# Texture and Color Feature Extraction from Ceramic Tiles for Various Flaws Detection Classification

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**Abstract:** Image analysis involves investigation of the image data for a specific application. Normally, the raw data of a set of images is analyzed to gain insight into what is happening with the images and how they can be used to extract desired information. In image processing and pattern recognition, feature extraction is an important step, which is a special form of dimensionality reduction. When the input data is too large to be processed and suspected to be redundant then the data is transformed into a reduced set of feature representations. The process of transforming the input data into a set of features is called feature extraction. Features often contain information relative to color, shape, texture or context. In the proposed method various texture features extraction techniques like GLCM, HARALICK and TAMURA and color feature extraction techniques COLOR HISTOGRAM, COLOR MOMENTS AND COLOR AUTO-CORRELOGRAM are implemented for tiles images used for various defects classifications.

***Keywords**: GLCM, HARALICK, TAMURA, COLOR HISTOGRAM, COLOR MOMENTS AND COLOR AUTO-CORRELOGRAM.*

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## I. Introduction

Texture is a very general notion that is difficult to describe in words. The texture relates mostly to a specific, spatially repetitive structure of surfaces formed by repeating a particular element or several elements in different relative spatial positions. John R. Smith and F. S. Chang, (**1996) [1]** defined texture as visual patterns with properties of homogeneity that do not result from the presence of only a single color. Texture features are useful in many applications such as in medical imaging R. S. Poulsenet al, **(1983)** [2], remote sensing M. Schrderet al, **(1998)** [3] and CBIR. In CBIR, there are many techniques to measure texture similarity, the best-established rely on comparing values of what are known as second-order statistics calculated from query and stored images. Essentially, they calculate the relative brightness of selected pairs of pixels from each image. From these, it is possible to calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity H. Tamura et al,**(1978)**[4], or periodicity, directionality and randomness F. Liu and R. W. Picard, **(1996)** [5]. Alternative methods of texture analysis for retrieval include the use of Gabor filters R. Manmatha and S. Ravela, **(1997)** [6].

Color is an important feature for image representation which is widely used in image retrieval. This is due to the fact that color is invariance with respect to image scaling, translation and rotation. Many color image classification methods use color histograms. In A. Vadivel et al (**2004**) [7] feature vectors are generated using the Haar wavelet and Daubechies' wavelet of color histograms. Another histogram based approach can be found in C. Carson et al, (**1999**) [8], where the so-called blob world is used to search similar images. Color histogram based classification approach, is efficient, quick and enough robust.

## II. TYPES OF TEXTURE FEATURE EXTRACTION

Many techniques have been used to extract texture features from images. Some of the commonly used methods are as follows:

- GLCM features
- Haralick features
- Tamura features

## III. TEXTURE FEATURES

Texture is defined as a repeated pattern of information or arrangement of the structure with regular intervals. In a general sense, texture refers to surface characteristics and appearance of an object given by the size, shape, density, arrangement, proportion of its elementary parts. A basic stage to collect such features through texture analysis process is called as texture feature extraction. Due to the signification of texture information, texture feature extraction is a key function in various image processing applications like remote sensing, medical imaging and content-based image retrieval. Texture is a conception that is easy to recognize but very difficult to define.

There are four major application domains related to texture analysis namely texture classification, segmentation, synthesis and shape from texture.

- Texture classification produces a classified output of the input image where each texture region is identified with the texture class it belongs.
- Texture segmentation makes a partition of an image into a set of disjoint regions based on texture properties, so that each region is homogeneous with respect to certain texture characteristics.
- Texture synthesis is a common technique to create large textures from usually small texture samples, for the use of texture mapping in surface or scene rendering applications.
- The shape from texture will reconstruct 3D surface geometry from texture information. For all these techniques, texture extraction is an inevitable stage. A typical process of texture analysis is shown in Figure 1.

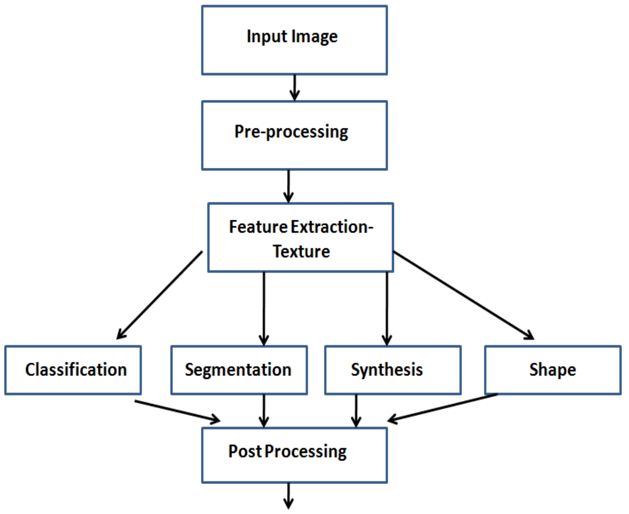


**Figure 1.**Different steps in the texture analysis process

## IV. TEXTURE FEATURE EXTRACTION

Neville et al (**2003**) [9] discussed texture features can be extracted using several methods such as statistical, structural, and model-based and transform information.

### 4.1Structural based Feature Extraction

Structural approaches R. M. Haralick, **(1979)** [10] represent texture by well-defined primitives and a hierarchy of spatial arrangements of those primitives. The description of the texture needs the primitive definition. The advantage of the structural method based feature extraction is that it provides a good symbolic description of the image; however, this feature is more useful for image synthesis than analysis tasks. This method is not appropriate for natural textures because of the variability of micro-texture and macro-texture.

### 4.2Statistical based Feature Extraction

Statistical methods characterize the texture indirectly according to the non-deterministic properties that manage the relationships between the gray levels of an image. Statistical methods are used to analyze the spatial distribution of gray values by computing local features at each point in the image and deriving a set of statistics from the distributions of the local features. The statistical methods can be classified into first order (one pixel), second order (pair of pixels) and higher order (three or more pixels) statistics.

### 4.3Model based Feature Extraction

Model based texture analysis such as fractal model and Markov model are based on the structure of an image that can be used for describing texture and synthesizing it. These methods describe an image as a probability model or as a linear combination of a set of basic functions. The Fractal model is useful for modeling certain natural textures that have a statistical quality of roughness at different scales and self-similarity, and also for texture analysis and discrimination.

### 4.4Transform based Feature Extraction

Transform methods, such as Fourier, Gabor and wavelet transforms represent an image in space whose co-ordinate system has an interpretation that is closely related to the characteristics of a texture. Methods based on Fourier transforms have a weakness in a spatial localization so these do not perform well. Gabor filters provide means for better spatial localization but their usefulness is limited in practice because there is usually no single filter resolution where one can localize a spatial structure in natural textures A. Materka and M. Strzelecki.,(**1998**)[11]. These methods involve transforming original images by using filters and calculating the energy of the transformed images.

## V. STATISTICAL BASED FEATURES

The three different types of statistical based features are first order statistics, second order statistics and higher order statistics as shown in Figure 2.

### 5.1First Order Histogram based Features

First Order histogram provides different statistical properties such as four statistical moments of the intensity histogram of an image. These depend only on individual

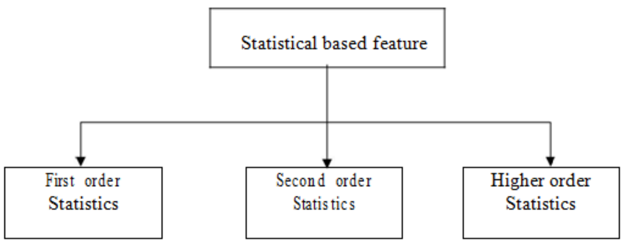


**Figure 2. Statistical based features**

Pixel values and not on the interaction or co-occurrence of neighboring pixel values. The four first order histogram statistics are mean, variance, skewness and kurtosis.

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A histogram $h$ for a gray scale image $I$ with intensity values in the range
$I(x,y) \in [0, K\text{-}1]$ would contain exactly $K$ entries, where for a typical 8-bit grayscale image, $K = 2^8 = 256$. Each individual histogram entry is defined as,
$h(i)$= the number of pixels in $I$ with the intensity value $I$ for all $0 \leq i < K$ .The Equation (4.1) defines the histogram as,

$$h(i) = cardinality\left\{(x, y) \mid I(x, y) = i\right\} \qquad (4.1)$$

$$\sigma = \sqrt{\sum_{n=-\infty}^{\infty} \frac{(I(x,y)-m)^2}{N}} \qquad (4.2)$$

$$\text{Skewness} = \sum_{n=-\infty}^{\infty} \frac{(I(x,y)-m)^3}{N\sigma^4} \qquad (4.3)$$

### 5.2Second Order Gray Level Co-occurrence Matrix Features

The GLCM is a well-established statistical device for extracting second order texture information from images. A GLCM is a matrix where the number of rows and columns is equal to the number of distinct gray levels or pixel values in the image of that surface.

Typically, the co-occurrence matrix is computed based on two parameters, which are the relative distance between the pixel pair $d$ measured in pixel number and their relative orientation $\theta$. Normally, $\theta$ is quantized in four directions (e.g., 0º, 45 º, 90 º and 135 º), even though various other combinations could be possible.

GLCM has fourteen features but between them most useful features are: angular second moment (ASM), contrast, correlation, and inverse difference moment, sum entropy and information measures of correlation. These features are thoroughly promising.

## VI. GRAY LEVEL CO-OCCURRENCE MATRIX

Basic of GLCM texture considers the relation between two neighboring pixels in one offset, as the second order texture. The gray value relationships in a target are transformed into the co-occurrence matrix space by a given kernel mask such as $3 \times 3$, $5 \times 5$, $7 \times 7$ and so forth. In the transformation from the image space into the co-occurrence matrix space, the neighboring pixels in one or some of the eight defined directions can be used; normally, four direction such as 0°, 45°, 90°, and 135° is initially regarded, and its reverse direction (negative direction) can be also counted into account. It contains information about the positions of the pixels having similar gray level values.

Each element ($i$, $j$) in GLCM specifies the number of times that the pixel with value $i$ occurred horizontally adjacent to a pixel with value $j$.

In Figure 3, computation has been made in the manner where, element (1, 1) in the GLCM contains the value 1 because there is only one instance in the image where two, horizontally adjacent pixels have the values 1 and 1. Element (1, 2) in the GLCM contains the value 2 because there are two instances in the image where two, horizontally adjacent pixels have the values 1 and 2.

Element (1, 2) in the GLCM contains the value 2 because there are two instances in the image where two, horizontally adjacent pixels have the values 1 and 2. The GLCM matrix has been extracted for input dataset imagery. Once after the GLCM is computed, texture features of the image are being extracted successively.

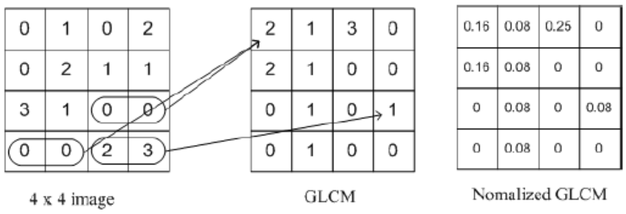

Figure 3: GLCM of a 4 × 4 image for distance $d$ = 1 and direction $\theta$=0

## VII. HARALICK TEXTURE FEATURES

Haralick extracted thirteen texture features from GLCM for an image. The important texture features for classifying the image into water body and non-water body are Energy (E), Entropy (Ent), Contrast (Con), Inverse Difference Moment (IDM) and Directional Moment (DM).

Andrea Baraldi and Flavio Parmiggiani (**1995**)[12] discussed the five statistical parameter energy, entropy, contrast, IDM and DM, which are considered the most relevant among the 14 originally texture features proposed by Haralick et al. (1973). The complexity of the algorithm is also reduced by using these texture features.

In the following, we will use $\{I(x, y), 0 \leq x \leq N_x - 1, 0 \leq y \leq N_y - 1\}$ to denote an image with G gray levels. The $G \times G$ gray level co-occurrence matrix $P_d^{\theta}$ for a displacement vector $d = (dx, dy)$ and direction $\theta$ is defined as follows. The element $(i, j)$ of $P_d^{\theta}$ is the number of occurrences of the pair of gray levels $i$ and $j$ which the distance between $i$ and $j$ following direction $\theta$ is $d$.

$P_d^{\theta}(i, j) = \# \{((r, s),(t, v)) : I(r, s) = i, I(t, v) = j\}$

Where $(r, s),(t, v) \in Nx \times Ny$; $(t, v) = (r + dx, s + dy)$.

Figure 4 shows the co-occurrence matrix $P_d^{\theta}$ with distance $d$ = 1 and the direction is horizontal ($\theta$ = 0). This relationship ($d$ = 1, $\theta$ = 0) is nearest horizontal neighbor. There will be ($Nx-$ 1) neighboring resolution cell pairs for each row and there are $Ny$ rows, providing R = ($Nx$ − 1) × $Ny$ nearest horizontal pairs. The co-occurrence matrix can be normalized by dividing each of its entry by $R$.

In addition, there are also co-occurrence matrices for vertical direction ($\theta$ = 90) and both diagonal directions ($\theta$ = 45,135). If the direction from bottom to top and from left to right is considered, there will be eight directions (0, 45, 90, 135, 180,

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225, 270, 315) (Figure 4). From the co-occurrence matrix, Haralick proposed a number of useful texture features.

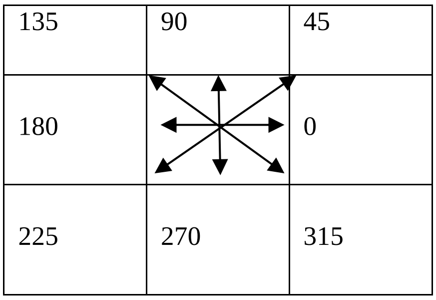


Figure 4: Eight directions of adjacency

### 7.1 Haralick Texture

Haralick extracted thirteen texture features from GLCM for an image. These features are as follows:

#### 7.1.1 Angular second moment (ASM) feature

The ASM is known as uniformity or energy. It measures the uniformity of an image. When pixels are very similar, the ASM value will be large.

$$f_1 = \sqrt{\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)^2} \qquad (4.4)$$

#### 7.1.2 Contrast feature

Contrast is a measure of intensity or gray-level variations between the reference pixel and its neighbor. In the visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view.

$$f_2 = \sum_{n=0}^{N_g-1} n^2 \left[\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)\right] \text{Where } n=|i\text{-}j| \qquad (4.5)$$

When $i$ and $j$ are equal, the cell is on the diagonal and $i - j = 0$. These values represent pixels entirely similar to their neighbor, so they are given a weight of 0. If I and $j$ differ by 1, there is a small contrast, and the weight is 1. If $i$ and $j$ differ by 2, the contrast is increasing and the weight is 4. The weights continue to increase exponentially as $(i - j)$ increases.

#### 7.1.3 Entropy Feature

Entropy is a difficult term to define. The concept comes from thermodynamics; it refers to the quantity of energy that is permanently lost to heat every time a reaction or a physical transformation occurs. Entropy cannot be recovered to do useful work. Because of this, the term can be understood as amount of irremediable chaos or disorder. The equation of entropy is:

$$f_3 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \log(p_{d,\theta}(i,j)) \qquad (4.6)$$

#### 7.1.4 Variance Feature

Variance is a measure of the dispersion of the values around the mean of combinations of reference and neighbor pixels. It is similar to entropy, answers to find solution of dispersion of the difference between the reference and the neighbor pixels in this window.

$$f_4 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i-\mu)^2 p_{d,\theta}(i,j) \qquad (4.7)$$

#### 7.1.5 Correlation Feature

Correlation feature shows the linear dependency of gray level values in the co-occurrence matrix. It presents how a reference pixel is related to its neighbor, 0 is uncorrelated, 1 is perfectly correlated.

$$f_5 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j) \frac{(i-\mu_x)(j-\mu_y)}{\sigma_x \sigma_y} \qquad (4.8)$$

Where $\mu_x$, $\mu_y$ and $\sigma_x$, $\sigma_y$ are the means and standard deviations of $p_x$ and $p_y$.

$$\mu_x = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} i.p_{d,\theta}(i,j) \; \mu_y = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} j.p_{d,\theta}(i,j)$$

$$\sigma_x = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i-\mu)^2 p_{d,\theta}(i,j) \; \sigma_y$$

$$= \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (j-\mu)^2 p_{d,\theta}(i,j)$$

For the symmetrical GLCM, $\mu_x = \mu_y$ and $\sigma_x = \sigma_y$

#### 7.1.6 Inverse Difference Moment (IDM) Feature

IDM is usually called homogeneity that measures the local homogeneity of an image. IDM feature obtains the measures of the closeness of the distribution of the GLCM elements to the GLCM diagonal.

$$f_5 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{1}{1+(i-j)^2} p_{d,\theta}(i,j) \qquad (4.9)$$

IDM weight value is the inverse of the Contrast weight, with weights decreasing exponentially away from the diagonal.

#### 7.1.7 Sum Average Feature

$$f_7 = \sum_{i=0}^{2(N_g-1)} i.p_{x+y}(i) \qquad (4.10)$$

Where $p_{x+y}(k) = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)$, $k=i+j= \{0, 1, 2\ldots..2(N_g-1)\}$

#### 7.1.8 Sum Variance Feature

$$f_8 = \sum_{i=0}^{2(N_g-1)} (i-f_7)^2 . p_{x+y}(i) \qquad (4.11)$$

#### 7.1.9 Sum Entropy Feature

$$f_9 = -\sum_{i=0}^{2(N_g-1)} p_{x+y}(i) \log(p_{x+y}(i)) \qquad (4.12)$$

#### 7.1.10 Difference Variance Feature

$$f_{10} = \sum_{i=0}^{(N_g-1)} (i-f_{10}')^2 . p_{x-y}(i) \qquad (4.13)$$

Where $p_{x-y}(k) = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)$, $k=|i\text{-}j|= \{0, 1, 2\ldots..(N_g-1)\}$

$$f_{10}' = \sum_{i=0}^{(N_g-1)} i.p_{x-y}(i)$$

#### 7.1.11 Difference Entropy Feature

$$f_{11} = -\sum_{i=0}^{2(N_g-1)} p_{x-y}(i)\log(p_{x-y}(i)) \quad (4.14)$$

**7.1.12 Information Measures of Correlation Feature 1**

$$f_{12} = \frac{HXY - HXY1}{max(HX,HY)} \quad (4.15)$$

**7.1.13 Information Measures of Correlation Feature 2**

$$f_{13} = (1 - exp(-2(HXY2 - HXY))^2 \quad (4.16)$$

where $p_y(j) = \sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)$

$$HX = -\sum_{i=0}^{N_g-1} p_x(i)log(p_x(i))$$

$$HY = -\sum_{i=0}^{N_g-1} p_y(i)log(p_y(i))$$

$$HXY = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)\log(p_{d,\theta}(i,j))$$

$$HXY1 = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p_{d,\theta}(i,j)\log(p_x(i)p_y(j))$$

$$HXY2 = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} p_x(i)p_y(j)\log(p_x(i)p_y(j))$$

## VIII. TAMURA TEXTUREFEATURES

Tamura et al (**1978**)[14]took the approach of devising texture features that correspond to human visual perception. They defined six textural features (coarseness, contrast, directionality, line-likeness, regularity and roughness) and compared them with psychological measurements for human subjects. The first three attained very successful results and are used in our evaluation, both separately and as joint values.

### 8.1 Coarseness ($f_{crs}$)

The coarseness has a direct relationship to scale and repetition rates and was seen by Tamura et al as the most fundamental texture feature. An image will contain textures at several scales; coarseness aims to identify the largest size at which a texture exists, even where a smaller micro texture exists. Computationally, one can take first the average at every point over neighborhoods the linear size of which are powers of 2. The average over the neighborhood of size $2^k \times 2^k$at the point $(x, y)$ is

$$A_k(x,y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1}\sum_{j=y-2^{k-1}}^{y+2^{k-1}-1}\frac{p_x(i,j)}{2^{2k}} \quad (4.17)$$

Where k = 0, 1….5 and $p\ (i, j)$ is located in the $(i, j)$ pixel intensity values. Then, for each pixel, which are calculated in the horizontal And the average intensity in the vertical direction between the windows do not overlap the difference.

$$E_{k,h}(x,y) = |A_k(x+2^{k-1},y) - A_k(x-2^{k-1},y)|$$

$$E_{k,v}(x,y) = |A_k(x,y+2^{k-1}) - A_k(x,y-2^{k-1})| \quad (4.18)$$

Wherein for each pixel, can make the maximum value E (either direction) to set the optimum value of $k$ dimensions. Finally, the roughness can be obtained by calculating the whole image and expressed as

$$F_{crs} = \frac{1}{M\times N}\sum_{i=1}^{m}\sum_{j=1}^{n} S_{best}(i,j) \quad (4.19)$$

Another form of the roughness characteristics of the intake is used to describe best histogram distribution, and not as simple as the above-described method of calculating the average $S_{best}$. This feature improved roughness can express a variety of different texture features of an image or region, and therefore more favorable for image retrieval.

### 8.2 Contrast

It is a statistical distribution of the pixel intensity obtained. Rather, it is defined by the $\alpha_4 = \mu_4/\sigma^4$ where $\mu_4$ is the fourth moment and $\sigma^2$ is the variance. Contrast is measured by the following formula:

$$F_{ccon} = \frac{\sigma}{{\alpha_4}^{1/4}} \quad (4.20)$$

### 8.3 Direction degrees

It is need to calculate the direction of the gradient vector is calculated at each pixel. And the direction of the vector mode are defined as

$$|\Delta G| = |\Delta_H| + |\Delta_V|/2$$

$$\theta = \tan^{-1}(\Delta_V/\Delta_H) + \pi/2 \quad (4.21)$$

Where in $\Delta_H$ and $\Delta_V$ are the following two 4x4 operator variation resulting horizontal and vertical directions by the image convolution.

| | | |
|---|---|---|
| -1 | 0 | 1 |
| -1 | 0 | 1 |
| -1 | 0 | 1 |

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 0 | 0 | 0 |
| -1 | -1 | -1 |

When the gradient vector of all the pixels is calculated, a histogram is constructed for the expression of $H_D$ θ value. The first range of values θ histograms was discrete, and then the corresponding statistics for each bin of |ΔG| is greater than the number of pixels in a given threshold. The histogram of an image for a clear directional exhibit a peak, for no apparent direction of the image is relatively flat performance. Finally, the overall image can be calculated by the directional sharpness of peaks in the histogram obtained is expressed as follows:

$$F_{dr} = \sum_p^{n_p}\sum_{\emptyset\epsilon w_p}(\emptyset - \emptyset_p)^2 H_D(i,j) \quad (4.22)$$

P represents the histogram of the peak type; $n_p$ is the histogram of all the peaks. For a peak p, $w_p$ represents all peaks included in the bin, and the bin having the highest $\varphi_p$ value.

### 8.4 Line-likeness

Line-likeness refers only the shape of the texture primitives. A line-like texture has straight or wave like primitives whose orientation may not be fixed. Often the line-like texture is simultaneously directional. Line-likeness ($f_{lin}$) can be computed as follows

$$f_{lin} = \frac{\sum_i^m\sum_j^n P_{Dd}(i,j)\cos[(i-j)\frac{2\pi}{n}]}{\sum_i^m\sum_j^n P_{Dd}(i,j)} \quad (4.23)$$

Where $P_{Dd}(i, j)$ is $n\times n$ local direction co-occurrence matrix of points at a distance $d$

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### 8.5 Regularity

Regularity refers to variations of the texture primitive placement. A regular feature for example chess board, textile, and wall paper etc., is composed of identical or similar primitives, which are regularly or almost regularly arranged. An irregular texture for example grassy field and cloud is composed of various primitives, which are irregularly or randomly arranged Jain, A.K., Farrokhnia, F (**1991**)[15]. Regularity (*f*reg) can be computed as follows Randen, T., Husøy, J.H (**1999**)[16]

$f_{reg} = 1 - r\,(\sigma_{crs} + \sigma_{con} + \sigma_{dir} + \sigma_{lin})$ (4.24)

where $r$ is a normalizing factor and $\sigma_{xxx}$ means the standard deviation of $f_{xxx}$

### 8.6 Roughness

Roughness refers the tactile variations of physical surface. According to the results of our psychological experiments on vision, we emphasize the effects coarseness and contrast. And approximate a measure of roughness by using these computational measures; i.e.

$f_{rgh} = f_{crs} + f_{con}$ (4.25)

Our intention lies in examining to what an extent such a simple approximation corresponds to human visual perception.

## IX. COLOR HISTOGRAM FEATURES

Color histogram is particularly suitable for those images are difficult to describe the automatic segmentation. The color histogram is based on the type of color space and the coordinate system. The most common color space is a RGB color space, because the majority of the digital image in this color space is expressed. It is necessary to calculate the color histogram; the color space is divided into several small color intervals between each cell into a bin of the histogram. This process is called color quantization. Then, by calculating the number of pixels between the colors of each cell falls within the color histogram can be obtained.

The histogram features that we will consider are statistical based features, where the histogram is used as a model of the probability distribution of the intensity levels. These statistical features provide us with information about the characteristics of the intensity level distribution for the image. We define the first-order histogram probability, $P(g)$, as:

$P(g) = N(g)/M$ (4.26)

M is the number of pixels in the image (if the entire image is under consideration then $M = N^2$ for an $N \times N$ image),and $N(g)$is the number of pixels at gray level $g$. As with any probability distribution all the values for $P(g)$ are less than or equal to 1, and the sum of all the $P(g)$ values is equal to 1. The features based on the first order histogram probability are the mean, standard deviation, skew, energy, and entropy.

### 9.1 Mean:

The mean is the average value, so it tells us something about the general brightness of the image. A bright image will have a high mean, and a dark image will have a low mean. We will use $L$ as the total number of intensity levels available, so the gray levels range from 0 to $L - 1$. For example, for typical 8-bit image data, $L$ is 256 and ranges from 0 to 255. We can define the mean as follows:

$\hat{g} = \sum_{g=1}^{L-1} g\,P(g) = \sum_{r}^{L-1} \sum_{c}^{L-1} \frac{I(r,c)}{M}$ (4.27)

### 9.2 Standard deviation

The standard deviation, which is also known as the square root of the variance, tells us something about the contrast. It describes the spread in the data, so a high contrast image will have a high variance, and a low contrast image will have a low variance. It is defined as follows:

$\sigma_g = \sqrt{\sum_{g=1}^{L-1} (g - \hat{g})^2\, P(g)}$ (4.28)

### 9.3 Skewness

The skew measures the asymmetry about the mean in the intensity level distribution. It is defined as:

$SKEW = \frac{1}{\sigma^3} \sum_{g=1}^{L-1} (g - \hat{g})^3\, P(g)$ (4.29)

The skew will be positive if the tail of the histogram spreads to the right (positive) and negative if the tail of the histogram spreads to the left (negative). Another method to measure the skew uses the mean, mode, and standard deviation, where the *mode* is defined as the peak, or highest, value:

$SKEW' = \frac{\hat{g} - mode}{\sigma_g}$ (4.30)

This method of measuring skew is more computationally efficient, especially considering that, typically, the mean and standard deviation have already been calculated.

### 9.4 Energy

The energy measure tells us something about how the intensity levels are distributed:

$ENERGY = \sum_{g=0}^{L-1} |P(g)|^2)$ (4.31)

The energy measure has a maximum value of 1 for an image with a constant value, and gets increasingly smaller as the pixel values are distributed across more intensity level values (remember all the $P(g)$ values are less than or equal to 1). The larger this value is, the easier it is to compress the image data. If the energy is high it tells us that the number of intensity levels in the image is few, that is, the distribution is concentrated in only a small number of different intensity levels.

### 9.5 Entropy

The entropy is a measure that tells us how many bits we need to code the image data, and is given by

$$ENTROPY = -\sum_{g=0}^{L-1} P(g)\,log_2|P(g)| \qquad (4.32)$$

As the pixel values in the image are distributed among more intensity levels, the entropy increases. A complex image has higher entropy than a simple image. This measure tends to vary inversely with the energy.

## X. COLOR MOMENTS

Color Moment In addition, due to the color distribution information mainly concentrated in the low-order moments, so using only colors the first moment (mean), second moment (Variance), and third moment (skewness) is sufficient to express the color distribution of the image. Compared with the color histogram, another advantage of this approach is that the features do not need to be quantified. Three low-order moments of colors expressed mathematically as:

**Mean**

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} p_{i,j} \qquad (4.33)$$

**Variance**

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{L-1}\left(p_{i,j} - \mu_i\right)^2} \qquad (4.34)$$

**Skewness**

$$s_i = \left(\frac{1}{N}\sum_{j=1}^{L-1}\left(p_{i,j} - \mu_i\right)^3\right)^{1/3} \qquad (4.35)$$

Here $p_{ij}$ is the image of the $j^{th}$ pixel in the $i^{th}$color component. Thus, the total moment of the color image has only nine components (three color components, each component of the three low-order moments).

## XI. COLOR AUTO-CORRELOGRAM

A color autocorrelogram is used as an image feature which is scalable for image retrieval on very large image databases. It expresses the spatial correlation of color changes with respect to the change in distance in contrast to a color histogram which captures only the color distribution in an image and does not include any spatial information [12A]. Therefore, the correlogram is one kind of spatial extension of the histogram and is extensively used over color histogram. As the histogram is the color distribution in an image I, the correlogram is the color correlation distribution in image I.

The highlights of color correlogram are as follows **[**5b**]*:***

- It represents the spatial correlation of pair of colors that changes with distance.
- It robustly tolerates large changes in appearance and shape caused by changes in viewing positions, camera zoom, etc.
- It is easy to compute.
- The size of the feature is fairly small.

The concept of color correlogram is illustrated in Fig. 5. In the image *I*, pick any pixel $p_1$of color $c_i$ and another pixel $p_2$at distance *k* away from $\boldsymbol{p_1}$, what is the probability that $p_2$is of color $c_i$?

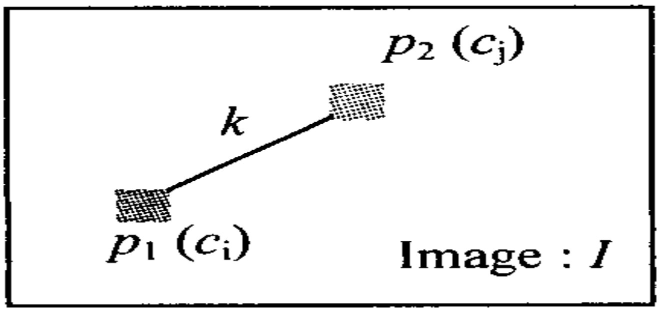


Fig.5 The concept of color correlogram

The auto-correlogram of image *I* can be defined for color $C_i$, with distance *k* [1]:

$$\gamma_{C_i}^{(k)}(I) \equiv \Pr[|\,p_1 - p_2\,| = k,\, p_2 \in I_{C_i} \mid p_1 \in I_{C_i}\,] \quad (4.36)$$

Correlogram can be stored as a table indexed by pairs of colors (*i,j*) where d-th entry shows the probability of finding a pixel *j* from pixel *i* at distance d. Whereas an auto-correlogram can be stored as a table indexed by color i where $d^{th}$ entry shows the probability of finding a pixel *i* from the same pixel at distance d. Hence auto-correlogram shows the spatial correlation between identical colors only .

The auto-correlogram integrates the color information and the space information. For each pixel in the image, the auto-correlogram method needs to go through all the neighbors of that pixel. So the computation complexity is $O(k * n^2)$, where *k* is the number of neighbor pixels, which is depended on the distance selection. The computation complexity grows fast when the distance k is large. But it's also linear to the size of the image.

## XII. EXPRIMENTAL RESULTS:

**Sample Input Tiles Image :**

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**Sample Output (Texture Features):**

GLCM Texture Features

| Parameters | GLCM |
|---|---|
| Mean | 104.6055 |
| Standard_deviation | 95.7142 |
| Skewness | 1.1551 |
| Kurtosis | 15.7995 |
| Energy | 0.5012 |
| Entropy | 0.9137 |
| Smoothness | 0.9999 |

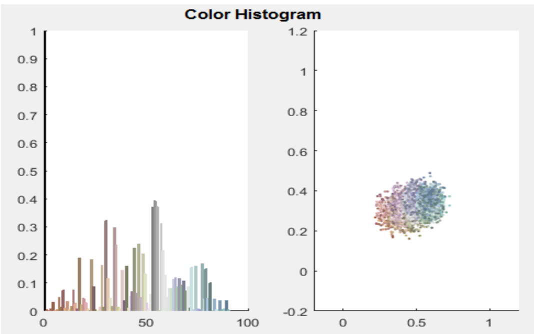
Haralick Texture Features

| Parameters | Haralick |
|---|---|
| Average | 3.5281 |
| Standard_deviation | 95.7142 |
| Angular_Second_Moment | 0.6056 |
| Kurtosis | 0.1428 |
| Energy | 0.7782 |
| Entropy | 1.0824 |
| Smoothness | 0.9999 |

Tamura Texture Features

| Parameters | Tamura |
|---|---|
| coarseness | 35.2000 |
| Contrast | 38.4536 |
| direction | -3.1852 |
| linelikeness | 0 |
| Regularity | 35.2000 |
| Roughness | 73.6536 |

**Sample Output (Color Features):**



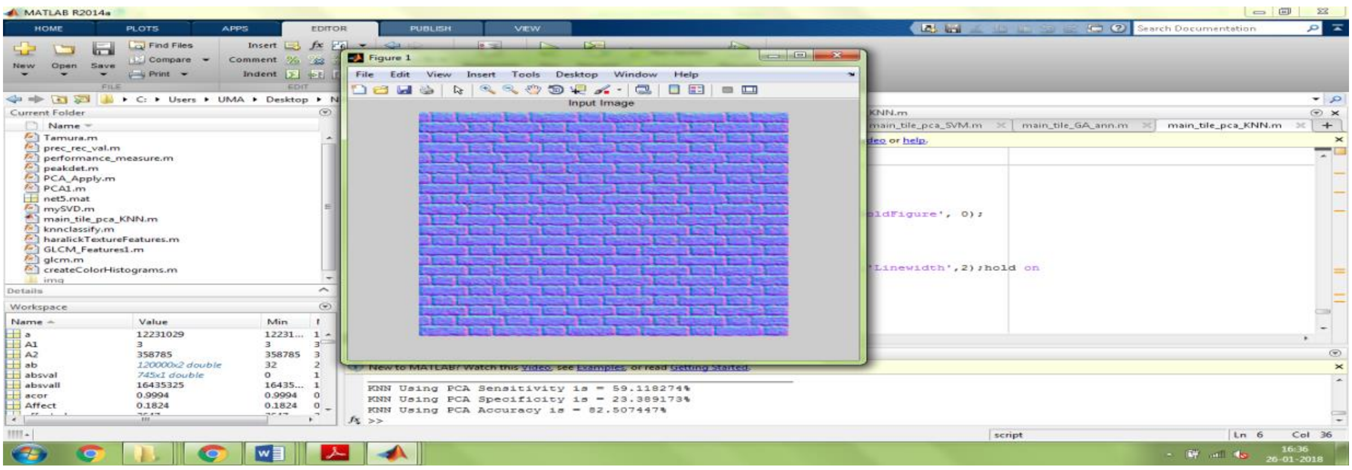

Color Histogram Statistics

| Parameters | Color_Statistics |
|---|---|
| Disimilarity | 0.9770 |
| Sum_Average | 0.5698 |
| Inertia | 0.0814 |
| Maximum_Probabilty | 15.9186 |
| Absolute_Value | 16448250 |
| Correlation | 0.8640 |
| Kurtosis | 2.8149 |

Color Moments Statistics

| Parameters | Color_Statistics |
|---|---|
| Mean | 137.0784 |
| Std_dev | 10.8731 |
| Skew | 5.0330 |

**Sample Output Screenshot (Texture Features)**



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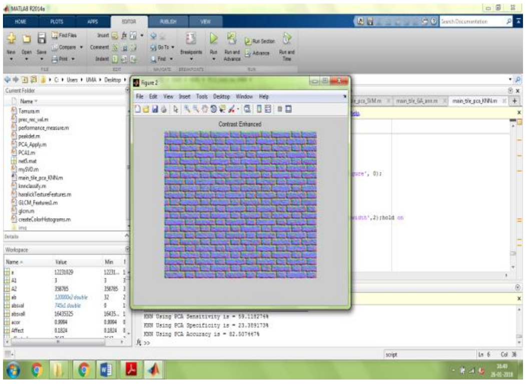
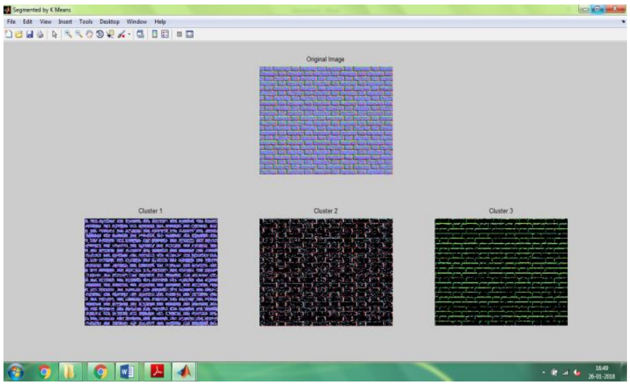
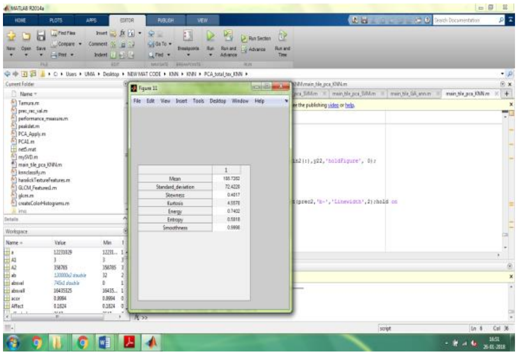
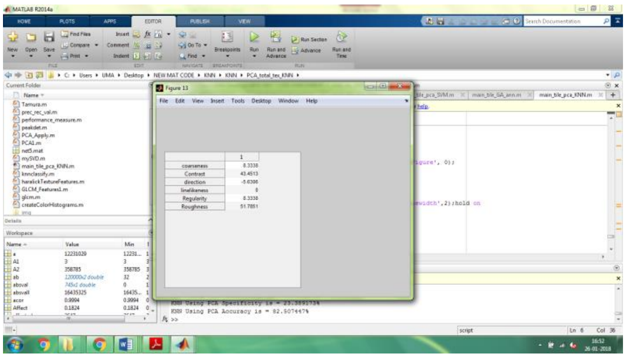
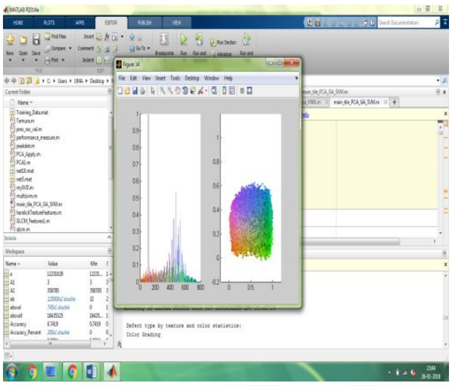


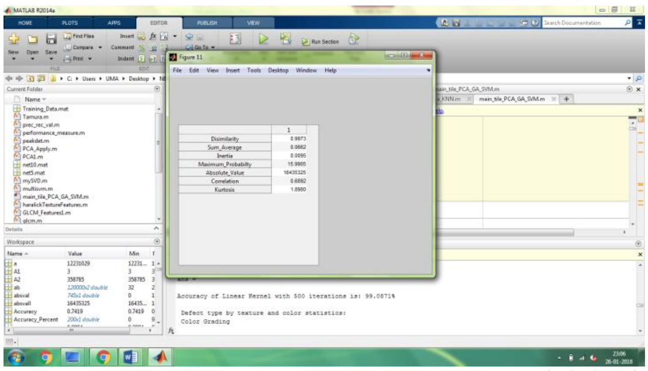


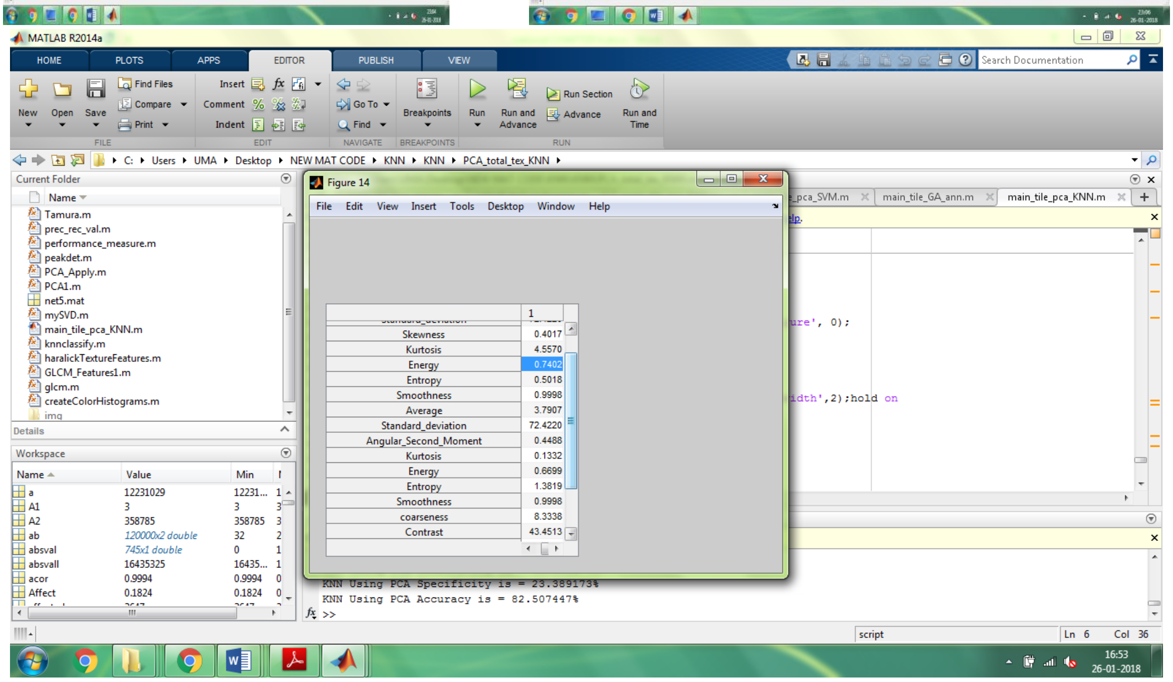





**Sample Output Screenshot (Color Features)**







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## XIII. CONCLUSION

Texture contains significant information about the basic arrangement of the surface. The Grey Level Co-occurrence Matrix method describes texture by creating statistics of the dispersal of intensity values as well as location and orientation of similar valued pixel. The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. Haralick Features describe the correlation in intensity of pixels that are next to each other in space. It contains information about how image intensities in pixels with a certain position in relation to each other occur together. Tamura reported that coarseness, contrast and directionality achieve successful correspondences with psychological measurements. However line-likeness, regularity, and roughness need further improvement due to their discrepancies with psychological measurements. Coarseness, contrast and directionality are regarded as major features; whereas line-likeness, regularity, and roughness are complements of first three features. Although the use of Tamura features is straight forward, but effective in texture description. Color histogram represents the frequency distribution of color bins in an image. It counts similar pixels and store it. The histogram features that we will consider are statistical based features, where the histogram is used as a model of the probability distribution of the intensity levels. These statistical features provide us with information about the characteristics of the intensity level distribution for the image. Since this feature captures the spatial correlation of colors in an image, it is effective in discriminating images. The correlogram can also be computed efficiently. Autocorrelograms on color spaces which are stable under lighting change and are also perceptually uniform.

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