CLASSIFIER COMPARISON FOR DEFECT DETECTION IN CERAMIC TILES USING GLCM

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Abstract

The ceramic tile manufacturing process is completely automated with the exception of visual inspection of the product (sorting stage). There are a number of methods for the automatic detection of multifarious range of ceramic tile defects and automatic sorting of them. In these methods it is necessary a trade-off between sorting accuracy and the rate of computation. In this paper we propose a system that uses machine-vision techniques for sorting the ceramic tiles. We apply the GLCM for texture features extraction of ceramic tiles.As the classifier, we use Bayesian,KNN and SVM. We investigate the performance of all the classifiers and SVM achieves higher level of accuracy.

KEYWORDS

feature extraction, GLCM, SVM, KNN and Bayesian, machine vision.

1.INTRODUCTION

In the production chain of ceramic tiles there are numerous ways for going to wrong. Every failure directly reflects on the final ceramic tile. The fmal production phase is sorting of ceramic tiles. Purposes of this phase are rejecting defective parts such as physical defect and color shading. In most cases the last phase of sort tile in classes ofquality is based on human perception capability. Human resources as controllers in this phase are very unreliable. In this case an automatic system fully replaces human resource. The great majority of ceramic tile faults are surface defects, such as cracks, dry spots, pin hole, etc. therefore surface inspection is one of the most important quality control tasks to be automated. Nowadays digital image processing is used to extract various features from images. One of the most important operations on digital image is to identify and classify various kinds of defects for classification. Therefore automating of stage for inspection of the product quality and classification of them leads to using machined vision and image processing systems.

2.PROPOSED METHODOLOGY

2.1.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.

2.2.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.

2.3.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 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.

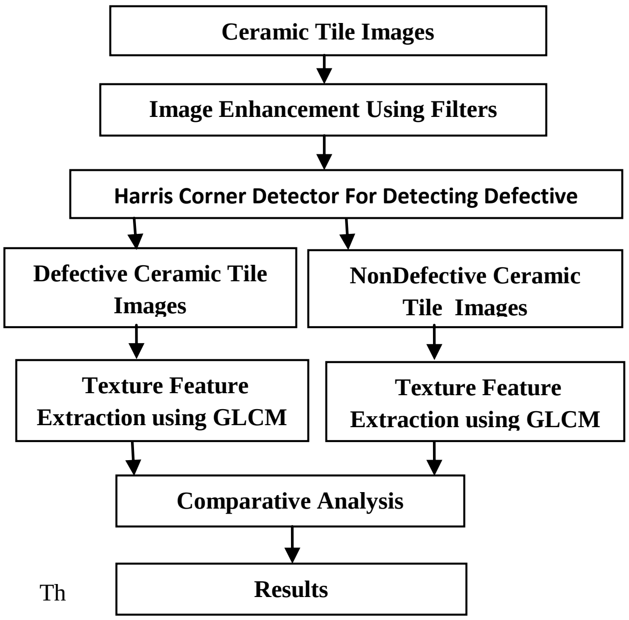

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Figure 1.Flowchart of proposed methodology

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

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

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

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

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

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

2.5.Classifiers

Following types of classification methods are discussed:

2.5.1 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.

2.5.2 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].

2.5.3 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.

2.6. Performance measure

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)

3. RESULT

Total no. of 12 images was used. Where, 6 images were defective and 6 images were nondefective. The classifiers are given combined datasheet of texture features of defective and nondefective tiles using GLCM.It has been concluded that SVM achieves highest accuracy among the other classifiers used used.The following features are calculated:

Table1.**Accuracy comparison of classification methods using texture features**

Selected features	Bayesian	KNN	SVM
TP	0	0	3
TN	6	4	5
FN	6	6	1
FP	0	2	3
PPV	Nan	0.00	0.50
NPV	0.50	0.40	0.83
Specificity	1.00	0.67	0.63
Sensitivity	0.00	0.00	0.75
Accuracy	**50.00**	**33.33**	**66.67**
GM	1.00	0.82	1.17

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