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# Color-Separation Framework for Ceramic-Tiles based on Few Labeled Data by HSV and SVM

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**Abstract:** The color-separation of ceramic-tiles is still dominated by human eye discrimination in actual production. According to the actual production, this paper proposes a ceramic-tile color-separation framework based on few labeled data training, which can realize the color-separation of ceramic-tiles with complex patterns. Firstly, the image with ceramic-tile only is obtained by image pre-processing, then the features are extracted by histogram statistics under HSV color space in sub-regions, and finally the support vector machine model is trained to obtain the classifier using the features extracted from a small number of training data and this classifier is applied to the automatic color-separation of ceramic-tiles. Experimental results of simulation and Practical application have proven the effectiveness of the proposed method.

## 1. Introduction

The ceramic-tile color difference (CTCD) is one of the important problems in ceramic-tile production. Ceramic-tile color different is caused by the existence of a large number of mineral raw materials containing different elements in the ceramic-tile formula, ceramic-tile is fired from these mineral raw materials, these minerals in different temperatures and environments, will show color difference (Cd), the formation of chromatic aberration. The color difference problem of ceramic-tile can not be eliminated, Because the raw material of ceramic-tile can not be kept constant.

At present, the color difference classification of ceramic-tile is still based on human eye recognition in the actual production, and only the people who are sensitive to color differences can quickly recognize the color difference of ceramic-tile. The link of manual discrimination of color difference is set up on the production line. The color-separation workers compare the color difference with naked eyes and need to put the suspected color difference tiles into the color room with uniform illumination to make color comparison with the sample tile. Therefore, designing an automatic identification system for CTCD is significant and necessary about production of ceramic tile fields.



In this paper, we focus on the automatic identification system for CTCD based on machine vision and machine learning technology. Recently, deep-learning based methods has been successfully proven about object classifier, object recognition, etc. However, deep-learning based methods demand a large amount of training data with similar distribution, while the captured data of CTCD has some limits in this project. Firstly, there are lots of unlabel samples in a single ceramic-tile production line while less ceramic-tile samples are labeled. Secondly, the CTCD from one ceramic-tile production line is tiny difference while the samples from different ceramic-tile production line have huge difference, for instance, different textures and patterns. It is difficult for utilizing the samples from different ceramic-tile production lines to train the deep-learning model, as shown in Fig.1. The image(a) and image(b) are the same type but color different tile image from one ceramic-tile production line, and the image(c) and image(d) are the same type but color different tile image from another ceramic-tile production line.

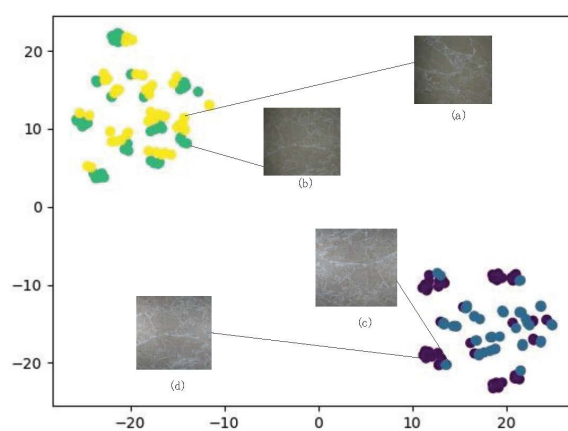


Fig1 Ceramic-tile color distribution map

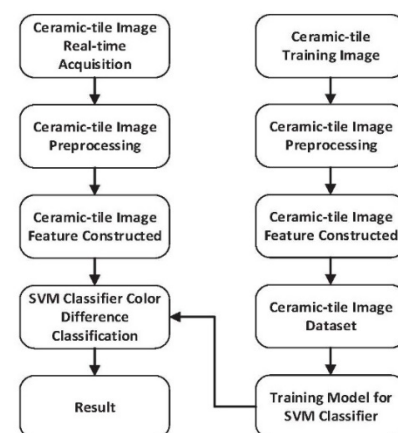


Fig2 Our color-separation framework

Therefore, we focus on the CTCD from single ceramic-tile production line, while assumed that we can obtain a bit labeled samples in each ceramic-tile production line. By this way, using few labeled data from a single production line, automatic color separation about CTCD can be realized. According to above introduction, we proposed a color-separation framework for CTCD under few labeled samples, as shown in Fig.2. Thanks to the proposed method for extracting color feature from ceramic-tile image, color separation of CTCD can be realized by using the SVM with few labeled samples.

The contributions of this paper are summarized as follows: (1) We construct a color-separation framework for CTCD under few labeled samples, which can automatically separate the color difference of ceramic-tile. (2) The color feature of ceramic-tile image can be extracted by the proposed method in HSV color space. (3) Extensive experiments demonstrate that the proposed framework performs a trade-off between model training time and color-separation accuracy in the actual production of ceramic-tile.

## 2. Related Work

With the development of machine vision and machine learning technology, there are many people proposed new approaches for color difference problem.

Yang Ling et al.[1] proposed a color difference measuring method which bases on the CIE 1976 -  $L^*a^*b^*$  space for ceramic-tiles. But the limiting condition is that the tiles have rather monotonic surface color with only a few character colors and the color difference formula can only measure two individual colors. Saeed Hosseinzadeh Hanzaei et al.[2] proposed a method which can automatically detect and classify the ceramic -tiles surface defects. They regard tile as a classification task and use support vector machine to complete this classification task. And Caihong Su et al.[3] brought out a new algorithm which is based on improved local hue accumulating histogram to automatically detect the defect of

ceramic-tile color. Xuri Tang et al.[4] proposed a method for color difference based on Histogram statistical values. They choose the H channel Histogram statistical value as feature vector to train classifier.

In this paper, we propose a color-separation framework for CTCD under few labeled samples based on HSV color space that can be used in actual production.

### 3. The proposed framework for CTCD

#### 3.1. Overview

To solve the existing problems, we construct a color-separation framework for CTCD under few labeled samples, which can automatically separate the color difference of ceramic-tile. First, we preprocess the tile images to obtain the image with ceramic-tile only. Second, we transform the ceramic-tile from the RGB model to the HSV model. Then, we divide the image into many sub regions and extract the feature of ceramic-tile by histogram statistics. Finally, the support vector machine classifier is trained using the features extracted from the training set consisting of a small number of images and the trained classifier is used to classify the tiles by color difference.

#### 3.2. Feature extraction of ceramic-tile

##### 3.2.1. Image preprocessing.

In a preset environment with uniform lighting, we capture the image of ceramic-tiles by a CCD camera that are used for model training and model testing. It is essential to perform image preprocessing before further processing. In this step, in order to obtain the image with ceramic-tile only, we detect the tiles corners to determine the position and posture of the tile. Then it is easy to correct the ceramic-tile image by affine transformation and obtain the image with ceramic-tile only.

##### 3.2.2. The HSV color model.

The initial image captured by the CCD camera is based on the RGB color model, and the RGB (Red, Green, Blue) color model is suitable for display colors, while the HSV (Hue, Saturation, Value) color model is more suitable for image processing and in line with the human eye's habit of observing colors[5]. The formula can be used to transform from RGB color space to HSV color space.

$$V = \max(R, G, B) \quad (1)$$

$$S = \begin{cases} V - \frac{\min(R, G, B)}{V} & \text{if } V \neq 0 \\ 0 & \text{if } V = 0 \end{cases} \quad (2)$$

$$H = \begin{cases} 60(G - B)/(V - \min(R, G, B)) & \text{if } V = R \\ 120 + 60(B - R)/(V - \min(R, G, B)) & \text{if } V = G \\ 240 + 60(R - G)/(V - \min(R, G, B)) & \text{if } V = B \end{cases} \quad (3)$$

##### 3.2.3. Constructed Color Feature of ceramic-tile.

The ceramic-tile images in our dataset have many complex textures, and we divided the ceramic-tile image into  $m \times m$  sub regions so that we can extract more texture detail features. For each sub regions, histogram statistics were performed on the channels of Hue, Saturation and Value. For Hue channel, we can extract feature vector  $f_H$  which could be normalized to size of  $1 \times 255$ ; For Saturation and Value channel, the feature vector  $f_S$  and  $f_V$  which could be extract as size of  $1 \times 255$  directly. The feature  $F_n^T = \{f_{Hn}, f_{Sn}, f_{Vn}\}$  of a sub regions could be obtain. Finally, the features corresponding to each sub regions are integrated to extract the image feature  $F^T = \{F_1, F_3, F_3 \dots F_{m^2-1}, F_{m^2}\}$ . The size of feature vector  $F^T$  is  $m^2 \times 3 \times 255$ . The size of the feature vector  $F^T$  depends on the number of sub-

regions divided, and the feature vector can be compressed according to the actual needs using methods such as principal component analysis[6] to help reduce the size of the trained model.

### 3.3. Training Model for CTCD

In our application scenario, for our extracted features, the support vector machine classifier can be trained with fewer training samples to obtain a classifier with good classification performance. For the training dataset  $T = \{(x_1, y_1), (x_2, y_2), \dots, (x_i, y_i), \dots, (x_q, y_q)\}$ , where  $x_i$  is the feature vector,  $y_i$  is the label information,  $q$  is the total number of label. Support vector machines were first proposed by Cortes and Vapnik in 1995, and have shown many unique advantages in solving small-sample nonlinear and high-dimensional pattern recognition[7]. The principle of SVM is to use the separation hyperplane as a linear function to separate the training data to solve the nonlinear classification problem. The optimization function of SVM to find the optimal classification surface (maximization generalization function) is defined as the optimization function for SVM to find the optimal classification surface is defined as follows:

$$Q(a) = \sum_{i=1}^n a_i - \frac{1}{2} \sum_{i,j=1}^n a_i a_j y_i y_j (x_i \cdot x_j) \quad (4)$$

Where  $x$  is the sample,  $n$  is the number of samples,  $y$  is the category number, and  $a_i$  ( $i = 1, 2, \dots, n$ ) is the Lagrange coefficient for function optimization, and the corresponding discriminant function is

$$D(x) = \text{sgn} \left( \sum_{i=1}^n a_i^* y_i (x_i \cdot x_j) + b^* \right) \quad (5)$$

## 4. Experimental results

We conducted three different experiments on our experimental platform to verify the effectiveness, stability and superiority of our feature extraction method. In the first experiment we tried to use statistical histograms of different channels with different number of training datasets. In the second experiment we tried color feature extraction in sub-regions and partial regions.

### 4.1. Simulation

#### 4.1.1. Experiment environment.

The experiment was conducted on a computer with Intel(R) Core(TM) i5-8500 six-core CPU and NVIDIA GeForce GTX 1050, using JetBrains Pycharm2019.2. The ceramic-tile images dataset include two kinds of different colors ceramic-tile which is difficult to distinguish with the people eye. The ceramic-tiles of these two colors numbers have similar but different complex patterns, 200 ceramic-tiles of each color number, a total of 400 ceramic-tile images. In order to verify that the features we designed can effectively reflect the color features of patterned ceramic-tiles, we conducted several experiments on the basis of our ceramic-tile dataset

#### 4.1.2. Single-channel and multi-channel feature extraction.

Among 400 ceramic-tile images of two color numbers, we randomly selected 112 of them as the training set for classifier training, and 288 of them were used as the test set. In order to simulate the condition that only a small number of images can be used for training in actual production, we set different training set ratios to train the classifier and observe the classification performance of the classifier. We performed histogram statistics on the Hue, Saturation, and Value channels respectively, and performed single-channel feature extraction and three-channel feature extraction to verify the feasibility of our feature extraction method.

TABLE1: The results of feature extracting by only one channel and both three channel. And the kernel function of the polynomial is selected as the kernel function of support vector machine classifier, setting the penalty parameter C to one and the dimension of the expression polynomial to three.

Total of train image	Total of test image	accuracy			
		h	s	v	Our model
12	288	59.71%	84.4%	85.66%	74.47%
22	288	88%	96%	93.7%	95.8%
34	288	94%	97%	94%	97.2%
45	288	96.50%	95.10%	94.05%	96.85%
57	288	98.25%	97.90%	95.10%	98.95%
68	288	98.60%	98.25%	96.85%	98.60%
79	288	99.30%	98.60%	97.90%	98.95%
91	288	99.30%	98.95%	98.60%	99.30%
102	288	99.30%	98.95%	98.25%	98.95%

In our preset experimental environment, the average time required for single-channel feature extraction for each image is 0.385 seconds, which for three-channel feature extraction is 0.41 seconds. The experimental results prove that the color feature extraction method we proposed for ceramic-tiles with complex patterns is effective. The classifier can complete the classification of ceramic-tiles with similar colors under the training of a small amount of data, and it can be faster under the three-channel color feature training. In actual production, different feature extraction methods can be selected according to different production requirements.

#### 4.1.3. Sub-regional and non-regional.

We designed a comparative experiment to verify that our proposed sub-region feature extraction method has better results for color feature extraction of ceramic-tiles with complex patterns compared to the method without sub-regions dividing. The experimental result show that our feature extraction method has better feature extraction performance compared to feature extraction without chunking when more than 50 training images are available to train the classifier.

TABLE2: The result of the experiment that feature extraction with sub-regions dividing and without sub-regions dividing. And the kernel function and parameter of support vector machine for this experiment are the same as for the first experiment.

Total of train image	Total of test image	accuracy	
		without dividing sub-regions	Our model
12	288	94.75%	74.47%
22	288	96.5%	95.8%
34	288	96.5%	97.2%
45	288	96.50%	96.85%
57	288	97.50%	98.95%
68	288	97.50%	98.60%
79	288	97.50%	98.95%
91	288	97.50%	99.30%
102	288	97.9%	98.95%

#### 4.2. Practical application

According to the actual production requirements, we built a platform for ceramic-tile image acquisition. It includes a conveyor belt, a camera and lights to meet the needs of image acquisition and automatic separation of ceramic-tile color difference. In the practical application, after ensuring that the production line is started, firstly, we collect and label a small portion of color difference tiles to constitute the training data set; then, we perform image feature extraction and model training using the method proposed above; finally, we use the trained model to perform real-time color grading of the tiles in the generated line.

In addition, we designed a tile color separation software, as shown in Fig.3. This software can discriminate the collected tile images in real time and count the number of tiles of corresponding colors, which provides corresponding data support for the next step of tile grading and color separation.

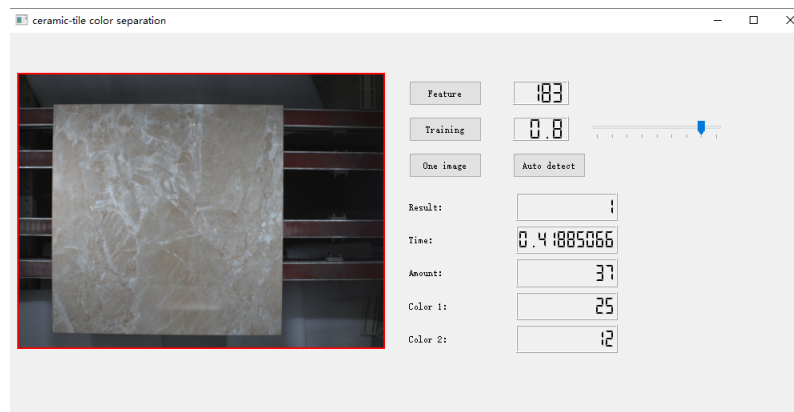


Fig3 Our ceramic-tile color separation software

## 5. Conclusion

In this paper, we discuss the current status of ceramic-tile color-separation and the difficulties encountered in automatic ceramic-tile color-separation in actual production. We propose a ceramic-tile color-separation method based on few training samples, build a ceramic-tile collection platform, compare our feature extraction method with other methods, and experimentally prove that our method has better performance in the premise of practical production.

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