An Effective Approach Towards Content-Based Human Facial Image Detection and Retrieval

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***Abstract*—The difficulties of locating a desired facial image in a large and varied collection are now the current main problem in this field. In order to search in such a large and varied images' collection, there is a growing need for efficient storage and retrieval techniques. In this research, an effective approach towards content-based human facial image detection and retrieval is proposed. The research proposes a technique of face segmentation based on which a new method of features extraction from the human face is developed. The capability and effectiveness of the RGB, HSV, and HSI color space models on facial image retrieval technique are investigated. The effect of the vectors dimension of the eigenfaces features and the color histogram features, and the distribution values of the color space coordinates on facial image retrieval are studied. Viola-Jones face detection method is employed to obtain the location, extent and dimensions of each face. Moreover, for the measurement of distance and classification purposes, Euclidean distance is utilized. Several experiments based on precision and recall approach were conducted to evaluate the proposed methods. The retrieval result of the facial image given by the proposed method showed excellent improvement comparing to those achieved when using the traditional method of visual features extraction.**

Keywords - image retrieval, face segmentation, face detection, eigenfaces, color space, face retrieval.

I. INTRODUCTION

The face is the most significant component of the human body that are normally used by humans to recognize each other; thus, facial images are the most common biometric characteristics used for human verification and identification. facial images have gained its importance due to its use in various aspects of life such as in airports, law enforcement applications and security systems. Numerous works are emerging for various purposes of face identification, verification, and retrieval used for different applications of facial images.

Content-based facial image retrieval (CBFIR) is a computer based vision technique that is applied to the problem of facial image retrieval, especially when searching for digital images of faces in a comprehensive database with similar features, which make the exact retrieval of the target face difficult or impossible through traditional techniques such as content-based image retrieval (CBIR) and face recognition technique (FERET). Although the main purpose of a face recognition system is to find the facial images of the same person for identification or verification task, a face retrieval system is also required to figure out facial images that look similar to the query face.

On the other hand, content-based image retrieval is a technique to find and retrieve images from a database using the visual contents of the image. Most of the basic image retrieval systems utilize low-level visual features extracted automatically using image-processing methods to represent the raw content of the image [1]. These features can be classified into general features or domain specific features. General visual content consist of the application independent features such as color, texture, shape, spatial relationship, and so on. On the other hand, domain specific visual content includes application dependent features such as human faces, fingerprint, etc. Retrieving image based on color usually yields images with similar colors, while image retrieval based on shape yields images that have clearly the same shape, and so on. Thus, such a system when utilized for the purpose of image retrieval using the general visual content is not effective with facial images.

Moreover, most of the features in the human facial image are domain specific. The features for a facial image are extracted using two methods. In the first method, the information theory concepts are employed by preparing a computational model that gives the best description of a face. This is done by deriving the related information included in the face. Eigenfaces method is one such method where information for the best description of a face is extracted from the facial image. The second is the components based method, where deformable templates and active contour models with excessive geometry and mathematics are used to extract the feature vectors of the facial parts such as nose, mouth, eyes and chin. Efficient retrieval system requires a robust method for extracting the features extraction that has the ability to achieve satisfactory retrieval performance. However, there are many intrinsic and extrinsic factors that can degrade the performance of facial image retrieval, with intrinsic factors such as facial expressions and aging that mostly affects facial appearance, and extrinsic factors such

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as illumination variation and pose change that affect the images [2].

The objective of this research is to take the above facts in consideration and investigate methods that can improve the performance of the current CBIR system for the purpose of facial image retrieval.

II. RELATED WORKS

Image retrieval is the task of browsing, searching, and retrieving images from a large database of digital images. The term content-based image retrieval was first used by T. Kato in 1992 [3]. He was interested in how shape and color information could be used to query a database of images. The term has been used to describe any technique uses the visual content for search and retrieval purpose. QBIC, from IBM [4], was one of the earliest CBIR systems that used the colors to retrieve images from a database. Wang and other researchers [5] used a segmentation model to divide the image into regions that ideally correspond to different objects and use those regions for retrieval. However, Leibe and his team [6] used a segmentation method as a way of integrating individual image cues showing that this combination scheme increases detection performance compared to any cue in isolation. In a joint study, Navarrete and Ruiz-Del-Solar [7] organized facial images in a tree structured self-organizing map. Projections of the principal component analysis (PCA) were used to form the map for features representation of the facial image in the image space. Each facial image represents a cluster in the whole image space. The objective of the study was a quick search and retrieval of the images in the database. In [8], a unified framework of structural information and statistical aspects of pattern description is proposed for pattern retrieval based on local feature sets. However, the method is not limited to facial images. More in depth reviews on image retrieval are provided in [1,9]. The currently used systems still have many limitations, especially in domain-specific applications, such as facial image retrieval [2]. In this research, content-based human facial image detection and retrieval model is proposed for retrieval human facial images from the database based on a new proposed method of human facial image segmentation technique.

III. FACE DETECTION

The aim of face detection in this research is to give the position and size of the face in the entire image. Learning-based face detection techniques are the most successful methods in terms of detection accuracy and speed. One of the most popular methods employed in this research is Viola & Jones method [10].The technique relies on a set of simple rectangular features, known as Haar-like features, to detect the intended face. These features are resemblance of Haar basis functions, which have been used by Papageorgiou and other researchers [11]. Integral image concept was first introduced as a new image representation technique. By utilizing this technique, rectangular features can be computed quickly. Integral image of any position is the sum of the pixels above and to the left of the position. For instance, the integral image at position x and y is the sum of the pixels above and to the left of x and y, then

$$ii(x,y)=\sum_{m=0}^{x}\sum_{n=0}^{y}i(m,n) \tag{1}$$

Here *i(x,y)* represents the original image and *ii(x,y)* is the integral image as shown in Fig.1. Four kinds of rectangles features are used with varying numbers of sub-rectangle: a tow horizontal rectangle features, a two vertical rectangle feature, a three-rectangle feature and a four-rectangle feature, as shown in Fig. 1.Within any image sub-window, the total number of Haar-like features, that will be generated based on the integral image method and the four rectangles features, is very huge. The feature set should be reduced to a small number of important features. AdaBoost learning method [12] was successfully employed to select a restricted number of critical features, which are used to create very efficient classifiers. Boosting is used for performing supervised learning. The key idea is to use a set of weak learners (classifiers) in order to create a single strong learner. Such as, a weak classifier $h_j(x)$ comprises of a feature *f*, a threshold θ_j and a parity p_j indicating the direction of the inequality sign [13]:

$$h_j(x)=\begin{cases}1, & if\, p_j f_j(x)<p_j\theta_j\\ 0, & otherwise\end{cases} \tag{2}$$

The strong classifier is shown in Eq. (3) where $h_t(x)$ is the weak classifier, a_t is the coefficient for h_t. Given a test sub-window *x*, it will be classified as a face if only the output is one.

$$h(x)=\begin{cases}1, & if \sum_{t=1}^{T} a_t h_t(x)>\theta\\ 0, & otherwise\end{cases} \tag{3}$$

Viola and Jones arranged the classifiers in cascade architecture as shown in Fig. 1. In the cascade architecture, a series of classifiers are applied to every sub-window. Negative sub-windows will be rejected and the positive ones sub-windows will be detected and selected in the beginning stages by the initial classifier with fewer features and less computational time. The cascade classifiers in the final stages with more features classify only the sub-windows that have passed the initial classifier. After several stages of processing the background region will be eliminated, while the focus will be more on the face-like region. The window that is used for scanning can be scaled to detect faces at multiple scales, as well as the features evaluated. The detector is applied on gray-scale images [2]. Fig. 2 shows some results of face detection method.

IV. FACIAL IMAGE SEGMENTATION

Facial image segmentation plays an essential role in some face detection systems in helping to extract only face part of a given large image based on skin-colors and non skin-colors classification [14].

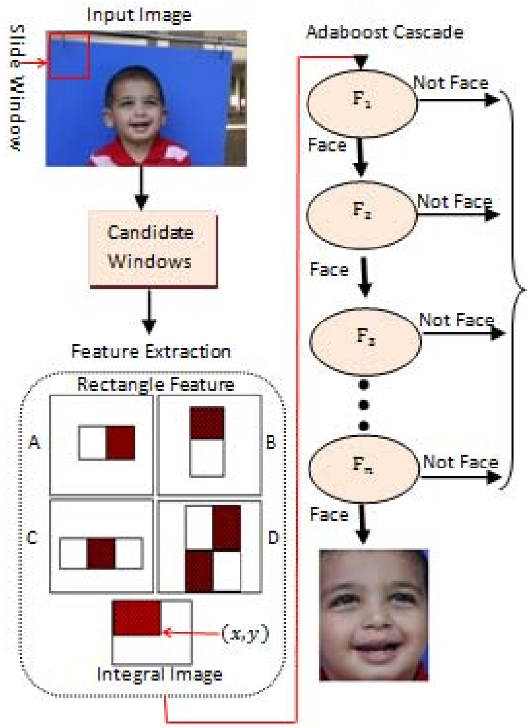

Fig. 1 : Face Detection Algorithm: Four Rectangular Features (a, b, c, and d).

Fig. 2 : Samples of Face Detection Results.

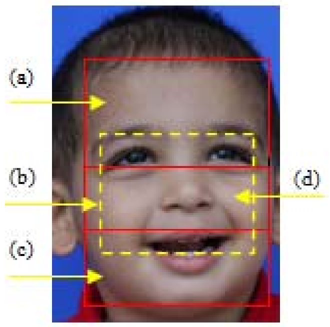

Fig. 3 : Proposed Template for Facial Image Segmentation Include Four Sub-template (a, b, c, and d).

In this study, a new facial image segmentation technique is proposed to improve the accuracy of the facial image retrieval performance, as shown in Fig. 3. The proposed method is based on the fact that every sub facial image has its spatial information of orientation and specific scale relevant to this sub-image.

Combination of the features vectors of each sub-image, independently extracted, is expected to produce more robust features vector. The research suggests the facial image to be segmented into four partitions based on human eyes and mouth level and the ratio of their height to face height, based on the assumption that image will always have at least one face. Each detected facial image is scaled to fixed size beginning by face detection step to optimize the candidate for face segmentation. In order to segment candidate's faces in the image, a template matching technique needs to be employed. The template consists of four sub-templates as shown in Fig. 3. The first sub-template is used for matching the upper region of the face until the eyes level, the second for matching the middle region of the face between the eyes level and mouth level, the third for matching the lower region of the face starting from mouth level and finally, the fourth sub-template is used for matching the region of the facial image center. The sub templates are scaled based on intensity extraction from facial images of different people. The aim of the sub-templates is to match each region of the face to be extracted independently.

After the facial image and the template have been matched, the segmented regions are projected into feature extraction algorithm to extract the features in each segment separately [2].

V. COLOR SPACE

Several color representations are currently in use for color image processing. However, the most popular and commonly used ones include RGB (red, green, blue), HSV (hue, saturation, value) and HSI (hue, saturation, Intensity) also known as HSL (hue, saturation, lightness/luminance). Three coordinates are specified for each model. This coordinates describe color position within the corresponding color space. The HSV and HIS color space models are derived from the RGB space cube [15] , where saturation $S = 1 - min(R,G,B)/I$, Intensity $I = (R+G+B)/3$, the value $V = max(R,G,B)$, and the hue defined as:

$$H = cos^{-1}\left(\frac{1/2\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}}\right) \tag{4}$$

The color models are available for image processing, but it is important to use the appropriate color space for each application. In this research, we investigate the capability and effectiveness of the models mentioned above with regard to the performance and accuracy of the facial image retrieval system [2].

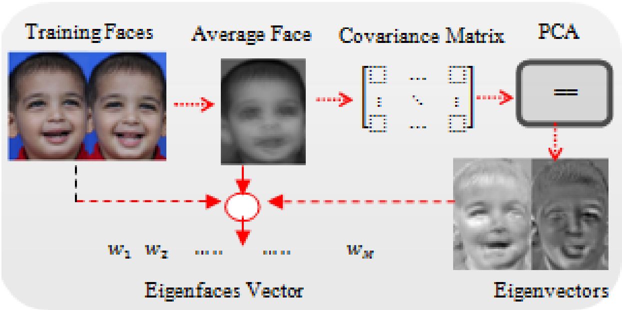

Fig. 4 : Eigenfaces Features Extraction.

VI. Features Extraction

Features extraction is the process of transforming the content of the images into various content features commonly known as feature vectors. In this research, color histogram is used as general visual content, while eigenfaces features are employed as domain specific visual content.

A. *Eigenfaces Features*

Eigenfaces is one of the most important methods used for face recognition. It is based on an information theory approach that decomposes facial images into a small set of characteristic feature images called eigenfaces. The idea is to find the principal component of the distribution of the set of facial images to extract information and capture the variation contained in these faces. Sirovich and Kirby [16] represented human faces using PCA, and Turk and Pentland [17] developed a face recognition technique using eigenfaces. For facial image retrieval, eigenfaces are calculated using PCA, such as in Fig. 4, where the following steps based on [17] are applied:

- Suppose the facial image set is $T_1, T_2, \ldots T_m$, Then, the mean face of the set is defined by

$$\Psi = \frac{1}{M}\sum T_M \tag{5}$$

- The mean face is subtracted from each original face vector

$$\Phi_i = T_i - \Psi \tag{6}$$

The covariance matrix is calculated as

$$C = \frac{1}{M}\sum_{n-1}^{M}\Phi_n\Phi_n^T = A.A^T, \tag{7}$$

where C is $N^2 x N^2$ and A is $N^2 xM$.

- The eigenvectors and eigenvalues of the covariance matrix are calculated. Consider the eigenvectors v of $A.A^T$ such that

$$A^T Av_i = u_i v_i \tag{8}$$
$$AA^T Av_i = u_i Av_i \tag{9}$$

The Av_i are the eigenvectors of $C = AA^T$.

- From these analysis, MxM matrix $L = AA^T$, $L_{mn} = \Phi_m^T\Phi_n$ is constructed, and M eigenvectors v_i of L can be found.
- The eigenfaces u_i ,are formed from M training facial images linear combinations, such that

$$u_i = \sum_{k-1}^{M} v_{lk}\Phi_i,\ l = 1,\ldots,M \tag{10}$$

B. *Color Histogram*

A color histogram is a common approach used in image retrieval system [1]. The computing methodology of the color histogram is based on the fact that images are represented as a series of pixel values, each corresponding to a visible color and similar images contain similar proportions of certain colors. The regions of human face contain unique characteristics of color distribution. In this research, color histograms are used to capture the special relations of these unique regions characteristics. A color histogram of a facial image is prepared by counting the number of pixels that correspond to a specific color in quantized color space. Color histogram refers to the probability mass function (pmf) of the image intensities and can be defined [18] by:

$$h_{A,B,C}(a,b,c) = N\,x\,P(A=a, B=b, C=c) \tag{11}$$

Here, A, B and C are the three-color channels, and N is the number of pixels in the image. The probability mass function of the image are indicated by p(x), $x = 0 \ldots X$, where X is the maximum luminance value in the image, the cumulative probability function is defined [19] as

$$P(x) = \sum_{i=0}^{x} p(i) \tag{12}$$

One of the problems with color histogram-based retrieval is the high dimensionality of the color histograms. Color quantization method is used to reduce the number of colors available in an image. Histogram values are normalized by dividing the number of pixels in each histogram bin by the total number of pixels in the image.

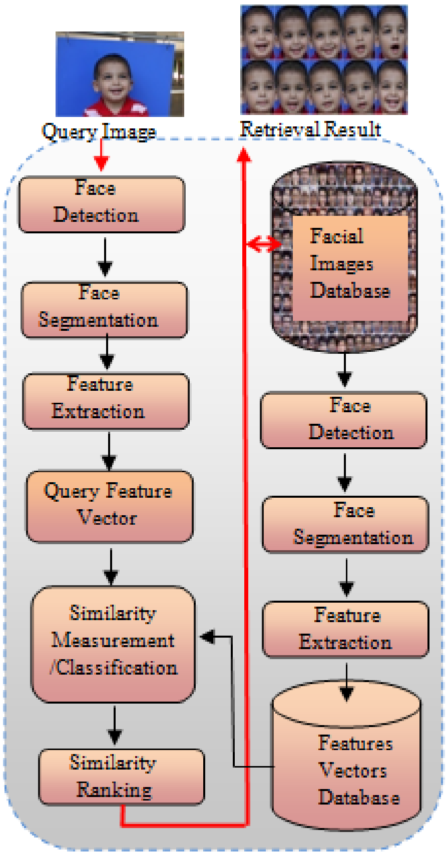

Fig. 5 : Content-based Human Facial Image Detection and Retrieval.

VII. Query And Retrieval Process

In this research, a prototype system was designed based on the combination of face detection, CBIR and FERET techniques, with the proposed method of facial image segmentation as shown in Fig. 5. In the query processing, the user provides an initial image to the system or selects one from the images database pool. This query image looks similar to the required facial image. During the retrieval process, the system automatically detects the facial image from the query image. The candidate facial image is segmented using the proposed method based on the eyes and mouth level, and eigenfaces features and color histogram features are extracted from each segment. Combinations of these features are used to identify and retrieve the similar faces to the query face from the database [2].

Euclidian distance approach is employed to compute the distance between the query features vector Q and the features vectors D in the database. Faces with the least distance are retrieved and displayed on top.

$$FacesSimilarityDistance(Q,D) = \left(\sum_{i=1}^{n}(Q_i - D_i)^2\right)^{\frac{1}{2}}. \quad (13)$$

VIII. Results And Discussion

Numerous experiments have been conducted to assess and evaluate the proposed method of facial image retrieval. The database that is used consists of 1500 local facial images database of 150 participants from the University of Malaya (UM) in Kuala Lumpur. Ten different images were taken of each participant of different race, gender, age, skin color, and so on. Facial images were taken at different times with different facial expressions (e.g., happy, sad, smiling, angry, etc.) and facial details (e.g., glasses, beard, mustache, and facial marks). A total of 750 images, half of the database, were utilized for training, and the rest was employed for the experiments. Precision and recall methods were applied to measurement of the performance efficiency of the retrieval methods, as defined:

$$Recall = \frac{Relevant\ Faces\ of\ The\ Retrieved\ Faces}{Total\ Relevant\ Faces} \quad (14)$$

$$Precision = \frac{Relevant\ Faces\ of\ The\ Retrieved\ Faces}{Total\ Retrieved\ Faces} \quad (15)$$

$$F-score = \frac{2 * Precision * Recall}{Precision + Recalll} \quad (16)$$

The facial image retrieval system differs from the face recognition method in which the system does not look for an identical image but only for similar images. Therefore, to evaluate the system performance during the retrieval process, a threshold to determine the level of the retrieval was not set but rather the number of the images to be retrieved was subject to a certain pre-determined value. Hence, following the method of precision and recall cut-off rank was considered as necessity. Therefore, the experiments were performed with different cut-off levels, that is, 10, 16, and 25. Conversely, the images taken into account are the images that are on the top (10, 16, and 25) of the displayed results.

The experimented three-color space models in this study were RGB, HSV, and HIS to find out which color space in the facial image retrieval system has the best performance. Considering the F-score measurement on the top 10 of the retrieved images, eigenfaces-based facial image retrieval in HSV color model showed better performance than in RGB and HIS color space models achieving 73.52% accuracy in comparison to 63.57%, and 60.16% accuracy in RGB and HSI respectively. Considering the recall measurement only, the best performance of the eigenfaces was with 86.43% accuracy within the top 25 retrieved images in HSV color space model as shown in Table 1. Color histogram-based facial image retrieval in RGB color space showed the best performance among the other color space models achieving 79.55% accuracy in comparison to 77.39% and 76.39% accuracy in HSV and HSI respectively. Considering the recall measurement only, the best performance of the color histogram belonged to HSV color space model with 85.72% accuracy within the top 25 retrieved images as shown in Table 2.

The three methods of features extraction were experimented based on the entire facial image, three segments of the facial image based on the eyes level and mouth level, and four segments including the center of the facial image. The first method is a traditional method, while the others are the proposed methods. Experiments were conducted using eigenfaces and color histogram features, separately and then using a combination of them. Considering the F-score measurement within the top 10 retrieved images, eigenfaces-based facial image retrieval achieved 73.52 %, 81.53%, and 81.97% accuracy using the traditional method, the first method, and the second method of feature extraction respectively, as displayed in Table 3.

The color histogram-based facial image retrieval achieved 79.55%, 86.53%, and 85.44% of accuracy, using the traditional method, the first method, and the second method of feature extraction respectively, as shown in Table 4. Integration color histogram and eigenfaces-based facial image retrieval achieved 79.49%, 89.51%, and 88.24% of accuracy, using the traditional method, the first method, and the second method of feature extraction respectively, as shown in Table 5. The results of the experiments show that extraction the features based on the three segments of the facial image in the first method improved the performance of the facial image retrieval technique comparing to the traditional method and the other methods. Considering the recall measurement only, the best performances of the system with this method are 91.61%, 90.9%, 93.1% of accuracy within the top 25 retrieved images using eigenfaces features, color histogram features and the integration of them, respectively, as shown in Table 3, Table 4, and Table 5.

Eigenfaces features have the capability to provide the significant features for face retrieval. The advantages of these features are that processing is fast and no heavy storage of data is required. However, there existent factors originating from the facial image itself, which could affect the performance of the eigenfaces processing. These include the facial hair, skin scarring and face multiple view. Actually, this has been a long-standing problem of most features extraction methods specially those depending on face parts modeling. Fig. 6 shows an example of a query dialogue.

Using the recall method of performance measure, Fig. 7 shows that 70% accuracy was achieved within the top 10 cut-off level; 70% within top 16 and 100% within top 25. It is noted that the relevant images in row 4 are slightly orientated to the left, while those in row 5 are slightly orientated downwards.

These results correspond to the fact that in face recognition different face images with same postures are considered similar rather than those of the same face images with different postures. The results of this example are considered the worst-case scenario of the system performance based on eigenfaces, as in some other runs the achieved accuracy was 100% within the first top 10 images.

One of the factors considered is the vector dimension of the eigenfaces features. The maximum number of eigenfaces that can be used per vector equals the size of the training vectors. For instance, if the training vectors set contain 750 images, the eigenfaces vector dimension would contain a maximum of 750 values, were plotted in a descending order as depicted in Fig. 8. It is observed that at the beginning, the eigenvalues are high, then sloping downwards to significantly lower values. Larger eigenvalues are indicative that the corresponding eigenvectors contain more information for high-level discrimination. Conversely, much less information will be found in eigenvectors with low eigenvalues. Consequently, the vectors with small eigenvalues were omitted in our research. In this example, the first eigenfaces that corresponded to the first eigenvalues position was chosen for eigenfaces features vector. This did not affect the results significantly.

For testing purpose, the system was trained and tested on different dimensions of eigenfaces vector features. The vector dimension was phased from 1 to 200 eigenfaces. Fig. 9 shows that after 20 eigenfaces per vector the recall accuracy does not improve significantly. This is because of the lack of discriminative information in weak eigenvalues.

Increasing the dimension of the vectors will not necessarily result in higher performance. Moreover, the existence of some trivial information may be consider as noise and will degrade the system performance, especially when the eigenfaces are combined with other features, let alone the complexity and time needed for selecting and processing each vector.

Facial image retrieval based on the color histogram algorithm has produced some excellent results in that it was able to retrieve most of the relevant images to the queried image. Unlike the eigenfaces features, performance of the color histogram algorithm somewhat depends on the dimension of the features vectors. With color histogram, increasing the size of the bines, would result in slight increase in the dimension of the features vectors, leading to improved retrieval performance. Results in Table 6 and Fig. 10 on the local database show the accuracies of the facial image retrieval system based on color histogram features with different sizes of bins.

It was noted that choosing the distribution values of the color space coordinates to represent the bines size, during the quantization processing, has influenced the color based facial image retrieval results. The accuracy will be based on the distribution of the colors in the image. For instance, if the red color distribution in the image is better than the other colors, then the red color should be given more focus than the other colors and thus will lead to better result.

While this influence is clear on color images database, as it is shown in Table 7 and Fig. 11 the distribution of the color space coordinate has no influence on gray level image database. This is because the three channels of the gray image carry the same information.

TABLE I. EIGENFACE-BASED FACE RETRIEVAL IN DIFFERENT COLOR SPACE MODELS WITH OUT SEGMENTATION

Color Space	Top Faces	Retrieved Faces	Relevant Faces	Recall	Precision	F-score
RGB	10	7500	4768	0.6357	0.6357	0.6357
	16	12000	5379	0.7172	0.4483	0.5517
	25	18750	5781	0.7708	0.3083	0.4404
HSV	10	7500	5514	0.7352	0.7352	0.7352
	16	12000	6096	0.8128	0.508	0.6252
	25	18750	6482	0.8643	0.3457	0.4939
HSI	10	7500	4512	0.6016	0.6016	0.6016
	16	12000	5104	0.6805	0.4253	0.5235
	25	18750	5542	0.7389	0.2956	0.4223

TABLE II. COLOR HISTOGRAM-BASED FACE RETRIEVAL IN DIFFERENT COLOR SPACE MODELS WITH OUT SEGMENTATION

Color Space	Top Faces	Retrieved Faces	Relevant Faces	Recall	Precision	F-score
RGB	10	7500	5966	0.7955	0.7955	0.7955
	16	12000	5966	0.7955	0.4972	0.6119
	25	18750	5966	0.7955	0.3182	0.4546
HSV	10	7500	5804	0.7739	0.7739	0.7739
	16	12000	6198	0.8264	0.5165	0.6357
	25	18750	6429	0.8572	0.3429	0.4898
HSI	10	7500	5729	0.7639	0.7639	0.7639
	16	12000	6077	0.8103	0.5064	0.6233
	25	18750	6311	0.8415	0.3366	0.4809

TABLE III. EIGENFACE-BASED FACE RETRIEVAL ON DIFFERENT SEGMENTS OF HUMAN FACE WITH HSV COLOR MODEL

Extraction Method	Top Face	Retrieved Faces	Relevant	Recall	Precision	F-score
Traditional Method	10	7500	5514	0.7352	0.7352	0.7352
	16	12000	6096	0.8128	0.508	0.6252
	25	18750	6482	0.8643	0.3457	0.4939
Three Segments	10	7500	6115	0.8153	0.8153	0.8153
	16	12000	6585	0.878	0.5488	0.6754
	25	18750	6871	0.9161	0.3665	0.5235
Four Segments	10	7500	6148	0.8197	0.8197	0.8197
	16	12000	6602	0.8803	0.5502	0.6772
	25	18750	6890	0.9187	0.3675	0.525

TABLE IV. COLOR HISTOGRAM-BASED FACE RETRIEVAL ON DIFFERENT SEGMENTS OF HUMAN FACE WITH RGB COLOR MODEL

Extraction Method	Top Face	Retrieved Faces	Relevant	Recall	Precision	F-score
Traditional Method	10	7500	5966	0.7955	0.7955	0.7955
	16	12000	5966	0.7955	0.4972	0.6119
	25	18750	5966	0.7955	0.3182	0.4546
Three Segments	10	7500	6490	0.8653	0.8653	0.8653
	16	12000	6690	0.892	0.5575	0.6862
	25	18750	6809	0.9079	0.3631	0.5187
Four Segments	10	7500	6408	0.8544	0.8544	0.8544
	16	12000	6635	0.8847	0.5529	0.6805
	25	18750	6770	0.9027	0.3611	0.5158

TABLE V. INTEGRATION OF EIGENFACES AND COLOR HISTOGRAM-BASED HUMAN FACE RETRIEVAL

Extraction Method	Top Face	Retrieved Faces	Relevant	Recall	Precision	F-score
Traditional Method	10	7500	5962	0.7949	0.7949	0.7949
	16	12000	6332	0.8443	0.5277	0.6495
	25	18750	6559	0.8745	0.3498	0.4997
Three Segments	10	7500	6713	0.8951	0.8951	0.8951
	16	12000	6915	0.922	0.5763	0.7093
	25	18750	7028	0.9371	0.3748	0.5354
Four Segments	10	7500	6618	0.8824	0.8824	0.8824
	16	12000	6839	0.9119	0.5699	0.7014
	25	18750	6968	0.9291	0.3716	0.5309

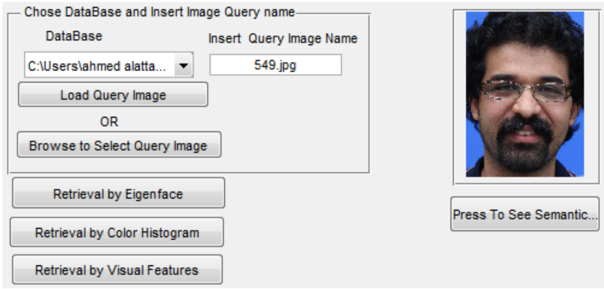

Fig. 6: Sample of Facial Image Query Based Eigenfaces Features.

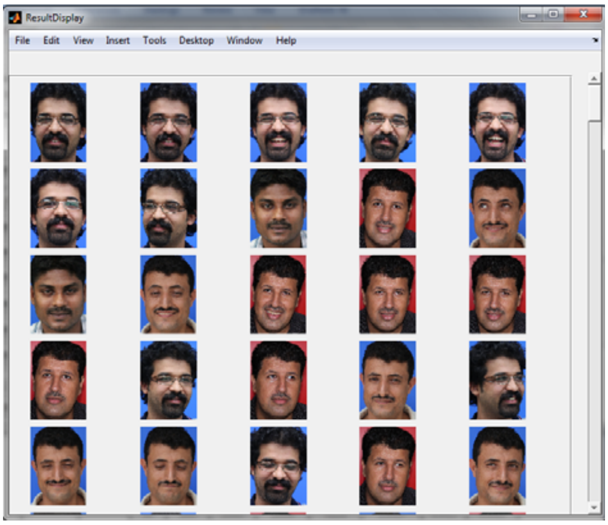

Fig. 7: Sample of Facial Image Retrieval Based Eigenfaces Features.

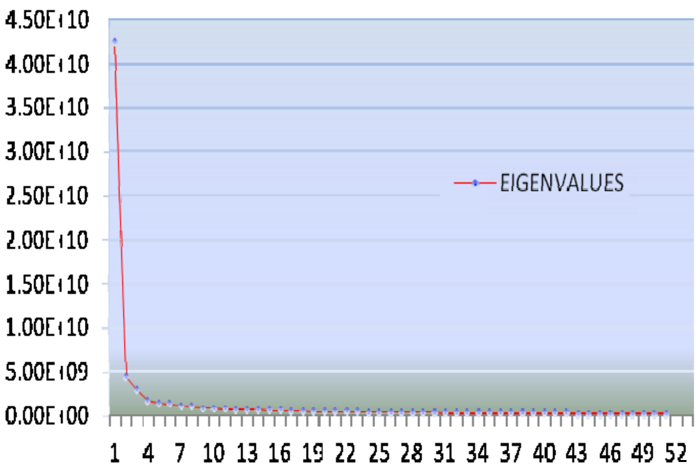

Fig. 8: The Eigenvalues of the First 50 Training Eigenvectors.

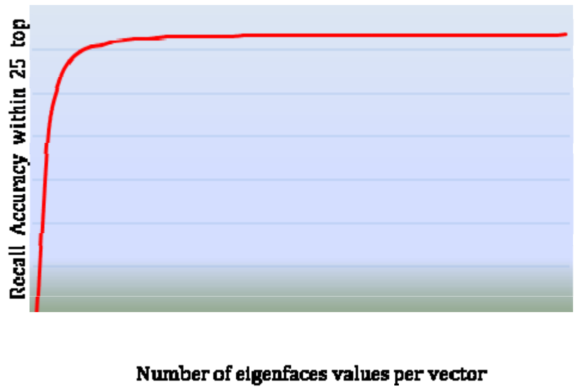

Fig. 9 : Facial Image Retrieval with Different Vector Dimension of Eigenfaces Features.

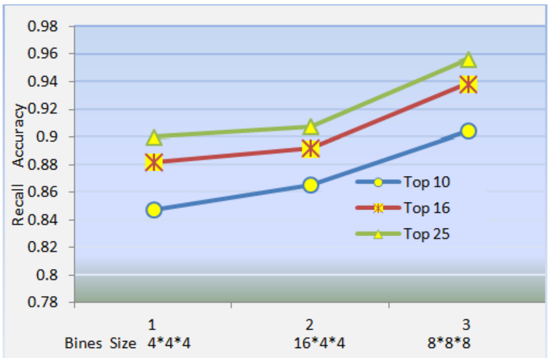

Fig. 10 : Color Histogram-based Face Retrieval with Different Size of Bins.

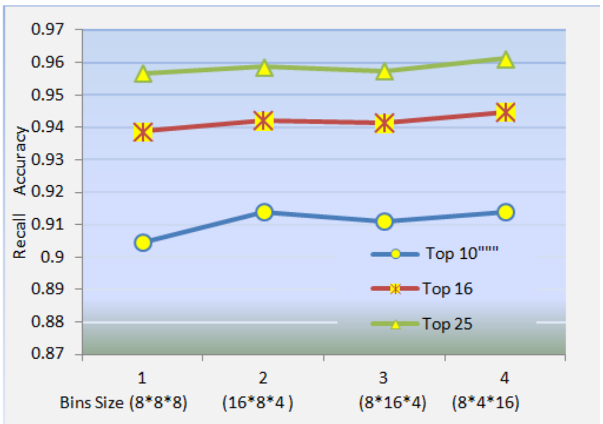

Fig. 11 : Color Histogram-based Face Retrieval with Different Distribution of the Color Space Coordinate.

TABLE VI. COLOR HISTOGRAM-BASED FACE RETRIEVAL WITH DIFFERENT SIZE OF BINS

Bins Size	Top Face	Retrieved Faces	Relevant	Recall	Precision	F-score
4*4*4	10	7500	6355	0.8473	0.8473	0.8473
	16	12000	6615	0.882	0.5513	0.6785
	25	18750	6754	0.9005	0.3602	0.5146
16*4*4	10	7500	6490	0.8653	0.8653	0.8653
	16	12000	6690	0.892	0.5575	0.6862
	25	18750	6809	0.9079	0.3631	0.5187
8*8*8	10	7500	6783	0.9044	0.9044	0.9044
	16	12000	7040	0.9387	0.5867	0.7221
	25	18750	7175	0.9567	0.3827	0.5467

TABLE VII. COLOR HISTOGRAM-BASED FACE RETRIEVAL WITH DIFFERENT DISTRIBUTION OF COLOR SPACE COORDINATE

Bins Size	Top Face	Retrieved Faces	Relevant	Recall	Precision	F-score
8*8*8	10	7500	6783	0.9044	0.9044	0.9044
	16	12000	7040	0.9387	0.5867	0.7221
	25	18750	7175	0.9567	0.3827	0.5467
16*8*4	10	7500	6854	0.9139	0.9139	0.9139
	16	12000	7065	0.942	0.5888	0.7247
	25	18750	7190	0.9587	0.3835	0.5478
8*16*4	10	7500	6833	0.9111	0.9111	0.9111
	16	12000	7060	0.9413	0.5883	0.7241
	25	18750	7180	0.9573	0.3829	0.547
8*4*16	10	7500	6854	0.9139	0.9139	0.9139
	16	12000	7086	0.9448	0.5905	0.7268
	25	18750	7208	0.9611	0.3844	0.5492

The colour histogram algorithm conducts image colour analysis without consideration for locations of colour components in the image. Consequently, object location information is obviously left out. In addition, this colour analysis generates similarity of colors as seen by the computer and may necessarily differ from those visualized by the human eyes. Semantically, this is a major weakness in the colour histogram analysis. The proposed method has addressed this weakness through the employment of the facial image segmentation algorithm.

Visual examples of facial retrieval based on the color histogram algorithm using the proposed method of facial image segmentation have been provided. Fig. 12 and Fig. 13 respectively show the results of visual query and image retrieval of the color histogram using the local database. The recall method of performance measure shows that 100% accuracy was achieved for the top 10, 16, and 25 cut-off levels, where all the 10 images related to the query image were retrieved in the first and second rows of the results frame. The results given in this example constitute the best achievement of face retrieval based on color histogram. It is also considered the best result of system performance based on color histogram, as in some other runs the achieved accuracies fall below 100% for the topmost 10 images provided in results tabulated earlier.

ix. CONCLUSION

In this research, a new method for content-based human facial image detection and retrieval model is proposed based on integration of the face detection, face recognition technique and the traditional content-based image retrieval technique. In addition, a new method of facial image segmentation for improving the performance of the features extraction process is also suggested. Integration of eigenfaces features and color histogram features were used as low level features, whilst the proposed method is applicable with different visual features.

Color space models RGB, HSV, and HSI were used to investigate in which color space the facial image retrieval technique shows the best performance. Experimental results showed that eigenfaces-based facial image retrieval in HSV model yields the best accuracy among the other models and the color histogram-based facial image retrieval in RGB color space showed the best performance among the other models.

Comparing to the traditional method of visual features extraction, the results reflect an excellent improvement in the facial image retrieval achieved based using the proposed method of visual features extraction.

Increasing the dimension of the eigenfaces vectors will not necessarily result in higher performance. Moreover, the existence of some trivial information may be consider as noise and will degrade the system performance, especially when the eigenfaces are combined with other features. Unlike the eigenfaces features, with color histogram, increasing the size of the bines, would result in slight increase in the dimension of the features vectors, leading to improved retrieval performance.

Choosing the distribution values of the color space coordinates to represent the bines size, during the quantization processing, has influenced the color based facial image retrieval results. The accuracy will be based on the distribution of the colors in the image.

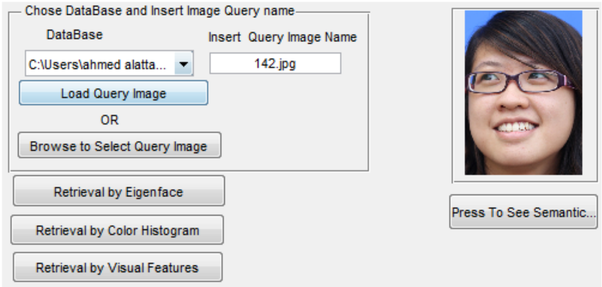

Fig. 12 : Example of Facial Image Query based Color Histogram Features.

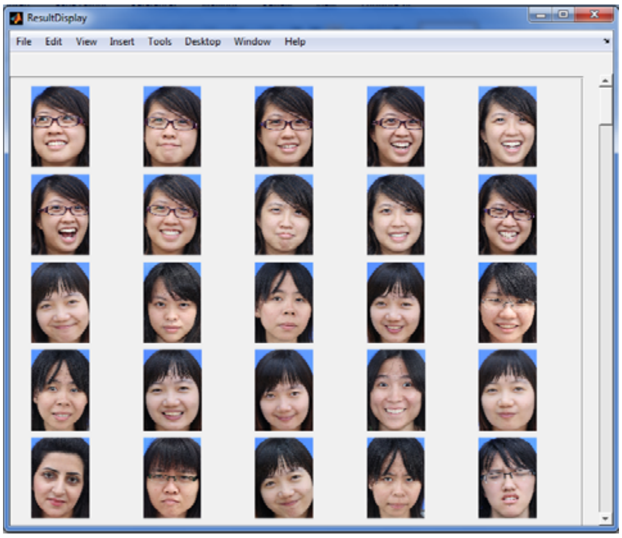

Fig. 13 : Example Results using Color Histogram based on Image Segmentation Technique.

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