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Improving Image Retrieval Through a Collection of Fast and Simple Visual Features Extraction

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Abstract: In this paper, we experimented a large set of feature extraction methods with fast and simple computation approaches. Some of those methods were proposed in different areas and domains and we thought of evaluating their ability in enhancing the image retrieval process. Several low-level image features are selected as part of our image retrieval system. Examples of feature extraction methods used include features related to RGB and HSV color schemes, color and texture features and finally features collected through the open source MaZda software. Based on conducting experiments, our proposed method for extracting features with less computation time and improved results in terms of retrieving accuracy. Similarity measures such as: Euclidean, Chebyshev and Manhattan were also used to measure distances between subject image and database images. A dataset of 1000 images from COREL database is used and classified into 10 different categories. Precision and recall metrics are used to evaluate the performance of the retrieval process. The final results showed a good, qualified image retrieval system that is capable in retrieving a good number of relevant images using color and texture features with normalized RGB histogram. Retrieving precision and recall were 78% and 51% respectively. In terms of similarity measures, Euclidean is shown to be the best of those evaluated for image classification then Chebyshev and finally Manhattan.

Keywords: image features, similarity retrieval, content-based retrieval, image retrieval, feature extraction methods, color and texture features

1 Introduction

Due to the continued spread and evolution of the Internet, decreasing the cost of storage devices, space, and increasing the number of available powerful computers, it is possible and necessary to efficiently control large multimedia information storages. Multimedia information includes: Digital images, graphics, audio, video, and text data. Among the different types of media information, text and images are the most widely used multimedia. Images are used as a base for representing and retrieving flash, videos and other multimedia information [3]. At the same time, image databases were commonly used in a wide range of application areas, such as: medicine, security, advertising and entertainment [4]. As such, the need for an efficient image retrieval tool is needed to select the appropriate image or images from a database of digital images based on user queries.

A content-based approach searches for the analysis of the actual content of the image rather than the image metadata (e.g.: Keywords, captioning or descriptions associated with the image). Currently, Content Based Image Retrieval (CBIR) technology starts taking another direction. It moved out of the laboratory into the marketplace as commercial products such as: Virage [5] and QBIC [6]. Figure 1 shows the main steps of CBIR technology.

Our work focuses on building an image retrieval system using hybrid techniques that retrieve images from a large database with best retrieving time and accuracy. The image dataset that we assembled consists of 1000 general-purpose images which is a subset of the COREL database. After the initial process and preparing of data collection, cleansers and storage, we will analyze and compare several possible similarity measures (used for either documents or image similarity) to compare them to find the best selection of algorithms based on the collected images.

The rest of this paper is organized as follows: Section 2 is a literature review and background of the

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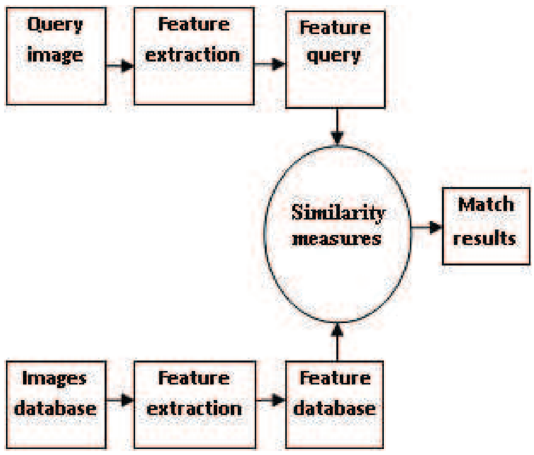

Fig. 1: The main steps of CBIR.

paper related terms and subjects. It presents the previous studies and theories regarding the paper subject such as content-based image retrieval, feature extraction methods, feature selection methods, and similarity measurement. Section 3 discusses the experiments and proposed method and their implementations. The results are analyzed in Section 4. Finally, Section 5 concludes the paper and provides ideas and suggestions for possible future work.

2 Related Works

Different research papers and studies discussed the image retrieval process and how can the extracted features affect the accuracy of the retrieving process. Additionally, there are several various types of existing CBIR systems presented in the past few years. In this section we will briefly visit the related work in the image retrieval field.

In [7], the authors presented a method for learning semantic. When the relevance feedback of the image retrieval process is performed, the system will analyze it and then combine the associated images into the same semantic category. The system then points to the images that are related to query as positive examples, otherwise the system selects the images that are unrelated to the query as negative examples. The associated images are in the same semantic category by assuming that the positive examples are related in semantic content. Thus, the system collects the relationships between the images in the retrieval process. The approach in this paper depends completely on relevance feedback in order to determine the images which are semantically similar. The authors used hypergraph to describe the relationship between the images and the associated rule hypergraph partitioning method (ARHP) to obtain semantic clustering. The authors, however, did not mention the types of the features that are used in the paper.

The authors in [8] presented a method for an image retrieval system which used the texture features. A single feature as this paper uses is not sufficient for the CBIR system, thus, multiple types of features and combinations of them are necessary. To extract the texture features from the images, they used a pyramidal wavelet transform where each image is decomposed to the third level into four sub images, as: high-high, high-low, low-high and low-low sub-bands. Using an energy level algorithm, they calculated the energy of all decomposed images. They used the Euclidean distance for calculating the similarity between the query image and the images in the database. The system is used in the medical field as diagnosis helper where little human intervention is the main advantage of this approach. They used Diabetic Retinopathy Database (DRD) for the evaluation. The precision rate was about 60% of DRD images. The dataset that the authors work on is only used for gray scale medical images.

In [9], the authors focused on the compression of the images based on binary signature bit-string to save the storage space. They decomposed the color distributions of an image into bins that generate a signature for the image content. Despite that the authors focused on the compression of the images, they used only one type of the features for the retrieving process. They presented a method for image retrieval based on the images' global color histograms (GCHs). They used the Euclidean distance for calculating the similarity between the query image and the images in the database.

According to [10], a survey of CBIR systems is conducted. The survey provides a comparison between image retrieval systems in terms of the practical characteristics such as: relevance feedback, querying, features, indexing data structures, matching measures, and result presentation. Examples of CBIR systems that were described in the survey are: ADL (Alexandria Digital Library), CBVQ (Content-Based Visual Query), FIR (Formula Image Retrieval), MARS (Multimedia Analysis and Retrieval System), QBIC [6], WISE (Wavelet Image Search Engine) and several others.

3 Methodology

In this section, the methodology followed in this paper will be discussed. We will discuss the details of the main steps in the research methodology. The main steps are: data collection, feature extraction and similarity measurement. In the following subsections, each step is discussed in details.

3.1 Data Collection

To evaluate the efficiency of the proposed method, an image dataset is collected from the COREL database[1]

[1] http://corel.digitalriver.com

which is divided into 10 image categories, each contains 100 images. The ten image categories are: Historical Buildings, Buses, Flowers, Horses, Dinosaurs, Elephants, Mountains, Food, Africa people, and Beach.

3.2 Using Different Types of Features

The aim of feature extraction is to automatically define a set of features to describe the content of each image. In this study, two types of image features are extracted: color and texture information. The features of the query image are extracted during the retrieval process. Using similarity measures (i.e. Euclidean, Chebyshev, and Manhattan distances) each one separately, the features of the query image are matched against the features of the images stored in the database. We compared between the three similarities measures to come up with the best selection of algorithms based on the collected images. The following sections discuss the selection of color and texture image extraction.

The following list contains the names and abbreviations of each feature set used in this work.

–Color Features (C).
–Color and Texture Features (CT).
–Features Extracted from MaZda Software (M).
–Color Features with RGB Histogram (RGBCT).
–Color Features with HSV Histogram (HSVCT).
–Color and Texture Features with RGB Histogram (RGBCT).
–Color and Texture Features with HSV Histogram (HSVCT).
–Color and Texture Features with Normalized RGB Histogram (NRGBCT).

3.2.1 Color Features (C)

With color feature, color moments descriptor technique is used. We started with getting the RGB array values of all the pixels from the image and working with each color array separately. The same features for the user query image are computed during the retrieval process. Based on the three similarity measures described previously, the features of the query image compare with the features saved in the database. Finally, a set of images with the smallest distance to the query image from the ranked list is retrieved.

3.2.2 Color and Texture Features (CT)

In this experiment, we tried to increase the features extracted from the image. In addition to the previous features of color moments, we used Haar wavelet translation technique to take advantage of the coefficient return from this technique. The pixel array values of R, G and B of the image are sent to Haar wavelet translation. The coefficient for each color, is retrieved. Then we used the color feature inside the texture feature. Again, the mean, standard deviation, skewness and kurtosis are computed from the return coefficient as features. Using the three similarity measures, the features of the query image are matched against the features saved in the database. A set of images with the smallest distance to the query image from the ranked list is retrieved.

3.2.3 Features Extracted from MaZda Software (M)

In this experiment, we used MaZda software [1,2] to extract the features for all image datasets and save them in a text file. The total features for all images are too large, 276 features for each image, so a reduction is required. Weka software is used to reduce the number of features extracted using techniques such as: ConsistencySubsetEval or Principle Components Analysis (PCA). After the reduction process, the numbers of features were eleven: WavEnLH_s-4, WavEnHH_s-3, ATeta4, ATeta2, RHD6LngREmph, CN5D6AngScMom, CV4D6SumAverg, CH4D6SumOfSqs, CZ2D6DifVarnc, CN1D6Entropy and Perc01. During the image saving process, the image is saved to the database with its features extracted from MaZda software which are read from the text file. During the retrieval process, the features of the query image are read from the text file according to the image name and matched against the features stored in the database. A set of images with the smallest distance to the query image from the ranked list is retrieved.

3.2.4 Color Features with RGB Histogram (RGBCT)

In this experiment, we used the color histogram that was selected based on an earlier experiment as the best color feature extraction because the global color content of the images can by correctly represented. Its performance and computation time are considered as satisfactory [11]. We computed the histogram as features for all the pixel values of R, G, and B of the subject image which is the distribution of the number of pixels 8 in the image [12]. As a result, during the images, storing process, only the image is saved to the database. During the retrieval process, the histogram of the query image and the images in the database are computed. This means that the retrieval process will take a long time. The query image histogram is compared with the image histogram in the database to obtain the similar images. A set of images with the smallest distance to the query image from the ranked list is retrieved.

3.2.5 Color Features with HSV Histogram (HSVCT)

As mentioned earlier, there are many existing color spaces that are used in current CBIR systems to represent color images such as: RGB, CMY, CIE-Lab, HSV (also known as HSL, HSB) and several others. Among them, HSV color space is selected to be used in our this experiment. HSV is composed of three color components which are: Hue, saturation (lightness), and value (brightness). It is a popular color space which is widely used in processing digital images. The hue attributes are sensitive for human vision. This process is started with getting the RGB array values of each pixel of each image. The histogram as a feature for all the pixel values of H, S and V of the subject image is computed. The same procedures of the previous experiment are repeated in this experiment also.

3.2.6 Color and Texture Features with RGB Histogram (RGBCT)

In this experiment, we combined the second experiment (i.e. Color and texture features) with RGB histogram experiment. We performed the similarity measure in two levels. After obtaining the most similar images using color and texture features, the query image is compared again with these images using color histogram from RGB color space. In other words, the process of finding the most similar images is going through two calculation stages. This procedure is better than previous ones in terms of accuracy. Instead of applying the two calculation stages on all images in the database, we applied just the first calculation on the complete set of images and the second calculation just on the obtained images from the first calculation.

3.2.7 Color and Texture Features with HSV Histogram (HSVCT)

We also combined the second experiment (i.e. Color and texture features) with HSV histogram experiment. The same procedures of the previous experiment are repeated in this experiment.

3.3 Using Our Proposed Approach

Based on all previous experiments, we proposed a method for extracting features with less computation time and good results in terms of retrieving accuracy. In this section, our proposed method followed is discussed.

3.3.1 Color and Texture Features with Normalized RGB Histogram (NRGBCT)

In the proposed method, we combined the second experiment (i.e. Color and texture features) with normalized RGB histogram. This approach uses the color and texture as the main features and refines the results based on normalized RGB histogram features. The normalization process for RGB histogram is implemented as follows:

1. Because we have three color components (Red, Green, and Blue), we distributed the value of the pixels into 3 intervals. Each interval contains 3 bins.
2. To increment the histogram, we have to get the index that will be incremented using equation 1.

$$I = R' + (G' \times N) + (B' \times 2 \times N), \qquad (1)$$

where I is the index value, N is the number of bins and R', G' and B' represent the result of multiplying the pixel value of R, G and B, respectively, by the number of bins and dividing the results by the maximum pixel value in the histogram which is 255.

During the image saving process, the image and its color and texture features from the second experiment are computed and stored in the database. During the retrieval process, the same features of the images in the database are computed from the query image. Using the three similarity distances, we calculated the similarity between the features of the query image and the features of the images in the database. The most similar images are obtained and the normalized histogram is computed for them. The query image normalized histogram is computed and compared again with obtaining images. The results were more accurate in comparison with all previous experiments. The process was also faster because the normalized histogram will not be computed for all images in the database.

4 Experimental Results

This section presents the experimental results of all methods and the proposed approach to build a CBIR system. The performance of the methods was evaluated and compared with each other. The proposed methods are also compared to other similar existing systems within the field which is LIRe. The following sections give a brief description of the experiments and detailed description of the results.

4.1 Dataset

Our dataset is a subset of the COREL database which is divided into 10 image categories, each contains 100 images. These ten categories are: Historical Buildings, Buses, Flowers, Horses, Dinosaurs, Elephants, Mountains, Food, Africa people and Beach. We used two images from each category for initial testing as shown in Figure 2.

4.2 Measuring Performance

Measuring the performance of the methods that we proposed and implemented to build the CBIR system was

Fig. 2: Test images sample.

necessary to evaluate the quality of those methods. The measurements, precision and recall, were calculated as performance metrics. The precision and recall measurements are widely used in measuring Information Retrieval (IR) systems' performance.

Precision is used to measure the accuracy of the outcome of a search process. It can be defined as the ratio between the numbers of relevant retrieved images with the total number of retrieved images and is given by equation 2. Precision directly evaluates the correlation of the query image to the test collection, and indirectly evaluates the completeness of the feature extraction algorithm. The value of precision is between [0.1 - 1.0]. The precision value, Pr, equals to 1 (or 100%) when every image retrieved to the user is relevant.

$$Pr = \frac{\text{number of relevant items retrieved}}{\text{total number of items retrieved}} \quad (2)$$

Recall is used to measure the ability of the developed system to retrieve all the related items in the test collection. A recall can be viewed as the probability that a retrieved image is relevant. It can also be defined as the ratio between the numbers of relevant retrieved images in the total number of the relevant images in the collection dataset. The equation of Recall is given by equation 3. The recall has also a value that is between [0.1 - 1.0]. Recall value is 1.0 (or 100%) when every relevant image in the test collection is retrieved in the test set.

$$Rc = \frac{\text{number of relevant items retrieved}}{\text{number of relevent items in collection}} \quad (3)$$

4.3 CBIR System Results

In this section, several experiments are conducted in order to test the performance of the proposed methods. To conduct a fair experiment, the same techniques of preprocessing and feature similarity measurement apply to all proposed and methods evaluated.

Table 1: Color Features Results

Image Category Name	Img Qry	Euclidean Distance		Chebyshev Distance		Manhattan Distance	
		Pr	Rc	Pr	Rc	Pr	Rc
Historical buildings	1	0.19	0.31	0.2	0.5	0.25	0.19
	2	0.23	0.49	0.23	0.57	0.21	0.33
Buses	1	0.25	0.39	0.22	0.51	0.28	0.28
	2	0.34	0.76	0.25	0.76	0.41	0.64
Dinosaurs	1	1	0.94	1	0.98	1	0.84
	2	1	0.98	0.98	1	1	0.83
Elephants	1	0.54	0.52	0.49	0.65	0.55	0.42
	2	0.66	0.57	0.53	0.69	0.77	0.4
Flowers	1	0.76	0.38	0.71	0.59	0.81	0.21
	2	0.9	0.27	0.74	0.39	1	0.2
Horses	1	0.25	0.5	0.25	0.6	0.26	0.32
	2	0.75	0.53	0.51	0.68	0.86	0.38
Mountains	1	0.65	0.15	0.55	0.32	0.64	0.09
	2	0.44	0.23	0.33	0.33	0.48	0.15
Food	1	0.48	0.48	0.43	0.6	0.58	0.38
	2	0.32	0.5	0.3	0.61	0.4	0.34
Africa people	1	0.63	0.78	0.41	0.87	0.35	0.61
	2	0.57	0.66	0.57	0.62	0.37	0.52
Beach	1	0.6	0.59	0.49	0.72	0.36	0.46
	2	0.53	0.76	0.31	0.55	0.32	0.58
Average		0.55	0.54	0.47	0.63	0.54	0.41

4.3.1 Color Features Results

In the first experiment, we used only color moments type of the color features of the images which are: mean, standard deviation, skewness, and kurtosis. We used the three similarity measures (Euclidean, Chebyshev, and Manhattan distances) to compare between the features of the query image and the features of the images saved in the database.

The results were poor as shown in Table 1. In Euclidean distance, the average precision was 55%, while average recall was 54%. In the Chebyshev distance, the average precision was 47%, while average recall was 63%. In a Manhattan distance, the average precision was 54%, while average recall was 41%. Euclidean distance similarity measurement was the best one in the precision value, but not for the recall value. The features extracted were not enough and different images may have the same features. This is explained by increasing the value of the retrieved images. As a result, we tried to increase the number of features to distinguish the images from each other. The comparison between the three similarity distances is shown in Figure 3.

4.3.2 Color and Texture Features Results

In this experiment, we increased the features extracted from the image. In addition to the previous features of

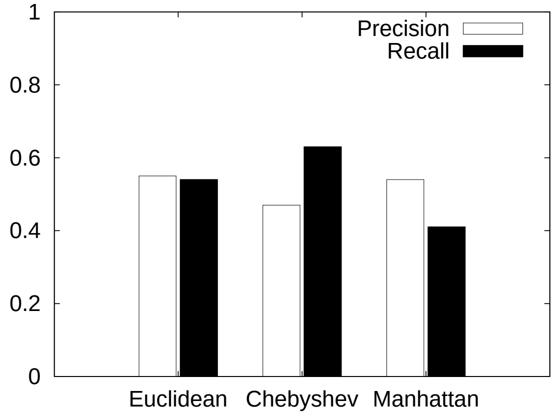

Fig. 3: Color Features Results.

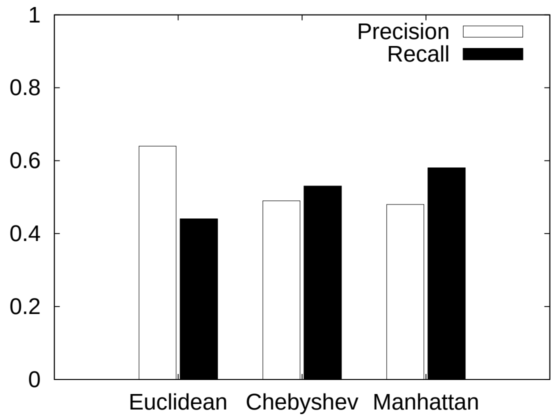

Fig. 4: Color and Texture Features Results.

color moments, we used Haar wavelet translation technique to take advantage of the coefficient return from this technique. Using the three selected similarity measures, the features of the query image are matched against the features saved in the database.

The results were better than previous experiments as shown in Table 2. This means that the features extracted have had the ability to distinguish (not much) between the images better than the previous experiment. Euclidean distance was the best one in the precision value, but not for the recall value. We note that the decreasing on the value of the retrieved images. The comparison between the three similarity distances is shown in Figure 4.

4.3.3 MaZda Features Results

In this experiment, we used MaZda software to extract the features for all images in the dataset. The features of the query image are matched against the features saved in the database using the same similarity measures. The results were relatively poor as shown in Table 3. Manhattan distance was the best one in the precision value, but not for the recall value. MaZda software converts the colored image to a gray scale before extracting the features, so the features will not be accurate enough. We note that the increase in the value of the retrieved images leads to an increase in the value of the recall. The comparison between the three similarity distances is shown in Figure 5.

Table 2: Color and Texture Features Results

Image Category Name	Img Qry	Euclidean Distance		Chebyshev Distance		Manhattan Distance	
		Pr	Rc	Pr	Rc	Pr	Rc
Historical buildings	1	0.26	0.24	0.23	0.45	0.21	0.44
	2	0.51	0.22	0.31	0.36	0.31	0.47
Buses	1	0.42	0.45	0.36	0.71	0.31	0.69
	2	0.42	0.7	0.31	0.84	0.34	0.89
Dinosaurs	1	1	1	0.96	0.96	0.99	0.95
	2	0.99	1	0.94	0.99	0.91	1
Elephants	1	0.61	0.23	0.39	0.4	0.4	0.53
	2	0.74	0.2	0.47	0.35	0.51	0.52
Flowers	1	1	0.05	0.92	0.11	1	0.2
	2	1	0.03	1	0.03	1	0.09
Horses	1	0.65	0.28	0.2	0.48	0.2	0.56
	2	0.44	0.25	0.24	0.39	0.25	0.46
Mountains	1	0.47	0.09	0.23	0.19	0.15	0.22
	2	0.24	0.08	0.17	0.2	0.12	0.15
Food	1	0.51	0.37	0.35	0.58	0.28	0.61
	2	0.37	0.42	0.29	0.62	0.24	0.64
African people	1	0.79	0.7	0.31	0.84	0.34	0.89
	2	0.72	0.73	0.69	0.69	0.61	0.59
Beach	1	0.84	0.85	0.69	0.72	0.8	0.88
	2	0.78	0.89	0.73	0.75	0.68	0.89
Average		0.64	0.44	0.49	0.53	0.48	0.58

4.3.4 Color Features with RGB Histogram Results

In this experiment, we used the color histogram. We computed the histogram as features [12] for all the pixel values of R, G and B of the image. During the retrieval process, the histogram of the query image and the images in the database are computed. So the retrieval process will take a long time. The query image histogram is compared with the image histogram in the database to obtain the similar images.

The results were poor as shown in Table 4 because different images may have the same histogram in addition to the long time for computing the histogram for all the images in the database. Euclidean distance was the best one in the precision value, but not for the recall value. We

Table 3: MaZda Features Results

Image Category Name	Img Qry	Euclidean Distance		Chebyshev Distance		Manhattan Distance	
		Pr	Rc	Pr	Rc	Pr	Rc
Historical buildings	1	0.24	0.49	0.2	0.46	0.33	0.46
	2	0.23	0.81	0.23	0.78	0.25	0.77
Buses	1	0.37	0.94	0.37	0.92	0.47	0.91
	2	0.49	0.93	0.51	0.88	0.52	0.94
Dinosaurs	1	0.51	0.99	0.51	0.99	0.68	1
	2	0.47	0.98	0.39	0.98	0.66	0.99
Elephants	1	0.14	0.95	0.13	0.95	0.17	0.93
	2	0.14	0.99	0.13	0.99	0.21	0.98
Flowers	1	0.52	0.88	0.37	0.88	0.64	0.83
	2	0.85	0.53	0.81	0.38	0.94	0.67
Horses	1	0.1	0.55	0.12	0.69	0.07	0.35
	2	0.13	0.89	0.13	0.95	0.15	0.86
Mountains	1	0.13	0.84	0.14	0.93	0.14	0.78
	2	0.16	0.85	0.16	0.85	0.17	0.84
Food	1	0.43	0.68	0.46	0.66	0.43	0.58
	2	0.16	0.88	0.15	0.9	0.2	0.81
African people	1	0.18	0.93	0.17	0.93	0.21	0.87
	2	0.17	0.88	0.16	0.89	0.2	0.84
Beach	1	0.16	0.86	0.16	0.88	0.2	0.85
	2	0.17	0.81	0.17	0.81	0.2	0.79
Average		0.29	0.83	0.27	0.84	0.34	0.8

Table 4: RGB Color Histogram Features Results

Image Category Name	Img Qry	Euclidean Distance		Chebyshev Distance		Manhattan Distance	
		Pr	Rc	Pr	Rc	Pr	Rc
Historical buildings	1	0.41	0.47	0.41	0.68	0.45	0.65
	2	0.5	0.95	0.49	0.91	0.45	0.87
Buses	1	0.59	0.83	0.55	0.91	0.56	0.97
	2	0.57	0.91	0.56	0.98	0.55	0.97
Dinosaurs	1	0.96	1	0.98	0.97	0.84	0.99
	2	0.99	1	0.95	0.96	0.88	0.98
Elephants	1	0.34	0.95	0.38	0.95	0.34	0.98
	2	0.4	0.85	0.54	0.89	0.34	0.98
Flowers	1	0.87	0.47	0.97	0.31	0.64	0.67
	2	0.97	0.33	0.84	0.61	0.36	0.61
Horses	1	0.74	0.56	0.47	0.65	0.23	0.98
	2	0.36	0.82	0.32	0.81	0.23	0.99
Mountains	1	0.29	0.49	0.38	0.29	0.36	0.84
	2	0.25	0.35	0.22	0.56	0.18	0.93
Food	1	0.15	0.8	0.16	0.89	0.2	0.72
	2	0.14	0.77	0.42	0.89	0.13	0.8
African people	1	0.46	0.43	0.47	0.78	0.28	0.49
	2	0.77	0.74	0.6	0.79	0.67	0.87
Beach	1	0.6	0.65	0.29	0.89	0.2	0.72
	2	0.73	0.78	0.42	0.89	0.45	0.8
Average		0.56	0.71	0.52	0.78	0.42	0.84

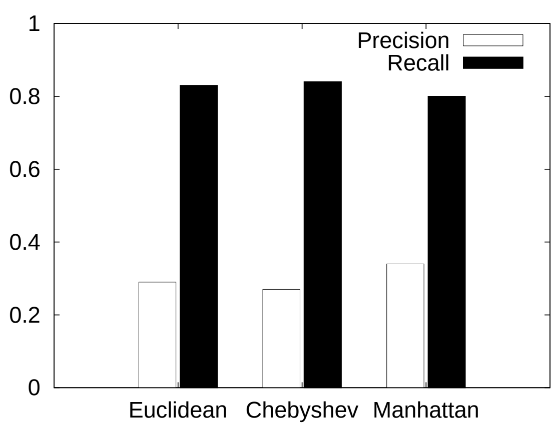

Fig. 5: MaZda Features Results.

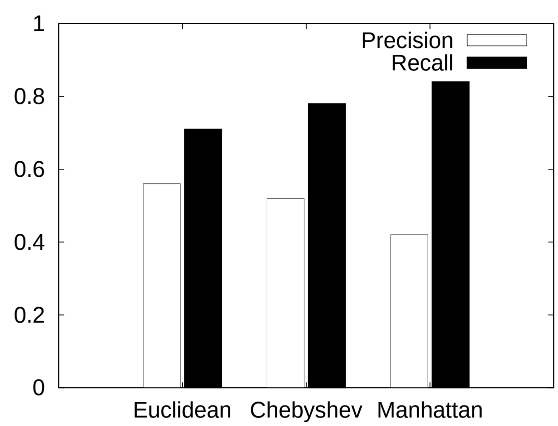

Fig. 6: RGB Color Histogram Features Results.

note that the increase in the value of the retrieved images leads to an increase in the value of the recall. The comparison between the three similarity distances is shown in Figure 6.

4.3.5 Color Features with HSV Histogram Results

In this experiment, we converted the RGB space to HSV color space. The histogram as a feature for all the pixel values of H, S and V of the image is computed. The same procedures of the previous experiment are conducted. The retrieval process will also take a long time and the results were better than previous experiments, but not accurate enough as shown in Table 5. Euclidean distance was the best one in the precision value, but not for the recall value. We note that the increase in the value of the retrieved images leads to an increase in the value of the recall. The comparison between the three similarity distances is shown in Figure 7.

Table 5: HSV Color Histogram Features Results

Image Category Name	Img Qry	Euclidean Distance		Chebyshev Distance		Manhattan Distance	
		Pr	Rc	Pr	Rc	Pr	Rc
Historical buildings	1	0.57	0.68	0.43	0.69	0.49	0.97
	2	1	0.09	0.43	0.24	0.5	0.99
Buses	1	0.49	0.87	0.37	0.66	0.66	0.79
	2	0.54	0.85	0.4	0.79	0.66	0.8
Dinosaurs	1	1	0.99	0.98	0.98	0.75	1
	2	0.92	0.99	0.98	1	0.83	1
Elephants	1	0.35	0.89	0.38	0.81	0.37	0.87
	2	0.36	0.85	0.41	0.78	0.36	0.76
Flowers	1	1	0.16	1	0.05	0.36	0.8
	2	0.42	0.66	0.41	0.8	0.24	1
Horses	1	0.35	0.73	0.24	0.68	0.39	0.99
	2	0.4	0.67	0.27	0.49	0.43	1
Mountains	1	0.52	0.13	0.54	0.99	0.28	0.95
	2	0.45	0.34	0.52	0.99	0.29	0.98
Food	1	0.38	0.54	0.53	0.95	0.26	1
	2	0.49	0.73	0.53	0.95	0.25	1
African people	1	0.4	0.76	0.32	0.63	0.27	0.58
	2	0.3	0.58	0.31	0.45	0.21	0.42
Beach	1	0.76	0.68	0.61	0.58	0.55	0.78
	2	0.82	0.71	0.72	0.68	0.49	0.49
Average		0.58	0.65	0.52	0.71	0.43	0.86

Table 6: RGB Color and Texture Features Results

Image Category Name	Img Qry	Euclidean Distance		Chebyshev Distance		Manhattan Distance	
		Pr	Rc	Pr	Rc	Pr	Rc
Historical buildings	1	0.85	0.53	0.87	0.72	0.85	0.73
	2	0.88	0.59	0.9	0.66	0.84	0.65
Buses	1	0.79	0.64	0.55	0.91	0.56	0.97
	2	0.66	0.93	0.56	0.98	0.55	0.97
Dinosaurs	1	0.92	1	0.85	1	0.77	1
	2	0.88	1	0.79	1	0.69	1
Elephants	1	0.73	0.65	0.47	0.77	0.41	0.66
	2	0.7	0.55	0.59	0.77	0.47	0.65
Flowers	1	0.96	0.25	0.93	0.42	0.96	0.27
	2	1	0.08	0.96	0.24	1	0.11
Horses	1	0.49	0.56	0.28	0.73	0.27	0.79
	2	0.53	0.87	0.3	0.75	0.3	0.71
Mountains	1	0.28	0.29	0.14	0.37	0.14	0.44
	2	0.14	0.24	0.14	0.35	0.16	0.45
Food	1	0.25	0.7	0.22	0.83	0.23	0.77
	2	0.65	0.68	0.42	0.89	0.21	0.77
African people	1	0.61	0.54	0.78	0.59	0.38	0.65
	2	0.72	0.6	0.64	0.49	0.59	0.76
Beach	1	0.67	0.89	0.72	0.67	0.64	0.59
	2	0.75	0.76	0.44	0.77	0.43	0.66
Average		0.67	0.62	0.58	0.7	0.52	0.68

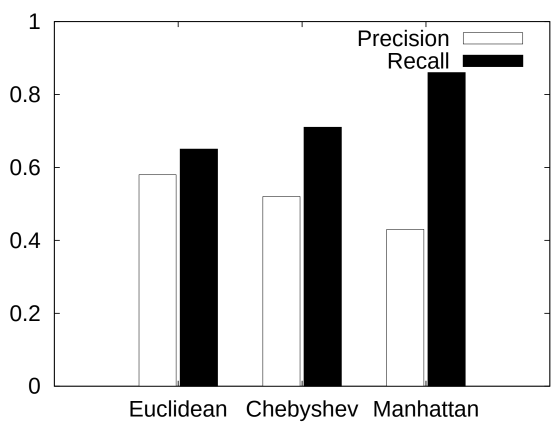

Fig. 7: HSV Color Histogram Features Results.

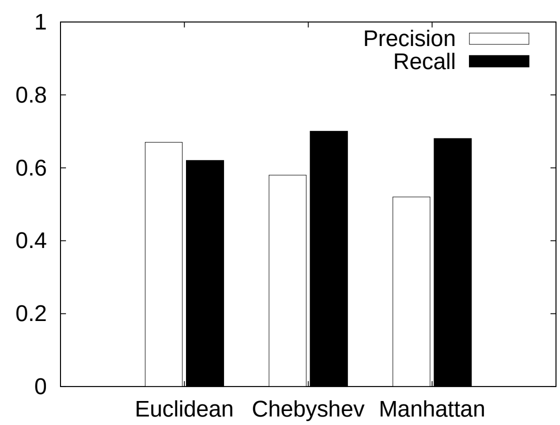

Fig. 8: RGB Color and Texture Features Results.

4.3.6 Color and Texture Features with RGB Histogram Results

In this experiment, we combined the second experiment (i.e. Color and texture features) with RGB histogram experiment. We performed the similarity measures in two levels: once using color and texture features and the other using color histogram from RGB color space.

This procedure is better than previous ones in terms of accuracy and speed. Instead of applying the two calculation stages on all images in the database, we applied just the first calculation on the complete set of images and the second calculation just on the obtained images from the first calculation. It also combined between the advantages of each experiment. As shown in Table 6, the results were improved but still not accurate enough. Euclidean distance was the best one in the precision value, but not for the recall value. The comparison between the three similarity distances is shown in Figure 8.

Table 7: HSV Color and Texture Features Results

Image Category Name	Img Qry	Euclidean Distance		Chebyshev Distance		Manhattan Distance	
		Pr	Rc	Pr	Rc	Pr	Rc
Historical buildings	1	0.73	0.58	0.5	0.87	0.45	0.8
	2	0.74	0.59	0.47	0.78	0.48	0.79
Buses	1	0.6	0.81	0.56	0.97	0.55	0.96
	2	0.58	0.91	0.55	0.97	0.55	0.99
Dinosaurs	1	1	1	0.98	1	0.98	1
	2	1	1	0.96	1	0.97	1
Elephants	1	0.62	0.55	0.39	0.66	0.39	0.83
	2	0.69	0.54	0.37	0.65	0.44	0.83
Flowers	1	0.96	0.24	0.96	0.27	0.98	0.55
	2	1	0.08	1	0.11	0.97	0.36
Horses	1	0.58	0.8	0.42	0.79	0.28	0.87
	2	0.5	0.87	0.51	0.71	0.31	0.87
Mountains	1	0.59	0.68	0.21	0.44	0.27	0.67
	2	0.59	0.64	0.25	0.45	0.28	0.59
Food	1	0.56	0.95	0.32	0.78	0.39	0.86
	2	0.82	0.9	0.29	0.78	0.36	0.86
African people	1	0.47	0.75	0.59	0.6	0.53	0.79
	2	0.53	0.79	0.5	0.89	0.62	0.68
Beach	1	0.52	0.69	0.55	0.93	0.73	0.57
	2	0.62	0.72	0.46	0.67	0.55	0.87
Average		0.68	0.7	0.54	0.72	0.55	0.79

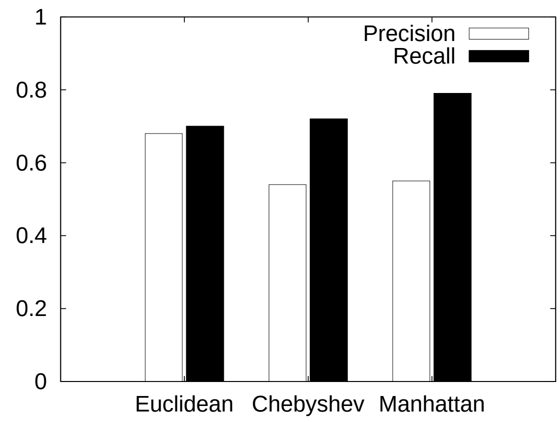

Fig. 9: HSV Color and Texture Features Results.

4.3.7 Color and Texture Features with HSV Histogram Results

We also combined the second experiment (i.e. Color and texture features) with HSV histogram experiment. The same procedures of the previous experiment are repeated in this experiment. The results were better than previous experiments in terms of accuracy as shown in Table 7 but still not accurate enough. Euclidean distance was the best one in the precision value, but not for the recall value. The comparison between the three similarity distances is shown in Figure 9.

4.4 Retrieving Results Using Proposed Approach

In this section, we present the results of the proposed method.

4.4.1 Color and Texture Features with Normalized RGB Histogram Results

In this proposed approach, we combined the second experiment (i.e. Color and texture features) with normalized RGB histogram. This approach uses the color and texture as the main features and refines the results based on normalized RGB histogram features. Using the three similarity distance, we calculated the similarity between the features of the query image and the features of the images in the database. The most similar images are obtained and the normalized histogram is computed for them. The query image normalized histogram is computed and compared again with obtaining images.

The results were more accurate in comparison with all previous experiments as shown in Table 8. The process was also faster because the normalized histogram was not computed for all images in the database. Euclidean distance was the best one in the precision value, but not for the recall value. The comparison between the three similarity distances is shown in Figure 10.

4.5 CBIR Approaches Comparison

In this section, a comparison between our proposed approach and LIRe has been made. We used the same image datasets which contain 1000 images for testing. Figure 11 compares the precision values between the proposed approach and LIRe using the dataset (1000 images). The precision value for the proposed approach is 78% and 55% for LIRe. Figure 11. shows a comparison of the recall values between the proposed approach and LIRe using the dataset (1000 images). The recall value of the proposed approach is 51% and 50% for LIRe.

4.6 Similarity Distances Results Analysis

In this section, we provide an analysis of the results of the three similarity distances that were used in the experimental studies.

Table 8: Color and Texture Features with Normalized RGB Histogram Results

Image Category Name	Img Qry	Euclidean Distance		Chebyshev Distance		Manhattan Distance	
		Pr	Rc	Pr	Rc	Pr	Rc
Historical buildings	1	0.73	0.87	0.38	0.41	0.44	0.49
	2	0.54	0.21	0.39	0.29	0.41	0.14
Buses	1	0.57	0.73	0.45	0.73	0.76	0.84
	2	0.8	0.83	0.45	0.73	0.66	0.82
Dinosaurs	1	1	0.97	0.98	1	1	0.9
	2	0.99	1	0.95	1	0.98	0.97
Elephants	1	0.55	0.43	0.59	0.2	0.28	0.49
	2	0.9	0.26	0.8	0.4	0.7	0.21
Flowers	1	1	0.13	0.85	0.35	1	0.15
	2	1	0.06	0.83	0.29	1	0.05
Horses	1	1	0.14	0.96	0.22	1	0.13
	2	0.6	0.37	0.91	0.42	1	1.64
Mountains	1	0.86	0.06	0.83	0.05	0.63	0.05
	2	0.63	0.17	0.42	0.11	0.7	0.19
Food	1	0.55	0.53	0.94	0.63	0.28	0.49
	2	0.66	0.63	0.8	0.7	0.46	0.57
African people	1	0.55	0.43	0.88	0.59	0.28	0.49
	2	0.97	0.89	0.85	0.79	0.7	0.21
Beach	1	0.77	0.6	0.96	0.49	1	0.15
	2	0.9	0.89	0.89	0.31	0.76	0.78
Average		0.78	0.51	0.76	0.49	0.7	0.49

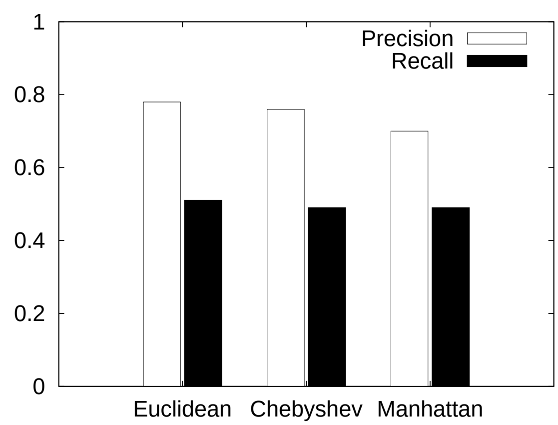

Fig. 10: Color and Texture Features with Normalized RGB Histogram Results.

4.6.1 Euclidean Distance

Euclidean distance was the best one as we stated previously. For the experiment, higher value of the precision was in the proposed approach that used color and texture features with normalized RGB histogram. A higher value of the recall was in the experiment that used features extracted from MaZda software. Euclidean distance results with all experiments are shown in Figure 12.

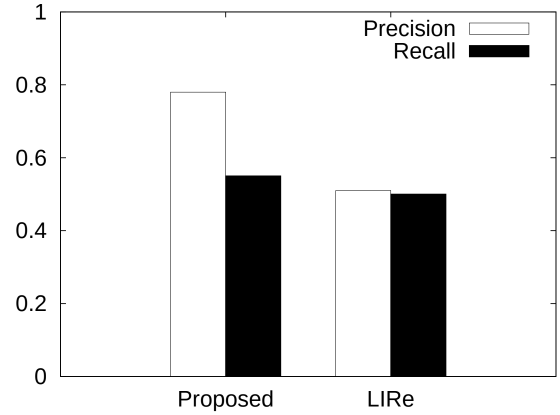

Fig. 11: Comparison between the proposed approach and LIRe.

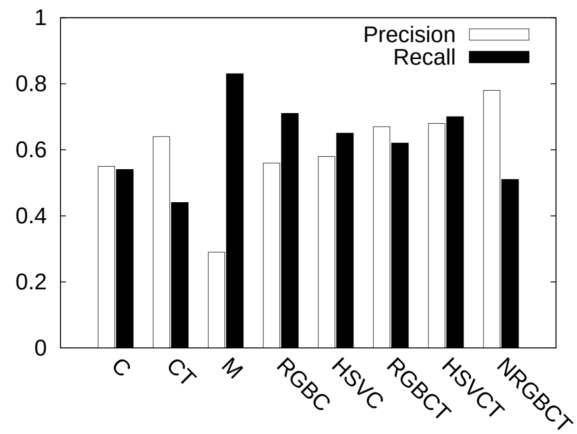

Fig. 12: Euclidean Distance Results with all experiments.

4.6.2 Chebyshev and Manhattan Distances

Regarding to Chebyshev, a higher value of the precision was in the experiment that used color and texture features with normalized RGB histogram. A higher value of the recall was in the experiment that used features extracted from MaZda software. Regarding to Manhattan, a higher value of the precision was in the experiment that used color and texture features with normalized RGB histogram. A higher value of the recall was in the experiment that used features of the HSV color histogram. Results of Chebyshev and Manhattan distances with all experiments are shown in Figures 13 and 14.

5 Conclusion and Future Work

Image retrieval systems try to automatically and quickly retrieve a set of images from huge repository of digital

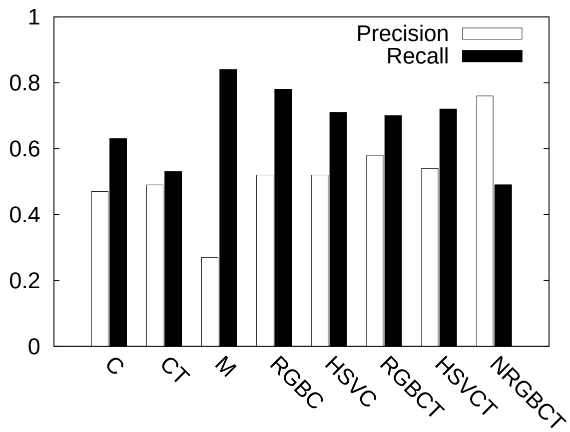

Fig. 13: Chebyshev Distance Results with all experiments.

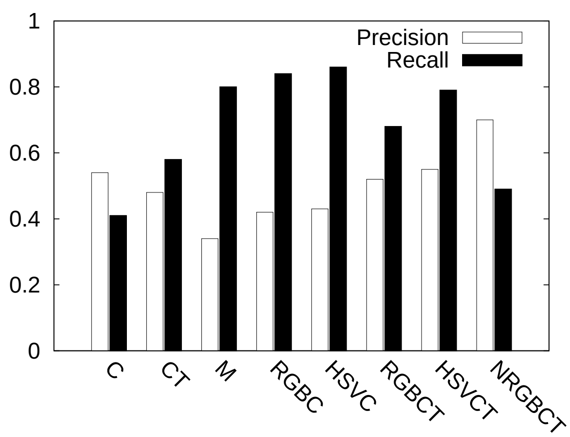

Fig. 14: Manhattan Distance Results with all experiments.

media which are similar to the query image. Such process has several applications in information processing applications and domains. In this paper, we evaluated several image retrieval approaches. Based on that evaluation, we proposed a method for extracting features with less computation time and good results in terms of retrieving accuracy. Images that were collected for the study case were collected from a public image database. We then collected several image features based on RGB and HSV color schemes, features along with features extracted using Mazda publicly available image processing software.

Different sets of experiments were designed and conducted to come up with the best retrieval scheme in terms of performance and retrieval accuracy. Feature selection methods are also combined with similarity measures to perform the retrieval process. In terms of similarity measures, unsurprisingly, we found out that Euclidean distance similarity measure can be best used for image retrieval then Chebyshev and finally Manhattan. In addition to the different retrieval schemes, we found out that the best selection was using a normalized RGB color feature scheme with features collected from evaluating images.

The implemented low-level features provide better matching results between images with more than 75% average precision. Thus, we can conclude that the implemented low-level features can be used in an image retrieval system that has gained good results.

As we mentioned, the feature extraction process affects significantly the quality of the retrieving process. In this work, only color and texture features are extracted from images. In the future work, we will replace the features of the color and texture which may be found the same in the images with features that will be strong in discrimination the image. Also, we will use the third one of features types which is the shape feature.

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