A fast embedded selection approach for color texture classification using degraded LBP

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Abstract—We propose a fast embedded selection approach for color texture classification using Local Binary Pattern (LBP). This texture descriptor transforms an image by thresholding the neighborhood of each pixel and coding the result as a binary number. The selection approach presented in this paper is based on a degraded definition of the color LBPs. To compute these degraded LBPs, we take care of choosing a relevant reduced neighborhood - or a combination of reduced neighborhoods - with respect to the analyzed textures. This leads to consider histograms with a lower dimension and so to reduce the computation times. We thus propose to determine the dimension of the selected feature subspace with these degraded color LBPs and to use this dimension for the classification with the classic LBPs. Experimental results carried out with benchmark databases in different color spaces show that this approach allows to obtain such good classification results than when the basic definition of LBP is used, while significantly reducing the learning time.

Keywords—Embedded selection, LBP, Histogram selection, Color texture, Supervised classification.

I. INTRODUCTION

Texture classification is a research topic that had led in recent decades to many studies for various image processing applications. In this framework, several authors have shown that taking into account both the spatial arrangement of the colors in the image plane and the color distribution in the color space outperforms the texture classification result provided by the analysis of gray levels [1], [2]. However, the use of color leads, on one hand, to choose a well-suited color space in which the textures are described and, on the other hand, to consider a higher dimensional feature space [3]. Because of the curse of dimensionality, most of the studies perform a selection in order to build a lower dimensional feature subspace in which a classifier operates [4], [5], [6]. By only selecting the most discriminant features, these approaches aim to improve the classification result, while decreasing the classification computation time and the storage requirements.

Different approaches are proposed in order to select a low dimensional feature subspace [7]. Wrapper approach is a feature selection procedure that uses the classification rate as a discrimination power of a feature subspace. It needs to classify all the images of a learning database for all the candidate feature subspaces, that involves an important learning time and classifier-dependent results. However, this approach gives good results and allows to easily determine the dimension of the feature subspace by searching the best classification rate. Contrary, filter approaches are feature selection procedures that evaluate the discrimination powers of different candidate feature subspaces without classifying the images. They are less time consuming but suffer to the difficulty to determine the dimension of the feature subspace to be selected. To obtain a good compromise between dimension selection, computation time and classification result, embedded approaches are preferred [8]. These approaches combine a filter approach to determine the most discriminating feature subspaces at different dimensions and a wrapper approach to determine the dimension of the selected subspace [9]. Because of the wrapper step, the learning is still time consuming.

In this paper, we aim to reduce the computation time of the wrapper step in the context of color texture classification using the Local Binary Pattern (LBP). The color LBP is widely used as texture descriptor for classification of color images [10]. It transforms an image by thresholding the neighborhood of each pixel and coding the result as a binary number. The approach presented in this paper uses a fully tried and tested embedded histogram selection approach [11] and proposes a degraded color LBP to faster determine the dimension of the selected feature subspace. This degraded version of color LBP consists in considering a relevant reduced neighborhood or a combination of reduced neighborhoods to compute LBP histograms. Once the dimension is determined with the degraded LBP, we use this dimension for the classification with the basic definition of LBP.

In the following, we first propose to describe the degraded color LBP histograms (see section II). Then, the proposed fast embedded selection approach is presented in section III and finally applied and tested with 4 different color spaces on benchmark databases in section IV. In this last section, the classification accuracies and the computation times obtained by the proposed approach will be compared with those obtained in [11].

II. DEGRADED COLOR LBP HISTOGRAMS

A. Color LBP histograms

The LBP operator has initially been proposed in 1996 by Ojala et al. to describe the textures present in gray level images [12]. It has then been extended to color by Mäenpää et al. and used in several color texture classification problems [10], [11].

The color of pixels is usually coded by three components represented in a 3-dimensional color space, denoted here
$C_1C_2C_3$. In order to characterize the whole color texture image, the LBP operator is applied on each pixel and for each pair of components $(C_k, C_{k'})$, $k, k' \in \{1, 2, 3\}$. Considering a pair of components, the color LBP operator consists in assigning to each pixel a label which characterizes the local pattern in a neighborhood. Each label is calculated by thresholding the color component of the neighbors by using the color component of the considered pixel. The result of the thresholding, performed for each neighboring pixel, is then coded thanks to a weight mask. In the basic version of the LBP operator, the $3 \times 3$ neighborhood is considered (see figure 1(a)). This 8-neighborhood leads to characterize the LBP value of each pixel by an 8-bits integer.

The corresponding distributions are represented in nine different histograms, integrating the global color texture information: three within-component LBP histograms ($(C_1, C_1)$, $(C_2, C_2)$ and $(C_3, C_3)$) and six between-component LBP histograms ($(C_1, C_2)$, $(C_2, C_1)$, $(C_1, C_3)$, $(C_3, C_1)$, $(C_2, C_3)$ and $(C_3, C_2)$). A color texture is thus characterized in a $(9 \times 256)$-dimensional feature space.

In this paper, we propose to select among these nine 256-dimensional histograms those which are the most discriminant ones during the learning stage of the classification process. In order to speed up the wrapper step of this learning stage, a degraded definition of the LBP is used.

### B. Choice of the neighborhood

Considering a reduced neighborhood to compute the color LBP allows to reduce the computation time. Indeed, as shown on the figure 1(b), the dimension of the LBP histogram depends on the weight mask and so on the number of considered neighbors. 8 neighbors give a $2^8 = 256$-dimensional LBP histogram and 4 neighbors give a $2^4 = 16$-dimensional LBP histogram.

In practice, the choice of the reduced neighborhood depends on the analysed textures [13]. That is the reason why we choose:

- the axial 4-neighborhood for textures which mainly contain vertical and/or horizontal patterns,
- the diagonal 4-neighborhood for textures which mainly contain diagonal patterns.

For the textures which do not present a specific direction, we propose to combine the two 4-neighborhoods. This original combination, done by concatenating the two resulting histograms, is very relevant since it allows to analyse all the 8 neighbors of a pixel, but with a $(2 \times 16)$-dimensional LBP histogram instead of a 256-dimensional LBP histogram.

Using a reduced neighborhood to compute the color LBP thus presents the advantage of decreasing the computation time. However, the rates of well-classified images can be degraded. To take advantage of a reduced computation time without lowering too much the final classification result, we propose to use this degraded definition of LBPs only during the wrapper step of the proposed embedded selection approach, as explained in the next section.

### III. FAST EMBEDDED SELECTION

The analysis of the color textures thanks to basic color LBP histograms involves to represent images in a $(9 \times 256)$-dimensional feature space. Several approaches have been proposed to reduce the dimension of such a feature space. Mäenpää et al. consider opponent color LBPs. Some authors select the most discriminant bins which constitute the LBP histograms [10]. Unlike to classic bin selection, we have proposed in a previous study another approach, which selects, out of the nine LBP histograms extracted from a color texture, those which are the most discriminant for the considered application [11]. This approach has allowed a significant result improvement compared to the without selection.

This histogram selection approach consists in selecting, during a supervised training stage, a discriminant subspace in which the classifier operates during a decision stage. For this purpose, we apply a holdout decomposition to the initial image dataset in order to build a training image subset and a testing image subsets. A measure of the histogram relevance, based on a within-class similarity measure, is first computed. This score is calculated for each candidate histogram thanks to the training images. The histogram intersection is used to evaluate the similarity between the histograms extracted from images of a same class.

Let $I_j^k$ be the $k^{th}$ training image of the class $j$ out of the $N_j$ available ones. $H$ be the candidate histogram to evaluate, $h$ be the corresponding normalized histogram and $Q$ be the number of histogram bins. The histogram intersection measure is defined as follows:

$$D(I_j^k, I_j^h) = \sum_{i=1}^{Q} \min(h[I_j^k](i), h[I_j^h](i)).$$  \hspace{1cm} (1)

1To normalize the histogram, the number of count in each bin is divided by the total count, so that the normalized values sum to 1 across all bins.
To measure the within-class similarity of a texture class $j$, the measure $SIM_j$ is considered:

$$SIM_j = \frac{2}{N_j(N_j - 1)} \sum_{k=1}^{N_j} \sum_{k'=k+1}^{N_j} D(I_j^k, I_j^{k'}).$$  (2)

We suppose that the higher the measure $SIM_j$ of within-class similarity is, the more relevant the histogram $H$ is.

The score $S$, which includes all within-class similarities, is thus defined as follows:

$$S = \frac{1}{M} \sum_{j=1}^{M} SIM_j,$$  (3)

where $M$ is the number of considered classes. The most discriminant histogram maximizes the score $S$. Indeed, we seek in this paper the representation that minimizes the within-class variation.

This score $S$ is computed for each histogram during the filter step and a feature ranking algorithm is performed. In order to determine the dimension $\hat{d}$ of the selected feature subspace, a wrapper approach then evaluates the 9 candidate subspaces composed of the $d$ first ranked histograms ($d \in \{1, \ldots, 9\}$). We propose to measure the rate $R_d$ of well-classified testing images obtained with each $d$-dimensional candidate subspace and to use these rates to evaluate the performances of the proposed approach in the next section. These rates are obtained thanks to the nearest neighbor classifier associated with the histogram intersection as a similarity measure. The selected subspace is the candidate subspace for which $R_d$ is maximum:

$$\hat{d} = \arg\max_{1 \leq d \leq 9} R_d.$$  (4)

It is at this wrapper step that we propose to consider the degraded color LBP histograms previously presented. Indeed, this step is the most computationally expensive since several classifications are done to determine the dimension $\hat{d}$ of the most relevant subspace.

IV. EXPERIMENTS

We propose to apply the proposed approach on three benchmark color texture databases: OuTex, VisTex and BarkTex [14], [15], [16].

Most of the authors who have assessed the efficiency of color texture classification algorithms, have used image test suites extracted either from the OuTex database or the VisTex one. Out of these different sets, the OuTex-TC-00013 and Contrib-TC-00006 test suite$^3$ are considered as benchmark databases for comparing performances. OuTex-TC-00013 is composed of 68 classes of material textures with 20 images per class whereas Contrib-TC-00006 contains 54 classes of natural textures with 16 images per class.

The BarkTex test suite$^3$ includes 6 tree bark classes, with 136 images per class. This image set has been built so that color texture images used as training and testing images are less correlated as possible [17]. Figures 2, 3 and 4 illustrate some textures of these three color texture sets.

![Fig. 2. Example of OuTex color textures: each image represents a class of texture.](image1)

![Fig. 3. Example of VisTex color textures: each image represents a class of texture.](image2)

![Fig. 4. Example of BarkTex color textures: each image represents a class of texture.](image3)

In order to show the interest of the proposed fast embedded selection approach for color texture classification, four color spaces are considered for experiments: RGB, YUV, $I_1I_2I_3$ and HSV. They are representative of the four color space

$^3$The BarkTex image test suite can be downloaded at [https://www-lisic.univ-littoral.fr/~porebski/BarkTex_image_test_suite.html](https://www-lisic.univ-littoral.fr/~porebski/BarkTex_image_test_suite.html)
families (primary, luminance-chrominance, perceptual and independent color component spaces) and do not require to know illumination and acquisition conditions. First, we propose in sections IV-A and IV-B to detail the results obtained by our selection approach on the color texture databases OuT ex, VisT ex and BarkT ex. We then discuss the computation time in section IV-C.

A. Dimension of the feature space

We notice that the textures of OuT ex and VisT ex do not present a specific direction whereas the BarkT ex textures mainly contain vertical patterns. To compute the degraded color LBP, we thus combine the two reduced 4-neighborhoods for OuT ex and VisT ex and we consider the axial 4-neighborhood for the BarkT ex set.

Figure 5 shows, for the BarkT ex set and for the different color spaces, the evolution of the rate $R_d$ (%) of well-classified testing images according to the dimension $d$ of the considered subspace, when a basic and a degraded color LBP are considered in the wrapper step.

We notice that the curves obtained by considering basic or degraded color LBPs have similar trends, whatever the considered color space. We thus propose to determine the dimension $\hat{d}$ of the selected feature subspace by using the degraded color LBP (solid curve) during the wrapper step, and to use this dimension $\hat{d}$ with the basic LBP (dashed curve) for the classification.

Table 1 compares the dimension $d$ determined by considering the basic or the degraded color LBP during the wrapper step of the selection scheme. In 9 cases out of 12, the dimension $d$ obtained with the degraded color LBP is the same than the one determined with the basic color LBP. In the other cases, it is the dimension that gives the second best rate with the basic color LBP which is found.

It should be noted that there is no rule which can be deduced about the LBP histograms which are the most discriminating. Indeed, in [11], it is shown that the within-component LBP histograms or the between-component ones can be first selected and that considering together the cross correlations features like $(C_1, C_2)$ and $(C_2, C_1)$ allows to improve the classification results compared to opponent color LBPs which only consider the three within-component LBP histograms and three out of six between-component LBP histograms.

B. Classification results

Table 2 shows the rates $R_{d}$ of well-classified testing images reached with the proposed degraded color LBP approach, for the OuT ex, VisT ex and BarkT ex sets.

$RGB$ is often considered as the color space that does not provide good classification performances. But as we can see in our case or in other studies where the performances of
Table 2. Rates $R_d$ of well-classified testing images reached with the proposed degraded color LBP approach, for the OuTex, VisTex and BarkTex sets.

<table>
<thead>
<tr>
<th>Color space</th>
<th>OuTex</th>
<th>VisTex</th>
<th>BarkTex</th>
</tr>
</thead>
<tbody>
<tr>
<td>RGB</td>
<td>92.50%</td>
<td>98.84%</td>
<td>81.37%</td>
</tr>
<tr>
<td>Yuv</td>
<td>89.56%</td>
<td>98.35%</td>
<td>79.17%</td>
</tr>
<tr>
<td>Lab</td>
<td>88.53%</td>
<td>97.92%</td>
<td>79.41%</td>
</tr>
<tr>
<td>HSV</td>
<td>91.03%</td>
<td>97.69%</td>
<td>81.00%</td>
</tr>
</tbody>
</table>

several color spaces are compared ([18], [19], [20]). RGB can sometimes give better classification results than the other color spaces. It confirms that the best color space depends on the considered application [3]. These results also show that the proposed approach that fast determines the dimension $d$ remains effective whatever the considered color space.

Furthermore, table 1 has shown that in 9 cases out of 12, the dimension $d$ obtained with the degraded color LBP is the same as the one determined with the basic color LBP and that in the 3 other cases, it is the dimension that gives the second best rate with the basic color LBP which is found. The classification result is thus slightly impacted compared to the basic approach presented in [11]: -0.37% on average for OuTex and -0.23% for VisTex when the determined dimensions are not the same.

Finally, the analysis of the classification rates presented in figure 5 shows that processing a selection allows to improve the classification results. Indeed, the improvement is on average 8.4% compared to the without selection step for the BarkTex set.

C. Computation time

The previous section has shown that the proposed approach almost gives as good results as those obtained with the full neighborhood. In order to show the benefit of considering a degraded color LBP, we propose to study the computation time of learning stage with the BarkTex set, when the basic or the degraded color LBP is considered. Theses times are detailed in table 3.

Table 3. Learning computation times obtained with the BarkTex set.

<table>
<thead>
<tr>
<th></th>
<th>Basic</th>
<th>Degraded</th>
</tr>
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<tbody>
<tr>
<td>Histogram extraction with the 8-neighborhood</td>
<td>7.31 s</td>
<td>7.31 s</td>
</tr>
<tr>
<td>Filter selection</td>
<td>2.48 s</td>
<td>2.48 s</td>
</tr>
<tr>
<td>Histogram extraction with the axial 4-neighborhood</td>
<td>none</td>
<td>3.67 s</td>
</tr>
<tr>
<td>Wrapper selection</td>
<td>76.33 s</td>
<td>6.94 s</td>
</tr>
<tr>
<td>Total</td>
<td>86.12 s</td>
<td>20.4 s</td>
</tr>
</tbody>
</table>

As we have previously seen, the proposed approach firstly considers a filter selection approach to build several candidate feature subspaces composed of basic color LBP. The computation time needed to extract the basic color LBP from the learning BarkTex images is 7.31 s and the time required to build the candidate feature subspaces with the ranking algorithm is equal to 2.48 s. In [11], no degraded LBP is considered. The time to extract histograms with the axial 4-neighborhood is thus 0 s. But the cost of the classifications needed to select the dimension $d$ is very high: 76.33 s. In the approach proposed in this paper, we consider a degraded color LBP during the wrapper step. We thus need to extract histograms with the axial 4-neighborhood, that costs 3.67 s more than the basic approach. However, the time to determine the dimension $d$ is significantly reduced: 6.94 s instead of 76.33 s.

So, with the classic approach proposed in [11], the learning time obtained with the BarkTex set is about 86 s. Considering the degraded definition of LBP to determine the dimension $d$ allows to obtain a learning time of 21 s. This degraded approach allows thus to give as good classification result, but with a 4 times faster learning stage.

V. Conclusion

This paper presents a fast embedded selection approach for color texture classification. It consists in considering a reduced neighborhood or a combination of reduced neighborhoods to compute LBP histogram during the wrapper step of the selection procedure. The results show that processing a selection allows to improve the classification rate and that the proposed approach almost gives as good results as those obtained with the full neighborhood while dividing by 4 the learning time. This approach is thus appropriate to reduce the high dimensional feature space generated by the analysis of the color and the texture. In a future work, we will exploit this fast embedded selection for a multi-space approach, where several color spaces are conjointly considered. This multi-space approach which gives encouraging results is time consuming. The time saving brought by our fast embedded selection procedure being proportional to the number of considered features, we expect a high learning time saving for the selection in the case of the multi-space approach.

REFERENCES


