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REGULAR PAPER

Query quality refinement in singular value decomposition to improve genetic algorithms for multimedia data retrieval

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Abstract With the development of internet and availability of multimedia data capturing devices, the size of Multimedia Digital Database (MDD) collection is increasing rapidly. The complex data presented by such systems do not have the total ordering property presented by the traditional data handled by Database Management Systems (DBMSs). The quality of the search experience in such systems is also normally a big challenge since users from various domains require efficient data searching, browsing and retrieval tools. This has triggered an important research topic in Multimedia information retrieval concerning efficient and effective image similarity search. Modern search algorithms are fast and effective on a wide range of problems, but on MDD with a large number of parameters and observations, manipulations of large matrices, storage and retrieval of large amounts of information may render an otherwise useful method slow or inoperable. The focus of this work is the application of image enhancement technique, using histogram equalization, to the images retrieved using singular value decomposition (SVD). SVD is a linear algebra technique used for discovering correlations within data. The approach, herein referred to as query quality refinement (QQR) technique, improves the image similarity search result, and when incorporated with genetic algorithms further optimizes the search. These beneficial applications can be extended to other different types of multimedia data in various areas such as the P2P and WiMAX networks.

Keywords Multimedia Digital Database · Singular value decomposition · Genetic algorithms · Multimedia information retrieval · Query quality refinement

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1 Introduction

The development of Database Management Systems (DBMS) was guided by the principle of retrieving the exact answer for every query posed over the database. Getting the exact answer is a fundamental requirement for the traditional applications of DBMS, based mainly on numbers and small character strings. However, new DBMS are being increasingly required to support more complex data types such as images, videos, audio, time series and DNA sequences, among others [1]. This type of data management systems approach has given rise to Multimedia Digital Databases (MDD). MDD are currently prevalent in many scientific applications ranging from entertainment, magnetic resonance, imaging to learning management systems. The information in such databases is supposed to be practically accessible to everyone who wishes to use it for varied applications. Images are one form of data found in MDD. Image collection is semi-structured, non-homogeneous, and massive in volume, and is usually stored in large disk arrays. 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 MDD with normally large number of parameters and a large number of observations, the search might not be as effective. MDD requires manipulations of large matrices, storage requirements and retrieval of large amounts of information, which may render an otherwise useful method slow or inoperable. 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 in this case is then 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. The problem is, given a set S of points in a metric space M and a query point $q \in M$, find the closest point in S to q. In many cases, M is taken to be d-dimensional Euclidean space and distance is measured by Euclidean distance or Manhattan distance. A wide range of methods that have been proposed for the similarity search in MDD are often based on techniques largely foreign to the IR field, with most common ones being those that transforms image features into discrete elements or terms. These data transformations performed by the feature extraction algorithms correspond to a dimensionality reduction, which leads to lose of details and imposes errors in the process, reducing the worthiness to execute exact answer algorithms when dealing with complex data [1]. To circumvent this difficulty, similarity search using singular value decomposition (SVD) is used in our work for retrieval process and to provide users with the desired objects if the underlying similarity model reflects their sense of similarity. 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 further refine the query results obtained from the SVD similarity search, an enhancement technique using histogram equalization (HE) is applied. Finally, genetic algorithms (GAs) are applied. Genetic algorithms allows for the performance of elegant and robust searches and optimization, which are specially useful for finding answers in complex or poorly understood search spaces.

Many researches have been done, using GA, to address the issue of effectively refining and improving image similarity search results. Despite the successes, little use has been made to enhance the retrieved image results from the various similarity search techniques and then used in GA query optimization. Jacob G. Martin and Khaled Rasheed, in [2] investigated the impact of the SVD on GAs, by exposing the most striking similarities between a given individual and a strategically chosen population of individuals. Enhancement techniques were, however, not applied to the retrieved image.

This work presents a new technique of enhancing retrieved image results from an SVD similarity search by HE enhancement process. These similarities are then used to influence the direction of the GA's search process by qualifying candidate individuals for reinsertion into the next generation based on their proximity to other individuals, whose fitness have already been computed [2].

The framework of our proposed MIR system is as shown in Fig. 1. A user submits an image-based query to the system. The system may avail a set of sample images to choose from or can ask from a user a text description of the required image. It then searches for similar matches in the document database and retrieves similar image results corresponding to those queries. The user evaluates the results based on the relevance [3]. To refine the search, the retrieved image results are HE enhanced, and finally GAs are applied to optimize the information retrieval efficiency.

The similarity between the query and retrieved documents is measured by different retrieval strategies that are based on the more frequent terms found in both the document and the query. The more relevant document is deemed to be the feedback to the query request. The retrieval effectiveness of the system is measured using two experiments based on: Euclidean distance content similarity measure and precision and recall, which measure, respectively, the percentage of the retrieved documents that are relevant, and the percentage of the relevant documents that are retrieved [3].

The remainder of this paper is structured as follows: Sect. 2 briefly introduces GAs and their application to image optimization retrieval. Section 3 discusses the Multimedia information retrieval (MIR) Using SVD similarities search by colors while the image enhancement procedure QQR is mentioned in detail in Sect. 4. Section 5 looks at the QQR enhancement experimental results and in Sect. 6, Image quality analysis is carried out to evaluate its

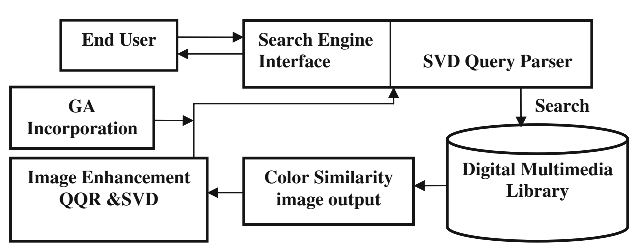


Fig. 1 The MIR system framework

overall enhancement effect on the image. Section 7 presents the incorporation of QQR results into GA for the final purpose of image optimization retrieval. Section 8 presents some chosen GA retrieval experiments plus evaluation, and Sect. 9 gives a conclusion of our proposal.

2 Genetic algorithms background

The growth in the number of documents in MIR has made it necessary to use the best knowledge or methods, especially those of GAs, in retrieving the most similar and relevant documents to the user query. Genetic algorithms are search and optimization methods that mimic natural selection and biological evolution to solve optimization and decision problems [2].

According to Holland, 1975, GAs are search algorithms based on the mechanics of the natural selection process (biological evolution). The most basic concept is that the strong tend to adapt and survive while the weak tend to die out. The optimization process is based on evolution, and the "Survival of the fittest" concept. GAs have the ability to create an initial population of feasible solutions, and then recombine them in a way to guide their search to the most promising areas of the state space. Each feasible solution is encoded as a chromosome, also called a genotype, and each chromosome is given a measure of fitness via a fitness (evaluation or objective) function. The chromosomes are either generated at random or, if one has some knowledge can be used to create part of the initial set of potential solutions. The fitness of a chromosome determines its ability to survive and produce offsprings. GAs are being more and more employed to solve problems involving search and optimization operations, mainly due to the robustness and simplicity they offer [4]. The GA have been applied to various kinds of domains such as autonomous robotics, knowledge discovery, power system, bankruptcy predictions, and computational economics [5].

Genetic algorithms (GAs) are not new to information retrieval [6]. They have been used to allow for the performance of elegant and robust searches and optimization, which are specially useful for finding answers in complex or poorly understood search spaces. Boughanem et al. [7], Horng and Yeh [8], and Vrajitoru [9], examine GAs for information retrieval and they suggested new crossover and mutation operators. Vrajitoru [9] examined the effect of population size on learning ability, concluding that a large population size is important. 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, GAs have two problem-dependent components: how to encode the solution space as chromosomes, and how to define the objective function [10].

3 Multimedia information retrieval and use of singular value decomposition

3.1 Decomposition for similarity retrieval

The complex data in multimedia systems usually do not have the total ordering property presented by the traditional data handled by DBMS [10]. The documents in such systems came into existence and demanded information retrieval functionality that no classical method was 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 (e.g. text) in terms of the other medium (e.g. images) [11]. 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 MIR system is required. MIR is the process of satisfying a user's stated information needs by identifying all relevant text, graphics, audio (speech and non-speech audio), imagery, or video documents or portions of documents from a multimedia document collection [12]. The central concern of MIR system is easily stated: given a collection of 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 [13]. 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 MIR 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. This then implies that multimedia objects cannot be meaningfully queried in the classical sense (exact search). Instead, 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 MIR 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 MIR 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 the 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 the retrieving similar operators for multimedia documents makes use of a mathematical factorization called the SVD. Briefly, SVD is used to decompose an image matrix X into the product of three separate matrices.

3.2 The basic idea of singular value decomposition technique in MIR

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. 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 less 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 [14]. 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 $\boldsymbol{X}$ (mxn) of rank r whose rows represent genes and columns represent individuals. The SVD expresses $\boldsymbol{X}$ as the product of three matrices:

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

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 $X^{\mathrm{T}}X$. The middle matrix denoted by Σ 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 $S_1 \geq S_2 \geq \cdots \geq S_n$. The $S_{i's}$ are called the singular values of $\boldsymbol{X}$, which indicates the weight, or importance, of a dimension [3]. $\boldsymbol{V}^{\mathbf{T}}$ is the transpose of $\boldsymbol{V}$. The SVD of $\boldsymbol{X}$ can also be represented as shown in Fig. 2.

From the view of Fig. 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.

3.3 SVD solution applied to multimedia data similarity search by colors

Color is mostly a combination of frequencies and is one of the most widely used visual features for content-based image retrieval. It is relatively robust and simple to represent. Various studies of color perception and color spaces have been proposed [15, 16]. Color has proven to be a very discriminant feature for object recognition and image similarity search on photographic images. Often, color

Fig. 2 Singular value decomposition model for MIR image representation

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

histograms are used to describe the dominant colors of an image [17]. 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 [18] in a MDD. 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 the instead color characteristic are maintained. They are authentic to different views of objects and are chosen as they are not dependent on excessive computational resources to be processed. Examples of their use in multimedia applications include scene break detection and querying a database of images [19]. 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 [20]. Similarity search using color vector requires searching for similar vectors in a high dimensional space. At run-time, a current MDDs' 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, we have used SVD approach. 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 $\boldsymbol{X}$ corresponding to the 16M color histogram of a stack of images from which we intend to do image color similarity comparison. A matrix example for the sample image from our multimedia database, together with the left eigenvector, singular values and the right eigenvector are shown in Figs. 3, 4, 5 and 6.

$$X = \begin{pmatrix} 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 \\ 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 \\ 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 \\ 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 \\ 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 \\ 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 \\ 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 \\ 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 & 227 \\ 228 & 228 & 229 & 229 & 228 & 228 & 227 & 226 & 227 & 227 \\ 226 & 227 & 228 & 229 & 230 & 230 & 230 & 230 & 229 & 229 \end{pmatrix}$$

Fig. 3 Multimedia image matrix representation

$$U = \begin{pmatrix} -0.3159 & -0.0520 & -0.1501 & 0.9354 & -0.0008 & 0.0005 & -0.0000 & 0.0000 & 0.0000 & 0.0000 \\ -0.3159 & -0.0520 & -0.1501 & -0.1328 & 0.9253 & -0.0347 & -0.0000 & 0.0000 & 0.0000 & 0.0000 \\ -0.3159 & -0.0520 & -0.1501 & -0.1342 & -0.1199 & 0.9179 & -0.0000 & 0.0000 & -0.0000 & 0.0000 \\ -0.3159 & -0.0520 & -0.1501 & -0.1337 & -0.1609 & -0.1767 & 0.8944 & -0.0004 & -0.0003 & -0.0000 \\ -0.3159 & -0.0520 & -0.1501 & -0.1337 & -0.1609 & -0.1767 & -0.2232 & 0.8661 & -0.0031 & 0.0000 \\ -0.3159 & -0.0520 & -0.1501 & -0.1337 & -0.1609 & -0.1767 & -0.2240 & -0.2916 & -0.8154 & -0.0000 \\ -0.3159 & -0.0520 & -0.1501 & -0.1337 & -0.1609 & -0.1767 & -0.2236 & -0.2871 & 0.4094 & -0.7071 \\ -0.3159 & -0.0520 & -0.1501 & -0.1337 & -0.1609 & -0.1767 & -0.2236 & -0.2871 & 0.4094 & 0.7071 \\ -0.3169 & -0.4633 & 0.8276 & -0.0000 & -0.0000 & -0.0000 & -0.0000 & -0.0000 & 0.0000 & 0.0000 \\ -0.3184 & 0.8739 & 0.3673 & -0.0000 & 0.0000 & -0.0000 & -0.0000 & 0.0000 & -0.0000 & 0.0000 \end{pmatrix}$$

Fig. 4 The left eigenvector

$$\Sigma = \begin{pmatrix} \text{1.0e+003 *} & & & & & & & & & \\ 2.2725 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.0043 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.0023 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.0000 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.0000 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.0000 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.0000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0000 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0000 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0000 \end{pmatrix}$$

Fig. 5 The singular values of X

$$V^T = \begin{pmatrix} -0.3159 & -0.5948 & -0.3448 & -0.4746 & 0.3566 & 0.0599 & -0.2595 & 0.0626 & 0.0147 & 0 \\ -0.3160 & -0.3938 & -0.1825 & 0.2798 & -0.2384 & 0.2322 & 0.6931 & -0.2001 & -0.0473 & 0 \\ -0.3163 & -0.2994 & 0.3453 & 0.4567 & -0.3058 & 0.2470 & -0.5356 & 0.1972 & 0.0470 & -0.0000 \\ -0.3164 & -0.0984 & 0.5075 & -0.2986 & -0.1180 & -0.5061 & 0.3083 & 0.4098 & 0.1017 & 0.0000 \\ -0.3164 & 0.2091 & 0.3042 & 0.0012 & 0.4065 & 0.2218 & 0.0541 & -0.3774 & 0.6355 & 0.0000 \\ -0.3164 & 0.2091 & 0.3042 & 0.0012 & 0.4065 & 0.2218 & 0.0579 & -0.0395 & -0.7378 & -0.0000 \\ -0.3163 & 0.3157 & -0.0613 & -0.5336 & -0.6091 & 0.2301 & -0.1310 & -0.2581 & -0.0639 & 0.0000 \\ -0.3162 & 0.4222 & -0.4269 & 0.1238 & 0.0834 & 0.2173 & 0.0909 & 0.6598 & 0.1626 & 0.0000 \\ -0.3162 & 0.1147 & -0.2236 & 0.2220 & 0.0092 & -0.4620 & -0.1390 & -0.2272 & -0.0563 & -0.7071 \\ -0.3162 & 0.1147 & -0.2236 & 0.2220 & 0.0092 & -0.4620 & -0.1390 & -0.2272 & -0.0563 & 0.7071 \end{pmatrix}$$

Fig. 6 The right eigenvector

The decomposition of the matrix $\boldsymbol{X}$ into the left eigenvector U, the right eigenvector V^{T} plus the singular (middle) vector Σ, is observed to be sparse, showing that the SVD process is useful and a practical empirical type of model.

The nonzero elements of Σ are always on its main diagonal, with the same dimension as $\boldsymbol{X}$, and the non-nonnegative diagonal elements in decreasing order.

To decompose the Matrix $\boldsymbol{X}$, 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 × 100 pixels), and constructed 16M (RGB color model) color histograms to build the $\boldsymbol{X}$ 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) [9]. We also reduced the effective number of colors in the histogram as per [21] 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*** [21] as shown in Fig. 7. For our SVD solution implementation and experiments, we adopted much of the methods used in [21]. The results shows that the values that show the most variability are the retained relevant eigenvalues for the problem.

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 50 Mb.

4 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 Sect. 3.3. In our proposal, this is done by enhancement through HE. Image enhancement is one of the most important issues in image processing technology. Its main purpose is to improve the

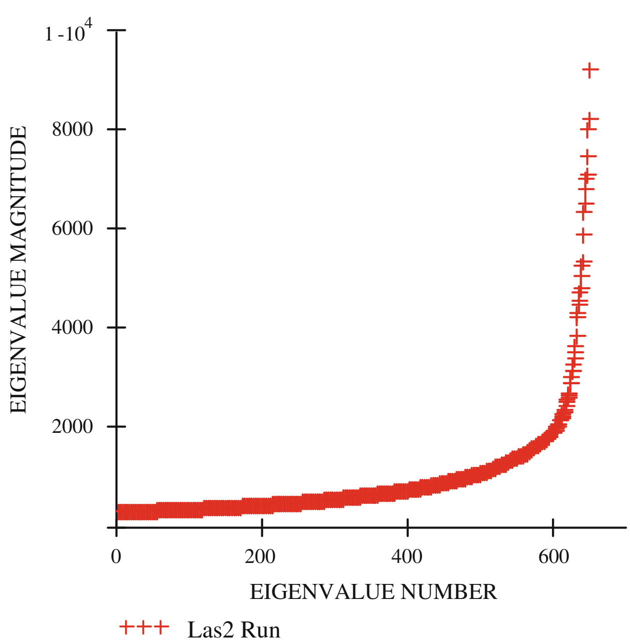


Fig. 7 Results of a SVD run

quality of an image from the human visual perspective. It does so by enlarging the intensity difference among objects and background [22]. 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 [23]. 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 [22]. 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 [24] 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 [25]. 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. $0 \le r \le 1$ for $0 \le T(r) \le 1$.

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 8 shows a gray-level transformation function that is both single-valued and monotonically increasing, as adopted from [13].

Let $P_r(r)$ and $P_s(s)$ be two different functions that denote the probability density functions of rvs $\boldsymbol{r}$ and $\boldsymbol{s}$, respectively [13], in a gray level image. Given that $P_r(r)$ and $\boldsymbol{T(r)}$ are known and satisfies condition (1), then the probability density function $P_s(s)$ of the transformed variable **s** can be obtained by setting

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

$$\text{So}\,\frac{\mathrm{d}s}{\mathrm{d}r} = P_r(r) \quad \because P_s(s) = \left[P_r(r)\frac{\mathrm{d}r}{\mathrm{d}s}\right] \tag{2}$$

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

This shows that the probability density function of the transformed variable $\boldsymbol{S}$ 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:

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

where $\boldsymbol{w}$ is a dummy variable of integration. The right side of the equation is recognized as the CDF of rvs 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

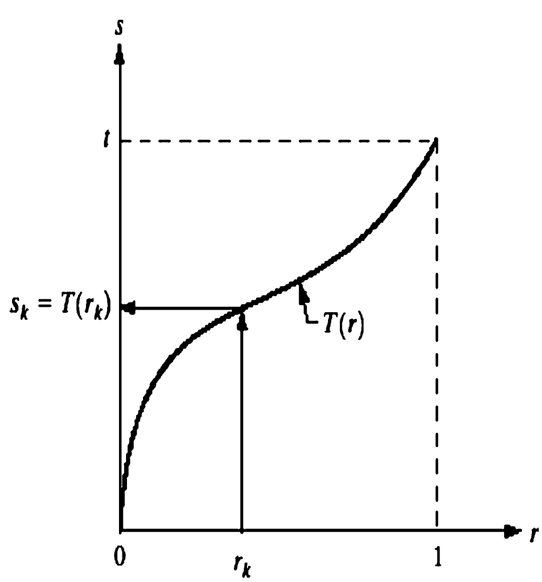


Fig. 8 A gray-level transformation function that is both single-valued and monotonically increasing

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:

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

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

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 Eq. (6) is what is referred to as the 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 Eq. (6). This procedure re-assigns the intensity values of the pixels and make their distribution uniform. The obtained results can further be enhanced using GAs. GAs are used to enhance image contrast [26]. Though we did not implement it in our proposal; we hereby just mention one procedure through which this can be achieved.

One method of doing this is by mapping the intensity of image values according to the predefined range for the gray-level image values. Each intensity value I is mapped to a new value B [27]. In this case, 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 $(j-1)$, Fig. 9, where j is a byte position in chromosome.

The value of curve B (j) is represented by:

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

where $I_{\max}$ and $I_{\min}$ represent maximum and minimum intensity values.

The fitness of each individual is measured by calculating the sum of edge intensities, which are produced by Prewitt transform of enhanced image [28]. 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. Thus, offsprings form a new generation which replaces the old one [28]. Such evolution process can be terminated using various

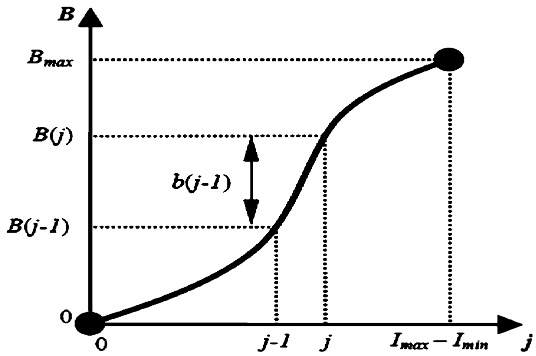


Fig. 9 Brightness mapping curve

conditions, for example, when fitness reaches a predefined threshold, evolution takes certain number of generations or fitness converges to a specific value [29]. The output of the enhanced image results using the HE procedure in this section is referred to as the QQR procedure. Output image forms the refined updated status of the query to be used in the next SVD similarity search experience of Sect. 3.3.

5 QQR enhancement experimental results

In our experiments, the range of the gray-level values of the images is [0, 255]. We have tested our results on 256 × 256 images retrieved from Sect. 3.3. The image size is 256 × 256. Figure 10a–c shows some of the original retrieved SVD RBG images.

The respective histogram results are shown in Fig. 11.

The histogram results confirm what we see if the MIR images are retrieved basically using SVD only. The resulting image has a poor dynamic range and 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 HE operator. The histogram results obtained from the experiments in Figs. 10 and 11 were reused to produce the final HE results shown in Figs. 12, 13. As a result, each pixel was assigned a new intensity value based on the previous intensity levels, giving the desired enhanced image results.

Several images were enhanced by the implementation of the proposed HE approach. 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 [26]. The results demonstrated that the proposed approach enhances the images effectively. The enhanced image results produced in the QQR then become the refined adjusted status of the query to be used in the next iterative search with SVD, forming the QQR–SVD retrieval procedure. The refined image results forms the ideal query image equivalent to that in the user's mind, hence narrowing the search space by retrieving only those images that are very similar to those being requested by a user.

6 Image quality analysis

The goal of evaluating the image quality at this stage 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 enhanced method QQR–SVD. The comparative results are valuated using objective and subjective methods. Objective methods are those that are defined by mathematical definition, such as peak signal to noise ratio (PSNR), human visual system (HVS), etc. On the other hand, the subjective ones which are based on the human

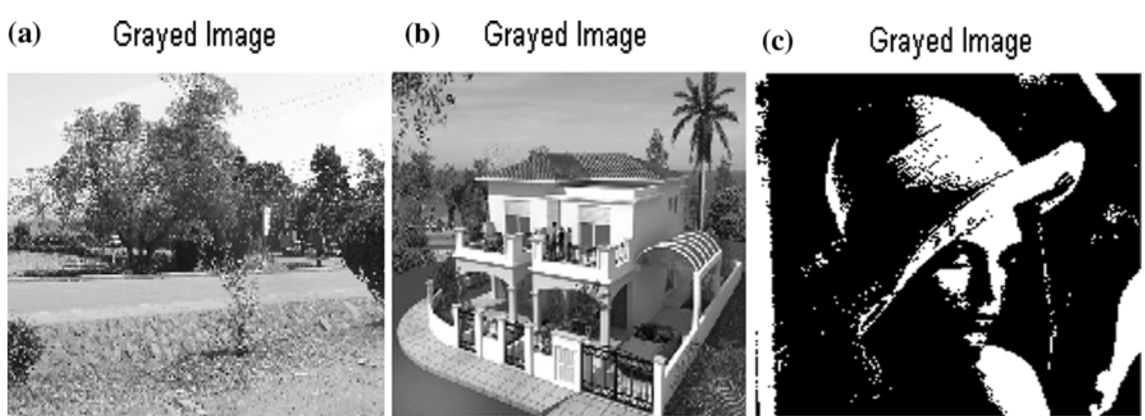


Fig. 10 Original RGB Images (**a**–**c**)

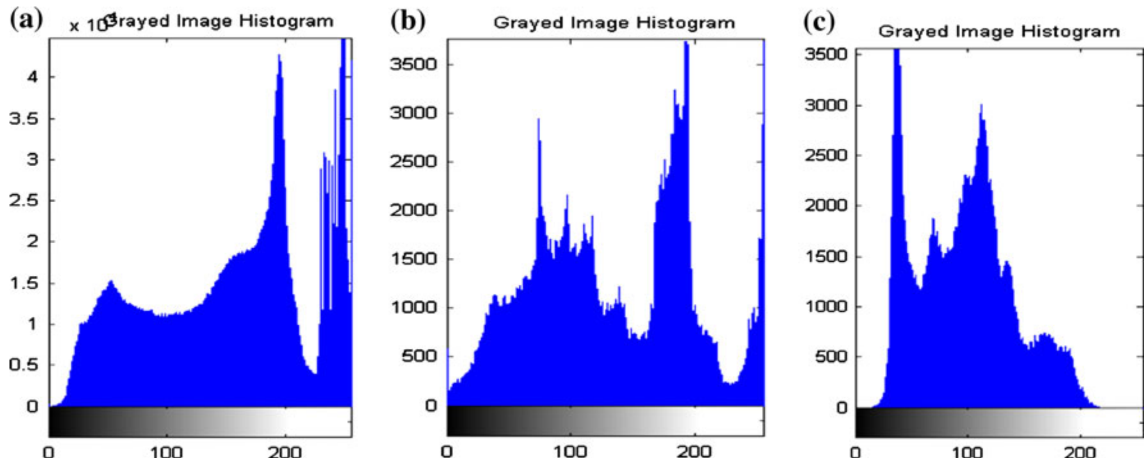


Fig. 11 **a–c** Saturation histograms of the original RGB images of Fig. 10

Fig. 12 Histogram equalized image results (**a–c**), with smoothed probabilities and improved visual quality

perception are specified by mean opinion score (MOS), which is a standard for evaluating image quality. Since human beings are the ultimate receivers in most multimedia applications, the most obviously reliable and commonly used assessment method of image quality is a subjective rating by human observers [26]. 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 [26]. 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 MOS [30] 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 procedure are saved in the JPEG format, automatically compressing them in that format. MOS Data for the test images were then calculated using:

$$\mathrm{MOS} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{score}_i \tag{8}$$

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″ × 8-2/16″ images were printed on 8.5″ × 11″ white paper with basis weight 20 lb 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 QQR, QQR-SVD. 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

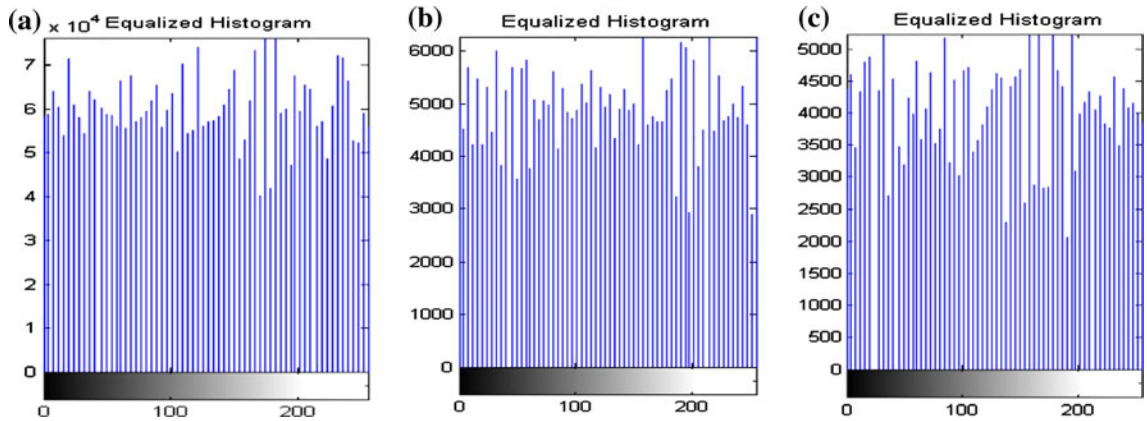
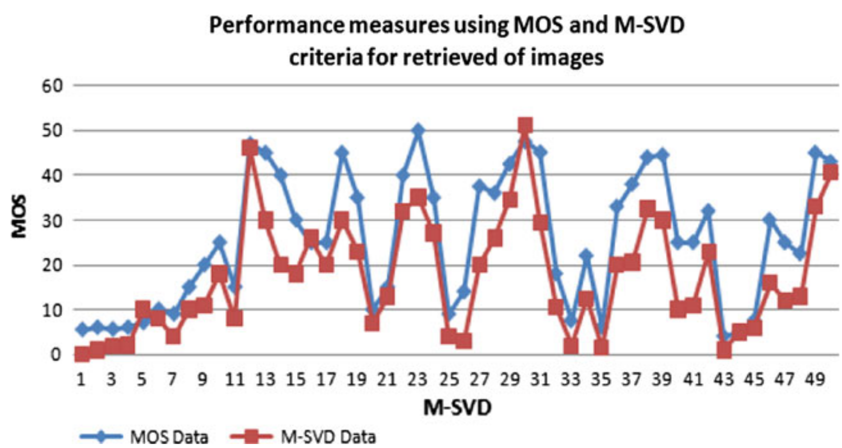


Fig. 13 Histograms of the equalized Image results (**a**–**c**)

Fig. 14 Performance measures using the MOS and M-SVD Criteria for the retrieved images



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) [31], is given by:

$$\text{M-SVD} = \frac{\sum_{i=1}^{(k/n)X(k/n)} |D_i - D_{\text{mid}}|}{(k/n)X(k/n)} \tag{9}$$

where D_i represents a bivariate graphical measure, D_{mid} represents the mid point of the sorted D_i's, $\boldsymbol{k}$ is the image size, and $\boldsymbol{n}$ is the block size. The graphical measure D_i 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:

$$D_i = \text{Sqrt}\left[\left(\sum_{i=1}^{n} (X_i - \bar{X})^2\right)\right], \tag{10}$$

where X_i are the singular values of the original block, $\bar{X}_i$ are the singular values of the distorted block, and n is the block size. The block size used in our experiments is 8 × 8 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 [31] for the two given levels of retrieval. The performance of the two measures and evaluated results are demonstrated using Fig. 14.

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–SVD was given a rating of good. The evaluation shows the performance of QQR–SVD search positively influences the similarity search results of image retrieval. The graphical results of Fig. 14 demonstrate the two performance measures.

7 Incorporation of QQR results into genetic algorithm for image similarity retrieval efficiency

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 solutions might not satisfy the retrieval needs of a user. The retrieval process, for a given query image, finishes at a point when the user is satisfied with the retrieved images [32]. Our final goal is to have our retrieval process formalized as an optimized similarity retrieval search process. The GA, initially published by John Holland [4], is used in our proposal to introduce a stochastic optimization and global approach for the image 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 [4]. Our proposal to incorporate QQR–SVD results into GAs is to optimize our method so that the "best solutions" can be preserved during the evolutions such that the search can gradually approach the desired similarity results. GAs have been proven to be the most powerful optimization techniques in a large solution space [32]. This explains the increasing popularity of GAs applications in image processing. There are several possible approaches of incorporating QQR–SVD results into GAs, but the one considered and evaluated here is based on qualifying candidate individuals for reinsertion [2]. Candidate images that are retrieved during QQR stage are qualified for reinsertion into the next generation process. QQR–SVD exposes the most striking similarities between a given vector and another set of vectors, improving the visual quality of the image from the human perspective. The final results are then used to influence the direction of the GA's search process. One benefit of this approach is that the fitness function need not be computed in order to determine that an individual closely resembles another individual whose fitness is already known. Starting with a population of randomly created and enhanced QQR–SVD individuals, our GA progressively breeds a population of the individuals over a series of generations using natural selection, crossover (recombination), mutation, and other genetic operations. This means then that solving a problem using GA requires specification of the following: (1) chromosome representation (population encoding), (2) fitness measure, (3) selection and, (4) GA operators.

7.1 Population encoding

Since a matrix data representation can be viewed simply as a generalization of a vector, Multimedia Digital Data retrieval is based on the vector space model. To implement a GA to perform similarity query, each possible solution from the QQR–SVD image set must be encoded as a chromosome. The core idea of population encoding is to treat the data representation of the image as a bulk of genes. Each gene is represented by an integer that indicates the number of pixels with similar characteristic color property in the image [33]. Our GA receives an initial population consisting of chromosomes corresponding to the relevant and the irrelevant documents, and the supposedly optimized query from QQR to SVD process. The vectors corresponding to the documents provided as feedback at the end of QQR–SVD procedure are subjected to a conversion process [34] to transform them into the chromosomes corresponding to the relevant documents and the irrelevant documents that our GA will work with. These chromosomes will have the same number of genes (components) as the query and the feedback documents have terms with non-zero weights. First, the set of terms contained in those documents and the query is calculated, and the size of the chromosomes will be equal to the number of terms of that set [34]. Each chromosome has a corresponding point in the search space. The algorithm starts with the initial solutions that are selected from a set of configurations in the search space using randomly generated solutions. Each of the initial solutions (called an initial population) is evaluated using a user-defined fitness function. A fitness function exists to numerically encode the performance of the chromosome [33].

7.2 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. According to the fitness value, GA's can choose "better genes" to form offspring [33]. Choosing an appropriate fitness function is very important [35]. Fitness function for our work was considered as the functions for precision and recall of the corresponding query. Retrieved images were ranked according to the similarity score. Precision and recall fitness function work well with ranked documents, where all assignments of the initial population are ordered according to their similarity score and the best are chosen to survive. The shortcoming of using recall and precision as fitness functions is that if no relevant documents are retrieved by a chromosome, then its fitness is zero. This will lead to loss of all genes for this chromosome [36]. Our fitness functions were based on the average of the best individual, for each generation. It was considered with the following set of parameters: probability of crossover ($P_c = 0.8$), and probability of mutation ($P_m = 0.7$). The objects that survived at the next generation were chosen with probability proportional to their rank. Fitness values were computed for the two generated new offsprings, and after that the best chromosomes survives for the next generation.

7.3 Selection stage

The chromosomes with better fitness values will survive to the next generation by a selection scheme [33], and can reproduce multiple copies in the next generation for reproduction. As the selection mechanism, the GA used "simple random sampling" [4]. The well-known roulette wheel selection strategy was employed as the selection mechanism in our model. This consisted in constructing roulette with the same number of slots as there were individuals in the population, and in which the size of each slot is directly related to the individual's fitness value. Hence, the best chromosomes on average achieved more copies, and the worst fewer copies [1]. 'The Elitist selection' strategy was also used as a compliment to the selection mechanism, whereby the most fit members of each generation are guaranteed to be selected [37], ensuring that the best individual was copied and not lost in the subsequent generations. If, after generating the new population, the best chromosome of the preceding generation is by chance absent, the worst individual of the new population is withdrawn and replaced by that chromosome [38]. A set of individuals that have high scores in the fitness function were selected to reproduce itself. Such a selective process results in the best-performing chromosomes in the population to occupy an increasingly larger proportion of the population over time. Processing the GA operators was done in each generation over the best two chromosomes. From the population of chromosomes, the best two chromosomes depending on the highest fitness values for precision or recall measures were selected. These two chromosomes were called parent 1 and parent 2. The two parents were then used to produce two new offsprings [36].

7.4 Operators

Crossover operator is the genetic operator that mixes two chromosomes together to form new offspring. Crossover occurs only with crossover probability P_c. Chromosomes that are not subjected to crossover remain unmodified [38]. The crossover operator creates new individuals by recombining genetic characteristics from its parents. Crossover operates by swapping corresponding segments of a string representation of a couple of chromosomes (called "parents") to produce two chromosomes (called "children"). In generating two new offsprings from the existing population, offsprings must have some inheritance from the two parents [36]. Our algorithm uses the simple one-point crossover: a cutting site is chosen at random and the children are obtained by each taking the first part from one parent and the second part from the other parent.

Mutation is the second operator used in our proposed system. Mutation involves the modification of the gene values of a solution with some probability P_m [38]. This operator guarantees the entire state-space is searched, given enough time. It restores lost information or adds information to the population. Mutation operates on a single chromosome: one element is chosen at random from the chain of symbols, and the bit string representation is changed with another one. When a mutation happens, a gene is randomly modified in the individual's chromosome. Mutations prevent search stagnation, enabling the exploration of search space's areas that could not be reached with crossover operator, depending on the initial population. After executing the three genetic operators, a new population was generated, and a new cycle began. The GA was executed until the maximum amount of time that was set to execute was satisfied. This was repeated until the best solution was arrived at [36]. Figure 15 presents an outline of execution cycle of the developed GAs.

8 GA retrieval experiments and evaluation

There are several experiments that can be implemented and used to evaluate the quality of an information retrieval system. In such experiments, some of the quality aspects often measured include system efficiency, effectiveness and other subjective aspects related to the user satisfaction. In this paper, we considered images in a MDD with over 6,000 images. The images were from various categories, including airplanes, animals, buildings, vehicles, furniture, human beings, environment, and text. Query images were selected at random and used in the SVD–GA and QQR–SVD–GA retrieval process. The efficiency of the proposed

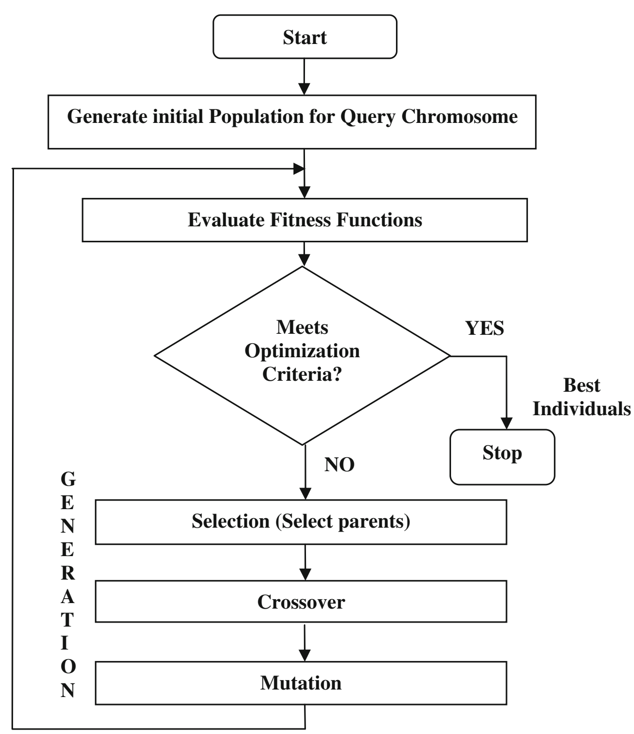


Fig. 15 Outline of execution of the developed genetic algorithms

system was then evaluated by computing the quality of responses using precision and recall, computing the Euclidean distances and by measuring the CPU time taken to retrieve a given image. In IRS, recall and precision are the two most widely used measures of retrieval performance [39]. We evaluated the results of the retrieval via these two classical measures, which formed the fitness function for our work. Recall and precision are often perceived as being inversely related, i.e., complementary and competitive [16]. Precision, ***P***, is defined as the number of relevant documents retrieved divided by the total number of documents retrieved. Recall, ***R***, is defined as the number of relevant documents retrieved divided by the total number of relevant documents in the index. Their mathematical expression is shown as follows:

$$P = \frac{\sum_d r_d . f_d}{\sum_d f_d},\ R = \frac{\sum_d r_d . f_d}{\sum_d r_d} \tag{11}$$

with $r_d \in \{0, 1\}$ being the relevance of document d for the user and $f_d = \{0, 1\}$ being the retrieval of document d in the processing of the current query. Both measures are defined in the range [0, 1]. The experiment was performed on several queries tested at crossover probability $P_c = 0.8$ and mutation rate $P_m = 0.7$ for the two GAs (Basic SVD–GA and QQR SVD–GA). The mean precision values at given recall intervals for the algorithm were implemented. The results of the experiment are as shown in Fig. 16.

The second evaluation technique uses the Euclidean distance, given by:

$$\sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2} \tag{12}$$

This measures the image content similarity. Image distance results between the two sets of retrieved images using the two named techniques, SVD–GA and QQR–SVD in relation to the query image. Results were obtained and their Euclidean distance computed. Then the graphical results are plotted and shown in Fig. 17.

Another comparison measure that was used to evaluate our proposal efficiency is CPU time that was required to process the retrieval executions for the two techniques.

We observe as shown in Fig. 18 that the performance of QQR–SVD–GA search considerably gives an improvement to the similarity search capability with a better cpu processing time than when basic SVD–GA search. This is attributed to the fact that the enhancement process refines the query image, narrowing the search space and hence retrieving only those images that are very similar to those being requested by a user.

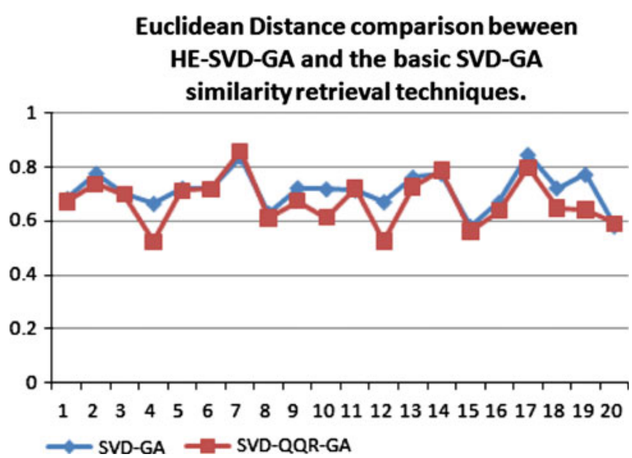


Fig. 17 Comparison of SVD–GA and QQR–GA retrieval performances

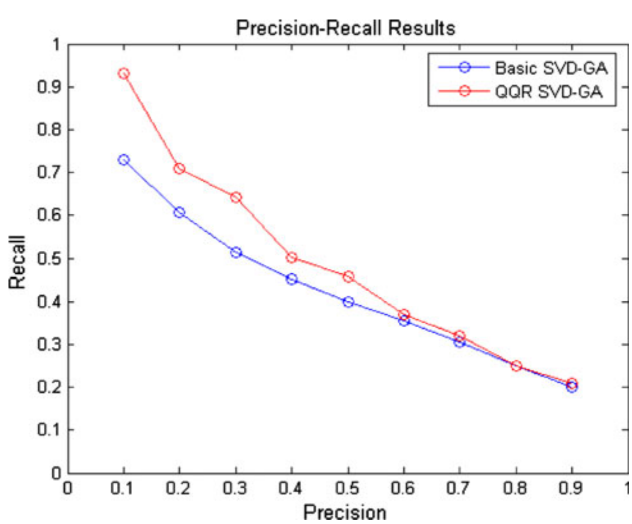


Fig. 16 Precision-recall experimental results

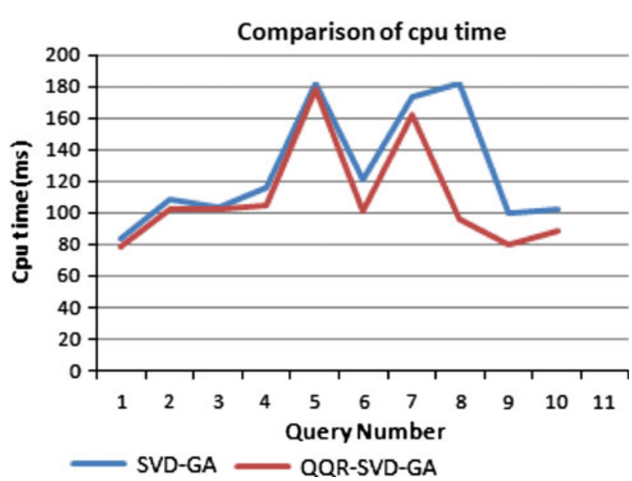


Fig. 18 Comparison of cpu processing time

9 Conclusion

In this study, we presented a method for improving the quality of image similarity search results from a MMD that addresses the quality of the search experience over complex data. SVD technique is applied in the paper to effectively provide dimensionality reduction of the MMD and perform simple similarity search from the database using color properties. QQR of the query results was enabled by image enhancement of the retrieved image results. The final QQR–SVD results are incorporated into GAs, based on qualifying candidate individuals for reinsertion into the next generation process. Results from several application domains show that using the technique greatly influence the amount of performance improvement of the multimedia image similarity data retrieval. Further testing and development on several different types of problems and parameter strategies, like the input/output time will be required in order to go beyond these attempts of exploiting the SVD in such a way as to exhibit positive phenomena in GAs.

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