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A Comparative Analysis of Texture Methods for Visual Object Categorization

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ABSTRACT

This paper presents a comparative study to the most common texture features analysis methods. In fact, there are two kinds of approaches have been proposed to extract the texture features for the purpose of object categorization, the former deals with the intensity pixels which derived the intensities texture and the second method dealing with the edge pixels which obtained the edge texture. However, to extract and make a comparative analysis to the texture maps there are several approaches have been presented in this research, i.e., Gradient, Co-occurrence matrix, Contrast and Edge Histogram Descriptor. A real world images dataset denoted by Caltech 101 dataset has been adopted to evaluate the proposed texture analysis methods. Mostly, the first 20 classes with 40 images per-class have been chosen to demonstrate the methods performance. Fundamentally, the objects of these images have almost isolated for the purpose of categorization. The experiment results show that the edge histogram descriptor outperformed the other proposed texture analysis methods with average accuracy 71.175±1.355775 because the edge histogram descriptor is less sensitive to the noise and variation of pixels intensities which most of the objects of Caltech 101 dataset profoundly affected.

2. INTRODUCTION

The fast growth in the Internet and the available image devices, such as digital cameras and image scanners has led to a tremendous increase in the management and organization demands of such digital libraries. Therefore, several kinds of research have involved and introduced an application for the purpose of object categorization. In fact, Visual Object Categorization (VOC) is considered one of the

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most challenging applications; hence it took the researchers' attention. The most common issue facing this application is the semantic gap, the differences between the low-level features and the richness of human mind concept [3, 7].

Several types of research have introduced various solutions that involve the use of object ontology or low-level features associated with the machine learning algorithms. With respect to the low-level features, the researchers introduced three kinds of features: color, texture, and shape. Mainly, the texture features have been widely utilized and viewed as a fundamental solution for various applications, such as: remote sensing, facial recognition, and object categorization [8].

However, the texture is seen as repeated patterns of information with regular intervals. It also indicates the surface properties and object appearance. The review of the literature shows that the there are four approaches that have introduced the extract the texture features. These approaches include, namely, the Structural, Statistical, Model, and Transform based features extraction [4].

In fact, the efficient methods for texture features extraction rely on the excellent analysis to the local features. Mostly, some of the texture features extraction methods are based on the pixel intensities while the other are based on the edge pixels. The Gray level Co-occurrence Matrix (GLCM) extracts the texture features based on the relationship of the pixels. There are three ways to extract the texture features of the GLCM method. These ways are based on pixels neighboring relationship; i.e., first-order statistics, second-order, and high-order statistics [5, 1].

Besides, two main factors were commonly used measure the texture information: (i) the roughness and (ii) smoothness of the object surface. Therefore, numerous statistical equations have been offered to measure the degree of roughness and smoothness of the object surface. In addition, there are other factors which can add valuable information to the texture features to measure the brightness and darkness of the texture [10]. In contrast, to obtain the edge texture features, diverse methods were presented; as a case in point is the Edge Histogram Descriptor (EHD) of MPEG-7 descriptors. Obviously, this descriptor has various characteristics which made it well-known and broadly used by several applications, such as: Content-Based Image Retrieval (CBIR) and Visual Object Categorization (VOC) [11; 2].

In this paper work, a valuable comparative analysis between the intensity and edge based texture features had been carried out. For the intensity-based texture features, two methods are proposed; namely, Gradient, and Co-occurrence Matrix. Besides, for the edge-based texture features, EHD is adopted to extract the texture features. Test results indicated that the first 20 categories of Caltech 101 dataset, which was chosen, to demonstrate the proposed methods performance.

3. TEXTURE MAP CONSTRUCTION

The texture is a complicated set of patterns, which provides valuable visual information. However, there are several texture characteristics that have been presented in the literature to show how the texture of the current regions behaves. Such characteristics include roughness, smoothness, regularity, density, coarseness, randomness, fineness, uniformity, etc. [9, 10]. Therefore, in this research paper, different methods are presented to extract the texture maps. Besides, several mathematical equations that measure the texture features were manifested in this research. The sections below illustrate the texture maps extraction methods and the mathematical equations for its analysis.

2.1. Co-occurrence Matrix:

A co-occurrence matrix is considered the second order statistical method that is widely used in the last two decades to extract the texture features. In fact, this approach takes into consideration the relationship between the neighboring pixels to generate the Co-occurrence matrix. To construct this matrix, the occurrence of the neighboring pixels in different directions (ex: vertical, diagonal (45 and 135) and horizontal) are counted [1, 9]. The order of the co-occurrence matrix depends on the relationship between the current pixel and its next neighboring pixels. However, in this research, the relationship between the first and third neighboring pixels is counted to generate the co-occurrence matrix. The main idea behind using the first and third neighboring pixels is, in some cases, due to the fact that the distribution of the gray level is very high. That is; if the first neighboring relationship did not succeed in capturing the probability distribution of the gray level, the third neighbor pixel will succeed. To calculate the co-occurrence matrix, the distance and the theta should be pre-defined $p(d, \theta)$. After calculating the co-occurrence matrix, different statistical equations have been proposed to analyze the texture features. The following figure presents an example of the calculation of the co-occurrence matrix [7].

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

(a)

i \ *j*	0	1	2
0	#(0,0)	#(0,1)	#(0,2)
1	#(1,0)	#(1,1)	#(1,2)
2	#(2,0)	#(2,1)	#(2,2)

(b)

8	2	0
2	4	0
0	0	4

$(1, 0^{\circ}, 180^{\circ})$
(c)

8	2	2
2	4	0
2	0	4

$(1, 90^{\circ}, 270^{\circ})$
(d)

4	2	1
2	2	0
1	0	2

$(1, 45^{\circ}, 225^{\circ})$
(e)

4	2	1
2	2	1
1	1	2

$(1, 135^{\circ}, 315^{\circ})$
(f)

FIGURE 1: An example of the Co-occurrence Matrix, (a) (4×4) Sub-image, (b) A General Form of Co-occurrence Matrix, (c), (d), (e), (f) are co-occurrence matrix results.

In fact, before calculating the co-occurrence matrix, the colors of the image are quantized into N levels. The aim of performing the quantization step is to ignore the redundant

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information and keep the adequate information as the human vision does. Besides, the co-occurrence matrix will be calculated for each image band (Red, Green, Blue, and Gray). The purpose of extracting the co-occurrence features from these bands is to capture every possible information from the entire image. The following equations are applied to analyze the texture features of the co-occurrence matrix [9].

1- Mean

$$\mu = \frac{\sum_i \sum_j P(i,j)}{N} \quad (1)$$

2- Standard Deviation

$$STD = \sqrt{\frac{1}{N \times M} \sum_{i=1}^{N} \sum_{l}^{M} \left(P(i,j) - Mean\right)^2} \quad (2)$$

3- Skewness

$$Skew = \frac{\frac{1}{N \times M} \sum_{i=1}^{N} \sum_{l}^{M} \left(P(i,j) - Mean\right)^3}{Standard\ Deviation^3} \quad (3)$$

4- Angular Second Moment or Energy

$$ASM = \sum_i \sum_j P(i,j)^2 \quad (4)$$

5- Contrast

$$Contrast = ij(i-j)^2 \sum_i \sum_j P(i,j) \quad (5)$$

6- Correlation

$$Correlation = \frac{\{\sum_i \sum_j (i,j) P(i,j)\} - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (6)$$

Where the $\mu_x \mu_y$ are the means values and the $\sigma_x \sigma_y$ are the standard deviation.

7- Entropy

$$Entropy = \sum_i \sum_j ij\, P(i,j) log P(i,j) \quad (7)$$

8- Inverse Difference Moment

$$IDM = \sum_i \sum_j \frac{P(i,j)}{1 + 2(i-j)} \quad (8)$$

9- Variance

$$Variance = \sum_i \sum_j (i-\mu)^2 P(i,j) \quad (9)$$

$where\ \mu\ is\ the\ mean\ value\ of\ the\ denisty;\ \ function\ P(i,j)$

10- Sum Average

$$SumAver = \sum_{i=2}^{2w} i P_{x+y}(i) \quad (10)$$

$where\ P_{x+y}(i) = \sum_{j,k;j+k=i} P(j,k).$

11- Sum Entropy

$$SumEnt = \sum_{i=2}^{2w} P_{x+y}(i) \log(P_{x+y}(i)) \quad (11)$$

12- Homogeneity

$$Homg = \sum_i \sum_j \frac{P(i,j)}{1 + |i-j|} \quad (12)$$

13- Difference Entropy

$$Diff_{Entropy} = \sum_{i=0}^{w-1} P_{x-y}(i) \log(P_{x-y}(i)) \quad (13)$$

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This set of mathematical equations has been used to measure the various characteristics of the texture maps. These characteristics involve the following: homogeneity, regularity, complexity, dependency, uniformity, correlations and others, which were constructed using the co-occurrence matrix. In fact, in this research, two levels of relationships between the neighboring pixels have used the first and third neighboring pixel. Therefore, the number of features for each band will be 26 features, and the total number of features will be 104 features extracted from each image.

2.2. Gradient Texture Analysis: A Gradient is another texture map method, which uses the edge density based on the pixel level contrast. In the literature, several methods have been introduced to extract the edge map. Such methods can be later employed for different purposes, such as features extraction, object segmentation, and texture analysis. In fact, the edge is essentially based on the intensity change of an image. Moreover, good edges are imperative to higher level processing. The edge detector is paramount in the area of computer vision. Certainly, different methods were proposed to extract strong edges, including the first and second order derivatives [6]. Simply, to construct the edge map, the relationship between the neighboring pixels should be taken into account. These edges will be used later as texture maps to be analyzed [8]. However, to extract the edges, two methods were used: the first and the second order derivative.

In this research, the second order derivative is used to construct the texture maps. Similar to the co-occurrence matrix, the colors of the images are quantized from 256 levels into N-level. This process will improve the processing time and act as the human vision does. Additionally, the texture maps will be constructed based on two areas, namely darkness and brightness. The main purpose of using this principle is to measure the texture into two different parts of the image. This can in turn give an indication of how the texture is distributed in the image. The following equation illustrates the Gradient of the second order:

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) + 2 * f(x) \qquad (14)$$

where $\frac{\partial^2 f}{\partial x^2}$ represents the Second-order derivative, $f(x)$ represents the current pixel and $f(x+1)$ and $f(x-1)$ represent the forward and backward pixels, respectively in (vertical, horizontal and diagonal).

The most important purpose of using the second order derivative is to capture the strong edges based on the different directions and values of the three color bands

Apart from that, various statistical equations are used to measure both the dark ad bright areas in this research. These statistical equations include the following: the Mean, Standard Deviation, Skewness, Central Moment with Low Order, Short Run Emphasis, Long Run Emphasis, Gray Level Non-uniformity, Run Length Non-uniformity, Run Percentage, Low Gray Level Run Emphasis, High Gray Level Run Emphasis, Short Run Low Gray-Level Emphasis, Short Run High Gray-Level Emphasis, Long Run Low Gray-Level Emphasis, Long Run High Gray-Level Emphasis, Entropy and Energy. The following section demonstrates this set of equations [9].

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1. Central Moment

$$\mu_p = \sum_{i=0}^{n} (x_i - \mu)^p * \text{probability}(x_i) \tag{15}$$

Where μ_p represents the moment of p order, E represents the expectation function, μ represents the mean, n represents the number of samples, and x_i represents the input sample.

2. Short Run Emphasis

$$SRE = \frac{\sum_{i=1}^{width} \sum_{j=1}^{hight} (\frac{P(i,j)}{j^2})}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{16}$$

3. Long Run Emphasis

$$LRE = \frac{\sum_{i=1}^{width} \sum_{j=1}^{hight} j^2 P(i,j)}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{17}$$

4. Gray Level Non-uniformity

$$GLNU = \frac{\sum_{i=1}^{width} [\sum_{j=1}^{hight} P(i,j)]^2}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{18}$$

5. Run Length Non-uniformity

$$GLNU = \frac{\sum_{j=1}^{hight} [\sum_{i=1}^{width} P(i,j)]^2}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{19}$$

6. Run Percentage

$$RP = \frac{1}{n} \sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j) \tag{20}$$

Where n represent the number of samples.

7. Low Gray Level Run Emphasis

$$SRE = \frac{\sum_{i=1}^{width} \sum_{j=1}^{hight} (\frac{P(i,j)}{i^2})}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{21}$$

8. High Gray Level Run Emphasis

$$LRE = \frac{\sum_{i=1}^{width} \sum_{j=1}^{hight} i^2 P(i,j)}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{22}$$

9. Short Run Low Gray Level Emphasis

$$SRLGE = \frac{\sum_{i=1}^{width} \sum_{j=1}^{hight} (\frac{P(i,j)}{i^2 j^2})}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{23}$$

10. Short Run High Gray Level Emphasis

$$SRHGLE = \frac{\sum_{i=1}^{width} \sum_{j=1}^{hight} (\frac{i^2 P(i,j)}{j^2})}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{24}$$

11. Long Run Low Gray Level Emphasis

$$LRLGLE = \frac{\sum_{i=1}^{width} \sum_{j=1}^{hight} (\frac{j^2 P(i,j)}{i^2})}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{25}$$

12. Long Run High Gray Level Emphasis

$$LRHGLE = \frac{\sum_{j=1}^{hight} [\sum_{i=1}^{width} i^2 j^2 P(i,j)]^2}{\sum_{i=1}^{width} \sum_{j=1}^{hight} P(i,j)} \tag{26}$$

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The number of features extracted from each channel of an image is 34 features. Additionally, the total number of features obtained from the entire region of interest for the four color channels is 136 features.

2.3. Edge Histogram Descriptor: During the last decades, several techniques were introduced to serve as texture feature extraction methods. These methods were introduced for different purposes. For instance, some of them were used for medical images and some for entirely texture image while others have been used for real world images [7, 2]. However, the perception of the human eyes is more sensitive to the edges of the image. As general speaking, the edges are divided into two parts based on the intensity or texture. The MPEG-7 descriptor was introduced a texture descriptor based on the local distribution of the edge histogram. This method was proved to be very useful in extracting the local texture features with real world images [11].

Generally, this descriptor was presented to describe the frequency distribution of the edges in different five angles (horizontal, vertical, two diagonal and non-directional). The analysis of the edge distribution makes this descriptor efficient even with the non-homogenous texture [11]. There are three levels of processing to get the local distribution of the texture edge of an image. First of all, the image is partitioned into 16 blocks, which are called sub-images. Next, the edge histogram filters are applied (ex.: horizontal, vertical, diagonal 45, diagonal 135 and non-directional) on each sub-image to extract the five texture edges. Moreover, the last step is to make normalization. Figure 2 gives an illustration of the sub-images and image blocks of the EHD descriptor.

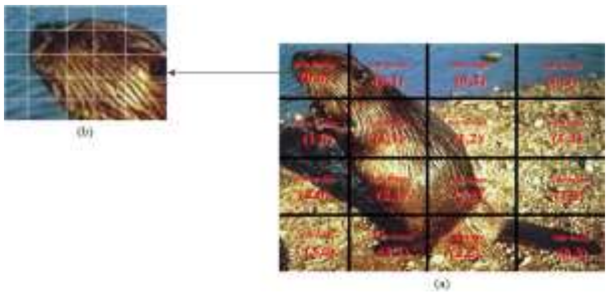

FIGURE. 2: Image partitioning process of EHD, (a) Dividing the Image into 16 Sub-images, (b) Dividing the Sub-Images Blocks.

4. PROPOSED TEXTURE FEATURE EXTRACTION METHODS

As it was mentioned before, three methods were used to extract the texture features from the region of interest. These methods include: the co-occurrence matrix, the gradient of the second order derivative and the edge histogram descriptor. For the co-occurrence matrix and the gradient of the second order derivative, the image channels are quantized from 256 levels into N levels. In fact, the best N quantization level for the co-occurrence matrix the gradient of the second order derivative and EHD is 16, 12 and 16, respectively. As it is stated earlier in section 2, the main gains of using quantization are to increase the system performance and to focus on the most dominating and adequate information as the human vision does. As the quantization further help apply the co-occurrence matrix and the gradient of the second order

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derivative on all image channels. The power of using all channels is to capture any potential information about the texture of the region of interest.

Besides, for the EHD, there are different sizes of image partitioning as have been shown in the literature. The most common one is (4×4), which means 16 sub-images will be constructed. After that, for each sub-image, five filters that represent the edge directions with the size of (2×2) were applied to extract the edge texture features. Certainly, after convolving each block of each sub-image the maximum value among the five edge types, it will then be compared with the edge strength threshold. If it is greater than the threshold, the block will have sufficient edges and the histogram will be built [11]. Figure 3 shows the five edge filters.

$$\begin{array}{|c|c|}\hline 1 & -1 \\ \hline 1 & -1 \\ \hline\end{array}$$
(a)

$$\begin{array}{|c|c|}\hline 1 & 1 \\ \hline -1 & -1 \\ \hline\end{array}$$
(b)

$$\begin{array}{|c|c|}\hline \sqrt{2} & 0 \\ \hline 0 & -\sqrt{2} \\ \hline\end{array}$$
(c)

$$\begin{array}{|c|c|}\hline 0 & \sqrt{2} \\ \hline -\sqrt{2} & 0 \\ \hline\end{array}$$
(d)

$$\begin{array}{|c|c|}\hline 2 & -2 \\ \hline -2 & 2 \\ \hline\end{array}$$
(e)

FIGURE 3: Edge Histogram Descriptor Filters, (a) Vertical Edge Filter, (b) Horizontal Edge Filter, (c) Diagonal 45 Edge Filter, (d) Diagonal 135 Edge Filter, (e) Non-Directional Edge Filter.

The last step, after building the histogram, is based on the strength edges. The histogram distribution is normalized and is then quantized for a binary representation. To conclude, this operation produces 80 bins of edge distributions that represent the entire image [2]. Figure 4 gives an illustration of the proposed texture feature extraction diagram.

After extracting the features by the proposed texture feature extraction methods, these features will be proceeded by the Support Vector Machine (SVM) classifier to get the final classification results. However, in this research, a libSVM with a Radial Basis Function (RBF) has been utilized to achieve the final classification accuracy.

5. RESULTS AND DISCUSSION

The first 20 classes of Caltech 101 dataset have been used to demonstrate the performance of the proposed texture extraction methods. To verify the strength of the proposed methods, ten random runs have been performed. To train and test the proposed methods, fifty percent of each class images have been used to train the classifier while the rest have been used to test the classifier. Table 1 and Figure 5 give full details to the achieved results of the proposed methods.

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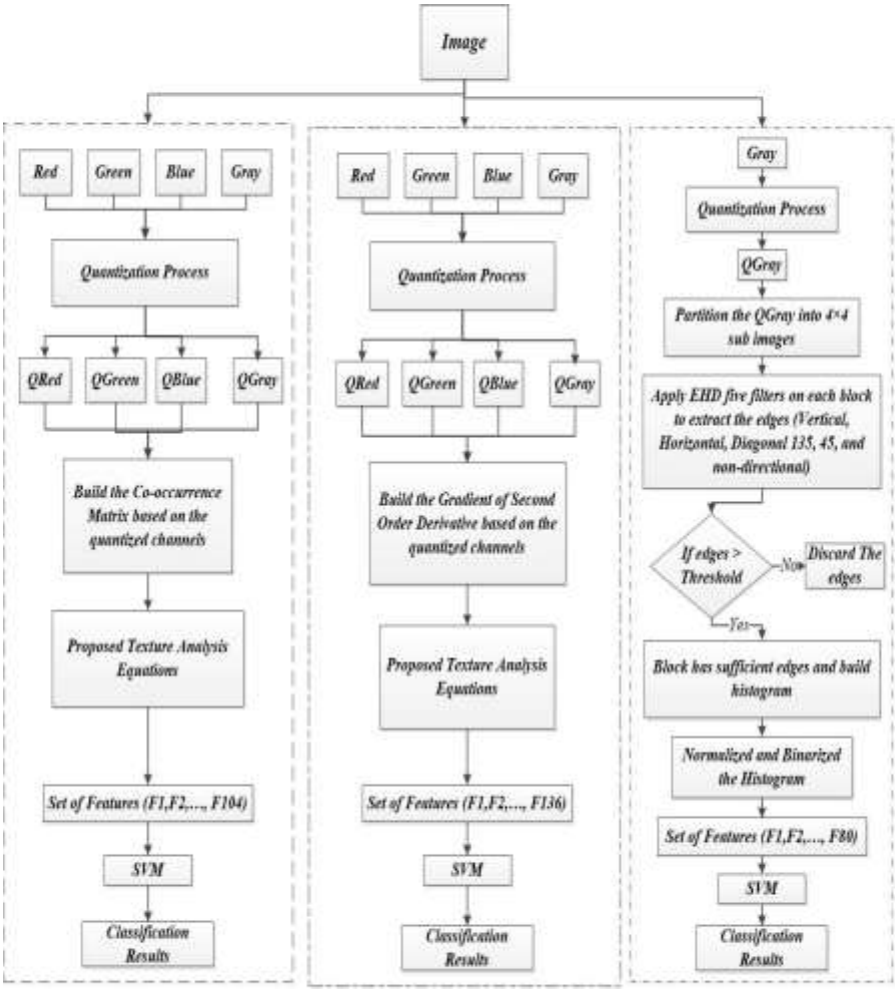

FIGURE 4: The proposed texture analysis method prototype

Table 1: Classification Accuracy Results of the Proposed Texture Feature Extraction Methods Based on Caltech 101 Dataset

Runs	Co-occurrence Matrix	Gradient of the Second Order Derivative	Edge Histogram Descriptor
1	43.25	45.75	69
2	42.25	45	69.25
3	44.75	49	71
4	40	45.75	72.75
5	41.25	50.25	69.75
6	41.5	45.25	71.25
7	43.25	49.5	67.75
8	41.5	50.75	69.5
9	42	47.75	71.25
10	44	49.75	70.25
Average %	42.375	47.875	**70.175**
STD	1.356696	2.133805	**1.355775**

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Based on the achieved results in Table 1 and Figure 5, it has become clear that EHD has outperformed the other state-of-the-art methods with average accuracy that is equal to 70.175 ±1.355775. Clearly, the main reason that makes EHD overcomes these descriptors is because EHD is based on edge texture when describing the texture distribution of an object. On the other hand, the state-of-the-art method relies on the intensity pixels which are highly affected by the significant intensity variations. In other words, this work shows that the texture based edges are more discriminative in describing the objects of the real world images even with complicated objects and scenes.

From the other side, the standard deviation shows that all proposed methods are not much stable with random training and testing. This parameter gives an indication that each class may include more than one template to represent it.

Besides, the t-test statistical was used to verify the significant results of the proposed methods. Obviously, the t-test shows that EHD is extremely and statistically significant when it is compared with the co-occurrence matrix and Gradient of the second order derivative.

However, as it was reported in the literature, the proposed texture extraction methods have been successfully applied to different kinds of images such as medical images, artificial images, and industrial images. Based on the review of the literature, these methods had shown distinctive results when they compared with other feature extraction methods such as color and shape. In this paper work, these methods were undertaken to real world images to verify their strength and show how much their features are distinctive for the purpose of visual object categorization. Apparently, the texture classification with real world images considered one of the most challenges task because of the board variation of the objects within the same class, complex objects and scenes, and high interference between object foreground and background. The experimental results showed that the proposed texture features extraction methods did not give high classification results compared to the results of the medical images, artificial images, and industrial images. On the other hand, the EHD showed more accurate results when it compared with the Gradient of the second order and Co-occurrence matrix because it based on edges in extracting the texture features. To conclude, using the edges in obtaining the texture features can be considered more valuable than using the intensity pixels for the real world images because the edges are more resistance to the images effects and produce distinctive features.

6. CONCLUSION

Categorization and retrieving real world images are among the most channeling tasks in the computer vision community. This is because of the great complicated objects and scenes. However, in this research, a comparative study was carried out based on the real world image dataset, called Caltech 101 dataset. The primary goal of this comparative study is to verify the strength and weakness of the two main approaches in extracting the texture features, which rely on edges and intensities. The results of the experiment reveal that the edge histogram descriptor outperforms the other state-of-the-art methods. This is because EHD is essentially based on edges in extracting the texture features that are much valuable with real world images. Besides, the state-of-the-art methods, which are primarily based on the intensities of pixels, are highly affected by the board variations of intensities. Lastly, the standard deviation reveals that the proposed methods are not much stable with random training and testing runs. This means that there is more than one template to represent each class of Caltech 101 dataset. To expose how many templates each class contains, the clustering technique can be appropriated for this purpose, a good suggestion for future work.

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