Combination of Wavelet Analysis and Color Applied to Automatic Color Grading of Ceramic Tiles

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Abstract

The automatic color grading of ceramic tiles is still a big challenge, which needs more researching work. The classifying methods based on color means or histograms can't meet current factory requests, because in modern building, various types and color patterns have been applied to floor & wall ceramic tiles. In this paper, a new method has been proposed to tackle the question that is wavelet texture analysis combined with color information. The selection of wavelet has been discussed, as well as the extraction and optimization of feature set based on wavelet decomposition of samples' color images. Knn classifier and the error rate have been used to evaluate classifying performance, and FFFS (Floating Forward Feature Selection) method has been applied to feature-sets' sub-optimization. The experimental results have shown that the sub-optimal wavelet textural features combined with color information well described the samples' clustering based on color, texture and resolution, and the classifying results have taken on very good agreement with experts'. The experiments also have shown the feature optimization greatly decreased feature vectors' dimensionality, and consequently decreased computational complexity.

1. Introduction

In ceramic tiles industry, the automation of visual inspection is still a difficult work because of the complexity of human visual perception. Nowadays, there are some published research [1,2,3,4] on the final inspection at which stage the major job include the grading tiles into distinct color categories or the rejection of tiles with defects and pattern faults, and some methods have been developed for color grading. For example, C. Boukouvalas etc. used the average either of all pixels of the tile for the grading of uniformly colored tiles [1], or the average of each chromatic category of the tile separately for the grading of two-colored tiles with well-defined large-scale pattern [2], and the color histogram [3,4] is considered the main method to deal with multi-colored randomly textured tiles.

Both methods are challenged when more colors and more complex patterns appearing on modern tiles' surface. The fatal limitation of color histogram is that it can't describe the spatial distribution of colors although with advantage of being invariant to translation and rotation, that means two tiles with different color distribution may be mistakenly graded to the same category when their histograms are similar but appearances maybe are different. So currently how to effectively conduct the color grading of multi-colored randomly textured tiles still need further efforts. In this paper, a new method based on wavelet analysis of color image is introduced.

We have learnt the visual perception of a colored tile is a combination of color, texture and scale (or the distance between the tile and human's eye). The change of scales will lead to change of textural appearance, as well as change of color perception. According to this, wavelet texture analysis is an effective tool because of good localization both in spatial region and frequency region. G. Van de Wouwer [5] made great efforts to add color information to wavelet texture analysis of gray images, namely the wavelet texture analysis of color images. It is a good method to combine information of color, texture and scales into a compound set of features. The experimental result shown it is feasible and effective when color grading multi-colored randomly textured tiles.

2. Wavelet Texture Analysis of Color Images

Mallat first proposed the term of multi-resolution analysis (or approximation) [6]. In his famous paper [6], He constructed the uniform framework of orthogonal wavelet base, and with the framework the multi-resolution representation of image decomposition was given, that makes it quick and easy to wavelet transform and reverse transform, which is called Mallat algorithm. Based on those works, Wouwer suggested the method to extend wavelet decomposition algorithms from gray image to color image, and the method to extract textural features [5].

2.1. Wavelet Decomposition of Gray Image

Given $\varphi(x)$ and $\psi(x)$ are scaling function and wavelet function respectively, and if define $h(n), g(n)$ as the impulse responses of discrete filters H, G, then

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the impulse responses of their mirror filters $\widetilde{H}, \widetilde{G}$ should be $\widetilde{h}(n), \widetilde{g}(n)$ [6]

$$\begin{aligned}&\widetilde{h}(n) = h(-n),\\ &h(n) = \langle \varphi_{-1}(x), \varphi(x-n) \rangle\end{aligned} \tag{1}$$

$$\begin{aligned}&\widetilde{g}(n) = g(-n),\\ &g(n) = \langle \psi_{-1}(x), \varphi(x-n) \rangle\end{aligned} \tag{2}$$

According to Mallat algorithm, we obtain the wavelet decomposition of image $I(x, y)$ [5]

$$\begin{cases} L_n = [\widetilde{H}_x * [\widetilde{H}_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2} \\ D_{n1} = [\widetilde{G}_x * [\widetilde{H}_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2} \\ D_{n2} = [\widetilde{H}_x * [\widetilde{G}_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2} \\ D_{n3} = [\widetilde{G}_x * [\widetilde{G}_y * L_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2} \end{cases} \tag{3}$$

where * denotes the convolution operator, $\downarrow 2,1$ ($\downarrow 1,2$) means keeping one sample out of two along the rows (columns), $L_n, D_{n1}, D_{n2}, D_{n3}$ represent the one approximation sub-image and the three detail sub-images respectively at a lower resolution and $L_0 = I(x, y)$ is the origin image. After decomposition, the image can be represented by wavelet coefficient set $\{L_d, D_{ni}\}_{1 \le n \le d,\, i=1,2,3}$, which is called multiscale representation of depth *d* of image $I(x, y)$.

The textural characteristics can be measured from the wavelet representation of image of which energy is the most important one. Usually energies of the detail sub-images are used as textural features because they are the high frequency part of origin image and include the primary textural information. Energy of the sub-image D_{ni} is defined as

$$E_{ni} = \int \left(D_{ni}(\vec{b}) \right)^2 d\vec{b} \quad \vec{b} \in R^2 \tag{4}$$

The wavelet energy signatures $\{E_{ni}\}_{1 \le n \le d,\, i=1,2,3}$ compose a textural feature set of given image with wavelet decomposition of *d* depth, which reflect the distribution of energy along the frequency axis over scale and orientation and have proven to be very useful for gray-level texture characterization [5].

2.2. Extension to Color Image

The most straightforward extension of the wavelet energy signatures to color images is to transform each color plane separately and compute the energies of each transformed plane, i.e. replace *I* by the R, G, and B-plane (when deal with RGB color images) consecutively in equation (3) and (4), and we denote such an energy by $E_{ni}^{X_j}$ where the X_j indicates the color plane (for example, $\{X_j\}_{j=1,2,3}$ represent R, G, and B plane respectively in RGB color image case).

Usually the three planes of color images aren't independent, so the wavelet coefficients between different color planes exist correlation. Wouwer define

$$C_{ni}^{X_j X_k} = \int D_{ni}^{X_j}(\vec{b}) D_{ni}^{X_k}(\vec{b}) d\vec{b} \tag{5}$$

and call the set $\{C_{ni}^{X_j X_k}\}_{1 \le n \le d,\, i=1,2,3}^{j,k=1,2,3,\; j \le k}$ the wavelet covariance signatures [5]. When $j = k$ the wavelet covariance signatures include the energies and the others represent the covariance between different color planes and consequently reflect the coupling between the color and texture properties of the image.

3. Wavelet Selection

With the development of wavelet analysis in recent years, a variety of wavelets of different properties have been constructed. Consequently in application a selection must be conducted to make features more efficient with suitable wavelet. In automation of tiles' inspection, the computational complexity is a key factor, so the first consideration is the selected wavelet must be able to apply Mallat algorithm. Nowadays there are several families of wavelet meeting this request such as Daubechies compact support wavlets, Coifman wavelets, biorthogonal spline wavelets and reverse biorthogonal spline wavelets etc. In this paper, we discussed the selection of suitable wavelet through classification performance comparison of 60 multicolored tiles which have been color graded as 6 categories by professional inspector.

Through following schemes, we conduct performance comparison:

(1) Samples. In this paper, test samples are necessary to evaluate performance of classification. To improve classification performance of limited samples, we construct test samples by leave-one-out method that is to take one out of the whole samples as test sample and the others as design samples.

(2) Classifier design. We choose Knn classifier with *k*=3, because it is simple, effective and robust.

(3) Feature extraction. More than twenty wavelets all of which support Mallat algorithm have been chosen to conduct decomposition on the sample tiles' color images and their wavelet covariance signatures have been extracted as feature sets.

(4) Performance evaluation. In this paper, we take error rate as error estimation, and define it as

$$\hat{e} = \frac{error\ classified\ samples\ total}{samples\ total} \tag{6}$$

Table 1 has shown the classifying performances of different wavelets of different orders from 1 depth of decomposition to 3 depth of decomposition consecutively.

Table 1. **Classifying performances of different wavelets**

wavelet	error rate %（Knn classifier with *k*=3）		
	1 depth	2 depth	3 depth
bior3.1	20	11.7	28.3
bior2.2	6.7	3.3	28.3
bior3.3	15	30	31.7
bior2.4	8.3	30	40
bior1.5	20	23.3	43.3
bior2.6	10	28.3	51.6
db2	10	21.7	28.3
db3	8.3	28.3	25
db4	11.7	13.3	18.3
db5	8.3	23.3	33.3
db6	11.7	13.3	25
db7	10	8.3	30
db10	11.7	28.3	30
coif1	13.3	10	23.3
coif2	13.3	23.3	33.3
coif3	13.3	30	48.3
coif4	13.3	31.7	53.3
coif5	13.3	10	46.7
rbio3.1	10	15	25
rbior2.2	13.3	16.7	23.3
rbior3.3	13.3	20	23.3
rbior2.4	13.3	26.7	30
rbior1.5	11.7	10	41.7
rbior2.6	11.7	26.7	48.3

biorNr.Nd-biorthogonal spline wavelet of Nd order;
dbN-Daubechies compact support wavelet of N order;
coifN- coifman wavelet of N order;
biorNr.Nd-reverse biorthogonal spline wavelet of Nd orde

We come to the conclusion that the classifying performance is much better when selecting biorthogonal spline wavelet of 2 orders. Also the table shown that the performance didn't go up with the wavelet decomposition depth. The phenomenon may be explained with resolutions (or scales) of images. In wavelet representation, the detail sub-images of different resolution describe the different physical construction of image, at lower resolution, which represent bigger physical construction and reflect the outline information of image. As we known, the wavelet decomposition conduct through high resolution to low resolution, that is more decomposition depth, more outline information will be included in feature set. In tiles' color grading, the outlines between tiles are very similar, so the superabundance of outline information make classifying performance worse.

4. Optimization of Feature Set

We have learnt the fact that classification performance does not always ascend with growth of feature set dimensionality that also has been verified by our foregoing experimental result in above section. Accordingly it's reasonable to conduct dimensionality reduction and feature selection in terms either of computational complexity or of classification performance [7]. For example, the feature set is of 36 dimensions after conducting wavelet decomposition of 2 depths on color image and extracting the wavelet covariance signatures as features, but not every one of which is good and efficient for classification. The optimization of feature set aims to search those features the most representational and the most efficient. In this question we must decide how many features and which features come to the best classification performance under given criteria. One answer to this question is full searching that is performance comparison of all possible feature combinations, but it is usually big time consuming despite good performance. So in practice, suboptimal methods are used to replace it. There are many alternative suboptimal methods, among which the FFFS (Floating Forward Feature Selection) is verified the best [8].

Based on the experiment in section 3, we select biorthogonal spline wavelet of 2 orders and conduct wavelet decomposition of 2 depths on color images of the same 60 tiles and extract the wavelet covariance signatures (of 36 dimensions) as their raw feature sets. Then optimize the raw sets by FFFS algorithm [9] with Knn as classifier and error rate as cost function. The experimental results have shown in figure 1.

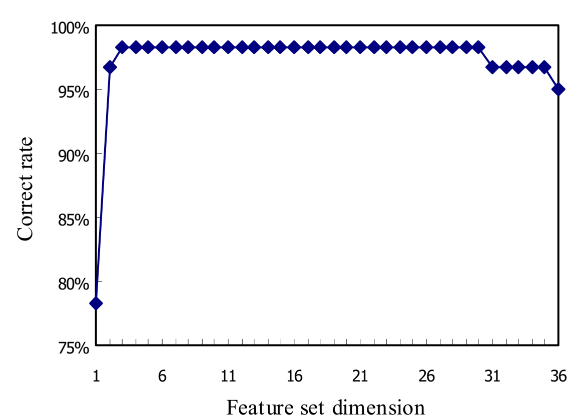


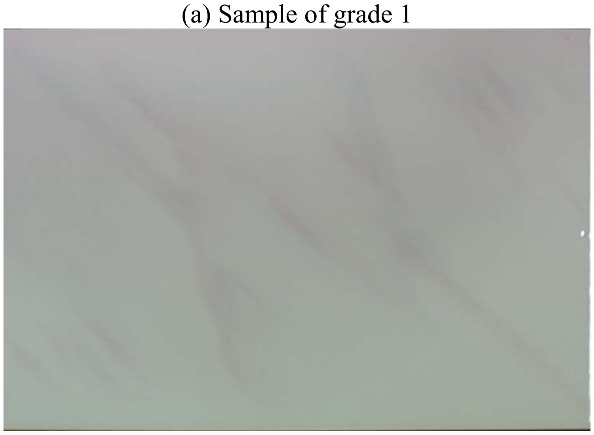
Figure 1. **Optimal feature set dimensionality and the corresponding classifying performances**

where the abscissa indicates dimensionality of selected feature set, and the ordinate indicates corresponding classifying performance (here namely correct rate $1-\hat{e}$).

Figure 1 shown that when the dimensionality of selected feature set is 3, the classification performance is up to saturation of correct rate 98.33% then hold on until the dimensionality is 31 at which point the classification performance begin to descend that means some bad features have been added.

From experimental data, when the dimensionality is 3, the optimal features combination is: the energy of horizontal detail sub-image of 1 depth decomposition on red color plane, the energy of horizontal detail sub-image of 1 depth decomposition on blue color plane, and the covariance signature between horizontal detail sub-images of 2 depth decomposition on red color plan and blue plane respectively. Additionally all the bad features of more than 31 dimensions are almost the energies of green color plane or covariance signatures between green color plane and the other two planes. By observation on sample tiles (see figure 2, two tiles of different color grading are taken as example), we found that all tiles have the similar pattern of alternate with red and blue color on white background, but the spatial distribution of red and blue color is different that discriminate tiles of one color grade from those of another color grade.

(a) Sample of grade 1



(b) Sample of grade 2

Figure 2. Various color grading tiles

4. Conclusion

Human's visual perception on colored tiles is a complex combination included colors, brightness and the spatial distribution (or texture) and even psychological factors. In addition, the textural perception will vary with distance between the tiles and human eyes that mean the resolution (or scale) must be taken into consideration. In the view of this point, wavelet texture analysis combined with color information should be an effective tool.

In this paper, the experimental results shown the wavelet representation of color image effectively describe the spatial distribution of colors and textural information over scale and direction, and the optimization of feature set not only drastically reduce feature set dimensionality (from 36 to 3) consequently greatly decreased computational complexity, but also improve classifying performance (from correct rate 96.7% to 98.33).

To summary it up, we come to the conclusions: first, the wavelet representation of colored image is a powerful tool for color grading of multi-colored randomly textural ceramic tiles; second, to effectively applied the tool, the wavelet selection and feature optimization must be conducted.

5. References

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