# Genetic Algorithm-Enhanced Retrieval Process for Multimedia Data

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***Abstract***

*The explosive growth of digital media content from various domains has given rise to the need for efficient techniques for retrieval of relevant information is getting more and more attention, especially in the large-scale Multimedia Digital Database (MDD) applications. It is for this reason that there has been an increased interest in the query reformulation for use in Multimedia Information Retrieval (MIR) using a combination of various techniques. In this paper, we propose a retrieval method that is formalized as an optimized similarity search process that combines Singular Value Decomposition (SVD), Query Quality Refinement (QQR) using Histogram Equalization and Genetic Algorithm (GA) enhancement. Experimental results show that the approach significantly narrows the search process by retrieving similar images satisfying the needs of the user.*

**Keywords:** *Multimedia Information Retrieval, Similarity Search, Genetic Algorithms, Singular Value Decomposition, Histogram Equalization, Query Quality Refinement.*

## 1. Introduction

The explosion of multimedia content in many domains has generated new requirements for more effective access to the global information repositories contained in them. Content extraction, indexing, and retrieval of multimedia data continue to be one of the most challenging and fastest-growing research areas [1].In particular, there is need to have robust techniques to retrieve multimedia information with new scalable browsing algorithms allowing access to very large multimedia databases, and semantic visual interfaces integrating the above components into a unified multimedia browsing and retrieval system. The focus of any information retrieval system is the ability by a user to search for relevant information within a collection of data which is relevant to the user's query by searching for matches from the document database. Efficient image searching, browsing and retrieval tools are required for such databases by users from various domains, including remote sensing, fashion, crime prevention, publishing, medicine, architecture, etc [2]. Though modern search algorithms are fast and effective on a wide range of problems, on Multimedia Digital Databases (MDD) with normally large number of parameters and a large number of observations, the search might not be as effective. The objects in the multimedia domain are treated as objects in a metric space, which can be compared with a metric function appropriately defined. The search technique that can be applied in such a case is an optimization problem for finding closest points of the features in the metric spaces. These closest points between a query vector and retrieved image gives rise to similarity data retrieval. Similarity search techniques in the large sets of complex MDD depend on good search algorithms and indexing structures. A wide range of methods have been proposed and Singular Value Decomposition (SVD) is one of them. SVD is a linear algebra decomposition technique applied for calculating singular values, pseudo-inverse and rank of a matrix. It has been shown experimentally and probabilistically that SVD should be able to expose the most striking similarities between a given vector and another set of vectors [2]. To improve the quality of an image from the human visual perspective, Query Quality Refinement (QQR) is carried out by enhancing the results from SVD similarity search using Histogram Equalization (HE).HE does so by enlarging the intensity difference among objects and background [3].However, the histogram equalization method often generates unnatural images with extreme contrast .So in order to obtain good contrast images suitable for the similarity search, the image is finally enhanced by GA .This image query result is the one that is re- used in the final retrieval optimization process. Figure 1 shows the framework of our proposed MIR system.

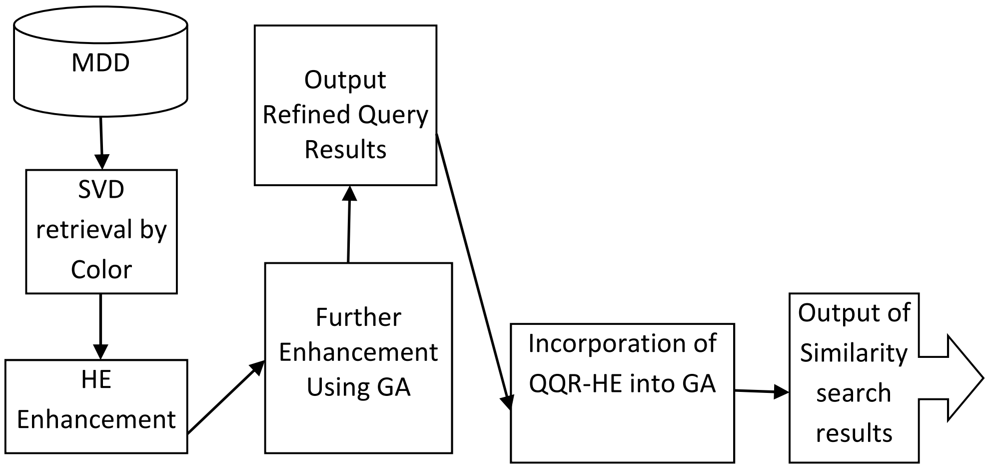



**Figure1.** The MIR System Framework.

The similarity between the query and retrieved image is measured by different retrieval strategies that are based on the more frequent terms found in both the image and the query.
The remainder of this paper is structured as follows: Section 2 briefly introduces Multimedia information retrieval and the application of SVD to multimedia information retrieval, section 3 discuses Image query quality refinement using histogram equalization while enhancement with genetic algorithms is presented in section 4. Section 5 shows the experiments and results, and section 6 gives the conclusion of the paper.

## 2. Multimedia information retrieval

The Complex data in multimedia systems usually do not have the total ordering property presented by the traditional data handled by Database Management Systems [4]. The documents in such systems demands Information Retrieval functionality that no classical method is able to answer, due to the medium mismatch problem. In the image database field, this is often called the medium clash problem. This problem refers to the fact that, when documents and queries are expressed in different media, matching is difficult, as there is an inherent intermediate mapping process that needs to reformulate the concepts expressed in the medium used for queries in terms of the other medium (e.g., images) [5].The vast amount of digital information in such databases have created a worldwide challenging need for new paradigms and techniques on how to browse, search and summarize multimedia collections. Generally, to afford an efficient multimedia content retrieval and consumption, a Multimedia Information Retrieval (MIR) System is required. The central concern of MIR system is easily stated: given a complex collection of information objects in multimedia documents (i.e., a complex information object), with components of different kinds, find those that are relevant to information needs of the user. The focus of any MIR system is its ability to search for information relevant to a user's needs within a collection of complex multimedia data. We can say therefore that the main goal of the MIR system is to help a user locate the most similar documents that have the potential to satisfy the user information needs. The earliest years of MIR were frequently based on computer vision algorithms which focused on feature based similarity search over images, video, and audio. Within a few years, the basic concept of the similarity search was transferred to several Internet image search engines including Webseek and Webseer [6]. Recently, there has been a surge of interest in a wide variety of media, and therefore the user seeking for the information can supply image, video, speech etc, as the query input. In this paper, we limit the scope of our work to the treatment of multimedia information retrieval using images. This media is by far the most investigated and therefore best understood one, therefore it suits the foundational work we are presenting here for MIR. The objects in the multimedia domain are treated as objects in a metric space, which can be compared with a metric function appropriately defined. A query in a multimedia database system usually requests the most similar objects to a given query object or a manually entered query specification. In response to this demand, a wide range of methods for Multimedia Information Retrieval have been produced, often based on techniques largely foreign to the IR field. Some popular techniques transform image features into discrete elements or terms. These so-called visual terms" are elegant because they enable image content to be described in much the same way as a text document. Techniques for creating visual terms from features almost always revolve around the idea of using linear algebra techniques to decompose the original image matrix into a set of reduced rank approximation that exposes the most striking similarities while preserving most of the relevant information. From the viewpoint of linear algebra, we can observe that a discrete image that we are limiting our scope to is an array of non-negative scalar entries which may be regarded as a matrix. Let such an image be designated as an image matrix *X*. Without loss of generality, we assume in the subsequent discussions that *X* is a MIR square image. Given a multimedia query object, the search for an exact match in a database requires the development of efficient and effective similarity search technique for the image matrix *X*. The technique described and applied in this paper for retrieving similar operators of multimedia documents makes use of a mathematical factorization called the Singular Value Decomposition (SVD). Briefly, SVD is used to decompose an image matrix X into the product of three separate matrices.

## 2.1. Singular value decomposition technique applied to multimedia information retrieval

Decomposition technique is an essential step for MIR data. The general criterion for decomposing the dimension is the desire to preserve most of the relevant information of the original MIR data according to some optimality criteria. Singular Value Decomposition (SVD) has been used in our work since it provided a method for decomposition and discovering correlations within the data. SVD is used to expose the most striking similarities between a given individual and a strategically chosen population of individuals [2]. It decomposes the large data matrix into a set of *k* orthogonal factors. The fewer important dimensions corresponding to “noise” due to word-choice variability are ignored. A reduced rank approximation to the original matrix is constructed by dropping these noisy dimensions [7]. In our proposal, SVD is used to deal with solving the difficult linear_least squares color problems terms in documents case. The first task is to represent the MIR image data as a term document matrix *X* (*mxn*) of rank *r* whose rows represent genes and columns represent individuals. The SVD expresses *X* as the product of three matrices as in Eq.(1) as:

$$X = U \Sigma V^T \tag{1}$$

The columns of the *U* matrix are made up of the orthonormal eigenvectors that span the space corresponding to the gene-gene auto-correlation matrix $XX^T$ and termed the left eigenvectors. Likewise *V* is a matrix whose columns consist of the orthonormal eigenvectors, termed right eigenvectors, that span space corresponding to the individual-individual auto-correlation matrix $X^T X$ .The middle matrix denoted by $\Sigma$ is a diagonal matrix with $\Sigma_{ij} = 0$ for $i \neq j$ and $\Sigma_{ii} = S_i \geq 0$ $\geq 0$ for $\forall_i$. The $S_{i's}$ are arranged in descending order with $S_1 \geq S_2 \geq \ldots \geq S_n$ .The $S_{i's}$ are called the singular values of *X*, which indicates the weight, or importance, of a dimension [7]. $V^T$ is the transpose of ***V*.** The singular value decomposition of *X* can also be represented as shown in Figure 2.

$$\left\{ \underbrace{\begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,n} \end{bmatrix}}_{n \quad documents} \Rightarrow \left[\begin{array}{cccc|c} u_{1,1} & u_{1,2} & \cdots & u_{1,k} & \cdots u_{1,n} \\ u_{2,1} & u_{2,2} & \cdots & u_{2,k} & \cdots u_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \ddots \vdots \\ u_{m,1} & u_{m,2} & \cdots & u_{m,k} & \cdots u_{m,n} \end{array}\right] \begin{bmatrix} S_{1,1} & \cdots & 0 \\ \vdots & & \vdots \\ & \ddots & \\ 0 & \cdots & S_{n,n} \end{bmatrix} \begin{bmatrix} v_{1,1} & v_{1,2} & \cdots & v_{1,n} \\ v_{2,1} & v_{2,2} & \cdots & v_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{k,1} & v_{k,2} & \cdots & v_{k,n} \\ \vdots & \vdots & \ddots & \vdots \\ v_{n,1} & v_{n,2} & \cdots & v_{n,n} \end{bmatrix} \right.$$

**Figure2.** Singular Value Decomposition model for MIR image representation.

From the view of Figure 2, the dimensions of each center can be reduced from $n$ to $k$ $(k<n)$.So the less important dimensions, from $k$ to $n$, corresponding to "noise" are ignored. The reduced rank approximation to the original representation is constructed by dropping these noisy dimensions.

## 2.2. SVD solution applied in MIR similarity search by colors

Color is mostly a combination of frequencies and is one of the most widely used [8] visual feature for content-based image retrieval. It is relatively robust and simple to represent. Various studies of color perception and color spaces have been proposed [9], [10]. Color has proven to be a very discriminant feature for object recognition and image similarity search on photographic images. Often, color histograms are used to describe the dominant colors of an image [11]. The color content of an image can be characterized by color histogram h(I, N, P), giving the frequency of occurrence, normalized with respect to the overall image pixel number P, each of the N colors quantizing the image color space. Besides being effective for characterizing the global color properties of an image, the color histogram representation is also useful to define a measure of similarity between two images [12] in a Multimedia Digital Database. Even though they are simple, color histograms are very practical in many applications due to their computational efficiency. Color histograms, do not capture the spatial correlations but instead color characteristic are maintained. Examples of their use in multimedia applications include scene break detection and querying a database of images [13]. A color histogram based on the full range of color values for the RGB model that uses 24 bits represents an equivalently large color vector, ( $2^{24} \approx$ 16M, representing a histogram which is often called the 16M color histogram).The color histogram is the most commonly used representation technique, statistically describing the combined probabilistic property of the three color channels[14]. Similarity search using color vector requires searching for similar vectors in a high dimensional space. At run-time, a current Multimedia Digital Databases' technology of similarity search cannot afford this high dimensional space cost. Due to this reason, some dimensionality reduction is needed. To provide for effective dimensionality reduction to the problem, SVD approach is used. Since most similarity search in MDD is performed by looking at the similarity of images using color properties, the SVD solution to the problem is applied by envisioning building a matrix $X$ corresponding to the 16M color histogram of a stack of images from which we intend to do image color similarity comparison.

To decompose the Matrix $X$, we used the SVD package, SVDPACK, from the NetLib repository. The decomposition was performed using the C version iterative las 2 method from SVDPACK for computing the SVD of large sparse real matrices for multimedia image data, available at: http://www.netlib.org/svdpack/. We carried out the experiments using a stack of several jpeg images (133 x 100 pixels), and constructed 16M (RGB color model) color histograms to build the $X$ matrix: columns identify image through a suitable ID while rows describe a color index C (combination of R,G,B values giving one of 16M colors values)[15]. We also reduced the effective number of colors in the histogram as per [16] and ran our SVD package on intel® Pentium(R) Dual CPU T3200 with 2.00 HZ, and 1.00 GHZ SDRAM. The $N$ largest values retained as much information about the original histograms of the stack of images. The SVD of the jpeg images yielded a new matrix containing the left and singular matrices corresponding to the $N$ largest singular values of $X$ [16] as shown in Figure 3. The results shows that the values that show the most variability are the retained relevant eigenvalues for the problem.

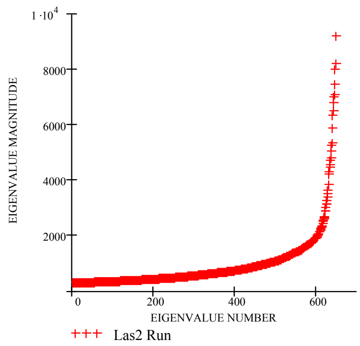



**Figure 3.** Results of a SVD run.

Comparing the similarity of the images on simple color bins histogram verses SVD reduced histogram shows that SVD process is an efficient empirical method to reduce the size of any function describing image properties for similarity purpose, and the final sparse formatted matrix used lesser memory of about 50Mb.

## 3. Image query quality refinement using histogram equalization

The next step is to refine the image results of the query obtained from the SVD similarity search of section3.2.In our proposal, this is done by enhancement through histogram equalization (HE).Image enhancement is one of the most important issues in image processing technology. Its main purpose is to improve the quality of an image from the human visual perspective. It does so by enlarging the intensity difference among objects and background [3]. Image features such as edges, boundaries, and contrast are sharpened in a way that their dynamic range is increased without any change in the information content inherent in the data [17].There are several techniques that have been developed for image enhancement, amongst them include contrast manipulation, noise reduction, HE, edge crispening and sharpening, filtering, pseudocoloring, image interpolation and magnification. HE is the simplest and most commonly used technique to enhance gray-level images. It is one of the most commonly used methods for image contrast enhancement. It is a technique by which the dynamic range of the histogram of an image is increased by assigning the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities. The main idea behind HE-based methods then is to re-assign the intensity values of pixels to make the intensity distribution uniform to utmost extent [3].Each pixel is assigned a new intensity value based on its previous intensity level. Thus when used for gray scale images, HE attempts to uniformly distribute the pixels of an image or just part of an image [18] to all the available gray levels L (e.g L=256, when 8 bits are used to represent each gray level). The assumption made by HE is that the pixel gray levels are independent identically distributed random variables (rvs) and the image is a realization of an ergodic random field. As a consequence, an image is considered to be more informative, when its histogram resembles the uniform distribution. From this point of view, grayscale HE exploits the theory of functions of the rv that uses the cumulative distribution function (CDF) of pixel intensity in order to transform the pixel intensity to a uniformly distributed rv. However, due to the discrete nature of digital images, the histogram of the equalized image can be made approximately uniform [19].We suppose the gray level $r$ is a continuous quantity and normalized in the range [0,1], with $r = 0$ representing black and $r = 1$ representing white. Consider the enhancement transform function to be given as s=T(r).Assume that the transformation function T(r) satisfies the following two conditions:

1. T( r ) is a single-valued and monotonically increasing for r in the interval [0,1];
2. $0 \leq T(r) \leq 1$ for $0 \leq r \leq 1$

Condition (1) is needed to guarantee that the inverse transformation will exist, and the monotonicity condition preserves the increasing order from black to white in the output image. A transformation function that is not monotonically increasing could result in at least a section of the intensity range being inverted, thus producing some inverted gray levels in the output image. Condition (2) is needed to guarantee that the output gray levels will be in the same range as the input levels. Figure 4 shows a gray-level transformation function that is both single-valued and monotonically increasing, as adopted from [6].

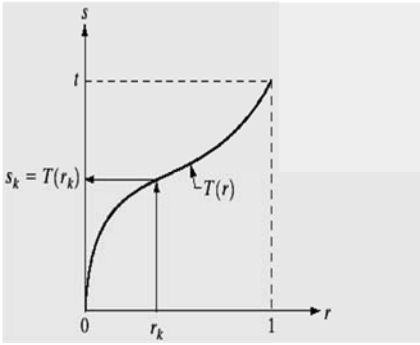



**Figure 4.**Gray-level transformation function, both single-valued and monotonically increasing.

Let $P_r(r)$ and $P_s(s)$ be two different functions that denote the probability density functions of random variables ***r*** and ***s*** respectively [6], in a gray level image. Given that $P_r(r)$ and *T(r)* are known and satisfies condition (1), then the probability density function $P_s(s)$ of the transformed variable **s** can be obtained by setting the given *S* and manipulating as shown in Eq.(3) to give the desired result, Eq.(3).

$$S = T(r) = \int_0^r P_r(w)dw, 0 \le r \le 1,$$

$$\text{So} \quad \frac{ds}{dr} = P_r(r) \quad \because \; P_s(s) = \left[ P_r(r)\frac{dr}{ds} \right] \tag{2}$$

$$\therefore P_s(s) = \left[ P_r(r)\frac{1}{P_r(r)} \right]_{r=T^1(s)} \tag{3}$$

This shows that the probability density function of the transformed variable ***S*** is determined by the gray-level PDF of the input image and by the chosen transformation function. A transformation function of particular importance in image processing has the form shown in Eq. (4) as:

$$S = T(r) = \int_0^r P_r(w)dw, 0 \le r \le 1 \tag{4}$$

where *w* is a dummy variable of integration. The right side of the equation is recognized as the Cumulative Distribution Function (CDF) of random variable *r*. Since Probability Density Functions are always positive, and recalling that the integral of a function is the area under the function, it follows that this transformation function is single valued and monotonically increasing, and, therefore, satisfies condition (1). Similarly, the integral of a probability density function for a variable in the range [0, 1] also is in the range [0, 1], so condition (2) is satisfied as well. For discrete values, the probability of occurrence of gray level $r_k$ in an image is approximated by Eq.(5) represented as:

$$P_r(r) = \frac{n_k}{n}, 0 \le r_k \le 1 \text{ , and } \quad k = 0,1,...L-1 \tag{5}$$

$$S_k = T(r_k) = \sum_{j=0}^{k} \frac{n_j}{n} = \sum_{j=0}^{k} P_r(r_j) \text{ , } 0 \le r \le 1 \text{ and } \quad k = 0,1,...L-1 \tag{6}$$

where $n$ is the total number of pixels in the image, $n_k$ is the number of pixels that have gray level $r_k$; and $L$ is the total number of possible gray levels in the image. Thus, a processed (output) image is obtained by mapping each pixel with level $r_k$ in the input image into a corresponding pixel with level $S_k$ in the output image via Eq.(6).The transformation (mapping) given in Equation (3.5) is what is referred to as the histogram equalization (HE). So given an image retrieved by SVD application to similarity search by colors, the process of enhancing the same for purposes of use in the retrieval of a refined and more similar image from the Multimedia Databases implies simply implementing Equation (3.5).This procedure re-assigns the intensity values of the pixels and make their distribution uniform.

## 4. QQR-HE-enhancement with genetic algorithms: the (QQR-HE-GA) process

The GA, initially published by John Holland [20], is used in our proposal to introduce a stochastic optimization and global approach for image enhancement and similarity search problems. The basic idea behind solving optimization problems, with few cost function evaluations, is to keep good solutions through a process of evolutionary competitions [20].GAs have been proven to be the most powerful optimization techniques in a large solution space [21]. This explains the increasing popularity of GAs applications in image processing.Genetic algorithms (GAs) are not new to information retrieval [22]. They have been used to allow for the performance of elegant and robust searches and optimization, which are specially useful to finding answers in complex or poorly understood search spaces. Boughanem et al. [23], Horng and Yeh [24], and Vrajitoru [25], examine GAs for information retrieval and they suggested new crossover and mutation operators. Vrajitoru examined the effect of population size on learning ability, concluding that a large population size is important [25].In nature, the selective pressure is exerted by the ambient. In a computational context, it is simulated by the application of an objective function that evaluates each individual's fitness. Usually genetic algorithms have two problem-dependent components: how to encode the solution space as chromosomes, and how to define the objective function [4].The basic idea behind solving optimization problems, with few cost function evaluations, is to keep good solutions through a process of evolutionary competitions [20].In this paper, we apply Genetic Algorithms (GAs) to further enhance the QQR-HE image quality in order to obtain a good contrast image suitable for the similarity search. This is achieved by mapping intensity of image values according to the predefined lookup-table (LUT) that defines a relation between input gray levels and output gray levels. The approach represents the relations between input and output gray levels by a lookup table (LUT), and the relations determined based on a curve by the Genetic Algorithm.

### 4.1. Representation of chromosome

To implement the GA, each possible solution from the image set must be encoded as a simple chromosome structure. The size of each chromosome is equal to *n*, where *n* represents the number of gray levels in the input image.

Each chromosome *x* of the image is represented by an integer byte, where each byte (gene) encodes the difference *b (j-1)* between values of transformed curve *B (j)* and *B (j-1,),* Figure 5, where *j* is a byte position in the chromosome.

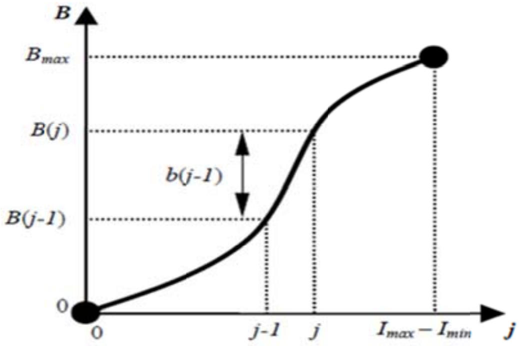



**Figure 5.** Brightness mapping curve

The value of curve *B (j)* is represented as in Eq. (7),

$$B(j) = \begin{cases} 0 & \text{J} = 0, \\ B(j-1) + b(j-1), 1 \le j \le I_{\max} - I_{\min}, \end{cases} \tag{7}$$

where $I_{\max}$ and $I_{\min}$ represent maximum and mini-mum intensity values.

## 4.2. Fitness Function

Each chromosome solution is evaluated by a predefined objective function. The value, derived from the objective function, is the fitness value, which represents the strength, or quality, of a solution. An individual fitness is measured by the sum of intensities of edges in an enhanced image, because a gray image with a visual good contrast includes many intensive edges. The values for each individual is measured and the sum of the intensity values of the enhanced image are calculated [26].The most fit individual is considered to be the one, which creates most intense edges. The least fit individuals are extinguished and their place is taken by newly created offsprings. In the proposed method, the number of edges and their overall intensity are used as fitness value for each chromosome because a gray image with good visual contrast includes many intensive edges (26). The fitness function is shown in Eq. (4.1):

$$fitness(x) = \log(\log(E(i(x)))) * n\_edges(i(x)) \tag{8}$$

where *fitness*(x) denotes the fitness value of chromosome x and *I*(*x*) is the enhanced image, *n_edges*(*I*(*X*)) represents the number of detected edges in the enhanced image which is calculated by a Sobel edge detector (27).The log–log measure of the edge intensity in Equation (4.1) is used to prevent producing un-natural images. The sum of the intensity values of the enhanced image is represented by *E*(*I*(*X*)), Eq.(9), which is calculated by the following expression [28]:

$$E(I(x)) = \sum_{x}\sum_{y}\sqrt{\delta h_1(x,y)^2 + \delta v_1(x,y)^2} \tag{9}$$

Where

$$\delta h_1(x,y) = g_1(x+1,y-1) + 2g_1(x+1,y) + g_1(x+1,y+1) - g_1(x-1,y-1) - 2g_1(x-1,y) - g_1(x-1,y+1) \tag{10}$$

and

$$\delta v_1(x,y) = g_1(x-1,y+1) + 2g_1(x,y+1) + g_1(x+1,y+1) - g_1(x-1,y-1) - 2g_1(x,y-1) - g_1(x+1,y-1) \quad (10)$$

as are represented as shown in Eq.(10) and Eq.(11) respectively.

### 4.3. Selection Algorithm

Selection of the individuals is done based on the fitness value of the solutions. The probability of selecting an individual is directly or inversely proportional to its fitness value [29]. The roulette wheel selection [30] is applied in our in proposed GA. Only individuals that have higher fitness are selected in the population, and they are survived to the next generation. On the other hand, individuals that have lower fitness are extinguished in the population because they do not have qualifications to survive to the next generation. In the selection process, $p_s * p_c$ individuals are selected to create the same number of individuals from them by crossover operator.

### 4.4. Crossover and mutation operators

Since our proposed method uses the two point crossover, *Ps*Pc* individuals are selected according to our selection process, where *Pc* is crossover rate. As *Ps*Pc* new individual is needed after doing crossover, two parents are selected and two new child are produced from them. Points in each parent are selected randomly and segments between these two points are substituted to produce new individuals. Finally, each new individual is sorted in ascending order to preserve structure. For each individual, a random number is produced, if it is lower than *Pm* (mutation constant), mutation will be done for that individual as mentioned follow. 5% of the individual chromosome elements are selected randomly for mutation. For each element a random integer number that should be less than or equal to the next element value and more than or equal to the previous element is generated. This random number is replaced by element.

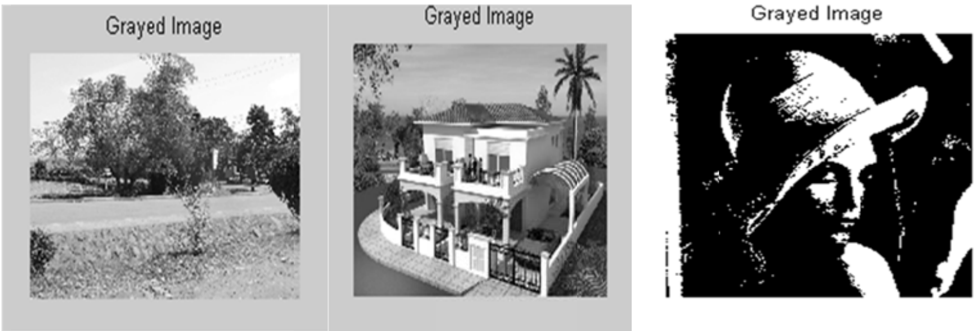
### 4.5. Terminating criteria

Terminating criteria is a condition that is used for ending the GA procedure. When the best fitness is kept a constant in ten generations, the genetic algorithm is completed. In the proposed work, the termination criteria is considered when the difference of best fitness in two last consecutive generations is less than $\in$.The value of $\in$ has been considered as 0.02× *best_fitness* (*best_fitness* is the fitness of last generation).

## 5. Experiments and results

### 5.1. QQR-HE experimental results

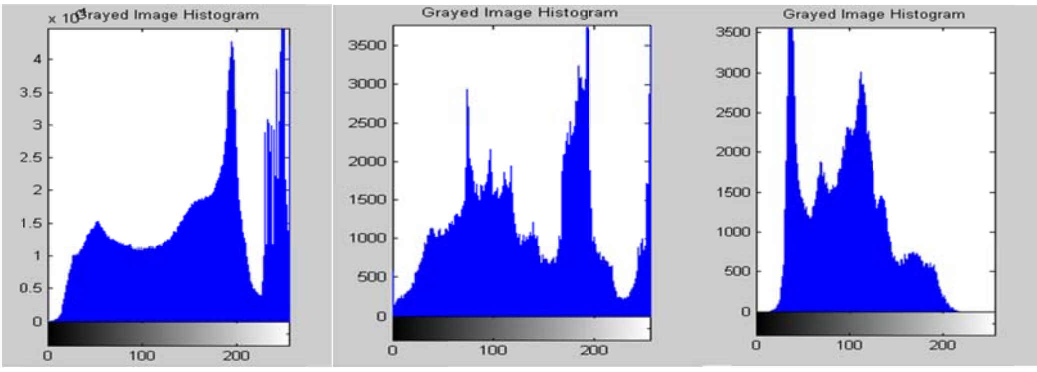
Figure 6 (a), (b) and (c) shows some of the retrieved SVD RBG images. In the experiments, the range of the gray-level values of the images is [0,255]. We have tested our results on 256x256 images retrieved from section 2.2. The image sizes are 256x256.




(a) (b) (c)

**Figure 6.** Retrieval Results of HE enhanced RGB Images (a), (b) and (c).

The respective histogram results of the images of Figure 6 (a), (b) and (c) are shown in Figure 7(a), (b) and (c).




(a) (b) (c)

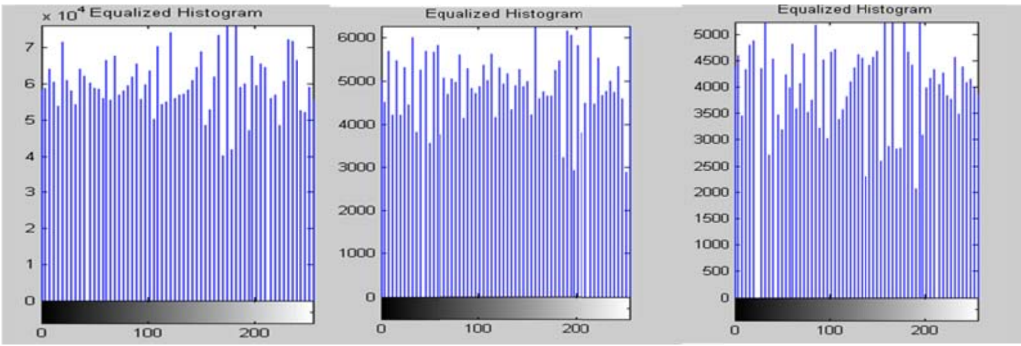
**Figure 7 .** Saturation histograms of the original RGB images (a), (b) and (c) of figure 10.

The results in figure 7 shows the histograms of the images retrieved by applying SVD alone. It shows the resulting image has a poor dynamic range that when used as a query image, gives rise to a broad search space. In order to improve the contrast of this image, without affecting the structure (*i.e.* geometry) of the information contained therein, we applied the histogram equalization operator. So the histogram results obtained from the experiments in Figure 6 and Figure 7 were reused to produce the desired enhanced image results shown in Figures 8, which have smoothed probabilities and improved visual quality.


(a) (b) (c)

**Figure 8.** Retrieved image results of HE-enhanced images (a), (b), (c),

The respective histogram results of the images of Figure 8 (a), (b) and (c) are shown in Figure 9 (a), (b) and (c).




(a) (b) (c)

**Figure 9.** Histograms of the HE-enhanced Image results (a), (b) and (c).

It is observed that histograms of the equalized images are uniform; spanning a fuller range of the gray scale without the need for further parameter specifications, leading to a conclusion that Image enhancement has as its main task to improve the visual quality of an image from the human perspective [31].Although HE can scale the histogram linearly and smoothly and do it automatically, the results of the processed image which forms a set of possible image query solutions might not satisfy the retrieval needs of a user. The retrieval process, for a given query image, should finish at a point when the user is satisfied with the retrieved images [32].Our final goal therefore is to apply the GA to further enhance the HE image quality in order to obtain a good contrast image suitable for the similarity search.

## 5.2. Evaluation of the image quality

The goal here is to identify the degree of deviation from the ideal situation. This evaluation is appropriate for predicting user acceptance of a retrieved image and at the same time for systems optimization. In general, the quality of the image retrieved by SVD similarity search is compared to that retrieved through the QQR-HE-GA process. The comparative results are valuated using subjective methods. To obtain reliable quality rating, subjective viewing tests have to be performed on the post-processed images. Subjective rating methodologies are divided into two primary categories, rating scale methods and comparison methods. In the rating scale methods, the subject views a sequence of images under comfortable conditions and assigns each image to one of several given categories. In the comparison method, the scale is based on a comparison within a set of images [31].To carry out a qualitative image analysis; a nonlinear mapping between the objective model outputs and subjective quality ratings was used. This is according to the Video Quality Experts Group (VQEG) Phase I testing and validation. The subjective model used the Mean Opinion Score (MOS) [28] while the objective model was carried out using M-SVD. In our proposed work, the retrieved images using SVD similarity search and those retrieved by QQR-HE procedure are saved in the JPEG format, automatically compressing them in that format.MOS data for the test images were then calculated using MOS expression shown in Eq.(12):

$$MOS = \frac{1}{N}\sum_{i=1}^{N} score_i \tag{12}$$

High quality printouts of the two categories of images were subjectively evaluated by approximately 20 observers. The images were printed out using a high quality Hewlett-Packard printer. The 8-2/16”x8-2/16” images were printed on 8.5”x11” white paper with basis weight 20lb and brightness 84. In the experiment, the observers were chosen among the undergraduate/graduate students and professors. About half of the observers were familiar with image processing, and the others only had computer science background. They were asked to rate the images using a 50-point scale within the two categories: those retrieved using SVD, and those retrieved as a result of query quality refinement, QQR-HE. For each test image, we displayed 50 retrieved images for each level against the original image, and asked the observers to rate them. As the proposed measure is not HVS-based, no viewing distance was imposed on the observers in the experiment. Grade 1 was assigned to the best image while grade 50 was assigned to the worst image. To evaluate distorted image sequence for the two levels of retrieved images, an objective model was carried out using a quality measure. This Quality measure, called Measurement SVD (M-SVD) [33], Eq. (13), is given by:

$$M - SVD = \frac{\sum_{i=1}^{(k/n)X(k/n)} \left| D_i - D_{mid} \right|}{\left(k/n\right) X \left(k/n\right)} \tag{13}$$

Where $D_i$ represents a bivariate graphical measure, $D_{mid}$ represents the mid point of the sorted $D_i$ 's, ***k*** is the image size, and ***n*** is the block size. The graphical measure $D_i$ , Eq. (14), computes the distance between the singular values of the original image block and the singular values of the retrieved image block, and is given by:

$$D_i = Sqrt\left[\left(\sum_{i=1}^{n} (X_i - \overline{X})^2\right)\right] \tag{14}$$

where $X_i$ are the singular values of the original block, $\overline{X}_i$ are the singular values of the distorted block, and *n* is the block size. The block size used in our experiments is 8x8 for the main reasons that it is a common block size in JPEG image processing applications. The numerical measure is a derivation from the graphical measure. The graphical measure consistently displays the type and amount of distortion as well as the distribution of error in all the images [33] for the two given levels of retrieval. Figure 10 demonstrates the performance measures of the two techniques.

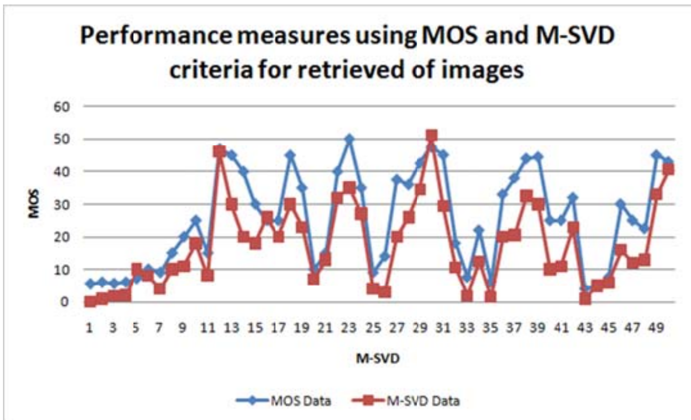



**Figure 10.** Performance Measures using the MOS and M-SVD Criteria for the retrieved images

For M-SVD, we considered the image block size, and noted that the smaller the size of the retrieved image block results in more detailed deviation leading to a higher correlation with the subjective evaluation, and vice versa. As for the subjective MOS measure, the effect was that for SVD, the average rating was fair while for QQR-HE-GA was given a rating of good. The evaluation shows that QQR-HE-GA search positively influences the similarity search results of image retrieval. Figure 11 shows the efficiency measures in terms of the CPU processing times taken for the retrieval executions in the two methods.

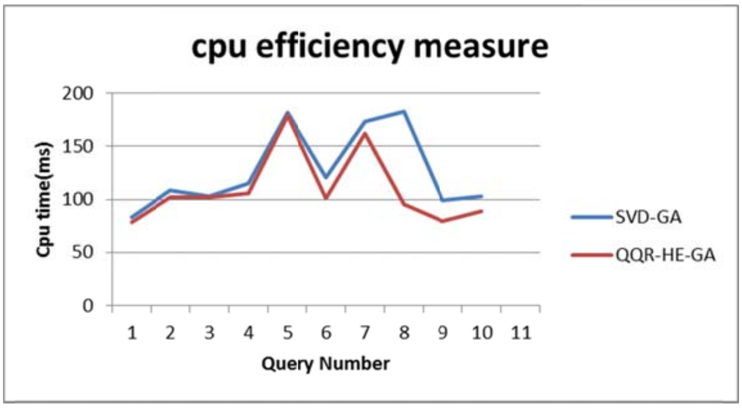



**Figure 11.**Comparison of cpu processing time

We observe that the performance of QQR-HE-GA search considerably gives an improvement to the similarity search capability with a better cpu processing time than when basic SVD search. This is attributed to the fact that the enhancement process refines the query image, and narrows the search space.

## 6. Conclusion

Based on the experimental results obtained in this study, the retrieval results from Multimedia Digital Databases by the Query Quality Refinement and the optimization by incorporation into the Genetic algorithms approach gives better results and narrows the search for similar images. The results from several application domains also shows that using the technique greatly influence the amount of performance improvement. Further testing and development on several different types of problems and parameter strategies, will be required in order to go beyond these attempts of exploiting the SVD and enhancement in such a way as to exhibit positive phenomena in Genetic Algorithms.

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