LBP HISTOGRAM SELECTION FOR SUPERVISED COLOR TEXTURE CLASSIFICATION

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ABSTRACT

In this paper, we propose a Local Binary Pattern (LBP) histogram selection approach. It consists in assigning to each histogram a score which measures its efficiency to characterize the similarity of the textures within the different classes. The histograms are then ranked according to the proposed score and the most discriminant ones are selected. Experiments, which have been carried out on benchmark color texture image databases, show that the proposed histogram selection approach is able to improve the classification performances.

***Index Terms*—** LBP, Histogram selection, Similarity score, Color texture, Supervised classification

1. INTRODUCTION

In the framework of texture classification, the use of color to characterize the texture contained in the images leads to consider high dimensional feature spaces. Most of the studies thus perform feature selection approaches in order to build a low dimensional feature space in which a classifier operates [1, 2, 3, 4, 5, 6]. By only selecting the most discriminant features, these approaches aim to improve the rates of well-classified images, while decreasing the classification processing time.

The Local Binary Patterns (LBPs) are widely used as texture features for classification of gray level images [7]. This is due to their inherent simplicity and robustness. This operator transforms an image by thresholding the neighborhood of each pixel and coding the result as a binary number. Usually, the histogram of this LBP image is then used for texture analysis. The extension of LBP to color leads to consider several LBP histograms and it is interesting to wonder whether all the information contained in these histograms is relevant to discriminate the textures. Many authors take an interest in the selection of the bins which constitute the LBP histograms in order to improve texture classification performances. Pietikäinen et al. list the different approaches that have been published on this subject [7].

In the same goal and in the framework of color texture classification, we propose an original approach which selects, out of the different LBP histograms extracted from a color texture, those which are the most discriminant for the considered application. We perform here a selection of histograms in its entirety, contrary to the approaches proposed by the previous authors, which perform a selection of LBP histogram bins.

In this paper, we first propose to briefly describe the color LBP histograms (see section 2). Then, the measure of histogram efficiency and the proposed histogram selection approach are presented in section 3 and finally applied and tested thanks to benchmark databases in section 4.

2. 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 [8]. It has then been extended to color by Mäenpää et al. and used in several color texture classification problems [7, 9].

The color of pixels is usually coded by three color components represented in a 3-dimensional color space, denoted here $C_1C_2C_3$. 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 the following weight mask $\begin{array}{|c|c|c|}\hline 1 & 2 & 4 \\ \hline 8 & & 16 \\ \hline 32 & 64 & 128 \\ \hline \end{array}$. To characterize the local pattern of the considered pixel, the weighted values are finally summed so that each label ranges from 0 to 255.

In order to characterize the whole color texture image, the LBP operator is applied on each pixel and for each pair of components $(C_k, C_{k'}),\quad k, k' \in \{1, 2, 3\}$. The corresponding distributions are thus represented in nine different histograms: 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 represented in a (9×256)-dimensional feature space.

Several approaches have been proposed to reduce the dimension of such a feature space. Some authors select the most discriminant bins which constitute the LBP histograms

[7]. Mäenpää et al. propose to consider opponent color LBPs (OCLBPs) which correspond to the three within-component LBP histograms and three out of six between-component LBP histograms [9]. The opposing pairs, such as (C_1, C_2) and (C_2, C_1) being highly redundant according to Mäenpää, he considers either of them to characterize color texture. It leads to a (6×256)-dimensional feature space.

In this paper, we propose 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. We perform here a selection of histograms and not a selection of histogram bins. The next section presents the measure which allows to evaluate the histogram efficiency in order to select the most discriminant ones to perform the classification.

3. SUPERVISED HISTOGRAM SELECTION

The proposed histogram selection approach consists in selecting, during a supervised training stage, a discriminant subspace in which the classifier operates during a testing stage. For this purpose, we apply a holdout decomposition to the initial image dataset in order to build a training and a testing image subset. In section 3.1, we first describe the score which allows to measure the histogram efficiency for characterizing the similarity of the textures within the different classes. The histogram selection approach is then presented in section 3.2.

3.1. Histogram similarity score

The proposed score is calculated for each candidate histogram thanks to the training images. It is based on a within-class similarity measure. In order to evaluate the similarity between the histograms extracted from images of a same class, there exist several measures which have been listed by Rubner et al. [10]. Since the objective of this paper is to show the interest of a histogram selection approach, we retain one of the simplest similarity measures which is the histogram intersection.

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[1] and Q be the number of bins. The histogram intersection measure is defined as follows:

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

To measure the within-class similarity of a texture class j, the measure SIM_j is considered:

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

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:

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

where M is the number of considered classes. The most discriminant histogram maximizes the score S.

3.2. Histogram selection procedure

Feature selection is grouped in two ways according to the feature evaluation measure: depending on the type (filter, wrapper or embedded approach) or on the way that features are evaluated (feature ranking or feature subset selection) [11]. The proposed selection approach is divided into two successive steps, a "filter"[2] and a "wrapper"[3] step. When they are jointly considered, it constitutes an "embedded" approach that allows to combine the high performances of a wrapper approach and the reduced processing time of a filter approach [11].

During the filter step, a feature ranking algorithm is performed. It consists in computing for each histogram the score S in order to measure its efficiency to characterize the similarity of the textures within the different classes. Once the score of each histogram is evaluated, the histograms are ranked in decreasing order according to the proposed score. A wrapper approach then evaluates the candidate subspaces composed, at the first step, of the histogram with the best score, at the second step, of the two first ranked histograms and so on. For this purpose, a classifier operates during the testing stage in each candidate subspace in order to classify the testing images. Here, we consider the nearest neighbor classifier associated with the histogram intersection as a similarity measure: the color texture to be classified is assigned to the class of the training image for which the similarity between the corresponding histograms is the highest. The selected color texture subspace is the one which maximizes the rate of well-classified testing images.

4. EXPERIMENTS

In order to show the interest of the proposed LBP histogram 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 families (the primary spaces, the luminance-chrominance spaces, the perceptual spaces and the independent color component spaces) and don't require to know illumination and

[1]To 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.

[2]A filter approach only takes into account the training images and does not thus totally depend on the classifier.

[3]A wrapper approach is based on the rate of well-classified images and is thus dependent of the classifier.

acquisition conditions [12]. First, we propose in section 4.1 to validate our approach on two well-known and widely used color texture sets: OuTex-TC-00013 and Contrib-TC-00006 [13, 14]. The partitioning used to build these two sets consists in extracting training and testing sub-images from a same original image. However, such a partitioning, when it is combined with a classifier such as the nearest neighbor classifier, leads to biased classification results [12]. That is why we propose in section 4.2 to detail the results of selection and classification on a third set build from the BarkTex database [15]. In this last relevant image test suite, the training and the testing sub-images come from different original images. This partitioning ensures that color texture images are less correlated as possible for evaluating color texture classification schemes.

4.1. Experiments on OuTex-TC-00013 and Contrib-TC-00006

Most of the authors who have assessed the efficiency of color texture classification algorithms, have considered image test suites extracted either from the VisTex database or the OuTex one [12]. Out of these different sets, two have often been used in the literature: the OuTex-TC-00013 and Contrib-TC-00006 test suites[4]. We first propose to validate our approach on these two color texture sets.

Table 1 shows the rates R of well-classified testing images reached with and without color LBP histogram selection. In the case of the without selection approach, the nine color LBP histograms are considered to classify the color texture images.

Table 1. Rates R of well-classified testing images reached with and without color LBP histogram selection, for the OuTex and VisTex sets. d represents the dimension of the considered LBP histogram feature space ($d = 9 \times 256$ without selection).

		With selection		Without selection
		R	d	R
OuTex	RGB	92.94%	9×256	92.94%
	YUV	89.56%	9×256	89.56%
	$I_1I_2I_3$	88.97%	8×256	88.68%
	HSV	91.03%	8×256	90.44%
VisTex	RGB	98.84%	4×256	98.61%
	YUV	98.61%	4×256	97.22%
	$I_1I_2I_3$	97.92%	6×256	96.99%
	HSV	97.69%	8×256	97.45%

First, we notice that the classification results obtained with the OuTex and VisTex sets are consistent with those obtained by the different studies which have applied a color texture classification algorithm on these two image sets. Indeed, their results range from 85.2% to 96.6% for the OuTex set and from 97.7% to 100% for the VisTex one [12].

The classification results obtained with the OuTex set show that the nine LBP color histograms seem to be relevant for classifying the OuTex color textures. Indeed, the best rates of well-classified testing images are obtained by considering all the LBP histograms, for two of the four considered color spaces (RGB and YUV), that is to say without operating a selection. For the $I_1I_2I_3$ and HSV color spaces, the proposed selection procedure allows to slightly increase the classification results of about 0.44% with a slightly reduced feature space dimension (8 LBP histograms out of 9).

For the VisTex image set, the relevance of the proposed histogram selection procedure is much more significant. Indeed, the best rate of well-classified testing images (98.84%) is obtained with the RGB color space by considering 4 LBP histograms out of the 9 available ones. Generally, the classification results are slightly improved of about 0.69%, while the classification time of the testing stage is decreased since the dimension of the feature space is reduced.

In order to analyze with more detail the results of selection and classification brought by our approach, we propose to apply it on the BarkTex set presented in the next section. It allows to work with training and testing images which are less correlated, since they come from different original images, and so to better measure the relevance of the color texture classification approach.

4.2. Experiments on BarkTex set

4.2.1. BarkTex set

The BarkTex database includes six tree bark classes, with 68 images per class [15]. To build the BarkTex set[5], a region of interest, centered on the bark and whose size is 128×128 pixels, is first defined. Then, four sub-images whose size is 64×64 pixels are extracted from each region. We thus obtain a set of $68 \times 4 = 272$ sub-images per class.

In order to ensure that color texture images used for the training and the testing stages are less correlated as possible, the four sub-images extracted from a same original image all belong either to the training subset or to the testing one: 816 images are thus used for the training and the remaining 816 for the testing stage.

4.2.2. Analysis of LBP histogram selection and classification

The histogram selection procedure proposed in this paper first assigns to each histogram independently a score S which measures its efficiency to characterize the similarity of the textures within the different classes. The histograms are then

[4] `http://www.OuTex.oulu.fi/temp/`

[5] The BarkTex image test suite can be downloaded at `https://www-lisic.univ-littoral.fr/~porebski/BarkTex_image_test_suite.html`

ranked in decreasing order. Table 2 presents the results of the color LBP histogram selection computed from BarkTex images, coded either in the RGB, YUV, $I_1I_2I_3$ or HSV color space.

Table 2. LBP histogram selection results obtained with the BarkTex set.

Rank	RGB LBP Histogram	RGB S	YUV LBP Histogram	YUV S	$I_1I_2I_3$ LBP Histogram	$I_1I_2I_3$ S	HSV LBP Histogram	HSV S
1	B, B	0.8326	Y, V	0.9417	I_1, I_3	0.9682	S, S	0.8346
2	R, R	0.8320	Y, U	0.9338	I_1, I_2	0.9575	H, H	0.8319
3	G, G	0.8320	V, Y	0.8647	I_3, I_1	0.9200	V, V	0.8190
4	R, G	0.7477	U, Y	0.8503	I_2, I_1	0.9045	S, V	0.6411
5	B, G	0.7431	Y, Y	0.8322	I_1, I_1	0.8330	H, S	0.6191
6	G, R	0.7345	U, U	0.8113	I_2, I_2	0.8239	S, H	0.6157
7	G, B	0.7257	V, V	0.8081	I_3, I_3	0.8079	H, V	0.6152
8	B, R	0.6023	U, V	0.5981	I_2, I_3	0.7787	V, S	0.5335
9	R, B	0.5950	V, U	0.5785	I_3, I_2	0.7115	V, H	0.5264

Figure 1 presents the classification results reached with the Barktex set for the four considered color spaces. It shows the rate of well-classified testing images depending on the dimension of the LBP histogram feature subspace.

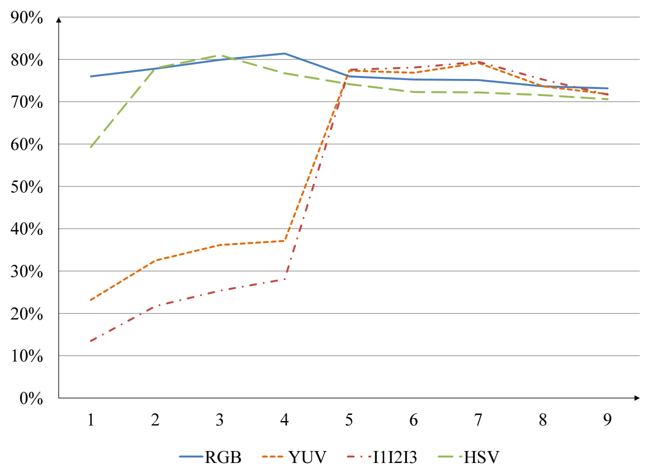

Fig. 1. Rate of well-classified BarkTex testing images depending on the dimension of the LBP histogram feature subspace.

In Table 3, the best rates of well-classified testing images reached thanks to color LBP histogram selection and those obtained without selection are presented. It also shows the classification accuracies reached by considering OCLBPs.

By analyzing Figure 1 and Table 3, we can see that the histogram selection significantly improves the classification results, whatever the considered color space. The improvement reaches on average 8.4% compared to the without selection approach, while reducing the dimension of the feature space. Moreover, by comparing the results provided thanks to histogram selection and those obtained by OCLBPs, we notice that the proposed approach allows to increase the classification results by on average 7.2% by considering a feature space with a lower dimension in two out of four cases.

Table 3. Rates R of well-classified testing images reached with and without color LBP histogram selection, for the BarkTex set. d represents the dimension of the considered LBP histogram feature space ($d = 9 \times 256$ without selection and $d = 6 \times 256$ with OCLBPs).

	With selection R	With selection d	Without selection R	OCLBPs R
RGB	81.37%	4×256	73.16%	73.90%
YUV	79.17%	7×256	71.81%	71.08%
$I_1I_2I_3$	79.41%	7×256	71.69%	74.51%
HSV	81.00%	3×256	70.59%	72.67%

As already shown in previous studies, we also notice that the color space choice influences the performances reached by a color texture classifier [12, 16].

5. CONCLUSION

This paper presents a score based LBP histogram selection for color texture classification. It consists in assigning to each histogram a score which measures its efficiency to characterize the similarity of the textures within the different classes. The histograms are then ranked according to the proposed score in order to select the most discriminant ones and thus build a low dimensional relevant subspace, in which a classifier operates.

In the case of LBP histograms, the proposed selection approach differs from those which have yet been published since we perform here a selection of histograms in its entirety, contrary to the approaches proposed by the previous authors, which perform a selection of histogram bins.

Experiments on OuTex and VisTex sets show that the proposed approach allows to reach classification results which are consistent with those obtained by the other different studies. Moreover, by analyzing the classification results obtained with the BarkTex set, we show that the proposed histogram selection significantly improves the accuracy, whatever the considered color space.

These experiments also confirm that the color space choice influences the performances reached by a color texture classifier. That is why it seems interesting to apply the proposed histogram selection procedure in the framework of a multi-color space approach.

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