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Robust Content-based Image Retrieval System for Face Recognition

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***Abstract*— many types of biometric systems are used for different purposes. Face recognition is considered the most effective biometric system due to the fact that it requires the least amount of human interaction. This attracted many researchers to pay a lot of attention to the field of face recognition and its applications. One of the approaches used in face recognition systems is using Content-Based Image Retrieval (CBIR). As its name implies, CBIR uses the actual visual contents of an image to retrieve similar images from a database or a set of images. The visual contents of images are described with features obtained using various feature extraction techniques.**

This research proposes a new robust face recognition system based on CBIR. The efficiency of two types of mathematical features is evaluated and compared in terms of accuracy, required CPU processing time and robustness against different challenges such as changes in scaling and lighting conditions in order to use the best features as new face recognition features. The mathematical investigated features are: Harris-Stephens features and Minimum Eigenfeatures. The proposed system combines several methods to implement a fast and accurate CBIR system for face recognition. The proposed system is also compared with other modern face recognition systems using two published face images databases

***Keywords*—component, face recognition; feature extraction; content-based image retrieval; Harris-Stephens features; minimum eigenfeatures.**

I. Introduction

Biometric is the term used to describe the process of using modern statistical approaches to measure biological objects in addition to using distinctive physiological and behavioral characteristics. The face, iris, fingerprint and signature are some examples of these biometric identifiers or characteristics. A biometric system is fundamentally one of pattern recognition systems used for determining the authenticity of physiological and/or behavioral identifiers uniquely related to that person to recognize him . There are many purposes for using biometric. Face recognition systems are considered to require the minimum amount of human interaction when different types of biometric identification systems are compared. This makes face recognition the most effective type among biometric systems [1]. Thus, it drew the attention of researchers to do a lot of work in the field of face recognition and in the applications utilizing it such as security, forensic, surveillance, human-computer interface, computer access, e-Banking and e-Commerce, etc.,

Several techniques were introduced in literature to be used in face recognition systems. An important technique for face recognition is using Content-based image retrieval (CBIR. "Content-based" is an indication to the fact that the actual contents in the image will be analyzed and used in the search instead of the traditional textual descriptions [2The actual image contents are the colors, shapes, textures derived from the image by performing image processing techniques. In CBIR, the search query is an image. All the images in the dataset are searched to retrieve the most similar images to the input query image.

The similarity of the two images, the query and the image in the dataset, can be measured by computing the similarity between the feature vectors of these images [3]. Similarity measures are essential authentication at airports [7], etc

Human face perception is an essential and major part of the capability of the human visual system. Although it is considered as a usual task for humans [8], trying to perform a similar task by a computerized system is still an open research area. The first traced work that considered face recognition goes back to the 1950s in the field of psychology [9]. In engineering, the start of research on face recognition is traced to the 1960s [10]. Automatic machine face recognition was first done by Kelly in the 1970s [11]. During the past few decades, researchers from different fields such as engineers, neuroscientists, psychophysicists presented new work on face recognition.

Several face recognition algorithms have been suggested. In general, face recognition systems include three main steps [12]. Fig. 1 outlines these steps

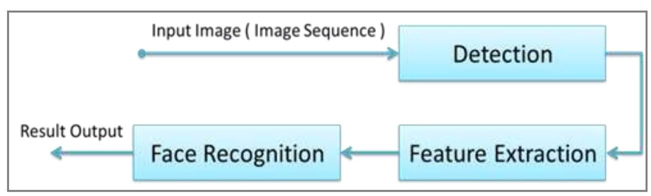

Fig. 1. Main stages of face recognition systems.

In the detection step, face edges are detected, segmented and localized to find the face and extract it from the background in the image. Feature extraction is calculating the features from the image. Image features are the visual features, statistical features, algebraic features and transform coefficient features. The final step, which is face recognition, is the process of classifying the extracted image features for identifying the processed face image.

Artificial intelligence techniques have been used widely in face recognition and have been found beneficial. Li and Yin [13] introduced a face recognition system in which the face image is decomposed to three levels with a wavelet transform. The Fisherfaces method [14] is then applied on the three low-frequency sub-images. Then, RBF neural network is used for cascading classifiers yielding better performance than individual classifiers

Content-based image retrieval (CBIR) also received researchers' attention as an approach for face recognition. CBIR is a term used to describe using actual image visual contents for retrieving similar images. "Content-based" indicates that the contents of the image are analyzed for the search and not textual words. The image contents are the shapes, colors, textures, or other information derived from the image. The main focus in research investigating face recognition based on CBIR is to find image representations (features) which lead to accurate and effective face recognition

CBIR was first presented in the literature by Hirata and Kato in 1992 [15]. They proposed automatic image retrieval from a database based on the color and shape and used the term Content-based Image Retrieval for their proposal.

Kumar et al. [16] used the intensity of image pixels in addition to magnitude and orientation of edges as features for searching face images based on textual descriptions. Their work included experiments using the features with and without normalization.

Park et al. [17] proposed using soft biometric traits such as scars, marks, and tattoos in order to increase the speed of face image matching in addition to individualize the task of face search. Besbas et al. [18] investigated the problem of features selection, for Content Based Face Image Retrieval in Walsh Hadamard Transform (WHT) domain. The face image features extraction in the spectrum domain of natural and sequence order Walsh Hadamard Transform is analyzed Denys and Nel [19] used eigenspace method for face recognition. This method is expanded into an eigenface, eigenmouth, eigeneye, and eigennose algorithm. This increases the recognition rate of faces, by splitting the face into regions and using high recognition results in one area to guide the recognition of the remaining areas, even if one or more of these areas are occluded.

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II. System Overview

This paper introduces a CBIR-based face recognition system. Although there are many approaches used for face recognition in literature, the approach using CBIR for face recognition has many advantages. The most important one is the ability of CBIR technique to retrieve similar images from huge databases and images datasets. This section describes the theory of the techniques used for implementing the system in addition to algorithm implementation.

a) Viola-Jones Face Detector

Detecting the face using Viola-Jones algorithm is based on three concepts. The combination of these concepts leads to real-time effective face detection. These concepts include: the Integral Image, AdaBoost classifier and Cascading classifiers [20].Image intensities are not used directly and reminiscent of Haar Basis functions are used as features. The integral image, which is an intermediate image presentation, allows fast features evaluation. To compute the integral image value at a location *x, y*, the sum of the pixels above and to the left of that location is calculated [20]:

$$ii(x,y) = \sum_{x' \le x, y' \le y} i(x', y') \qquad (1)$$

where *ii(x, y)* refers to the integral image point at *x,y* and *i(x, y)* is the original image pixel. The integral image is the double integral of the original image.

Three types of features are calculated to be used in face detection. The first is the two-rectangle feature which is the difference between the sums of the pixels values in two horizontally or vertically adjacent rectangular regions of the same shape and size. In the three rectangular feature evaluation, three rectangles are defined: two outside rectangles and a center rectangle. It subtracts the sum of the outside rectangles from the center rectangle. A four-rectangle feature finds the difference between a diagonal pair of rectangles. Fig. 2 illustrates these features.

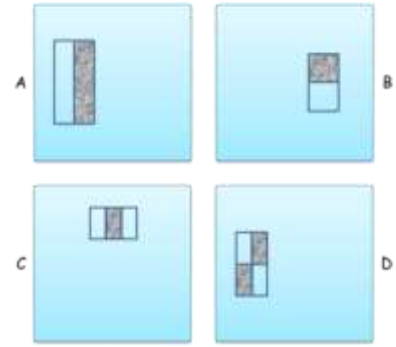

Fig. 2 Rectangular features: (A) and (B) The two-rectangle feature, (C) The three-rectangle feature, (D) The four-rectangle feature.

b) Harris-Stephens Features

Harris and Stephen [21] presented an algorithm for interest point detection. Their algorithm is a modified version for the Moravec corner detector [22], which has been utilized for feature extraction in computer vision application such as image matching, object recognition, tracking, motion detection and 3D reconstruction.

For an image *I*, let *I(x, y)* represent the pixels intensity of the image. Harris-Stephens is an extension for the principle of Moravec's corner detector. This extension is achieved by considering the local auto-correlation energy computed using Equation (2) [21]:

$$S(x,y) = \sum_{u,v} w(u,v)\,[I(x+u, y+v) - I(u,v)]^2 \qquad (2)$$

where *(u, v)* is a neighborhood of *(x, y)*. Typically, *w(u, v) =1* if and only if $|x\text{-}u| \le s$ and $|y\text{-}v| \le s$, given *2s-1* is the size of the square window patch.

To achieve invariance with changes in rotations, Harris-Stephens uses a smooth Gaussian circular window with

$$w(u,v) = \exp\left(-\frac{u^2+v^2}{2\sigma^2}\right) \qquad (3)$$

and:

$$u^2 + v^2 \leq s^2 \qquad (4)$$

where *s* represents the circular window radius size.

When a window patch is enclosed within a constant shaded region, a small change of energy will be the result of shifts in every direction. When a window patch is straddling an edge, the shift in the direction of the edge will result in a small change of energy. However, movements that are perpendicular to that edge will cause in significant change of energy. When a window patch is at a corner or at an isolated point, every movement in any direction will cause a large change of energy.

Equation (5) is the bilinear form used for approximating the energy function at the point *(x, y)* [21]:

$$E(u,v) = [u\ v]M_{x,y}[u\ v]^T \qquad (5)$$

where $M_{x,y}$ is a 2×2 positive definite matrix. This matrix can be computed as [21]:

$$M_{x,y} = \sum_{u,v} w(u,v)\begin{bmatrix}\left(\frac{\partial I}{\partial x}\right)^2 & \frac{\partial I}{\partial x}\frac{\partial I}{\partial y} \\ \frac{\partial I}{\partial y}\frac{\partial I}{\partial x} & \left(\frac{\partial I}{\partial y}\right)^2\end{bmatrix}$$
$$= \sum_{u,v} w(u,v)\nabla I(u,v)\left(\nabla I(u,v)\right)^T \qquad (6)$$

with $\nabla I(u,v)$ is the discrete image gradient [21]:

$$\nabla I(u,v) = [I(u+1,v) - I(u-1,v)I(u,v+1) - I(u,v-1)]^T \quad (7)$$

Thus, the energy is independent of a constant intensity shift represented by [21]:

$$I(x,y) = I(x,y) + c \qquad (8)$$

symmetric matrix Mx,y is the smoothened variance-covariance matrix of the intensity gradient at the pixel (x, y). Given α and β are the eigenvalues of the matrix M, they are geometrically interpreted as the elongations of the ellipsoid axes defined by M. For both α and β having small values, the point is considered to be in a flat area. If one of α or β has a large value, the point is on an edge. If the values for both α and β are large, the point is on a corner and the determinant of M is large. To avoid calculating the SVD for the matrix M in order to retrieve the eigenvalues, the following detector response is used:

$$R = \alpha\beta - k(\alpha+\beta)^2 = \det M - k\left(Trace(M)\right)^2 \qquad (9)$$

withk [0.04, 0.06]. Based on R the pixels can be categorized as follows:

R > 0: the pixel is a corner pixel.

R 0: the pixel is considered to be in a flat region.

R < 0: the pixel is an edge pixel.

After R is computed for all image pixels, a pixel is labeled a corner if and only if it is a local maximum. A pixel is defined as an edge if and only if it is a local maximum in the x or the y direction. Low and high thresholds with non-maxima suppressions are used and spurs and short edges are deleted. This leads to a more accurate set of real edges and corners that excludes visual putative surfaces. The response R has a maximum value that is independent changes in intensity. However, Harris-Stephens has a disadvantage that it is not scale-invariant. Fig. 3 illustrates pixel categories.

Fig. 3. *Point categories: a) flat region b) edge c)*

c) Minimum Eigenfeatures

This method, which is also known as Shi- Tomasi method, uses the minimum eigenvalue algorithm for feature points detection. As in Harris-Stephens' features described earlier, the same energy function is computed using Equation (5). However, Shi and Tomasi showed experimentally that another criterion to compute response is better. This response is computed using Equation (10) [23]:

$$R = min(\alpha, \beta) \quad (10)$$

where*α* and *β* are two eigenvalues produced by Performing an eigenvalue analysis of the matrix $M_{x,y}$. If *R* has a value greater than a threshold, it is described as a corner. In Harris-Stephens scoring criteria, the eigenvalues are used in the functions (trace, det), but Shi and Tomasi use the eigenvalues directly

d) Similarity Measuring

The nearest neighbor ratio method eliminates not clear matches and uses a threshold. It matches a feature vector to its nearest neighbor in the feature set when the nearest neighbor passes a ratio test. The distances between the feature vector to its first and second nearest neighbors in the feature set is compared for the ratio test compares [24, 25].

To define the set of nearest neighbors, the sum of squared differences (SSD) distance is used. The SSD is computed using Equation (11):

$$SSD = \sum_{(i,j)\in W}(I_1(i,j) - I_2(x+i, y+j))^2 \quad (11)$$

e) System Implementation

This research proposes a new face recognition system that uses CBIR with new face recognition features. Fig. 4 outlines the flowchart for the proposed face recognition algorithm. As it can be seen in the figure, the proposed algorithm includes several stages

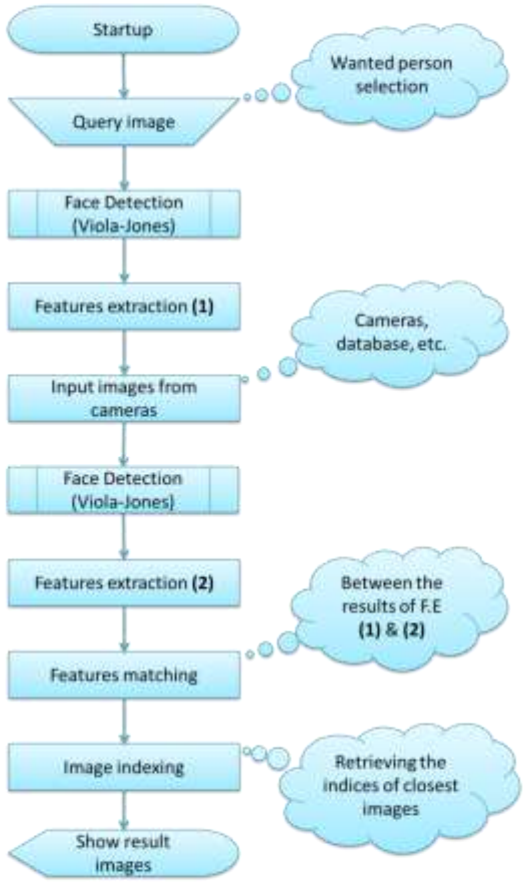

Fig. 4. The proposed CBIR face recognition system flowchart

The first stage is to input a query image for the person who needs to be recognized to the system. Viola-Jones face detector is then applied on the provided query image to detect potential face objects in the image. The selection of Viola-Jones face detector to be used in the implementation is because the Viola-Jones detector is very fast and accurate when comparing it to other face detectors. The user then views the detected candidate faces and selects the face to be searched for. Fig. 5 shows how the system displays the extracted candidate faces and numbers them to allow selection.

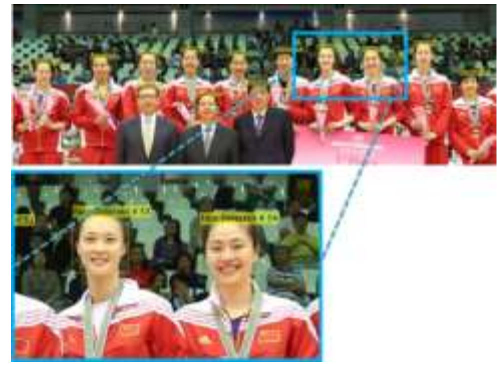

Fig. 5. The face selection stage.

The next step is to extract the features used in face recognition from the selected face query image. The features extracted are the Harris-Stephens features which are found to be more effective to use than Minimum Eigenfeatures, as will be discussed in details in next section

Then, after the wanted face image is selected, the images which will be searched for the matching faces are input to the system. The sources for these images vary. A set of image files or an image database can be used as a collection of images to be searched. The images can be collected from videos recorded by live cameras where video frames are used by the system in order to search them for the matching faces.

The images are then pre-processed by Viola-Jones face detector, just like the query image. All the detected faces are given indices and linked to the source image. Then, Harris-Stephens features are calculated for the faces images. The features which were extracted from the query image and from the images to be searched and matched are compared in order to find the faces which have the highest similarity and get their indices to retrieve matching images. The CBIR system will return an ordered collection of images which are most similar to the query image. Fig. 6 shows an example for the implemented CBIR system. When searching for the query image in the images dataset, the most similar images are retrieved.

III. Experiments and Results

Two face image datasets were used for testing. The first of these databases is the Face Recognition Dataset, University of Essex, UK [26]. The Face Recognition Dataset has images of 395 people, both males and females. Each person has 20 images. The images have high variety as collecting the dataset included people of several origins. Most of the included individuals are of age 18-20 years old and some older individuals are included. In addition, some of them are wearing glasses and growing beards.

The second is a dataset consisting of 4000 face images for 40 subjects of different ages and genders [27]. The images of this dataset were taken in a university and a hospital.

The first part of experiments was carried out in order to investigate the performance of different type of features to be used in the feature extraction stage of the proposed system. The two types of features that were subject of study are: Harris-Stephens features and Minimum Eigenfeatures. In order to evaluate these features, the matching ratio for the two types of features was computed. The matching ratio between two face images is defined with Equation (12):

$$Matching\ Ratio = \frac{matched\ feature\ points}{total\ feature\ points\ in\ query\ image} \times 100\% \quad (12)$$

where the number of matched feature points is the number of feature point that the feature matching process successfully matched and the number of total feature points in the query face image is the number of detected feature points in the given face image to be searched for.

There are many factors which cause changes in the face image scales such as the distance from the camera and the camera resolution. Regardless of the type of change caused by these factors, i.e. up-scale or down-scale, the accuracy will be degraded.

Fig. 7 shows the up-scale and down-scale of an image in which the size of interest area is 1.24 megapixels. A 20%-up-scale was applied to the image. Then, a 20%-down-scale was applied. The matching ratio was calculated for the up-scaled and down-scaled images using the two feature types.

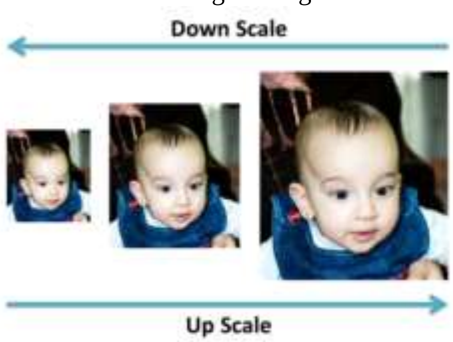

Fig. 7. Up-scaling and down-scaling an image.

Fig. 8 illustrates the matching ratios in addition to a comparison with the matching ratio of using the image in Original image (100% scale). The figure clearly shows that the negative effect of using down-scale, which causes loss in image data, is more significant. It can also be clearly seen that using Harris-Stephens features achieves noticeably more robustness against changes in scale.

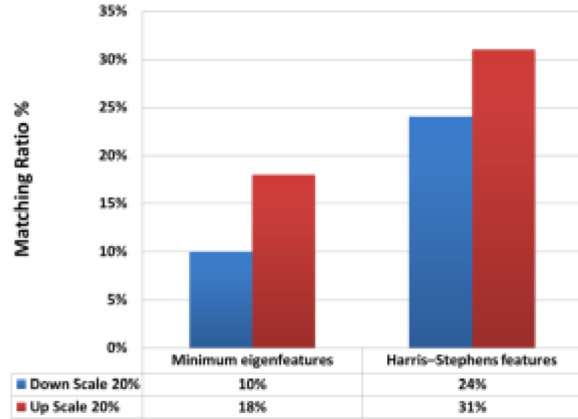

Fig. 8. The effect of up and down scaling on matching ratio.

The experiments also included testing effectiveness of the system with retrieving matching images which were taken under different lighting conditions giving different image brightness. Fig. 9 shows an example of face images with different brightness

Fig. 9. Face images with different brightness.

To evaluate the performance of the system with images having different brightness, a face image is processed to produce 6 images with different brightness ratios. Table 1 shows the matching ratios between the original image and each of the produced images using the two types of features.

TABLE 1: Matching Ratios between an Image and Images with Different Brightness Levels

Brightness Ratio	Minimum eigenfeatures matching Ratio	Harris-Stephens features matching Ratio
+60%	16.8%	7.4%
+40%	52.9%	33.3%
+20%	55.2%	35.2%
0%	100%	100%
-20%	71.5%	55.6%
-40%	72.4%	55.6%
-60%	58.8%	46.3%

It can be concluded from the table that increasing the brightness affects the matching ratio when using the minimum eigenfeatures less than it does when using Harris-Stephens features. Also, decreasing the brightness affects the matching ratio when using Harris-Stephens features more than when using minimum eigenfeatures. To sum up, using minimum eigenfeatures is more robust against changes in brightness than Harris-Stephens features.

The University of Essex Face Recognition Data was used to evaluate the presented face recognition system to retrieve possible matching faces. In this experiment, 20 random face images were used as queries to search form their matches in the rest of the dataset. A note to be mentioned is that the sample query images include face images with various facial expressions and the dataset to be searched contains other images for the same person with different facial expressions. Table 2 shows that minimum eigenfeatures retrieves the correct matching face as the first candidate 34% of the times and using Harris-Stephens features retrieves the correct match as the first candidate 54% of the times. As a conclusion, Harris-Stephens features have the highest rate of retrieval for correct face matches as first candidates.

TABLE 2: Accuracy of First Retrieved Candidate

Features	1st Candidate	2nd Candidate	3rd Candidate	≥4th Candidate
Minimum eigenfeatures	34%	30%	21%	15%
Harris–Stephens features	54%	20%	9%	17%

In general, feature extraction requires a minimum number of pixels in the interest area. If the number of pixels in the area of interest was less than the minimum accepted number of pixels, the feature extraction process will fail. Fig. 10 shows the minimum accepted area required for each of the three feature extraction methods investigated in this work.

It can be seen that the minimum eigenfeatures algorithm is better than Harris-Stephens algorithm in terms of the minimum accepted area required. When the value of minimum required area is smaller, it is more possible to detect feature points accurately in smaller areas of interest.

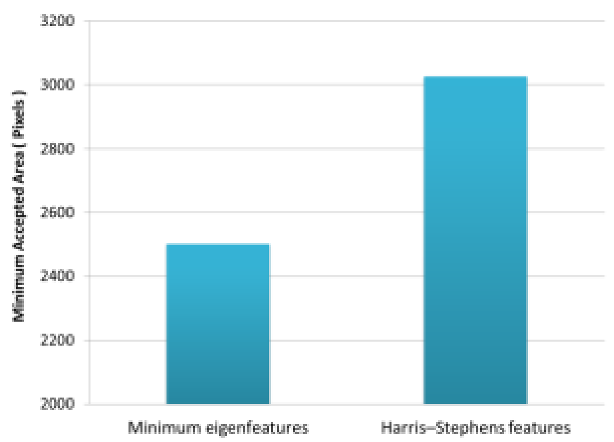

Fig. 10. Minimum accepted area for feature extraction algorithms.

Another aspect for evaluating the two types of features should be considered. This aspect is the required processing time. For this experiment, the time required is measured using the function timeit available on Mathworks [28]. Time measurements have been performed in the following specifications:

- Windows 7 64-bit,
- Intel(R) Core(TM) i7-2670QM CPU @ 2.20GHz
- 6M Cache,
- 6144MB RAM
- MATLAB R2013a software package

Using the same set of samples which have different face areas, Fig. 11 shows the required CPU time for each one of the two algorithms. From the figure, it can be concluded that Harris-Stephens features requires the least amount of processing time.

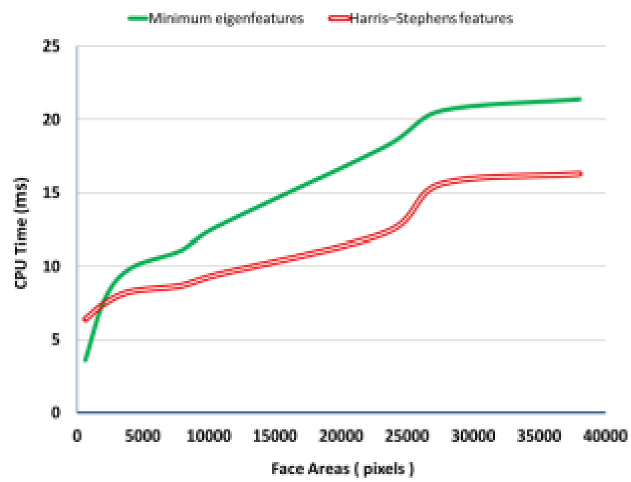

Fig. 11. The required CPU time for feature extraction algorithms

From the experiment above, the number of pixels that can be processed per millisecond by each algorithm can be derived. Fig. 12 illustrates the throughput for each algorithm. The Harris-Stephens algorithm has higher throughput.

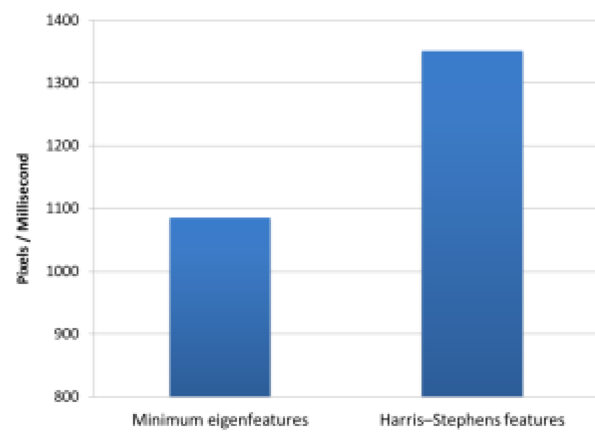

Fig. 12. The throughput for feature extraction algorithms

To sum up all experimental work, Table 3 presents a comparison between the two types of features in term of several specifications. In order to perform this comparison, the values for each specification are normalized. Normalization is the process of adjusting values that were measured using different scales to a common scale. It is usually used before averaging. For example, to normalize the accuracy of finding the match as the first candidate, the following calculations are performed:

$$Normalized\ accuracy = \frac{accuracy}{max.\,accuracy} \times 100\%$$

and thus:

$$Normalized\ accuracy\ of\ Harris - Stephens\ features$$
$$= \frac{54}{54} \times 100\% = 100\%$$

and:

$$Normalized\ accuracy\ using\ eigenfeatures$$
$$= \frac{34}{54} \times 100\% = 63\%$$

TABLE 3: Comparison Between the Two Types of Features

Specifications (Normalized)	Minimum eigenfeatures	Harris–Stephens features
Performance (CPU Time)	78%	100%
Accuracy (First candidate)	63%	100%
Resolution (Minimum Accepted Area)	100%	83%
Up Scale (Zoom in)	58%	100%
Down Scale (Zoom out)	42%	100%
Brightness (40% Increasing)	100%	63%
Brightness (40% Decreasing)	100%	77%
Average	**77.3%**	**89%**

Overall, when taking in account all specifications, Harris-Stephens features give the better performance than minimum eigenfeatures, with a normalized average of 89%. Minimum eigenfeatures gives an average of 77.3%.

In this research, the percentage of the average retrieval rate, also called accuracy rate, is used to enable the comparison between the obtained results and CBIR-based face recognition techniques discussed in the related work. The following equation shows how this measure is obtained.

$$\text{Accuracy rate } \% = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} \times 100 \quad (13)$$

Table 4 summarizes the comparison between CBIR face recognition systems reported and the proposed system in respect of accuracy and the features used. It can be concluded that the proposed system achieves higher accuracy

TABLE 4: Comparasion between the proposed system and other systems

Features Comparison (Related Works)	CRI Rate %
[18] Walsh Hadamard Transform , 2013	91%
[18] Discrete Cosine Transform , 2013	91%
[18] Discrete Wavelet Transform , 2013	92%
[19] Eigenfeatures , 2006	79%
Proposed System	**92%**

IV. Conclusion

Face recognition is a growing research field. It has received a huge amount of attention from researchers due to the fact it is the most effective biometric recognition system. Many fields of applications benefit from robust and accurate face recognition techniques.

One of the many approaches proposed for face recognition is content-based image retrieval which uses the actual content of the image to retrieve similar images when the images database is huge. In this work, a new face recognition system using CBIR was introduced.

In order to implement the system, different types of features were investigated. These features are: Harris-Stephens features and Minimum Eigenfeatures. The effectiveness of these features in the face recognition system was evaluated by considering accuracy, required processing time, minimum accepted area of interest and robustness against changes such as scaling up or down and brightness variations. In terms of accuracy, Harris-Stephens features were found to be more accurate with the higher value of matching ratio. It also showed good robustness against up-scale and down-scale of images. However, minimum eigenfeatures were found to be more robust against change in brightness compared with the Harris-Stephens features.

The experiments also showed that Harris-Stephens features require the least amount of processing time. This makes Harris-Stephens features more suitable to use in the face recognition system.

The proposed system was also compared to modern face recognition systems reported in literature. The proposed system was found to be more accurate than these systems when tested on two published face images databases.

label, present them within parentheses. Do not label axes only with units. In the example, write “Magnetization (A/m)” or “Magnetization {A[m(1)]}”, not just “A/m”. Do not label axes with a ratio of quantities and units. For example, write “Temperature (K)”, not “Temperature/K”.

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