A Comparative Study of Texture Features for the Discrimination of Gastric Polyps in Endoscopic Video

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Abstract

In this paper, we extend the application of four texture feature extraction methods proposed for the detection of colorectal lesions, into the discrimination of gastric polyps in endoscopic video. Support Vector Machines have been utilized for the texture classification task. The polyp discrimination performance of the surveyed schemes is compared by means of Receiver Operating Characteristics (ROC). The results advocate the feasibility of a computer-based system for polyp detection in video gastroscopy that exploits the textural characteristics of the gastric mucosa in conjunction with its color appearance.

1. Introduction

Gastric cancer is the second most common cancer-related cause of death in the world [1]. Its symptoms are rarely alarming until late stages, and as a result they are usually ignored by the patients. Furthermore, over 40% of gastric malignancies appear as polyps. However, over the past 20 years, there has been a significant increase in survival rates, which is mainly due to the earlier detection of cancer precursors through screening and thorough symptom investigation. Standard video gastroscopy remains the most efficient minimally invasive procedure to detect even small-size lesions that allows biopsy and in many cases polyp resection [1]. A reliable system that would be capable of supporting the detection of gastric polyps could increase the endoscopist's ability to accurately locate them, and could contribute to the reduction of the duration of the endoscopic procedure, which discomforts the patients. Moreover, such a system would minimize the expert's subjectivity introduced in the evaluation of the clinical characteristics of the examined tissue.

Computer-based approaches that have been proposed in the literature for the discrimination of abnormal conditions of the gastric tract include the employment of edge detection methods for the detection of gastric ulcers [2] and the diagnosis of gastric carcinoma via classification of epidemiological data [3]. To the best of our knowledge, there has been no previous study regarding computer-based discrimination of gastric polyps in endoscopic video yet.

In this work, we investigate the appropriateness of four texture feature extraction methods proposed in the recent literature for the discrimination of colorectal lesions in endoscopic images or video, for the discrimination of gastric polyps. Namely, the surveyed schemes are the Color Wavelet Covariance [4], the Texture Spectrum Histogram [5][6], the Texture Spectrum and Color Histogram Statistics [7], and the Local Binary Pattern [8]. The classification task is assigned to Support Vector Machines (SVMs), as these have proven robust, resistant to the "curse of dimensionality" and suitable for texture classification [9].

The rest of this paper is organized in three sections. Section 2 describes the feature extraction methods used. In section 3, we appose the experimental results on the performance of the feature extraction methods for the discrimination of polyps from normal. Finally, the conclusions of this study are summarized in Section 4.

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2. Feature Extraction Methods

2.1. Texture Spectrum Histogram

The Texture Spectrum (TS) method has been proposed by Wang and He [10] and it is based on texture units which characterize the local texture information for a given pixel and its neighborhood. This scheme analyzes an image in the following way:

a) A 3×3 neighborhood of pixels is thresholded into three levels (0, 1 and 2) using the value of the center pixel. Representing the intensity value of the central pixel as V_0 and the intensity value of each neighboring pixel as V_i, the texture unit is defined as: $TU = \{E_1, E_2, \ldots, E_8\}$, where

$$E_i = \begin{cases} 0 & if \quad V_i < V_0 \\ 1 & if \quad V_i = V_0 \\ 2 & if \quad V_i > V_0 \end{cases} \tag{1}$$

for $i = 1, 2, \ldots, 8$. Each element of the TU has one of three possible values; therefore the combination of all the eight elements results in $3^8 = 6561$ possible TU's in total.

b) The values E_i in the thresholded neighborhood are multiplied by certain weights assigned to the corresponding pixels and are summed to obtain a single texture unit number N_{TU} for the corresponding pattern, using the following equation:

$$N_{TU} = \sum_{i=1}^{8} E_i \times 3^{i-1} \tag{2}$$

c) The above procedure is applied to all 3×3 neighborhoods, thus forming the texture spectrum distribution.

2.2. Texture Spectrum and Color Histogram Statistics

The Texture Spectrum and Color Histogram Statistics (TSCHS) method has been proposed by Tjoa and Krishnan [7] and utilizes statistical measures in order to provide an abstract representation of the texture spectrum histogram, applied on various image components C, such as intensity, hue and saturation. Once the histogram has been created, six statistical measures are utilized for its approximation, namely energy, mean, standard deviation, skew, kurtosis and entropy.

In addition, the output vector is complemented by separate color features, as gastrointestinal tumors exhibit exploitable color information [11]. For each image component C, certain lower L_1 and upper threshold L_2 values of the histogram of the regions of interest are selected. The color features β_C are defined as follows:

$$\beta_C = \sum_{i=L_1}^{L_2} Hist_C(i) \Big/ \sum_{i=0}^{L-1} Hist_C(i) \tag{3}$$

where $Hist_C(i)$ is the histogram amplitude at level i of a particular color component C, and L is the total number of levels considered.

2.3. Local Binary Pattern Histogram

The Local Binary Pattern (LBP) method has been proposed by Ojala et al [12] as a two-level version of the texture spectrum method which uses two levels for the representation of local texture patterns. The LBP values are calculated as follows:

$$E_i' = \begin{cases} 0 & if \quad V_i < V_0 \\ 1 & if \quad V_i \geq V_0 \end{cases} \quad (4)$$

$$LBP = \sum_{i=1}^{8} E_i' \times 2^{i-1} \quad (5)$$

The feature vectors are formed by the histogram bins of the LBP values distribution in an image region. The LBP method utilizes $2^8 = 256$ possible texture units instead of the 6561 units utilized in the TS method, leading to a more efficient representation of texture.

2.4. Color Wavelet Covariance

The Color Wavelet Covariance (CWC) features have originally been proposed as covariance estimates of the 2nd order statistical information inherent in the Discrete Wavelet Transform (DWT) of the color components of an image [4]. In this paper, instead of the standard DWT we employ the Discrete Wavelet Frame Transform (DWFT) which tends to decrease the variability of the estimated texture features and it results in a texture characterization invariant under translation [13].

The estimation of the CWC features requires that K-level DWFT is applied to each color component of the image. The 2nd-order statistical information of the wavelet coefficients is captured by means of co-occurrence matrices. Let $M_{C_i}^{B_j(k)}(a)$ be a co-occurrence matrix estimated over a detail image $B_j(k)$, $j = 1, 2, 3$, $k = 1, 2, \ldots K$ level of DWFT, of the color component C_i, $i = 1, 2, 3$, for a direction $a \in \{0, \pi/4, \pi/2, 3\pi/4\}$. Four representative statistical features are estimated over each detail image, namely the angular second moment, the correlation, the inverse difference moment and the entropy. The Color Wavelet Covariance of a Feature F, between the detail images $B_j(k)$ of the color components C_l and C_m, $l = 1, 2, 3$, $m = 1, 2, 3$ is estimated by the following equation:

$$CWC_{C_l, C_m}^{B_j(k)} = Cov\left(F_{C_l}^{B_j(k)}, F_{C_m}^{B_j(k)}\right), l \leq m \quad (6)$$

3. Results

The experimental evaluation of the four feature extraction methods presented in this paper aims to determine the most suitable feature set for the discrimination of gastric polyps from normal tissues in gastroscopic videos. Only adenomatous polyps have been considered in our study as the probability of them evolving into malignant tumors is higher than that of other polyps [14]. The average size of the polyps examined was 14mm. The videos were acquired with a standard gastroscope and were digitized at a 320×240-pixel resolution, which is supported by most conventional video frame grabbing devices. From each frame a 128×128-pixel region of interest was considered so as to capture only the useful part (dotted line in Fig. 1) of each gastroscopic video frame. We have focused on the use of low rather than high resolution videos, aiming to investigate the feasibility of a low-cost computer-based medical system, which combines both short processing times and bandwidth requirements, and thus it is potentially applicable in telemedicine applications.

Expert gastroscopists selected 1000 representative video frames, containing mostly close-up views of polyps and normal tissues, from which a total of 4000 non-overlapping sub-images of 32×32-pixel size was extracted. In the 128×128-pixel images it was quite difficult to find regions larger than 32×32-pixels which contain only abnormal tissues. Moreover, as most of the feature extraction methods used are based on statistics, the larger the population of pixels in the sub-image, the most informative the features are expected to be. So, half of the sub-images were acquired from image regions of verified normal tissues while the rest half were acquired from image regions of verified polyp tissues. Moreover, sub-images from dark image regions or regions of strong light reflections have not been included in the dataset because the textural characteristics of the corresponding tissues are either extenuated or distorted.

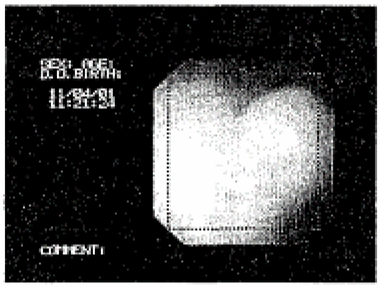
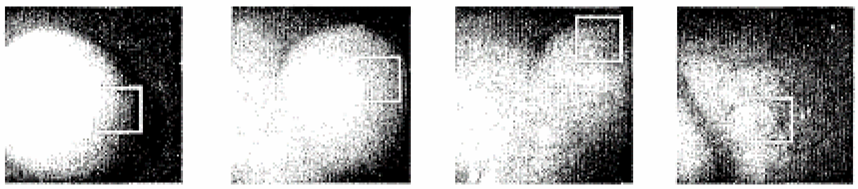


Figure 1. A raw video frame as acquired from the gastroscope

An example gastroscopic video frame sequence is presented in Fig. 2. The first three images (a-c) illustrate a benign-appearing malignant gastric polyp captured in a close-up view, whereas the larger part of the fourth image (d) illustrates normal gastric mucosa. The square regions marked on the video frames indicate sample sub-images that correspond to verified abnormal (a-c) and normal gastric tissues (d).

The TS and LBP feature extraction methods were applied only on the intensity image component. The TSCHS and the CWC schemes were applied on color spaces that have led to optimum performance in earlier studies [4][7]. Namely, these color spaces are the HSI and the $I_1I_2I_3$ respectively.



(a) (b) (c) (d)

Figure 2. Gastroscopic video frame sequence. The squares indicate sample sub-images corresponding to abnormal (a-c) or normal (d) tissues

Sample classification was realized using the Gaussian kernel-SVM. The Gaussian kernel usually has better boundary response as it allows for extrapolation, and most high-dimensional data sets can be approximated by Gaussian-like distributions similar to those used by RBF networks [15]. In accordance with the recommendation in reference [16] 10-fold cross validation was performed for the production of Receiver Operating Characteristics (ROCs) and average Areas Under Characteristics (AUCs) were obtained. The resulting ROCs are illustrated in Fig. 3. The estimated average AUC for each feature extraction method is 75.2±2.6% for the TS, 80.6±2.5% for the LBP, 87.5±2.1% for the TSCHS and 88.6±2.3% for the CWC method.

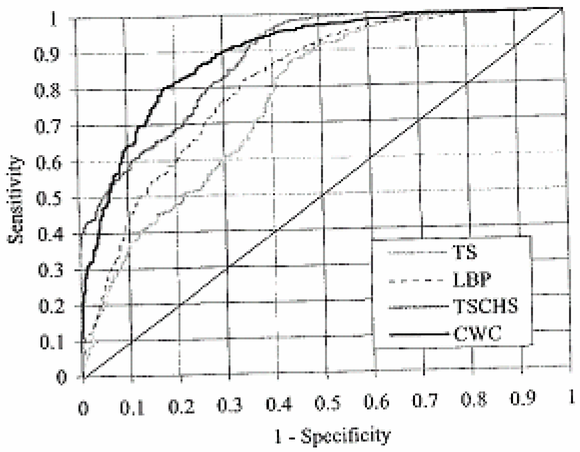


Figure 3. ROC curves obtained using various feature extraction methods

4. Conclusions

We have considered texture as a primary discriminative feature of gastric polyps. Four texture features that have been proposed in the literature for the discrimination of colonic lesions were utilized for the discrimination of gastric polyps, and their performance was compared by means of ROC analysis. The results show that the development of a computer-based medical system using texture features for the detection of gastric polyps is feasible. Moreover, color information, encoded either jointly or separately in the feature vectors, enhances gastric polyp discrimination. The performances of the spatial and of the wavelet domain color texture features employed are comparable.

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