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Texture Classification Using scLBP and kd-tree

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ABSTRACT: In this paper, we propose a sorted consecutive local binary pattern (scLBP) for texture classification. Conventional methods encode only patterns whose spatial transitions are not more than two, whereas scLBP encodes patterns regardless of their spatial transition. Conventional methods do not encode patterns on account of rotation-invariant encoding; on the other hand, patterns with more than two spatial transitions have discriminative power. The proposed scLBP encodes all patterns with any number of spatial transitions while maintaining their rotation-invariant nature by sorting the consecutive patterns. In addition, we introduce dictionary learning of scLBP based on kd-tree which separates data with a space partitioning strategy. Since the elements of sorted consecutive patterns lie in different space, it can be generated to a discriminative code with kd-tree. Finally, we present a framework in which scLBPs and the kd-tree can be combined and utilized.

KEYWORDS: Local binary pattern, texton dictionary, texture classification.

I. INTRODUCTION

LBP employs the sign part of local differences, whereas CLBP combines the discriminative representation of patterns, including the sign (CLBP_S) and magnitude (CLBP_M) portions of local differences, as well as the center pixel's grey level (CLBP_C). The local difference of the pth neighborhood is calculated around the center pixel and its pth neighborhood pixel. The rotation- invariant pattern of LBP and CLBP is taken by the condition of $U(x, y) \leq \beta$, where β is set to two in most cases. Even if a pixel that is encoded by 00011111 (LBP= 5) rotates counter clockwise at 90°, LBP of the pixel is equal to five, as illustrated in Fig. 1. This is because its bit codes are simply shifted left by two bits (01111100) and its summation is unchanged. However, this encoding procedure has an unavoidable problem that causes it to neglect some patterns by assigning the same code. P + 1 is assigned to LBP when the spatial transitions of LBP codes are more than two, such as 00010111 or 01100110. Consequently, although 00010111 and 01100110 are different patterns, they have the same value of P + 1. This leads LBP to neglect information about any local binary pattern of pixels whose spatial transition is more than two. The neglected pixels can be found in Figure 1.2, where several pixels are shown to have more than two spatial transitions.

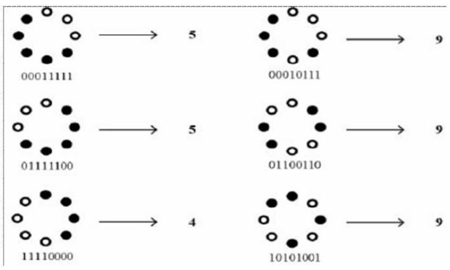

Fig. 1: Examples of **LBP** encoding: Patterns in the left column have two spatial transitions, whereas patterns in the right column have more than two spatial transitions.

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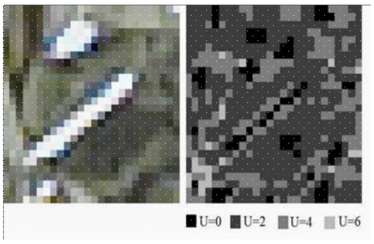

Fig. 2: Visualization of spatial transitions: Part of a texture image (left) and representation of spatial transitions of the left image with $R = 3$ and $P = 24$ (right).

To distinguish between 00010111 and 01100110, if β is set to four, then some differing patterns with the same summation of bits are not distinguishable; e.g., 00010111 and 11110000. Moreover, 00010111 and 01100110 are indeed different patterns; however, they also have the same code by four when β = 4. Therefore, although information about some patterns is discarded, most studies use β = 2 for rotation-invariant encoding. To overcome the above rotation-invariant LBP encoding limitation, sorted consecutive LBP (scLBP) and dictionary learning based on kd-tree is proposed. scLBP sums all consecutive bit neighborhood patterns and sorts them. For example, "11001000" has consecutive bits of "11," ,"00," "1," and "000"; therefore, summation of the number bits gives {2, 2, 1, 3}. To distinguish a zero bit from a one bit, we separate them into a zero-bit pattern sum {2, 3} and a one-bit pattern sum {2, 1}. We then respectively sort them to {3, 2}, {2, 1} and concatenate them to {3, 2, 2, 1}, which is the sorted consecutive LBP. Because scLBP is a vector representation, it must be generated to a code by kd-tree for dictionary learning of scLBP. Because of biased distribution of scLBP, we use uniform separation criterion for determining the splitting plane instead of sequential ordering for cycling all axes. The sequential order rule does not enable a tree to sufficiently grow for scLBP. In contrast, the uniform separation criterion ensures that the tree sufficiently grows without much pruning.

This framework combines and utilizes scLBP and kd-tree. The main contributions of this paper are as follows:

scLBP: We present scLBP, which encodes all LBP patterns, regardless of their spatial transition, in a rotation-invariant manner. Dictionary Learning: We introduce dictionary learning of scLBP based on kdtree. Because of its space partitioning data structure, scLBP with kd-tree achieves outstanding performance.

II. OBJECTIVE OF THE PROJECT

Most objects have their own distinct texture, such as the surface of materials, natural scenes, and human skin. By analyzing these textures, many useful applications, including material classification, scene understanding, and face recognition, can be developed. Consequently, texture analysis is an area of active research. Various approaches in texture analysis have been proposed, including filter-based methods such as Gabor and wavelet, use of bidirectional features, and co-occurrence matrix-based approaches. scLBP, which is based on the LBP operator. Of the many variations of LBP, we exploit CLBP—the most successful LBP variant recently utilized in the texture analysis field. Although CLBP is a successful method, it disregards patterns whose spatial transitions are more than *β*. However, our suggestion of sorted consecutive LBP (scLBP) encodes all patterns of the sign and magnitude components in a rotation-invariant manner.Before extracting patterns, we first filter the texture image with a Gaussian kernel. This filtering makes the textured image smooth and reduces overly complex patterns that have too many spatial transitions.

The raw feature, scLBP, is assigned to a code by kd-tree, which is a texton dictionary or "codebook." Conventionally, *k*-means is used as the texton dictionary in texture classification however, we exploit kd-tree, a space partitioning data structure. Because each element of scLBP lies in a different space, scLBP_S, scLBP_M, and CLBP_C represent different data spaces. Nevertheless, sequential ordering for determining split plane of kd-tree cannot be used with scLBP because scLBP_S and scLBP_M have biased distributed elements that may be selected as the splitting plane by kd-tree because of its sequential selection.

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III. THEORETICAL BACKGROUND

scLBP, is based on the LBP operator. Of the many variations of LBP, we exploit CLBP—the most successful LBP variant recently utilized in the texture analysis field. scLBP, is assigned to a code by kd-tree, which is a texton dictionary or "codebook." Conventionally, *k*-means is used as the texton dictionary in texture classification, however, we exploit kd-tree, a space partitioning data structure.

Concept of proposed system: scLBP, encodes all LBP patterns, regardless of their spatial transition, in a rotation-invariant manner. Dictionary learning of kd-tree is combined with scLBP. First, we filter the input image using a Gaussian kernel to reduce complicated patterns. The filtered image is normalized by its standard deviation and mean value. This procedure reduces illumination variations. scLBP is then extracted from the image and codes are assigned to it by kd-tree. Codes are generated at each class of texture; moreover, the maximum depth of the kd-tree is set as nine or seven to balance speed and accuracy. Histograms from the codes are generated and concatenated to form a single histogram. We further normalize the histogram by the squared root and classify it using a support vector machine (SVM) with a radial basis function.

Sorted Consecutive Local Binary Pattern: scLBP is based on the LBP operator. Of the many variations of LBP, we exploit CLBP— the most successful LBP variant recently utilized in the texture analysis field. Although CLBP is a successful method, it disregards patterns whose spatial transitions are more than *β*. However, our suggestion of sorted consecutive LBP (scLBP) encodes all patterns of the sign and magnitude components in a rotation-invariant manner. Before extracting patterns, we first filter the texture image with a Gaussian kernel.This filtering makes the textured image smooth and reduces overly complex patterns that have too many spatial transitions. This is because there is a strong possibility that these complex patterns are caused by noise, which would make the features less discriminative.

Following Gaussian filtering, we take consecutive LBP (cLBP) on the sign and magnitude binary bits. (Prefix "c" is lower case to distinguish cLBP from CLBP, which refers to "complete LBP.") The sign binary bit is defined as $\ddot{s}p = q\ d_p\ (x, y)$, while the magnitude binary bit is defined as $\ddot{m}\ p = tm_p, C_M$. In addition, we take scLBP_M on the magnitude binary bit $\ddot{m}\ p$. To achieve a more discriminative representation, we separate $\ddot{m}\ p$ into positive and negative parts. Obtain *scLBP_M*+ and *scLBP_M*−, in a similar way by taking scLBP_S. Finally, scLBP is obtained by concatenating scLBP_S, scLBP_M+, and scLBP_M−. Further, we add binary patterns from the center pixel (CLBP_C) to scLBP. Consequently, scLBP is defined as scLBP = {scLBP_S, scLBP_M±, CLBP_C} where scLBP_M$^{\pm}$ = scLBP_M+,scLBP_M^{-}.

Dictionary Learning of kd-Tree: The raw feature, scLBP, is assigned to a code by kd-tree, which is a texton dictionary or "codebook." Conventionally, *k*-means is used as the texton dictionary in texture classification, however, we exploit kd-tree, a space partitioning data structure. Because each element of scLBP lies in a different space, scLBP_S, scLBP_M, and CLBP_C represent different data spaces.Dictionary learning of kd-tree is combined with scLBP. First, we filter the input image using a Gaussian kernel to reduce complicated patterns. The filtered image is normalized by its standard deviation and mean value. This procedure reduces illumination variations. scLBP is then extracted from the image and codes are assigned to it by kd-tree. Codes are generated at each class of texture; moreover, the maximum depth of the kd-tree is set as nine or seven to balance speed and accuracy. Histograms from the codes are generated and concatenated to form a single histogram. We further normalize the histogram by the squared root and classify it using a support vector machine (SVM) with a radial basis function.

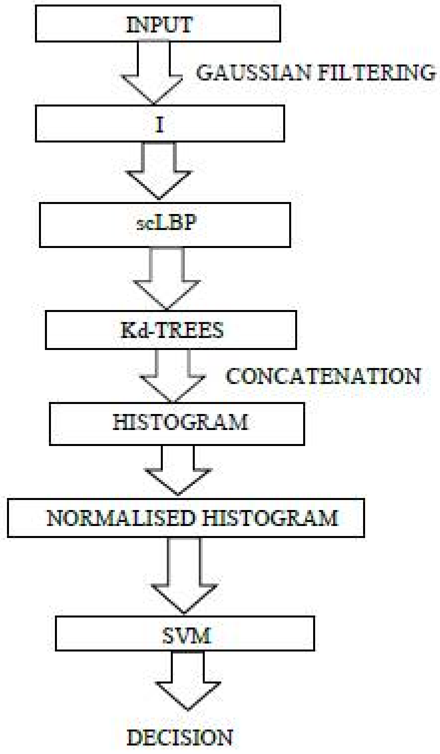

Fig. 3: Methodology

IV. EXPERIMENTAL EVALUATION

Effect of Gaussian Filtering: The Gaussian filtering makes patterns smooth such that the number of complicated patterns due to noise is reduced and the performance of scLBP is improved. Hence, in this subsection, we show that changes occur in the classification rate and frequency of the complicated patterns as sigma is increased. The larger the sigma of the Gaussian filter, the more the image becomes blurred.

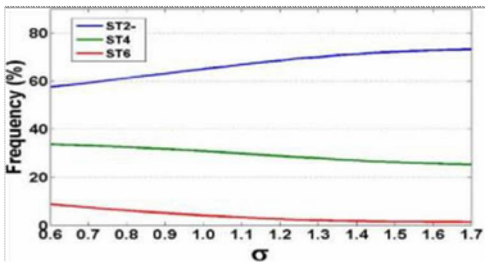

Fig. 4: Frequency of patterns of different spatial transitions. The patterns were extracted from more than 100 samples of the Outex dataset.

The performance of scLBP with variance in sigma is shown in Fig. 5 scLBP had the best classification rate at $\sigma = 1.35$. This result can be interpreted as indicating that complicated patterns with many spatial transitions (e.g., ST4 or ST6) have discriminative power, but that too many complicated patterns reduces overall performance. Therefore, Gaussian filtering makes scLBP robust with an optimal proportion of complicated patterns.

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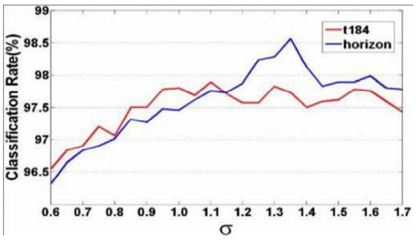

Fig. 5: Classification rate of the outex dataset over different sigma of Gaussian filter; “t184” and “horizon” are outex benchmark sets.

After Gaussian filtering, we did not consider the complicated patterns whose spatial transitions were more than six. This was because there were very few cases in which a pattern had more than six spatial transitions these patterns do not influence classification performance.

Pruning Conditions of kd-Tree **:** The number of leaf nodes on a kd-tree determines the dimensionality of the histogram. The factors used to determine the number of leaf nodes are the maximum depth, *Ndepth*, and the minimum threshold number of features, *N*F. Therefore, we inspected the relationship between the classification rate, *Ndepth*, and *N*F. Fig. 6 shows that the classification rate decreased from *N*F = 100. There was no significant difference in the classification rate less than *N*F = 100; hence, we set *N*F in the range of 10 to 100 for the five datasets.

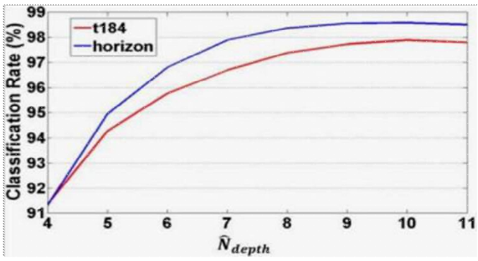

Fig. 6: Classification rate of outex data over different *Ndepth*.

IV. CONCLUSION

ScLBP encodes consecutive LBP patterns in a sorted manner, dictionary for scLBP based on kd-tree. scLBP encodes all types of patterns regardless of its spatial transitions; kd-tree is used for a dictionary learning of scLBP. A framework is proposed for effective combination and utilization of scLBP and kd-tree. A first step in our framework, Gaussian filtering reduces the presence of too many complicated patterns and thereby improves the performance of our method. A key contribution of our method is that it encodes all local binary patterns in a rotation-invariant manner. Conventional LBP-based methods, on the other hand, disregard some patterns whose spatial transitions are more than two because they are not distinguishable on LBP . Our method, in contrast— scLBP with kdtree can distinguish them and assign unique patterns, while maintaining the rotation invariant characteristic with the sorted consecutive approach. We verified in our experiments that scLBP has discriminative power to classify texture images and that kd-tree sufficiently grows by the uniform separation criterion.. To the best of our knowledge, this work is the first study to use tree-based dictionary learning while considering LBP-like patterns that have more than two spatial transitions in the texture analysis area. We believe that scLBP can be used to analyze texture images by other methods and that dictionary learning can be adopted by other raw features.

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