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SURVEY

Color Texture Analysis: A Survey

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ABSTRACT In the field of image processing, texture features and color are fundamental visual cue with complementary roles. They are used in many applications and in a large variety of areas such as quality control, content-based image retrieval, remote sensing, industrial inspection, surface inspection, object recognition, and medical image analysis. For this purpose, a large number of algorithms have been proposed for texture feature extraction. Some of them are dedicated to gray-scale images while others aim at processing both color and texture. It has been shown that, for many cases, the use of color improves the performance of gray level texture classification. This paper provides a comprehensive survey of the texture feature extraction methods that consider both texture and color information. We propose a categorization of these methods into seven classes, two of them being very recent. For each method, we present the concept, the advantages and drawbacks, and we give examples of application.

INDEX TERMS Chrominance, classification, color texture, feature extraction, image processing, image synthesis, luminance, segmentation, shape from texture, texture.

I. INTRODUCTION

Texture can be seen as spatial distributions of the luminance or as visual patterns appearing in an image. Color texture can be defined as a spatio-chromatic pattern defined as the distribution of colors over a surface [1]. It is therefore a visual pattern characterized by its chromatic and / or structural variation [2]. In the field of image processing, texture features are fundamental visual cue. This is why they are used in many applications and in a large variety of areas. Many algorithms have been proposed so far to extract texture features for gray-scale images [3]. However, because color is an important issue in human vision, we very often have to deal with color images. This is why algorithms have also been proposed for color texture feature extraction. It has been shown that the use of color can improve the performance of gray level texture classification (see, e.g., [4]).

It is common to classify descriptor methods of color images into three groups [5]:

- *pure color methods (or spectral methods)* that describe the color content of an image without taking into account its spatial distribution. These methods are therefore quite robust to rotation, scale variations, and viewpoint variations but sensitive to the illumination conditions
- *pure texture methods (or spatial methods)* that discard chrominance (color) and therefore take into account only spatial variations of luminance (gray level). These methods are therefore quite sensitive to rotation, scale variations, and viewpoint variations but robust to the illumination conditions.
- *hybrid methods* that combine color and texture information together.

Methods that combine color data and texture have themselves been classified into three other subgroups [6]:

- *parallel approaches*: these methods consider color and texture separately: color is measured globally (e.g., a color histogram is computed independently) and texture is evaluated ignoring color. The results of the two analyses are combined; this leads to a feature vector. In this group we can find methods as LBP and color information features [7].
- *sequential approaches*: for these methods, there are two steps. The first one consists in applying color indexing to the original color image (conversion of the original image to single channel through color quantization for instance). In the second step, the indexed image is processed as grayscale texture. Therefore, these approaches

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TABLE 1. Classes and corresponding methods presented in the survey.

Classes	Methods	Section
Approaches based on co-occurrence matrices	- Color co-occurrence matrices	Section II-A
	- Integrative co-occurrence matrices	Section II-B
	- Co-occurrence matrices and chromatic features	Section II-C
Approaches based on histograms or statistics computation	- Color histograms	Section III-A
	- Fuzzy color histograms	Section III-B
	- Histograms of color ratios	Section III-C
	- Marginal histograms	Section III-D
	- Multilayer coordinated cluster representation	Section III-E
	- Color statistics	Section III-F
	- Chromaticity moments	Section III-G
	- Average color differences	Section III-H
Transform-based, filter-based, and operator-based approaches	- Wavelets and co-occurrence histograms	Section IV-A
	- Dual tree-complex wavelet transform and chromatic features	Section IV-B
	- Gabor features	Section IV-C
	- Gabor and chromatic features	Section IV-D
	- Opponent Gabor features	Section IV-E
	- Color ranklets	Section IV-F
	- Tex-Mex color features	Section IV-G
	- Morphological texture descriptors	Section IV-H
	- Granulometry	Section IV-I
LBP-based approaches	- LBP-based features	Section V-A
	- Opponent color LBP	Section V-B
Graph-based approaches	- Shortest paths in graphs	Section VI-A
Deep learning approaches	- Convolutional neural networks	Section VII-A
Entropy- and fractal-based approaches	- Univariate entropy-based measures	Section VIII-A
	- Multivariate entropy-based measures	Section VIII-B
	- Fractal descriptors	Section VIII-C

are based on a segmentation procedure: after the color segmentation of the histogram, the texture features are determined on basis of the segment indices. The colors are processed to obtain a single channel image and the latter is analysed by conventional texture approaches. In this group, we can find methods such as those presented in [8], [9].
- *integrative approaches*: these methods rely on spatial relations of pixels. They are divided into two subclasses: *single-band methods* if each color channel is considered separately (the gray-scale texture analysis is applied on each color channel separately), and *multiple-band methods* if several channels are considered jointly. An example of such methods is presented in [10].

Our goal in this work is to propose a list of the main methods that have been published so far for color texture analysis. We will focus on the basic principles and concepts of each method rather than on a full and thorough development of each algorithm. However, for each method we give references where details can be found. Furthermore, our goal is not to compare the methods, nor to present an in-depth review of their specific characteristics or application domains. A comparison of some methods can be found in [11].

As far as we are concerned, no equivalent paper has been proposed recently. González-Rufino et al. compared color texture features but this was for a single application only (discriminiation of cells categoris in histological images of fish ovary) [12]. Palm [6] as well as Bianconi et al. [13] proposed other studies but they are now out of date as many papers have been published in the recent years. More recently, Bianconi et al. proposed an interesting historical overview of color and texture descriptors for visual recognition but their approach is only historical and focuses only on descriptors for gray-scale and color images (not specific to color images) [14].

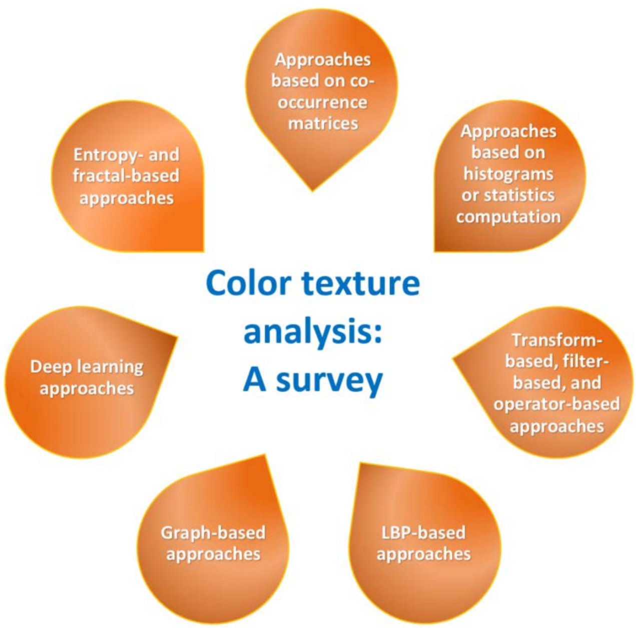

FIGURE 1. Representation of the classes presented in the survey.

In what follows, the texture feature extraction methods are divided into seven classes corresponding to seven different approaches, see Fig. 1 and Table 1: approaches based on co-occurrence matrices; approaches based on histograms or satistics computation; transform-based, filter-based, and operator-based approaches; LBP-based approaches; graph-based approaches; and finally the probably most recent ones, the deep learning approaches; and entropy- and fractal-based approaches. For each method, we first focus on the presentation of the concept. Then, we expose advantages and drawbacks for each of them. We finally mention studies that use them.

II. APPROACHES BASED ON CO-OCCURRENCE MATRICES

This class of methods based on co-occurrence matrices is composed of the following algorithms: color co-occurrence matrices, integrative co-occurrence matrices, and co-occurrence matrices and chromatic features.

A. COLOR CO-OCCURRENCE MATRICES

1) CONCEPT

This method consists in computing the probability of occurrence of same pixel color between each pixel and its adjacent ones in an image. This probability is the attribute of the image [15]. More precisely, for each pixel, a 3×3 convolution mask is generated. This mask is divided into four blocks of 2×2 pixels. Each of these blocks contains the ''center'' pixel. These blocks are then replaced by motifs of scan pattern, as described in [15]. Afterwards, the distribution within the two-dimensional motifs of scan pattern matrix is computed. The corresponding probability is the attribute of the image color variation.

2) ADVANTAGES AND LIMITATIONS

The texture feature extracted from the color co-occurrence matrices describes the direction of texture but not its complexity. This is why Lin et al. also proposed to take the difference between pixels of scan patterns as texture features [15]. Moreover, this color co-occurrence matrices method is sensitive to the noise variation in images.

3) EXAMPLES OF APPLICATIONS

The color co-occurrence matrices have been used for image retrieval [15].

B. INTEGRATIVE CO-OCCURRENCE MATRICES

1) CONCEPT

The integrative co-occurrence matrices method consists in computing a co-occurrence matrix for each color channel separately (3 monochrome features) and between pairs of color channels (intra-channel analysis and inter-channel analysis, respectively) [6], [16].

2) ADVANTAGES AND LIMITATIONS

The method gave good results for classification purposes and the method is fast enough for many real-time applications [16].

3) EXAMPLES OF APPLICATIONS

The integrative co-occurrence matrices method has been used for comparison purposes in a study dealing with color texture classification [13].

C. CO-OCCURRENCE MATRICES AND CHROMATIC FEATURES

1) CONCEPT

Co-occurrence matrices of color images have been proposed by Arvis et al. [16]. They are based on the co-occurrence matrix and Haralick features. One of the methods uses joint color-texture features (fusion of color and texture features). For this purpose, a change in the color space is first performed. This leads to one channel containing the luminance information and two channels containing chrominance information. Some texture features are then determined from the luminance channel while others (named color features) are computed from the chrominance channels. The co-occurrence matrix is computed using a quantization method, as described in [16].

2) ADVANTAGES AND LIMITATIONS

Based on comparisons with other co-occurrence matrix methods, the quantization method did not give very good results for color texture classification [16].

3) EXAMPLES OF APPLICATIONS

The method has been tested for the classification of images [16].

III. APPROACHES BASED ON HISTOGRAMS OR STATISTICS COMPUTATION

This class of methods based on histograms or statistics computation is composed of the following algorithms: color histograms, fuzzy color histograms, histograms of color ratios, marginal histograms, multilayer coordinated cluster representation, color statistics, chromaticity moments, and average color differences.

A. COLOR HISTOGRAM

1) CONCEPT

In the color histogram method, given a discrete color space defined by its axes (e.g., red, green, blue), the color histogram is computed by first discretizing the colors in the channel into a number of bins and counting the number of image pixels in each bin [11], [17]. A histogram of each chromatic channel of the image is thus obtained. In [17] and other studies [13], [18], the image under study is first converted to the $rg - by - wb$ color space. In the latter color space, the axes are divided into different sections. To compare histograms, a similarity measure – the histogram intersection – sums up the minimum values of two histograms for each histogram bin [17]. There are two types of color histogram: global color histogram and local color histogram. Local color histograms focus on the individual parts of an image and consider the spatial distribution of pixels that are lost in global color histograms.

2) ADVANTAGES AND LIMITATIONS

Color histograms have the advantage of being simple to compute and are invariant to translation, rotation about an axis perpendicular to the image. Moreover, they only change slightly with rotation about other axes, and change of distance to the object [17]. Different objects lead to different histograms. This is why color histogram may be a good representation for objects identification. However, two colors are considered as being the same if they fall into the same bin. This equivalence function is not ideal for recognition [17]. Moreover, small changes in the image might result in large changes in the histogram and two images with similar color distribution lead to similar histograms. Furthermore, the method should be avoided when illumination conditions are variable or unknown [19]. Finally, with the color histograms, the spatial information is not taken into account [19], [20].

3) EXAMPLES OF APPLICATIONS

The color histogram has been used by Cusano et al. for comparison purposes [18] and was also the basis for other studies [21], [22].

B. FUZZY COLOR HISTOGRAM

1) CONCEPT

The fuzzy color histogram method has been proposed to overcome some drawbacks of the color histogram method, such as the sensitivity to lighting variations and noise [23]. In the fuzzy color histogram method, a conversion to the L*a*b* space is first performed and, then, the color space is fuzzily partitioned based on perceptual similarity [23]. Thus, each color triple is assigned a membership value related to color. This value is calculated from a set of triangular membership functions and fuzzy rules. The value is from 0 to 1 and refers to the ten following classes: black, darkgray, red, brown, yellow, green, blue, cyan, magenta, and yellow.

2) ADVANTAGES AND LIMITATIONS

It has been reported that the fuzzy color histogram method is less sensitive, than the color histogram method, to changes in the images (e.g., lighting variations, noise) [23]. However, it is less computationally efficient.

3) EXAMPLES OF APPLICATIONS

The fuzzy color histogram has been use as a background for other studies [24], [25].

C. HISTOGRAM OF COLOR RATIOS

1) CONCEPT

The histograms of color ratios are computed from the ratios between a given pixel and its neighbors. These histograms are used as feature vectors [18].

2) ADVANTAGES AND LIMITATIONS

The color ratios are independent of a change in surface orientation, viewpoint, and direction of the illumination [26].

3) EXAMPLES OF APPLICATIONS

The histograms of color ratios have been used for classification purposes [18].

D. MARGINAL HISTOGRAMS

1) CONCEPT

In the marginal histograms method, the 1D histograms of each channel are concatenated [27].

2) ADVANTAGES AND LIMITATIONS

The method has the advantage of having good robustness against translation, rotation, and changes of the viewing angle. However, marginalization relies on the assumption that the color coordinates are uncorrelated, which might not be entirely correct. Furthermore, the presence of steady illumination conditions is highly recommended. Finally, the method being a spectral method, the spatial information is lost.

3) EXAMPLES OF APPLICATIONS

The method was used in [28] for classification purposes.

E. MULTILAYER COORDINATED CLUSTER REPRESENTATION

1) CONCEPT

The multilayer coordinated cluster representation (CCR) is an extension of the CCR to color images. CCR is a texture descriptor that is based on the probability of occurrence of elementary binary patterns (texels) defined over a square window [29]. In the multilayer approach, the first step consists in a color indexing. Then, the image plane is subdivided into a stack of binary layers (one layer corresponds to a color of a predefined palette) where a pixel is 0 or 1 depending if its color label matches or not the one of the layer. Afterwards, for each layer the histograms of occurrence of the binary patterns are computed in a 3×3 square window. Finally, all the histograms are concatenated [13]. Another approach is presented in [30].

2) ADVANTAGES AND LIMITATIONS

The method is insensitive against rotation thanks to the use of rotation-invariant texels [29].

3) EXAMPLES OF APPLICATIONS

The multilayer CCR has been used for classification tasks [29].

F. COLOR STATISTICS

1) CONCEPT

Color statistics (soft color descriptors) can be used to form feature vectors for each channel in the color space: mean, mean+standard deviation+moments, percentiles.

2) ADVANTAGES AND LIMITATIONS

The advantage of the color statistics is that they are very easy to compute and they have interesting properties, e.g., invariance to geometric transformations. However, as for any spectral methods, any spatial information is lost and the presence of steady illumination conditions is highly recommended.

3) EXAMPLES OF APPLICATIONS
The color statistics were used by Lopez et al. for the application of surface grading [31]. Niskanen et al. used centiles from normalized cumulative channel histograms for defect detection capability for softwood lumber [32].

G. CHROMATICITY MOMENTS
1) CONCEPT
In this method, the image is first transformed to the CIE XYZ space; then, the chromaticity diagram is determined [33]. The chromaticity diagram is a 2D representation of an image where each pixel leads to a pair of (x, y) values. Its trace and two-dimensional distribution (i.e., histogram) are computed as described in [33]. They can be characterized by sets of moments. A set of moments is therefore computed to characterize the color texture, after obtaining a rescaled and a discretized version of the diagram [33].

2) ADVANTAGES AND LIMITATIONS
The advantage of the chromaticity moments method is that it is a simple and computationally low-cost method [33].

3) EXAMPLES OF APPLICATIONS
The chromaticity moments method has been used by Cusano et al. [18] and by Iakovidis et al. [34] for comparison purposes.

H. AVERAGE COLOR DIFFERENCES
1) CONCEPT
The average color differences method is an extension of the semi-variogram to color images. In this method, variograms are used to describe the spatial dependence between a pixel and its neighbors [35], [36]. This dependence is mesured through the average color as a function of the distance between pixels along one direction; the difference between a given pixel and neighbor pixels located on given displacements is associated to variograms.

2) ADVANTAGES AND LIMITATIONS
The average color differences method might be an interesting texture feature extraction method but it has the drawback of being few documented: only a few papers use this method for color images.

3) EXAMPLES OF APPLICATIONS
The average color differences was used in a few studies [13], [18].

IV. TRANSFORM-BASED, FILTER-BASED, AND OPERATOR-BASED APPROACHES
This class of methods based on a transform, on filters, or on operators is composed of the following algorithms: wavelets and co-occurrence histograms, dual tree-complex wavelet transform and chromatic features, Gabor features, Gabor and chromatic features, opponent Gabor features, color ranklets, Tex-Mex color features, and morphological texture descriptors including granulometry.

A. WAVELETS AND CO-OCCURRENCE HISTOGRAMS
1) CONCEPT
In this method, for each of the channel (RGB space) wavelet-based features are first extracted from each texture block of the image and of its complement (the complement image is computed by replacing the value of each pixel by its complement to the greatest intensity level). The co-occurrence histograms are then computed from the wavelet coefficients. The normalized cumulative histogram is used to compute the features: slope of the regression line, mean, and mean deviation [37].

2) ADVANTAGES AND LIMITATIONS
The wavelet method has computational advantages over other methods for texture classification [38].

3) EXAMPLES OF APPLICATIONS
The wavelets and co-occurrence histograms method has been used for comparison purposes by Bianconi et al. [13].

B. DUAL TREE-COMPLEX WAVELET TRANSFORM AND CHROMATIC FEATURES
1) CONCEPT
In this method, a dual tree-complex wavelet transform (DT-CWT) applied on the monochromatic plane is combined with chromatic features [39]. It has been shown that the DT-CWT leads to better results than the discrete wavelet transform for texture analysis [40].

2) ADVANTAGES AND LIMITATIONS
DT-CWT has the advantage, over the discrete wavelet transform, of having moderate redundancy, near shift invariance, and directional selectivity [39], [40].

3) EXAMPLES OF APPLICATIONS
Barilla and Spann used the DT-CWT in a classification method for real world scene images [39].

C. GABOR FEATURES
1) CONCEPT
In this method, a set of Gabor filters is used to extract local orientation and scale information from different color bands [1]. These filters have been shown to parallel the mechanisms used in the early stages of human visual perception. For each color plane, texture features are computed through the mean and standard deviation of the absolute value of the transformed image [13].

Some authors also proposed the Gabor features on Gaussian color model: in this case, the first step is to convert the RGB image into the Gaussian color model, as described in [41]. The second step is to extract the Gabor features as mentioned above.

Other authors proposed the normalized color space representation in which the color image is first changed to a matrix of complex numbers as $P_1 + jP_2$ to reduce the number of its dimensions, going from 3 (color space) to two, as described in [42]. This leads to three possible color coordinates pairs. The new matrix is then processed with classic filtering methods, such a bank of Gabor filters to obtain rotationally invariant features [13], [18]. The filtering procedure is considered to be a chromatospatial operation.

2) ADVANTAGES AND LIMITATIONS

The method relying on the Gabor filtering has two main drawbacks: (i) the appropriate selection of the filters; (ii) the texture features might be correlated since the outputs of the filter bank are not mutually orthogonal [4]. In the normalized color space representation, the drawback is that the dimensionality reduction generates three possible and equivalent color pairs. The appropriate color coordinates pair has therefore to be chosen among the three obtained. This is done through the determination of the least significant color component in the original image. This task can be performed through the variance, the range, the eigenvalues, or some normalized scalars [42].

3) EXAMPLES OF APPLICATIONS

The Gabor features were used by Cusano et al. [18] for comparison purposes. In this case, the texture measurement relies on two sequential steps: (i) color measurement with the Gaussian color model; (ii) spatial measurement through Gabor filtering [13]. Vertan et al. reported that, using the normalized color space representation, the recognition rate – for both regular and irregular textures – overcomes the recognition rates obtained with other color space normalizations [42].

D. GABOR AND CHROMATIC FEATURES

1) CONCEPT

In this method, the texture information extracted from the luminance (Gabor features as mentioned in part IV-C) is combined with the chromatic features.

2) ADVANTAGES AND LIMITATIONS

Some authors have shown that Gabor and chromatic features can produce a higher classification accuracy than the co-occurrence approach [4]. However, the results are worse than those given by the discrete cosine transform features [4].

3) EXAMPLES OF APPLICATIONS

This method has been used for classification purposes [4], [18].

E. OPPONENT GABOR FEATURES

1) CONCEPT

It is also possible to work with the opponent Gabor features (the term "opponent colors" means all pairs of different color channels): the opponent features are computed from couples of color planes [43]. In the latter case, two kinds of features can be obtained from the normalized difference of the Gabor transforms: (i) features obtained at the same scale and orientation on couples of color planes; (ii) features obtained at different scales and orientations on couples of different color channels.

2) ADVANTAGES AND LIMITATIONS

The opponent Gabor features have the advantage of capturing the texture patterns of spatial interactions between spectral bands.

3) EXAMPLES OF APPLICATIONS

The opponent Gabor features have been used for texture comparison purposes in [13], for face recognition in [44], and for image classification [45].

F. COLOR RANKLETS

1) CONCEPT

The ranklet transform is a procedure that does not consider the values of the pixels but their relative rank of neighboring pixels (in a region, number of pixels having an intensity lower than the one of the central pixel). The color in images is taken into account by using inter- and intra-channel ranklet features. In the color ranklet procedure, the ranklet transform is applied both within and between color channels in the RGB space. Then, from each ranklet transform, the texture features are obtained by computing the mean and standard deviation of the ranklet values [46]. The use of inter-channel features stems from the opponent process theory of the human color vision that is used in other texture feature extraction methods, as described in this review.

2) ADVANTAGES AND LIMITATIONS

The color ranklet method is sensitive to rotation. Bianconi et al. proposed to remove this sensitivity against rotation by considering the discrete Fourier transform of the feature vector given by ranklet-based features (mean values or standard deviations) for a given pair of color channels and window size [46].

3) EXAMPLES OF APPLICATIONS

The ranklet method was used in an automatic search engine, based on the visual content, to perform queries in a database of granite images [47].

G. TEX-MEX COLOR FEATURES

1) CONCEPT

The Tex-Mex (from TEXture features using Morphological EXtrema filters) color features are computed through the use of the convex color sieve, which is an extension to the color domain of the morphological operator sieve [48], [49]. The sieve performs a decomposition by scale where, for images, scale is a function of area. Sieves can be regarded as a cascade of morphological filters where the sieve operator removes extrema at a given scale [50]. The convex color sieve relies on convex hulls of the spectral coordinates to determine color extrema. Then, they are merged to their nearest neighbor using the Euclidian distance measure. The process is iterated through different scales, which leads to a set of "sieved" images. Finally, the mean and standard deviation of the differences between two successive sieved images (granule image) are computed to give the texture features.

2) ADVANTAGES AND LIMITATIONS

The Tex-Mex color features have the advantage of being rotationally-invariant as the different steps used in the algorithm are not affected by rotation of the original image.

3) EXAMPLES OF APPLICATIONS

Examples of applications can be found in [13] and [50].

H. MORPHOLOGICAL TEXTURE DESCRIPTORS

1) CONCEPT

To get the morphological texture descriptors, a mathematical morphology is used, upon which color and texture information are jointly processed [51]. The morphological texture descriptors are granulometry and morphological covariance, as described in [51].

2) ADVANTAGES AND LIMITATIONS

Authors have shown that this approach outperforms other state-of-the-art morphological texture descriptors [51].

3) EXAMPLES OF APPLICATIONS

The morphological texture descriptors for color images have been used for classification purposes [51].

I. GRANULOMETRY

1) CONCEPT

In this method, morphological operators are applied to each color channel separately. For this purpose, the image is transformed with a family of openings and closings and normalized with the sum of the pixel values. The result obtained is a function of the size of the structuring elements.

2) ADVANTAGES AND LIMITATIONS

It has been shown that the color granulometry features lead to better image classification performances than the grayscale features [35]. Moreover, when using illumination invariant features with granulometry, the classification of color images was found even better [35]. This was not the case for grayscale images. When using non-illumination invariant images, the granulometry method leads to worse results than other methods such as the variogram [35].

3) EXAMPLES OF APPLICATIONS

Hanbury et al. used the granulometry method for texture classification [35].

V. LBP-BASED APPROACHES

This class of methods based on local binary pattern (LBP) is composed of the following algorithms: LBP-based features and opponent color LBP.

A. LBP-BASED FEATURES

1) CONCEPT

Many algorithms have been proposed for color images, based on LBP, such as the spatially weighted order binary pattern (SWOBP) where local difference signs and magnitudes used in complete LBP are extended to three-dimensional color space and then used to weight and encode color orders in the spatial domain [52]. Hosny et al. proposed to extract both local and global features by using LBP and multi-channel orthogonal radial substituted Chebyshev moments [53].

Cusano et al. also proposed the use of LBP to analyze the texture of local images: their method combines a histogram of LBPs with a feature encoding the distribution of local color contrast (LCC). The latter feature is the histogram of the color contrast values [54]. LCC is obtained through a comparison of the color at a location to the average color in a surrounding neighborhood. This method has the advantage of being robust to changes in illumination [54].

Other algorithms have been proposed to improve LBP-based results, such as the orthogonal combination of LBP extended to color spaces [55], the local combination adaptive ternary pattern that encodes both color and local information [56], the improved local ternary patterns extended for color properties [57], the color local pattern (CLP) [58], the multichannel adder-based LBP and multichannel decoder-based LBP (mdLBP) [59], the softly quantized color LBP [60], the local binary pattern for color images where a color pixel is treated as a vector having m-components and form a hyperplane [61], and more recently the left to right LBP, the top to down LBP, the curve surface LBP, and the cube diagonal LBP [62], the mean distance LBP combined with color features and co-occurrence matrix [63], the multiple channels LBP that uses both the correlation information among multiple color channels and characteristics in a single color channel [64], and new descriptors called LBPL and LBPL + LBPC that represent color cue as the correlation of pixels after deriving three regression lines in a local window and deriving LBP-like patterns [65].

Spatial interactions between colors of the neighboring pixels can also be studied. For this purpose, an order relation between colors can be obtained with a vectorial approach [10], [66].

The quaternion representation can also be used to represent the pixel color [67], [68], [69]. Vipparthi et al. proposed the use of quinary values instead of binary values [70].

Other color LBP variants have been proposed. Some of them are presented in: Banerji et al. [71] and Fekriershad et al. [72]. Recently, Porebski et al. proposed the combination of LBP bin and histogram selections [73]. Lee et al. proposed the color norm pattern and the color angular patterns via LBP texture operation as another color LBP variant [74].

Texture and color can also be computed separately: LBP-based methods are used for texture and color centiles are used as color descriptors. They are then merged [32].

2) ADVANTAGES AND LIMITATIONS

SWOBP has been shown to be robust to changes in illumination, rotation, pose, and scale [52].

3) EXAMPLES OF APPLICATIONS

Vipparthi et al. used the color directional local quinary patterns for content based indexing and retrieval [70]. Niskanen et al. used LBP and centiles (cumulative probability distribution of each color channel divided by the percentage required) in surface detection of parquet slabs [32].

B. OPPONENT COLOR LBP

1) CONCEPT

The opponent color local binary pattern (OCLBP) has been proposed as a joint color-texture operator where the term ‘‘opponent colors’’ refers to all pairs of color channels [44], [75], [76]. The method relies on LBP that is applied to all color channels, separately, and to pairs of color channels (in the latter case, the center pixel is from one channel and the neighboring pixels from the other). Three inter-channel LBP histograms and six intra-channel histograms are obtained and concatenated into a single distribution. However, as opposing pairs (e.g., G-B and B-G) are highly redundant, three inter-channel histograms can be removed. Nevertheless, the choice of the histograms can be improved based on the data and this is why the extended OCLBP has been proposed [77].

Improved OCLBP (IOCLBP) has also been proposed: IOCLBP considers intra- and inter-channel features, as does OCLBP, but with a local thresholding scheme that is different [5].

2) ADVANTAGES AND LIMITATIONS

OCLBP and IOCLBP have the advantage of capturing the spatial interaction between spectral bands. However, it has been shown that the opponent color texture descriptors suffer from the illumination change [75]. Some authors proposed to associate OCLBP and IOCLBP with LCC, a descriptor that has been designed to be robust with respect to changes in illumination [5]. Bianconi et al. have shown that IOCLBP outperforms OCLBP in color texture classification [5].

3) EXAMPLES OF APPLICATIONS

OCLBP has been used for face recognition [44]. Moreover, it has been shown that IOCLBP is particularly interesting for the classification of fine-grained color texture, as found in histological images [5].

VI. GRAPH-BASED APPROACHES

This class of methods based on graphs is composed of the shortest paths in graphs algorithm.

A. SHORTEST PATHS IN GRAPH

1) CONCEPT

In the shortest paths in graph method, the color image is modeled as a graph through two and complementary ways: (i) each color channel separately (3 graphs are therefore obtained); (ii) the color channels together (one graph representing the whole image is obtained). The graph represents tolopogical properties of the texture. Then, statistical moments from the shortest paths between specific vertices of the graph are computed. For the case where three graphs are obtained, each shortest path belongs only to one channel. This leads to feature vectors [78].

2) ADVANTAGES AND LIMITATIONS

The method presented here is not robust to different conditions of luminance. However, the method is robust, but not invariant, to different conditions of rotation [78].

3) EXAMPLES OF APPLICATIONS

The shortest paths in graph method has been used in studies to compare performances with other methods for classification purposes (see, e.g., [79] and [80]).

VII. DEEP LEARNING APPROACHES

This class of methods based on deep learning relies on the convolutional neural networks (CNN).

A. CONVOLUTIONAL NEURAL NETWORKS

1) CONCEPT

CNN are a combination of modules (layers) that lead to complex structures. For texture feature extraction on color images, pre-trained networks are often used: the feature are extracted with the pre-trained network (where the last layers are removed). However, fine tuning and full training can also be used. We will not go deeper into this part as it is already very well described in a recent paper [14]. Moreover, different studies tested the concept [5], [81]. A recent work using CNN for color texture extraction is the one of Simon et al. who proposed the DeepLumina method that uses features from the deep architectures as well as the luminance information from the RGB color space for classification [82].

VIII. ENTROPY- AND FRACTAL-BASED APPROACHES

The feature extraction measures of this class of methods are composed of algorithms relying on univariate entropy-based measures as well as on multivariate entropy-based measures. Fractal-based methods have also been proposed, as described below.

A. UNIVARIATE ENTROPY-BASED MEASURES

1) CONCEPT

Three different univariate entropy-based approaches have been proposed to extract texture features from color images: the single-channel bidimensional fuzzy entropy $FuzEnC_{2D}$ that considers the characteristics of each channel separately, and two multi-channel bidimensional fuzzy entropy measures $FuzEnV_{2D}$ and $FuzEnM_{2D}$ that take into consideration the inter-channel characteristics of the image [83]. Each of these three measures is based on the bidimensional version of the fuzzy entropy [84]. The main differences between the three algorithms rely in the way the similarity degrees are calculated.

2) ADVANTAGES AND LIMITATIONS

The three measures showed a reliable behavior with different parameters and with different color spaces [83].

3) EXAMPLES OF APPLICATIONS

The methods have been used to analyze dermoscopic images of malignant melanoma and benign melanocytic nevi [83].

B. MULTIVARIATE ENTROPY-BASED APPROACHES

1) CONCEPT

Multivariate entropy approaches have also been proposed for texture feature extraction of color images [85]. The principle relies on a natural bidimensional extension of the multivariate entropy algorithms proposed for univariate signals where entropy is computed in a unified way for all channels (see, e.g., [86] and [87]). The methods being very recent, they deserve more in-depth studies and have to be launched on a large number of datasets.

2) ADVANTAGES AND LIMITATIONS

It has been shown that multivariate entropy approaches do not lead to color image classification results as good as those given by deep learning approaches. However, they have the advantage of being based on well-known unidimensional entropy measures. Furthermore, they are applicable to any and small datasets (no need to train the method on large databases) [85]. Moreover, a multiscale approach can also be used to study the texture at different spatial scales [85].

3) EXAMPLES OF APPLICATIONS

Several multivariate entropy approaches have been tested on different kinds of color images for classification purposes [85].

C. FRACTAL DESCRIPTORS

1) CONCEPT

Several authors proposed to use fractal descriptors for the analysis of color images [88], [89], [90]. Thus, Backes et al. proposed to use the fractal dimension to analyze color texture [90]. Their work relies on the computation of the complexity for the three R, G, and B color channels and to study, also, all channels in combination. An alternative of this method has been proposed more recently [91].

2) ADVANTAGES AND LIMITATIONS

The fractal descriptors are particularly interesting for natural textures that show no periodic structure (such as clouds, smoke, leaves…).

3) EXAMPLES OF APPLICATIONS

The method has been used to classify images from the VisTex database [92] as well as natural texture images [90].

IX. CONCLUSION AND FUTURE CHALLENGES

Color and texture are two of the most important characteristics used for image analysis and pattern recognition. Color texture analyses use textural and chromatic properties. Many methods have been proposed for the extraction of texture features in color images as feature extraction is usually the first step for texture classification. In this work we proposed a comprehensive survey of the texture feature extraction methods published for color images. We divided them methods into seven classes, two of them being very recent: in the scope of the hand-crafted approaches, the most recent class for texture features extraction is the one based on entropy measures. These methods have the advantage of relying on well-known unidimensional entropy measures. Moreover, they can be associated to multiscale approaches to study the texture at different spatial scales. On the other hand, deep learning has led to very interesting results for tasks as segmentation and classification. Each category (handcrafted approaches and deep learning approaches) has its drawbacks and advantages. In spite of the success of deep networks, the ‘‘black boxes’’ that they represent is still a major disadvantage for some fields (e.g., biomedical field). The hand-designed methods, even if they can lead to worse accuracies and are often designed for a very precise domain, have the advantage of being computationally more interesting and do not require a training step. We have to combine all this for the future and propose new approaches taking the advantages of each category.

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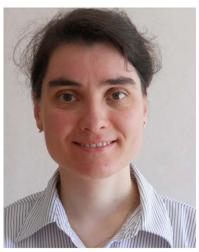

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