Advanced Methods for Localized Content Based Image Retrieval

Radhey Shyam[1], Pooja Srivastava[2]

[1] **Department of Computer Science & Engineering,
SRMGPC Lucknow, India**

[2] **Department of Electronics & Communication,
SRMGPC, Lucknow, India**

Abstract

Localized Content based image retrieval is an effective technique for image retrieval in large databases. It is the retrieval of images based on visual features such as color, texture and shape. In this paper, our desired content of an image is not holistic, but is localized. Specifically, we define Localized Content-Based Image Retrieval, where the user is only interested in a portion of the image, and the rest of the image is irrelevant. Some work already has been done in this direction. We are interested to retrieve the images on basis of shape and texture.

Keywords: *Color, Images, Large Databases, Shape, Texture, Visual Features.*

1. Introduction

Localized Content-Based Image Retrieval is the retrieval of images based on visual features such as color, texture and shape [4][5][6][7]. In old methods which used text-based image retrieval in which manually annotated keywords as metadata which is highly inefficient consider the scenario given below:

Fig. 1 Sample Database

In this we have entered "Buildings" in the search box. We have got about 2340 results but all images are not relevant. Here the need arises for Localized Content Based Image Retrieval to get only the relevant images with using features as a input parameters like, color, shape and texture, hence we get only the images related to Historic Buildings [3][7].

Our database consists of the images of moon taken at different positions and angles. Our objective is to check that the query image is of moon or not and if it is of moon then whether it exists in database or not.

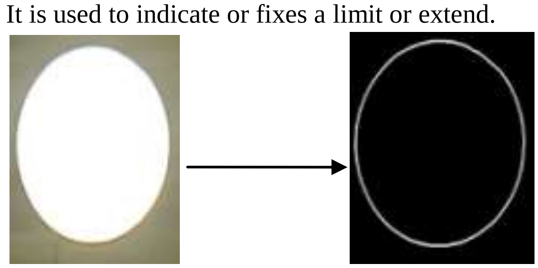
2. Proposed Model

2.1. Shape

Shape may be defined as the characteristic surface configuration of an object; an outline or contour. It permits an object to be distinguished from its surroundings by its outline. Shape is the most efficient of all metrics like color and texture. Our model includes following:-

2.1.1. Boundary extraction

It is used to indicate or fixes a limit or extend.



Original Image Boundary Extracted Image

Fig. 2 Boundary Extraction

Now we will perform localization on the boundary extracted image. For localization we use the entropy based method [2]. The entropy measurement provides a set of values based on the high and low level information corresponding to regions where the object is located.

2.1.2. Entropy Theory

Given events $a_1, a_2 \ldots a_n$ occurring with probabilities $p_1, p_2, \ldots p_n$, the Shannon entropy is defined as [2]:

$$H = \sum_{i=1}^{m} p_i \log \frac{1}{p_i} = -\sum_{i=1}^{m} p_i \log p_i \tag{1}$$

2.1.3. Applying Entropy

The area we are interested in high information areas such as circle, rectangle etc. The results of this process are points to regions of importance for shape localization. On the basis of entropy we can conclude that in the given figure there is a circle or not.

Fig. 3 Entropy of the Image

Entropy of above image = **3.6842,** Entropy after applying boundary extraction of above image = **0.1908**

2.1.4. Mapping Images

Now if we find the shape as here we are interested in circle then we will use any similarity comparison technique for example Euclidean distance, the formula is given by

$$d = \sqrt{\sum_{i=1}^{N} (F_Q[i] - F_{DB}[i])^2} \tag{2}$$

Where d is the Euclidean distance, FQ[i] is the i^{th} query image feature, FDB[i] is the corresponding feature in the feature vector database and N is the number of images in database [3].

2.2. Texture

Everyday texture terms - rough, silky, bumpy - refer to touch. A texture that is rough to touch has a large difference between high and low points and a space between highs and lows approximately the same size as a finger [4][7].

Fig. 4 Different Texture

After the shape retrieval now we can conclude that image is in the database but it is of moon is not sure now we will do texture retrieval to check whether it is of moon or any other circular shaped image like ball or sun etc.

3. Proposed Algorithms for Texture Retrieval

3.1. Grey Level Co-occurrence Matrix, GLCM

The GLCM is a tabulation of how often different combinations of pixel brightness values occur in an image. Here is a simple test image for working out examples. The values are image grey levels.

Fig. 5 Grey Level Co-occurrence Matrix

3.1.1. Framework for the GLCM

Spatial relationship between two pixels: LCM texture considers the relation between two pixels at a time, called the reference and the neighbor pixel. In the illustration below, the neighbor pixel is chosen to be the one to the east (right) of each reference pixel. This can also be expressed as a (1, 0) relation: 1 pixel in the x- direction, 0 pixels in the y- direction.

3.1.2. Separation between two pixels

All representations of the GLCM include only the 16 data cells.

Table 1: GLCM

Neighbor pixel value -> Reference pixel value:	0	1	2	3
0	0,0	0,1	0,2	0,3
1	1,0	1,1	1,2	1,3
2	2,0	2,1	2,2	2,3
3	3,0	3,1	3,2	3,3

A different co-occurrence matrix exists for each spatial relationship (above to, diagonal) [8]

$$\begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 2 & 2 & 2 \\ 2 & 2 & 3 & 3 \end{bmatrix}$$

Filling in the matrix framework for the east (1, 0) spatial relationship:

$$\begin{bmatrix} 2 & 2 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Twice in the test image the reference pixel is 0 and its eastern neighbor is also 0. Twice the reference pixel is 0 and its eastern neighbor is 1. Three times the reference pixel is 2 and its neighbor is also 2.

3.2. Making the matrix symmetrical around the diagonal

The texture calculations require a symmetrical matrix. The next step is therefore to get the GLCM into this form. A symmetrical matrix means that the same values occur in cells on opposite sides of the diagonal. For example, the value in cell 3, 2 would be the same as the value in cell 2, 3. The east matrix calculated above is not symmetrical.

3.3. Normalization: The GLCM expressed as a probability

After making the GLCM symmetrical, there is still one step to take before texture measures can be calculated. The measures require that each GLCM cell contain not a count, but rather a probability. The simplest definition of the probability of a given outcome is the number of times this outcome occurs, divided by the total number of possible outcomes.

The combination (2, 2) occurs 6 times out of 24, for a probability of 1/4 or 0.250. The probability of 2, 3 is 1/24 or .042.

This process is called normalizing the matrix. Normalization involves dividing by the sum of values.

$$P_{i,j} = \frac{Vi,j}{\sum_{i,j=0}^{N-1} Vi,j} \tag{3}$$

where i is the row number and j is the column number.

3.3.1. Normalization equation

3.3.1.1. Calculating texture measures from the GLCM Groups of texture measures

3.3.1.2. Contrast group

Measures related to contrast use weights related to the distance from the GLCM diagonal. The Contrast:

$$\sum_{i,j=0}^{N-1} Pi,j(i-j)2 \tag{4}$$

3.3.1.3. Contrast equation's Explanation

When i and j are equal, the cell is on the diagonal and (i-j) =0. These values represent pixels entirely similar to their neighbor, so they are given a weight of 0. If i and j differ by 1, there is a small contrast, and the weight is 1. If i and j differ by 2, contrast is increasing and the weight is 4.The weights continue to increase exponentially as (i-j) increases.

Example: for the horizontal GLCM, Contrast equals (Contrastweights: multiplication result) X (horizontalGLCM) =

Table 2. horizontal GLCM

0	**1**	**4**	**9**		**0.166**	**0.083**	**0.042**	**0.0**
1	**0**	**1**	**4**		**0.083**	**0.166**	**0.0**	**0.0**
4	**1**	**0**	**1**		**0.042**	**0.0**	**0.249**	**0.042**
9	**4**	**1**	**0**		**0.0**	**0.0**	**0.042**	**0.083**

Table 3. Sum of all elements in the multiplication result table = **0.586**

0.0	**0.083**	**0.168**	**0.0**
0.083	**0.0**	**0.0**	**0.0**
0.168	**0.0**	**0.0**	**0.042**
0.0	**0.0**	**0.042**	**0.0**

3.3.1.4. Computations detail

$0.166*(0-0)^2 + 0.083*(0-1)^2 + 0.042*(0-2)^2 + 0*(0-3)^2 + 0.083*(1-0)^2 + 0.166*(1-1)^2 + 0*(1-2)^2 + 0*(1-3)^2 + 0.042*(2-0)^2 + 0*(2-1)^2 + 0.250*(2-2)^2 + 0.042*(2-3)^2 + 0*(3-0)^2 + 0*(3-1)^2 + 0.042*(3-2)^2 + 0.083*(3-3)^2$
= 0.166(0) + 0.083(1) + 0.042(4) + 0.083(1) + 0.166(0) + 0.042(4) + 0.25(0) + 0.042(1) + 0.042(1) + 0.083(0)
= 0.083 + 0.168 +0 .083 + 0.168 + 0.042 +0 .042
= 0.586

3.3.1.5. Dissimilarity (DIS)

In the Contrast measure, weights increase exponentially (0, 1, 4, 9, etc.) as one moves away from the diagonal. However in the dissimilarity measure weights increase linearly (0, 1, 2, 3….).

$$\sum_{i,j=0}^{N-1} Pi,j\,|\,i-j\,| \qquad (5)$$

3.3.1.6. Dissimilarity equation

Homogeneity weights values by the inverse of the Contrast weight, with weights decreasing exponentially away from the diagonal:

$$\sum_{i,j=0}^{N-1} \frac{Pi,j}{1+(i-j)2} \qquad (6)$$

3.3.1.7. Homogeneity equation

3.3.1.7.1. Texture measures Group

Measures related to orderliness, Orderliness means: how regular the pixel values are within the window.

Example: the two images below have the same degree of horizontal contrast (every pixel is one less than its eastern neighbor). But the degree of order is quite different:

Table 4. Texture Measure Group

1	**2**	**3**	**4**		**3**	**4**	**3**	**2**
1	**2**	**3**	**4**		**1**	**2**	**3**	**4**
1	**2**	**3**	**4**		**2**	**3**	**4**	**5**
1	**2**	**3**	**4**		**4**	**5**	**6**	**7**

In the more orderly image on the left, each pair of values occurs many times: 2 are next to 1 four times, 3 are next to 2 four times, etc. For the less orderly image, combinations occur less often: 2 is next to 1 only once, 3 next to 2 three times, and so on

3.3.1.7.1. Principle behind orderliness measures

Orderliness measures, like contrast measures, use a weighted average of the GLCM values. The weight is constructed related to how many times a given pair occurs, so

a) A weight that increases with commonness will yield a texture measure that increases with orderliness.
b) A weight that decreases with commonness yields a texture measure that increases with disorder

3.3.1.7.2. Weights in orderliness measures

Since the $P_{i,j}$ values in the GLCM are already a measure of commonness of occurrence; it makes sense to use them in some form as weights for themselves.

ASM and Energy use each $P_{i,j}$ as a weight for itself. High values of ASM or Energy occur when the window is very orderly.

$$\sum_{i,j=0}^{N-1} Pi,j2 \qquad (7)$$

3.3.1.7.3. ASM equation

The square root of the ASM is sometimes used as a texture measure, and is called Energy.

$$\text{Energy}=\sqrt{ASM} \qquad (8)$$

3.3.1.7.4. Energy equation

The term entropy is a notoriously difficult term to understand; the concept comes from thermodynamics. It refers to the quantity of energy that is permanently lost to heat every time a reaction or a physical transformation occurs. Entropy cannot be recovered to do useful work. Because of this, the term is used in non technical speech to mean permanent chaos or disorder. Also, as with ASM, the equation used to calculate physical entropy is very similar to the one used for the texture measure.

Energy is, in this context, the opposite of entropy. Energy can be used to do useful work. In that sense it represents orderliness. This is why Energy is used for the texture that measures order in the image.

3.3.1.7.5. Descriptive Statistics on the GLC Matrix

The third group of GLCM texture measures consists of statistics derived from the GLC matrix. These are

3.3.1.7.5.1. GLCM Mean

$$\mu_i = \sum_{i,j=0}^{N-1} i(Pi,j) \quad \mu_j = \sum_{i,j=0}^{N-1} i(Pi,j) \tag{9}$$

3.3.1.7.5.2. GLCM Mean Equations

The left hand equation calculates the mean based on the reference pixels,

3.3.1.7.5.3. GLCM Variance

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(i-\mu_i\right)^2 \quad \sigma_j^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(j-\mu_j\right)^2 \tag{10}$$

3.3.1.7.5.4. Standard deviation equation

$$\sigma_i = \sqrt{\sigma_i^2} \qquad \sigma_j = \sqrt{\sigma_j^2} \tag{11}$$

3.3.1.7.5.5. GLCM Correlation

The Correlation texture measures the linear dependency of grey levels on those of neighboring pixels. GLCM Correlation is quite a different calculation from the other texture measures described above. As a result, it is independent of them and can often be used profitably in combination with another texture measure. It also has a more intuitive meaning to the actual calculated values: 0 is uncorrelated, 1 is perfectly correlated.

3.3.1.7.5.6. GLCM Correlation equation

$$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right] \tag{12}$$

4. Conclusion

The dramatic rise in the sizes of images databases has stimulated the development of effective and efficient retrieval systems. The development of these systems started with retrieving images using textual connotations but later introduced image retrieval based on content. This came to be known as Content Based Image Retrieval. Systems using it to retrieve images based on visual features such as color, texture and shape, as opposed to depending on image descriptions or textual indexing. In this paper, we have given the concept for shape and texture for localized objects like a moon in scenery.

Acknowledgments

The authors would like to thank the anonymous reviewers, their comments helped improve this manuscript.

References

[1] E.Loutas, I.Pitas, and C.Nikou, “Probabilistic Multiple Face Detection and Tracking Using Entropy Measures”, *IEEE Trans. on Circuits and Systems for Video Technology*, VOL. 14, NO. 1, Jan. 2004.

[2] S. Nandagopalan, Dr. B. S. Adiga, and N. Deepak “A Universal Model for Content-Based Image Retrieval” *World Academy of Science, Engineering and Technology* 46 2008.

[3] H.B.Kekre, Sudeep D. Thepade, “Image Retrieval using Color- Texture Features Extracted from Walshlet Pyramid”, *ICGST International Journal on Graphics, Vision and Image Processing (GVIP)*, Volume 10, Issue I, Feb.2010, pp.9-18.

[4] www.icgst.com/gvip/Volume10/Issue1/P1150938876.html.

[5] H.B.Kekre, Sudeep D. Thepade, “Image Retrieval using Augmented Block Truncation Coding Techniques”, *Proc. ACM Int. Conf. on Advances in Computing, Communication and Control (ICAC3-2009)*, 23-24 Jan 2009.

[6] Rouhollah Rahmani, Sally A. Goldman, Hui Zhang, Sharath R. Cholleti, and Jason E. Fritts “Localized Content Based Image Retrieval”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Special Issue, November, 2008.

[7] Manimala Singha and K.Hemachandran, “Content Based Image Retrieval using Color and Texture”, *Signal & Image Processing : An International Journal (SIPIJ)* Vol.3, No.1, February 2012.

[8] Ranjan Parekh, "Improving Texture Recognition using Combined GLCM and Wavelet Features", *International Journal of Computer Applications (0975 – 8887),* Volume 29– No.10, September 2011.

Radhey Shyam has received MCA Degree from IET Lucknow in 1997, M. Tech (CSE) from UPTU Lucknow in 2008. He has worked over 4 years as Software Engineer / System Analysts in CMC Ltd., MIS, SA and TSL. He has worked over 5 years as Lecturer (Adhoc) in Department of CSE, IET Llucknow. From last 5 years, He is Assistant Professor working in Department of Computer Science & Engineering, SRMGPC, Lucknow, India. He has authored a Text Book "Introduction To UNIX and C Programming" published from BPB Publication in 2003. He has published Number of Technical papers in National / International Journals / Proceedings. His current research direction includes Signal Processing, Image Analysis, Intelligence Computations, Soft Computing, Biometrics, Machine Learning and Computer Vision.

Pooja Srivastava is Assistant Professor in the Department of Electronics and Communication, SRMGPC, Lucknow, India, has published various research papers in International Conferences/Journals. She is having more than 5 years of teaching experience. Her research interest includes Communication, Error Control Coding, Turbo Codes, Pattern Recognition, Image Processing, OFDM System and other Transmission Techniques, VLSI Design of Communication System for Wireless high speed Data Communication.