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# OCRM: Optimal Cost Region Matching Similarity Measure for Region Based Image Retrieval

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***Abstract***

*Content Based Image Retrieval (CBIR) has been the most significant area in the applications of Pattern recognition and Computer Vision for the last three decades. However, there are many open problems left unresolved. Among these, one of the current problems of CBIR is to obtain an effective Similarity Measure. The CBIR systems make use of Integrated Region Matching (IRM) to match segmented images which is computationally economic, but it is not a metric distance whereas systems that use Minimum Cost Region Matching (MiCRoM) as a similarity measure is a metric distance, but computationally expensive. In order to address the above problem, this paper has developed the Optimal Cost Region Matching (OCRM) similarity measure for region based image retrieval. The proposed OCRM uses the north-west corner rule of the Transportation problem that fulfills the monge property. The experiment carried out on 1000 color images taken from the Corel database that are compared with IRM, and MiCRoM similarity measures.*

***Keywords:*** *IRM, MiCRoM, CBIR, OCRM, Similarity Measure, Transportation problem, Monge condition*

## 1. Introduction

Since 1970`s, the Content Based Image Retrieval (CBIR) has been playing a vital role in the image database management and image retrieval. There is a fast progress in the computer speed and space with the decline in the memory cost, due to which large number of image database are used in various applications like medicine, entertainment, satellite, biometric etc. This in turn made the necessity to search for the image in the image database. The CBIR system is playing an important role in the retrieval of images from large databases [1, 2, 3, 26]. This system [4] examines the images from the database by utilizing pictorial indications. It is well capable and efficiently developed for retrieving images pertaining to the speed and precision. Thus, the system extracts the features from the Query and Target images and measure the similarity among these images based on given features. In Order to represent an image, there are many recent approaches [4, 12, 20, 21, 22] like segmenting the image into a number of regions with the goal to extract the objects in the image. Until now, no supervised segmentation algorithm introduced, to obtain an accurate segmentation and good reasonable results.

The motivation for this paper is to obtain similarity measures [5, 6, 24, 25] for the images that is both optimal and computationally economic. The Integrated Region Matching (IRM)

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[5] is a Similarity Measure for region based image comparison. To utilize the maximum information about an image, IRM integrates the properties of all segmented regions. With each image segmentation, the features like color, shape, size, and the spatial position of the acquired regions extracted. Then the regions matched using the Integrated Region Matching (IRM) similarity measure. This distance measure is not a metric so it cannot use the metric access structures or filtering techniques.

Since the IRM matches the individual regions. The main objective of the similarity distance is to match segmented images. Even though the solutions obtained with every specific regions of image combined, the complete content of the image cannot be compared. To overcome this, the Minimum Cost Region Matching (MiCRoM) metric distance method [6] is used. MiCRoM is a region based Image Retrieval (IR) approach, to match the contents of segmented images. The main objective of MiCRoM is to measure the similarity using the minimum-cost network flow problem for the target and query image. [7, 8, 23]. The use of metric measures is to decrease the search space and number of comparisons and make use of Metric Access methods.

## 2. Proposed Methodology

In the proposed Content Based Image Retrieval CBIR System, feature extraction and representation is the first and foremost step. Then the image partitioned in terms of the fixed number of blocks. Based on the fixed number of blocks, this paper proposed a novel scheme called Optimal Cost Region Matching (OCRM) for the effective and efficient image retrieval that satisfies the human perception in an accurate way. The entire process represented in Figure 1 and explained in detail.

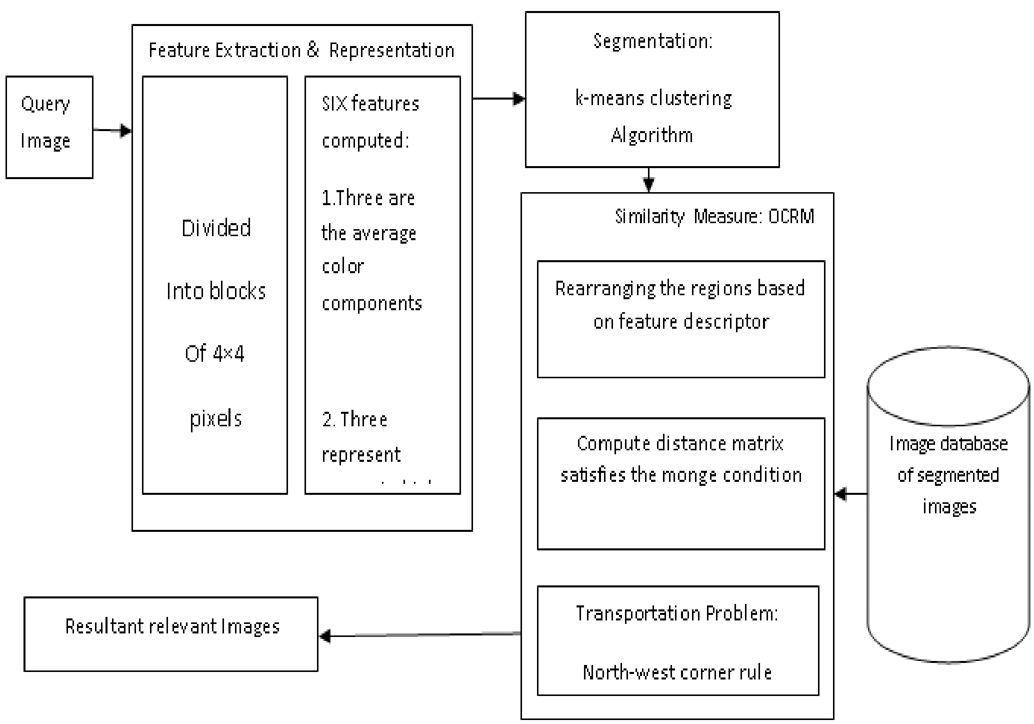


**Figure 1. The OCRM similarity measure**

 

### 2.1. Feature Extraction and Representation

In the first step, the image divided into blocks of 4 × 4 pixels and obtained the feature vector for every block. This block size considered to enhance the effectiveness of color and texture features. The proposed methodology computes six features for each and every block in which three of them are the usual color components in a 4 × 4 block and the other three signify dynamism in high occurrence groups of the wavelet transforms[10,16],i.e. the square root of the second order instant of wavelet coefficients. The LUV color space [14, 15] mentioned in this paper, to extract the color components where L encrypts luminance; U and V encrypt color information (chrominance). The other three features acquired by applying Daubechies-4 wavelet alter to the L component of the image. After one-level wavelet transformation, the 4 × 4 block disintegrated into four frequency bands: LL, LH, HL, and HH bands. Each band contains 2 x 2 coefficients such as $C_{k,l}$ , $C_{k,l+1}$ , $C_{k+1,l}$ $and$ $C_{k+1,l+1}$ are the coefficients of wavelet bands LH, HL and HH). Equation (1) computes the texture feature $f_b$ as follows:

$$f_b = \sqrt{\frac{C_{k,l}^2 + C_{k,l+1}^2 + C_{k+1,l}^2 + C_{k+1,l+1}^2}{4}} \tag{1}$$

Where $b$ is one of the LH, HL, and HH bands .The inspiration for using the features, mined from high frequency bands is that they reproduce texture properties in a proficient way.

### 2.2 Segmentation

The next step in the proposed method is to segment the image in terms of blocks having 64 regions depending on extracted color and texture features, which resemble to the substances present in the image. Here the number of regions fixed to satisfy the properties of monge matrix. The segmentation of images based on color and frequency features using the k-mean's algorithm [13, 17, 18, 19]. The k-means algorithm segment, the feature vectors into numerous groups where every group corresponds to one region of the segmented image. One of the foremost advantages for using the k-means clustering algorithm for dissection is that the blocks in each region need not be neighborhood blocks.

### 2.3 OCRM: Optimal Cost Region Matching Similarity Measure

The proposed OCRM derives a distance matrix that satisfies the monge condition between Region descriptors. For the Distance Matrix, a novel similarity measure derived based on the transportation problem.

**2.3.1 Computation of Monge Distance Matrix:** The Region Descriptors computed, after segmentation from features of the respected regions. Then the regions sorted in an ascending order based on the region descriptor. There will be a rearrangement in the regions and then the distance calculated between the query image and the target image depending on the equation (2).

$$d_{i,j} = |q_i - t_i| \tag{2}$$

Where $d_{i,j}$ is the distance between the region descriptor of the query image and target image $q_i$ is the region descriptor of the $i^{th}$ region of the query image and $t_j$ is the region descriptor of the $j^{th}$region of the target image

 

$$d_{i,j} + d_{i+1,j+1} \le d_{i,j+1} + d_{i+1,j} \tag{3}$$

According to monge property, Equation 3 is always true. Therefore, the $d_{i,\,j}$ obtained after the rearrangement in the regions in the sorted order always satisfies the monge property.

*Proof:*
Assume, $d_{ij} = |q_i - t_j|$

We have to show that,

$$d_{i,j} + d_{i+1,j+1} \le d_{i,j+1} + d_{i+1,j}$$

Note that, $q_i < q_{i+1}$ and $t_j < t_{j+1}$
Since we have sorted the array

Case 1: $q_i \le t_j \le q_{i+1} \le t_{j+1}$
Following defined as: $d_{ij} = t_j - q_i$

$$d_{i+1,j+1} = t_{j+1} - q_{i+1}$$
$$d_{i,j+1} = t_{j+1} - q_i$$
$$d_{i+1,j} = q_{i+1} - t_j$$

Therefore,

$$d_{ij} + d_{i+1,j+1} = t_j - q_i + t_{j+1} - q_{i+1} = t_j - q_{i+1} - q_i + t_{j+1}$$

And

$$d_{i,j+1} + d_{i+1,j} = t_{j+1} - q_i + q_{i+1} - t_j = q_{i+1} - t_j - q_i + t_{j+1}$$

Since in this case $q_{i+1} > t_j$
We have $d_{i,j} + d_{i+1,j+1} \le d_{i,j+1} + d_{i+1,j}$ as required

Similarly, there are five more cases

Case 2: $q_i \le q_{i+1} \le t_j \le t_{j+1}$
Case 3: $t_j \le q_i \le t_{j+1} \le q_{i+1}$
Case 4: $t_j \le t_{j+1} \le q_i \le q_{i+1}$
Case 5: $t_j \le q_i \le q_{i+1} \le t_{j+1}$
Case 6: $q_i \le t_j \le t_{j+1} \le q_{i+1}$

In all these cases, easily shown that

$$d_{i,j} + d_{i+1,j+1} \le d_{i,j+1} + d_{i+1,j}$$

Therefore, the matrix thus generated is a Monge Matrix.

Finally, similarity measure is the essential metric in the course of image retrieval, to choose the effectiveness and efficiency of retrieval techniques**.** A new similarity measure based on the transportation problem called North-West Corner rule, proposed for the distance matrix. The North-West Corner rule, the Lowest Cost Entry rule, and Vogel's method are used for finding the initial feasible solution of the transportation problem. When the distance matrix satisfies the monge property, the North-West Corner rule is the method that gives the optimal solution with less computational time. This rule provides an optimum solution of the transportation problem for all source and demand vectors 'a' and 'b' with $\sum_{i=1}^{m} a_i = \sum_{j=1}^{n} b_j$ only if the cost matrix, C is a Monge Matrix [8, 9, 11]. Given $m \times n$ cost matrix C with items from R, a nonnegative source vector $a = (a_1, \ldots a_m)$ and a nonnegative demand vector $b = (b_1, \ldots b_m)$ such that $\sum_{i=1}^{m} a_i = \sum_{j=1}^{n} b_j$, the Classical Hitchcock Transportation Problem (TP) can formulated as follows:

$$\min \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} x_{ij}$$

$$s.t. \sum_{j=1}^{n} x_{ij} = a_i \quad for\ all \quad i = 1, \ldots.., m,$$

$$\sum_{i=1}^{m} x_{ij} = b_j \quad for\ all \quad j = 1, \ldots.., n,$$

$$x_{ij} \geq 0 \quad for \quad all \quad i, j.$$

An example of a test case images having five regions shown. The Table 1 and 2 shows the region descriptor values and area size of the query and target images. The distance matrix obtained from the region descriptor of the query image and target images shown in the Table 3. The distances computed for the Table 3 using IRM, MiCRoM, and the North-west corner method listed in Table 4. From the Table 4, it is evident that the MiCRoM similarity measure using Lowest Cost entry rule gives the optimal distance.

The Table 5 and 6 shows the region descriptor values after sorting by the proposed method of query and target images respectively. The Table 7 shows the distance matrix formed by the proposed method, which satisfies the monge property. The distances computed from the Table 7 using IRM, MiCRoM, and Optimal Cost Region Matching (OCRM) similarity measure using the North-west Corner method listed in Table 8. From the Table 8, it is evident that the optimal solution obtained from MiCRoM and OCRM similarity measures. The MiCRoM yielded the optimal solution after three iterations whereas the proposed OCRM yield the same optimal solution with the single iteration. Therefore, the proposed method is better than the other methods.

**Table 1. The query image: regions, Region descriptors, and areas**

| Regions | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Descriptors | 8 | 6 | 7 | 2 | 8 |
| Areas | 0.15 | 0.1 | 0.1 | 0.3 | 0.35 |

**Table 2. Target image: regions, region descriptors and areas**

| Regions | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Descriptors | 9 | 2 | 7 | 3 | 1 |
| Areas | 0.25 | 0.2 | 0.15 | 0.2 | 0.2 |

 

**Table 3. The Distance matrix of the query image and target image**

| regions | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| **1** | 1 | 6 | 1 | 5 | 7 |
| **2** | 3 | 4 | 1 | 3 | 5 |
| **3** | 2 | 5 | 0 | 4 | 6 |
| **4** | 7 | 0 | 5 | 1 | 1 |
| **5** | 1 | 6 | 1 | 5 | 7 |

**Table 4. Distances between query and target images**

| **Similarity measure** | **Method** | Distance(Q,T) |
|---|---|---|
| IRM | Lowest cost entry rule | **2.2** |
| MiCRoM | Optimal solution of Lowest cost entry rule | **1.9** |
| **-** | North-west Corner Method | **3.9** |

**Table 5. Query image: regions, region descriptors and areas**

| Regions | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Descriptors | 2 | 6 | 7 | 8 | 8 |
| Areas | 0.3 | 0.1 | 0.1 | 0.15 | 0.35 |

**Table 6. Target image: regions, region descriptors and areas**

| Regions | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Descriptors | 1 | 2 | 3 | 7 | 9 |
| Areas | 0.2 | 0.2 | 0.2 | 0.15 | 0.25 |

**Table 7. The Distance matrix of the query image and target image**

| regions | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| **1** | 1 | 0 | 1 | 5 | 7 |
| **2** | 5 | 4 | 3 | 1 | 3 |
| **3** | 6 | 5 | 4 | 0 | 2 |
| **4** | 7 | 6 | 5 | 1 | 1 |
| **5** | 7 | 6 | 5 | 1 | 1 |

 

**Table 8. Distances between query and target images**

| **Similarity measure** | **Method** | Distance(Q,T) |
|---|---|---|
| IRM | Lowest cost entry rule | 2.0 |
| MiCRoM | Optimal solution of Lowest cost entry rule | **1.9** |
| OCRM | North-west Corner Method | **1.9** |

## 3. Experimental Results

The proposed OCRM tested with the general-purpose image database from COREL consisting of nearly 1000 images. These images are stored in JPEG format with size 384 x 256 or 256 x 384. According to the k means clustering algorithm each image obtains 64 Regions with 6 features for each cluster. When a query image is given, its features computed and the image segmented into 64 Regions. The segmented query image then compared against each of the segmented images stored in the database using IRM, MiCRoM and the proposed OCRM methods. The ten closest images from the database retrieved as similar images to the query image.

The Figures 2, 3 and 4 show the results of IRM, MiCRoM and OCRM methods respectively for top ten retrieved images for the query image #200 (Building image). The Table 9 shows the results of the query image #200 in the recovery process. The Table 10 and Figures 5, 6 shows Precision $v_{s.}$ a number of images returned and Precision $v_s$ recall plots for the query image #200. The retrieved results in the Table 9, 10 and Figures 5, 6 show that the OCRM and MiCRoM gives the equal results whereas IRM gives less precision and recall value for top 5 ,10 and 20 images

The Figures 7, 8 and 9 show the results of IRM, MiCRoM and OCRM similarity measures for 10 retrieved images respectively of the query image #524(Elephant image). The Table 11 shows the results for the query image #524 in the retrieval process. The Table 12 and Figures 10, 11 shows Precision $v_{s.}$ a number of images returned and Precision $v_s$ recall plots for the query image #524. The retrieved results in the Table 11, 12 and Figures 10, 11 show that the OCRM and MiCRoM gives the equal results whereas IRM gives less precision and recall value for top 5 and 10 images.

The Figures 12, 13 and 14 show the results of IRM, MiCRoM and OCRM methods for 10 retrieved images respectively of the query image #618(Flower image). The Table 13 shows the results for the query image #618 in the retrieval process. The Table 14 and Figures 15, 16 shows Precision $v_{s.}$ a number of images reverted and precision $v_s$ recall plots for the query image #618.

Finally, the results retrieved in the Table 13, 14 and Figures 15, 16 represent that IRM, MiCRoM and OCRM retrieve same result for top 5 and 10 images whereas for top 20 images, IRM gives comparatively less precision and recall value compared to MiCRoM and OCRM.

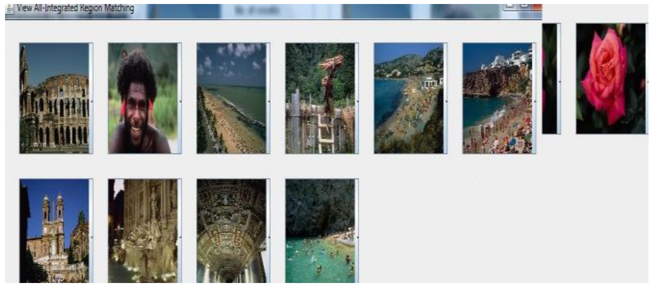


**Figure 2. The ten relevant images of the query image #200, using IRM**

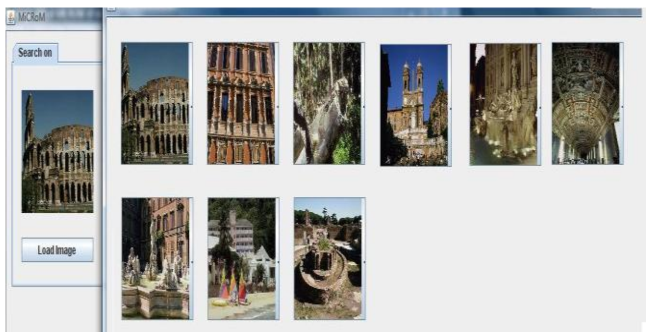


**Figure 3. The ten relevant images of the query image #200, using MiCRoM**

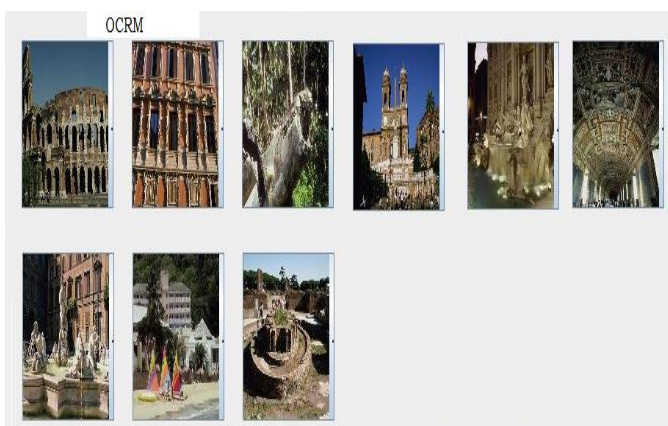


**Figure 4. The ten relevant images of the query image #200, using OCRM.**

**Table 9. The Retrieval results of the query image #200**

| Query #200 | IRM | MiCRoM | OCRM |
|---|---|---|---|
| 5 | 1 | 4 | 4 |
| 10 | 4 | 8 | 8 |
| 20 | 6 | 13 | 13 |

**Table 10. The precision of image #200**

| Query #200 | IRM | MiCRoM | OCRM |
|---|---|---|---|
| 5 | 0.2 | 0.8 | 0.8 |
| 10 | 0.4 | 0.8 | 0.8 |
| 20 | 0.3 | 0.65 | 0.65 |

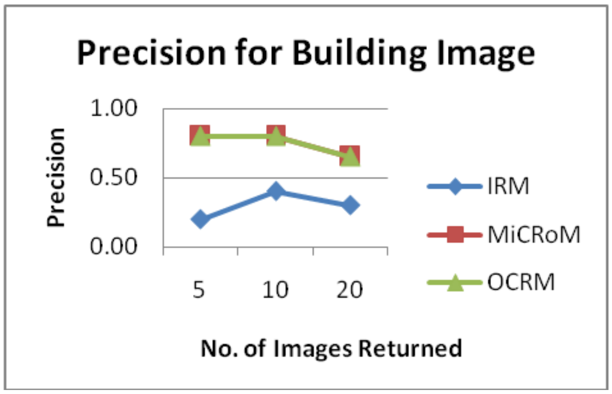


**Figure 5. The Precision for the query image #200**

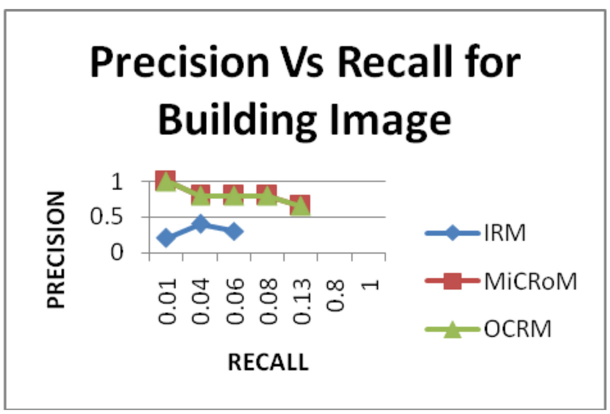


**Figure 6. The Precision vs. Recall for the query image #200(Building)**


**Figure 7. The ten relevant images of the query image #524, using IRM**

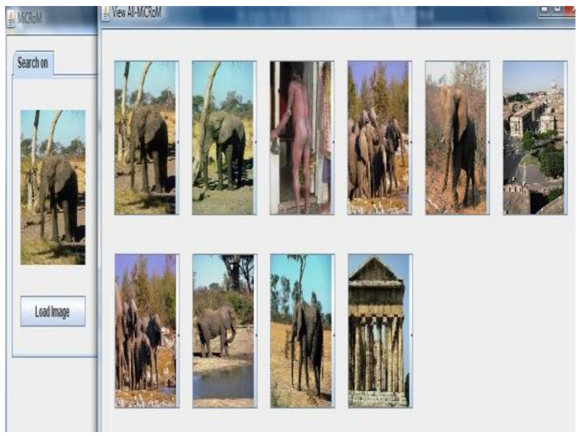


**Figure 8. The ten relevant images of the query image #524, using MiCRoM**


**Figure 9. The ten relevant images of the query image #524, using OCRM**

**Table 11. The Retrieval results of the query image #524**

| Query #524 | IRM | MiCRoM | OCRM |
|---|---|---|---|
| 5 | 3 | 4 | 4 |
| 10 | 6 | 7 | 7 |
| 20 | 13 | 13 | 13 |

**Table 12. The Precision of image #524**

| Query #524 | IRM | MiCRoM | OCRM |
|---|---|---|---|
| 5 | 0.6 | 0.8 | 0.8 |
| 10 | 0.6 | 0.7 | 0.7 |
| 20 | 0.65 | 0.65 | 0.65 |

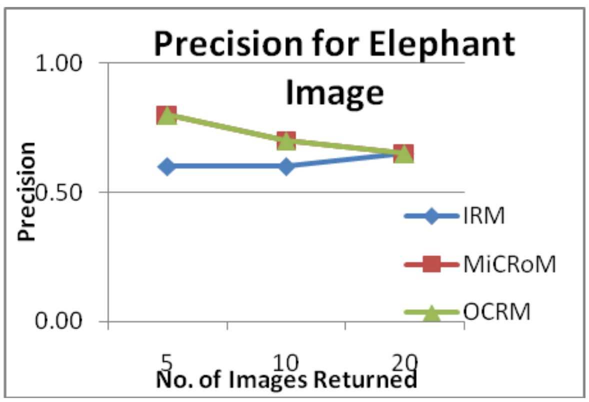


**Figure 10. The Precision for query image #524**

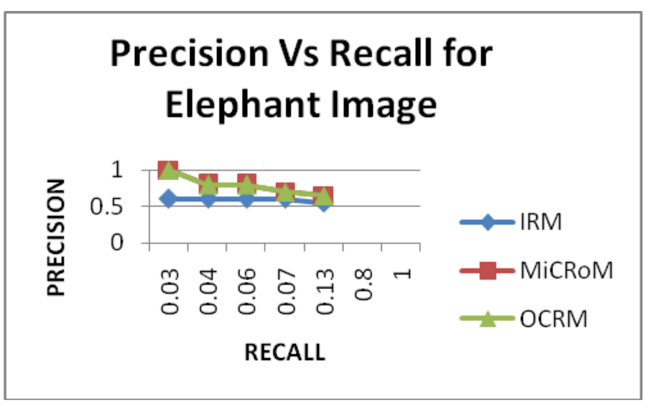


**Figure 11. The Precision Vs Recall for query image #524(Elephant)**

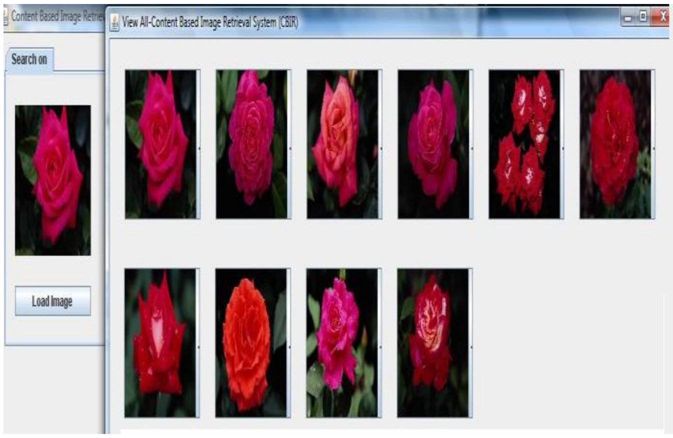


**Figure 12. The ten relevant images of the query image #618, using IRM**

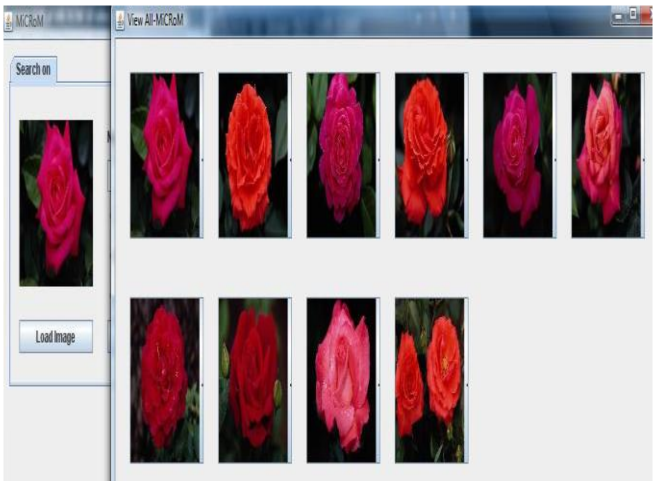


**Figure 13. The ten relevant images of the query image# 618, using MiCRoM**


**Figure 14. The ten relevant images of the query image #618, using OCRM**

**Table 13. The Retrieval results of the query image #618**

| Query #618 | IRM | MiCRoM | OCRM |
|---|---|---|---|
| 5 | 5 | 5 | 5 |
| 10 | 10 | 10 | 10 |
| 20 | 18 | 20 | 20 |

**Table 14. The Precision of image #618**

| Query #618 | IRM | MiCRoM | OCRM |
|---|---|---|---|
| 5 | 1 | 1 | 1 |
| 10 | 1 | 1 | 1 |
| 20 | 0.9 | 1 | 1 |


**Figure 15. The Precision for the query image #618**

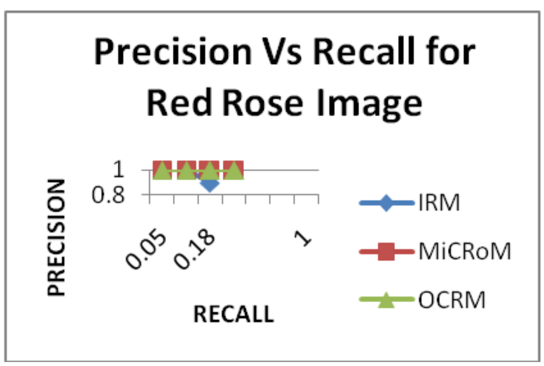


**Figure 16. The Precision vs. Recall for the query image #618(Red Rose)**

## 4. Conclusion

The experimental results proved that the proposed OCRM method, and obtains optimum solutions with less number of iterations. Tables and graphs clearly indicate that for all images, the IRM gives comparatively less precision and recall value compared to that of MiCRoM and OCRM. Even though MiCRoM and OCRM are superior to that of IRM, OCRM is computationally economic than the other two. The OCRM similarity measure gives a metric distance, which is computationally inexpensive. This method successfully proved that after a rearrangement of regions in sorted order it always satisfies the monge condition. The North-West corner rule provides an optimum solution to the transportation problem only if the distance matrix fulfills the monge condition. This measure also satisfies with the human observation of similarity and is easily computable. As a result, the OCRM always obtains an optimal distance measure that is efficient and is computationally economic.

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