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Integral Scale Histogram Local Binary Patterns for Classification of Narrow-band Gastroenterology Images

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Abstract— **The introduction of various novel imaging technologies such as narrow-band imaging have posed novel image processing challenges to the design of computer assisted decision systems. In this paper, we propose an image descriptor refered to as integrated scale histogram local binary patterns. We propagate an aggregated histogram of local binary patterns of an image at various resolutions. This results in low dimensional feature vectors for the images while incorporating their multiresolution analysis. The descriptor was used to classify gastroenterology images into four distinct groups. Results produced by the proposed descriptor exhibit around 92% accuracy for classification of gastroenteroloy images outperforming other state-of-the-art methods, endorsing the effectiveness of the proposed descriptor.**

I. INTRODUCTION

Cancer is one of the leading causes of death worldwide. It is responsible for 7.6 million (or 13%) of all deaths from a total of 58 million deaths worldwide in 2008 (World Health Organization). Gastroenterology Imaging is today a necessary tool for physicians to detect cancer effectively. It is a rapidly evolving technological area with novel imaging modalities such as Narrow-Band Imaging (NBI), Capsule endoscopy or High Definition Endoscopy. Computer Aided Decision (CAD) systems are increasingly desirable both for assisted diagnosis and training of the clinicians, as they need to adapt themselves to these emerging technologies. However, given the specific nature of images collected in in-body imaging scenarios (out of focus areas, illumination gradients, reduced color spaces, lack of geometrical structures, lens distortion etc.), traditional image processing algorithms used for more conventional scenarios (e.g. multimedia archives) do not behave satisfactorily. Our previous research on the classification of gastroenterology images shows the importance of texture in analysing these images [1].

Texture is an important visual cue which plays a significant role in various applications such as image classification, segmentation etc. The perception of visual texture arises from variations in the image intensity. Very often, these variations are visualized as patterns, structures or random intensity distributions usually referred to as image texture [2]. In the context of image classification related applications, it is important to quantify the image texture in the form of highly discriminative features that can help achieve good classification results. One such application is the classification of gastroenterology (GE) images where the presence or absence of cancer in an image can be identified by the use of visual texture of the images (Fig. 4). The presence/absence of patterns and regularity/irregularity of vasculature in the images can be a valid parameter to classify the images. Conceptually these parameters correspond to the texture of the images. Significant research has been done on texture feature extraction and many texture descriptors are available in the literature [3]. Previously, texture feature extraction for gastroenterology images has been done mostly using multiresolution filter based methods [4], [5], [6] given that they have the power to do a multiresolution analysis, which has proved to be very useful in the past. However, most of these methods are computationally intensive. One of the feature extraction techniques that has been very successful over the past years for texture feature extraction is local binary patterns (LBP) [7]. Their effective usage for the classification of gastroenterology images has been demonstrated in the past [8]. They are highly discriminative and computationally very efficient as compared to the filter based methods.

In this paper, we extend the idea towards multiresolution analysis of texture images using local binary patterns in [9], [10] and propose integral scale histogram local binary patterns (ISH-LBP) for classification of gastroenterology images. The rest of the paper is organized as follows: we will briefly explain the local binary patterns (Section II), followed by the proposal of the novel feature set (Section III). We will later explain our dataset (Section IV) followed by the presentation of our results (Section V). We conclude the paper with a brief discussion and future work in the subject area (Section VI).

II. LOCAL BINARY PATTERNS (LBP)

The original LBP operator is a very powerful texture descriptor that was originally introduced by Ojala et al. [7]. LBP is a gray level invariant texture measure and is a useful descriptor to model texture images. In the literature, the LBPs have shown excellent performance in many comparative studies, in terms of both computational efficiency and application to texture classification. The original LBP descriptor labels the pixels of an image by thresholding the 3×3 neighbourhood of every pixel with the value of the central (reference) pixel and concatenating the results binomially in the form of a number. The function used for thresholding in the basic LBP [11] can be formally represented as

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$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p,\ s(x) = \begin{cases} 1 & x \leq 0 \\ 0 & x > 0 \end{cases} \quad (1)$$

where g_c and g_p represent the gray level intensities of the reference pixel and its neighbors respectively, while p is the index of the neighbor. P represents the total number of neighbors, and R represents the radius of the circular set of neighbors surrounding the reference pixel. If g_c is $(0, 0)$, then the coordinate of each neighbor g_p is determined according to its index p and parameter (P, R) as $(R\cos(2\pi p/P), R\sin(2\pi p/P))$. The gray level values of the neighbors which are not located at the image grids are typically estimated by an interpolation operator. A parameter to quantify the uniformity of the LBP is defined as

$$\begin{aligned} U(LBP_{P,R}) = &|s(g_{P-1} - g_c) - s(g_0 - g_c)| + \\ &\sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \end{aligned} \quad (2)$$

which corresponds to the total number of spatial transitions in the pattern (bitwise 0/1 changes). The motivation for using uniform LBPs is their ability to detect the important intrinsic characteristics of textures like edges, spots, corners and line edges (Fig. 1).

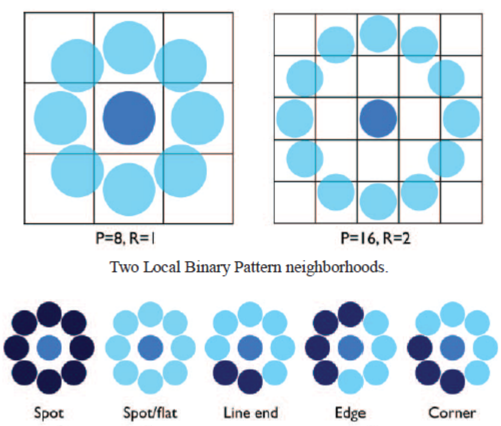


Fig. 1: Uniform Local Binary Patterns

III. Integral Scale Histogram Local Binary Patterns (ISH-LBP)

Multiresolution analysis of images using LBP is possible by using a joint histogram of LBPs calculated at various resolutions (varying values of R). However, it is well known that the estimation of exact joint probability density functions is not feasible due to the computational complexity and statistical unreliability of large multidimensional histograms [12]. This also complicates the classification process due to curse of dimensionality resulting in very sparse representation of data in the feature spaces.

To address these issues, we introduce the ISH-LBP method which computes the LBP histograms at various resolutions and merges this information in the form of a cumulative histogram. To extract these histograms, we construct each bin of the histogram by counting the total number of pixels falling into that bin at various resolutions. Then by accessing the individual bins of these cumulative histograms we can immediately calculate the number of pixels in a specific region which fall into every bin, and hence we obtain the histogram of images at various resolutions. We define an integral multiresolution histograms as follows:

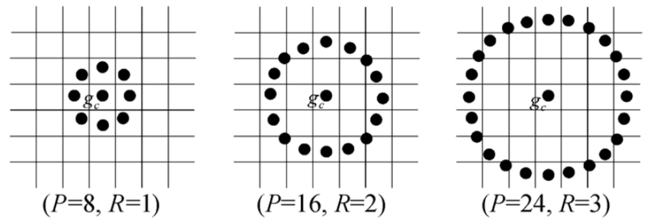


Fig. 2: Local Binary Patterns calculated at various resolutions.

$$H(b_i) = \bigcup_{j=1}^{P} f(x_j, b_i) \quad (3)$$

where $f(.)$ represents the frequency of occurrence of a

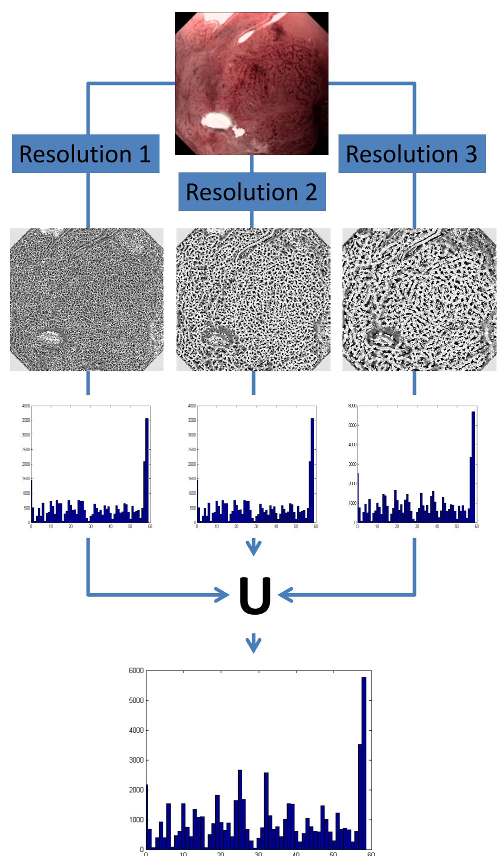


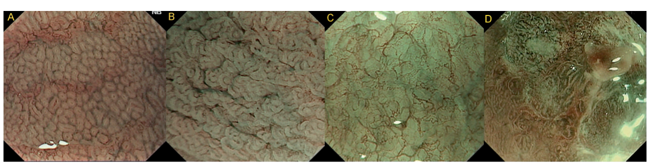
Fig. 3: Visual illustration of the proposed Integral Scale Histogram Local Binary Patterns

uniform LBP represented by the b^{th} bin in the histogram and the $\bigcup$ is the union operator which is defined as follows: $H(b_i)$ is equal to the sum of the previously visited LBP histogram bin values, that is the sum of all $f(.)$ at various resolutions for a given bin b_i.

Although we may loose some ability to distinguish among the target classes in the feature space using the proposed methodology as compared to the joint LBP histograms at various scales, we obtain a low dimensional feature vector thus solving the problem of curse of dimensionality. The proposed feature set can be used to classify the images using standard machine learning algorithms. It should be noted that the calculation of the histogram is very simple involving only a summation operation over and above the LBPs which are considered to be computationally very efficient. On top of that, we can obtain a low dimensional multiresolution analysis which alleviates the problem of curse of dimensionality.

IV. Materials

For the study presented in this paper, we have focused on the specific scenario of narrow-band imaging (NBI) for the classification of Barrett's esophagus. When NBI is used, the visibility of mucosa in the gastrointestinal tract is complemented by the enhancement of vessels due to the absorption of narrow bands of light by the blood vessels presenting a very rich visualization of the tissue. Singh et al. [13] presented a proposal for the classification of NBI images.



Type	
I	Round pits with regular microvasculature
II	Villous/ridge pits with regular microvasculature
III	Absent pits with regular microvasculature
IV	Distorted pits with irregular microvasculature

Fig. 4: Singh's proposal for the classification of NBI images into their respective classes.

For our experiments, the acquisition of NBI images was done using Olympus GIF-Q160Z endoscope at Karolinska Universitessjukhuse, Sweden during regular clinical work. Videos from 84 patients were recorded and analyzed for diagnosis purposes. A total of 197 images were acquired from the videos of these patients representing events or neighborhood of an event. These images were provided to one physician in the Portuguese Institute of Oncology, Coimbra for a detailed clinical evaluation. A software for annotating the images was designed for him based on the requirement specifications requested by the physicians which include selection of the Region of Interest (ROI), classification of images into groups, classification of images into sub-groups (according to Singh's proposal) and confidence level of the physician. The acquired dataset is distributed as follows: 18.3% (36) Group I, 33% (72) Group II, 8.12% (16) Group III and 37% (73) Group IV images.

V. Experimental Results

For our experiments presented in this paper, we have used only the clinically relevant regions which were annotated by the physicians. These regions were obtained using the software that was used for the annotations of the images. We have used uniform LBP with 8 neighbors at 4 different radii: 1, 1.5, 2 and 2.5. Since uniform LBP are used, a 59 dimensional feature vector is generated for every image. For the purpose of classification, we have used support vector machines [14] which is based on the concept of constructing a decision hyperplane that maximizes the margin of segregation between the classes. The Weka data mining tool [15] was used for the classification results presented in this paper. Our objective is to classify the NBI images as: normal (Group I), pre-cancer (Group II and Group III) or cancer (Group IV).

The classification performance is quantified using the overall classification accuracy. We have also evaluated the comparative performance of the descriptors using the area under the receiver operating characteristics (ROC) curves [16]. We have used 10-fold cross validation for all the results presented here.

		Automatic			
		Group I	Group II	Group III	Group IV
Manual	Group I	35	1	0	0
	Group II	2	64	1	5
	Group III	1	0	14	1
	Group IV	0	3	2	68

TABLE I: Confusion matrix for the classification of NBI images using Cumulative Histogram LBPs.

Results show that the proposed descriptor obtains very good classification results giving an average overall classification accuracy of 92% on the challenging dataset of NBI images. In particular, only one normal image (Group I) is misclassified as a precancer tissue (Group II) and none of the cancer tissues (Group IV) are classified as normal (Group I). It should be noted that the misclassification of cancer images (Group IV) as precancer (Group II or III) is not a bad situation from a medical perspective as the proposed descriptor can be used at least to raise alarms while conducting the endoscopic examinations paving the way for automated detection of cancer in the images.

A. Comparison with other methods

We have compared the performance of our proposed descriptor with several other state-of-the-art filtering based methods. These methods have shown very good performance in various texture feature extraction scenarios given their ability to perform a multi-resolution analysis of the images. For our comparison, the state-of-the-art methods were implemented on the dataset used in this paper. The test bed for the state-of-the-art methods was exactly the same as used for the proposed descriptor. Parameter setting of these methods was done by an empirical exhaustive search over their possible ranges.

	A_z	Accuracy
Proposed	**0.96**	**91.8%**
Riaz et al. [1]	0.85	82.3%
Manjunath et al. [17]	0.83	80.7%
T. Ojala et al. [7]	0.82	68.7%
T. Ojala et al. [18]	0.74	58%

TABLE II: Overall performance of various visual descriptors (A_z - Area under the ROC curve).

Experiments show that the proposed feature set outperforms all other methods which were considered in this paper. We attribute this performance to the richness of the LBP features given that they perform a spatial analysis of the pixels based on a small neighborhood. The other methods such as those used by Riaz et al. [1] and Manjunath et al. [17] are based on Gabor filters, which use a Gaussian kernel for filtering the images. This results in smoothing of the images in the resulting filter responses, effectively compromising on the very detailed content in the images. The importance of this multiresolution analysis is evident from the significant gain in performance achieved using the proposed descriptor as compared to uniform LBPs (Table II)

VI. Discussion

In this paper, a texture descriptor based on local binary patterns (LBP) was proposed. The traditional multiresolution LBP use joint distribution of LBP histograms at various resolution which have a shortcoming of very high dimensionality and thus a sparse representation of image features. We have addressed this issue by propagating a single histogram for various resolutions of LBP giving a low dimensional multiresolution feature vector. The proposed features are used for classifying the gastroenterology images for the detection of cancer. Our results show the superiority of the proposed descriptor as compared to other state-of-the-art feature extraction methods. Although good results were obtained, it should be noted that the image descriptor is not invariant to image transformations (such as rotation and scaling). The lack of strong control on the endoscopic probe can result in visualizing an endoscopic video from various directions (resulting in rotation) while maintaining the camera tip at an unknown distance from the tissue (scale and illumination changes). Research has been done on proposing invariant descriptors (Riaz et al. [1]) using Gabor filters however the multiresolution LBPs have shown more promising classification results. This is because of the very local nature of LBP features which can effectively capture the rich texture attributes which are more relevant from a clinical perspective. However, it should be noted that LBPs are invariant to illumination gradients in the images which are an important characteristic of endoscopic images.

In the future, we aim to extend our work to research on novel image descriptors based on LBP, which are invariant to rotation as well as scale changes in the images. We hope that if these variables are somehow incorporated within the framework of LBPs, we can further improve the classification results.

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