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Target Search Techniques for Content-Based Image Retrieval Systems

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Abstract— Content-based image retrieval (CBIR) has received much research interest since couple of decades. In CBIR systems, searching of a desired image from multimedia database is known as target search process. The techniques which are available today are having slow convergence rate and they also not guarantee to search desired image. To overcome these disadvantages, four new methods are proposed. It is observed that these four methods are able to search the desired image accurately with fast convergence rate. The experimental results show that the iterations required to search the desired image are reduced considerably.

***Index Terms*—Content-Based Image Retrieval (CBIR), Slow Convergence and Target Search.**

I. INTRODUCTION

In today's electronic world the usage of multimedia data including real time videos has been increased due to the popularity of digital devices and personal computers. Vast amount of multimedia data brings a lot of significant challenges for retrieving the contents successfully from large-scale multimedia databases [9]. Gigabytes of multimedia content are produced by every user of cell phone, digital camera or PC and are being made available as multimedia database. The main concern is how to find out desired data from such huge collection. Content-based image retrieval (CBIR) systems are built-up as an answer to above mentioned problems [7]. In recent days, retrieval of multimedia data has received much research attention and the most admired research area is CBIR [9]. In a typical CBIR system, low-level visual image features (e.g., color, texture, and shape) are automatically extracted for image descriptions and indexing purposes. For searching the desirable images, a user presents an image as an example which similar to the target image and the system returns a set of similar images based on the extracted features [5]. In CBIR systems with relevance feedback (RF), a user can mark returned images as positive or negative, which are then fed back into the systems as a new refined query for the next round of retrieval. The process is repeated until the user is satisfied with the query result. Such systems are effective for many practical CBIR applications. [3] There are three general types of image search: target search, category search and open-ended search. In target search an exact target image has to be found out by user from image database, such as a logo of a particular company. In category search an ideal category images are searched by users such as image of 'dogs'. In open-ended search, user search in a specific database without any goal [2]. In this paper the target search is mainly focused. An effective CBIR system needs to have an efficient search mechanism and an accurate set of visual features. The degree of similarity between two images is evaluated through standard mathematical distances measures, like Euclidian distance [8]. The techniques which are available today follow a common strategy that these techniques revisit the checked images and hence lead to the following disadvantages:

A. Desired Target Image Not Found

While searching the desired image from multimedia database, it can take much iteration to search it. When searching process is going on for many iteration, it may be trap at any instant but there is also possibility that the user don't have knowledge about it. [4]

B. Slow Convergence

If the previously checked images are included in the calculation of the current centroid, it results in re-visiting of some of the images. This reduce the rate of searching and suffers from slow convergence, longer search time and disk access overhead. [4] Four target search methods are proposed to overcome above disadvantages. All these methods follow a common strategy that all these methods do not re-visit checked images hence reduce the search space. If the Voronoi diagram concept is used in the search process it produces the results within few milliseconds. Voronoi diagrams aggressively reduce the search space and move towards the target image, thus significantly speeding up the convergence. Experimental results confirms that the all these methods are more superior to the earlier techniques.

II. OVERVIEW OF THE TARGET SEARCH SYSTEMS

The goals of target search methods are avoiding local maximum traps, getting fast convergence, reducing resource requirements, and guarantee to find the target images. Re-visiting the already checked images is one of the several shortcomings of existing techniques that leads to the local maximum trap problem and slow convergence; the idea of leaving out checked images is the main motivation for a new design principle. It is assumed that users are able to accurately identify the most relevant image from the returned images, and this most relevant image is the closest to the target image among the returned ones [4]. In target search, the ultimate goal is to locate the target images, and if none is found, the final 'precision, and 'recall' of the search is zero. In CBIR with RF, the traditional recall and precision can be computed for individual iterations. For target search, precision and recall can be calculated, if after several, say 'i', iterations the target image is found, the average precision and recall are 1/(i.d) and 1/i, where 'd' is the fixed number of images retrieved at each iteration. In short, the number of iterations to find a target image is not only the most significant measure of efficiency, but also the most significant indicator of precision and recall. Therefore,

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number of iterations is used as the important measure for theoretical analysis and experimental evaluation of the proposed four target search methods [4]. The flow chart shows the operation of the target search system. A query for target search is defined as $I = (p_I, Q_I, G_I, F_I, W^I, d)$ where p_I denotes the number of query points in I, Q_I the set of n_I query points in the current search space W^I, G_I the set of weights associated with Q_I, F_I the distance function, and d the number of points to be retrieved in each iteration (see Flow chart.).

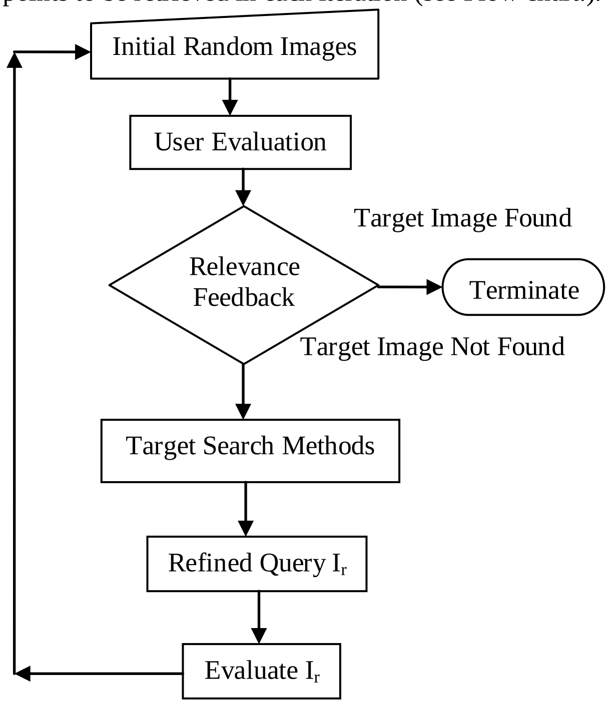

Fig 1. Flow Chart

As discussed earlier, various techniques have been proposed to automatically determine n_I and Q_I as well as adjusting, G_I and F_I for improved retrieval efficiency. For single-point movement techniques, $p_I = 1$; for multiple-point movement techniques, $p_I > 1$. Use of the model (Flow chart) for four typical types of queries: sampling query, constrained sampling query, k-NN query and constrained k-NN query. For a sampling query set $p_I = 0$ and $W^I = W$, for a constrained sampling query, set $p_{I=}$ 0, for a k-NN query with single-point movement techniques, set p_I=1 and W^I=W, for a k-NN query with multiple-point movement techniques, p_I>1 and W^I=W, For a constrained k-NN query with single-point movement techniques, set p_I=1 while for a constrained k-NN query with multiple-point movement techniques, p_I>1. This definition is a generalized version of $I = (p_I, Q_I, G_I, F_I)$ defined in [6], where the search space is assumed to be the whole database for every search. In the generalized definition, W^I is included to account for the dynamic size of the search space, which shrinks gradually after each iteration. Let I_s denote the starting query, I_r a refined query at a feedback iteration, I_t a target query which results in the retrieval of the intended target, and R_d the query result set.

III. TARGET SEARCH METHODS

The goal of proposed target search methods is to try 'to search particular image from a huge set of multimedia data'. In all the four target search methods re-visiting of previously examined images is avoided using the relevance feedback approach (that is by marking retrieved images relevant or irrelevant).

A. *Naive Random Scan Method*

The NRS method randomly retrieves d different images at a time until the user finds the target image or the remaining set is exhausted, see algorithm for NRS. Specifically, at each iteration, a set of 'd' random images is retrieved from the set W^I (i.e. unchecked set of images) for relevance feedback (Step 2 and Step 6), and W^I is then reduced by d (Step 3 and Step 7). Clearly, the naive scan algorithm does not suffer local maximum traps and is able to locate the target image after some finite number of iterations. In the best case, NRS takes one iteration, while the worst case requires $\left\lceil \frac{|W|}{d} \right\rceil$. On an average NRS can find the target in

$$\left[\sum_{i=1}^{\lceil |W|/d \rceil} i / \lceil |W|/d \rceil = (\lceil |W|/d \rceil + 1 \right] \quad (1)$$

iterations. Therefore, NRS is only suitable method for a small database set.

Algorithm for NRS (W, d)

Input: The whole image set 'W' and number of retrieved images at each iteration 'd'
Output: Target image (query) 'q_t'
Step 1: $I_s \rightarrow (0, Q_I, G_I, F_I, W, d)$
Step 2: $R_d \rightarrow$ Evaluated query result set with I_s using randomly retrieved d points in W
Step 3: $W^I \rightarrow (W - R_d)$
Step 4: **while** q_t not found in R_d
Step 5: $I_r \rightarrow (0, Q_I, G_I, F_I, W^I, d)$
Step 6: $R_d \rightarrow$ Evaluated query result set with I_r using randomly retrieved d points in W^I
Step 7: $W^I \rightarrow (W^I - R_d)$
Step 8: **end**
Step 9: **return** 'q_t'

B. *Local Neighbouring Movement Method*

Existing techniques allow already checked images to be reconsidered, which leads to several major drawbacks. Non-re-retrieval strategy is applied to one such method, such as Mind Reader [1], to produce the LNM method. LNM is similar to NRS except Step 5 and Step 6, see algorithm for LNM as follows. Specifically, I_r is constructed such that it moves towards neighboring relevant points and away from irrelevant ones, and a k-NN query is now evaluated against W^I instead of W (Step 5 and Step 6). When LNM encounters a local maximum trap, it enumerates neighboring points of the query, and selects the one closest to the target.

Algorithm for LNM (W, d)

Input: The whole image set 'W' and number of retrieved images at each iteration 'd'
Output: Target image (query) 'q_t'
Step 1: $I_s \rightarrow (0, Q_I, G_I, F_I, W, d)$

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Step 2: $R_d \rightarrow$ Evaluated query result set with I_s using randomly retrieved d points in W
Step 3: $W^l \rightarrow (W - R_d)$
Step 4: **while** q_t not found in R_d
Step 5: $I_r \rightarrow (p_I, Q_I, G_I, F_I, W^l, d)$ based on user's relevance feedback
Step 6: $R_d \rightarrow$ Evaluated query result set with I_r using constrained *k*-NN query
Step 7: $W^l \rightarrow (W^l - R_d)$
Step 8: **end**
Step 9: **return** 'q_t'

Therefore, LNM can overcome local maximum traps, though it may take much iteration to do so. Again, one iteration is required in the best case. To simplify the following worst-case and average-case complexity analysis, it is assume that W is uniformly distributed in the n-dimensional hypercube and the distance between two nearest points unity.

C. Neighbouring Divide-And-Conquer Method

Although LNM can overcome local maximum traps, it does so inefficiently, taking many iterations and in the process returning numerous false outcome. To speed up convergence, Voronoi diagrams are used in NDC to reduce search space. Specifically, NDC searches for the target as follows, see algorithm for NDC. From the starting query I_S, d points are randomly retrieved (Step 2). Then the Voronoi region VR_i is initially set to the minimum bounding box of W (Step 3). In the while loop, NDC first determines the Voronoi seed set R_{d+1} (Step 6 to Step10) and p_i, the most relevant point in R_{d+1} according to the user's relevance feedback (Step 11). Next, it constructs a Voronoi diagram VD inside VR_i using R_{d+1} (Step 12). The Voronoi cell region containing q_i in VD is now the new VR_i (Step13). Because only VR can contain the target, it can safely reduce out the other Voronoi cell regions. To continue the search in VR_i, NDC constructs a k-NN query using q_i as the anchor point (Step 15), and evaluates it (Step 16). The procedure is repeated until the target q_t is found. When NDC encounters a local maximum trap, it employs Voronoi diagrams to aggressively reduce the search space and move towards the target image, thus significantly speeding up the convergence. Therefore, NDC can overcome local maximum traps and achieve fast convergence.

Algorithm for NDC (W, d)

Input: The whole image set 'W' and number of retrieved images at each iteration'd'
Output: Target image (query) 'q_t'
Step 1: $I_s \rightarrow (0, Q_I, G_I, F_I, W, d)$
Step 2: $R_d \rightarrow$ Evaluated query result set with I_s using randomly retrieved d points in W
Step 3: $VR_i \rightarrow$ the minimum bounding box of W
Step 4: iteration $\rightarrow$ 1
Step 5: **while** q_t not found in R_d
Step 6: **if** iteration $\neq 1$ **then**
Step 7: $R_{d+1} \rightarrow R_d + \{q_i\}$
Step 8: **else**
Step 9: $R_{d+1} \rightarrow R_d$
Step 10: **end**
Step 11: $q_i \rightarrow$ the most relevant point from R_{d+1}
Step 12: construct a Voronoi diagram VD inside VR_i using points in R_{d+1} as Voronoi seeds
Step 13: $VR_i \rightarrow$ Voronoi cell region associated with the Voronoi seeds q_i in VD
Step 14: $W^l \rightarrow$ set of the points from W that are inside VR_i except q_i
Step 15: $I_r \rightarrow (1, \{q_i\}, Q_I, G_I, F_I, W^l, d)$
Step 16: $R_d \rightarrow$ Evaluated query result set with I_r using constrained *k*-NN query
Step 17: iteration $\rightarrow$ iteration+1
Step 18: **end**
Step 19: **return** 'q_t'

D. Global Divide-and-Conquer Method

To reduce the number of iterations in the worst case in NDC, GDC method is proposed. Instead of using a query point and its neighboring points to construct a Voronoi diagram, GDC uses the query point and 'd' points randomly sampled from VR_i. Specifically, GDC replaces Step 15 and Step 16 in NDC with, see algorithm for GDC. Similar to NDC, when encountering a local maximum trap, GDC employs Voronoi diagrams to aggressively reduce the search space and move towards the target image, thus significantly speeding up the convergence. Therefore, GDC can overcome local maximum traps and achieve fast convergence.

Algorithm for GDC (W, d)

Input: The whole image set 'W' and number of retrieved images at each iteration'd'
Output: Target image (query) 'q_t'
Step 1: $I_s \rightarrow (0, Q_I, G_I, F_I, W, d)$
Step 2: $R_d \rightarrow$ Evaluated query result set with I_s using randomly retrieved d points in W
Step 3: $VR_i \rightarrow$ the minimum bounding box of W
Step 4: iteration $\rightarrow$ 1
Step 5: **while** q_t not found in R_d
Step 6: **if** iteration $\neq 1$ **then**
Step 7: $R_{d+1} \rightarrow R_d + \{q_i\}$
Step 8: **else**
Step 9: $R_{d+1} \rightarrow R_d$
Step 10: **end**
Step 11: $q_i \rightarrow$ the most relevant point from R_{d+1}
Step 12: construct a Voronoi diagram VD inside VR_i using points in R_{d+1} as Voronoi seeds
Step 13: $VR_i \rightarrow$ Voronoi cell region associated with the Voronoi seeds q_i in VD
Step 14: $W^l \rightarrow$ set of the points from W that are inside VR_i except q_i
Step 15: $I_r \rightarrow (0, Q_I, G_I, F_I, W^l, d)$
Step 16: $R_d \rightarrow$ Evaluated query result set with I_r using randomly retrieved d points in W^l
Step 17: iteration $\rightarrow$ iteration+1
Step 18: **end**
Step 19: return'q_t'

IV. HANDLE INACCURATE RELEVANCE

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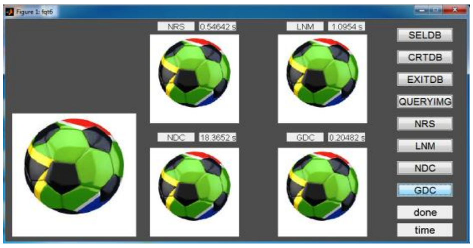
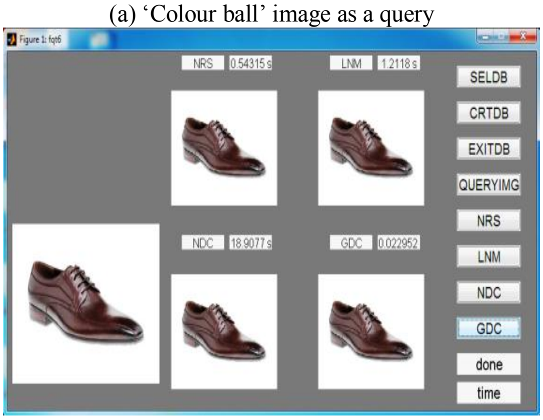
FEEDBACK

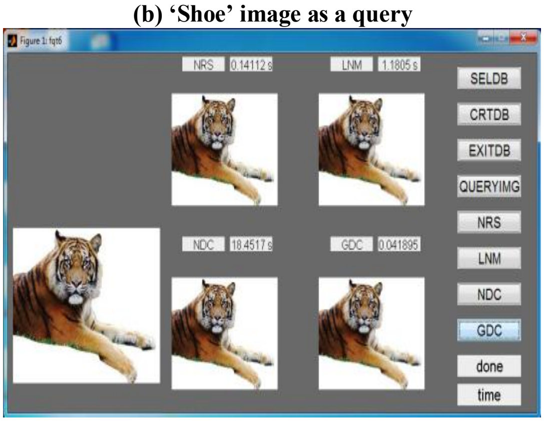
User's inaccurate relevance feedback is a major issue for CBIR systems with RF. It is a need to make the system less sensitive to users' uncertainty. It is assumed that users accurately picked the most relevant image out of the returned images for each iteration. In practice, however, users could make a wrong choice, or they might pick several apparently good choices instead of settling on one in a target search query. Hence, assumption should not make that the system is always presented with correct queries. To deal with this situation, in each iteration, a single query point that is a weighted centroid of all the picked images is constructed, as in MARS and Mind Reader. Detecting user's inaccurate relevance feedback is a difficult and open problem. It should rely on short-term memory, the last few relevance feedbacks to predict the general direction towards the destination, and focus on warning users if their feedbacks seem to be contradictory (our technique is only able to give a summary warning to the user, who may not be able to tell which one among the previous steps is inaccurate). Such a warning points out to the users that their consecutive feedbacks appear contradiction, and is helpful to users in providing a better relevance feedback for the subsequent rounds. To ensure system is less sensitive to user's inaccurate relevance feedback, in design and in implementation the following steps have taken. First, still keep the LNM besides GDC and NDC in the prototype. Although converging slowly, LNM is robust against inaccurate relevance feedback because it basically enumerates the candidate images. Second, the above proposed methods are used to automatically monitor user's feedbacks, and issue warnings if inconsistent behaviors are detected. These warnings prompt the users to re-evaluate their feedbacks.



(a) 'Colour ball' image as a query



(b) 'Shoe' image as a query



(c) 'Tiger' image as a query

Fig.2: GUI Window for All Four Target Search Method

V. RESULT AND DISCUSSION

A. Result

NRS, LNM, NDC and GDC methods find the target image with very fast convergence rate, and avoid local maximum traps. From the figure shown below, it is clear that GDC is faster among all the methods. In Fig.1(a) 'colour ball' image is taken as query, shows that GDC requires 0.2048s time to search the target image, while NDC, LNM and NRS require 18.3652s, 1.0954s and 0.5464s respectively. From the Fig.1(b) and Fig.1(c) in which 'shoe' and 'tiger' images are taken as queries respectively, it is observed that if the query image is changed, the time require to search will be changed but it remains lesser in GDC than the other methods. Hence by changing the query image and calculating the required time to search, different results are obtained but in all the results GDC requires less time than other methods. Table I shown below gives the values of required time to search target image in tabular form and the same is shown in Fig. 1, in which time required to search the target image is less for GDC than other methods.

Table I: Comparison of All Four Methods On The Basis Of Hit Time.

Sr. No.	Method Name	Time Required for Obtaining Target Image (s)		
		Ball	Shoe	Tiger
1.	NRS	00.5464	00.5432	00.1411
2.	LNM	01.0954	01.2118	01.1805
3.	NDC	18.3652	18.9077	18.4517
4.	GDC	00.2048	00.0229	00.0419

B. Discussion

The brief summary of the four target search methods to search target image is shown below;

- NRS takes the randomly retrieved'd' points while proceeding towards the target point. Hence NRS suits to the small set of database.
- LNM takes nearest neighbour points to reach the target point.

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- NDC and GDC exploit Voronoi diagrams to reduce the search space and move towards target point.
- NDC uses the nearest neighbour points and query point to construct a Voronoi diagram.
- GDC uses the randomly retrieved points with query point to construct a Voronoi diagram.

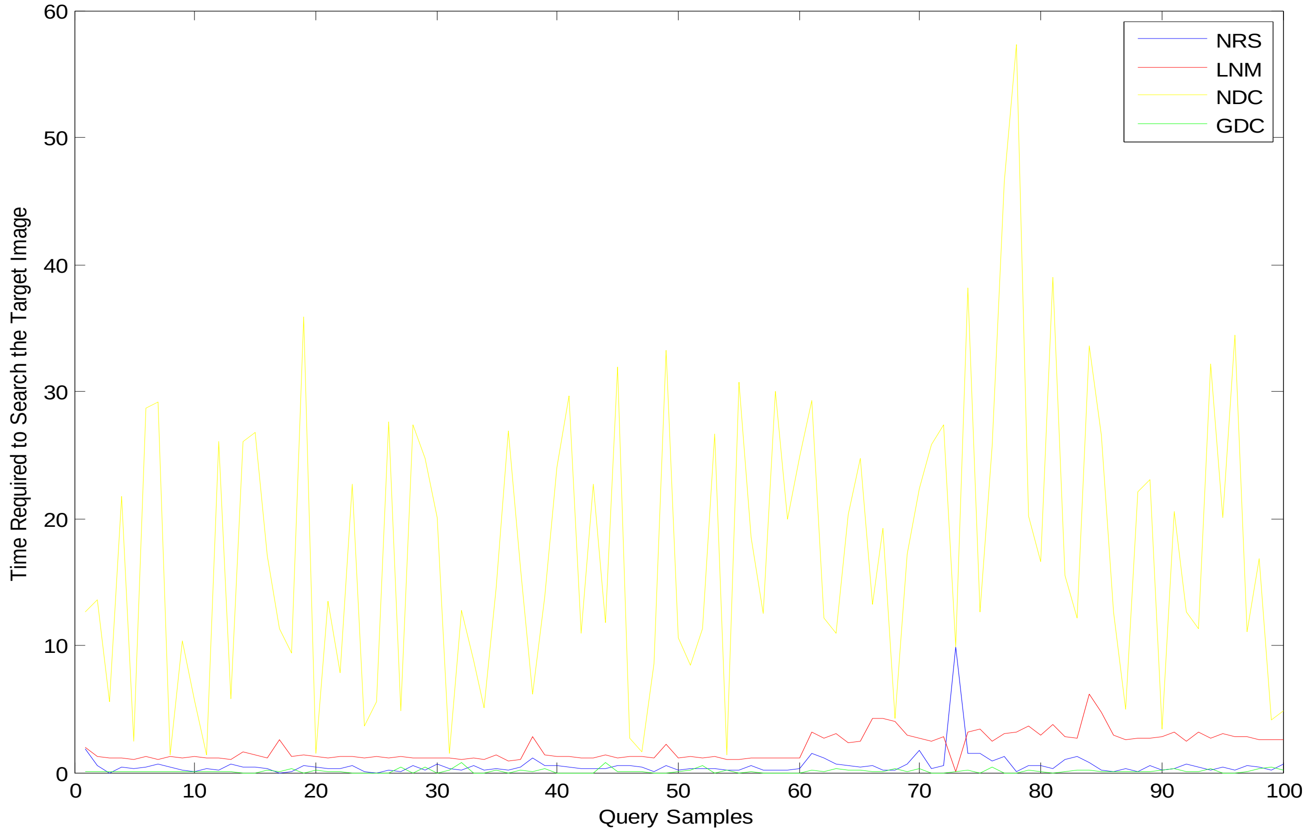

Fig. 3: Comparison of all four methods on the basis of hit time

The Fig. 3 shows the comparison of all four target search methods; NRS, LNM, NDC and GDC on the hit time basis. It is observed that NRS, LNM and GDC just taking fraction of second time to search the target image, but NRS and GDC not guaranty to find the target image always. In contrast LNM and take little more time but find the target image always. In the figure, zero time indicates that target image is not found. The average time for the hundred query samples of each method is: 0.634424s for NRS, 2.132765s for LNM, 14.30369s for NDC and 0.179673s for GDC. The related database and search results of all methods are made available online [10].

VI. CONCLUSION

Target search methods are very efficient ways to search the intended target image from large image database. The use of relevance feedback approach in target search methods gives accurate results. All the four algorithms developed for implementation of target search methods are able to find the intended target image with a very fast convergence rate. It is also found that these four algorithms easily avoid the local maximum traps. Further, using the Voronoi diagram concept in NDC and GDC produces the results within few milliseconds. Both the disadvantages in earlier techniques are overtaken using these four techniques.

VII. FUTURE SCOPE

Currently the CBIR is one of the main research topics, in future, work can be done on object(s) retrieval from video database which can be further used in investigation processes.

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