

IHBM: Integrated Histogram Bin Matching For Similarity Measures of Color Image Retrieval

V. Vijaya Kumar¹, N. Ganeswara Rao², A.L.Narsimha Rao³, and V.Venkata Krishna⁴

¹*Professor & Dean, Department of CSE, G.I.E.T., Rajahmundry,
JNT University Kakinada, A.P., India.*

²*Research Scholar and Associate Professor, Dept of CSE, Gudlavalleru Engg.College,
Gudlavalleru, JNT University Kakinada, A.P., India.*

*Professor & Head, Department of CSE, Satya college of Engineering & Technology,
Palwal, Delhi NCR. INDIA*

⁴*Professor & Principal, C.I.E.T., Rajahmundry, JNT University Kakinada, A.P., India.
vijayvakula@yahoo.com, vijay.gnani@gmail.com, vakula_krishna@yahoo.co.in*

Abstract

The selection of “proper similarity measure” of color histograms is an essential consideration for the success of many methods. The Histogram Quadratic Distance Measure (HQDM) is a metric distance. Till today, this method is supposed to be the better choice, But it holds a disadvantage that it can compute the cross similarity between all elements of histograms. Therefore, computationally it is more expensive. This paper proposes a method that is known as Integrated Histogram Bin Matching (IHBM) which is also a metric method, and overcomes the disadvantages of the HQDM. The proposed IHBM first matches the closest Histogram Bin Pair according to the distance matrix determined from color histograms, which satisfies the Monge condition. After matching histogram bins, the similarity measure is computed as a weighed sum of the similarity between histogram bin pairs, with weights determined by the matching scheme. The proposed IHBM is experimented on 1000 color images and results are compared with the existing methods.

Keywords: Image Retrieval, Similarity Measures, Histogram based Image Retrieval

1. Introduction

Now a days in the field of multimedia technology, the Content based Image retrieval (CBIR) is proved to be one of the most exciting and fastest growing research area [1, 2, 3, 4, 5]. The progress in automatic feature extraction and image content analysis had accelerated the development of new functionalities for searching, filtering, and accessing images based on perceptual features like color [6, 7, 8, 10], texture [9, 26] shape [10, 11], and spatial composition [12]. The CBIR system retrieves the relevant images from the Image database, thus it addresses the problems of text based annotation system with high precision and recall. Further, it also reduces the semantic gap between user and the system. Though the perceptual features just like color distributions and color layout provide a poor analysis of the actual semantic content of the images, the content based query proved to be the best system for indexing and accessing images based on the similar visual features. In the literature, a good number of prototypes for image retrieval systems are proposed [1,2,5,13,14] which include Diogenes, Atlas, WISE, Image Rover, Web Seek, Image Scape, Web Seer, PictoSeek, WebMars, etc.

One of the most commonly adopted technique for the applications related to Content Based Image Retrieval and Pattern Recognition, is itself histogram matching technique [15]. Any two patterns can be matched by matching corresponding histograms. The size of the histogram will be determined basically by the number of features and the resolution taken by each feature. The retrieval effectiveness is the crucial factors to value of the Histogram metrics. The Retrieval effectiveness exhibits the efficiency of histogram metric in capturing the subject. By measuring the impact in retrieving images, which are perceptually equal to query images, indicates perceptual image dissimilarity.

The demerits of Minkowski-form metrics [18] can be achieved by comparing only “like” bins. Quadratic form metrics [16, 18, 19], cross relation of the so called bins should be taken into account. By using pair wise weighting factors, the quadratic form metrics would compare all bins and weight of the inter bin distance. A quadratic-form metric for histogram based image retrieval [16] was developed by the IBM QBIC system [5, 6]. It is helpful to compare the cross bins, which require $O(n^2)$ operations for implementation. That is why it is more expensive. Hence, the proposed method, Integrated Histogram Bin Matching (IHBM) would lend its help to overcome the shortcomings of the Histogram Quadratic Distance Measure.

The remainder of the paper is organized as follows: Section (2) focuses on existing Histogram similarity measures, Section(3) focus on proposed IHBM, section(4) describes experimental Result, and section(5) describes the Conclusions.

2. Overview of Existing Methods

This section presents some of the popularly existing histogram similarity measures [16, 18, 19], namely, Histogram Intersection (HI), Histogram Euclidean Distance (HED) and Histogram Quadratic Distance Measures (HQDM).

2.1 Histogram Intersection (HI)

Histogram Intersection [18, 19] is for color image retrieval and to find known objects within images using color histograms,

$$D_{HI}(q,t) = \sum_{i=0}^{M-1} |h_q(i) - h_t(i)|$$

Where $D_{HI}(q,t)$ is the distance between query image q and target image t , and h_q and h_t are the color histograms of query and the target images respectively and m is the number of bins of histogram.

2.2 Histogram Euclidean Distance (HED)

The Euclidean distance [18, 19] is, as follows: given histograms h_q and h_t

$$D_{HED}(q,t) = (h_q - h_t)^T (h_q - h_t) = \sum_{i=0}^{M-1} (h_q(i) - h_t(i))^2$$

$D_{HED}(q,t)$ is the distance between query image q and target image t , and h_q and h_t are the color histograms of query and the target images respectively, moreover, M is the number of bins of histogram.

The Figure.1 shown below represents the Minkowski distance measures stated above.

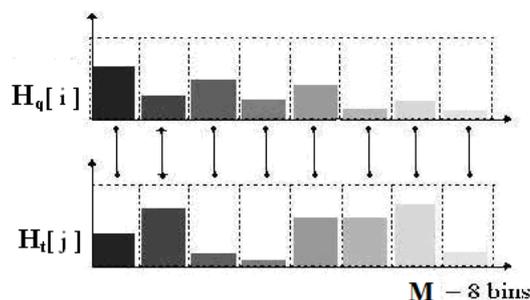


Figure 1. The Minkowski distance measures

2.3 Histogram Quadratic Distance Measures (HQDM)

A Histogram Quadratic Distance Measure is used in IBM QBIC system for color histogram based image retrieval [16,18,19]. In [19], it is reported that quadratic distance metric between color histograms provides more desirable results than "like-bins" that are only comparisons between color histograms. The quadratic form distance between histograms \$h_q\$ and \$h_t\$ given by

$$D_{HQDM}(q,t) = (h_q - h_t)^T A (h_q - h_t)$$

Where \$D_{HQDM}(q,t)\$ is the distance between query image \$q\$ and target image \$t\$, and \$h_q\$ and \$h_t\$ are the color histograms of query and the target images respectively and \$A = [a_{ij}]\$ and \$a_{ij}\$ denotes the similarity between image histograms with bins \$i\$ and \$j\$. The Quadratic form metric is a true distance metric when \$a_{ij}=a_{ji}\$ and \$a_{ii}=1\$.

The HQDM is computationally more expensive than the Minkowski form metrics since it computes the cross similarity between all histogram bins as shown in Figure.2.

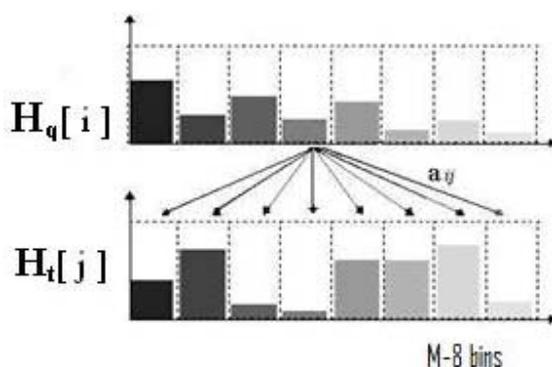


Figure 2. The quadratic distance measure

3. Proposed Method

The three main steps of the Proposed method is given below

1. Conversion of RGB space into HSV space for Quantization.

2. Compute the inter-bin distances matrix HISTd (Q, T) between all pairs of images. Where HISTd (Q, T) satisfies the monge property as given in equation 1, Q is query image and T is target image.
3. Computation of similarity measure using the proposed approach IHBM.

3.1.1 HSV Color Space

The determination of the optimum color space is an open problem, certain color spaces have been found to be well suited for the content-based query-by-color. The proposed method used HSV(Hue, Saturation and Value) Color space, because it is natural and is approximately perceptually uniform.

3.1.2 HSV Quantization

HSV Quantization gives 18 hues, 3 saturations, 3 values, and 4 gray levels, which results 166 bins[19,20] for each image. Then color histogram is computed for 166 bins, and then it is normalized.

3.2 Distance between histogram bins

To compute the distance between a bin pair, HISTd (Q_i, T_j) is determined by the color characteristics of the histogram bins[20]. HISTd (Q_i, T_j) can be computed a priori, independent of the Query image and target images. A Monge distance matrix D_{Q,T} is computed from the HISTd (Q_i, T_j) which is constant[25]. This distance matrix satisfied Monge condition i.e. $m \times m$ matrices $D_{Q,T} = [d_{i,j}]$ which fulfill the so-called Monge property[21] given in equation 1.

$$d_{i,j} + d_{i+1,j+1} \leq d_{i,j+1} + d_{i+1,j} \quad \text{--- (1)}$$

$$\text{where } 1 < i < m, 1 < j < m$$

Distance matrix D_{Q,T} satisfies the discrete Monge condition. Then Hoffmann [25] pointed out that greedy approach gives an optimal solution.

3.3.1 Integrated Histogram Bin Matching (IHBM)

IHBM (Integrated Histogram Bin Matching), is a novel metric Similarity measure to compare the color feature of quantized images. The main idea of this, consists of modeling the comparison of color-quantized images as a Transportation problem [21,22,23,24]. Transportation model deals with the determination of a minimum-cost plan for transporting a commodity from a number of supply nodes to a number of demand nodes.

At the time of the Partition the nodes are divided into two sets m and n, where nodes in m are supply nodes and nodes in n are demand nodes, and for each arc (i, j), i is in m and j is in n. Let Z denote total transportation cost, let x_{ij} denote the no. of units shipped from supply node i to demand node j, and c_{ij} denote the cost of shipping a unit shipped from supply node i to demand node j.

The general form of the Transportation problem is then

$$\begin{aligned} \text{Minimize } Z &= \sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij} \\ \sum_{j=1}^n x_{ij} &= s_i \quad \text{for all } i = 1, 2, \dots, m \\ \sum_{i=1}^m x_{ij} &= d_j \quad \text{for all } j = 1, 2, \dots, n \\ x_{ij} &\geq 0 \quad \text{for all } i \text{ and } j \end{aligned}$$

where s_i denotes Supply Constraints and d_j denotes demand Constraints.

For matching histogram bins of two images, the closest histogram bin pair is considered first. If the bins are of the same size then the two most similar bins are matched otherwise a partial match occurs. This process is repeated until all the histogram bins are matched completely. After matching histogram bins, the similarity measure is computed as a weighted sum of the similarity between histogram bin pairs, with weights determined by the matching scheme. This is known as Integrated Histogram Bin Matching (IHBM), which emphasizes the integration of histogram bins in the retrieval process. The Figure.3 represents the similarity measure mechanism of the proposed IHBM approach with 8 bins.

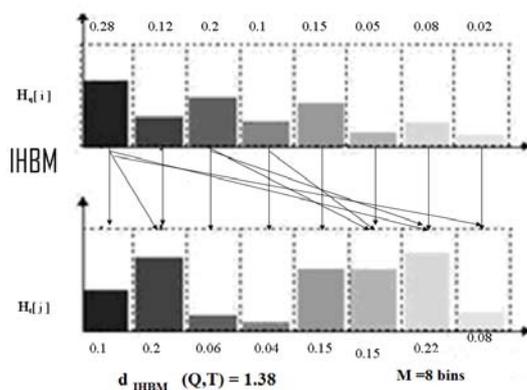


Figure 3. IHBM approach

3.3.2 Algorithm

```

BEGIN
1  DQ,T = HISTd (Q, T)
2  Detect and compute the Monge sequence
   di,j + di+1,j+1 ≤ di+1,j + di,j+1
3  for each pair of histogram Bins Qi ∈ Q and Tj ∈ T
4  Qi.status = 0
5  Tj.status = 0
6  sort out the computed distances DQ,T in non-decreasing order
7  DIHBM = 0
8  for each distance DQ,T in non- decreasing order
9    if Qi.status = Tj.status = 0
10     if Qi.size < Tj.size
11       w = Qi.size
12       Tj.size = Tj.size - w

```

```

13         Qi. status = 1
14     else
15         w = Tj. size
16         Qi. size = Qi. size - w
17         Tj. status = 1
18         if Qi. size = 0 then Qi. status = 1
19     DIHBM = DIHBM + w × DQ,T
20 END
    
```

3.3.3 Metric property

To prove the proposed similarity measure, $D_{IHBM}(Q,T)$ satisfies the conditions : non-negativity, commutative and triangle inequality, the following proofs are given.

1. $D_{IHBM}(Q,T)$ has non-negativity property: $D_{IHBM}(Q,T) \geq 0$.

Proof: $D_{IHBM}(Q,T)$ is nothing but the sum of $D_{Q,T}$ and each $D_{Q,T}$ has non-negativity property. Therefore, $D_{IHBM}(Q,T)$ also has the non-negativity by definition.

2. $D_{IHBM}(Q,T)$ has commutative property: $D_{IHBM}(Q,T) = D_{IHBM}(T,Q)$.

3. D_{IHBM} satisfies the triangle inequality property:

$$D_{IHBM}(P,Q) \leq D_{IHBM}(Q,R) + D_{IHBM}(R,P) .$$

Proof. Let the assignments $P_i \rightarrow Q_i$ be the assignments of $D_{IHBM}(P,Q)$. Let $Q_i \rightarrow R_i$ be the assignments of $D_{IHBM}(Q,R)$. Then P_i is assigned to Q_j by $P_i \rightarrow Q_i \rightarrow R_i$. Now by considering $D_{P,R} \leq D_{P,Q} + D_{Q,R}$ because D has Monge property. And $D_{IHBM}(P,Q)$ is an optimal greedy solution satisfies Monge Sequence. Since $D_{IHBM} = D_{IHBM} + w \times D$,then $D_{IHBM}(P, R) \leq D_{IHBM}(Q, R) + D_{IHBM}(R, P)$. Therefore $D_{IHBM}(P, Q) \leq D_{IHBM}(Q, R) + D_{IHBM}(R, P)$.

4. Experimental Results

The proposed method IHBM and Histogram Intersection (HI), Histogram Euclidean Distance (HED) and Histogram Quadratic Distance Measures (HQDM) are applied on the following red rose flower, elephant and horse image. The retrieval effectiveness is measured, based on the Precision rate of all the four methods considered and they are listed in the tables. Recall measure that indicates the proportion of the relevant images returned is also evaluated for all the images considered, on all the four methods.

The Query image and retrieved relevant images of red rose, elephant and horse images are shown in Figure. 4, 7 and 10 respectively for all the four methods considered.

The precision Vs the number of images returned and precision Vs Recall for the red rose, elephant and horse images are plotted for the four methods considered in the Figure.5,6, 8,9 and 11,12 respectively.

Query 1: Red rose



Figure 4. The results of the query image and retrieved relevant images of HI, HED, HQDM and IHBM methods for the image Red rose

Table1. Precision for TOP 5, 10 and 20 images

Red rose	HI	HED	HQDM	IHBM
TOP 5	5	4	5	5
TOP 10	10	9	10	10
TOP 20	18	15	18	19

The Table 1 clearly indicates the IHBM, HI and HQDM methods show similar results which are superior than HED method for Top 5 and Top 10 red rose images. For TOP 20 red rose images, IHBM outperforms the other three methods.

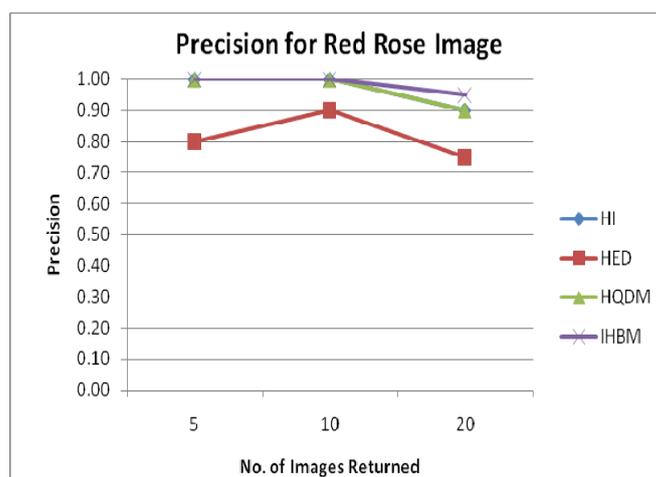


Figure 5. Precision Vs No. of Images returned for Red rose image

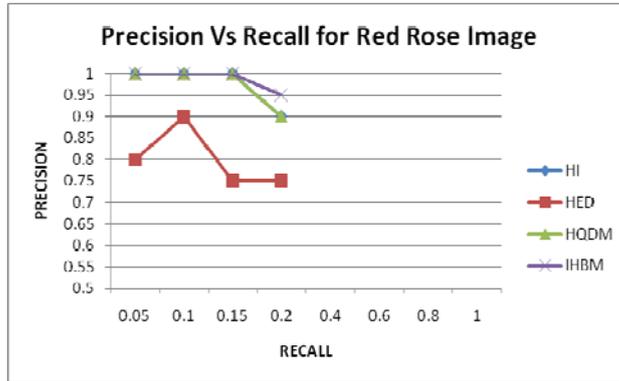


Figure 6. Precision Vs Recall for red rose image

Query 2: Elephant

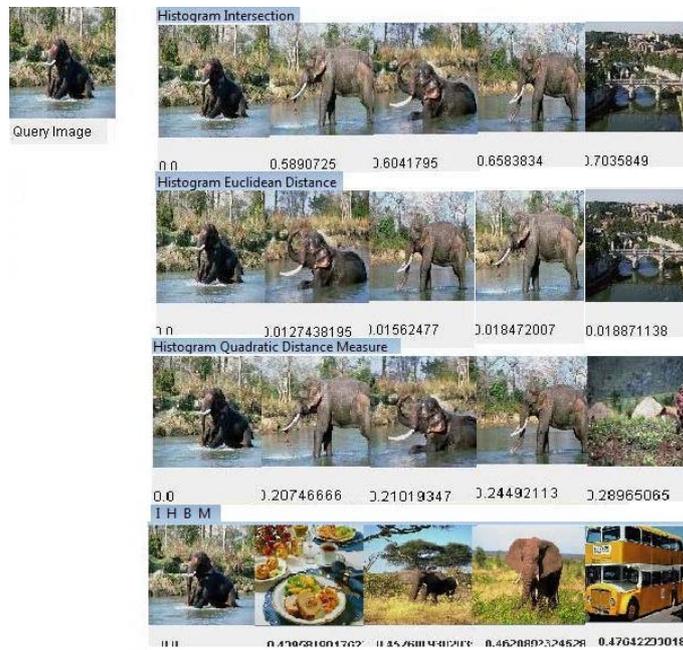


Figure 7. The results of the query image and retrieved relevant images of HI, HED, HQDM and IHBM methods for the image elephant

Table 2. Precision for TOP 5, 10 and 20 images

Elephant	HI	HED	HQDM	IHBM
TOP 5	4	4	4	3
TOP 10	4	4	4	7
TOP 20	4	4	6	10

For elephant image, the proposed IHBM method clearly outperforms the remaining three methods as shown in Table 2. The Table 3 shows the same precision results for all the four methods considered.

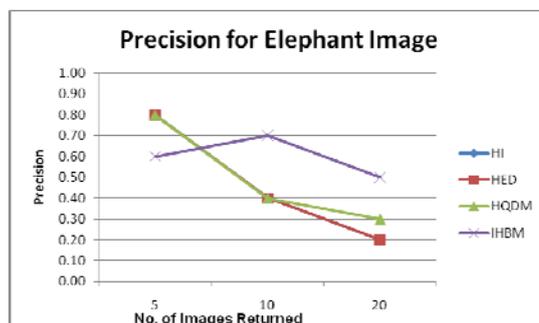


Figure 8. Precision Vs No. of Images returned for Elephant image

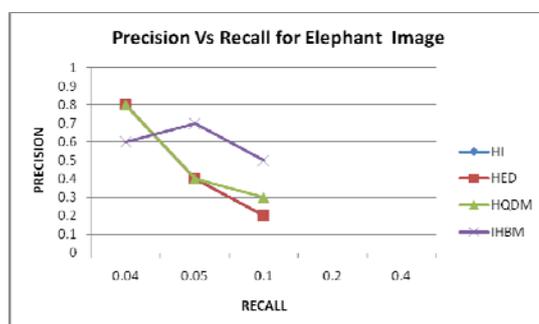


Figure 9. Precision Vs Recall for Elephant image

Query 3: Horse



Figure 10. The results of the query image and retrieved relevant images of HI, HED, HQDM and IHBM methods for the image horse

Table 3. Precision of HI, HED, HQDM and IHBM for TOP 5, 10 and 20 images

Horse	HI	HED	HQDM	IHBM
5	5	5	5	5
10	10	10	10	10
20	20	19	20	20

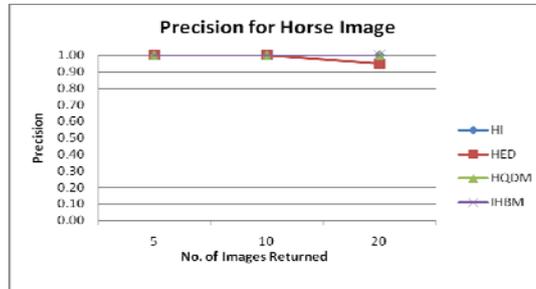


Figure 11. Precision Vs No. of Images returned for Horse image

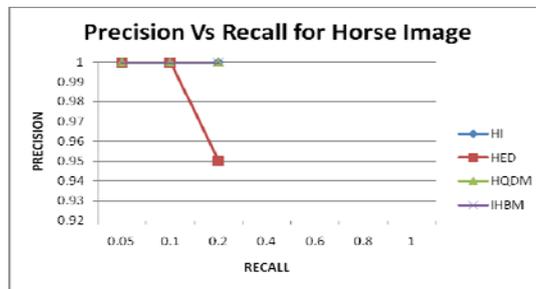


Figure 12. Precision Vs Recall for horse image

5. Conclusions

The proposed IHBM is experimented on 1000 color images and the experimental results with the help of tables and graphs clearly indicate the proposed method IHBM is more accurate and efficient than the three existing methods i.e. HI, HED and HQDM. The proposed method is proved as metric, which satisfies non-negativity, commutative and triangle inequality properties.

Acknowledgements

The authors would like to express their cordial thanks to Dr. Nageswara Rao Vallurupalli, Chairman, and Sri. Satyanarayana Rao Vallurupalli, Secretary & Correspondent, Gudlavalluru Engineering College, Gudlavalluru and thanks to K.V.V. Satya Narayana Raju, Chairman, Chaitanya Institutions and K. Sashi Kiran Varma, Secretary, GIET, Rajahmundry for providing Research facilities at SRRF Labs. Authors would like to thank Dr. G.V.S. Anantha Lakshmi for her invaluable suggestions and constant encouragement that led to improve the presentation quality of the paper.

References

- [1] L. Liu, D. Zhang, G. Lu and W.Y. Ma, A Survey of Content-based Image Retrieval with High-level Semantics, Pattern Recognition, Vol. 40, No. 1, pp. 262-282, 2007.

- [2] M.S. Lew, N. Sebe, C. Djeraba and R. Jain, "Content-Based Multimedia Information Retrieval: State of the Art and Challenges", *ACM Transactions on Multimedia Computing, Communications and Applications*, Vol. 2, No. 1, pp. 1-19, February 2006.
- [3] M. L. Kherfi and D. Ziou, universities de sherbrooke, A. Bernardi, Laboratoires Universitaires Bell," Image Retrieval from the World Wide Web: Issues, Techniques, and Systems In ,*ACM Computing Surveys*, Vol. 36, No. 1, March 2004, pp. 35–67.
- [4] Sameer Antani, Rangachar Kasturi, and Ramesh Jain. A Survey on the Use of Pattern Recognition Methods for Abstraction, Indexing and Retrieval of Images and Video. *Pattern Recognition*, 35:945–965, 2002.
- [5] M.Flickner et al., Query by image and video content: the QBIC system, *IEEE compute.* 28(9), 23-32(1995)
- [6] W. Niblack, et al., The QBIC Project:Querying images by content using color, texture, and shape, storage and retrieval for image and video databases,*SPIE*1908.
- [7] J. M. Fuertes, M. Lucena, N. Perez de la Blanca, and J. Chamorro-Martinez. A Scheme of Color Image Retrieval from Databases. *Pattern Recognition Letters*, 22:323–337, 2001.
- [8] M.Swain and D.Ballard, "Color Indexing", *Int. Journal of Computer Vision*, vol.7, no. 1, pp. 11-32, 1991.
- [9] W.Y.Ma and B.S manjunath, textured-based pattern retrieval from image databases. *Multimedia Tools Appl.* 1(2),35-51(1996)
- [10] H.v Jagadish ,A retrieval technique for similar shapes,*ACM,proc.Int.Conf.Manag.Data(SIGMOD)*,(1991).
- [11] A.Jain and A.Vailaya, "Image Retrieval using Color and Shape, *Pattern Recognition*, vol. 29, no. 8, pp. 1233-1244, 1996.
- [12] W.F.Cody et al., Querying multimedia data from multiple repositories by content: the garlic project, *visual Database Systems : Visual Information Management*, Chapman & Hall, New York 1995, pp.17-35.
- [13] J.R.Smith and S.-F. Chang, "Visual Seek: A Fully Automated Content based Image Query System", *Proc. ACM Multimedia Conf.*, Boston, MA, 1996.
- [14] a.Pentland ,R .W Picard and S. Sclaroff , photobook:Tools for content-based manipulations of image databases ,*Storage and Retrieval for still Image and video Databases II ,proc.SPIE 2185.IS & T/SPIE* February 1994.
- [15] Fan-Di Jou, Kuo-Chin Fan *, Yang-Lang Chang , "Efficient matching of large-size histograms" *Institute of Computer Science and Information Engineering, National Central University, Chung-Li 32054, Taiwan, ROC Pattern Recognition Letters* 25 (2004) 277–286
- [16] Hafner, J., Sawhney, H.S., Equitz, W., Flickner, M., Niblack,W., 1995. Efficient color histogram indexing for quadratic form distance functions. *IEEE Trans. Pattern Anal.Machine Intel.* 17 (7), 729–736.Jou, F.D., 2003.
- [17] Vito Di Gesu and Valery Starovoitov. Distance-Based Functions for Image Comparison. *Patter Recognition Letters*, 20:207–214, 1999.
- [18] J.R.Smith and S.-F Chang,Integrated spatial and feature image query, *Multimedia Syst.* 7(2) ,129-140 (1999).
- [19] J. R. Smith. *Integrated Spatial and Feature Image Systems: Retrieval, Analysis and compression* . PhD thesis, Columbia University, New York,NY, February 1997
- [20] John R. Smith and Shih-Fu Chang,"Tools and Techniques for Color Image Retrieval" *Columbia University Department of Electrical Engineering and Center for Telecommunications Research* New York, N.Y. 10027
- [21] J. Li, J.Z. Wang, G. Wiederhold, IRM: integrated region matching for image retrieval, in:*Proceedings of the Eighth ACM Multimedia Conference*, 2000, pp. 147–156.
- [22] Yossi Rubner, Carlo Tomasi and Leonidas J. Guibas, The Earth Mover's Distance as a Metric for Image Retrieval, *International Journal of Computer Vision* 40(2), 99–121, 2000
- [23] Hamdi A. Taha. *Operations Research*. Prentice Hall, 1982.
- [24] svetlozar T.rachev "Mass transportation problems-vol1:theory", ,springer.
- [25] Rainer E. Burkard *, Bettina Klinz Rüdiger Rudolf " Perspective of Monge properties in optimization"- *Discrete Applied Mathematics* 70 (1996) 95-161
- [26] N Gnaneswara Rao, V Vijaya Kumar, and V Venkata Krishna"Texture Based Image Indexing and Retrieval." *IJCSNS International Journal of Computer Science and Network Security*, Vol. 9 No. 5 pp. 206-210,May 2009.

Authors



Vakulabharanam Vijaya Kumar received integrated M.S. Engg, degree from Tashkent Polytechnic Institute (USSR) in 1989. He received his Ph.D. degree in Computer Science from Jawaharlal Nehru Technological University (JNTU) in 1998. He has served the JNT University for 13 years as Assistant Professor and Associate Professor and taught courses for M.Tech students. He has been Dean for Dept of CSE and IT at Godavari Institute of Engineering and Technology since April, 2007. His research interests include Image Processing, Pattern Recognition, Network Security, and Steganography, Digital Watermarking, and Image retrieval. He is a life member for CSI, ISTE, IE, IRS, ACS and CS. He has published more than 80 research publications in various National, Inter National conferences, proceedings and Journals.



N.Gnaneswara Rao received B.E. (ECE) degree from Andhra University (S.R.K.R. Engineering College) in 1996 and received his M.Tech (CS) post graduation from the JNTU Hyderabad in 2002. He is pursuing PhD at JNTU Kakinada in the area of Content Based Image Retrieval. He has been working in Gudlavalleru Engg College since 2000. He is a life member for CSI, ISTE, CRSI, IETE and a member of ACM, IET, IEEE. He has published Ten research publications in various National, and International conferences.



A.L.Narsimha Rao received the B.Tech. (CSE) from Nagpur University in 1997. He completed his M. Tech. (CSE) from Osmania University in 1999. He received his Ph.D in CSE recently. He worked as Assistant Professor in Pretoria University, South Africa for two years (2002-2004). He is having 13 years of teaching experience in INDIA & Abroad in various Engineering Colleges. Presently he is working as a Professor, academic head & Head of the department (CSE) in Satya college of Engineering & Technology, Palwal, Delhi NCR, INDIA. He has published research papers in various National, Inter National conferences, proceedings and Journals.



V Venkata Krishna received the B.Tech. (ECE) degree from Sri Venkateswara University. He completed his M. Tech. (Computer Science) from JNT University. He received his Ph.D in Computer Science from JNT University in 2004. He worked as Professor and Head for ten years in Mahatma Gandhi Institute of Technology, Hyderabad. After that, he worked as a principal for Vidya Vikas College of Engineering, Hyderabad, for two years, and he worked as Principal for Chaitanya Institute of Science and Technology, Kakinada from past one year. In addition, presently he is working as Principal for Chaitanya Institute of Science and Technology, Kakinada from past one year. He is an advisory member for many Engineering colleges. He has published 20 research articles. Presently he is guiding 10 research scholars. He is a life member of ISTE and CSI.