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Topological Attribute Patterns for texture recognition[☆]

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ABSTRACT

An efficient texture modeling framework based on Topological Attribute Patterns (TAP) is presented considering topology related attributes calculated from Local Binary Patterns (LBP). Our main contribution is to introduce new efficient mapping mechanisms that improve some typical mappings for LBP-based operators in texture classification such as rotation invariant patterns (*ri*), rotation invariant uniform patterns (*riu*2), and Local Binary Count (LBC). Like them, the proposed approach allows contrast and rotation invariant image description using more compact descriptors by projecting binary patterns to a reduced feature space. However, its expressiveness, and then its discrimination capability, is higher, since it includes additional information, related to the connected components of the binary patterns. The proposed mapping, evaluated and compared with different popular mappings, validates the interest of our approach. We then develop Complemented Patterns of Topological Attributes (CTAP) that generalize TAP model and exploit complemented information to further enhance its discrimination capability, and evaluate it on different texture datasets.

1. Introduction

For two decades, Local Binary Patterns (LBP) [1] have been extensively used for texture analysis, an important area of computer vision. Their decisive advantages are their low computational cost and their invariance to contrast changes, which made them attractive not only to texture recognition, but also to many other areas of computer vision.

The presented work consists of three main contributions for LBP approach. First, a family of novel mappings $TAP^{\mathcal{A}}$ is presented by considering topology-related attributes extracted from binary patterns. Second, we propose a simple yet efficient mapping $TAP^{\mathcal{A},t}$, an improved version of the first ones, that allows to improve their discrimination power in complemented schemas while reducing the curse of dimensionality of the feature space. The two proposed mappings do not increase significantly the computational cost of basic LBPs. They extend and improve several typical mappings such as *riu*2 or LBC, and are also compatible (and then can be combined) with most of the other variants. Third, we investigate the proposed mappings in complemented frameworks combining with a LBP variant to construct an efficient descriptor that is comparable to recent advances in texture classification.

The remaining of this paper is organized as follows. The next section recalls LBP works more specifically related to our work. Section 3 presents a new mapping mechanism, developed from the preliminary work [2]. Section 4 presents an application of our mapping model to LBP variants for effective texture recognition. Section 5 is a comparative evaluation of the different descriptors derived from our models.

2. Related works

2.1. General form of LBP

Local Binary Patterns are introduced in a generic form in [3] as a binary code to present the local structure of a texture image by considering the center pixel and its P neighbors sampled on the centered circle of radius R. The sample values can be calculated by interpolation. For a scalar valued image I, the general form of the

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LBP encoding is defined as follows, for every pixel $\mathbf{p}$:

$$\mathrm{LBP}_{P,R}(\mathbf{p}) = \sum_{i=0}^{P-1} s(I(\mathbf{q}_i) - I(\mathbf{p}))2^i, \tag{1}$$

where the $\{\mathbf{q}_i\}$ represent the P points sampled on the circle of center $\mathbf{p}$ and radius R, and

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, \text{otherwise}. \end{cases} \tag{2}$$

2.2. Mapping of the LBP labels

In practice, the basic LBP labels are not much used because of the high dimensionality of the descriptor when the number of neighbors is large. They are projected into a limited-dimensional space based on a mapping mechanism.

The circular nature of the neighborhood justified the definition and use of local binary *uniform patterns* that is the most popular mapping of LBP labels. A LBP is said uniform when the number of bit-transitions (1–0 or 0–1) in its binary chain is at most 2. Uniform LBP based encodings (denoted LBP^{u2}) consist in discarding non uniform patterns in the global representation.

Another important notion related to the circular coding is the rotation invariant LBP, defined as: $\mathrm{LBP}^{ri}_{P,R} = \min_{0 \leq i < P}\{ROR(\mathrm{LBP}_{P,R}, i)\}$, where $ROR(x, i)$ is the right circular bit-wise shift of i bits on the P-bit number x. The rotation invariant form of uniform patterns (denoted LBP^{riu2}), has shown impressive results for texture classification.

Zhao et al. [4] introduced Local Binary Count (LBC), inspired from [5], as an alternative mapping for LBP patterns. It discards most of the structural information of LBP by merely counting the number of 1s in the binary code. Good results have been reported on rotation invariant texture classification using statistics of LBC features.

LBP mappings based on uniform patterns ignore all the geometry of non-uniform patterns that can bring important information about textural structures. Several authors have dealt with non-uniform patterns to enhance the representation power of LBP^{riu2}. Liao et al. [6] and then Bianconi et al. [7] proposed to use dataset dependent dominant patterns. Nanni et al. [8] used random subspace to train features based on non-uniform patterns. Zhou et al. [9] combined non-uniform patterns by analyzing their structure and occurrence probability. Fathi and Naghsh-Nilchi [10] encoded the patterns having 4 transitions of bit (0–1 or 1–0) like *riu*2 patterns by counting their number of 1s. The other patterns are encoded by considering their number of bit transitions.

2.3. LBP-based variants

The basic LBP having several limitations, such as small spatial support region, loss of local textural information, rotation and noise sensitivities, a lot of LBP variants [11] have been introduced. Different neighborhoods, such as elliptical [12], three-patch or four-patch approaches [13] have been employed to exploit anisotropic information. In encoding step, three values $\{-1, 0, 1\}$ are used in Local Ternary Patterns [14] to address the issue of LBP instability on near constant image areas. Multi-structure approach [15] is considered to represent information at larger scales. Exploiting non-uniform patterns [2,6,8–10] is introduced to capture more useful textural information. Guo et al. [16] used a complementary component related to the magnitude of the differences. In another work, Guo et al. [17] proposed to incorporate variance as a local contrast measure into LBP histogram to take into account complementary information ignored in LBP encoding. Nguyen et al. then developed this approach by introducing Statistical Binary Patterns (SBP) [18] that explore different order moments. In [19], the discriminative patterns are selected based on a three-layered learning framework. A linear model based descriptor is introduced in [20] to take into account the microscopic configuration and local structures. Nanni et al. [21] reported a comparison for extracting features given the co-occurrence matrix using region-based approaches. In [22,23], a more general class of LBP-based methods, namely Histograms of Equivalent Patterns, has been developed.

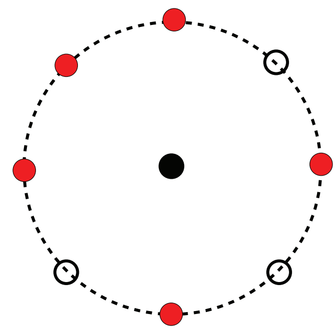

Fig. 1. TAP approach.

3. Topological Attribute Patterns

3.1. Topology related attributes

The local descriptors used by our texture model embed and generalize several rotation invariant descriptors, including uniform patterns and local binary count. They are based on a family of numerical attributes that are calculated on the original LBP. Consider the support of $\mathrm{LBP}_{P,R}$ as a set of P points on a circle, where two consecutive points are said adjacent (see Fig. 1). Topological information can then be extracted from the LBP using the connected components (circular runs) of 1s in the pattern. We will consider the following attributes:

- Number of connected components of 1s (#)
- Length of the largest run of 1s (M)
- Length of the smallest run of 1s (m)

All these attributes are rotation invariant. # is a topological measure, whose importance in the characterisation of shape is attested by a number of works in digital topology, in particular in the detection of critical points in thinning algorithms [24]. The uniform patterns correspond to # = 1 or 0. M and m can be seen as extensions of the uniform pattern values to non uniform patterns. Fig. 1 illustrates a non-uniform binary pattern (10111010) of 8 bits; with $\# = 3$, $M = 3$, $m = 1$.

These attributes are not independent; all configurations of values are not possible and must respect the following constraints:

1. $m \leq M$
2. $0 \leq \# \leq \lfloor P/2 \rfloor$
3. if $\# = 0$, $m = M = 0$
4. if $\# = 1$, $1 \leq m = M \leq P$
5. if $\# > 1$, $1 \leq M \leq P - 2\# + 1$
6. if $\# > 1$, $1 \leq m \leq \lfloor P/\# \rfloor$ - 1

3.2. Texture modeling

The purpose of this work is to evaluate the contribution of the different topological attributes in texture description. The main idea is to propose a series of mappings for encoding binary patterns. First, we present $\mathrm{TAP}^{\mathcal{A}}_{P,R}$ mappings that have been firstly considered in a preliminary paper [2]. Second, we propose a new series of mappings, so called $\mathrm{TAP}^{\mathcal{A},t}_{P,R}$, that are more efficient than the previous ones in complemented schemas.