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Computer Vision System for Automatic Surface Inspection of Plain Ceramic Wall Tile

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Abstract: This study describes an automated computer vision system for plain ceramic wall tile surface inspection. The system is designed to detect surface cracks on the inspected tile at its final stage of production and to categorize its into either accept or reject class based on the complexity of the occurring and detected cracks. Hardware implementation for the system consists of a monochrome CCD area scan camera with a 512×512 resolution, ring-light illuminating unit and an IBM-PC compatible Pentium IV MMX 2.4 GHz computer. Our approach to cracks detection involves the application of image edge enhancement and detection algorithms to the captured digitized image of the inspected tile using Prewitt masks and the development of efficient image thresholding algorithms to segment out the cracks from the image background. Some geometric features useful for tile classification were selected and measured from the detected cracks. Classification algorithms were developed by training and testing the network with enough number of the measured features from all defective tile samples stored in the database by means of iterative, learning algorithms. Simulations and experiments conducted on real tile images show the correctness and efficiency of the developed algorithms computed and implemented in this study in real-time.

Key words: Computer vision system, surface inspection, ceramic wall, tile

INTRODUCTION

Many kinds of automatic visual inspection systems have been developed in last decade in the area like cold rolled strips, printed-circuit boards and food (Hao *et al*., 2003; Sprague *et al*., 1991; Ni *et al*., 1997). Such systems have permitted 100% inspection of the manufactured items at all production phases including the final stage of the manufacturing process.

Ceramic tile industry is very competitive in the present time. The tile manufacturers have taken significant advantage of the strong evolution in the world of automation in the recent years by automating all its production phases through various technical innovations. However, they are still using human inspector to visually examine the tile surface at its final stage of production before packaging. The objective of surface inspection is tile classification on the basis of defects (such as cracks, bumps and depressions) and their dimensions (Boukouvalas *et al*., 1995). The practice of inspecting tiles manually with human eye is time consuming and suffers at times from being ineffective due to inspector fatigue or boredom (Newman and Jain, 1995). It is obvious that the automation of this obsolete and subjective inspection task would increase the robustness and consistency of the product quality.

In this study, a PC-based real-time computer vision system for automatic inspection of plain ceramic wall tile at a rate of three tiles per second. The proposed system is to be adapted in actual tile manu-facturing industry for everyday usage.

SYSTEM OVERVIEW

Figure 1 shows a schematic block diagram of our surface inspection system. The prototype consists of

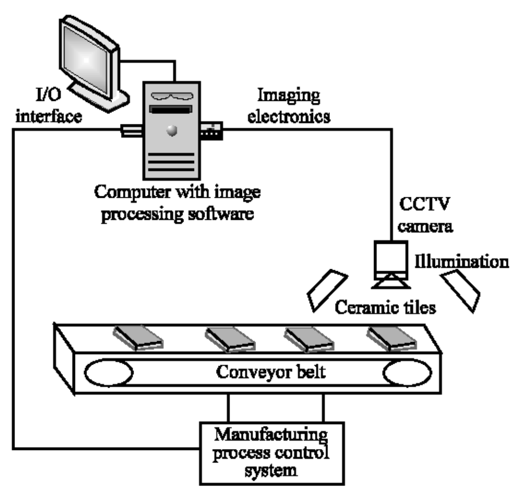

Fig. 1: Imaging system

Fig. 2: Ring-shaped illumination

illuminating unit, imaging system and all the necessary hardware for simulating plant conditions. To achieve sufficient strong and even illumination on the tile surface area to be inspected, ring-shaped illumination is used in the experimental set up as used by Aborisade (2005). Figure 2 shows the illumination scheme is made up of 8 small lamps each with luminous intensity of 1044.45 cd and arranged in a ring 30 cm in diameter. An optimal level of visual information is achieved by maintaining a constant level of illumination at a ring height of approximately equal to the ring radius.

The imaging system dealt with real-time image acquisition and processing is constructed using a monochrome CCD area scan camera interfaced to a Pentium computer through Mercury PCI video capture card. The system configuration relies on the PCI Video capture card to digitize the analogue image captured by the camera into 512 by 512 pixels at 8-bit grey-level resolution. The digitized image is loaded into host computer's system memory and transferred to the host CPU for real-time processing and analyzing using the developed fast processing and classification algorithms, computed and implemented in C^{++} on an IBM-PC compatible Pentium IV MMX 2.4 GHz Computer to achieve the design objectives.

IMAGE PROCESSING AND CLASSIFICATION ALGORITHMS

The starting point of the algorithm is the application of edge enhancement operations to the input image in order to highlight the sharp transitions such as the edges of objects in the tiles surface image. Figure 3 shows an example of the acquired input image through which image edge enhancement and detection algorithms are applied using spatial convolution process (also referred to as a finite impulse response filter).

The Eq. 1 for the spatial convolution process is derived by Gregory and Baxes (1994). This is computed as:

$$v(m,n) = \sum_{(k,l)\in W}\sum a(k,l)\,y(m-k,n-l) \qquad (1)$$

where:

- $y(m,n)$ and $v(m,n)$ = The input and output images, respectively
- w = A suitably chosen window
- $a(k,l)$ = The filter weight also called convolution mask

The 3×3 mask used in the algorithms (represented by a pair of masks A_1, A_2) measured the gradient of the image y (m, n) in 2 orthogonal directions. Defining the bidirectional gradients:

$$g_1(m,n) \triangleq (Y, A_1)_{m,n},\; g_2(m,n) \triangleq (Y, A_2)_{m,n}$$

the vector magnitude as derived by Jain (1989) is computed as:

$$g(m,n) = \sqrt{g_1^2(m,n) + g_2^2(m,n)} \approx |g_1(m,n)| + |g_2(m,n)| \qquad (2)$$

where, $g_1(m,n)$ and $g_2(m,n)$ are defined using Prewitt mask proposed by Luo (1998) as:

$$g_1(m,n) = (G+H+I)-(A+B+C)$$
$$g_2(m,n) = (C+F+I)-(A+D+G) \qquad (3)$$

The gradient at location (m, n) was thresholded to obtain the edge map of the defect, which is defined as:

$$\varepsilon(m,n) = \begin{cases} 1 & (m,n)\in I_g \\ 0, & \text{otherwise} \end{cases} \qquad (4)$$

where:

$$I_g \triangleq \{(m,n);\, g(m,n) > \tau\} \qquad (5)$$

and τ (threshold value) is the median value of the global histogram of image intensity values of the edge-enhanced image of the inspected tile. Figure 4 is an example of the enhanced images with the respective image histogram. Figure 5 is the resulting thresholded image of the samples.

After the segmentation of cracks from the image, discriminant functions was developed to classify tiles into either a reject class or accept class based on a set of image features extracted in real time. Depending on the number of defects and their dimensions, ceramic wall tiles are grouped into 3 namely; 1st class, 2nd class and waste. First class and 2nd class tiles were grouped into one accept class because they can all be present with none or very few acceptable defects, while waste are grouped into reject class because of the present of unacceptable defects. The 1st step in tiles classification is the selection

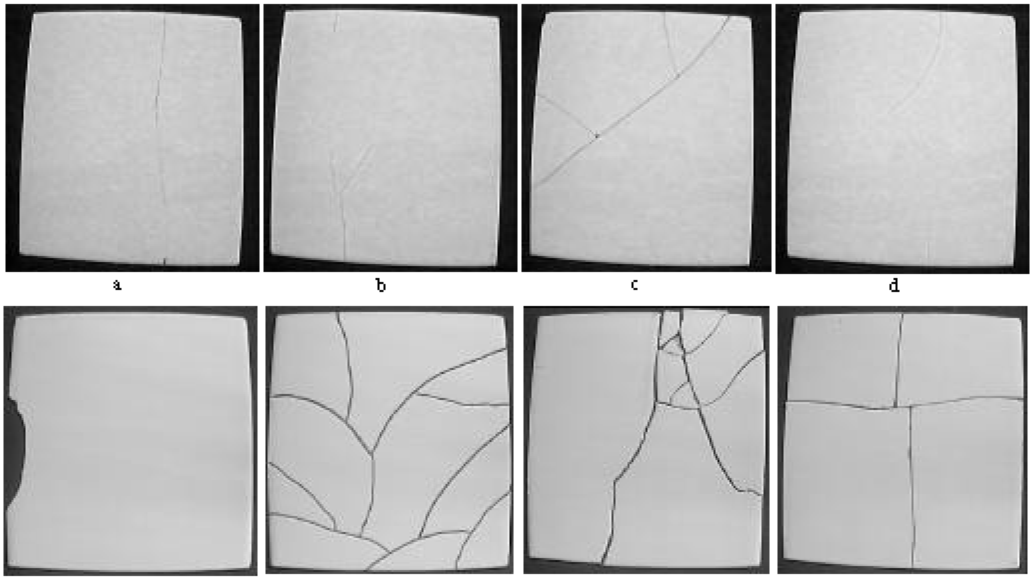

Fig. 3: Example of defective ceramic wall tile images

of discriminatory features. Five features were computed for each class. Most of these features did not provide meaningful information for distinguishing accepts from reject classes. The 1st step in selecting useful features was to determine feature variance, which is a numerical value that indicates how variable the feature value is within classes is computed by Eq. (6) as:

$$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2 \qquad (6)$$

where:

- N = The number of training samples that were measured
- $\bar{x}$ = The mean of the features measurement
- x_i = The ith actual measurement

As it was difficult to select discriminatory features from the feature variance thus, useful features were selected by determine the distance between the means of 2 classes normalized by the variances.

$$V_{ij} = \frac{\left|\bar{x}_i - \bar{x}_j\right|}{\sqrt{\sigma_i^2 + \sigma_j^2}} \qquad (7)$$

Of the entire 5 features measured, area and equivalent diameter values of the segmented defect were found to have large between-class distance and hence were considered as the best feature used in ceramic tiles classification. The measured features of a crack is written in form of pattern vector as:

$$z = (z_1, z_2, \dots, z_n)^T \qquad (8)$$

where, each z_i is the ith descriptor of the given crack (e.g., area, major axis length, minor axis width, extent and equivalent diameter).

The decision (or discriminant) function used in classifying tiles into categories are defined as:

$$d_i(z) = \sum_{k=1}^{K+1} w_{iK} f_K(z) \qquad (9)$$

where:

- w's = Coefficients
- f's = Known functions of z

This is generated from training patterns (i.e., pattern vectors whose class identity is known) by means of iterative, learning algorithms. The coefficients of the decision function are obtained using increment-correction training algorithms. The algorithm at kth iterative step is computed by Eq. 10 as:

$$\begin{aligned} w_i(k+1) &= w_i(k) + \alpha_k X(k) \\ &\operatorname{sgn}\left\{r_i\left[X(k)\right] - w_i'(k)X(k)\right\} \end{aligned} \qquad (10)$$

where:

- $w_i(k)$ = The coefficient estimates at kth iterative step
- α_k = The correction factors

Using the definition of the sgn function defined by:

$$\operatorname{sgn}\left(w_i'X\right) = \begin{cases} 1 & \text{if } w_i'X > 0 \\ -1 & \text{if } w_i'X \le 0 \end{cases} \qquad (11)$$

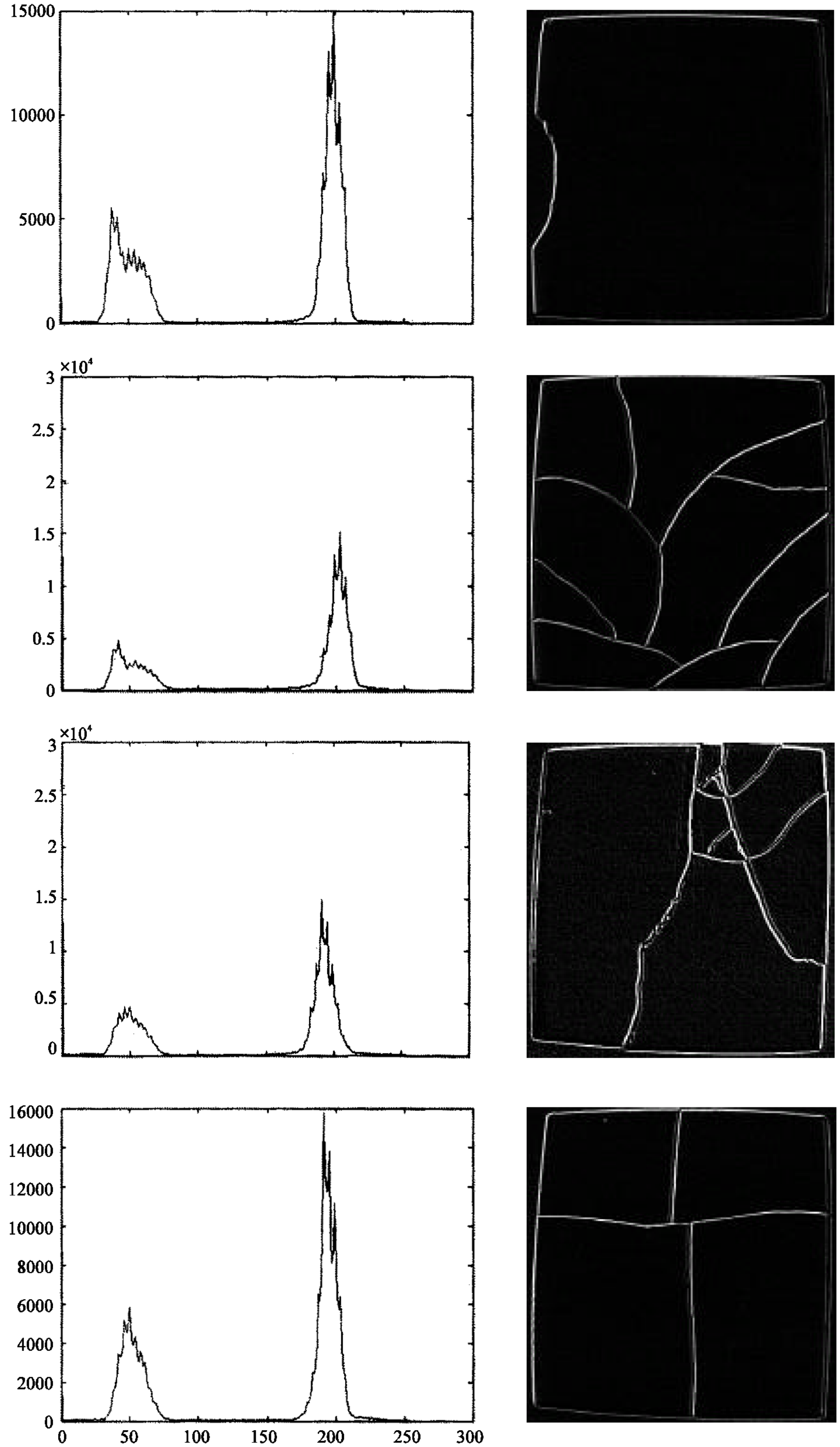

Fig. 4: The results of edge enhancement and with the respective image histogram generation for some samples tiles

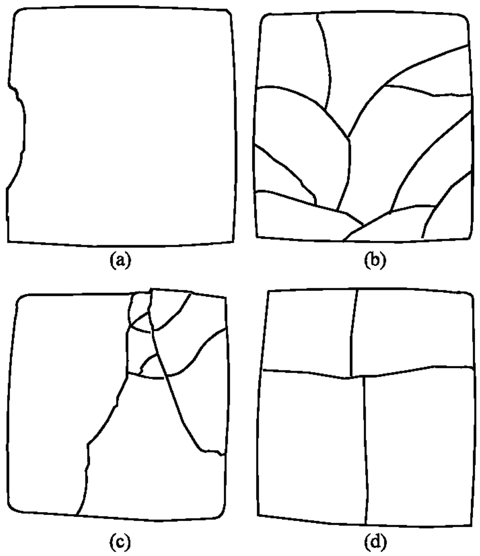

Fig. 5: The results obtained by threshold Fig. 4

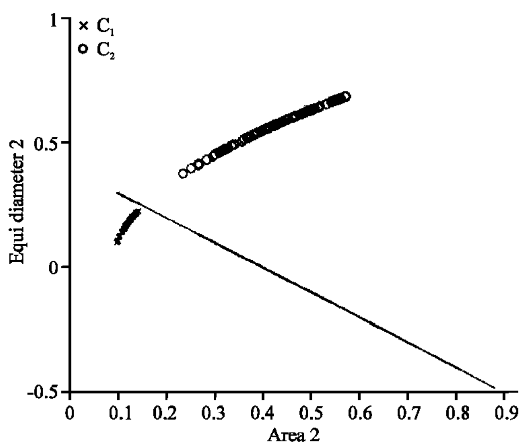

Fig. 6: 2-D feature space rep. of training data with decision surface

Coefficient belonging to pattern class c_1 and c_2 in the equivalent form is expressed as:

$$w_i(k+1)=\begin{cases} w_i(k)+\alpha_k X(k) & \text{if } w_i'(k)X(k) < r_i\left[X(k)\right] \\ w_i(k)-\alpha_k X(k) & \text{if } w_i'(k)X(k) \geq r_i\left[X(k)\right] \end{cases} \quad (12)$$

thus, at k = 100 coefficients for class c_1 and c_2 are computed as:

$$w_1=\begin{pmatrix} 0.1134 \\ 0.1566 \\ 0.9464 \end{pmatrix} \text{ and } w_2=\begin{pmatrix} -0.0233 \\ 0.0114 \\ 0.9030 \end{pmatrix} \quad (13)$$

The boundary between classes c_1 and c_2 using the above coefficients is determined by computing values of z for which d_i (z) = d_j (z), or:

$$\sum_{k=1}^{K+1} w_{iK} f_K(z) - \sum_{k=1}^{K+1} w_{jK} f_K(z) = 0 \quad (14)$$

The 2-D feature space representation of training database samples feature vectors of ceramic tile belonging to class c_1 and c_2 and the decision boundary d (z) = d_i (z) - d_j (z), between them is shown in Fig. 6. In order to classified the unknown tiles designated as Ψ, its decision function is calculated and compared with the decision boundary between the 2 classes. This is computed as:

$$\psi=\begin{cases} \text{good} & \text{if } d(y) \leq d(z) \rightarrow y \in c_1 \\ \text{bad} & \text{if } d(y) > d(z) \rightarrow y \in c_2 \end{cases} \quad (15)$$

where, d (y) is the decision function of an unknown ceramic tile of feature vector y.

EXPERIMENTAL RESULTS

The following section presents the results of training the system for cracks detection and grouping of the inspected tiles into categories. Samples used in the experiments for training of the system are made of 200 digitized defectives plain ceramic tiles of size 200×200 mm. Figure 3 shows samples of the digitized defectives tile images used in the defect detection and tiles classification algorithms. The results of image enhancement of the sample images are shown in Fig. 4. The result of image histogram employed in determination of the appropriate threshold value for the image being processed is also shown in the Fig. 4. Defects such as cracks are detected on the enhanced images of the tiles by thresholding process; the results of this are shown in Fig. 5 for some samples. The first task in tile classification is to determine, which geometric features should be used to discriminate between object classes. For each class and for each feature under scrutiny, distance between means of the 2 classes normalized by variances is computed. Table 1 shows the between class distance results using area, major axis length, minor axis width, extent and equivalent diameter feature attributes of the object. For efficiency purposes because of there high between class values, area and equivalent diameter feature attributes are used to successfully train the system for object classification.

The 2-D feature space representation of selected discriminating features, measured from each of the

Table 1: Between class distance result obtained

Feature/ Defect class	Between class distance: Area Minor defect	Area Major defect	Major axis length Minor defect	Major axis length Major defect	Minor axis length Minor defect	Minor axis length Major defect	Equivalent diameter Minor defect	Equivalent diameter Major defect	Extent Minor defect	Extent Major defect
Minor defect	0.000	3.148	0.000	1.402	0.000	0.143	0.000	4.572	0.0000	0.3080
Major defect	3.148	0.000	1.402	0.000	0.143	0.000	4.572	0.000	0.3080	0.0000

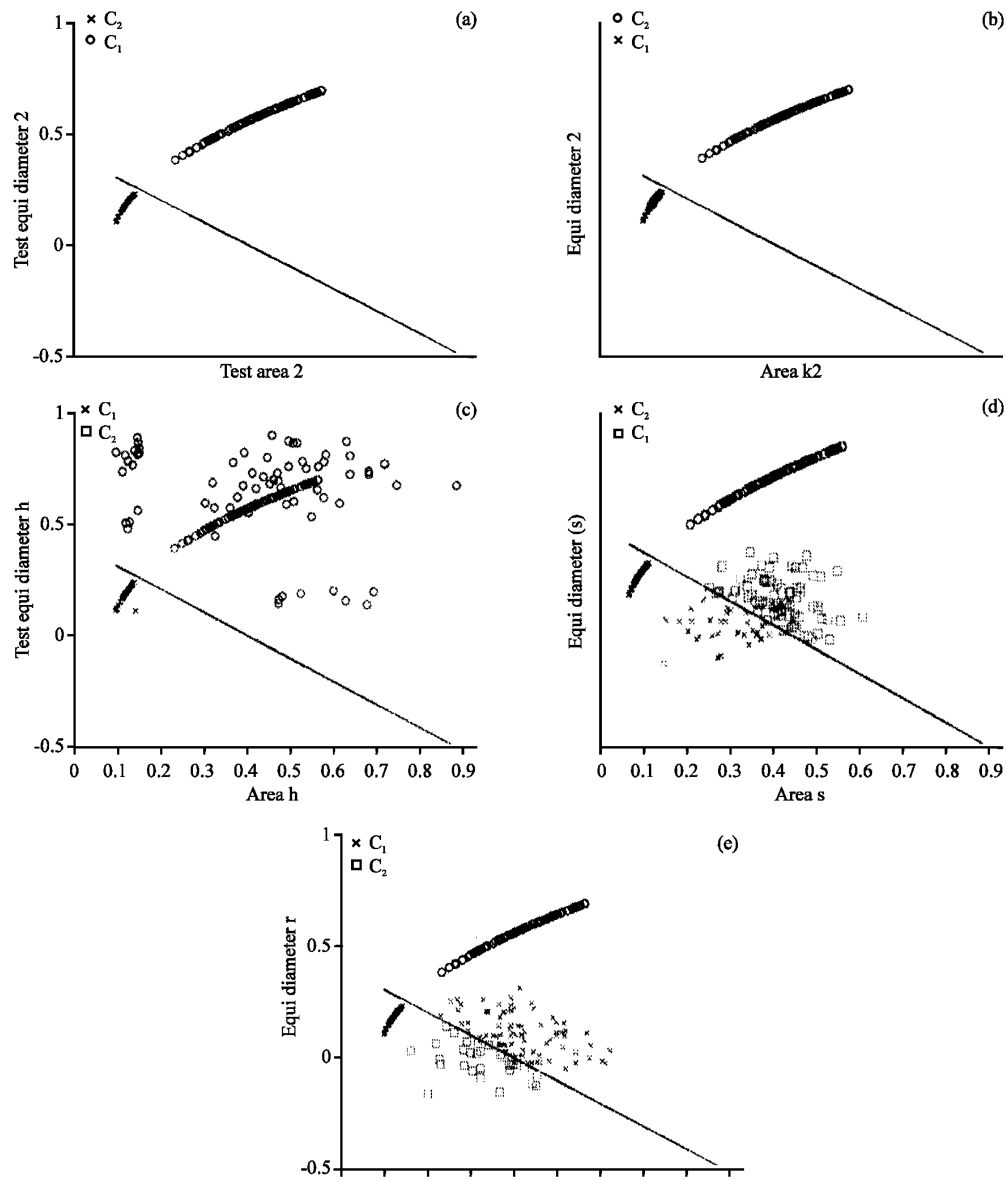

Fig. 7: 2-D feature space rep. of testing data with decision surface, a: 2-D feature space rep. with 60 test samples, b: 2-D feature space rep. with 80 test samples, c: 2-D feature space rep. with 100 test samples, d: 2-D feature space rep. with 120 test samples, e: 2-D feature space rep. with 140 test samples

acquired object classes stored in the database is shown in Fig. 6. Also, in Fig. 7 is the decision boundary between object classes. After training, the system was tested using 70-190 unknown test samples of varying measured feature vectors. Graphical categorization of unknown sampled using classification algorithm is shown in Fig. 7. Table 2

Table 2: Percentage correct classification/error rate per samples

No. test tile samples	Correct classification/class (%) C_1	C_2	Error rate
60	50.00	50.00	0.00
80	1.25	98.75	0.00
100	30.00	67.35	2.65
120	33.33	64.50	2.17
140	60.71	37.14	2.15

shows the computed result generated to show the system performance when tested with various unknown sample images.

CONCLUSION

An efficient automated cracks detection and ceramic wall tiles classification system is presented. By using this system cost, time and also many conflicts in the tiles industry may be reduce since this system may be used as a standard for the ceramic tiles quality control. This project started with the acquisition of images with a monochrome CCD area scan camera under constant illumination. The major problem in this project is to obtain the necessary image analysis and object classification methods to quickly and accurately detect and measured the discriminating feature of surface cracks in ceramic tiles. These problems were solved by using Prewitt edge-enhancement method and by incorporating image thresholding method. With the decision theoretic network, classification rules was built very easily by simply training the network with enough number of sample defective tiles images and implement the nature of decision function classification into ceramic tile quality.

The study has shown promising experimental results for cracks detection and tiles classification. Simulations and experiments conducted on real tile images show the correctness and efficiency of algorithms. In the future research, much can still be done toward the goal of obtaining better error rate for the system to be implemented in real industry.

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