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Efficient data mining for local binary pattern in texture image analysis

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ABSTRACT

Local binary pattern (LBP) is a simple gray scale descriptor to characterize the local distribution of the gray levels in an image. Multi-resolution LBP and/or combinations of the LBPs have shown to be effective in texture image analysis. However, it is unclear what resolutions or combinations to choose for texture analysis. Examining all the possible cases is impractical and intractable due to the exponential growth in a feature space. This limits the accuracy and time- and space-efficiency of LBP. Here, we propose a data mining approach for LBP, which efficiently explores a high-dimensional feature space and finds a relatively smaller number of discriminative features. The features can be any combinations of LBPs. These may not be achievable with conventional approaches. Hence, our approach not only fully utilizes the capability of LBP but also maintains the low computational complexity. We incorporated three different descriptors (LBP, local contrast measure, and local directional derivative measure) with three spatial resolutions and evaluated our approach using two comprehensive texture databases. The results demonstrated the effectiveness and robustness of our approach to different experimental designs and texture images.

1. Introduction

Texture analysis has a wide variety of applications in image processing and computer vision such as image segmentation (Malik, Belongie, Leung, & Shi, 2001), image retrieval (Howarth & Rüger, 2005; Manjunath & Ma, 1996), object recognition (Samal, Brandle, & Zhang, 2006; Tan & Triggs, 2007), medical image analysis (Castellano, Bonilha, Li, & Cendes, 2004; Kwak et al., 2014), and remote sensing (Zhu & Yang, 1998). Numerous methods are available to extract robust and reliable texture information from an image. These include a co-occurrence matrix (Haralick, Shanmugam, & Dinstein, 1973), Markov Random Field (MRF) (Cross & Jain, 1983), Gabor filtering (Bovik, Clark, & Geisler, 1990), wavelet transform (Laine & Fan, 1993), principal component analysis (PCA) (Turk & Pentland, 1991), and local discriminative analysis (LDA) (Etemad & Chellappa, 1997). Recently, a local texture descriptor, called local binary pattern (LBP) (Ojala, Pietikainen, & Maenpaa, 2002), has gained much attention due to its low computational complexity, gray-scale and rotation invariance, robustness to illumination changes, and excellent performance in many applications (Ahonen, Hadid, & Pietikainen, 2006; Nanni, Lumini, & Brahnam, 2010; Tajeripour, Kabir, & Sheikhi, 2008; Wang, Gong, Zhang, Li, & Zhuang, 2006; Zhao & Pietikainen, 2006).

LBP is a simple descriptor that compares the gray level of a pixel and its local neighborhood and generates a binary pattern code. Binary pattern codes are often summarized into a histogram, and a bin in the histogram corresponds to a unique binary code. Numerous variants of LBP have been proposed to improve upon the basic LBP. It includes variants in neighborhood topology (Liao & Chung, 2007; Petpon & Srisuk, 2009; Wolf, Hassner, & Taigman, 2008) and thresholding and/or encoding (Fu & Wei, 2008; Guo, Li, You, Zhang, & Liu, 2012; Guo, Zhang, & Zhang, 2010; Guo, Zhang, Zhang, & Zhang, 2010; Iakovidis, Keramidas, & Maroulis, 2008; Jin, Liu, Lu, & Tong, 2004; Nanni et al., 2010; Tan & Triggs, 2007; Zhang, Gao, Zhao, & Liu, 2010; Zhu & Wang, 2012). Some researchers have also proposed alternative manners of exploiting the binary pattern codes; for example, "uniform" patterns group the binary pattern codes by the number of bit transitions. Linear or non-linear dimensionality reduction methods sought to utilize only the useful pattern codes (Chan, Kittler, & Messer, 2007; Hussain & Triggs, 2010; Lumini, 2010; Nanni, Lumini, & Brahnam, 2012; Shan, Gong, & McOwan, 2005; Shan, Zhang, Su, Chen, & Gao, 2006; Smith & Windeatt, 2010; Topi, Timo, Matti, & Maricor, 2000; Zhao, Lin, & Tang, 2007).

Although LBP and its variants perform well, their combinations often outperform the individual descriptors; for instance, a

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multi-resolution LBP showed an improvement over single resolutions (Ojala et al., 2002; Guo et al., 2012) and a joint histogram of LBP and a variance measure descriptor of local contrast (VAR) outperformed each of the descriptors (Ojala et al., 2002). Combining complementary descriptors in a multi-resolution setting appears to be best utilizing the capability of LBP. However, a simple approach of integrating several LBP variants into a single- or multi-dimensional histogram may be undesirable. There are many LBP variants and numerous ways to combine them. Each combination is represented in a high-dimensional feature space. Estimating the exact densities or probabilities of such features requires huge training images, and noisy features would adversely affect texture analysis (Ojala et al., 2002). Conventional dimensionality reduction methods may be ineffective because it is still restricted to how the initial feature pool was prepared and may lead to another issue of interpreting the resulting (or transformed) features or an additional computational burden on a testing phase. Hence, an alternative, efficient, and effective method to fully utilize LBP and its variants is needed.

In this paper, we propose a data mining approach for LBP and its variants (Fig. 1). The basic and variants of LBP with multiple radii are computed, and frequent pattern mining discovers the binary pattern codes that frequently occurred within training images. The frequently occurred pattern codes can be any combination of LBP and its variants and form the initial feature pool. Since they are frequent, the density (or probability) estimation is reliable. A two-stage feature selection method selects the most discriminative features. In the first stage, features are ordered by their relevance with the given class labels using a mutual information-based criterion. In the second stage, forward feature selection chooses the best feature set with the highest discriminative capability on the training images. A histogram is built using the selected features and used for texture analysis. We evaluate our approach on the texture images from the public texture databases.

The rest of the paper is organized as follows. In Section 2, we briefly review LBP and its variants. In Section 3, we describe our approach. In Section 4, training and validation datasets are presented. In Section 5, the experimental results are demonstrated. Finally, we conclude in Section 6.

2. Local binary pattern and its variants

2.1. Basic LBP

Local binary pattern (LBP) (Ojala et al., 2002) is a gray scale texture descriptor that utilizes the distribution of the gray levels of local neighborhood pixels. Given a (center) pixel c in an image I (Fig. 2), it examines its neighboring pixels $p(p = 0, \ldots, P-1)$ in a radius R and generates a binary pattern code as follows:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{1}$$

$$s(x) = \begin{cases} 1, & \text{if } x \geqslant 0 \\ 0, & \text{if } x < 0 \end{cases}. \tag{2}$$

where g_c and g_p represent the gray level of the center pixel and its neighborhood pixels, respectively. The coordinates of the neighborhood pixels are computed as $(R\cos(2\pi p/P), -R\sin(2\pi p/P))$ and

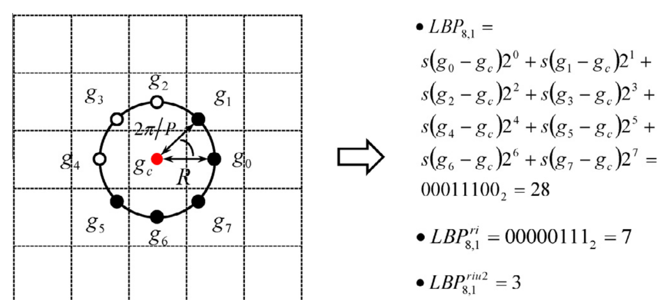

Fig. 2. Description of LBP computation. A binary code is computed for a pixel c (red circle) and its 8 neighborhood pixels in a radius 1 and further converted to a decimal number. A black and white circle denote a binary digit of 0 and 1, respectively, generated by a thresholding function $s(\cdot)$. g_c and g_p correspond to the gray level of the center pixel c and the neighborhood pixels $p(p = 0, \ldots, P-1)$, respectively. $LBP_{P,R}$ denotes LBP using P neighborhood pixels in a radius R. $LBP^{ri}_{P,R}$ and $LBP^{riu2}_{P,R}$ represent rotation-invariant and "uniform" rotation-invariant LBPs, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

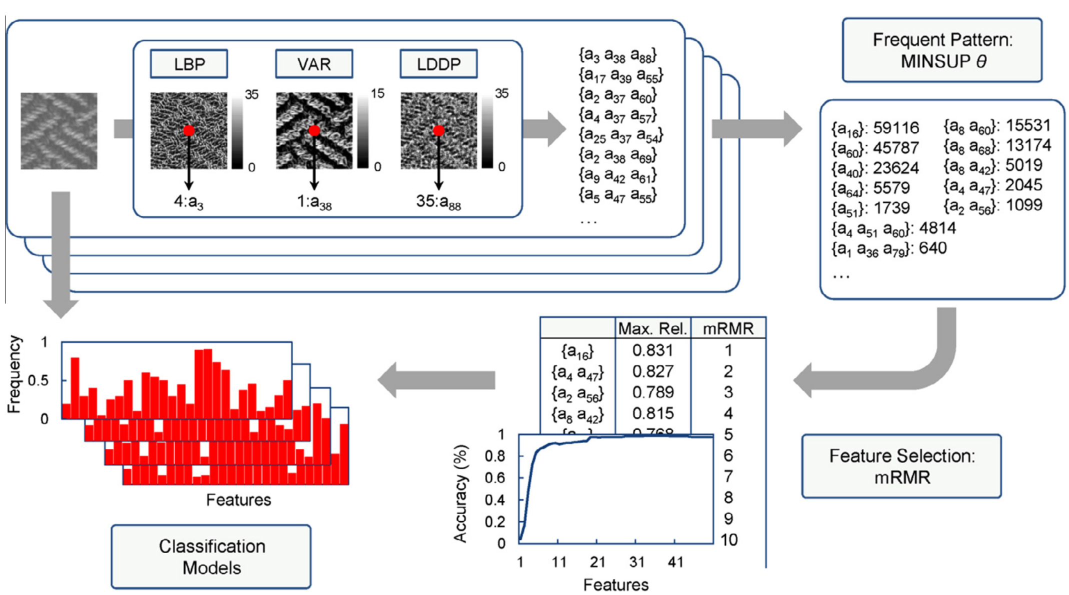

Fig. 1. Illustration of our proposed framework. Pattern codes are individually generated using LBP, VAR and LDDP with 8 neighbors and a radius 1 for the given images. Frequent patterns are mined with a minimum support threshold (MINSUP) θ and mutual information-based feature selection method chooses the most discriminative patterns. Finally, classification models (or histograms) are constructed for the images.