin and nLayer are the parameters of TriZ, as defined above.

After the features were extracted from these images, six representative classification algorithms were utilized to evaluate how