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Abstract

This chapter has reviewed the basic concepts and various methods and techniques for processing textured images. Texture is a prevalent property of most physical surfaces in the natural world. It also arises in many applications such as satellite imagery and printed documents. Many common low level vision algorithms such as edge detection break down when applied to images that contain textured surfaces. It is therefore crucial that we have robust and efficient methods for processing textured images. Texture processing has been successfully applied to practical application domains such as automated inspection and satellite imagery. It is also going to play an important role in the future as we can see from the promising application of texture to a variety of different application domains.

1. Introduction

In many machine vision and image processing algorithms, simplifying assumptions are made about the uniformity of intensities in local image regions. However, images of real objects often do not exhibit regions of uniform intensities. For example, the image of a wooden surface is not uniform but contains variations of intensities which form certain repeated patterns called visual texture. The patterns can be the result of physical surface properties such as roughness or oriented strands which often have a tactile quality, or they could be the result of reflectance differences such as the color on a surface. We recognize texture when we see it but it is very difficult to define. This difficulty is demonstrated by the number of different texture definitions attempted by vision researchers. Coggan's [1]

has compiled a catalogue of texture definitions in the computer vision literature and we give some examples here. • “We may regard texture as what constitutes a macroscopic region. Its structure is simply attributed to the repetitive patterns in which elements or primitives are arranged according to a placement rule.” [2]
• “A region in an image has a constant texture if a set of local statistics or other local Chapter 2.1 The Handbook of Pattern Recognition and Computer Vision (2nd Edition), by C. H. Chen, L. F. Pau, P. S. P. Wang (eds.), pp. 207-248, World Scientific Publishing Co., 1998. 2 properties of the picture function are constant, slowly varying, or approximately periodic.” [3]
• “The image texture we consider is nonfigurative and cellular... An image texture is described by the number and types of its (tonal) primitives and the spatial organization or layout of its (tonal) primitives... A fundamental characteristic of texture: it cannot be analyzed without a frame of reference of tonal primitive being stated or implied. For any smooth gray-tone surface, there exists a scale such that

when the surface is examined, it has no texture. Then as resolution increases, it takes on a fine texture and then a coarse texture." [1]

• "Texture is defined for our purposes as an attribute of a field having no components that appear enumerable. The phase relations between the components are thus not apparent. Nor should the field contain an obvious gradient. The intent of this definition is to direct attention of the observer to the global properties of the display — i.e., its overall "coarseness," "bumpiness," or "fineness." Physically, none numerable (aperiodic) patterns are generated by stochastic as opposed to deterministic processes. Perceptually, however, the set of all patterns without obvious enumerable components will include many deterministic (and even periodic) textures." [3]

• "Texture is an apparently paradoxical notion. On the one hand, it is commonly used in the early processing of visual information, especially for practical classification purposes. On the other hand, no one has succeeded in producing a commonly accepted definition of texture. The resolution of this paradox, we feel, will depend on a richer, more developed model for early visual information processing, a central aspect of which will be representational systems at many different levels of abstraction. These levels will most probably include actual intensities at the bottom and will progress through edge and orientation descriptors to surface, and perhaps volumetric descriptors. Given these multi-level structures, it seems clear that they should be included in the definition of, and in the computation of, texture descriptors." [2]

2.1 Motivation

Texture analysis ploys a significant and valuable area study in machine vision. Most natural surface exhibit texture vision system deals with the textured world surrounding it. This division will show the position texture perception from two Paints of view. Human vision or Psyche Physics and the practical machine vision applications[2].

2.1.1 Psyche Physics

The discovery of tiger among the foliage is a perceptual task holds life and death. Consequence for someone trying to stay alive in the juncle. The success of the tiger in disguising itself is a failure of the visual system observing it.

The failure is able to distinct figure from ground figure-ground separation is an issue which is of intense interest to Psyche Physics.[8]

The figure-ground departure can be based on various cues such as brightness, color, form texture, etc. for an example the tiger in the forest.

Texture plays a main rote. The concealment is successful because the visual system of the observer is unable to separate (or segment) the two texture of the foliage and the tiger skin. What are the visual developments that allow one to distinct figure from aground using the s texture cue?

The question is the main motivation among Psyche Physics for studying texture View the performance wby it is significant to study the Psyche Physics of texture perception is that This is known as texture are classification. The goal of texture Classification then is to give a map of the input image each uniform area is identified with the texture class it fits to as shown in figure 1.

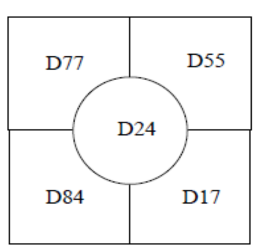


Figure 1 (The goal of texture classification)

We could also find the texture limits even if classifying this texture surfaces is not possible. This is then the second type of difficult that texture analysis research attempts to solve- texture division. The goal texture division is to obtain the boundary map shown in figure 2 [5].

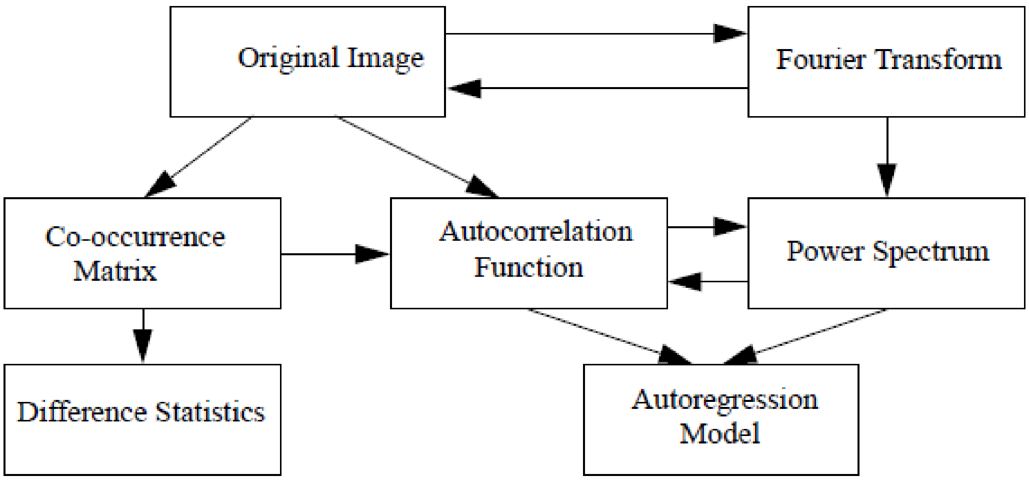


Figure2 (The interrelation between the various second-order statistics and the input image)

Texture synthesis is often used to compare between image applications. It is also helps to computer graphics where the goal is to reduce things which are realistic looking as Possible figure 3 set of synthetically shape from texture problem one example of a general class vision hitches known as human visual of various texture is assessed in contradiction of the performance of the system when doing the Same task. For example Consider texture Pair, first described by julesz [7].

The image consists of two areas with different texture tokens. Close study of image will specify this fact to the human observer.

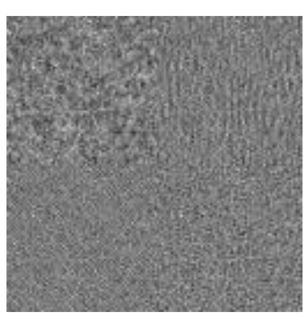


Figure 3 Four textures generated by Gaussian Markov random field models.

Many researchers, one instant application of image texture is the a known lodgment of image regions using texture properties. For example we can classify the five different textures and their identities as cotton canvas. Straw matting raffia herringbone weave, and pressed calf leather. Texture is the main visual cue in identifying these types of homogeneous areas.

"shape from X". This was first officially pointy out in the precaution literature by [6]. The is to extract three-dimensional shape information from Various such as stereo, goal shading, and texture.[6]

2.2Texture Analysis Problems

There are servel methods of modeling and extracting texture structures can be practical in four broad categories: texture classification, synthesis, texture, and shape from texture we now review this four areas.[8]

2.2.1Texture segmentation

Texture segmentation is problem because one usually does not know a priori what types of textures exist in an image, how many diverse textures there are, and what areas in image have which textures. one even does not need to know which exact textures exist in the image in order to do texture division. All that is needed is a way to tell that to textures usually in adjacent regions of the images are not the same.

The two main methods to performing texture segmentation are analogous to approaches for image vision region based methods or boundary- based approaches. Apply alaplacian-of Gaussian (LoG or v2G) filter to the image. For computational competence. The v2G filter can be approached with a difference of Caussians (DoG) filer. The size of the DoG filter is strong minded by the sizes of the two Gaussian filters. Tuceryan and Jain used ……. for the first Caussian and ……. area document analysis and character application. Document dispensation has application ranging from email address recognition to analysis and *clarification map. In many mail document processing applications (such as the recognition destination address and zip code information on envelopes), the first stage is the capability to isolate the areas in the background.[10]*

Texture is a property of areas; the texture of an opinion is meaning. Must include gray values in a spatial neighborhood. The scope of this neighborhood upon the texture type, or the size of the primitives defining the texture.

For the second.

According to Marr, this is the ratio at which a DoG filter best approximates the corresponding………. filter [5].

Choice those pixels that lie on a local strength maximum in the filtered image. A Pixel in the cleaned image is Said to be on a local maximum if its magnitude is larger than six or more of its eight nearest neighbors. This results in a binary image for example, applying steps and 2 to the image in Figure 4(a) yields the binary image in Figure 4 (b).

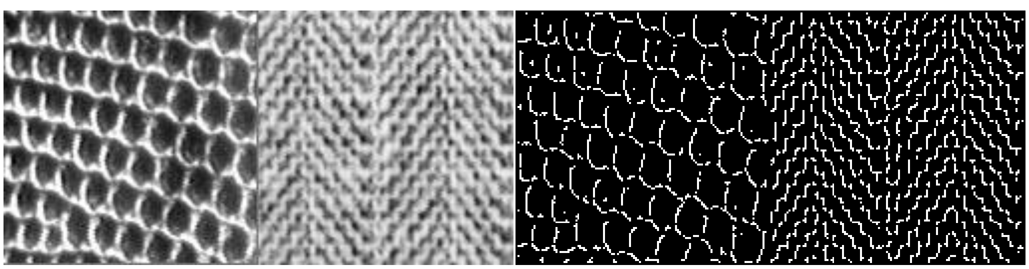


Figure 4. (a) An example texture pair from Brodatz's album (b) the peaks detected in the filtered image, and

2.3 Document Processing

One of the valuable applications of machine vision and image analysis has been in the includes the spatial supply of gray levels. Thus, two- dimensional histograms are reasonable texture analysis tools.

Texture in an image can be apparent at diverse Scales or stage of resolution E10 For example, consider the texture signified in a brick- wall At a coarse resolution, the texture is apparent as formed by the individual bricks in the wall the interior

Particulars in the brick are lost. At a higher resolution when only a few bricks are in the field of view, the apparent texture displays the details in the brick.

A region is apparent to have texture when the number of primitive matters in region is huge. Only a few Primeval matters are present then a group of countable objects is apparent stead of a textured image[4].

2.4 GLCM

Texture is an important characteristics used in identifying regions of interest in an image. Grey Level Co-occurrence Matrices (GLCM) is one of the earliest methods for texture feature extraction proposed by Haralick et.al. [12]

back in 1973. Since then it has been widely used in many texture analysis applications and remained to be an important feature extraction method in the domain of texture analysis. Fourteen features were extracted by Haralick from the GLCMs to characterize texture [11]

. Many quantitative measures of texture are found in the literature [3, 4, 5,6]. Dacheng et.al used 3D co-occurrence matrices in CBIR applications. Kovalev and Petrov used special multidimensional co-occurrence matrices for object recognition and matching. Multi-dimensional texture analysis was introduced in which is used in clustering techniques. The objective of this work is to generalize the concept of co-occurrence matrices to n-dimensional Euclidean spaces and to extract more features from the matrix. The newly defined features are found to be useful in CBIR applications. This paper is organized as follows. The theoretical development is presented in section 2, where the generalized co-occurrence matrices and trace are defined and the numbers of possible co-occurrence matrices are evaluated. Section 3 illustrates the use of trace in CBIR by comparing its performance with the Haralick features. Section 4 concludes the paper illustrating the future works.[12]

2.4.1 THEORETICAL BACKGROUND

In 1973 Haralick introduced the co-occurrence matrix and texture features for automated classification of rocks into six categories [1]. These features are widely used for different kinds of images. Now we will explore the definitions and background needed to understand the computation of GLCM.

2.4.2 Construction of the Traditional Co-occurrence Matrices

Let I be a given grey scale image. Let N be the total number of grey levels in the image. The Grey Level Co-occurrence Matrix defined by Haralick is a square matrix G of order N, where the (i, j)th entry of G represents the number of occasions a pixel with intensity i is adjacent to a pixel with intensity j. The normalized co-occurrence matrix is obtained by dividing each element of G by the total number of co-occurrence pairs in G. The adjacency can be defined to take place in each of the four directions (horizontal, vertical, left and right diagonal) as shown in figure1. The Haralick texture features are calculated for each of these directions of adjacency [10].

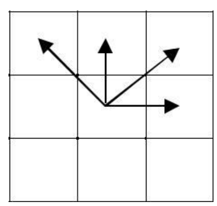


Figure 5. The four directions of adjacency for calculating the Haralick texture features

The texture features are calculated by averaging over the four directional co-occurrence matrices. To extend these concepts to n-dimensional Euclidean space, we precisely define grey scale images in n-dimensional space and the above mentioned directions of adjacency in n-dimensional images.

2.4.3 Generalized Gray Scale Images

In order to extend the concept of co-occurrence matrices to n-dimensional Euclidean space, a mathematical model for the above concepts is required. We treat our universal set as Z^n. Here $Z^n = Z \times Z \times \ldots \times Z$, the Cartesian product of Z taken n times with itself. Where, Z is the set of all integers. A point (or pixel in Z^n) X in Z^n is an n-tuple of the form $X=(x_1,x_2,\ldots,x_n)$ where $x_i \in Z$

$\forall i = 1, 2, 3...n$. An image I is a function from a subset of Z^n to Z. That is $f : I \rightarrow Z$ where $I \subset Z^n$. If $X \in I$, then X is assigned an integer Y such that $Y = f(X)$. Y is called the intensity of the pixel

X. The image is called a grey scale image in the n-dimensional space Z^n . Volumetric data [11] can be treated as three dimensional images or images in Z^3 .[11]

2.4.4 Generalized Co-occurrence Matrices

Consider a grey scale image I defined in Z^n . The gray level co-occurrence matrix is defined to be a square matrix Gd of size N where, N is the N be the total number of grey levels in the image.

the (i, j)th entry of Gd Represents the number of times a pixel X with intensity value i is separated from a pixel Y with intensity value j at a particular distance k in a particular direction d. where the distance k is a nonnegative integer and the direction d is specified by $d = (d_1, d_2, d_3, ..., d_n)$, where

$i \in \{0, k, -k\}$ $\forall i = 1, 2, 3,..., n$.

As an illustration consider the grey scale image in Z^3 with the four intensity values 0, 1, 2 and 3.

The image is represented as a three dimensional matrix of size 4*4

2.4.5 Trace

In addition to the well known Haralick features such as Angular Second Moment, Contrast, Correlation etc. listed in [1], we define a new feature from the normalized co-occurrence matrix, which can be used to identify constant regions in an image. For convenience we consider n=2, so that the image is a two dimensional grey scale image and the normalized co-occurrence matrix becomes the traditional Grey Level Co-occurrence Matrix[10].

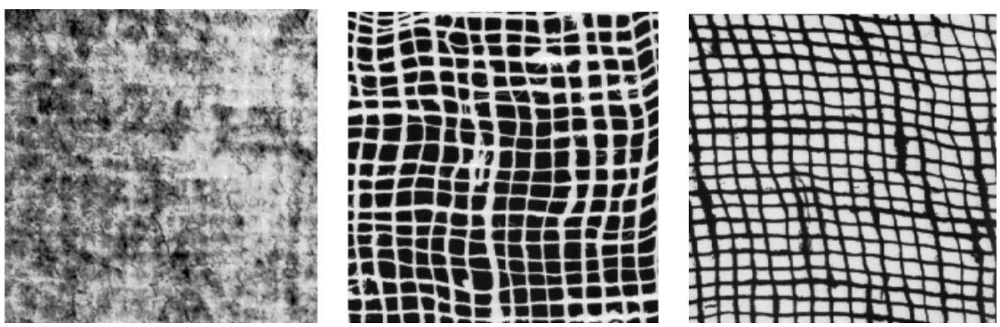


Figure 6. Sample images taken from Brodatz texture album

Consider the images taken from the Brodatz texture album given in figure 2. The majority of the nonzero entries of the co-occurrence matrices lie along the main diagonal [12] so that we treat the trace (sum of the main diagonal entries) of the normalized co-occurrence matrix as a new feature. Trace of GN d (i , j) is defined as

Trace = $\sum$GNd (i, i)

From the definition of the co-occurrence matrix, it can be seen that an entry in the main diagonal is the (i, i)th entry. This implies two pixels with the same intensity value i occur together. Thus higher values of trace implies more constant region in the image. The computed values of the trace of the normalized co-occurrence matrices in Figure 2 with k=1 are 0.0682, 0.2253 and 0.2335 for the left, middle and right images respectively. Obviously the left image contains less

2.4.5.1 Image Retrieval Using Trace

The numerical value of trace provides only a measure of the amount of constant region in an image. Thus we divide the main diagonal entries of the co-occurrence matrix into four equal parts and the sum of the elements in each quarter is taken to be a measure of the image texture feature for image retrieval, giving a four dimensional vector. The database is queried using the first and the fourth images from all the 36 different classes. Eight images are retrieved in each run. The average precision is found to be 0.8194[11].

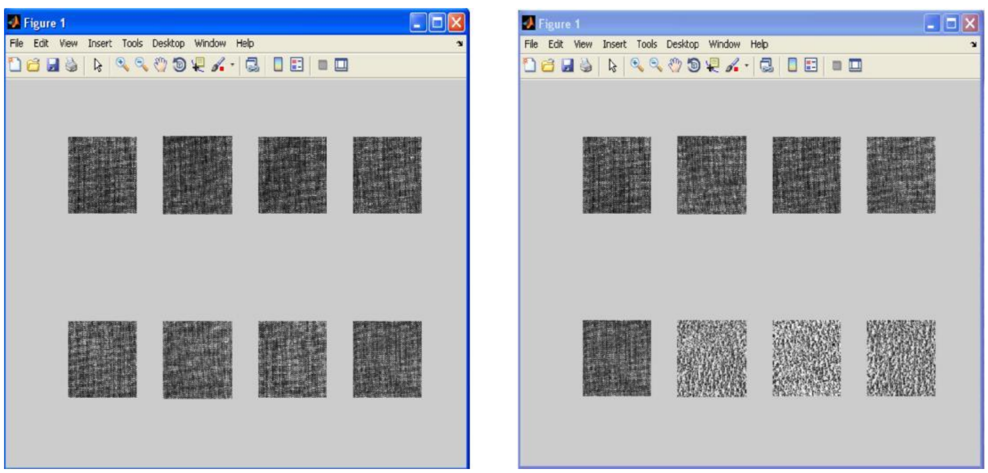


Figure7. Screen shots of the output for the same query image using the trace features (left) and the Haralick features (right)

2.4.5.2 Comparison of Results with Haralick features

Conducting the same experiment using the well known Haralick features Contrast, Correlation, Energy and Homogeneity we obtain an average precision of 0.7222. Here also we use a four dimensional feature vector for querying the database. This is a clear indication of the improvement of performance using the proposed features [12]

3.1 The algorithm

1- Read the image file of Diseases leaves.
2- Extract GLCM Features for each image of Diseases leaves.
3- Store the Features in the Diseases database.
4- Read the image file of Healthy leaves.
5- Extract GLCM Features for each image of Healthy leaves.
6- Store the Features in the Healthy database.
7- Insert the test image.
8- Extract GLCM Features for test image.
9- Measure distance between the Features of the test image with Features for each images in the Diseases database.
10- take Less distance and store it in R1.
11- Measure distance between the Features of the test image with Features for each images in the Healthy database.
12- take Less distance and store it in R2 .
13- if (R1>R2) then the test image is Healthy leaf
else its Diseases leaf.

3.2 The structure of project

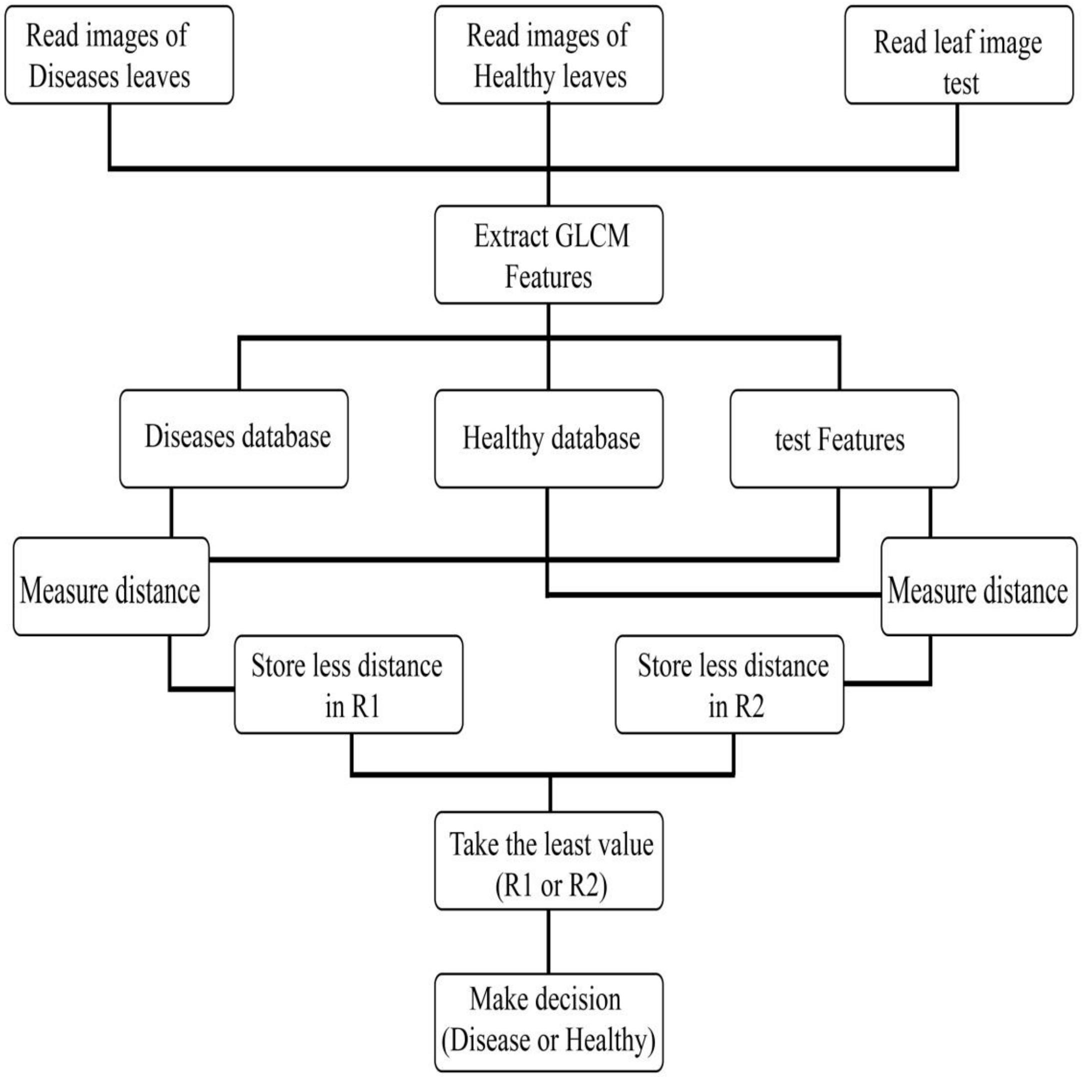


Figure (10) structure project

3.3 Test and Result:

in this case, we chosen a one sample from (sound plant) and one of (infected plant) and applied in the code , the result of each one is :

3.3.1 infected plant

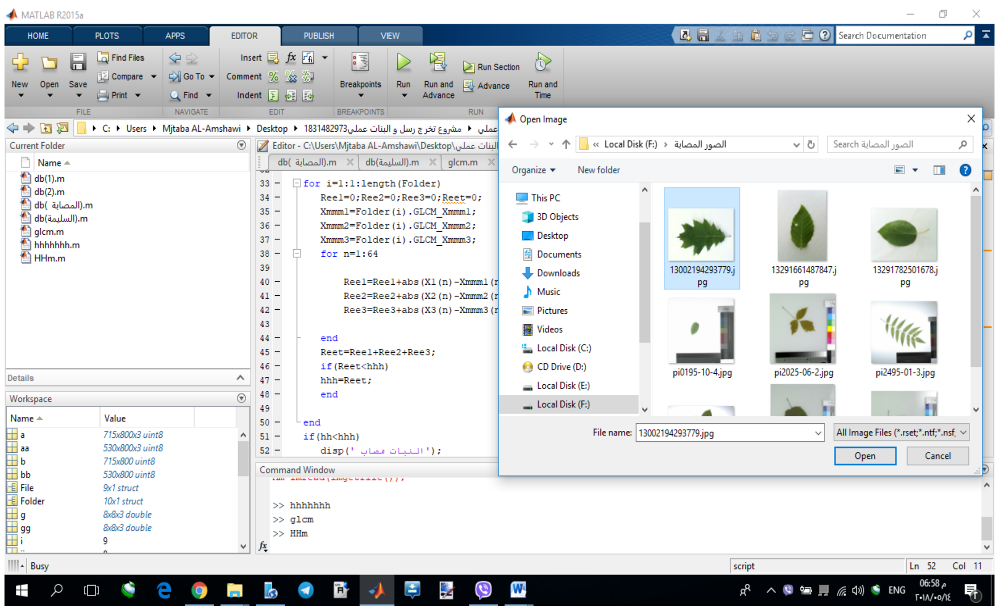


Figure (11) select infected plant

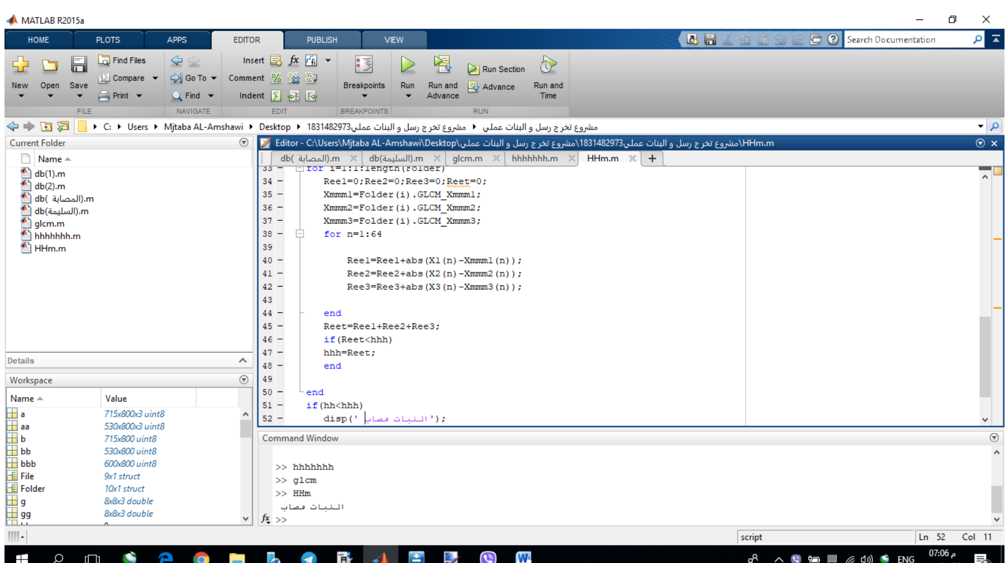
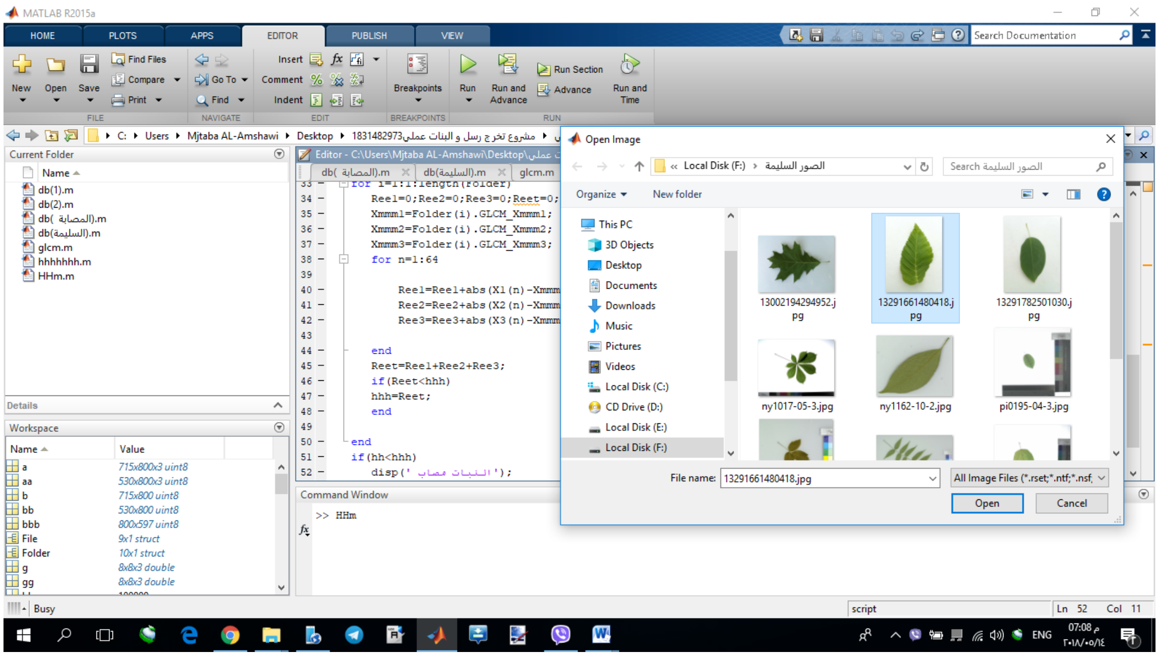


Figure (12) the result of infected plant

3.3.2 Sound plant



Figre (13) select sound plant

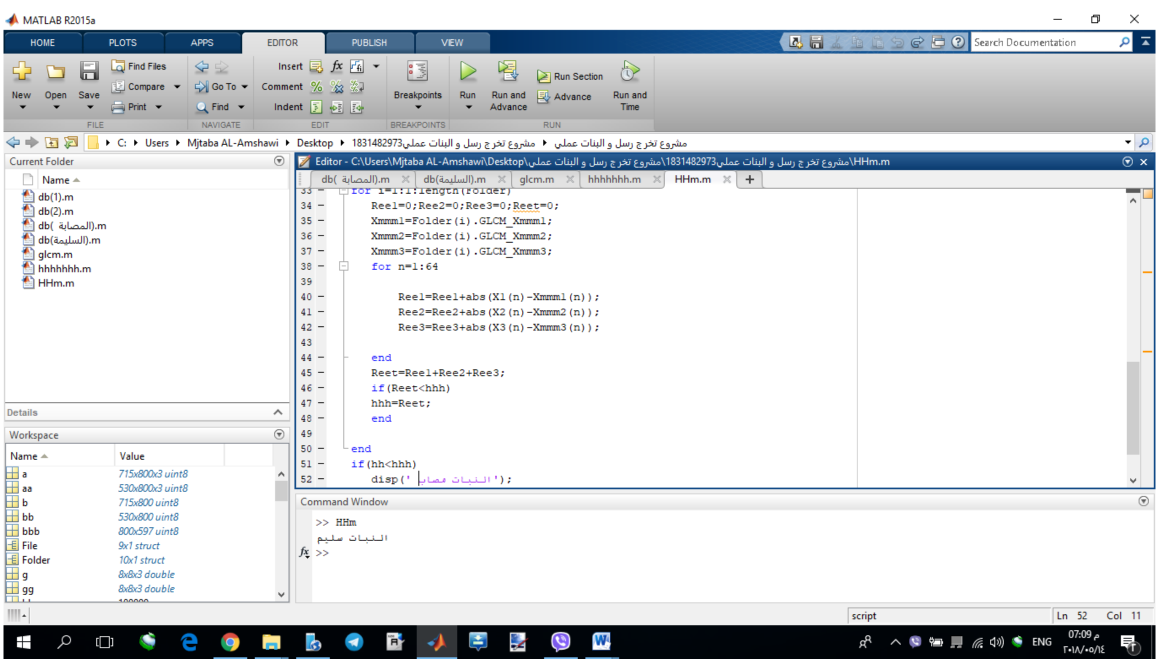


Figure (14) the result of sound plant

4. CONCLUSION AND FUTURE WORK

The research work attempted to investigate the use of GLCM textural parameters as an image quality metric. The proposed method discussed the relevance of radius and angle which happen to be the most crucial input parameters in GLCM processing. It can be concluded that the most appropriate value of radius for analysis would be one as closely spaced pixels are more likely to be correlated than those which are spaced far away. The radius which must be used in computing the GLCM may be obtained from the autocorrelation function of the image. The radius value at which the normalized autocorrelation function of the image becomes too small can serve as an upper bound on the value which may be used for computing the GLCM. No definite conclusion can be drawn regarding the value of angle. For most of the studies, it might be appropriate to calculate the textural parameters for all the four values of angle and use the average value. Thus GLCM happens to be a good discriminator in studying different images however no such claim can be made for image quality. The analysis of the results shows that the nature of the curve of textural parameter versus image size may not always follow a specific trend for chosen values of radius and angle. Performing exhaustive processing for all possible radius and angle values could be considered as an option and then choosing the most appropriate set of graphs. This however reduces the chances of automating the entire process. Hence the search for the best image quality metric continues.

Future research will include datasets that represent texture classes that differ more subtlely. Furthermore, it will be interesting to establish whether this finding holds true for computer generated images as well.

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