

A Statistical Identification Model (SIM) For Textural Images

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Abstract

The extraction of Textural Images Properties and its Identification relative to one of textural Images groups was and still the main concern for many researchers and studies in many application fields that because of the wide applicability for such kind of studies on many applications. This research came for building a application model to determine Identification textural pieces to belong to one of proposed textural groups or not belong to any textural Images in the Experiment based on statistical model parameters for determine the range of convergence or divergence for each texture thoughtful, also research included percentages to the range of determining to belong to random piece textural to one of the textural images of the study. Discrimination process depend on the parameters of the proposed model. Experimental data representation as (24) textural images divided into (3) main groups. Experimental results showing the ability of textural features for identify and discriminate of textural part to belong to main textural images with difference identification ratio depending on (textural kinds , textural features). The proposed model can be adopted for many images application such as (MRI, Remote Sensing).

Keywords: Textural Image, Textural Features, Classification models, Gray Scale, Feature Extraction, Log transformation, MSE.

Introduction

The Identification of Images textures was and still the focus of attention for many studies and researches. In this research we study a set of texture image belong to many groups by getting statistical features represent part or complete texture area, we can get part of Texture not known in previously to be one of the textural group known or not belong to any of them.

The experimental results showed that the proposed model able to distinguish part of texture and determine its group. Also the results showed discrimination process depend on the type of texture image in addition to discrimination model. The proposed model can be applied on a medical images (MRI) or Remote Sense Images. Also classification results can be compared with other models by use Mean Square Error for each of them.

Aim of research is building a Statistical Identification Model (SIM) that can be used to discriminate part of texture that belong to one of textural image.

Textural Analysis

Today, texture analysis plays an important role in many tasks, ranging from remote sensing to medical imaging and query by content in large image data bases. The main difficulty of texture analysis in the past was the lack of adequate tools to characterize different scales of textures effectively. The development in multi-resolution analysis such as Gabor and wavelet transform have helped to overcome this difficulty.

Textures are complex visual patterns composed of entities, or sub patterns, that have characteristic brightness, color, slope, size, etc. Thus texture can be regarded as a similarity grouping in an image [1]. The local sub pattern properties give rise to the perceived lightness, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, granulation, etc., of the texture as a whole[2].

Texture analysis is important in many applications of computer image analysis for classification or segmentation of images based on local spatial variations of intensity or color. A successful classification or segmentation requires an efficient description of image texture. Important applications include

industrial and biomedical surface inspection, for example for defects and disease, ground classification and segmentation of satellite or aerial imagery, segmentation of textured regions in document analysis, and content-based access to image databases. However, despite many potential areas of application for texture analysis in industry there is only a limited number of successful examples. A major problem is that textures in the real world are often not uniform, due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high [3]. Approaches to texture analysis are usually categorized into:

- 1- structural
- 2- model-based
- 3- transform and
- 4- statistical

The structural approaches [4] represent texture by well defined primitives (micro texture) and a hierarchy of spatial arrangements (macro texture) of those primitives. The advantage of the structural approach is that it provides a good symbolic description of the image; however, this feature is more useful for synthesis than analysis tasks.

Model based texture analysis [5][6] using fractal and stochastic models, attempt to interpret the image texture by use of, respectively, generative image model and stochastic model.

Transform methods of texture analysis, such as Fourier [2], Gabor [7] and wavelet transforms[8] represent an image in a space whose coordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size).

Statistical approaches do not attempt to understand explicitly the hierarchical structure of the texture. Instead, they represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image.

Feature Extraction

In computer vision and image processing the concept of feature is used to denote a piece of information which is relevant for solving

the computational task related to a certain application. More specifically, features can refer to

- * the result of a general neighborhood operation (feature extractor or feature detector) applied to the image,
- * specific structures in the image itself, ranging from simple structures such as points or edges to more complex structures such as objects.

Other examples of features are related to motion in image sequences, to shapes defined in terms of curves or boundaries between different image regions, or to properties of such a region.

The feature concept is very general and the choice of features in a particular computer vision system may be highly dependent on the specific problem at hand [9]. When feature extraction is done without local decision making, the result is often referred to as a feature image. Consequently, a feature image can be seen as an image in the sense that it is a function of the same spatial (or temporal) variables as the original image, but where the pixel values hold information about image features instead of intensity or color. This means that a feature image can be processed in a similar way as an ordinary image generated by an image sensor. Feature images are also often computed as integrated step in algorithms for feature detection.

Statistical Identification Model (SIM)

In this research we deal with statistical Identification model (SIM) see Fig.(1).

The identification model depends on the following parameters [10][11] :

$$\begin{aligned}
 g_{(0,0)} &= 0.6636 \\
 g_{(-1,-1)} &= g_{(-1,1)} = g_{(1,-1)} = g_{(1,1)} = 0.4005 \\
 g_{(-1,0)} &= g_{(0,-1)} = g_{(0,1)} = g_{(1,0)} = 1.4336
 \end{aligned}$$

$$h_{(s_1, s_2)} = \sum_{i=0}^2 \sum_{j=0}^2 g_{(i+s_1-1, j+s_2-1)} y_{(i+s_1-1, j+s_2-1)} \dots\dots\dots (1)$$

Where

$$\begin{aligned}
 s_1 &= 1, \dots, N-1 \\
 s_2 &= 1, \dots, M-1
 \end{aligned}$$

$y_{(s_1, s_1)}$: Array of textural image

M * N : Size of Image

With

$$\hat{X}_1 = \frac{\sum_{s_1=1}^{N-1} \sum_{s_2=1}^{M-1} y_{(s_1, s_2)} h_{(s_1, s_2)}}{\sum_{s_1=1}^{N-1} \sum_{s_2=1}^{M-1} h^2_{(s_1, s_2)}} \dots\dots\dots (2)$$

$$\hat{X}_2 = \frac{1}{MXN} \sum_{s_1=1}^{N-1} \sum_{s_2=1}^{M-1} [y_{(s_1, s_2)} \hat{X}_1 h_{(s_1, s_2)}]^2 \dots\dots\dots (3)$$

$$\hat{\alpha} = \hat{X}_1 / (1 + g_{(0,0)} * \hat{X}_1) \dots\dots\dots (4)$$

$$\hat{\beta} = \hat{X}_2 * (1 - g_{(0,0)} \hat{\alpha})^2 \dots\dots\dots (5)$$

For each textural images we get (α_i, β_i) with (i=1,...,24 (number of textural image=24)). As main identification feature and for each textural images we used (10) randomized pieces and recalculated the identification feature (α_{ij}, β_{ij}) with (j=1,...,10 (number of random sample textural=10)).

Investigation process for textural features depend on Mean Square Error (MSE) with the following general form [12]:

$$MSE_i = \sum_{j=1}^{10} (\hat{\theta}_{ij} - \hat{\theta}_i) / 10 \dots\dots\dots (6)$$

where the

$$\hat{\theta}_{ij} : \hat{\alpha}_{ij} \text{ And / Or } \hat{\beta}_{ij}$$

$$\hat{\theta}_i : \hat{\alpha}_i \text{ And / Or } \hat{\beta}_i$$

To find the belonging for randomized textural pieces depend on the nearest value of estimated part to the feature of textural image in the following form:

$$\psi_i = \min |\hat{\theta}_{ij} - \hat{\theta}_i| \dots\dots\dots (7)$$

Where

$$i=1, \dots, 24$$

$$j=1, \dots, 10$$

In order to find identification powerful for textural features we can use:

$$T_\alpha = A_\alpha / A \dots\dots\dots (8)$$

$$T_\beta = A_\beta / A \dots\dots\dots (9)$$

Where:

A_α : Number of correct identification for α features

A_β : Number of correct identification for β features

A: Total number of identification process.

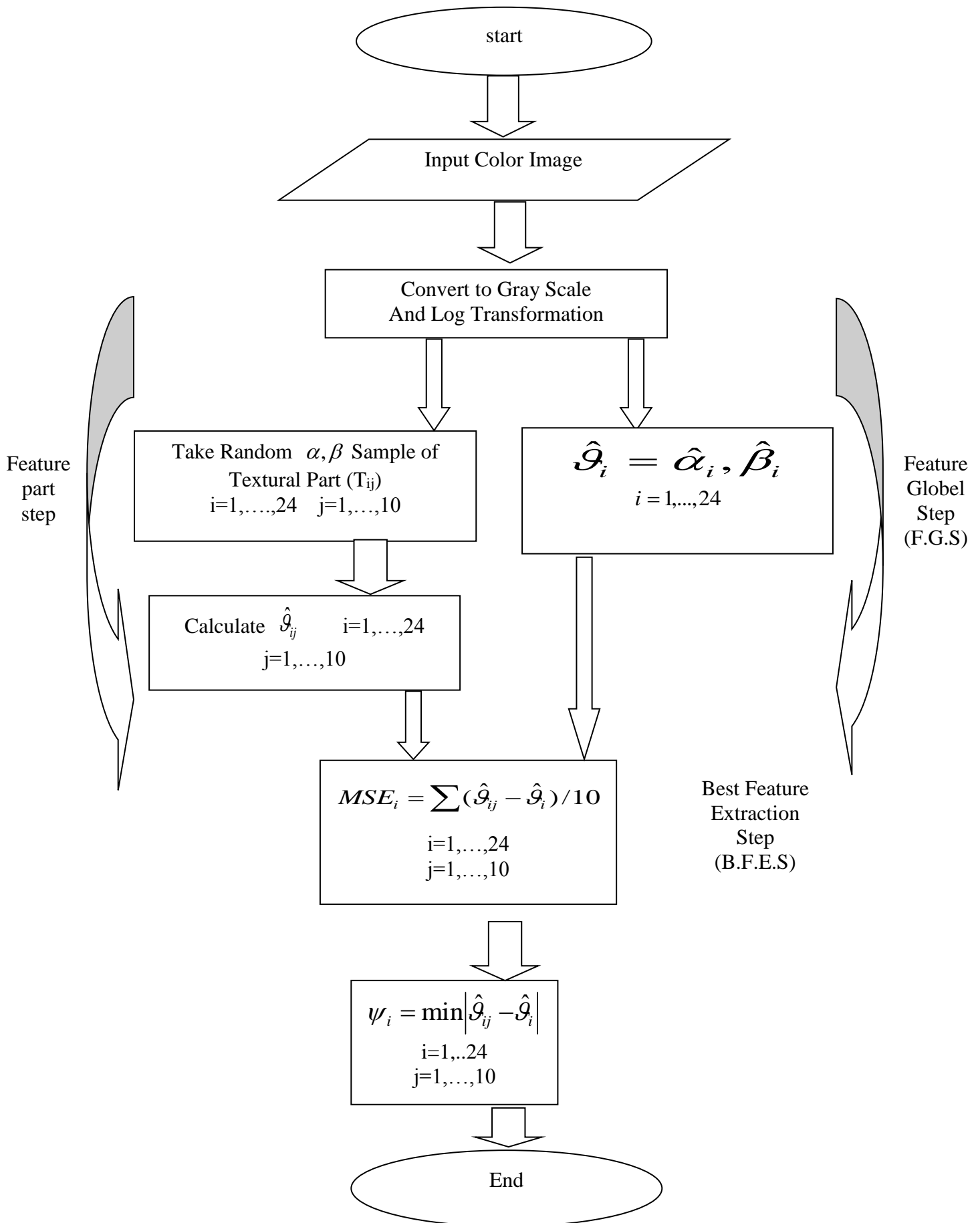
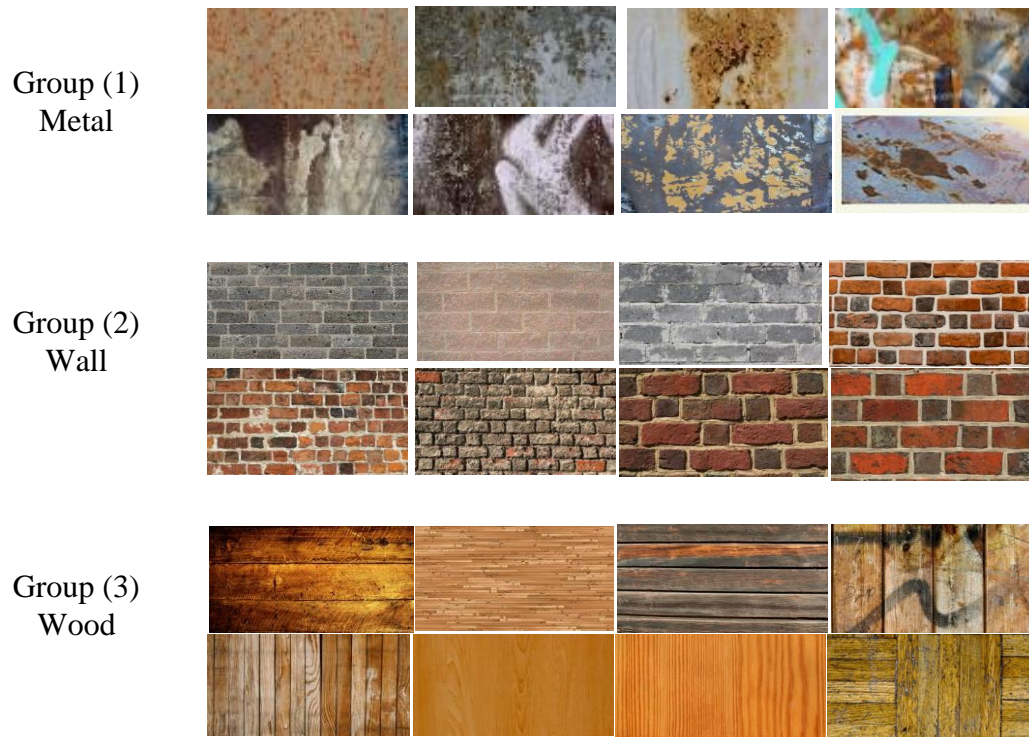


Fig.(1) Block diagram of (SIM) Model.

Experimental Data

In this research the experimental data represent textural images which they are (24) belong to with three main groups each of them consist of (8) samples, see Table (1):

*Table (1)
Represent Experimental Data.*



Experimental Result

After application of statistical features on texture in Table (1), we have the following results in Table (2) and (3), Fig. (2) and (3) from the note that.

Table (2)
The values of (α) and (β) For Three Groups.

<i>Texture group</i>	<i>Texture No.</i>	<i>α</i>	<i>β</i>
G1	1	1.50693185	1.02311738
	2	1.50693185	1.06726109
	3	1.50693186	1.35016667
	4	1.50693186	1.47890769
	5	1.50693186	1.53227535
	6	1.50693186	1.63704481
	7	1.50693185	1.06726105
	8	1.50693185	1.06726139
<i>Texture group</i>	<i>Texture No.</i>	<i>α</i>	<i>β</i>
G2	1	1.50693187	1.98121494
	2	1.50693187	2.13941684
	3	1.50693187	2.33650653
	4	1.50693187	2.42982053
	5	1.50693187	2.6364643
	6	1.50693187	2.84216251
	7	1.50693187	2.42982053
	8	1.50693187	2.6364643
G3	1	1.50693187	2.93995936
	2	1.50693187	3.16000465
	3	1.50693188	3.32641872
	4	1.50693188	3.54323844
	5	1.50693188	3.72104179
	6	1.50693188	3.87193833
	7	1.50693188	3.52641871
	8	1.50693188	3.24323841

Table (3)
The values of MSE (α) and MSE (β).

<i>Texture group</i>	<i>Texture No.</i>	<i>MSE α</i>	<i>MSE β</i>
G1	1	1E-15	0.179577423
	2	9E-16	0.173054934
	3	7E-16	0.256502422
	4	4E-16	0.295569479
	5	4E-16	0.342759564
	6	4E-16	0.381113065
	7	4E-16	0.421013065
	8	4E-16	0.443313066
G2	1	4E-16	0.511691228
	2	4E-16	0.611408024
	3	2E-16	0.714692409
	4	2E-16	0.758558021
	5	1E-16	0.830884186
	6	1E-16	0.974543394
	7	1E-16	0.982543794
	8	1E-16	0.999543395
G3	1	1E-16	1.025258297
	2	1E-16	1.170769475
	3	4E-16	1.227211931
	4	2E-16	1.389002021
	5	1E-16	1.544134275
	6	1E-16	1.659842894
	7	1E-16	1.779842811
	8	1E-16	1.789984289

When depending on Equations. (8,9) we get :

$$T_{\alpha} = 204 / 240 * 100 = 85\%$$

$$T_{\beta} = 215 / 240 * 100 = 90\%$$

This means the Identification power for this Model can be strong for (α) and for (β).

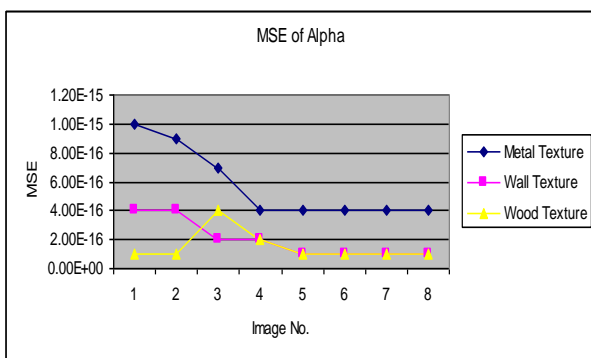


Fig.(2) MSE of Alpha for eight texture Images of three texture types.

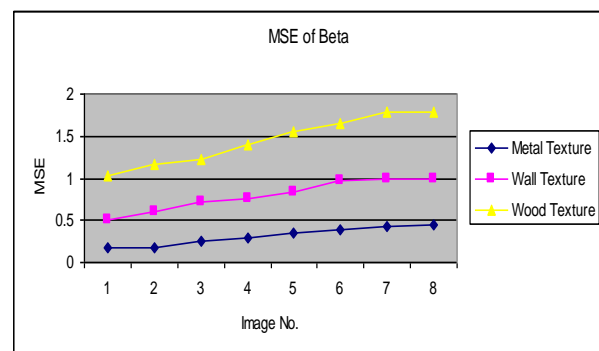


Fig.(3) MSE of Beta for eight texture Images of three texture types.

In Fig.(2) and Fig.(3) we can show that the MSE value wood texture was minimum comparing with (Metal and Wall) except texture number (3) for (α). Also for (β) we can show that MSE value for Metal texture was minimum comparing with (Wall and Wood).

Conclusions and Suggestions

- 1- Identification process depend on textural kind, and textural size;
- 2- The suggested model showing identification ability for discrimination process;
- 3- Identification and discrimination for textural images can be done by taking (α, β) at the same time as a classification rule in order to get better results;
- 4- The proposed model can be use for recognition process in characters and finger recognition;
- 5- Taking another model and compare discrimination and identification results to show better results.

References

- [1] Rosenfeld, A.; Kak, A.; “*Digital Picture Processing*”; vol. 1; Academic Press; 1982.
- [2] Levine, M.; “*Vision in Man and Machine*”, McGraw-Hill; 1985.
- [3] Ojala, T.; Pietikäinen, M.; “Texture classification, Machine Vision and Media Processing Unit”; University of Oulu; Finland.
- [4] Haralick, R.; “Statistical and Structural Approaches to Texture”; *Proc. IEEE*; 67; 5; pp786-804; 1979.
- [5] Cross, G.; Jain, A.; “Markov Random Field Texture Models”; *IEEE Trans. Pattern Analysis and Machine Intelligence*; 5;1; pp 25-39; 1983.
- [6] Pentland, A.; “Fractal-Based Description of Natural Scenes”; *IEEE Trans. Pattern Analysis and Machine Intelligence*; 6; 6; pp 661-674; 1984.
- [7] Daugman, J.; “Uncertainty Relation for Resolution in Space, Spatial Frequency and Orientation Optimised by Two-Dimensional Visual Cortical Filters”; *Journal of the Optical Society of America*; 2; pp 1160-1169; 1985.
- [8] Laine, A.; Fan, J.; “Texture Classification by Wavelet Packet Signatures”; *IEEE Trans. Pattern Analysis and Machine Intelligence*; 15; 11; pp1186-1191; 1993.
- [9] Wikipedia, the free encyclopedia; Feature “computer vision”.
- [10] Peter, G.; Sebastian, N.; “On feature combination for multiclass object classification”; Germany; 2009.
- [11] Zhanhua, G.; Lei, Z.; David, Z.; “Rotation invariant texture classification using LBP variance (LBPV) with global matching”; Elsevier; 2010 [IVSL].
- [12] Gupta, S.C.; Kapoor, V.K.; “Fundamentals of mathematical statistics”; Sultan chand and Sons Educational publishers-Delhi; 1995.

الخلاصة

ان استخلاص خصائص النسيج الصوري وتحديد عائدتيه الى واحدة من مجموعة انسجة صوريه كان ومايزال الشغل الشاغل للكثير من الدراسات والبحوث، وبسبب الامكانية العالية لاستخدام هذا النوع من التجارب على العديد من التطبيقات تم استخدامه في مجالات تطبيقية مختلفة. لقد جاء هذا البحث كمحاولة لبناء نموذج تطبيقي لتحديد عائدتيه قطع من نسيج صوري لتكون عائدة الى واحد من مجموعه انسجه صورية او ان لا تعود الى اي نسيج صوري ضمن البحث وذلك بالاعتماد على معلمات نموذج احصائي يحدد مدى التقارب او التباعد لكل نسيج صوري مدروس، كما وتضمن البحث النسب المئوية لمدى تحديد عائدتيه قطع نسيجية عشوائية الى واحد من انسجة الدراسة. اظهرت النتائج قدرة الخصائص الصورية المستخدمة في البحث على تعريف وتمييز قطع النسيج وتحديد عائدتيها وينسب تمييز مختلفة وحسب (نوع النسيج الصوري) و (موقع القطعة النسيجية المأخوذة ضمن النسيج الكلي). ويمكن الاستفادة من نتائج البحث في بناء نماذج لاستخلاص خصائص الانسجه للعديد من الصور من بينها صور التحسس النائي والصور الطبية.