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# Marble Slabs Quality Classification System using Texture Recognition and Neural Networks Methodology

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**Abstract.** This article describes the use of an LVQ neural network for the clustering and classification of marble slabs according to their texture. The method used for the recognition of textures is based on the Sum and Difference Histograms, a faster version of the Co-occurrence Matrices. The input of the network is a vector of statistical parameters which characterize the pattern shown to the net, and the desired output is the class to which the pattern belongs (supervised learning). The samples chosen for testing the algorithms have been marble slabs of type “Crema Marfil Sierra de la Puerta”. The neural network has been implemented using MATLAB.

## 1 Introduction

Marble products have their principal application in covering surfaces for decoration, using small pieces of marble (slabs). The requirements needed for quality do not refer only to technological parameters (such as endurance or polish rate), but to aesthetic appearances, such as color homogeneity, texture, or spots. However, as a natural material, marble is heavily heterogeneous and therefore, there are not two marble slabs alike.

These requirements make necessary the classification of marble slabs into homogeneous classes or groups. But, it is not feasible to intervene in the extraction of the raw material, and so, the classification process is carried out at the end of the production line, where human experts evaluate the product according to visual parameters. This kind of classification presents two major problems: (a) the subjective criteria of the operator (even different operators), and (b) the visual fatigue after a period of time. This generates poor results from an aesthetic point of view.

To solve this two problems, we present in this article an automatic system for the inspection and classification of marble slabs in production line according to their texture, by using artificial color vision and neural networks. In it, a vector

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of texture features is extracted from each pattern (slab), and then classified into the correct class with an LVQ neural network.

# 2 System Overview

In our system, the marble slabs in the production line pass under a CCD color camera (located perpendicular to the slab plane), which obtains the color image for the entire slab. The camera is placed in a closed box with a specific illumination system to avoid influences of external lighting and thus assure that the slab does not receive any reflects from other materials. In this way, the image obtained does not need any subsequent treatment to overcome the effects of irregular light condition. The color approach used in our system, instead of monochrome, is necessary since the slabs present different tones. Once the image background has been removed, the remaining image presents 256 gray levels for each one of the three color channels.

After the image has been captured, it is transmitted to the computer and transformed from RGB-color space to IHS-color space. The algorithm was also tested with other color spaces (XYZ, DIF (using the differences between components, R-B, R-G and G-B), UVW, YIQ and KL (Karhunen-Loève transform)). Then a texture recognition algorithm called *Sum and Difference Histograms* (SDH) [1] is used to extract texture-dependant features of the slab image. This method extracts a vector of statistical parameters as texture features for each pattern. Once the network is trained, the feature vector is presented at the input of the net, and the output will give the class to where that pattern belongs to.

## 2.1 Characteristics of a Marble Slab

The proposed system has been designed to work with any type of marble slabs, but for testing the classification algorithm we have chosen slabs of the type "Crema Marfil Sierra de la Puerta", which is the type of major production in the Region of Murcia. This kind of slabs presents small gradient of colors and hardly-distinguishable veins in the surface. As a natural product, in a marble slab we can not find any repeated structures. For this reason, we have used statistical methods to extract texture features, instead of structural methods, which are not of application here.

At this point, we have to remark that the difficulty of this research is that all the slabs of the type "Crema Marfil Sierra de la Puerta" present a very similar texture (described above), and that they must be classified into subclasses. This approach is very different from the classical texture segmentation problem, where the aim is to distinguish, for a particular image, zones with different textures.

# 3 Feature Extraction

The approach used in this article to classify marble slabs into groups has been to analyze their texture. When the human expert examines the slab, the classi-

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fication that he or she makes is based on the visual appearance of color tone and veins distribution of the slab. For this reason, it is necessary to use a method capable of analyzing the texture of the image. Previous approaches [2] considering only the first-order histogram (color tone) achieved unsatisfactory results.

The SDH algorithm implemented in our system for texture recognition is based on the Spatial Grey Level Dependence Method or Co-occurrence Matrices [3, 4, 5]. Because each one of the three channels of the color image presents 256 gray levels, the requirements of memory-storage and time-consumption with [3] are huge (processing of three $256 \times 256$-matrices). The SDH method offers an alternative to the usual co-occurrence matrices used for texture analysis. Experimental results [1] indicate that SDH are as powerful as co-occurrence matrices for texture discrimination, with the advantage of a decrease of computation time and memory storage.

This algorithm is as follows: let be a discrete texture image defined on a $K \times L$ rectangular grid, and denoted by $\{y_{k,l}\}$, where $\{k = 1, \dots, K;\ l = 1, \dots, L\}$. Let $G = \{1, 2, \dots, N_g\}$ be the set of the $N_g$ quantized grey levels for each one of the three channels of the color image. Let us consider two picture elements separated by the vector distance $(d_1, d_2) \in D$ (where $D$ specifies the texture region to analyze):

$$\begin{cases} y_1 = y_{k,l} \\ y_2 = y_{k+d_1,l+d_2} \end{cases} \tag{1}$$

Both the sum and difference vectors contain $s_{k,l}$ and $d_{k,l}$ elements respectively, defined as follows:

$$\begin{cases} s_{k,l} = y_{k,l} + y_{k+d_1,l+d_2} \\ d_{k,l} = y_{k,l} - y_{k+d_1,l+d_2} \end{cases} \tag{2}$$

The SDH uses two normalized $[2N_g - 1]$-dimensional vectors, formed each one with $P_s(i)$ and $P_d(j)$ elements, defined as follows:

$$\begin{array}{ll} P_s(i) = h_s(i)/N; & (i = 2, \dots, 2N_g) \\ P_d(j) = h_d(j)/N; & (j = -N_g + 1, \dots, N_g - 1) \end{array} \tag{3}$$

$$\text{with} \begin{cases} h_s(i; d_1, d_2) = h_s(i) = \mathrm{Card}\{(k,l) \in D,\ s_{k,l} = i\} \\ h_d(j; d_1, d_2) = h_d(j) = \mathrm{Card}\{(k,l) \in D,\ d_{k,l} = j\} \\ N = \mathrm{Card}\{D\} = \sum_i h_s(i) = \sum_j h_d(j) \end{cases} \tag{4}$$

Thus, for each color image (three color channels) there are six 511-dimensional vectors: $P_{s1}$, $P_{d1}$, $P_{s2}$, $P_{d2}$, $P_{s3}$ and $P_{d3}$. In our case, $N_g = 256$.

Once the six histogram vectors have been calculated, we extract statistical information from them, in order to reduce the dimensionality of the set of characteristics used for describing the texture. Table 1 gives the list of features [1] used in our case.

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| FEATURE | FORMULA |
|---|---|
| mean | $\mu = \frac{1}{2}\sum_i i\, P_s(i)$ |
| energy | $\sum_i P_s(i)^2 \sum_j P_d(j)^2$ |
| entropy | $-\sum_i P_s(i)\log\{P_s(i)\} - \sum_j P_d(j)\log\{P_d(j)\}$ |
| contrast | $\sum_j j^2 P_d(j)$ |
| homogeneity | $\sum_j \frac{1}{1+j^2} P_d(j)$ |

Table 1: Statistical features used for classification with SDH.

# 4 Classifier

The LVQ Network [6] is a method for training competitive layers in a supervised manner. It learns to classify input vectors into target classes chosen by the user. An LVQ network consists of two weight layers. The first layer is a competitive layer (CL), which learns to classify input vectors forming subclasses, and the second layer transforms the competitive layer's subclasses into target classifications defined by the user (target classes).

The learning rule assures that competitive neurons move towards input vectors which belong to their class, and away from input vectors that belong to other classes. So, the advantages that this network presents in relation to the unsupervised algorithm are two: (1) the target classes are chosen by the user, and (2) the convergence of the algorithm is faster.

The input to the network is a 15-elements vector: for each color channel we have used the mean, energy, entropy, contrast and homogeneity features. The output of the network is a binary-type one: the winning neuron will give '1', and '0' for the others. So, the designed network presents 15 neurons in the input layer, a specific number of neurons in the CL (see Sect.5), and 10 neurons in the output layer (10 different classes were considered in our application).

# 5 Experimental Results

The classification software was executed on a 166MHz PC computer. The LVQ network was implemented using the Neural Network Toolbox of MATLAB [7], and the image processing and feature extraction software were developed in C++ language under MSDOS.

For the LVQ network, the design parameters were the following: 50 neurons in the CL, 5000 epochs for training, and 0.05 for learning rate. The number of neurons in the CL is larger than the number of neurons in the output layer to allow assigning the neurons in the CL according to the importance of each class: the more important the class, the greater the number of neurons assigned to this class.

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Seven color spaces were tested for classification: RGB, XYZ, IHS, DIF, UVW, YIQ and KL. For each one, three training series were made, according to the values of $(d_1, d_2)$ (nearest neighbours directions of a pixel): (1) using the mean of the statistical parameters for the neighbours in the directions $(1, 0)$ and $(0, 1)$, (2) the same for $(1, 1)$ and $(1, -1)$, and (3) using the mean of the statistical parameters for the neighbours in the directions $(1, 0)$, $(0, 1)$, $(1, 1)$ and $(1, -1)$.

For each series, 5 training sets were made, each one containing different patterns: for each class, all but one patterns were used for training and one for testing (leaving-one-out method), rotating the patterns used for testing in each training, so that, for the 5 trainings, all the patterns were used as both training patterns and test patterns, but never simultaneously. Therefore, 105 trainings were made for all color spaces. A total of 44 patterns were used for training and testing the system.

| Color Space | Directions of the nearest neighbours | | | Mean |
|---|---|---|---|---|
| | (1,0),(0,1) | (1,1),(1-1) | (1,0),(0,1),(1,1),(1,-1) | |
| RGB | 85.4 | 89.1 | 87.3 | 87.3 |
| XYZ | 85.4 | 89.1 | 87.3 | 87.3 |
| IHS | 92.7 | 92.7 | 87.3 | 90.9 |
| DIF | 83.6 | 83.6 | 80.0 | 82.4 |
| UVW | 80.0 | 81.8 | 83.6 | 81.8 |
| YIQ | 85.4 | 85.4 | 74.5 | 81.8 |
| KL | 89.1 | 85.4 | 83.6 | 86.0 |
| Mean | 85.9 | 86.7 | 83.4 | |

Table 2: Results obtained for the classification, in %.

The results (number of correct pattern classified, in %) are shown in Table 2. As it can be seen, the best results have been achieved with the IHS color space and for the mean of the directions $[(1, 1), (1, -1)]$, with 92.7% of patterns classified correctly. Other good results correspond to the RGB, XYZ and KL color spaces.

## 6 Conclusion

By using the automatic inspection system proposed, we may reduce costs and increase the quality control in the classification of marble slabs in production line, with a significantly higher performance when it is compared to the traditional classification system. The algorithms used for feature extraction and classification perform high-speed processing and low-memory storage requirements. The result is that marble slabs are classified according to their color texture features, thus achieving an objective, uniform-through-time classification, which derives in an homogeneous classification criterion.

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The employment of a neural network improves the classification results rather than any other classic methods. In particular, the use of the LVQ network allows to classify non-linear regions by associating several subclasses to one target class. At the same time, the generalization ability of neural networks performs a better classification.

The processing time to make a decision is not very critical in our system. The software implemented is faster enough to perform the classification on-line. However, once the system works correctly, the final goal in this project is to implement the texture-feature extraction system and the neural network classifier on Very Large Scale Integration circuits to make the system run in real-time in production line and with low-cost requirements.

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