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Comparative Effect of Distance Metrics on Selected Texture Features for Content-Based Image Retrieval System

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Abstract

The effect of distance metrics on the retrieval performance of CBIR system characterized by texture features was evaluated in this paper. Tamura and Gabor Wavelet transform texture features were used to create the feature vector database and to match 4 sample query images respectively with the image database of 400 and 600 images of four different classes Euclidean distance, Manhattan distance, Cosine angle distance, Quadratic-form distance and Pearson correlation were used. The retrieval performance was evaluated using the average precision with the distance measures. Evaluated results from the CBIR system algorithm shows that Manhattan distance metric gave the best retrieval performance on the used two set of image database.

Keywords: Content-Based Image Retrieval, Feature extraction, Distance metrics

1. Introduction

Advancement in image acquisition and data storage technologies has resulted into creation of large image dataset of diverse modalities and for different application domain. However, as the volume of digital image libraries are growing rapidly for different applications (ranging from personal image library to web images), developing technique for image retrieval has become a major challenge. Our objective solution approach is to develop system that employs feature derivable from an image, such as colour, texture and shape to retrieve image from large image database. Such systems are generally known as Content-Based Image Retrieval (CBIR) system. Techniques that are used in developing CBIR systems (either basic or sophisticated type) are largely dependent on feature extraction and similarity measure among other things. The technique is expected to produce systems that are time efficient and accurate [1].

The importance of texture as feature used to characterize image feature database in CBIR system cannot be overemphasized. Texture is a very important low-level property of majority of images (especially natural image e.g. fruit, skin, cloud, rock, tree, fabric etc). Though not well defined, texture can be viewed as the representation of visual content over a region of pixels, depicting repetition of patterns over such region in an image. The importance of texture is evident in the number of published articles that employs it as part of their feature descriptors [5-10].

Methods used to extract useful texture information are numerous example includes Tamura features [2], Wold decomposition [11, 12], co-occurrence matrices [20, 21] and multi-resolution filtering techniques such as Gabor filtering [13] and wavelet transform [14, 15]. However, Tamura, co-occurrence matrices and Gabor Wavelet features are widely used for image retrieval [16]. This work is thus prompted to gain insight into the effect that choice of distance metric will have on the retrieval performance of CBIR system characterized by such texture feature.

The remainder of this article is organized as follows; Section 2 presents the study on Tamura and Gabor wavelet texture feature extraction techniques. Section 3, discussed Content-Based Image Retrieval system Algorithm used for the experiment. Section 4 presents the experimental results. The section 5 presents conclusions.

2. Visual Feature Extraction

Feature extraction is the base for image retrieval. The extracted visual image features are formed as Feature Vector Database. The features can be classified as general features such as texture, shape and colour. Compared to all the visual features, texture features possess the properties for capturing semantic features in images because it has an inclusive contribution of various grey levels within the image. Also texture has potentials as periodicity and scale. It is this that makes texture a particularly interesting facet of images. Tuceryan and Jain categorize the various texture analysis methods into four groups: statistical, geometrical, model-based and signal processing-based [18]. The most commonly used statistical texture analysis methods are Tamura feature, shift invariant principal component analysis (SPCA), Fourier power spectra, Wold decomposition, and co-occurrence matrices. In this section, Tamura texture features and signal processing with Gabor wavelets are studied.

2.1 Tamura Features

Tamura et al took the approach of devising texture features that correspond to human visual perception [1]. They defined six textural features (coarseness, contrast, directionality, line-likeness, regularity and roughness) and compared them with psychological measurements for human subjects. The first three attained very successful results and are used in our evaluation, both separately and as joint values.

Coarseness has a direct relationship to scale and repetition rates and was seen by Tamura *et al* as the most fundamental texture feature. An image will contain textures at several scales; coarseness aims to identify the largest size at which a texture exists, even where a smaller micro texture exists. Computationally one first takes averages at every point over neighbourhoods, the linear size of which is powers of 2. The average over the neighbourhood of size $2^k \times 2^k$ at the point (x, y) is

$$A_k(x,y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} f(i,j)/2^{2k} \tag{1}$$

Then at each point one takes differences between pairs of averages corresponding to non-overlapping neighbourhoods on opposite sides of the point in both horizontal and vertical orientations. In the horizontal case this is

$$E_{k,h}(x,y) = \left| A_k(x+2^{k-1}, y) - A_k(x-2^{k-1}, y) \right| \tag{2}$$

At each point, one then picks the best size which gives the highest output value, where k maximizes E in either direction. The coarseness measure is then the average of $Sopt(x,y) = 2^{k_{opt}}$ over the picture.

Contrast aims to capture the dynamic range of grey levels in an image, together with the polarization of the distribution of black and white. The first is measured using the standard deviation of grey levels and the second the kurtosis α_4. The contrast measure is therefore defined as

$$F_{con} = \sigma/(\alpha_4)^n \quad \text{where} \quad \alpha_4 = \mu_4/\sigma^4 \tag{3}$$

μ_4 is the fourth moment about the mean and σ^2 is the variance. Experimentally, Tamura found $n = 1/4$ to give the closest agreement to human measurements. This is the value we used in our experiments.

Directionality is a global property over a region. The feature described does not aim to differentiate between different orientations or patterns, but measures the total degree of directionality. Two simple masks are used to detect edges in the image. At each pixel the angle and magnitude are calculated. A histogram, H_d of edge probabilities is then built up by counting all points with magnitude greater than a threshold and quantizing by the edge angle. The histogram will reflect the degree of directionality. To extract a measure from H_d the sharpness of the peaks are computed from their second moments.

2.2 Gabor

One of the most popular signal processing based approaches for texture feature extraction has been the use of Gabor filters. These enable filtering in the frequency and spatial domain. It has been proposed that Gabor filters can be used to model the responses of the human visual system. Turner [19] first implemented this by using a bank of Gabor filters to analyze texture. A bank of filters at different scales and orientations allows multichannel filtering of an image to extract frequency and orientation information. This can then be used to decompose the image into texture features.

Our implementation is based on that of Manjunath et al [3, 4]. The feature is computed by filtering the image with a bank of orientation and scale sensitive filters and computing the mean and standard deviation of the output in the frequency domain.

Filtering an image $I(x,y)$ with Gabor filters g_{mn} designed according to [3] results in its Gabor wavelet transform:

$$W_{mn}(x,y) = \int I(x,y) g^*_{mn}(x-x_1, y-y_1) dx_1 dy_1 \tag{4}$$

The mean and standard deviation of the magnitude $|W_{mn}|$ are used to for the feature vector. The outputs of filters at different scales will be over differing ranges. For this reason each element of the feature vector is normalized using the standard deviation of that element across the entire database.

3. Content-Based Image Retrieval system Algorithm Using Tamura and Gabor Wavelet Transform

CBIR (Content Based Image Retrieval) have received intensive courtesy in the literature of image information retrieval, and consequently an expansive range of techniques has been implied. The flow of algorithm involved in the proposed CBIR system is shown in Fig. 1. The basic step involved in the algorithm is in the following phases:

- Phase I:Visual Feature Extraction
- Phase II: Classification of Features
- Phase III: Similarity measurements

3.1 Phase I: Visual Feature Extraction

Features are used to represent the characteristics of images, extract the most conspicuous features that represent maximum relevant information and form a complete feature vector database. The most widely used features in CBIR and medical imaging is texture features. In this study Tamura texture features and Gabor Wavelet Transform are used for feature extraction

3.2 Phase II: Classification of Features

The feature vectors optimized in different points of a texture images are not identical. Training the classification systems with these optimized features could raise the accuracy rate. The elements of image feature sets are categorized into a limited number of separable, discrete classes using a mathematical classification process. The steps are: (1) Train the classification-system on the Optimized feature set associated with the classes of interest. (2) Using classification decision rule, the classification-system decides which class apiece optimized features pixel most looks like the features. The most widely used classification algorithms are K-nearest neighbor, Fuzzy C-Means clustering, Decision Tree, and Bayesian Classification.

3.3 Phase III: Similarity Measurements

A query image is any one of the images from image database that are similar to the query image specified by a user. This query image is processed to compute the feature vector. Distance metrics are calculated between the query image and every image in the database. This process is repeated until all the images in the database have been compared with the query image. After completing the distance algorithm, an array of distances is obtained and which is then sorted. In the presented work five types of similarity distance metric are used as given below:

3.3.1 Euclidean Distance

Euclidean distance is the most common metric for measuring the distance between two vectors and is discussed and implemented in a number of content based image retrieval approaches. It is applicable when the image feature vector elements are equally important and the feature vectors are independent of one another. The Euclidean distance can simply be described as the ordinary distance between two values. It is given by the square root of the sum of the squares of the differences between vector components. The Euclidean distance between the feature vectors $P=(p_1, p_2, \cdots, p_n)$ and $Q=(q_1, q_2, \cdots, q_n)$ is expressed by

$$ED = \sqrt{\sum_{k=1}^{n} (p_k - q_k)^2} \tag{5}$$

where n is the length of the feature vector and D is the distance between the two vectors. The Euclidean distance provides the most obvious approach to calculating the distance between two feature vectors along with one that is very simple to implement with a low level of complexity. For these reasons it provides a good method for feature vector comparison.

3.3.2 Manhattan distance

If the Euclidean distance is considered as the straight line distance between points then the Manhattan distance is the two sides of a square approach. It is this that gives the technique its name since Manhattan is laid out in city blocks forcing you to walk 2 sides of a square in order to get anywhere. The Manhattan distance between feature vectors $P=(p_1, p_2, \cdots, p_n)$ and $Q=(q_1, q_2, \cdots, q_n)$ is expressed by

$$MD = \sum_{k=1}^{n} |p_k - q_k| \tag{6}$$

3.3.3 Cosine angle distance

If we consider two vectors P and Q where $P=(p_1, p_2, \cdots, p_n)$ and $Q=(q_1, q_2, \cdots, q_n)$ then $Cos\theta$ may be considered as the cosine of the vector angle between P and Q in n dimension [17]. CAD is define as follows

$$CAD(P,Q) = \frac{\sum_i p_i q_i}{\sqrt{\sum_i p_i^2 \sum_i q_i^2}} \tag{7}$$

One important property of vector cosine angle is that it gives a metric of similarity between two vectors unlike Euclidean distance, which give metrics of dissimilarities

3.3.4 Quadratic-form distance

The quadratic distance between two feature vectors P and Q is given by:

$$QD(P,Q) = (h_p - h_q)^T A(h_p - h_i) \tag{8}$$

where $A=[a_{ij}]$ is a similarity matrix. a_{ij} denotes the similarity between elements with indexes i and j.

3.3.5 Pearson correlation

The pearson correlation coefficient between feature vectors $P=(p_1, p_2, \cdots, p_n)$ and $Q=(q_1, q_2, \cdots, q_n)$ is expressed by

$$PC = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{p_i - \overline{p}}{\sigma_p}\right)\left(\frac{q_i - \overline{q}}{\sigma_q}\right) \tag{9}$$

where $\overline{p}$ and $\overline{q}$ are the average of values of p and q also σ_p and σ_q are the standard deviation of these values respectively.

4.0 Experimental Results

This proposed CBIR framework is implemented in MATLAB platform with two image database used to check the performance of the algorithms developed. The first database consists of 400 images of 4 different classes while the second image database consists of 600 images of the same number of classes. Some representative sample images which are used as query images as shown in Figure 2.

To evaluate the algorithms Tamura and Gabor Wavelet Transform methods are used in extracting only the features that are useful in retrieving images from the database. This simplifies the system, increases the accuracy and degrades the complexity of the system. Tamura combined with Gabor Wavelet Transform feature extraction method are used to compare with it. We have used five different similarity measures (Euclidean distance, Manhattan distance, Cosine angle distance, Quadratic-form distance and Pearson correlation) to match 4 sample query images with the image database of 400 and 600 images of four different classes respectively. Average Precision is calculated and the graph is drawn between Average precision with distance measures as shown in Fig. 3 and Fig. 4.

The Precision performance analysis of Fig. 3 shows that, for Tamura feature; Manhattan metric distance gave a better retrieval performance when compared to other distance metric in terms of their precision why for the Gabor Wavelet transform; Manhattan metric distance also gave a better retrieval performance when compared to other distance metric, likewise when both texture feature of Tamura and Gabor filter are combined, Manhattan distance metric also came tops in terms of their retrieval performance.

Performance analysis of Fig. 4 shows that for Tamura texture feature; Cosine distance gave a better retrieval performance compared to other metric distances while for Gabor wavelet transform; Manhattan distance metric came tops. Manhattan distance metric also gave a better retrieval performance compared to other metric distance when both texture features are combined.

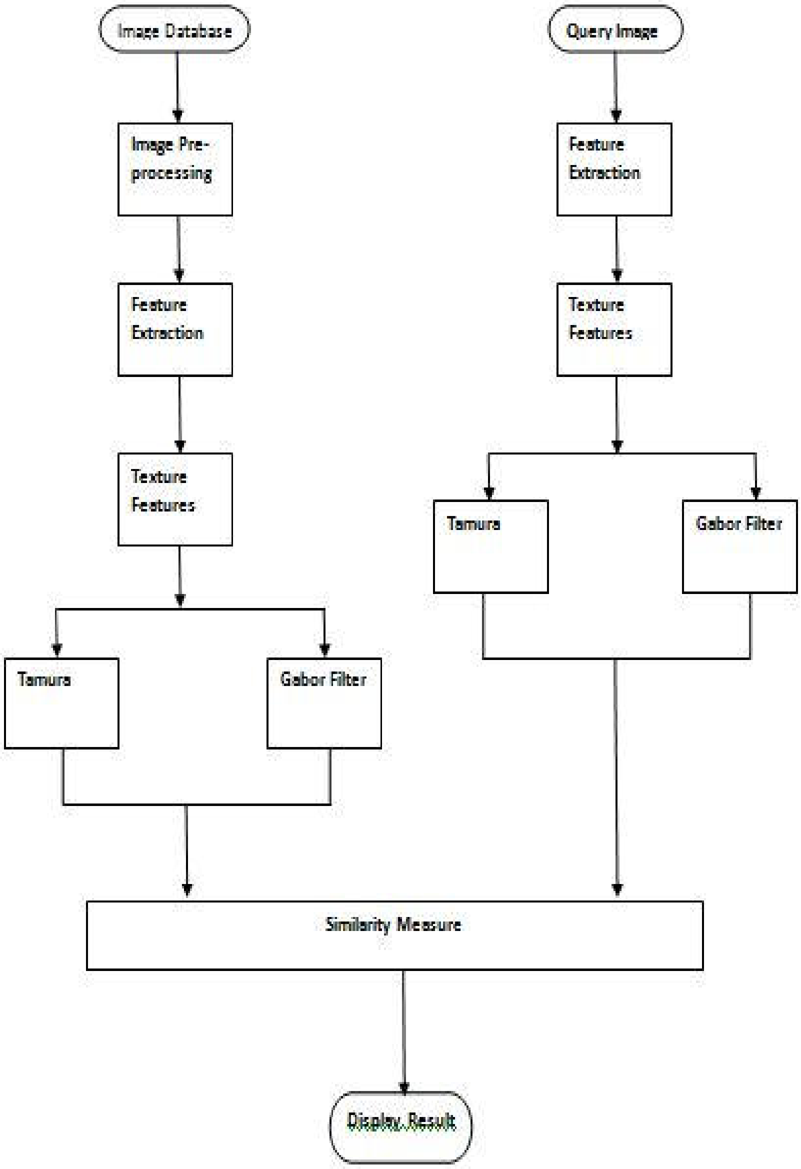

Figure 1: Diagrammatic Representation of Content-Based Image Retrieval System

5.0 Conclusion

The search for the relevant information in the large database has become more challenging. More précised retrieval techniques are needed in such cases. In this paper framework for content based image retrieval system was presented. Texture Features are extracted using Tamura feature and Gabor Wavelet transform and stored in a feature vector database. Euclidean distance, Manhattan distance, Cosine angle distance, Quadratic-form distance and Pearson correlation were used to match the four sample query image with four classes of [Buildings, Portraits, Human picture and Animals] 400 and 600 images from image database. Results from the CBIR system algorithm shows the performance with respect to retrieval accuracy of each distance measure using Tamura feature, Gabor Wavelet transform features and combination of both texture feature extraction method.

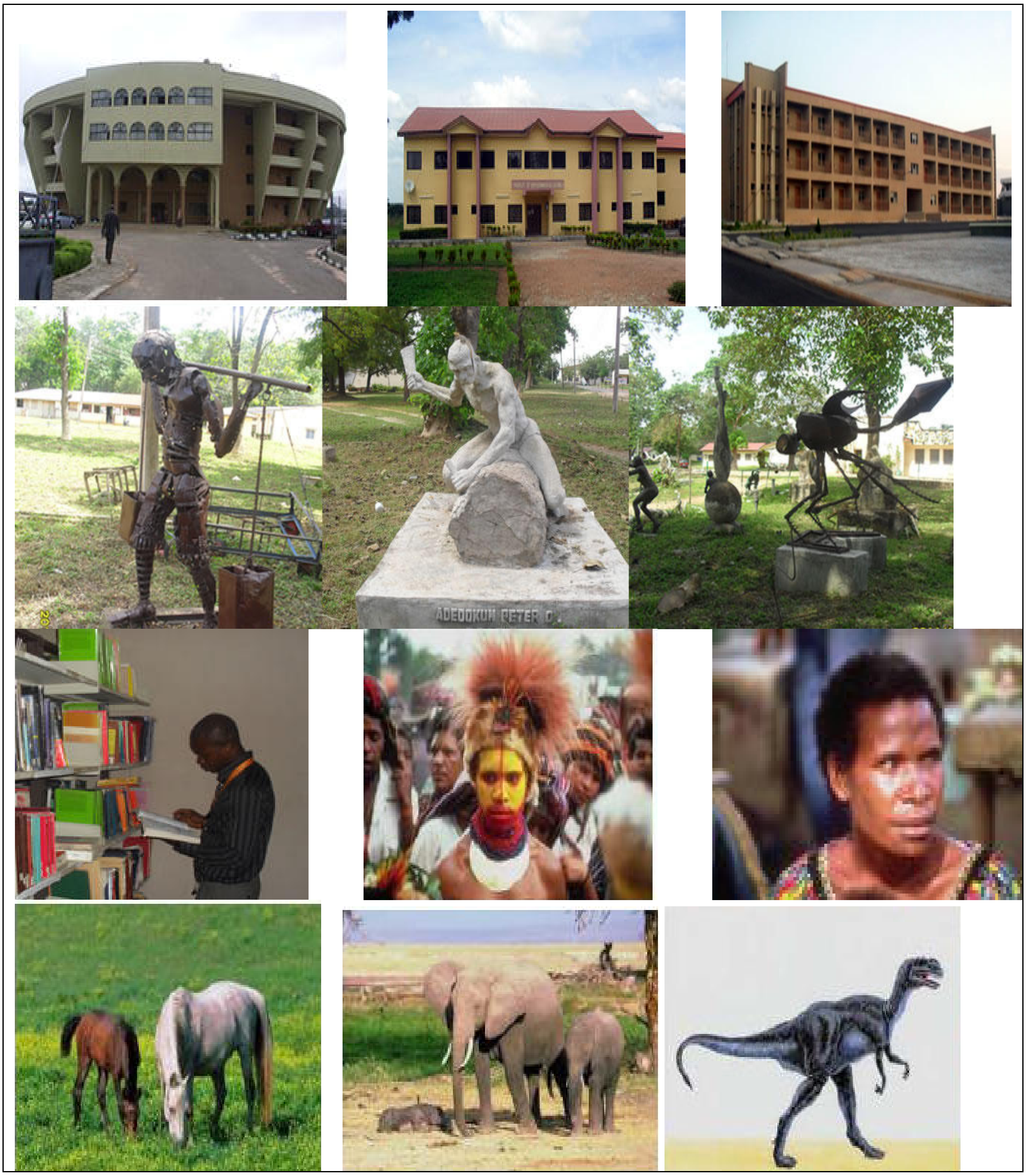

Figure 2: Sample Query Images of the first and second image database

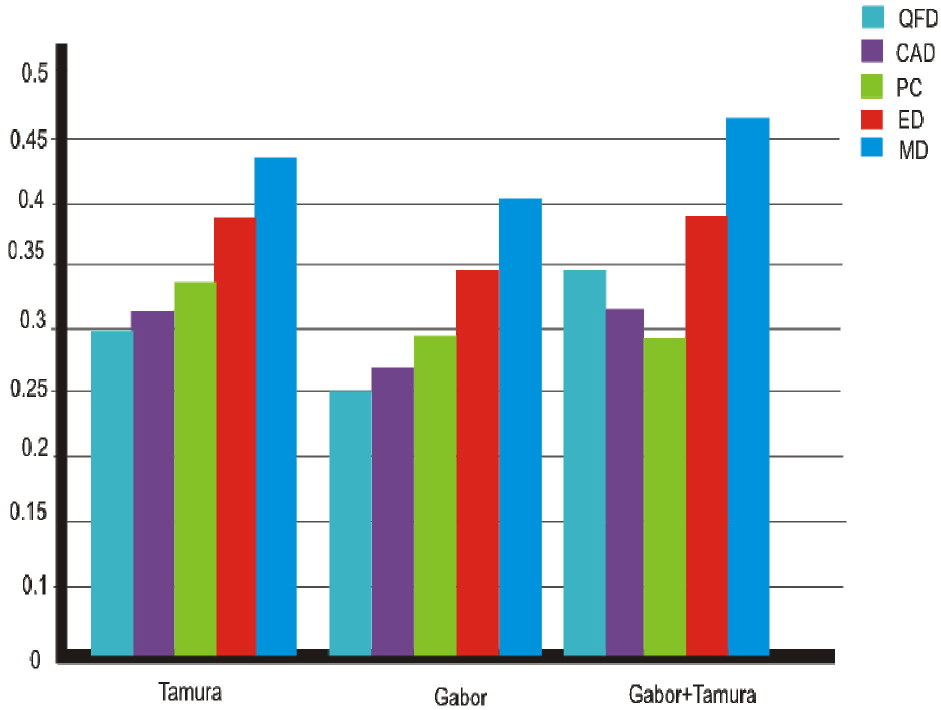

Figure 3: Precision performance analysis for 400 Image database

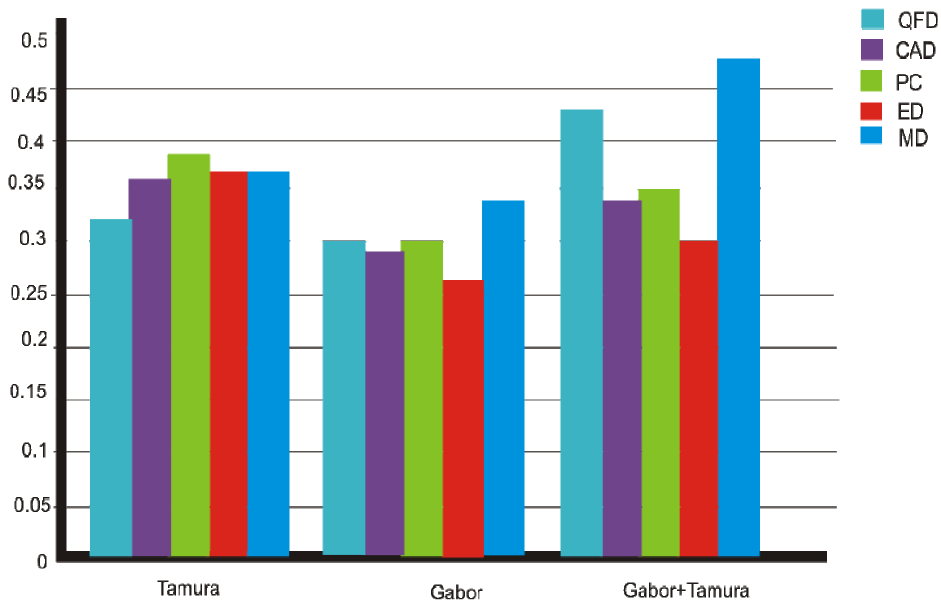

Figure 4: Precision performance analysis for 600 Image database

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