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Improving Web Based Image Retrieval with Fuzzy Descriptors Relevance Feedback Technique

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Abstract. There is a huge increase in the multimedia data, such as images and videos on the internet. This is because of the sudden large increase in the use of computers and digital devices all around the world in various fields. The needs of retrieval systems that deal with huge data repositories of multimedia databases have increased with time The goal of the proposed system is to increase both the accuracy of the retrieved images and the speed of image retrieval. And Decrease the difference between low-level features and the human precipitation of image features "semantic gap". These objectives will be achieved by the combination between fuzzy relevance feedback techniques. Also, in order to satisfy these goals, low level feature extraction algorithms, deriving high-level semantic features, similarity, measurement, and query by keyword are utilized in the system. The evaluation of the retrieved results of this system showed that the system is working in an effective way for an online processing system.

Keywords: image descriptors, image processing, relevance feedback, semantic gap

1 Introduction

A huge amount of images are generated in our everyday life as the fast growth of advanced digital capturing devices for multimedia, such as digital camera and mobile-photography phone. Through WWW, the collective image repository will be further bigger and bigger because of the speeding exchange of these life images. The needs of a retrieval system that deals with these heterogeneous huge data repositories of multimedia databases have increased with time Thus a system that can filter images based on their content would provide better indexing and return more accurate results, Very few tools are currently available for searching for images and videos over the Internet because these tools have to deal with aspects of the image retrieval Field [1].

Image retrieval can be defined as the task of searching for images in an image database. As shown in Fig. 1, image retrieval techniques can be classified into three categories: text-based image retrieval (TBIR), content-based image retrieval (CBIR), and semantic-based image retrieval (SBIR).

TBIR is used to manually annotate the image in the database with keywords, or descriptions. This process is used to describe both image contents and other metadata of the image such as: image file name, image and image format, image size, and image dimensions. Then, the user formulates textual or numeric queries to retrieve all images that are satisfying some of the criteria based on these annotations, as shown in Fig. 2. However, there are some drawbacks in TBIR [2]. The first drawback is that the most descriptive annotations must usually be entered manually. Manually annotation for a large image database is impractical. The second drawback is that the most images are very rich in its content and has more details. The annotator may give different descriptions to images with similar visual contents. Also, textual annotations are language-dependent.

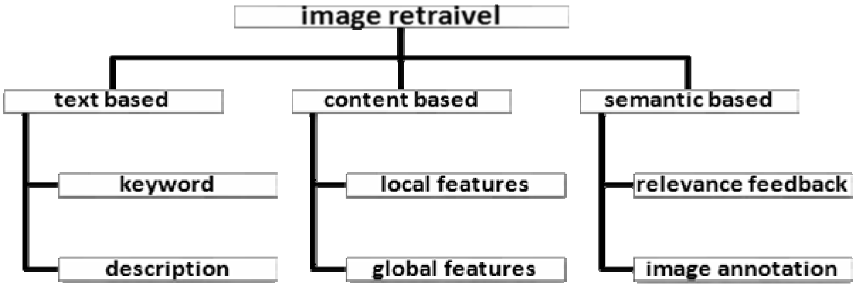


Fig. 1. Image retrieval categories

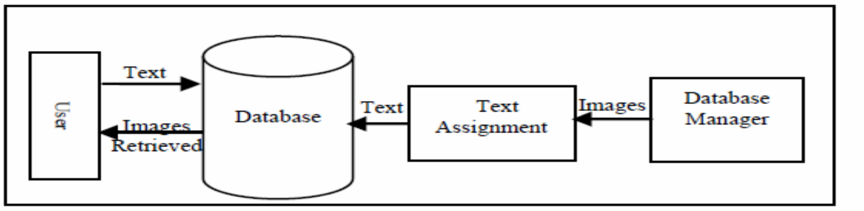


Fig. 2. TBIR system

CBIR is used recently instead of text based image retrieval as proposed solutions for drawbacks of TBIR. The dependence on the visual contents of the images leads to better retrieval accuracy than the dependence on annotating text that may contain misleading keywords. Implementing the CBIR system (see Fig. 3) would help in order to discover the problems and other errors that were hard to be tracked theoretically. Examples of such effective systems are Enser, IBM Query By Image Retrieval (QBIR), Virage, Candid, Phonebook, Netra, Pichunter, Viper, Wipe and Compass [2].

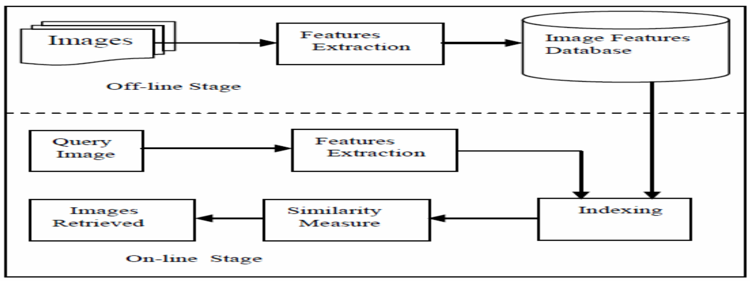


Fig. 3. CBIR system

CBIR has one main well- known limitation which is the semantic gap that has been a research area by many of researchers to solve that problem. Semantic gap mean that the difference between the high level concepts which is the human precipitation of the image and low level features extracted from images. As a result, the user using any of the CBIR systems will not be able to get results satisfies his/her needs. SBIR can be made by extraction of low-level features of images to identify meaningful and interesting regions/objects based on the similar characteristics of the visual features. Then, the object/region features will go into semantic image extraction process to get the semantics description of images to be stored in database. Image retrieval can be queried based on the high-level concept. The semantic mapping process is used to find the best concept to describe the segmented or clustered region/objects based on the low features. This mapping will be done through supervised or unsupervised learning tools to associate the low-level features with object concept and will be annotated with the textual word through image annotation process [2-3].

In order to decrease semantic gap problem, there is a new concept called “relevance feedback” that reduces greatly the semantic gap problem. relevance feedback propose to enhance the outputted retrieval results from the system by learning user`s feedback. Feedback processing step is used to have the appropriate reaction from the system to the user queries that guarantee the user's satisfaction. According to the established indexing system, the relevance feedback will proceed [4].

This paper proposes an improved image retrieval system, that combines between two techniques content based image retrieval and semantic based image retrieval in this improved system there is a group of newly introduced efficient descriptors such as Color and Edge Directivity Descriptor (CEDD), Fuzzy Color and Texture Histogram (FCTH), and join color descriptor (JCD). These descriptors are developed in order to have a smaller size and storage requirements without affecting the performance of processing of the system. In addition, it will speed up the performance of the system efficiently and satisfying the customer needs. Also improved CBIR system is using automatic relevance feedback (RFA) instead of using the heavily classification techniques for enhancing the output of each descriptor. This auto relevance feedback will allow the pre-saved learning which is helping to fix any deviations in images.

The rest of the paper is organized as follows: Section 2 describes some of the recent related works. The detailed description of proposed system has been made in section 3. In section 4, the results and discussions on the dataset are given. Finally, conclusions are drawn in section 5.

2 Literature Survey

CBIR systems has received a major interest to solve problems that are targeting huge databases of images, the challenge was the semantic gap between user and computers way of precisions. In addition, other main problems that CBIR system face is that the way of generating a query in this kind of systems and also, assessing the system outcomes accurately [5]. There are a large number of CBIR systems have been established for "commercial" purpose such as QBIC which is considered from one of the first established search engines in this field [6]. Lately, more newly search engine systems have been established for example, T.J. Watson, VIR, AMORE and Bell Laboratory WALRUS [7]. In addition, to other search engines have been developed for the "academic" purpose, one of the first search engines that has been established in this field called MIT Photobook [8]. Nowadays, the most popular CBIR systems are Berkeley Blobworld, Columbia Visualseek and Webseek Natra, and Stanford WBIIS [9].

The basic idea of any CBIR system is to extract "signature" of all the images in the database according to the original values of each pixel in it. This signature is important for compacting the image for representation and linking it to the semantics of the image [10]. There are three main basic types for the CBIR systems ways of the extraction of features such as "histogram, color layout, and region-based search". Other systems associate both the outputted results with "individual algorithms". Also there are two types of search techniques for any query "partial search" and "global search"; "partial search" will retrieve and measure the similarity of images according to specific region of the image. However, the "global search" will retrieve and measure the similarity of images according to their general "properties" [11].

In the current literature, Current image retrieval techniques can be classified into five categories. (1)Query Techniques:- titled as query by example, the system will carry out "similarity search" by using this queried image, in order to fetch for all the relevant similar images in database that matches the queried image low-level features. There are many benefits of using this technique in the CBIR systems for example, removes the difficulties of describing images with words. but There are many disadvantages such as Bad querying performance and Complex interfaces. (2) Global Feature Extracted:- Searching image libraries for a specific image, Performed by comparing Feature vectors of a search image With the feature vectors of all Images in the database, benefits of using these technique that it is the first step toward image understanding disadvantages of this technique Semantic gap arise, More computation, and Very slow [12]. (3) Region Based CBIR Systems: -The benefit of using the Region-based retrieval systems is to recover the problems of (global feature based search) through dealing with the image at the "object-level". Another important thing is that the segmentation of image to divide it into regions, in the decomposition each region related to objects. (4) Relevance feedback: - an interactive mechanism for the user to progressively refine the search results by marking the images in the results as \relevant or \irrelevant to the search query and then repeating the search using this additional information. Finally, by the relevance feedback, the preferred images will be returned to the system in a "round-by-round basis" [13-14]. (5) Fuzzy system:- There are many reasons of using the fuzzy technique is that it has a great tool for information "representation and processing", has the ability of "ambiguity and vagueness" management, handle the problems of the "object recognition and scene analysis", and it has a great ability to present the human knowledge in form of fuzzy logic [11, 13].

To develop web image retrieval system, there are still many technical challenges and problems. (1) Scalability: - cannot scale to billions of photos. (2) Vocabulary: - what kinds of image features should be used? How to map them to words? The most generally utilized method is clustering. (3) Content quality: - Web search engine is effective because it can use link analysis to obtain quality and importance measurement (e.g. Page Rank) for Web pages. For images, it is hard to obtain similar kind of measurement because the links are typically not directly associated with images. (4) Distributed computing for Web-scale multimedia analysis: -Because of the large volume of image data we need to process and index, the system has to be a distributed system, consisting of hundreds of powerful servers [15].

This paper presents a new web based image retrieval system that overcomes most of the problems that other systems face by decreasing the difference in image between low-level features and the human precipitation of image features which is called "semantic gap", through using relevance feedback techniques, in addition new improved system overcome the problem of the session time out that occurs in most of web based image retrieval systems by using the appropriate descriptors which are developed with special focus to their size and storage requirements in order to retrieve the most accurate results with the lowest retrieval time.

3 Proposed Methodology

The aim of the proposed system is to increase both the accuracy of the retrieved images and the speed of retrieval. This is planned to be achieved through selecting the best predictor among different classification techniques. The first aim of this project is to suggest a new CBIR system that overcomes most of the problems that other CBIR systems face. The main tasks of the new system are to decrease the difference in image between low-level features and the human precipitation of image features which is called "semantic gap". Then, the second of this project, is to decrease the time of retrieval of the needed images by using the appropriate descriptors.

In the proposed system, there was focus to overcome about the use of large size of descriptors by a group of newly introduced descriptors such as Color and Edge Directivity Descriptor (CEDD), Fuzzy Color and Texture Histogram (FCTH), and Join Color Descriptor (JCD) Therefore, the improved system descriptors well-developed to have better focus on having smaller "size and storage requirements" without affecting its ability to perform well. The new feature descriptors will have great ability to combine both features; such as "color and texture information" into only a single histogram that ranging its size from "23 and 74 bytes per image". in addition The main reason for using the RFA in the descriptors is to enhance the outputted results from the system through learning the user`s information needs.

Fig. 4 shows the general data flow diagram of the proposed system, There are two main categories of CBIR system which are feature extraction in an off-line processing and other way is that the image retrieval system in on-line processing. The feature extraction of every image contents in database such as "color, shape, texture, and spatial information" will be extracted automatically in the off-line processing. This extracted information about every image will be according to the original values of each pixel. Then, the CBIR system will have another database which is known-as "feature database" will be used to store these extracted features. The signature is having a component called feature data which is having the extracted features extracted from each image. These stored signatures (compacted features) for each image will be reduced compared to the size of the original features in image. This is the beneficial reason of using these images signatures (compacted features) to be stored in database for its smaller size and to gain an improved correlation between image representation and visual semantics.

On the other hand, the other category of CBIR system is the on-line retrieval of images. This is allows the user to query an image by uploading it into the system to retrieve the similar images based on the queried image. The system calculates the similarity measurement between both the distance of queried image feature vector and the other target feature vectors stored in the database. The system should be provided with an efficient images indexing mechanism for searching appropriately all the databases with no defects in desired retrievals. In addition, after having these similarity measures the system will retrieve the desired and similar images of queried image based on the classification and ranking functions in system. However, in the on-line CBIR system, the RFA will be already embedded in the descriptors so there is no need for the user interaction to allow feedback in system. This is because the CBIR system automatic relevance feedback will use the pre-saved information to allow direct feedback in the system as shown in the Fig. 4.

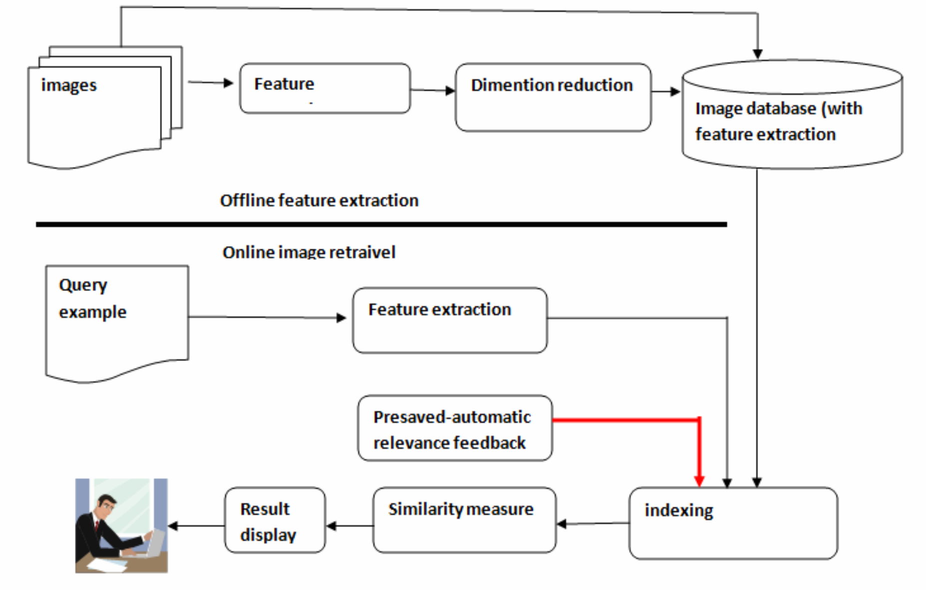


Fig. 4. Framework for improved system

The proposed system is allowing the user to select the querying method. Then, the user selects which method of querying that will be used. The user uploads the image; if the chosen method was the query by similarity. Then, the system will extract the features from the image using descriptors (CEDD, FCTH and JCD) and select needed dataset. These extracted features retrieved from image will be used with the selected classifier to search and compare in an online processing manner for similar images with the same content. Otherwise, if user chose the query by ROI, it's required to upload image in order to crop the region of interest from it. Then, this cropped region will be used as the new queried image that the descriptors will extract features from it and then, user selects needed dataset. These extracted features will be used with the selected classifiers to search and compare in an online processing manner for similar images of same content. The last option is searching by keyword in which the user will choose category, color and enter the description of image if needed. The database will retrieve all the images with the same keyword description. Finally, the result will be retrieved based upon the selected method of querying as shown in the Fig. 5 following subsections discuss each step in details.

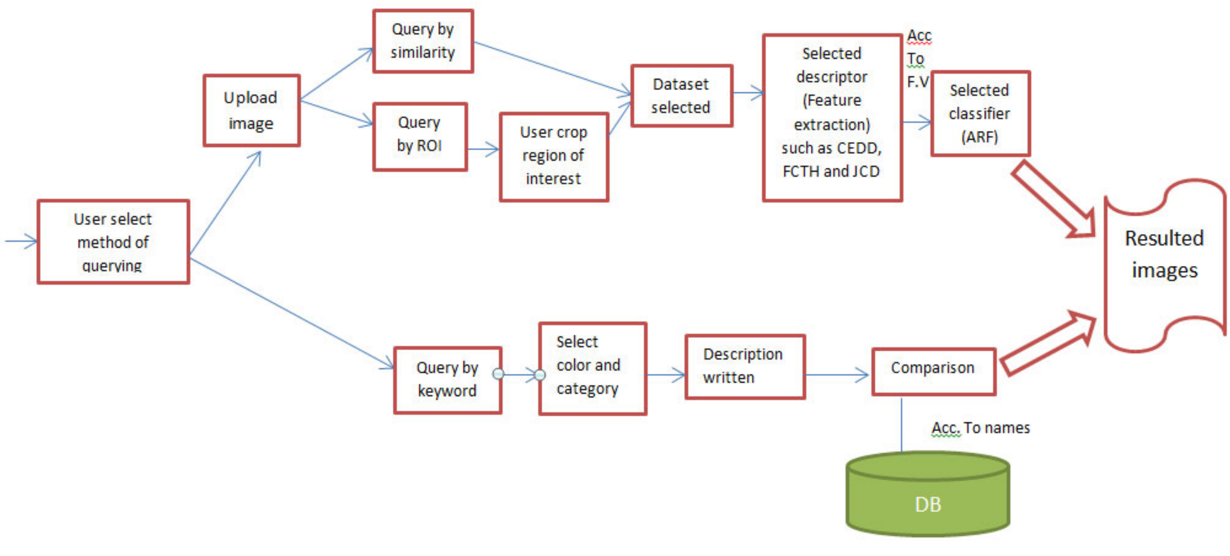
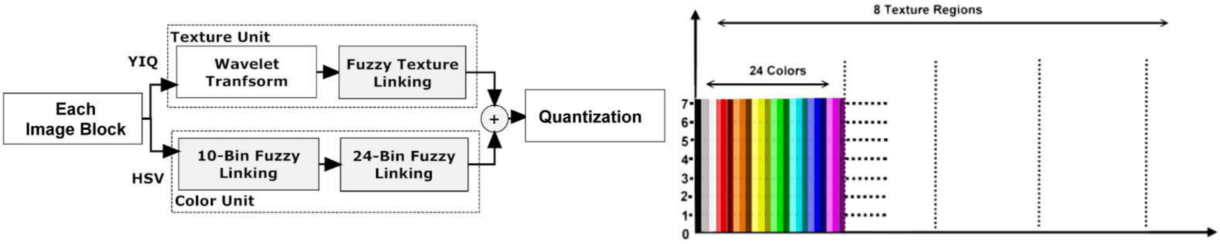


Fig. 5. Data flow diagram of improved system

3.1 Feature Extraction

The system will extract the features from the image using descriptors (CEDD, FCTH and JCD). These extracted features retrieved from image will be compared in an online processing manner for similar images with the same content.

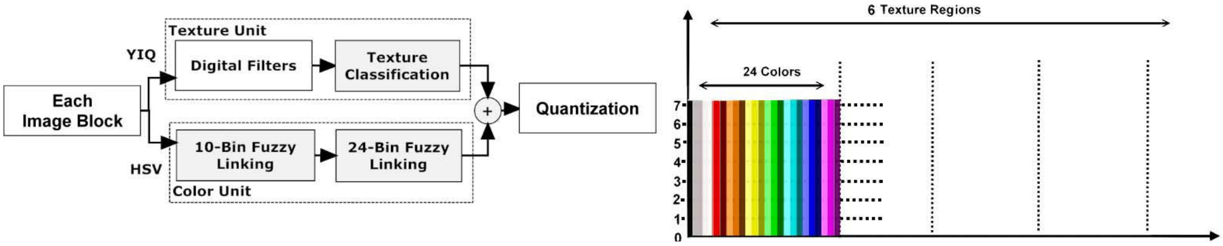
1-CEDD and FCTH descriptors. CEDD and FCTH use the same color information, as it results from 2 fuzzy systems that map the colors of the image in a 24-color custom palette. First fuzzy system in FCTH is established by 8 regions. This first fuzzy system takes any precious "decision" with respect to the image texture. Second fuzzy system, each of the divided 8 regions is spitted into other 24 established regions with respect to the image color. To retrieve the description for the image (texture and visual descriptor) [16]. Fig. 6 shows the general data flow diagram of FCTH Implementation.



(a) (b)

Fig. 6. FCTH implementation flowchart [10]

First fuzzy system in CEDD is established by 6 regions/ bin histogram that makes use of the five "digital filters" suggested by CEDD 64 the MPEG-7 EHD with respect to texture of image. The second fuzzy system, each of the divided 6 regions is splitted into other 24 established regions/ bin color histogram with respect to the image color. To retrieve the description for the image (texture and visual descriptor) [17]. Fig. 7 shows the general data flow diagram of CEDD Implementation.



(a) (b)

Fig. 7. CEDD implementation flowchart [10]

2-JCD (join color descriptor). This algorithm is a join between the CEDD and FCTH algorithms. JCD algorithm takes the best of extracted features from both of the two algorithms merged together. This merge mechanism is achieved in order to take the best of the best features retrieved from both of them that will improve the performance and decrease the processing time [18]. Also, JCD It is made up of 7 texture areas, with each area made up of 24 sub regions that correspond to color areas [10].

3-Tanimoto classifier. In order to measure the similarity of the images on the basis of JCD, the Tanimoto coefficient is used, just as in the CEDD and FCTH. The distance T of images (a) and (b) is determined as Tab and is calculated as follows [19]:

$$T_{ab} = T(JCD(a))^{m}_{n,}\ JCD(b)^{m}_{n}$$

$$= \frac{(JCD(a)^{m^T}_{n,}\ JCD(b)^{mT}_{n}}{(JCD(a)^{m^T}_{n}\ (JCD(a)^{m}_{n,+}(JCD(b)^{m^T}_{n,}\ JCD(b)^{m}_{n} - JCD(a)^{m^T}_{n,}\ JCD(b)^{m}_{n}} \qquad \textbf{(1)}$$

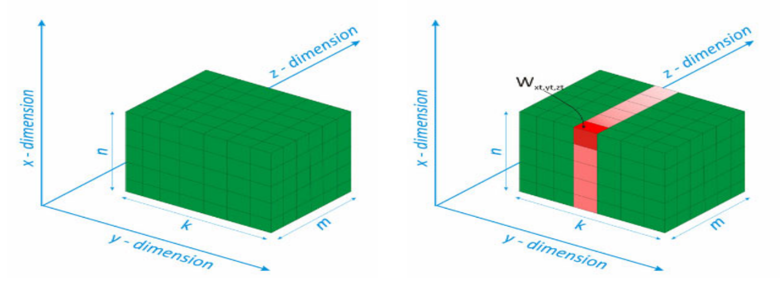
Where $JCD(a))^{m^T}_{n}$ is transport vector of $JCD(a))^{m}_{n}$ T is the transposed vector of the $JCD(a))^{m}_{n,}$ In the absolute congruence of the vectors the Tanimoto coefficient takes the value 1, while in the maximum deviation the coefficient tends to zero [10].

3.2 Relevance Feedback

The use of the above descriptors in the huge databases doesn't guarantee the retrieval of a pure, successful and precious visualization distinguishes between these random images. Chatzichristofis et al. [20] have published the RFA; this algorithm is based on the users' feedback on the retrieved images in the learning phase. The feedback will be in the form of grades or ranks of these images. Accordingly, the search engine uses these ranks to satisfy the user requirements in future queries. In offline CBIR system (RFA) will be used while implementing the descriptors in the development phase. RFA propose in the descriptors is to enhance the outputted retrieval results from the system by learning user`s feedback. However, in the on-line CBIR system, the RFA will be already embedded in descriptors so there is no need for the user interaction. This is due to that on-line CBIR system automatic relevance feedback will use the pre-saved information to allow feedback in the system directly.

Most of relevance feedback techniques are based on modifying the values of the search parameters so that they better represent the concept consistent with the user's option [21]. The search parameters are computed as a function of the relevance values assigned by the user to all the images retrieved so far. For instance, relevance feedback is frequently formulated in terms of the modification of the query vector and/or in terms of adaptive similarity metrics. Pattern classification methods such as support vector machine (SVMs) have been used in Relevance Feedback (RF) techniques. Also, the user searching for a subset of images using the above descriptors, sometimes does not have a clear and accurate vision of these images. He/she has a general notion of the image in quest but not the exact visual depiction of it. Also, sometimes there is not an appropriate query image to use for retrieval [22]. To sum up, the proposed Automatic Relevance Feedback (ARF) algorithm has succeeded to recover from all these previous mentioned problems. This is achieved by having a mechanism to "fine tune" the outputted results, the user selects from the first round of retrieved images one or more, as being relevant to his/her initial retrieval expectations. Information extracted from these selected images, is used to alter the initial query image descriptor [23].

Initially, the image query is changed from one-dimensional descriptor to three-dimensional vector (Wx, y, z). Where x, y and z represents the texture, dominant color, and the variation of the dominant color respectively. x £ [1, n], y £ [1, k] and z £ [1, m]. Where n, k and m represents the number of all texture, colors and maximum variation in colors. The main benefit from these alterations to the x, y and z dimensions will simplify the access to deeper information of descriptors [19]. Fig. 8 illustrates the vector.



(a) (b)

Fig. 8. (a) The three-dimensional vector $W_{x, y, z}$.; (b) The alteration of the values of the vector element $W_{xt,yt,zt}$ and its associated elements [23]

For example, the extraction of the bin descriptor of the same variation (z axis) of a dominant color (y axis) for each different texture (x axis) is accomplished by holding the two dimensions (y, z) constant, while x dimension takes all its allowable values in the interval [1, n], The transformation of the descriptor to the three-dimensional vector is based on the following equation [22, 24]:

$$i = (k \times m) \times x + m \times y + z \quad \textbf{(2)}$$

$$x = \left[\frac{i}{k \times m} \right] \quad \textbf{(3)}$$

$$y = \left[\frac{i \text{ - } x \times (k \times i)}{m} \right] \quad \textbf{(4)}$$

$$Z = i - x \times (k \times m) - (y \times m) \quad \textbf{(5)}$$

Where i is the position of the bin inside the descriptor and x, y, z is the position of the same bin inside the three-dimensional vector Wx, y, z. Initially, the value of each vector element is equal to the value of the corresponding descriptor bin. When the user selects a relevant image from the retrieval results, each bin of that selected image's descriptor Xi updates the corresponding value of the Wx, y, z vector in a Kohonen Self Organized Featured Map (KSOFM) manner so that it moves closer to the new value emerging from Xi [25]:

$$\mathrm{w}_{\mathrm{xt,yt,zt}}(\mathrm{t}+1) = \mathrm{w}_{\mathrm{xt,yt,zt}}(\mathrm{t}) + \mathrm{L}(\mathrm{t}) \times (\mathrm{X}_{\mathrm{xt,yt,zt}} - \mathrm{w}_{\mathrm{xt,yt,zt}}(\mathrm{t})) \quad \textbf{(6)}$$

Where Xxt, yt, zt is the transformed three-dimensional vector of the selected image query descriptor Xi based on Eq. Each time a user selects another relevant image, an epoch t start. This epoch ends after all the elements of vector Xxt, yt, zt of the selected relevant image are used to update the corresponding values of Wxt, yt, zt according to Equation 6, L(t) defines the rate of the vector element readjustment.

4 Experimental Results

The testing and evaluation of the CBIR system is for both the query by similarity and query by ROI (cropping). The testing will be divided into two types which is the visual and performance testing. The first type of testing is that the visual testing by analyzing visually the retrieval images with respect to each descriptor. However, the performance testing will be divided into four different ways. Firstly, the test will be done for various random chosen images with also a various changing number of images in dataset. Secondly, the test will be repeated with a fixed random chosen image with a various number of images in dataset. Thirdly, the test will be repeated again with varied images and fixed number of images (250) in dataset. Finally, the test is that having a test for a range of images from (small to large) ones with respect to a fixed size of dataset (250). All of these testing methods will be done in order to test the system accuracy of image retrievals (logical order), retrieval time and similarity measures.

4.1 The Visual Testing

After analyzing the output of the system in most of the trials, the JCD is having a much better results because the JCD descriptor is the time of joining the selected best features of both CEDD and FCTH as shown in the following figures. This is the main reason that made the JCD has the best visual output retrievals compared to others.

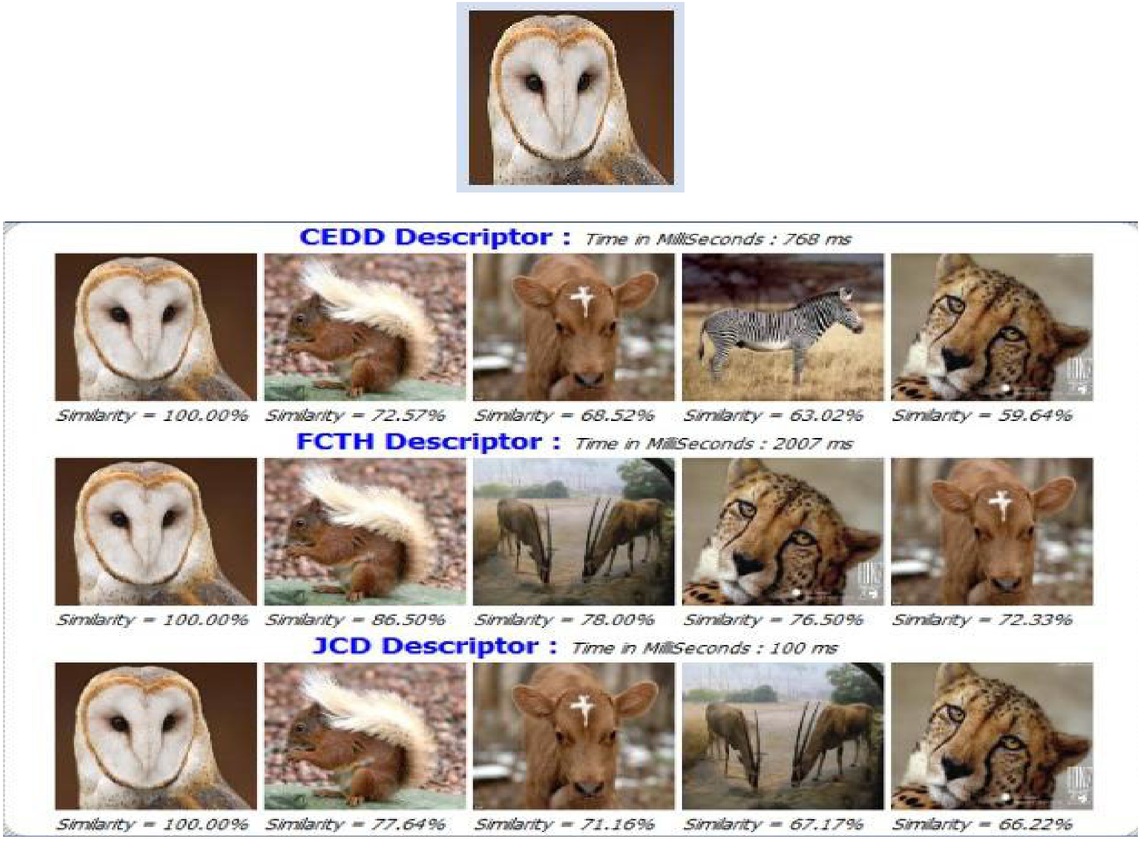


Fig. 9. Query by similarity for 100 images in dataset

Fig. 10. Query by similarity for 200 images in dataset

Fig. 11. Query by similarity for 300 images in dataset

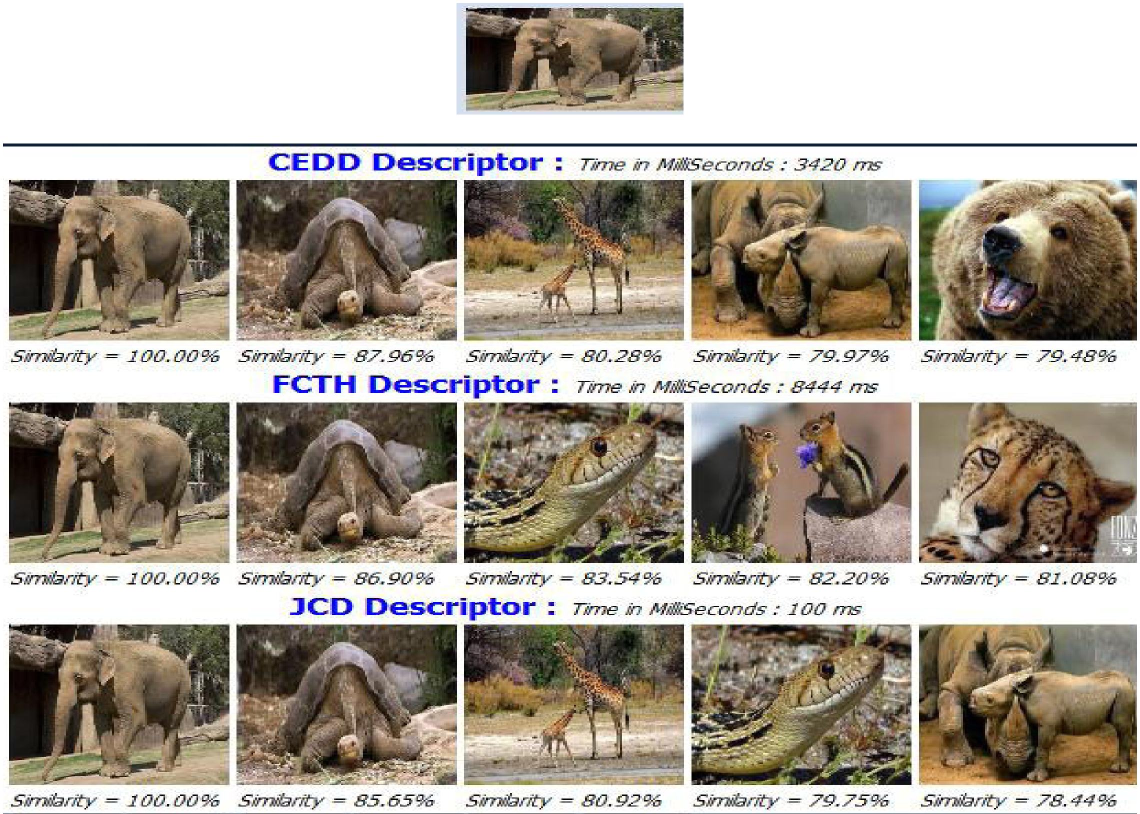
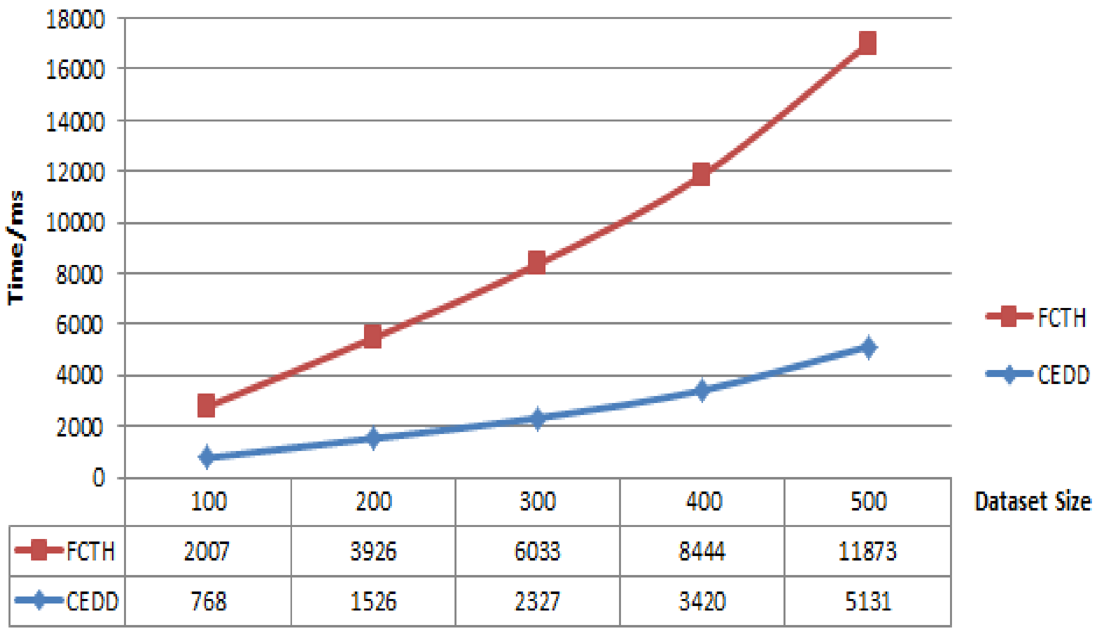


Fig. 12. Query by similarity for 400 images in dataset

Fig. 13. Query by similarity for 500 images in dataset

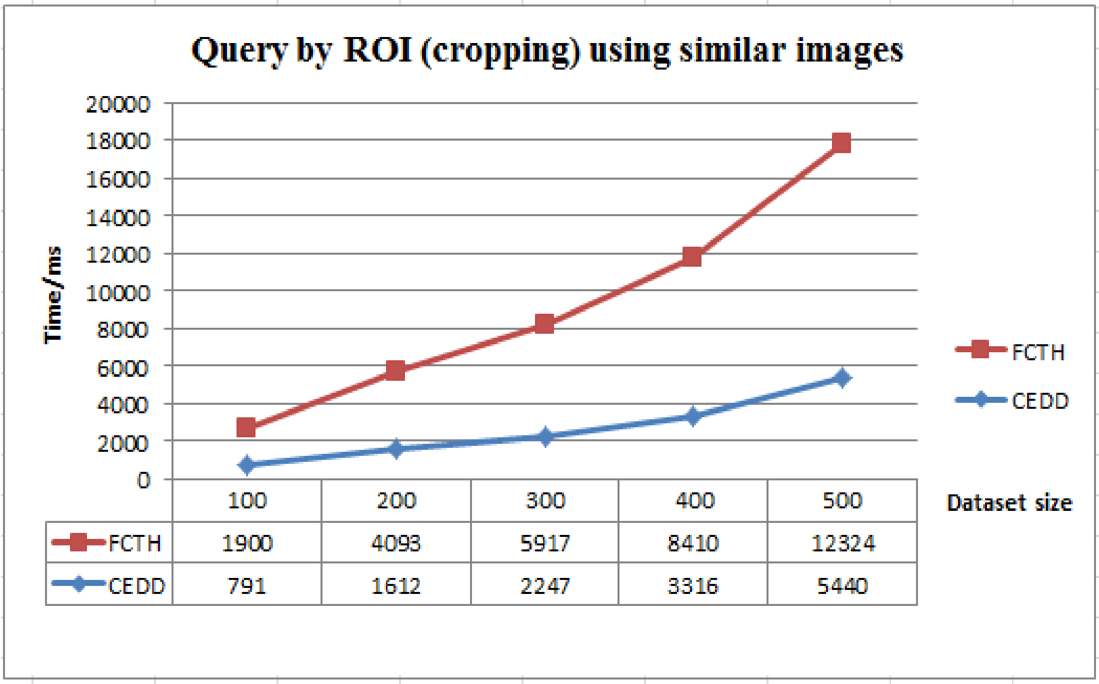
4.2 Performance Testing

The performance testing will be divided into four different ways. Firstly, the test will be done for various randomly chosen images with also a various changing number of images in the dataset.



	100	200	300	400	500
FCTH	2007	3926	6033	8444	11873
CEDD	768	1526	2327	3420	5131

Fig. 14. Query by similarity (CEDD-FCTH) using different images

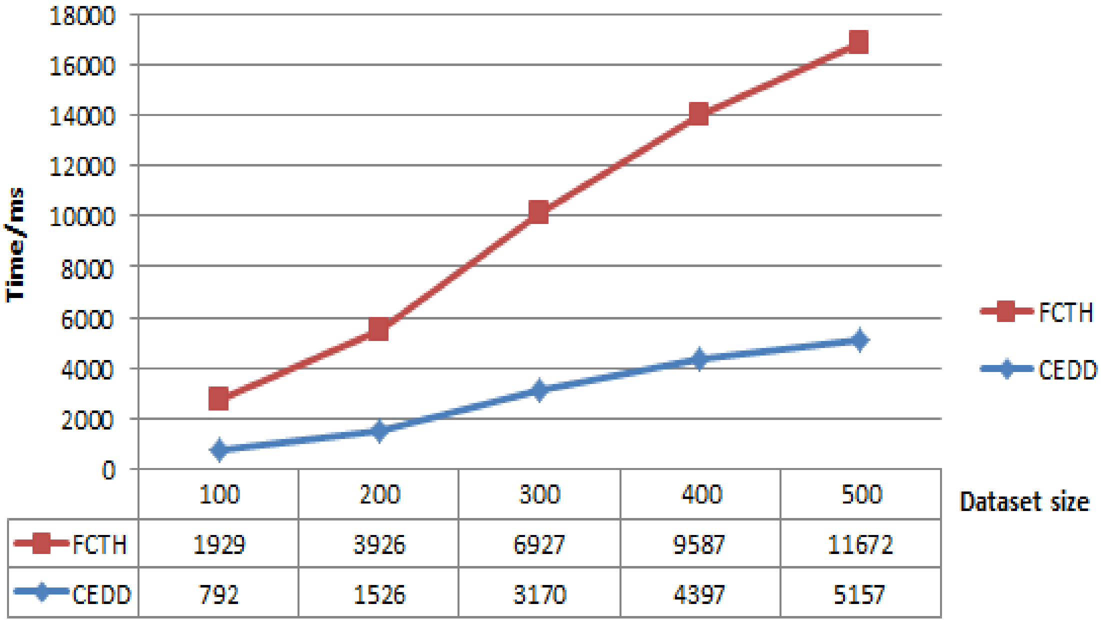


	100	200	300	400	500
FCTH	1900	4093	5917	8410	12324
CEDD	791	1612	2247	3316	5440

Fig. 15. Query by ROI CEDD-FCTH

This test has been done for random chosen different images such as (panda, tiger, flower, bird, horse) and also they have different colors. This graph shows the CEDD descriptor is much better than that FCTH and it will perform well and in an acceptable manner as database increases.

Secondly, the test will be done for the same random chosen images with also a various number of images in the dataset. This type of testing will make sure if the concluded decision about the first way of testing is right or not.



	100	200	300	400	500
FCTH	1929	3926	6927	9587	11672
CEDD	792	1526	3170	4397	5157

Fig. 16. Query by similarity using similar images

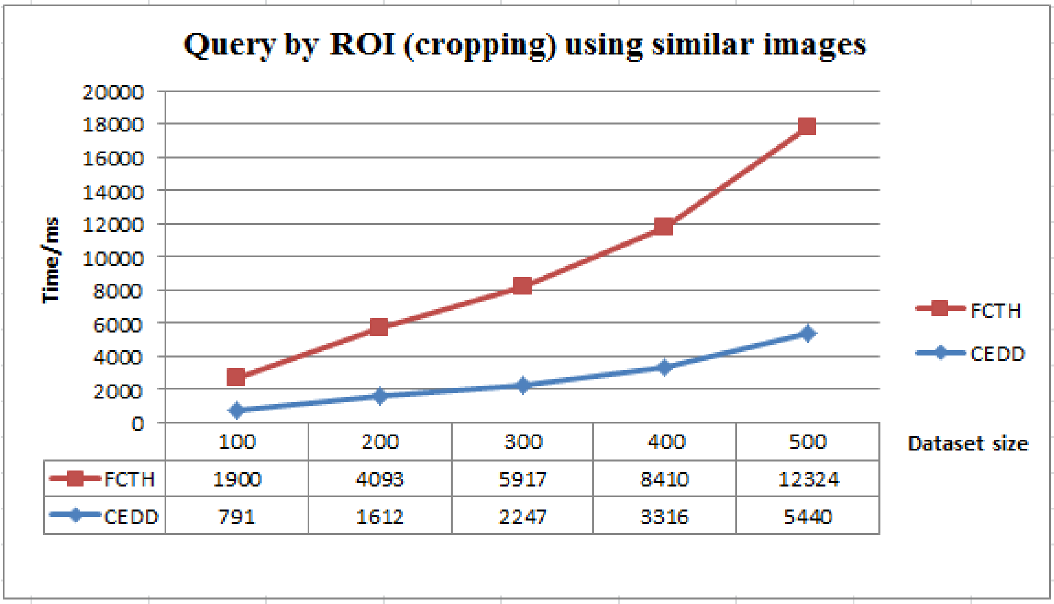


Fig. 17. Query by ROI using similar images

This graphs show the CEDD has proved to be more efficient as the size of dataset increases than FCTH.

Thirdly, the test will be done for the varied random chosen images with a fixed number of images in dataset for both methods.

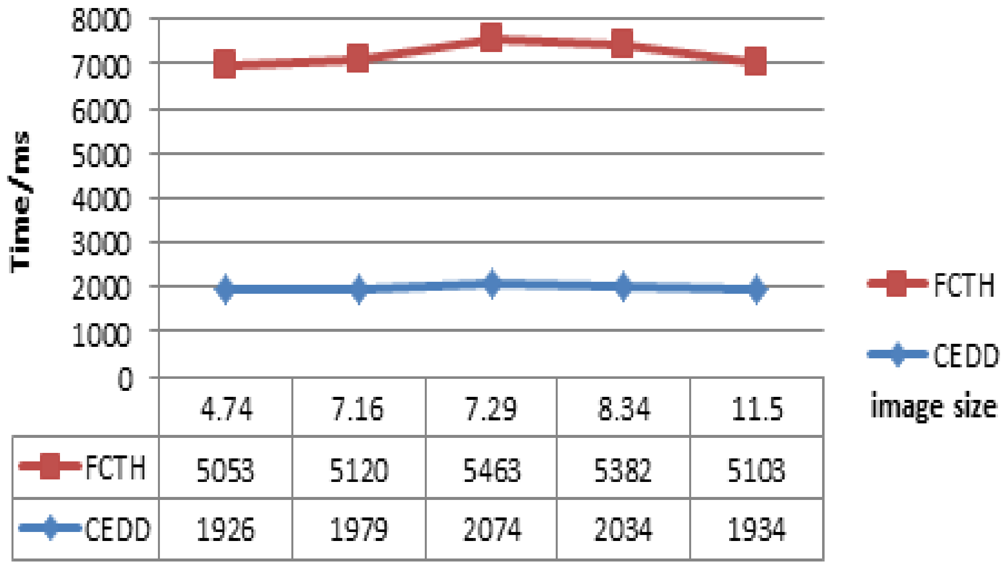


Fig. 18. Query by similarity using a different image size in KB (250 data set)

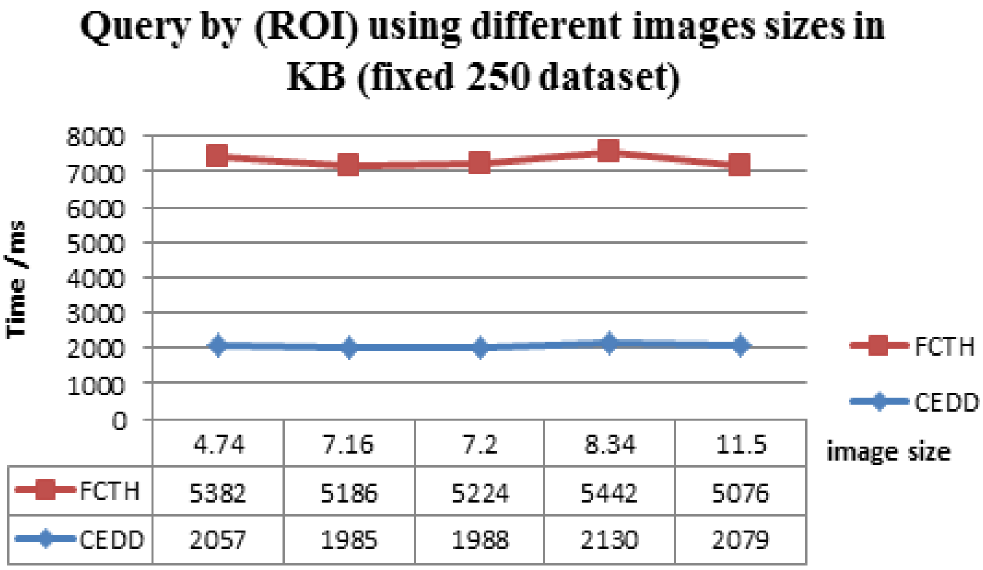


Fig. 19. Query by ROI using different images sizes in KB (250 Dataset)

After all of these testing ways the CEDD has been represented as an efficient descriptor that can be used in any size of the dataset or even with any size of image used.

Fourthly, the last test will be done for the varied sizes (KB & MB) of randomly chosen images with a fixed number of images in dataset (250) images.

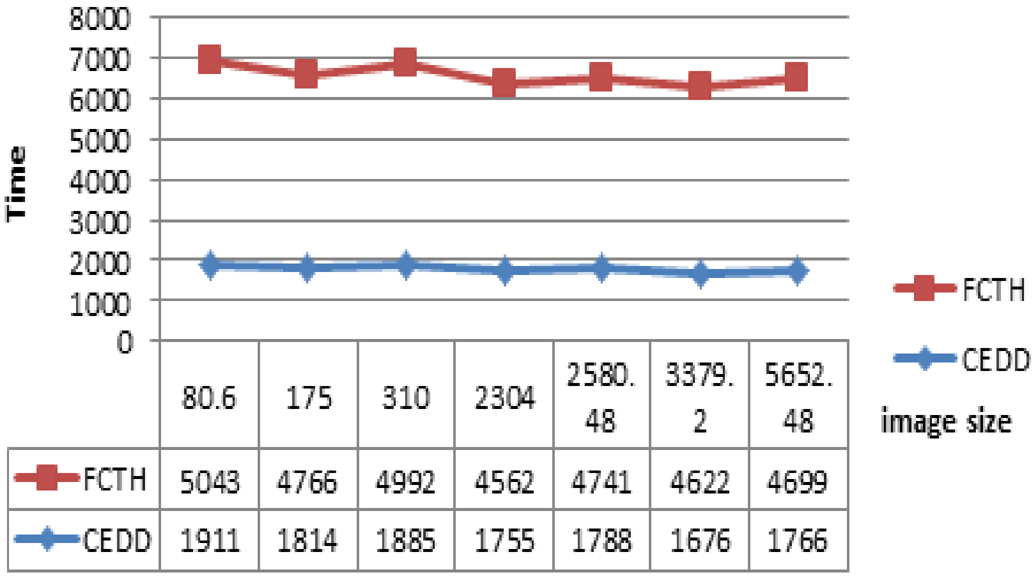


Fig. 20. Query by similarity of different image sizes (MB & KB) of fixed size dataset (250)

After all of these testing ways the CEDD has been represented as an efficient descriptor that can be used in any size of dataset or even with any size of image used.

5 Conclusions and Discussions

This paper proposes a new CBIR system that mainly provides an online web based image retrieval system. This system will use the most effective descriptors that allow an online processing. These descriptors such as (CEDD, FCTH and JCD) have enhanced the retrieval results greatly. The automatic relevance feedback (ARF) will be used to classify and increases the efficiency of the resulted images retrieved. The ARF will be suitable technique in the online CBIR system through learning the user`s information needs. Finally, the evaluation of the retrieved results of this system showed that the system is working in an effective way for an online processing system; search and retrieve images from huge databases with small time taken for the retrievals of each descriptor used.

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