Parallel-Sequential Texture Analysis

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Abstract. Color induced texture analysis is explored, using two texture analysis techniques: the co-occurrence matrix and the color correlogram as well as color histograms. Several quantization schemes for six color spaces and the human-based 11 color quantization scheme have been applied. The VisTex texture database was used as test bed. A new color induced texture analysis approach is introduced: the parallel-sequential approach; i.e., the color correlogram combined with the color histogram. This new approach was found to be highly successful (up to 96% correct classification). Moreover, the 11 color quantization scheme performed excellent (94% correct classification) and should, therefore, be incorporated for real-time image analysis. In general, the results emphasize the importance of the use of color for texture analysis and of color as global image feature. Moreover, it illustrates the complementary character of both features.

1 Introduction

The origin of the color name *lilac* lies in the Sanskrit *nilla 'dark blue'*, of which the Persian made *nIlak 'bluish'*, from *nIl 'blue'*. In the Arabic, the meaning evolved to a description of a plant with flowers of this color: the *Sering*. In 1560, the *Sering* was brought to Vienna, by an Austrian ambassador. From there, the plant reached France and the word's meaning evolved to *"a variable color averaging a moderate purple"*[1].

The latter example illustrates that there is more with colors than one would think at first glance. The influence of color in our everyday life and the ease with which humans use color are in stark contrast with the complexity of the phenomenon color, a topic of research in numerous fields of science (e.g., physics, biology, psychology, and computer science). Despite their distinct views on color, scientists in these fields agree that color is of the utmost importance in image processing, both by humans and by computers. However, the use of color analysis increases the computational cost for image analysis algorithms, since instead of one dimension, three dimensions are present. Therefore, color images are often converted to gray-scale images, when texture analysis has to be performed (e.g., see Figure 1). Not surprisingly, with this conversion texture information is lost; e.g., using a standard conversion, red, green, and blue can result in the

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same gray-scale. Nevertheless, as Palm [2] already denoted: "The integration of color and texture is still exceptional". However, in the literature three distinct approaches to combine color and texture can be found: parallel, sequential, and integrative [2]. In the parallel approach, color and texture are evaluated separately, as shown in Figure 1. Sequential approaches use color analysis as a first step of the process chain: After the color space is quantized, gray-scale texture methods are applied, as shown in Figure 2. The integrative method uses the different color channels of an image and performs the texture analysis methods on each channel separately.

Palm [2] used an integrative method to test classification results on color textures and found that the use of color improved classification performance significantly. Drimbarean and Whelan [3] used three texture analysis methods on five different color spaces, with one (coarse) color quantization scheme in an integrative method to test classification results. The use of color improved performance, but no single color space outperformed the others. Mäenpää and Pietikäinen [4] used five different color spaces and two texture analysis techniques to determine whether color and texture should be used in parallel or sequential. They concluded that combining color and texture gave only minimal performance improvement, and that, when combining color and texture, the sequential approach should be preferred.

However, no reports are available that combine studies toward the influence of varying the color space, the quantization scheme, and the way color and texture are combined, for either the parallel approach, the sequential approach, or a combined approach. In this paper, each of these variations is applied. Moreover, the new parallel-sequential approach is introduced: the color correlogram combined with the color histogram.

In the next two sections, we discuss the color spaces and the quantization schemes applied on them and the texture analysis technique used. In Section 4, the texture processing schemes, the texture database, and the classifiers used are briefly described. As baselines, the co-occurrence matrix, the color histogram, and the color correlogram are applied, in Section 5. In Section 6, the new parallel-sequential approach is introduced and directly compared with the parallel approach. We end this paper with a conclusion.

2 Color

A color space specifies colors as tuples of (typically three) numbers, conform to certain specifications. For image processing purposes, color spaces are often quantized. The color space in which this is done determines the perceptual intuitivity of the quantization up to a high extend. Moreover, the axes of the color space can be quantized, using a different scheme for each axis. Again, this depends on the color space of choice.

A color space is perceptually intuitive if distances between points in that space (i.e., 'colors') have a relation to perceived closeness of these 'colors' by human observers. If that relation is constant one can even speak of perceptual uniformity. In this section, we describe the color spaces used and the quantization schemes applied on them. The quantization of color images transformed into gray-scale images will not be described for every color space since it is the same for every color space: the gray-scale axis is divided in the number of bins needed for the specific quantization scheme.

A quantization scheme, either applied to gray-scale or to color images, provides the means to determine an intensity or color histogram. Such a histogram can be determined for parts of the image as well as for the image as a whole. The latter application of the intensity or color histogram is applied in the current research. It describes the global color characteristics of an image.

The RGB (Red, Green, and Blue) color space is the most used color space for computer graphics and is not perceptually uniform. Each color-axis (R, G, and B) is equally important and is quantized with the same precision. The conversion from a RGB image to a gray value image simply takes the sum of the R, G, and B values and divides the result by three.

The HSV (Hue, Saturation, and Value) color space is more closely related to human color perception than the RGB color space [5] and is perceptually intuitive but not perceptually uniform. Hue is the color component of the HSV color space. When Saturation is set to 0, Hue is undefined and the Value-axis represents the gray-scale image. The most common quantization of HSV is in 162 ($18 \times 3 \times 3$) bins.

The YUV and YIQ color spaces have been developed for television broadcasting. The YIQ color space is the same as the YUV color space, where the I-Q plane is a 33° rotation of the U-V plane. The Y signal represents the luminance of a pixel and is the only channel used in black and white television. The U and V for YUV and I and Q for YIQ are the chromatic components. The Y channel is defined by the weighted values of R(0.299), G(0.587), and B(0.144), where the weights resemble the intensity values of the R, G, and B components. The YUV and YIQ color spaces are not perceptually uniform. When the YUV and YIQ color spaces are quantized, each axis is quantized with the same precision. In addition, to optimize color appearance, the YUV color space is often sampled. The samplings we used to construct the color correlogram are: 4:4:4, 4:2:2, and 4:1:1, where the numbers denote the relative amount of respectively Y on each row, U and V on each even-numbered row, and U and V on each odd-numbered row in the image.

The first color space developed by the Commission Internationale de l'Eclairage (CIE) is the XYZ color space. The Y component is the luminance component defined by the weighted sums of R(0.212671), G(0.715160), and B(0.072169). The X and Z are the chromatic components. The XYZ color space is not a perceptually uniform color space. In quantizing the XYZ space, each axis is quantized with the same precision.

The CIE LUV color space is a projective transformation of the XYZ color space that is perceptually uniform. The L-channel of the LUV color space is the luminance of the color. The U and V channels are the chromatic components. So, when U and V are set to 0, the L-channel represents a gray-scale image. In quantizing the LUV space, each axis is quantized with the same precision.

Another view on color representation is the concept of 11 color categories (i.e., black, white, red, green, yellow, blue, brown, purple, pink, orange, and gray), as introduced by Berlin and Kay [6]. Since then, several researchers discussed the topic; see Derefeldt et al. [7] for an overview. Van den Broek et al. [8] developed a method to describe the complete HSI color space, based on a limited set of experimentally determined, categorized colors. This method provided a unique color space segmentation, which can be applied as an 11 color categories, quantization scheme.

3 Texture

Before texture can be analyzed, either a simple color to gray-scale conversion followed by a gray-scale quantization or a color quantization scheme has to be applied, as discussed in the previous section. Next, several texture analysis techniques can be applied, both for general and for specific purposes. We have chosen for one of the more intuitive texture descriptors: the co-occurrence matrix [9], which was developed for intensity based texture analysis. However, it can also be applied for color induced texture analysis; then it is denoted as the color correlogram [10], a sequential color-based texture analysis method: first color is quantized and second texture is analyzed.

3.1 The Co-occurrence Matrix / The Color Correlogram

The co-occurrence matrix $C_{\bar{d}}(i,j)$ counts the co-occurrence of pixels with gray values i and j at a given distance $\bar{d}$. The distance $\bar{d}$ is defined in polar coordinates (d, α), with discrete length and orientation. In practice, α takes the values $0°$, $45°$, $90°$, $135°$, $180°$, $225°$, $270°$, and $315°$. The co-occurrence matrix $C_{\bar{d}}(i,j)$ can now be defined as:

$$C_{\bar{d}}(i,j) = \Pr(\mathrm{I}(p_1) = i \wedge \mathrm{I}(p_2) = j \mid |p_1 - p_2| = \bar{d}), \quad (1)$$

where $\Pr$ is probability, and p_1 and p_2 are positions in the gray-scale image I.

The algorithm yields a symmetric matrix; hence, only angles up to $180°$ need to be considered. A single co-occurrence matrix can be defined for each distance d by averaging four co-occurrence matrices of different angles (i.e., $0°$, $45°$, $90°$, and $135°$).

The color correlogram is the color-based equivalent of the co-occurrence matrix. So, for the color correlogram, not the intensity is quantized, but a color space is quantized. In Equation 1, i and j denote two gray-values. Subsequently, the color correlogram can be defined by Equation 1, with i and j being two color values.

Because of the high dimensionality of the matrix, the individual elements of the co-occurrence matrix are rarely used directly for texture analysis. Instead, textural features can be derived from the matrix. In previous research [11], we determined which feature-distance combinations, derived from the co-occurrence matrix or color correlogram, perform best. The best classification was found using a combination of four features: entropy, inverse difference moment, cluster prominence, and Haralick's correlation, with $d = 1$. Consequently, this configuration was chosen for this research.

4 Method

For the co-occurrence matrix, the color histogram, and the color correlogram, for each color space, five quantization schemes were applied. A complete overview of the schemes applied is presented in Table 1. In total, 170 different configurations were applied: 30 for the co-occurrence matrix, 20 for the color histogram, 45 for the color correlogram, and 75 for the combined approaches.

The VisTex texture database [12], which consists of 19 labeled classes, was used as test bed both for the baselines (see Section 5) and for the comparison between the parallel and parallel-sequential approach for texture analysis (see Section 6). The classes

Table 1. The quantization schemes applied on the six color spaces and on the 11 color categories, for each texture descriptor. Note that YUV* is sampled for the color correlogram (see Section 2).

Color space	Co-occurrence matrix	Color histogram / Color correlogram
RGB	8, 16, 32, 64, 128	8, 64, 216, 512, 4096
HSV	8, 16, 32, 64, 128	27, 54, 108, 162, 324
YIQ, YUV*, XYZ, LUV	8, 16, 32, 64, 128	8, 27, 64, 125, 216
11 colors		11, 27, 36, 70, 225

Table 2. The *best* classification results (%) of the color histogram, the co-occurrence matrix, and the color correlogram, for several color space - quantization scheme (#bins) combination.

Color space	Co-occurrence matrix		Color histogram		Color correlogram	
	#bins	%	#bins	%	#bins	%
RGB	8	56%	4096	87%	8	68%
HSV	32	58%	27	88%	162	74%
YIQ	8	54%			125	53%
YUV 4:4:4	8	54%			27	52%
XYZ	64	56%			27	71%
LUV	8	58%	64	84%	27	66%
11 colors			11	84%	27	72%

with less than 10 images were not used in this experiment. This resulted in four classes: bark (13 images), food (12 images), fabric (20 images), and leaves (17 images). In order to generate more data for the classifiers, we adapted the approach of Palm [2] and Mäenpää and Pietikäinen [4]: the original images were split into four sub-images, resulting in a database of 248 textures.

For all research described in this paper, a combination of three classifiers was used: a linear discriminant classifier, a 1-nearest neighbor classifier, and a probabilistic neural network, taken from the MATLAB® library using their default parameters. The output of this classifier combination was determined using the technique of majority voting [13]: when at least two of the three classifiers agree on the class label of a sample image, this label is given else the label false is given. The training and test set for the classifiers were composed using random picking, with the prerequisite that each class had an equal amount of training data.

5 Three Baselines

As a first baseline, the co-occurrence matrix as standard, intensity-based texture analysis is used. The results are presented in Table 2. The complete results are available online [14]. The CIE LUV quantized in 8 bins and the HSV color space quantized in 32 bins performed best with a classification performance of 58%. Overall, the performances among different color spaces were about the same. Hence, for intensity-based texture analysis, the choice of color space is not essential. The quantization scheme chosen is important, usually a lower number of bins performs better: In no instance, the largest number of bins gave the best results.

Next to texture, the global color distribution within an image is frequently used as feature for image classification and image retrieval. Therefore, as a second baseline, we conducted an image classification experiment, using color solely by calculating the color histograms. In Table 2, the best four classification results are presented. The complete results are available online [14]. Classification by use of quantizations of the RGB color space results in a low performance (i.e., ranging from 19–48%), except for the 4096 bin quantization scheme (as used in QBIC [15]). However, the latter suffers from an unacceptable computational load, especially for real-time image analysis applications (e.g., content-based image retrieval). Therefore, the RGB color space is not suitable for color-based image classification. The classification using the coarsest LUV quantization (8 bins) did have a poor performance. All other quantizations, using the LUV color space, resulted in high classification performance. The color-based texture classification, using the coarse 11 color quantization scheme, performed well (84%) (see Table 2), especially when considering its low computational complexity. The 27 and 162 bins quantizations of the HSV color space performed best with 88% and 89%.

As the third baseline, sequential texture analysis is performed (see Figure 2), with the color correlogram using six different color spaces. The results are presented in Table 2. In addition, the 11 color categories scheme was applied using several quantization schemes (see Section 4). The HSV color space performed best in combination with the color correlogram (see Table 2). This can be explained by the relatively high precision in color (Hue) quantization of the HSV 162 bins scheme. However, the color correlogram founded on the 11 color categories also performed good with 72% precision.

An interesting result is the fact that using more bins usually does not improve performance. In no instance, the largest number of bins gave the best results. This result emphasizes the importance of using a coarse color quantization scheme such as that of the 11 color categories in which one can represent colors [7].

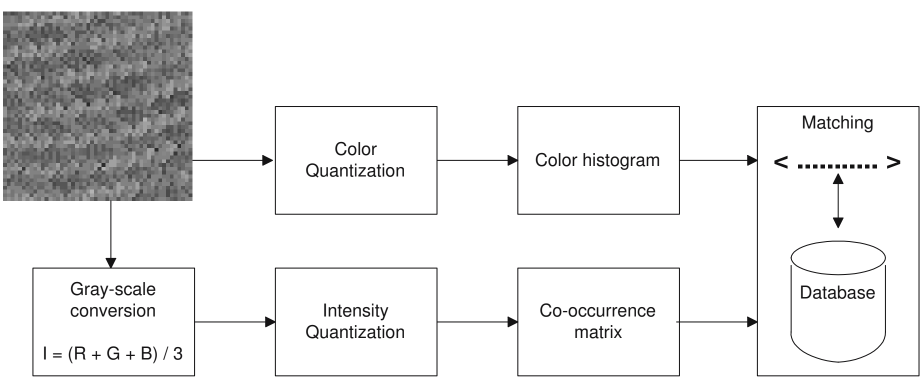

Fig. 1. The parallel approach for texture analysis, using global color features and local intensity differences. In parallel, the color histogram is determined, after the quantization of color, and the co-occurrence matrix is calculated, after the conversion to gray-scale and the quantization of gray values.

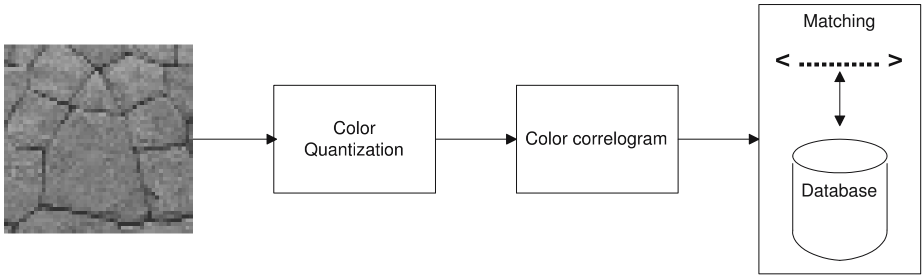

Fig. 2. The sequential approach for texture analysis: after color quantization the color correlogram is utilized.

6 Parallel-Sequential Texture Analysis: Color Histogram and Color Correlogram

In the previous sections, we have discussed the classification of the VisTex images, using intensity-based texture features (i.e., the co-occurrence matrix), color histograms, and a sequential of color and texture: the color correlogram. However, better classification results may be achieved when these methods are combined.

In the current section, a new color induced texture analysis approach is introduced: the parallel-sequential approach, which combines the color correlogram and the color histogram, as is visualized in Figure 3. This new approach is compared with the parallel texture analysis approach: the co-occurrence matrix combined with the color histogram, as is visualized in Figure 1.

First, the color histogram data and texture features were concatenated. The six best color histograms were used in combination with both the two best quantization schemes of each color space (for the color correlogram) and the best intensity quantization scheme (for the co-occurrence matrix). The RGB color histogram was excluded since it only performs well with a quantization that is computationally too expensive (see Table 2).

In Table 3, the results of the parallel approach (i.e., combination of color histogram and co-occurrence matrix, see also Figure 1) are provided. In general, the color his-

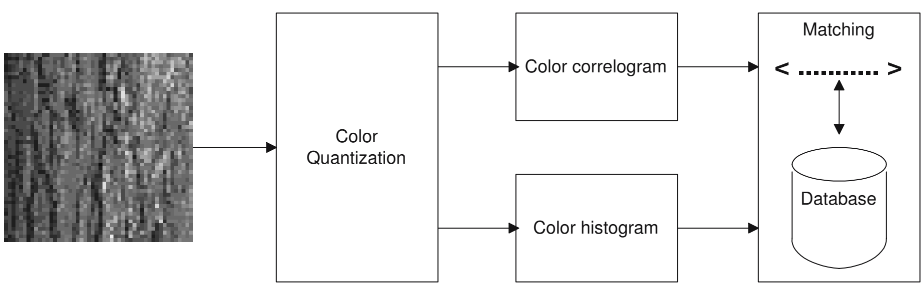

Fig. 3. The new parallel-sequential approach for texture analysis which yields in parallel: global color analysis, using the color histogram, and color induced texture analysis, using the color correlogram.

Table 3. The classification results of *the best combinations* of color histograms with co-occurrence matrices (the parallel approach, see also Figure 1) and with color correlograms (the parallel-sequential approach, see also Figure 3), using several quantizations of color spaces.

		Color histogram				
		11 colors	HSV-27	HSV-162	LUV-64	LUV-125
Co-occurrence matrix	HSV-32	88%	90%	92%	82%	90%
	LUV-8	84%	89%	92%	82%	88%
	RGB-8	84%	89%	92%	82%	88%
	XYZ-64	87%	84%	91%	79%	90%
	YUV/YIQ-8	83%	87%	92%	81%	89%
Color correlogram	11 colors-27	**94%**	92%	**96%**	92%	89%
	HSV-27	93%	87%	92%	92%	91%
	LUV-27	90%	89%	91%	88%	89%
	RGB-8	92%	91%	93%	86%	87%
	XYZ-27	87%	89%	92%	84%	**94%**

togram based on the HSV 162 bins quantization scheme performed best ($91 - 92\%$). However, the computationally much cheaper 11 color quantization scheme did also have a high performance (88%), when combined with the on HSV 32 bins based co-occurrence matrix (see Table 3). Therefore, the latter combination should be taken into account for real-time systems, using color and texture analysis.

The new parallel-sequential approach has a correct classification ranging from 84% to 96% (see Table 3). So, the combination color histogram with color correlogram improved the classification performance significantly, compared to each of them separately (cf. Table 2 and 3).

The configurations using coarse color quantizations for the definition of the color correlogram, outperformed the more precise color quantizations for all color spaces. The 11 color categories color quantization using 27 bins for the color correlogram, performed best on average (92.6%), followed by the HSV-27 bins configuration (91.0%). Concerning the color histogram configurations, the highest average correct classification was provided by the HSV-162 bins color histogram (92.8%), followed by the 11 color categories color histogram with 91.2%.

The best color correlogram - color histogram combinations were: the 11 colors, 27 bins correlogram & 11 colors histogram, the 11 colors, 27 bins correlogram & HSV-162 color histogram, and the XYZ, 27 bins correlogram & LUV-125 color histogram (the percentages are denoted bold in Table 3). When considering the computational complexity of these combinations, the first combination should be preferred, with its feature-vector of size 15: 11 colors + 4 features derived from the 11 colors 27 bins color correlogram, as described in Section 4.

7 Conclusion

Determining the optimal configuration for color-based texture analysis is very important since the success of image classification and image retrieval systems depends on this configuration. Therefore, in this paper, a series of experiments was presented exploring a variety of aspects concerning color-based texture analysis. The color histogram, the co-occurrence matrix, the color correlogram, and their combinations (i.e., the parallel and sequential approach) were compared with one another, using several color spaces and quantization schemes. A new texture analysis method: the parallel-sequential approach, was introduced.

The worst classification results were obtained when only intensity-based texture analysis (i.e., the co-occurrence matrix) was used, the best classification performance in this setting was 58% for the HSV and CIE LUV color spaces. Including color sequentially, using the color correlogram, gave better results (74%). The parallel approach (i.e., color histogram combined with the co-occurrence matrix improved the performance substantially (see Table 3). However, by far the best classification results were obtained using the new parallel-sequential approach (i.e., color histogram and color correlogram combined, a performance of 96% correct classification was obtained, using the HSV 162 bins color histogram in combination with the color correlogram for the 11 color categories with 27 bins. These results indicate that the use of color for image analysis is very important, as classification performance was improved by 38%, compared with the most widely used, intensity-based, co-occurence matrix. Moreover, in general, coarse color quantization schemes perform excellent and should be preferred to more precise schemes.

The success of the parallel-sequential approach emphasizes the importance of both the global color distribution in images, as identified by the color histogram, and the importance of the utilization of color with the analysis of texture. As was shown, ignoring color in either texture analysis or as a global feature impairs the classification of image material substantially. Moreover, the complementary character of global color and color induced texture analysis is illustrated.

Follow-up research should challenge the parallel-sequential approach, by exploring and comparing different texture analysis methods with the parallel-sequential approach introduced in this paper. Moreover, the use of combining texture analysis methods should be investigated since it might provide the means to increase classification results [16]. Preferably, this research should be conducted using a much larger database of textures.

Regardless of texture analysis methods, note that the computationally inexpensive and well performing 11 color categories are human-based. In further work, we will investigate whether the texture analysis techniques discussed in the current paper can mimic human texture classification. This is of the utmost importance as it is the human who will use and judge the systems in which texture analysis techniques are incorporated [8,15].

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