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Content Based Image Retrieval a Comparative Based Analysis for Feature Extraction Approach

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ABSTRACT
Content Based Image Retrieval is a significant and increasingly popular approach that helps in the retrieval of image data from a huge collection. Image representation based on certain features helps in retrieval process. Here we are using an efficient image retrieval technique which uses dynamic dominant color, texture and histogram features of an image. As a first step an image can be uniformly divided into coarse partitions. The centroid of each partition will be selected as its dominant color after the above coarse partition. A texture representation for image retrieval based on GLCM (Gray Level Co-occurrence Matrix) can be used. Although a precise definition of texture is untraceable, the notion of texture generally refers to the presence of a spatial pattern. Color histogram is the most commonly used color presentation. Color histogram yields better retrieval accuracy. Histogram of an image represents relative frequency of occurrence of various gray levels. It is a spatial domain technique. After that we are applying Euclidean distance, Neural Network and target search methods algorithm for retrieval of images from the database and making a comparison based approach between them to see which method helps in fast retrieval of images in terms of distance and time.

***Keywords* -** Color feature extraction, Euclidean distance, Histogram based extraction, Image database, Neural network, Neighboring Divide-and-Conquer Method and Global Divide-and-Conquer Method, Texture feature extraction, Threshold=800.

I. INTRODUCTION

As the propagation of video and image data in digital form has increased, Content Based Image Retrieval (CBIR) has become a prominent research topic. Therefore an important problem that needs to be addressed is fast retrieval of images from large databases. To find images that are perceptually similar to a query image, image retrieval systems attempt to search through a database. CBIR can greatly enhance the accuracy of the information being returned and is an important alternative and complement to traditional text-based image searching. For describing image content, color, texture and histogram features have been used. Color is one of the most extensively used low-level visual features and is invariant to image size and orientation. Without any other information, many objects in an image can be distinguished solely by their textures. Texture may describe the structural arrangement of a region and the relationship of the surrounding regions and may also consist of some basic primitives. Histogram feature can also be extensively used for retrieval systems. So, CBIR system that is based on dominant color, texture and histogram can be implanted

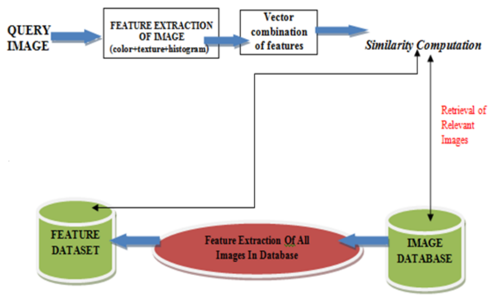

Fig 1: block diagram of cbir working

1.1. Aim and Objective

Content Based Image Retrieval (CBIR) has become a major research area. To search for and browse through video and image databases located at remote sites, increased bandwidth availability will allow the users to access the internet in the near future. Therefore an important problem that needs to be addressed is fast retrieval of images from large databases. Image retrieval systems attempt to search through a database to find images that are perceptually similar to a query image. CBIR can greatly enhance the accuracy of the information being returned and is an important alternative and complement to traditional text-based image searching. It aims to develop an efficient visual content-based technique to search, browse and retrieve relevant images from large-scale digital image collection .Color, texture and histogram features have been used for describing image content. Research and development issues in CBIR cover a range of topics, many shared with mainstream image processing and information retrieval. Some of the objective can be: Extracting color, texture and histogram features from images, providing compact storage for large image databases, matching query and stored images in a way that reflects human similarity judgments.

1.2. Proposed Work

To describe image from the different aspects for more detailed information in order to obtain better search results and to express more image information, here it can be considered the dominant color, texture and histogram features combined. The proposed method is based on dominant color, texture and histogram features of image. After extraction of features from database and saving all the features in feature dataset we apply a query input image where features are extracted from the image and combined in a vector form. Then we have used fast retrieval algorithms such as Euclidean distance, Neural Network and Target methods. After extraction of features a comparisons is made between the three algorithms on the basis of time and distance. Time here in terms means retrieving the images from database and distance means the distance between query image and target images

II. Literature Survey

In number of Content Based Image Retrieval systems are described in alphabetical order, which is mentioned below. If no querying, indexing data structure, matching features or result presentation is mentioned, then it is not relevant to the system, or no such information is known to us.

A. AMORE (Advanced Multimedia Oriented Retrieval Engine)

Developer: C & C Research Laboratories NEC USA, Inc.

Matching: Initially an association among regions in the query and target image is found. Regions associated to the same regions in the other image are fused. The histogram resemblance among two regions is based on the number of pixels of overlap, a type of pattern matching. The distance in HLS space between the uniform region colors act as the color similarity between two regions.

Result presentation: Without an explicit order, the retrieved images are revealed like thumbnails. Result images were displayed as a scatter plot, with histogram and color similarity values at the axes, or on a perspective wall in a research version of the system.

B. BDLP (Berkeley Digital Library Project)

Developer: University of California, Berkeley.

Matching: **T**ext strings are used as storage medium for image features. For instance, a representation of a sky with clouds might have little large white regions, and a large amount of blue, and would have a feature text string ―mostly blue large white few. Matching is done by substring matching, e.g. with query string ―large white%.

Result presentation: The retrieved photos are presented unordered, with id-number, photographer, and collection keys.

C. CANDID (Comparison Algorithm for Navigating Digital Image Databases)

Developer: Computer Research and Applications Group, Los Alamos National Laboratory, USA.

Matching: On the normalized Euclidean distance or the inner product of two signatures, the distinction among two image signatures is based.

Result presentation: Each related Gaussian division makes some involvement to the distinction measure and each pixel is assigned to one cluster. Each pixel is tinted depending on the contribution made to the resemblance measure so as to illustrate which parts of the images contribute to the match.

D. DIOGENES

Developer: Department of EECS, University of Illinois at Chicago.

Matching: String matched with names in the system index built off-line by a web crawler is the query name. A number of distance values were yielded as an image taken from the web is compared to the training images. To situate person names and to decide their degree of involvement with the face image, the text of the web page is analyzed. To a classifier, the distance values and degrees of association are key in, which combines them with a Dempster-Shafer theory of evidence, a generalization of Bayesian theory of subjective probability.

Result presentation: Without any explicit order, the images in the database associated with the query name are shown.

E. FIDS (Flexible Image Database System)

Developer: Department of Computer Science and Engineering, University of Washington, Seattle, WA, USA.

Matching: The L1 distance are the distances between the histograms. Some weighted difference is the distance between wavelet coefficients. By taking the weighted sum, maximum, or minimum of the individual feature distances, which conserve metric properties, an overall distance can be composed.

Result presentation: No accurate distances among query and images require to be considered as the images can be ordered on their lower bound. On the other hand, the user can select of how many of those the true distance must be calculated.

F. PICASSO

Developer: Visual Information Processing Lab, University of Florence, Italy.

Matching: After a fast selection of the database images that contain all the colors of the query, the pyramidal structure of each candidate image is analyzed from top to bottom to find the best matching region for each query region in a query by color regions. By a weighted sum of distances between the computed region attributes (color, region centroid's position, area and histogram), the matching score between a query region and a candidate image region is given. By summing all the scores of the matched query regions, the similarity score between the query image and a candidate image is obtained. First images are filtered according to the spatial relationships and positions of the delimited MERs, based on the 2D string representation in a histogram based query. To the images that have passed this filtering step, 1D elastic matching is applied. The systems warps each contour over the candidate image's histogram located in the same relative position as the query contour, if the sketch contains k contours. Both the match between the deformed contour and the edge image and the amount of elastic energy used to warp the query contour is taken into account by the similarity score between the deformed contour and the image object. In minimizing E – M, a gradient descent technique is used.

Result presentation: In decreasing similarity order, the query results are presented to user.

The font size for **heading is 11 points bold face** and **subsections with 10 points and not bold.** Do not underline any of the headings, or add dashes, colons, etc.

III. PROPOSED APPROACH

Only simple features of image information cannot get comprehensive description of image content. We consider the color, texture and histogram features combining not only be able to express more image information, but also to describe image from the different aspects for more detailed information in order to obtain better search results. The proposed method is based on dominant color, texture and histogram features of image.

Retrieval algorithm is as follows:

Step1: Uniformly divide each image in the database and the Query image into 8-coarse partitions as shown in Fig.2.

Step2: For each partition, the centroid of each partition is selected as its dominant color.

Step3: Obtain texture features (Energy, Contrast, Entropy and homogeneity) from GLCM.

Step4**:** Obtain histogram features of the images in the database as well as for query images.

Step5: construct a combined feature vector for color, texture and histogram features.

Step6: find the distances between feature vector of query image and the feature vectors of target images using weighted and normalized Euclidean distance.

Step7: sort the Euclidean distances and after sorting apply bubble sort to get the most relevant images.

Step8**:** Apply neural network approach and train the data and then again apply Euclidean distance approach on train data to sort the images**.**

Step9: Now apply Target methods on the feature vector of query image and the feature vectors of image database.

Step10: Now we will do a comparative based analysis on three algorithms and see which algorithms retrieves fast relevant images and which algorithm takes less time to retrieves the images.

3.1. Color feature representation

In general, color is one of the most dominant and distinguishable low-level visual features in describing image. Many CBIR systems employ color to retrieve images, such as QBIC system and Visual SEEK. In theory, it will lead to minimum error by extracting color feature for retrieval using real color image directly, but the problem is that the computation cost and storage required will expand rapidly. So it goes against practical application. In fact, for a given color image, the number of actual colors only occupies a small proportion of the total number of colors in the whole color space, and further observation shows that some dominant colors cover a majority of pixels. Consequently, it won't influence the understanding of image content though reducing the quality of image if we use these dominant colors to represent image.In the MPEG-7 Final Committee Draft, several color descriptors have been approved including number of histogram descriptors and a dominant color descriptor (DCD)[4, 6]. DCD contains two main components: representative colors and the percentage of each color. DCD can provide an effective, compact, and intuitive salient color representation, and describe the color distribution in an image or a region of interesting. But, for the DCD in MPEG-7, the representative colors depend on the color distribution, and the greater part of representative colors will be located in the higher color distribution range with smaller color distance. It is may be not consistent with human perception because human eyes cannot exactly distinguish the colors with close distance. Moreover, DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution. We will adopt a new and efficient dominant color extraction scheme to address the above problems [7, 8]. According to numerous experiments, the selection of color space is not a critical issue for DCD extraction. Therefore, for simplicity and without loss of generality, the RGB color space is used. Firstly the image is uniformly divided into 8 coarse partitions, as shown in Fig. 2. If there are several colors located on the same partitioned block, they are assumed to be similar. After the above coarse partition, the centroid of each partition is selected as its quantized color. Let X=(XR,XG,XB) represent color components of a pixel with color components Red, Green, and Blue, and Ci be the quantized color for partition i. After coarse partition of the R, G and B slices we are taking average values of each block. After getting the averages we will combine the averages.

1.3. Extraction of texture of an image

Most natural surfaces exhibit texture, which is an important low level visual feature. Texture recognition will therefore be a natural part of many computer vision systems. In this paper, we propose a texture representation for image retrieval based on GLCM. GLCM [11, 13] is created in four directions with the distance between pixels as one. Texture features are extracted from the statistics of this matrix. Four GLCM texture features are commonly used which are given below. GLCM is composed of

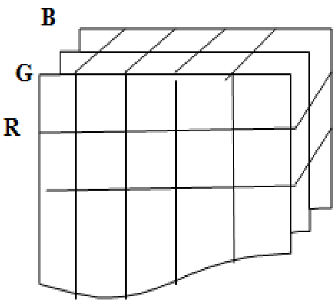

Fig. 2 coarse division of rgb in 8 partitions

the probability value, it is defined by which expresses the probability of the couple pixels at direction and d interval. When and d is determined, is showed by Pi, j. Distinctly GLCM is a symmetry matrix and its level is determined by the image gray-level. Elements in the matrix are computed by the equation shown below:

$$P(i,j|d,\theta)=\frac{P(i,j|d,\theta)}{\sum_i \sum_j P(i,j|d,\theta)}$$

GLCM expresses the texture feature according the correlation of the couple pixels gray-level value at different positions. It quantificationally describes the texture feature. In this paper, four texture features are considered. They include energy, contrast, entropy, homogeneity.

$$\text{Energy} \quad E=\sum_x \sum_y P(x,y)^2$$

It is a texture measure of gray-scale image represents homogeneity changing, reflecting the distribution of image. Gray-scale uniformity of weight and texture.

$$\text{Contrast} \quad I=\sum\sum (x-y)^2 P(x,y)$$

Contrast is the main diagonal near the moment of inertia, which measures how the values of the matrix are distributed and number of images of local changes reflecting the image clarity and texture of shadow depth. Large Contrast represents deeper texture.

$$\text{Entropy} \quad S=-\sum_x \sum_y P(x,y)\log P(x,y)$$

Entropy measures randomness in the image texture. Entropy is minimum when the co-occurrence matrix for all values is equal. On the other hand, if the value of co -occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random.

$$\text{Homogeneity}= \sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$

Homogeneity measures number of local changes in image texture. Its value in large is illustrated that image texture between the different regions of the lack of change and partial very evenly. Here p(x, y) is the gray-level value at the Coordinate (x, y). The texture features are computed for an image when distance =1 and direction =0°, 45°, 90°, 135°. In each direction four texture features are calculated. They are used as texture feature descriptor. Combined feature vector of Color and texture is formulated**.**

1.4. Extraction of Histogram of an image

Color histogram is the most commonly used color presentation. Color histogram yields better retrieval accuracy. Histogram of an image represents relative frequency of occurrence of various gray levels. It is a spatial domain technique.

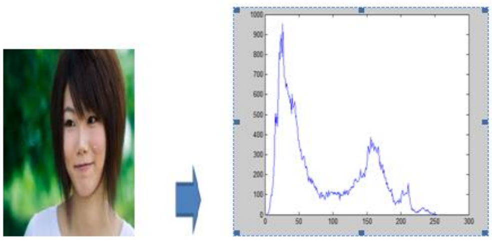

Fig. 3 histogram plotting

1.5. Image Database

The image set comprises 300 images in each of 10 categories. The images are of the size 256 x 384 or 384X256. But the images with 384X256 are resized to 256X384.

1.6. Feature Database
Feature Database contains all the extracted features of all the images present in the image database.

IV. PROPOSED ALGORITHM

4.1. Euclidean Distance

It is used for fast retrieval of target images from the database. The Euclidean distance is the straight-line distance between two pixels. Euclidean distance here is used to match extracted features of query image with the feature database and then finds the images where features are matching with feature database images after match it sorts out that images which are having shortest distance from the query image and gives us the relevant images. We have used pdist that is pairwise distance between pair of objects. The direct Euclidean distance between an image P and query image Q can be given by the equation:

$$ED = \sum_{i=1}^{n} \sqrt{(Vpi - Vqi).(Vpi - Vqi)}$$

1.7. Neural Network approach
In neural network we have both inputs and outputs given and we have to train the neurons to get the exact outputs we required. Here we have given inputs all the extracted features of the images an output is given in the form of 10,20,30……n .Now, we have to train the neurons here. The work flow for the neural network design process has six primary steps:

- ✓ collect data
- ✓ create the network,
- ✓ configure the network,
- ✓ initialize the weights and biases,
- ✓ train the network,
- ✓ validate the network and
- ✓ use the network.

Neural network training can be made more efficient if you perform certain preprocessing steps on the network inputs and targets. In multilayer networks, sigmoid transfer functions are generally used in the hidden layers. These functions become essentially saturated when the net input is greater. If this happens at the beginning of the training process, the gradients will be very small, and the network training will be very slow. In the first layer of the network, the net input is a product of the input times the weight plus the bias. If the input is very large, then the weight must be very small in order to prevent the transfer function from becoming saturated. It is standard practice to normalize the inputs before applying them to the network. Generally, the normalization step is applied to both the input vectors and the target vectors in the data set. In this way, the network output always falls into a normalized range. The network output can then be reverse transformed back into the units of the original target data when the network is put to use in the field. It is easiest to think of the neural network as having a preprocessing block that appears between the input and the first layer of the network and a postprocessing block that appears between the last layer of the network and the output, as shown in the following figure.

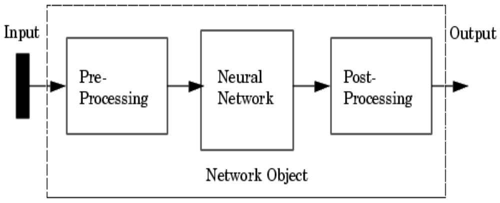

Fig. 4 neural network architecture

4.3. Target methods
4.3.1. Neighboring Divide-and-Conquer Method
To speed up convergence, we propose to use Voronoi diagrams in NDC to reduce search space. The Voronoi diagram approach finds the nearest neighbors of a given query point by locating the Voronoi cell containing the query point.Specically, NDC searches for the target. From the starting query Qs, k points are randomly retrieved (line 2). Then the Voronoi region VRi is initially set to the minimum bounding box of S (line 3). In the while loop, NDC first determines the Voronoi seed set S_k+1 (lines 6 to 10) and pi, the most relevant point in S_k+1 according to the user's relevance feedback (line 11). Next, it constructs a Voronoi diagram VD inside VRi using S_k+1 (line 12). The Voronoi cell region containing pi in V D is now the new VRi (line 13). Because only VRi can contain the target, we can safely prune out the other Voronoi cell regions. To continue the searching VRi, NDC constructs a k-NN query using pi as the anchor point (line 15), and evaluates it (line 16). The procedure is repeated until the target pt is found. When NDC encounters a local maximum trap, it employs Voronoi diagrams to aggressively prune 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.

NEIGHBORING DIVIDE CONQUER(S, k)
Input:
Set of images S
Number of retrieved images at each iteration k
Output:
Target image pt
01 Qs ← h0; PQ; WQ; DQ; S; ki
02 S_k ← EVALUATEQUERY (Qs) /* randomly retrieve k points in S */
03 VRi ← the minimum bounding box of S
04 iter ← 1
05 while user does not find pt in Sk do
06 if iter 6= 1 then

07 $S_k+1 \leftarrow \begin{cases} S_k + pi \\ \end{cases}$
08 else
09 $S_k+1 \leftarrow S_k$
10 endif
11 pi ← most relevant point € S_k+1
12 construct a Voronoi diagram VD inside VRi using points in S_k+1 as Voronoi seeds
13 VRi ← the Voronoi cell region associated with the Voronoi seed pi in V D
14 S0 ← such points € S that are inside VRi except pi
15 Qr ← h1:{ pi } ; WQ; DQ; S0; ki
16 Sk ← EVALUATEQUERY (Qr) /* perform a constrained k-NN query */
17 iter ← iter + 1
18 end do
19 return pt

4.3.2. Global Divide-and-Conquer Method

To reduce the number of iterations in the worst case in NDC, we propose the GDC method. Instead of using a query point and its neighboring points to construct a Voronoi diagram, GDC uses the query point and k points randomly sampled from VRi. Specifically, GDC replaces lines 15 and 16 in NDC with:

15 Qr ← h0; PQ; WQ; DQ; S0; ki
16 Sk ← EVALUATE QUERY (Qr) /* randomly retrieve k points in S0 */

Similar to NDC, when encountering a local maximum trap, GDC employs Voronoi diagrams to aggressively prune 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. In the first iteration, S_k = p1; p2; pg is the result of k = 3 randomly sampled points, of which ps is picked as pi. Next, GDC constructs a Voronoi diagram and searches the V R enclosing ps. At the second iteration, S_k+1 = fps; p4; p5; p6g and p5 is the most relevant point pi. In the third and final iteration, the target point is located.GDC takes 3 iterations to reach the target point.

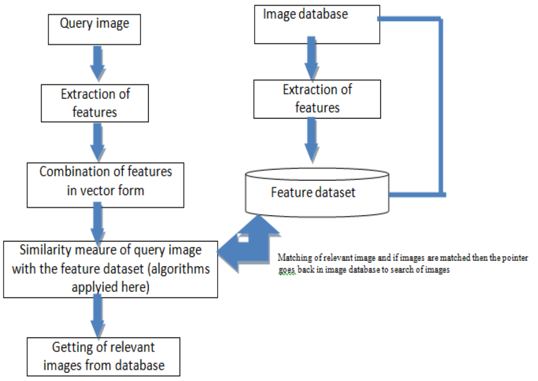

Fig. 5 working of proposed work

V. COMPARISON BASED APPROACH

After we have applied all the algorithms we are going to do a comparative based analysis to see which algorithms retrieves fast relevant images from the database. We have made analysis by using distance and timing approach ,i.e., which algorithm will fastly retrieval the images within short time and having smallest distance between query image and target images. After comparison based approach we have found Euclidean distance find out the relevant images and takes less time than neural and target methods.

VI. RESULT AND CONCLUSION

The algorithm has been implemented in MATLAB-10 in Window 7 and run on CPU 2.80GHz PC. The input images are obtained from Internet. Using the RGB color space as on HSV the accuracy is found to be 92.0%.

Output of Algorithms

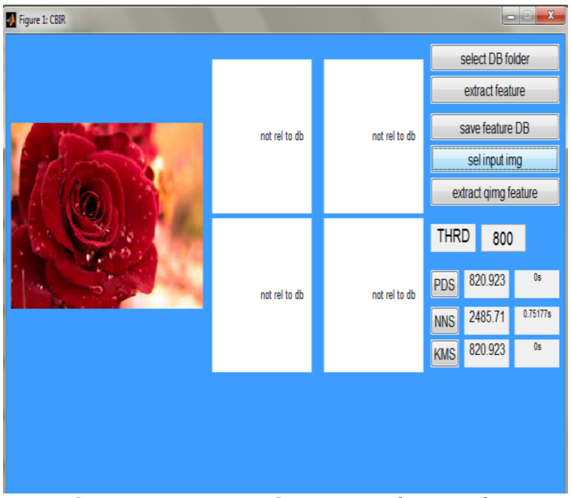

Fig. 6 selecting query image and not getting of images if not related to database by using the algorithms

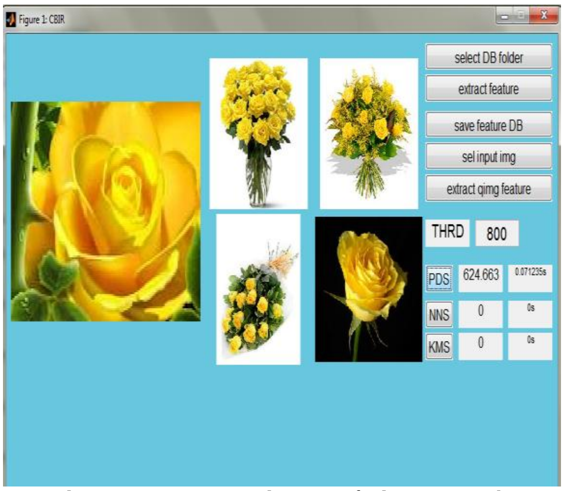

Fig. 7 selecting query image and getting of relevant image by using euclidean distance approach

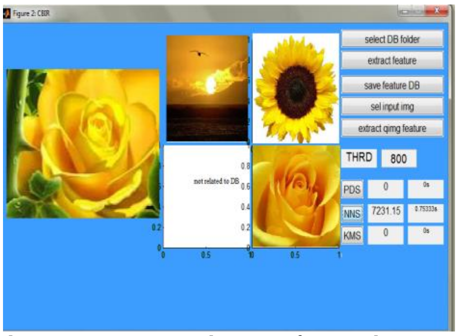

Fig.8 selecting query image and getting of some relevant image by using neural network approach

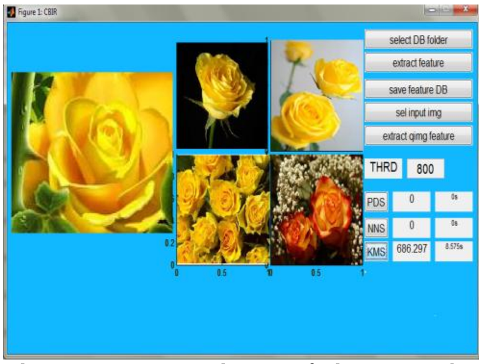

Fig.9 selecting query image and getting of relevant image by using target methods approach

The above figures show that having threshold 800 and by using Euclidean Distance (PDS), Neural Network approach (NNS) and Target Search methods (KMS) we got the relevant images but Euclidean Distance approach gives more perfect images than Neural Network and Target Methods.The time required to retrieve images from database for Euclidean distance is also less than that of Neural Network approach and Target Methods and distance of query image and target images is also less in Euclidean distance than Neural Network approach and Target Methods..

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