INTEGRATED APPROACH FOR DEFECT DETECTION IN CERAMIC TILES

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ABSTRACT

Quality control is an important issue in the ceramic tile industry. Price of ceramic tiles also depends on purity of texture, accuracy of color, shape etc. Considering this criteria, an integrated defect detection and classification technique has been proposed which plays an important role in ceramic tiles industries to detect the defects and to control the quality of ceramic tiles.GLCM extracts the texture features and these features together with color features are used for analysis in classifiers such as SVM, KNN and Bayesian. Experimental results illustrated that every classifier gives highest accuracy with HSV.

Keywords

feature extraction, GLCM, SVM, KNN and Bayesian.

1.INTRODUCTION

Every day, we capture huge amount of images which are very difficult to maintain manually within a certain period of time. So, the concept and application of the digital imaging grows rapidly. Digital image processing is used to extract various features from images. This is done by computers automatically without or with little human intervention. One of the most important operations on digital image is to identify and classify various kinds of defects. Ceramic tiles industry sector is now a very important sector for manufacturing the ceramic

tiles. All production phases are technically maintained until the final stage of the manufacturing process appeared. Sometimes checking is needed for the ceramic tiles if they are able to serve customer needs, i.e. to find defected tiles. So, it is an important task to categorize the ceramic tiles after production based on surface defects. The manual method of defects inspection is labor intensive, slow and subjective. Although automated sorting and packing lines have been in existence for a number of years, the complexity of inspecting tiles for damage and selecting them against the criteria of a manufacturer i.e. automated defected tiles inspection have not been possible. Again ,human judgment is influenced by expectations and prior knowledge. In many detection tasks for example, edge detection, there is a gradual transition from presence to absence. On the other hand, in "obvious" cases, most naive observers agree that the defect is there, even when they cannot identify the structure. Such a monitoring task is of course tedious, subjective and expensive. For all these reason no one can deny the significance of automated defect detection and classification system.

The objective of our research is to propose an efficient defect detection and classification technique which will be able to find out image defects at a high rate within a very short time.

2.EXISTING METHODS FOR DEFECT DETECTION

In the previous years, some proposed defect detection methods have been proposed to find out the image defects. But they have some limitations that can be described briefly as follows:

In [5], H. Elbehiery et al. presented some techniques to detect the defects in the ceramic tiles. They divided their method into two parts. In the first part, Existing method consisted with the captured images of tiles as input. As the output, they showed the intensity adjusted or histogram equalized image. After that, they used the output of first part as input for the second part. In the second part of their algorithm, different individual complementary image processing operations have been used in order to identify various kinds of defects. Prevailing task emphasized on the human visual inspection of the defects in the industry. But their system is not automated which is very much necessary in the manufacturing process. Again their proposed method is operation redundant because they apply their second part on every test image to identify various types of defects. Moreover, their proposed method is very time consuming.

In [3], C. Boukouvalas et al. concerned about the problem of automatic inspection of ceramic tiles using computer vision. They applied techniques for pinhole and crack detectors for plane tiles based on a set of separable line filters, through textured tile crack detector based on the wigner distribution and a novel conjoint spatial-spatial frequency representation of texture, to a color texture tile defect detection algorithm which looks for abnormalities both in chromatic and structural properties of texture tiles. But, using separate filtering techniques for different types of defects is not a good idea at all, because in such case high computational time is a major issue for applying a large number of operations. Again, their procedure is an automated visual inspection system where they only show the defects making them clear to detect the defects found on image.

3.PROPOSED METHODOLOGY

3.1.Data pre-processing

Ceramic tile images contain speckle noise and to remove the noise various filters are used.The basic steps of the proposed methodology are shown in fig.

3.2.Image enhancement using filters

Unsharp filter is a contrast enhancement filter.An unsharp filter is an operator used to sharpen images. The name comes from a publishing industry process in which an image is sharpened by subtracting a blurred (unsharp) version of the image from itself.

3.3.Harris Corner Detection Method

The Harris corner detection method avoids the explicit computation of the eigenvalues of the sum of squared differences matrix by solving for the following corner metric matrix, *R*:

$$R = AB - C^2 - k(A+B)^2$$

Where,

$$A = (I_x)^2 \otimes w$$

$$B = (I_y)^2 \otimes w$$

$$C = (I_x I_y)^2 \otimes w$$

where I_x and I_y are the gradients of the input image, *I*, in the *x* and *y* direction, respectively. The $\otimes$ symbol denotes a convolution operation. The variable *k* corresponds to the sensitivity factor. You can specify its value using the **Sensitivity factor (0<k<0.25)** parameter.

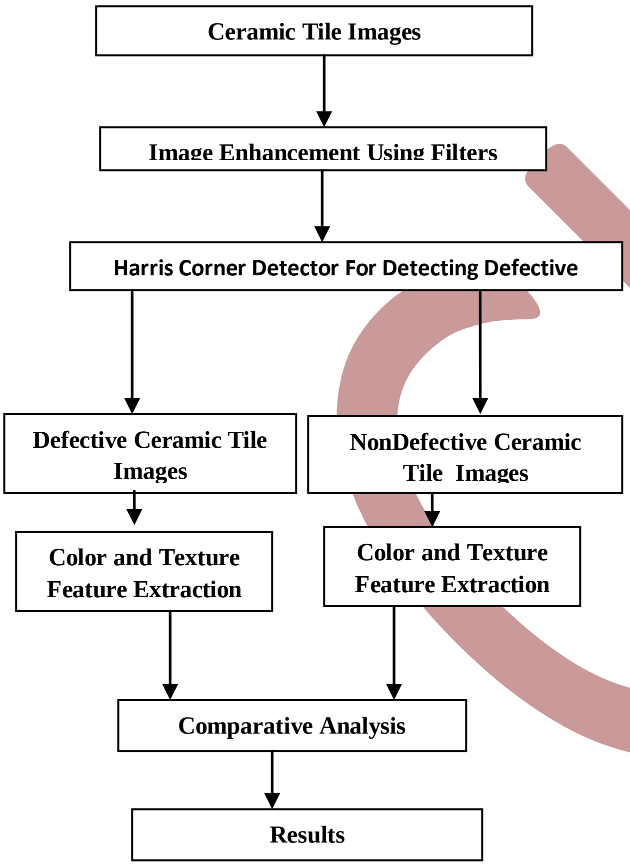

Figure 1.Flowchart of proposed methodology

3.4.TEXTURE ANALYSIS AND FEATURE EXTRACTION

Use Gray-co-matrix and extract features from that. GLCM calculates the probability of a pixel with the gray-level value *i* occurring in a specific spatial relationship to pixel with the value *j*. The number of gray levels in the image determines the size of the GLCM .Although there is a function in Matlab Image Processing toolbox that computes parameters Contrast, Correlation, Energy, solidity and Homogeneity, the paper by Haralick suggests the tabulation form where few more parameters that are also computed here [18].

There are following feature extraction equations:

Correlation: $\dfrac{\sum_{i=0}^{L} \sum_{j=0}^{L} (ij)P(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y}$

Difference-Entropy: $\sum_{i=0}^{L} P_{x-y}(i)\log(P_{x-y}(i))$

Difference-Variance: $\sum_{i=0}^{L} (i - \sum_{j=0}^{L} jP_{x-y}(j))^2 P_{x-y}(i)$

Sum –average: $\sum_{i=2}^{2L} iP_{x+y}(i)$

Sum-Entropy: $-\sum_{i=2}^{2L} P_{x+y}(i)\log(P_{x+y}(i))$

Sum-of-Squares: $\sum_{i=0}^{L} \sum_{i=0}^{L} (i-\mu)^2 P(i,j)$

Sum-Variance: $\sum_{i=0}^{2L} (i - F5)^2 P_{x+y}(i)$

Contrast: $\sum_{n=0}^{L} n^2 \left(\begin{array}{l} \sum_{i=0}^{L} \sum_{j=0}^{L} P(i,j) \\ |i-j| = n \end{array} \right)$

Energy: $\sum_{i=0}^{L} \sum_{i=0}^{L} (P(i,j))^2$

Entropy: $-\sum_{i=0}^{L} \sum_{j=0}^{L} P(i,j)\log P(i,j)$

Local-Homogeneity: $\sum_{i=0}^{L} \sum_{j=0}^{L} \dfrac{P(i,j)}{1+(i-f)^2}$

Cluster Shade:

$$\sum_{i=0}^{L} \sum_{j=0}^{L} (i - E_x + j - E_y)^3 P(i,f)$$

Cluster-Prominence:

$$\sum_{i=0}^{L} \sum_{j=0}^{L} (i - E_x + j - E_y)^4 P(i,f)$$

3.5.COLORSPACE ANALYSIS AND FEATURE EXTRACTION

Color is the most vital visual feature for humans. By color representation we mean the overall color of image content when used as a “global” feature. The non-uniformity of RGB color space is eliminated by HSV and YCbCr color space before extracting the features[16].

3.5.1 RGB to HSV color model conversion

The HSV stands for the Hue, Saturation and Value. The value represents intensity of a color, which is decoupled from the color information in the represented image. The hue and saturation components are intimately related to the way human eye perceives. The transformation equations for RGB to HSV color model conversion is given below

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

$$S=\frac{V-\min(R,G,B)}{V}$$

$$H=\frac{G-B}{6S},\ if\ V=R$$

$$H=\frac{1}{3}+\frac{B-R}{6S},if\ V=G$$

$$H=\frac{2}{3}+\frac{R-G}{S},if\ V=B$$

3.5.2 RGB to YCbCr color model conversion

Y is the luminance component and Cb and Cr are the blue-difference and red-difference chroma components. The conversion equations from RGB to YCbCr color model is given below:

$$[Y\ Cb\ Cr]=\begin{bmatrix}65.481 & 128.553 & 24.966\\ -37.797 & -74.203 & 112.00\\ 112.00 & -93.786 & -18.214\end{bmatrix}\begin{bmatrix}R\\ G\\ B\end{bmatrix}+[16\ \ 128\ \ 128]$$

3.6.CLASSIFIERS

Following types of classification methods are discussed:

3.6.1 Support vector machine

Support vector machine (SVM) are basically linear classifiers. SVM is widely accepted classifier, considered very effective for pattern recognition, machine learning and bioinformatics (protein classification and cancer classification) [12]. In SVM, a separator hyperplane between two classes is chosen to minimize the functional gap between two classes, the training data on the marginal sides of this optimal hyperplane called support vector. The Learning process is the determination of those support vectors. For non linearly- separable data, SVM maps the input vector from input space to some normally higher dimension feature space given by kernel function. The kernel function is an important step is successful design of a SVM in specific classification task.

3.6.2 K-nearest neighbour

The *k*-nearest neighbor's algorithm (*k*-NN) is a method for classifying objects based on closest training examples in the feature space. KNN is a type of instance-based learning, or lazy learning where the function is only approximated locally and all computation is deferred until classification. The *k*-nearest neighbor algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its *k* nearest neighbors (*k* is a positive integer, typically small). If $k = 1$, then the object is simply assigned to the class of its nearest neighbor [12].

3.6.3 Bayesian classifier

Bayesian classifiers have been used in many areas of medicine. For example, to built a Bayesian classifier to predict breast cancer. And also given that sonographic features predictive of malignancy have been extensively studied and the sensitivity and specificity of these features for malignancy are readily available [12]. In simple terms, a naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature, given the class variable.

3.7. PERFORMANCE MEASURES

Quantitative measurement of classification accuracy is calculated in term of true positive (TP), true negative (TN), false positive (FP), false negative (FN) with respect to the ground truth. Performance metrics calculation:

- PPV=*TPTP+FP*
- NPV=*TNTN+FN*
- Specificity SP =*TNTN+FP*
- Sensitivity SE=*TPTP+FN*
- Accuracy = 100*((TP+TN)/n)

4. RESULT

Total no. of 12images was used. Where 6 images were defective and 6 images were nondefective. The classifiers are given combined datasheet of texture and color features of defective and nondefective tiles with different colorspace.It has been concluded that HSV achieves highest accuracy among the other colorspaces used.The following features are calculated:

Table1.Accuracy comparison of classification methods using texture features with RGB

Selected features	Bayesian	KNN	SVM
TP	7	11	5
TN	8	3	11
FN	5	1	1
FP	4	9	7
PPV	0.73	0.55	0.42
NPV	0.69	0.75	0.92
Specificity	0.75	0.25	0.61
Sensitivity	0.67	0.92	0.83
Accuracy	**70.83**	**58.33**	**66.67**
GM	1.19	1.08	1.20

Table2.Accuracy comparison of classification methods using texture features with YCbCr

Selected features	Bayesian	KNN	SVM
TP	8	11	5
TN	9	3	9
FN	4	1	3
FP	3	9	7
PPV	0.73	0.55	0.42
NPV	0.69	0.75	0.75
Specificity	0.75	0.25	0.56
Sensitivity	0.67	0.92	0.63
Accuracy	**70.83**	**58.33**	**58.33**
GM	1.19	1.08	1.09

Table3.Accuracy comparison of classification methods using texture features with HSV

Selected features	Bayesian	KNN	SVM
TP	9	11	10
TN	8	6	7
FN	3	1	5
FP	4	6	2
PPV	0.69	0.65	0.83
NPV	0.73	0.86	0.58
Specificity	0.67	0.50	0.78
Sensitivity	0.75	0.92	0.67
Accuracy	**70.83**	**70.83**	**70.83**
GM	1.19	1.19	1.20

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