Visual Inspection of Ceramic Tiles Surfaces Using Statistical Features and LVQ of Artificial Neural Networks.

Ibrahim El-Henawy
Dept. of Computer Science, Faculty of Computer and Information Sciences, Zagazig University, Zagazig, Egypt,
Henawy2000@yahoo.com

Samir Elmougy
Dept. of Computer Science, College of Computer and Information Sciences, King Saud Univ., Riyadh 11543, Saudi Arabia,
mougy@ccis.ksu.edu.sa

Ahmed El-Azab
Dept. of Computer Science, Misr for Engineering and Technology(MET) Academy, Mansoura, Egypt,
ahmed.elazab@yahoo.com

Abstract: A product inspection is an important stage in the product manufacturing process before packing process. Visual inspection is an application of computer vision and image processing. Using Automatic Visual Inspection (AVI) in ceramic tile inspection gives more reliable, fast, robust, and less human intervention, increases processing stability, and improves overall production performance. Many approaches had been applied for this purpose starting from primitive pixel by pixel comparison to advanced techniques such as statistical, structural, and signal processing techniques. In this paper, we use statistical approach as a feature extraction approach for visual inspection of ceramic tiles surfaces defects with neural network classification techniques. Our results show that statistical techniques used for extracting ceramic tile features with LVQ neural networks classifiers give subtle results especially LBP and GLCM which give 96% and 90% of correct classification respectively.

Keywords:- Visual Inspection, neural networks, statistical approach, structural techniques, signal processing techniques, ceramic tiles.

1. Introduction

A product inspection is an important stage in product manufacturing process before packing process. It is applied to many types of products such products like wood [1], steel [2], textile [3], stone [4], plastic products [5] and ceramic tiles [6, 7]. All stages of ceramic tiles industry are done in automatic processes except the final stage of the manufacturing process where it is still performed manually to sort tiles into distinct categories or to reject those found with much defects and faults. This manual process may not give acceptable results because the human inspectors may vary in judgment according to tiredness, or changing in lighting conditions. Boukouvalas justified the commercial and safety benefits for using Automatic Visual Inspection (AVI) in ceramic tile inspection as follows [6]:

- Giving more robust and less costly inspection.
- Producing a significant reduction of human intervention in dusty and unhealthy environment.
- Saving time and efforts in manual inspection.
- Increasing the processing stability and improving overall production performance.

A typical visual inspection system held on production line shown in Figure (1) [7].

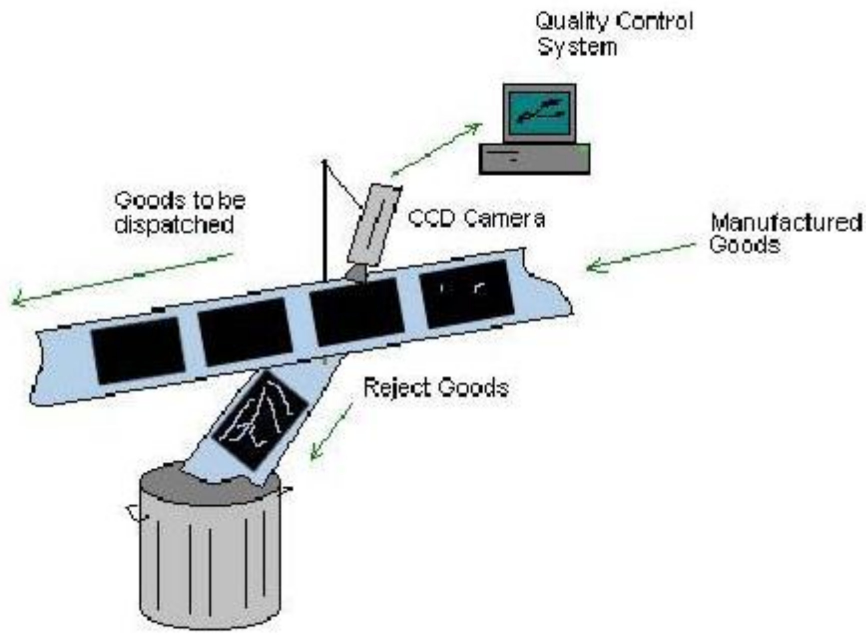

Figure 1. A typical visual inspection system held on production line

In this paper, we consider the statistical feature extraction approach. We use histogram properties, co-occurrence matrix, LBP and LVQ neural network for supervised pattern classification. This paper is organized as follows. Overview of visual inspection process is discussed in Section 2 followed by a short discussion for each step. Proposed feature extraction is presented in Section 3. LVQ neural network structure and its algorithm explained in Section 4. Experimental results are shown in Section 5. Finally, conclusion and future work in Section 6.

2. Visual inspection process

There are four main steps in visual inspection process as shown in Figure (2). These steps are image acquisition, preprocessing, feature extraction, and classification (Recognition). The first step of visual inspection process is image acquisition which means capturing the image of the tile using a CCD (Charge-Coupled Device) camera held on production line. The second step is pre-processing which means making the captured image suitable for processing and feature extraction by applying some operations such as contrast stretching, rotation and thresholding on the captured image. The third and fourth steps are explained in details in Section 2.1 and 2.2 respectively.

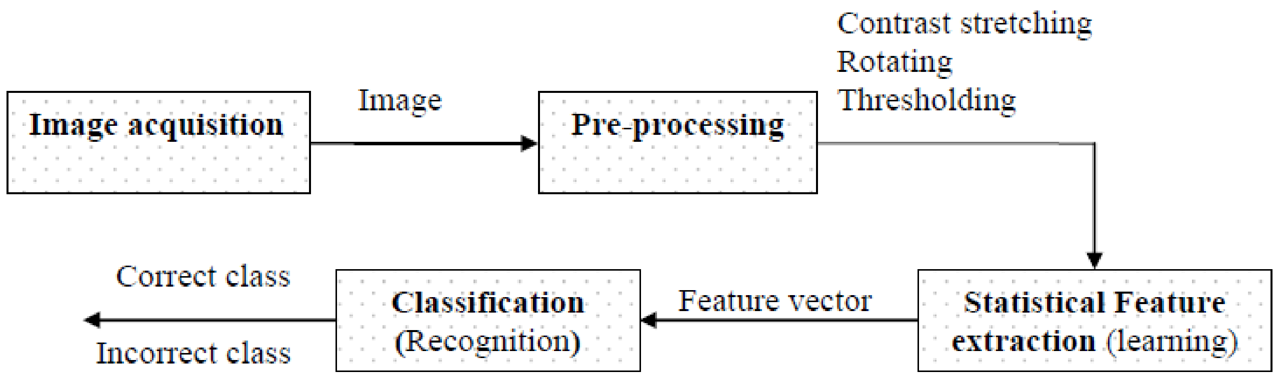

Figure 2. Inspection process steps

2.1 Feature extraction

For pattern recognition, a set of feature is extracted from the image to be classified (learning) and to be assigned to a specific class using classifiers. There are many techniques for feature extraction and textural defect detection. Tuceryan and Jain [8] divided these techniques into four approaches as the following:

(a) Statistical Approach

In this approach, spatial distribution of gray values is analyzed by computing local features at each point in the image, and derives a set of statistics from the distributions of the local features. Depending on the number of pixels, defining the local feature statistical methods can be further classified into a first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics. In the first-order, statistics estimate properties (e.g. average and variance) of individual pixel values with ignoring the spatial interaction between image pixels. In the second and higher-order statistics, estimate properties of two or more pixel values occur at specific locations relative to each other. The most widely used statistical methods are co-occurrence features and gray level differences [9].

(b) Geometrical methods

In this approach, texture is considered to be composed of texture primitives with attempting to describe the primitives and the rules governing their spatial organization. The primitives may be extracted by edge detection with a Laplacian-of-Gaussian or difference-of-Gaussian filter by adaptive region extraction, or by mathematical morphology [6]. Image edges and contours are often used as primitive elements.

(c) Model-based methods

Model based methods depend on hypothesizing the underlying texture process, and then constructing a parametric generative model which could have created the observed intensity distribution. The intensity function is considered to be a combination of a function to represent the known structural information on the image surface and an additive random noise sequence [10].

(d) Signal processing methods

In this type of techniques, some methods such as Fourier transform Cosine transform and Wavelet transform are used to analyze the frequency content of the image. There is another view for feature extraction is given by Xianghua Xie [11]. He divided the approaches to statistical (histogram properties, co-occurrence matrix, local binary pattern, autocorrelation and registration-based), structural (primitive measurement, edge features, skeleton representation and morphological operations), filter based (spatial domain filtering and frequency domain filtering), and model based approaches (fractal models, random field model and texem model).

2.2 Classification

Classification means assigning a specified pattern to a class amongst different classes according to similarity criteria. These classes may be previously determined or not. If the class previously determined the classification is said to be supervised and unsupervised otherwise. The most known classification techniques are artificial neural network (such as LVQ and Back propagation), and statistical techniques (Maximum likelihood and k-Nearest Neighbors).

3. Feature Extraction using Statistical Approaches

As we discussed before, spatial distribution of gray values is analyzed by computing local features at each point in the image, and derives a set of statistics from the distributions of the local features. In the following subsections, we discuss the statistical methods that we use in this paper.

3.1 Histogram Features of Images

Histogram of a digital image with L total possible intensity level in the range [0, G] is defined as the discrete function:

$$H(r_k)= n_k \tag{1}$$

where r_k is the k-th intensity level in the interval [0, G], n_k is the number of pixels in the image whose intensity level is r_k and, G is the number of gray scale colors equal 255. The normalized histogram is obtained by dividing all elements of $h(r_k)$ by the total number of pixels in the image [12] which is denoted by n as:

$$p(r_k) = \frac{h(r_k)}{n} = \frac{n_k}{n} \tag{2}$$

3.2 Co-Occurrence Matrix

Another important method in statistical approach is the Gray Level Co- Occurrence Matrix (GLCM) which is one of the earliest texture feature extraction method and widely used nowadays introduced by Haralick [13, 14]. GLCM is a second order statistics rather than histogram, which is first order statistics. It is an N×N matrix represents the relation between the pixel and other pixels adjacent to it in a specific direction or displacement and it is defined as in Equation [3]:

$$Cd(i,j)=|\{(r,c): I(r,c)=I \text{ and } I(r+dr, c+dc)=j\}| \tag{3}$$

Although there is a problem with driving texture measure from the co-occurrence matrices when choosing the displacement vector d. Zucker [15] showed that the solutions for this problem is to use a $\chi 2$ statistical test given in Equation [4] to select the value(s) of d that have the most structure; that is to maximize the value:

$$X2(d)= \sum_{i} \sum_{J} \frac{Nd2[I,j]}{N_d\,[i]\, N_d\,[j]} \tag{4}$$

After computing the gray level co-occurrence matrix, normalizing co-occurrence matrix is required by using the following [Equation 5]:

$$N_d\,[i,j] = \frac{C_d\,[i,j]}{\sum_i \sum_J C_d\,[i,j]} \quad \text{(between 0 and 1)} \tag{5}$$

Normalizing the co-occurrence values to lie between zero and one and allow them to be thought as probabilities in a large matrix is given in Equation [5]. As soon as $N_d[i, j]$ is computed, the important features can be extracted from it.

3.3 Local Binary Pattern (LBP)

LBP was first introduced by Ojala et al in 1996 [16] as a shift invariant complementary measure for local image contrast. LBP operator works with the 8-neighbours of the pixel and using the value of the center pixel as a threshold. An LBP code for a 3×3 neighborhood is produced by multiplying the thresholded values with weights given to the corresponding pixels, and summing up the result and computing the contrast of the image by subtracting the average of the gray levels below the center pixel from the average of gray levels above (or equal to) the center pixel. As shown in Figure [4].

LBP has the average of a simple computation and an invariant to image rotation [11]. Also LBP can be computed according to various neighborhood.

Sizes and distances 4×4 or possibly 5×5. In basic form of this method, LBP operator in one neighborhood of the image is defined as in Equation [6]:

$$\mathrm{LBP}_{P,R} = \sum_{i=0}^{P-1} s(g_i - g_c)2^i, \qquad s(x) = \begin{cases} 1, & x \geq 0, \\ 0, & x < 0. \end{cases} \tag{6}$$

Where the gray value of the central pixel is gc and the gray value of the i th neighbor is gi. According to this definition, it is seen that the output of the operator is P bit binary number with 2P distinct values.

4. Feature Extraction of Ceramic Tiles using Statistical Approaches

In this paper, we apply the statistical feature extraction on 100 gray scale images of resolution 256×256. Features extracted from these images are then compared using LVQ neural networks. The key reason of using statistical feature extraction is the speed of computation and robustness of capturing properties [2, 9, 11, 16]. In the following subsections, we discuss our using and implementing of histogram, Gray Level Co-Occurrence Matrix, and Local binary pattern as methods of feature extraction for ceramic tiles.

4.1 Histogram Method

Figures [3a] and [3b] show the image of both normal and defective tile with the defects shown in [3c]. The corresponding histograms for Figures [3a] and [3b] are shown respectively in Figures [3c] and [3d]. The features extracted from the histogram are mean (Equation [7]), variance (Equation [8]), skewness (Equation [9]), kurtosis (Equation [10]) and many others. In this paper, we use histogram features shown in Table [1].

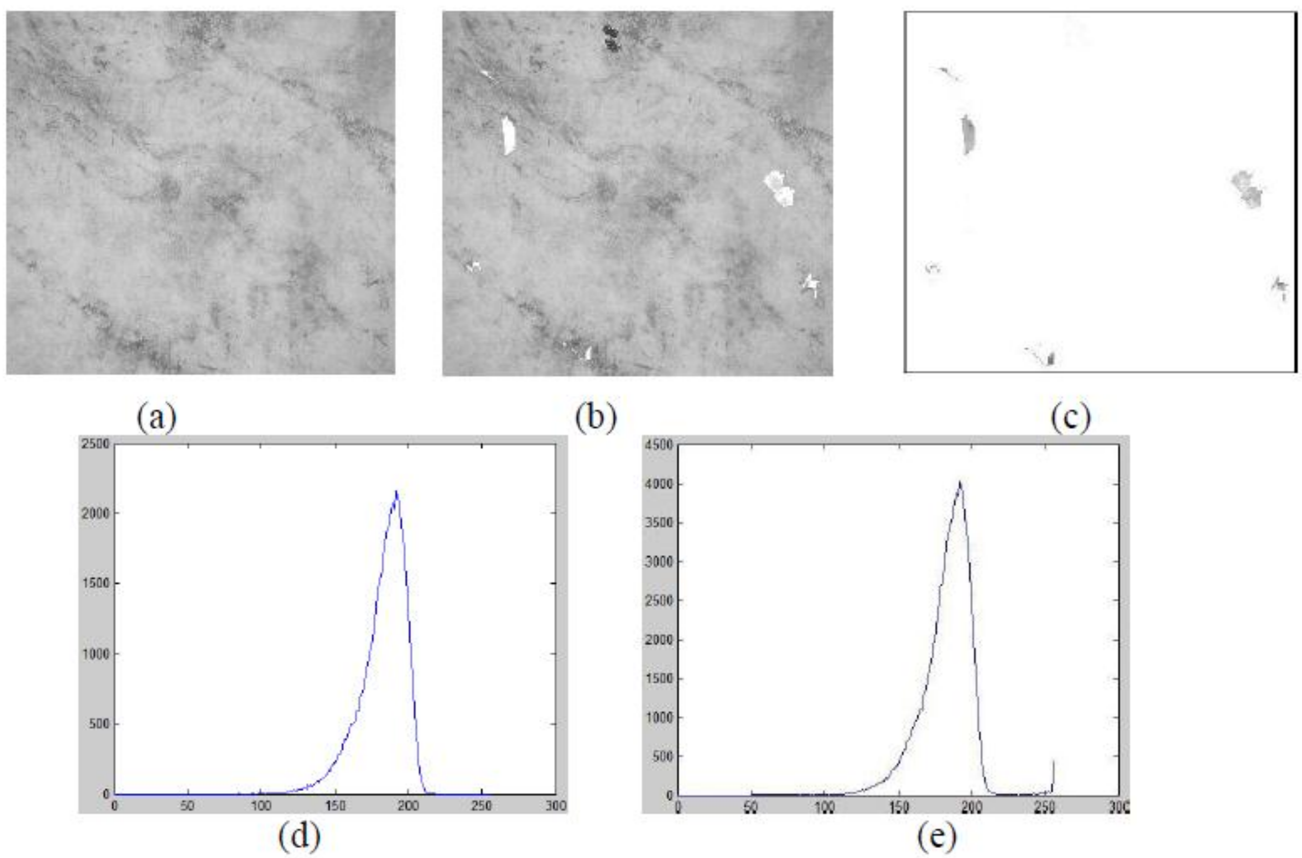

Figure 3. A normal tile (a), defective tile (b), the defects of image b (c) and corresponding histogram for each one ((d) and (e))

Table (1) Histogram, LBP features.

Mean	$\bar{x} = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i$	(7)
Variance	$\sigma^2 = \frac{\sum (X-\mu)^2}{N}$	(8)
Skewness	$skew(X) = \frac{E[(X-\mu)^3]}{\sigma^3}$	(9)
Kurtosis	$kurt(X) = \frac{E[(X-\mu)^4]}{\sigma^4}$	(10)

4.2 Co-Occurrence Method

The Co-Occurrence matrix computed from the ceramic image is used to extract some features. First feature extracted from GLCM is entropy (Equation [11]) that measures the disorder of an image texture. The second feature is energy (Equation [12]) that measures uniformity of an image texture. The third feature is homogeneity (Equation [13]) that measures the local homogeneity of a pixel pair. The fourth feature is contrast (Equation [14]) that measures local contrast of an image and Table [2] shows the features of GLCM where a vector of these features is used for the classification phase.

Table [2] GLCM Feature

Feature name	Equation	
Entropy	$Entropy = -\sum_i \sum_j N_d[i,j] \log_2 N_d[i,j]$	(11)
Energy	$Energy = \sum_i \sum_j N_d^2[i,j]$	(12)
Homogeneity	$Homogeniety = \sum_i \sum_j \frac{N_d[i,j]}{1+\lvert i-j \rvert}$	(13)
Contrast (Inertia)	$Inertia = \sum_i \sum_j (i-j)^2 N_d[i,j]$	(14)

GLCM on 4×4 of a sample of sub-image we are using is shown in Figure [4] and the corresponding features are shown in Table [3].

1	1	0	0
1	1	0	0
0	0	2	2
0	0	2	2

(a)
4 × 4 image

C_{ij}	0	1	2
0	4	0	2
1	2	2	0
2	0	0	2

(b)
$C_{(1,0)}$

C_{ij}	0	1	2
0	2	0	1
1	2	1	1
2	0	0	1

(c)
$C_{(1,1)}$

Figure 4. 4 ×4 sub image (a), GLCM at C (1, 0) and C (1, 1) (b) and (c)

Table [3] GLCM features for sub-image in Figure (4)

	$C_{(1,0)}$	$C_{(1,1)}$
Energy	0.22222	0.18750
Entropy	-2.25121	-2.50103
Inertia	0.83333	0.87513
Homogeneity	0.80555	0.97294

4.3. Local Binary Pattern Method

LBP and Contrast (C) are computed for the ceramic tile as shown in Figure [4]. The implementation in Figures [5a, 5b] show LBP for normal and defective tiles of Figure [3a, 3b] while Figures [5c, 5d] show Contrast for normal and defective tiles of Figures [3a, 3b].

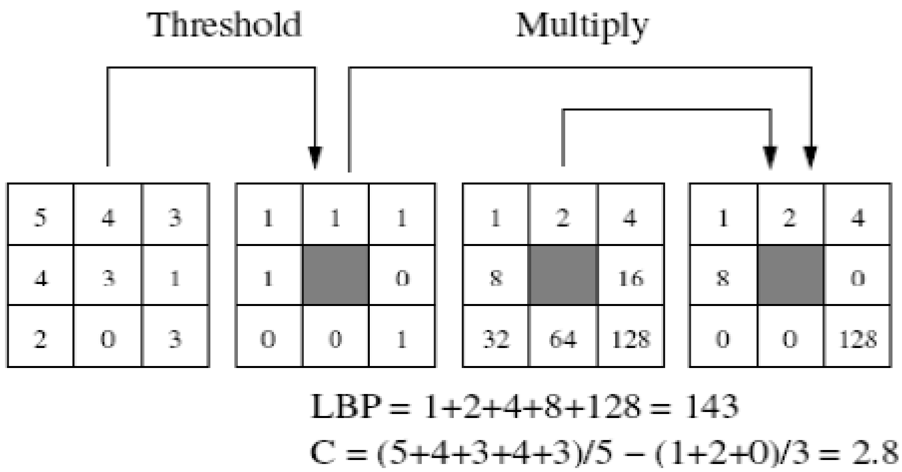

Figure 4. Computing the LBP and Contrast from [17]

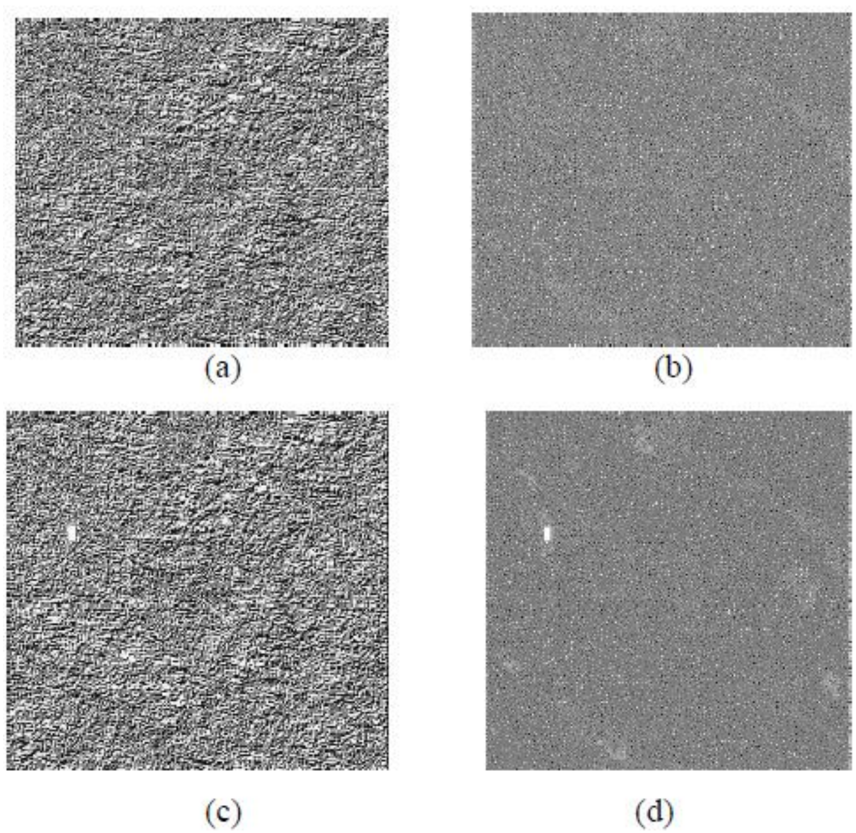

Figure 5. LBP and Contrast for tiles in Figure (3)

5. LVQ structure

We use LVQ neural network for ceramic tiles classification. LVQ is a supervised version of the Self-Organizing Map (SOM) algorithm by Kohonen in 1986 [18]. The strength of LVQ over other supervised neural network techniques, like Back Propagation, is trained significantly faster and can handle data with missing values. The LVQ neural network structure shown in Figure [6] consists of two layers. The first layer called the input layer which contains the neurons for the input vectors while the second layer called output layer consists of two neurons representing the two classes; the first one for normal (defect free) tile and the other for abnormal (defected) ones.

The main idea of LVQ is that for each input vector, calculate the neuron that is closest to it using a distance measurement, like Euclidian distance Equation [15], to determine the winner neuron and then update its weights by "winner-take-all" principle [19]. LVQ neural network algorithm is shown in Figure [7].

$$d(i,j)=\sqrt{(|x_{i_1}-x_{j_1}|^2+|x_{i_2}-x_{j_2}|^2+...+|x_{i_p}-x_{j_p}|^2)} \qquad (15)$$

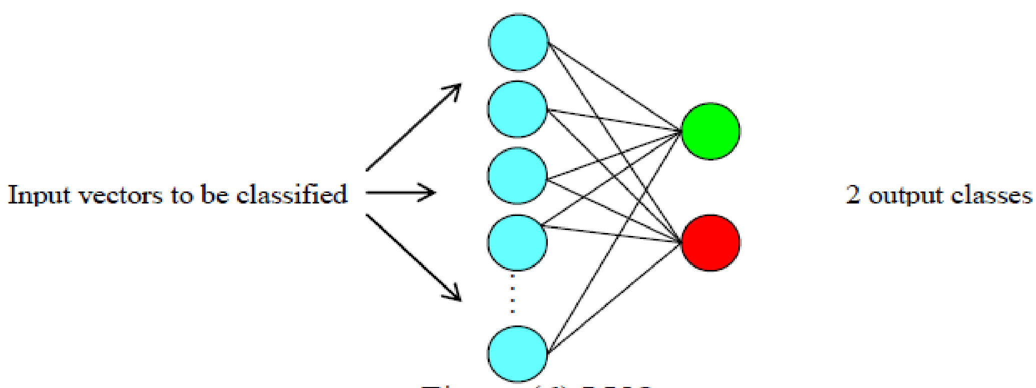

Figure (6) LVQ structure

Step 0: Initialize the reference vectors.
Step 1: Repeat until no. of training reached ***OR*** when all classes are true
Step 1.1: For each training input pattern **x**
-Step 1.1.1: Find Euclidian distance that is minimum among all output nodes
-Step 1.1.2: Update **wj** based on class matches the input vector's class **x**.
* If class(**x**) == class (**wj**) then **wj** = **wj** + α(**x** – **wj**).
* If class(**x**) != class(**wj**) then **wj** = **wj** – α (**x** – **wj**).
Step 1.2: Reduce the learning rate

Figure (7): LVQ algorithm.

6. Experimental Results

LVQ network was trained three different times on our tiles data set images using different features extracted from the previous techniques. The first time training by using the histogram extracted features which listed in Table (3) as the following:

Histf = {mean, variance, skewness, kurtosis}

Second time training by using GLCM extracted features as the following; Coocf = {energy, contrast, entropy, homogeneity} Third time training by combining both of LBP/ contrast extracted feature as the following:

LBP/Contrastf = {LBP_mean, LBP_variance, LBP_skewness, LBP_kurtosis, Contrast_mean, Contrast_variance, Contrast_skewness, Contrast_kurtosis}

Classification Accuracy (CA) is computed using the following equation:

$$CA=\frac{No.of \cdot correct.tiles}{Total \cdot No.of \cdot tiles}\times 100 \tag{16}$$

Features	CA (%)
Histogram	84
GLCM	90
LBP/Contrast	96

6. Conclusion and Future work

Statistical techniques used for extracting ceramic tile features with LVQ neural networks classifiers give subtle results, especially GLCM and LBP that gives 90% and 96% of correct classification respectively. These results show that LBP is the better statistical feature extraction method than GLCM and Histogram methods. One of the proposed future works is to use statistical and signal processing techniques for inspecting color ceramic tiles with computation speed up.

7. References

[1] F. Pernkopf. “Detection of surface defects on raw steel blocks using Bayesian network classifiers”. Pattern Analysis and Applications, 7:333–342, 2004.

[2] O. Silv´en, M. Niskanen, and H. Kauppinen, “Wood inspection with non-supervised clustering”, Machine Vision and Applications, 13:275–285, 2003.
[3] I. Rossi, M. Bicego, and V.Murino. “Statistical classification of raw textile defects”, In IEEE Internationa Conference on Pattern Recognition, volume 4, pages 311–314, 2004.
[4] J. Liu, and J. MacGregor, “Estimation and monitoring of product aesthetics: Application to manufacturing of engineered stone countertops”. Machine Vision and Applications, 16(6):374–383, 2006.
[5] T. Petkovic, J. Krapac, S. Loncaric and M. Sercer, "Automated visual inspection of plastic products", Procedings of the 11th International Electrotechnical and Computer Science Conference ERK 2002, pp. 283-286, Portoroz, Slovenia, 2002.
[6] C. Boukouvalas, J. Kittler, R. Marik, M. Mirmehdi, and M. Petrou, “Ceramic tile inspection for colour and structural defects”, Proceedings of AMPT95, ISBN 1 872327 01 X, pp. 390–399, August 1995.
[7] H. M. Elbehiery, A. A. Hefnawy, and M. T. Elewa, “Visual Inspection for Fired Ceramic Tile's Surface Defects Using Wavelet Analysis”, GVIP(05), No. V2, pp. 1-8, January 2005.
[8] M. Tuceryan, and A. Jain, “Texture Analysis”, Handbook of Pattern Recognition and Computer Vision, chapter 2, pages 235–276, World Scientific, 1998.
[9] M. M. Trivedia “Object Detection Based on Gray Level Co-occurrence”. Computer vision, Graphics, and image processing, vol. 28, pp: 199-219, 1984.
[10] S. W. Zucker and D. Terzopoulos, “Finding Structure in Co-occurrence Matrices for Texture Analysis”. Computer graphics and image processing, vol. 12; pp: 286- 308, 1980.
[11] X. Xie. “A Review of Recent Advances in Surface Defect Detection using Texture analysis Techniques". Electronic Letters on Computer Vision and Image Analysis 7(3):1-22, 2008.
[12] R. C. Gonzalez, R. E. Woods, and S. L. Eddins, "Digital Image Processing Using Matlab", PEARSON Prentice Hall, 3rd Ed, pp 76-88, 2004.
[13] R. Haralick, K. Shanmugam, and I. Dinstein, “Texture features for image classification”, IEEE Transactions on Systems, Man, and Cybernetics, SMC- (6), pp: 610-621, 1973.
[14] A. Monadjemi, “Towards Efficient Texture Classification and Abnormality Detection”, PhD Thesis, University of Bristol, UK, 2004.
[15] S. W. Zucker and D. Terzopoulos, “ Finding Structure in Co-occurrence Matrices for Texture Analysis” Computer graphics and image processing, vol. 12; pp: 286-308, 1980.
[16] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns", IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(7):971–987, 2002.
[17] T. Maenpaa, and M. Pietikainen, "Texture analysis with local binary patterns", Handbook of Pattern Recognition and Computer Vision, pages 197–216, World Scientific, 3rd Edition, 2005.
[18] D. T. Pham, and S. Sagiroglu, "Neural network classification of defects in veneer boards", Professional Engineeriing, Vol 214, p.255-258, 2000.

[19] Laurene Fauseett, “Fundamentals of Neural Networks Architectures: Algorithms and Applications”, Florida Institute of Technology. Prentice hall, pp: 187-195. 1994.