Hyper-spectral features applied to colour shade grading tile classification

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Abstract: In this paper, hyper-spectral images are employed for colour shade grading tile classification. Our goal is to design a machine vision system that can estimate the sufficient similarity of tiles, or same appearance to the human eye. We use spectral representations of colour, and spectral features to distinguish tiles of the same class but with subtle differences in their colour shade grading. A laboratory system for colour shade grading measurements is built and a method for calibrating such a system is introduced. Experiments with three classes of tiles are presented and discussed.

Key–Words: computer vision, hyper-spectral, spectral features

1 Introduction

The ceramic tile manufacturing industry has benefited significantly of the automation process in recent years. All production phases have been addressed through various technical innovations, with the exception of the final stage of quality control process. The quality control stage can be divided into two consecutive steps:

i Sort tiles into distinct categories depending on the number of defects and their dimensions.

ii Classify tiles without defects in different colour shade gradings or human colour intensities.

1.1 Automated tile inspection

Human methods for tile inspection are an intensive, slow and subjective task [1]. It is particularly difficult for human inspectors to detect slight and progressive colour changes in tiles.

Though ceramic tiles manufacturing has been highly automated in all production phases; one of the most difficult phases to be automated seems to be the final stage: sorting of ready-made tiles according to the criteria ”same appearance to the human eye”. Same class tiDear Prof./Dr./Mr./Ms.

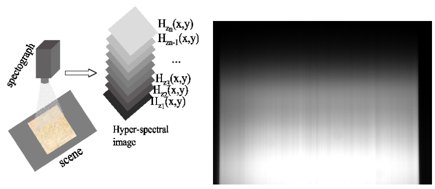
Thank you for sending this paper for possible publication in this WSEAS Conference.

Please, write down or print out or save the ID number of your paper that our server automatically gave to you (as a Web Page some minutes ago)les, should look the same. The problem is how we can ensure that tiles really look the same, for instance, independently of light conditions or random variances on their surfaces. Since the human visual system is subjective and limited, several automatic machine vision approaches have been proposed.

In practice, visual quality control for tiles is not simple due to the fact that several defects may appear on tiles because of manufacturing failures; making more difficult the classification process. Also, the variation of illumination on the tile affects the classification. Some aspects to consider are: local defect detection, textures on surfaces, sufficient colour measurements and spatial and temporal variation in illumination. A lot of research effort is done in the area of tile classification with RGB coloured images [2] and [3], and defect detection in tiles [4]; and several automatic machine vision approaches have been proposed. We addressed our efforts to extract features from hyper-spectral images of tiles, since spectral imaging is a relatively new field and we apply hyper-spectral images to the solution of these problems which have already been treated in the colour domain [1].

1.2 Spectral images

According to some authors, if an image consists of 10-15 bands, it is often called a multi-spectral image, if the number of bands increases, it is then called a hyper-spectral image [5]. In any case, a hyper-spectral image can be considered as an image cube where the third dimension is represented by hundreds of contiguous spectral bands (see figure 1a). As a result, a hyper-spectral pixel is actually a vector with dimensions equal to the number of spectral bands. Such between-band spectral information is very useful and can be used for spectral characterization. Many measures proposed in single processing and pattern recognition can be used for this purpose. A sample spectral image for a tile can be seen in figure 1b.



(a) Acquisition of a hyper-spectral image (b) Sample spectral image

Figure 1: . a) Acquisition of a hyper-spectral image. b)Sample spectral image.

The aim of our work was obtaining a system able to classify tiles based on their colour shade grading, by using features obtained from hyper-spectral images and then, evaluate the computed feature performance by using a traditional recognition technique as is k-Nearest Neighbour classifier or self-organizing maps. We worked with three different types of tiles each of them classified into three different colour shade grading.

The paper is organized as follows, section 2 shows the system built for the experiments. The experiments are described in section 4, results are commented in 5 and the conclusions are shown in section 5.

2 Acquisition system

In this section, we explain how we developed an specific laboratory system to acquire hyper-spectral images of tiles and a method to calibrate this system.

2.1 System set up

Our system is composed of an ImSpector V7 spectrograph with a range of 400-710 nm, and a slit-size of 13 μm. According to the characteristics of the ImSpector, this slit-size corresponds with a spectral resolution of 1 nm, resulting in approximately 310 distinguishable wavelength bands. The ImSpector was coupled with a Jai CV-M300 (double speed scanning, 1/2” CCD , 768 (h) x 524 (v) resolution) and we used a PC-Vision card with 4 MB on-board memory. Light source used was an halogen focus of 500W which was connected through an stabiliser circuit, which allowed us to control the luminance of the focus.

The system is composed of a platform which is moved with the help of a PC controlled stepper motor. With an endless screw connected to this motor, we achieved a precision of 0.2 mm in the platform movement. The set formed by the camera and the spectrograph was located over the platform. All the system was covered with a light protection. The platform was covered with black material to avoid having distortions in images due to reflections from the background (see figure 2).

To avoid damaging the camera and inducing more noise in the CCD by the heat produced by the halogen lamp we protected the camera with a cover made of aluminium.

(a) Side view (b) Stepper motor

Figure 2: The system from different points of view. a) Side view c) Stepper motor.

2.2 Calibration

We studied two different aspects to calibrate the system, on one side, light variances and, on the other side, the width of the line captured by the spectrograph. Light variances affect any visual system since more or less light can increase or decrease the intensity average over the scene. These variations will affect the results obtained in the recognition stage because the perceived colour shade grading can vary significantly. Another point to bear in mind, is the width of the line captured by the spectrograph.

Other authors ([5]) have discussed about the calibration of spectral imaging systems focusing mainly on the type of light used and on the camera CCD; no information about the width of the line integrated by the spectrograph is given.

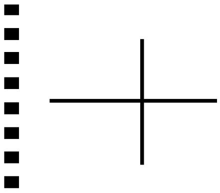


Figure 3: Two patterns used for focusing and calibration: line dotted and two crossed lines.

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Please, write down or print out or save the ID number of your paper that our server automatically gave to you (as a Web Page some minutes ago) For the first issue, the light constancy, we used two different sources; an array of LED's (DCM Systems, PRL-350 model IL043AB) and an halogen focus of 500W. For both of them we conducted the same experiment; we illuminated a white sheet of paper on the platform under the camera, and during a day, we took a picture of the sheet each 10 seconds; then we calculated the mean intensity value of each picture. In the case of the LED's array a significant shift was found and plots shew that the emitted light begins loosing stability in a period of an hour. The halogen performance was better because it gave us more stable light than the LED's array.

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The second issue was the line width of each acquisition; for us it is an important aspect in the calibration of such a system. The width of each acquisition, tells us how many significant pictures we needed to take to cover the complete tile and how much we had to move the tile before taking the next picture. Therefore, we need to study how would affect the distance from the object to the camera. The line width has a linear relationship with the distance from the camera to the tile. To obtain this relationship the optical parameter of the CCD sensor, the lens and the spectrograph are needed, because some of these parameters are not exactly known we obtain this relationship experimentally.

For this purpose a pattern with a dotted line drawn on it (see figure 3) is used. We acquired images of the pattern by shifting the platform each milimeter, this process was repeated moving the camera from the lowest position at 110 mm to the highest at 370 mm. For each height, a contrast measure of every obtained image in the sequence was calculated and a plot was drawn (see figure 4). This plot shows how, as the calibration pattern enters the field of view, the image contrast increases; once the pattern covers the spectrograph field of view the contrast reaches its maximum and remains more or less constant, until the pattern starts leaving the spectrograph field of view. The difference in the plot between the point the contrast starts increasing, and the point the contrast reaches its maximum corresponds to the line width of the spectrograph.

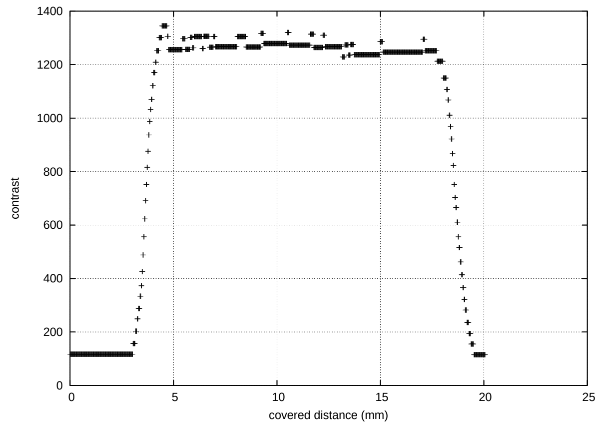

Figure 4: Contrast response for the line width calibration pattern, with the camera at 250 mm height.

We calculated a regression line with the data from the experiments (see figure 5). This line served us to know which width we would integrate depending on the distance of the camera to the object.

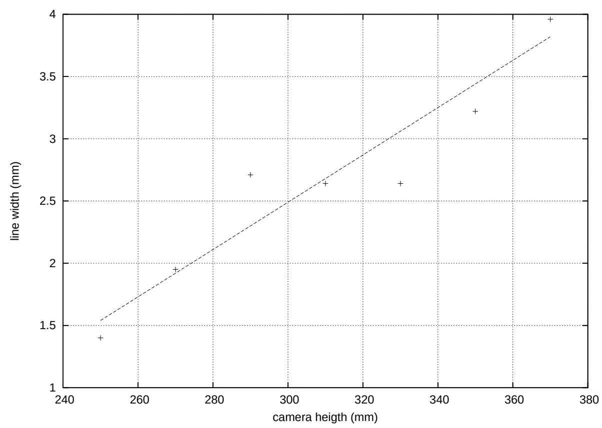

Figure 5: Regression line obtained for spectrograph line width.

Two patterns can be used to focus the spectrograph image adequately (see figure 3), the dotted line pattern mentioned above and a pattern consisting of two crossed lines ([6]).

3 Data set

3.1 Data set

We used three different types of tiles in our experiments. For each of these types, we had three different classes each having a different colour shade grading. Each class has 30 tiles, thus, the total number of tiles is 270. In all cases, the colour shade grading of two of the classes were very similar while the other one is clearly different. On the other hand, surface of the tiles were random textured. These two aspects make the problem more difficult. The types we used for the experiments were: *Blue Countryside* which corresponds to navy blue tiles with irregular darker spots of blue, class *Santiago's Way* which corresponds to grey tiles spotted of darker points, and finally *Mediterranean Green* which are green tiles mixed with white.

3.2 Hyper-spectral features

A hyper-spectral image is generally acquired by hundreds of spectral channels (see figure 1a). As a result, a scene pixel vector is usually represented by a vector, in which each component contains specific spectral information provided by a particular channel. These images can be seen as a 3-dimensional matrix $H(x, y, z)$ which can be decomposed into a number of 2-dimensional $H_z(x, y)$ matrices, with the dimensions of the picture, each showing the response of a spectral channel z. See figure 1b for a sample hyper-spectral image of a tile.

The amount of information contained by these hyper-spectral images is huge. For this reason we used the mean and variance of each bands in the hyper-spectral images as a more compact feature set. Being $H(X, Y, Z)$ the mathematical representation of an image of X columns, Y rows and Z spectral bands. The mean and variance values of each band z are obtained as follow,

$$\overline{x}_z = \frac{1}{X \times Y} \sum_{i=1}^{X} \sum_{j=1}^{Y} H(i, j, z) \tag{1}$$

$$\overline{S}_z = \frac{1}{X \times Y} \sum_{i=1}^{X} \sum_{j=1}^{Y} \left(H(i, j, z) - \overline{x}_z\right)^2 \tag{2}$$

4 Experiments

Tiles of the same type were captured one by one mixing tiles of different classes. This way if an important illuminance shift appeared, this would affect equally the three classes avoiding to be misled in classification. As tiles had a size of 200×200 mm we located the camera at a height of 310 mm over the platform in order to acquire a complete line of 200 mm. At this distance, the line width we integrated was of 2.68 mm (see section 2.2). To avoid errors introduced in the camera by the heat coming from the light source and possible fluctuations of the halogen light, we calibrated the system by means of a white pattern before capturing each tile. An image of this pattern was captured to be sure light conditions were still within a range, in case of a significant shift in the luminance, the halogen lamp was adjusted. Tiles were placed on the platform which moved under the camera, the platform was shifted 2 mm and stopped until the acquisition of the image was done, and then, shifted again; this process was repeated until the entire tile was captured. We allowed an overlap between images of 0.6 mm. A total amount of 120 images were taken per tile, removing all those which were too close to the edges, we kept about 100 per tile.

Spectral information was extracted for each tile by processing all images taken for it, and considering each image as formed bDear Prof./Dr./Mr./Ms.

Thank you for sending this paper for possible publication in this WSEAS Conference.

Please, write down or print out or save the ID number of your paper that our server automatically gave to you (as a Web Page some minutes ago)y a number of bands, ranging from 1 (the entire tile as a band) to 310 (the biggest accuracy). For each number of spectral bands classification experiments were performed training a k-NN classifier ([7]), ranging k from 1 to 15. Also, experiments were done with self-organizing maps ([8]) for 310 spectral bands, training networks of 16, 25,49 and 64 nodes, and a number of iterations ranging from 50 to 300.

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5 Results

In figure 6 we show the result using a k-NN classifier with $k = \{1, 3\}$ and up to 30 spectral bands, result with more than 30 band do not vary. In table 1 best results for each type of tile, depending on k are shown, in case of draw of two or more groups of bands, we kept the smallest number of band. A success rate of 0.79 is obtained for the *Blue Countryside* type with 9 spectral bands, a success rate of 0.91 is obtained for the *Santiago's Way* type with 3 bands, and a success rate of 0.67 is obtained for the *Mediterranean Green* type with 5 bands. Increasing the number of band does not necessarily improve results.

We used principal component analysis (PCA, ([7]) when the number of bands was bigger than 3 in order to keep the number of features small. We reduced data dimensionality to 2 and 3 dimensions, and then used these reduced features to feed the k-Nearest Neighbour classifier. Previous results were not improved.

In table 2, we show results for self-organizing maps. These results do not improve those obtained with k-NN classifiers. We used 310 bands in these experiments. For each type of tiles there are two rows, one with the training iterations of the network and the other one with the recognition percentage. On the left, the number of nodes of the network. For each network size, the number of iterations with the best results is shown.

In tables 3, 4 and 5 we present the confusion tables for $k = \{1, 3\}$. In this table the quantity of tiles that were classified as belonging to each class are shown. Analysing the results we see that we can easily distinguish between the class with a bigger colour shade grading difference and the other two. For class *Mediterranean Green* we did not achieve these results because we were provided only with classes whose colour shade grading were very near one to each other. In order to correctly classify these classes more feature or more sample should be obtained to improve the classifier results.

k	Blue Count.		Medit. Green		Sant. Way	
	N. bands	*% Rec.*	*N. bands*	*% Rec.*	*N. bands*	*% Rec.*
1	9	79%	5	68%	2	85%
3	3	77%	3	65%	3	91%

Table 1: Results obtained by the k-NN classifier with different values of k and different number of spectral bands for each tile type.

Number of nodes	Blue Count.		Med. Green		Sant. Way	
	Iter.	*% Rec.*	*Iter.*	*% Rec.*	*Iter.*	*% Rec.*
16	200	68.7%	300	40.8%	250	81.1%
25	300	71.6%	250	45.4%	50	89.0%
49	200	67.4%	250	43.7%	150	92.2%
64	300	72.27%	300	41.7%	100	93.7%

Table 2: Results obtained by the self-organizing map for the tile type *Blue Countryside*, *Mediterranean Green* and *Santiago's Way*.

6 Conclusion

We have developed and calibrated a system to capture hyper-spectral images. We have captured images of tiles and we have extracted features from the

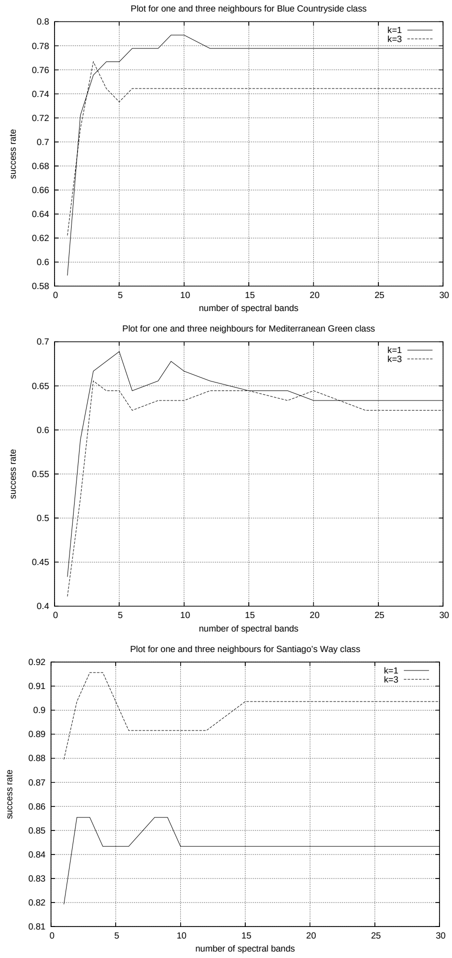

Figure 6: Plots for one and three neighbours for Blue Countryside, Mediterranean Green and Santiago's Way tiles.

$k = 1$	MedGre1	MedGre2	MedGre3
MedGre1	15	4	9
MedGre2	8	19	8
MedGre3	7	7	13
$k = 3$	Med1	Med2	Med3
MedGre1	18	2	7
MedGre2	6	24	6
MedGre3	6	4	17

Table 3: Confusion table for *Mediterranean Green*.

$k = 1$	Camp408	Camp409	CAmp425
Camp408	23	10	0
Camp409	7	19	1
Camp425	0	1	29
$k = 3$	Camp408	Camp409	CAmp425
Camp408	22	11	0
Camp409	8	18	1
Camp425	0	1	29

Table 4: Confusion table for *Blue Countryside*.

$k = 1$	Camino22	Camino24	Camino25
Camino22	28	0	2
Camino24	0	24	2
Camino25	0	3	24
$k = 3$	Camino22	Camino24	Camino25
Camino22	28	0	2
Camino24	0	24	2
Camino25	0	3	24

Table 5: Confusion table for *Santiago's Way*.

hyper-spectral bands to represent them. These features have been used to classify the tiles depending on their colour shade grading. k-NN classifiers and self-organizing maps have been used.

From the obtained results we can confirm that hyper-spectral images can obtain better results in colour shade grading classification than gray images, that is, when the number of bands is 1. Experiments show that, although a large number of spectral bands is not necessary, a number of bands bigger than 3 is often desirable. This fact makes us think that multi-spectral images will obtain better results than RGB colour images, where the number of spectral band considered is only 3.

From the confusion tables (see tables 3, 4 and 5), we think this is a good method to distinguish tiles depending on their colour shade grading, in the case that their colour shade gradings are far from each other. In the case they are close, maybe we would need a more accurate capture system or more elaborate features.

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