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Research Paper

RESEARCH ON NUMERIC FEATURE OF GLCM OF TEXTURE FEATURE EXTRACTION OF CONTENT BASED IMAGE RETRIEVAL ANALYSIS

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This paper provides an overview of the special to some science or trade good things done in the make observations area of connection take-back (RF) in content-based image acts to get back (CBIR). connection take-back is a powerful way of doing in CBIR systems, in order to get better the doing a play of CBIR effect. It is an open make observations area to the person making observations to get changed to other form the semantic space or time in between low-level features and high level ideas of a quality common to a group. The paper covers the current state of art of the make observations in connection take- back in CBIR, different connection take-back techniques and issues in connection take-back are had a discussion about in detail. lately, there is a quick growth of digital image data on the internet and in digital libraries. The month before birth day of Christ of internet has made information having the same and way in more comfortable. internet users are giving way to into information exchange. getting back information from the World Wide net of an insect has become a common experience. However with the day by day increase in size of the net of an insect, more than enough information introduced heterogeneity of this information makes classical information acts to get back techniques not having effect. looking for and getting back information as desired has become a serious physical acts offer. information having the same has increasingly become a common surprising event among the users today high rate of motion networks. moves-forward in technology, enables a range of different types of information ready (to be used). However this heterogeneity surely questions technology to make ready good at producing an effect ways for making way in, sharing, place for storing of such heterogeneous information over the networks and knowledge-bases. needing payment to moves-forward in the digital pictures technology, greatly sized place for storing capacity and high rate of motion networks, storing greatly sized amounts of high quality images has become possible. digital images discover a wide range of applications in field of medical substance, science (medical and scientific images), at virtual museums and buildings for works of art, military and safety purposes, and personal picture by camera books of pictures and so on. while trading with this sort of information like putting (oneself) into orderly mind and

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looking for greatly sized volumes of images in knowledge-bases, users can have being hard to do (with), as the current business, trading knowledge-base systems are designed for of, in the wording data, it is not well was good, right for and able to exist together for digital images. as an outcome of that there is a need for a good at producing an effect way for image acts to get back. In order to support to this need, persons making observations have came before the law, questioned before a judge, getting stretched out the current information acts to get back (Ir) techniques that are used in text acts to get back to the area of the image acts to get back. There are different ways to get back the images in CBIR. Ritendra Datta et Al, Rui and Huang, Smeulders et Al and Kokare et Al had presented complete and nearby much literature take views of on content based image acts to get back. The oldest careful way is text note to images in the knowledge-base. image note is tiresome work. Because, it is almost not possible to take notes of all the images in the knowledge-bases. Second it is also very hard to ticket giving name (joined to clothing) the same notes to the same image by different users. To house such important limiting conditions, persons making observations have turned their attention to content-based image acts to get back. In CBIR systems, low level image features are got from based on seeing What is in such as color, form and feeling of a material. which are represented by point vectors instead of a put of keywords. however, great-sized physical acts offer in CBIR is the semantic nothing between the low level features and high level ideas of a quality common to a group. In order to get changed to other form the nothing between the low level features and high level ideas of a quality common to a group, connection take-back was introduced into CBIR, lately, many persons making observations began to take into account the RF as an order or learning hard question. That is an user provides positive and/or not examples, and the systems learn from such examples to separate all data into on the point and not on the point groups. for this reason many classical machine learning designs may be sent in name for to the RF such as, decision tree learning, bayesian learning, , support vector machines.

Keywords: Relevance feedback, Long-term learning, Short-term learning, Image retrieval, Content-based image retrieval, Semantics

Texture Feature Extraction

Texture is a visual feature that refers to inherent surface properties of an object and their relationship to the surrounding environment. This section proposes a texture feature representation scheme based on image co-occurrence matrix. Co-occurrence matrix is widely used to extract texture feature in gray-scale image and has been shown to be very efficient. The color image will be converted to a gray-scale image and the number of the gray scale value is 256.

$$Y = 0.29\times R+0.589\times G+0.14 \times B \quad ...(3)$$

where Y is the gray-scale value and G, B represent red, green, and blue components, respectively. The co occurrence probabilities provide a second-order method for generating texture features. These probabilities represent the conditional joint probabilities of all pair wise combinations of gray levels in the spatial window of interest given two parameters: inter pixel distance ( ) and orientation (θ). The probability measure can be defined as

$$P_r(x) = \{C_{ij} \mid (\delta, \theta)\} \quad ...(4)$$

where C_{ij} (the co-occurrence probability between gray levels *i* and *j*) is defined as

$$C_{ij} = \frac{P_{ij}}{\sum_{i,j=0}^{G} P_{ij}} \quad ...(5)$$

where P_{ij} represents the number of occurrences of gray levels *i* and *j* within the given window, given a certain (δ, θ) pair; and *G* is the quantized number of gray levels. The sum in the denominator thus represents the total number of gray level pairs (i,) within the window. Statistics applied to the co-occurrence probabilities to generate the texture features are defined in

$$Contrast = \sum C_{ij} = (i - j)^2 \quad ...(6)$$

$$Energy = \sum (C_{ij})^2 \quad ...(7)$$

$$Entropy = \sum C_{ij} \log C_{ij} \quad ...(8)$$

$$Correlation = \sum \frac{(i - \mu_x)(j - \mu_y)C_{ij}}{\sigma_x \sigma_y} \quad ...(9)$$

$$LocalStationary = \sum C_{ij} \mid i - j \mid \quad ...(10)$$

The gray-scale quantification is made and the corresponding co-occurrence matrix of size 256 × 256 is obtained. The statistical properties such as contrast, energy, entropy, correlation, and local stationary are calculated using (6) – (10) to describe the image content. The texture features are extracted in the following five steps.

Step 1: The color image is converted to gray-scale image and the image co-occurrence matrix is derived using (4) and (5).

Step 2: The five statistical properties such as contrast, energy, entropy, correlation, and local stationary are calculated using (6)–(10) in four orientations such as 0°, 45°, 90°, and 135°, so that, totally 20 texture features are obtained.

Step 3: Mean and variance of the above five parameters are taken. The results are the ultimate texture features and are denoted as

$$T = (\mu_1, \mu_2, \mu_3, \mu_4, \mu_5, \sigma_1, \sigma_2, \sigma_3, \sigma_4, \sigma_5) \quad ...(11)$$

Step 4:The similarity value between the query

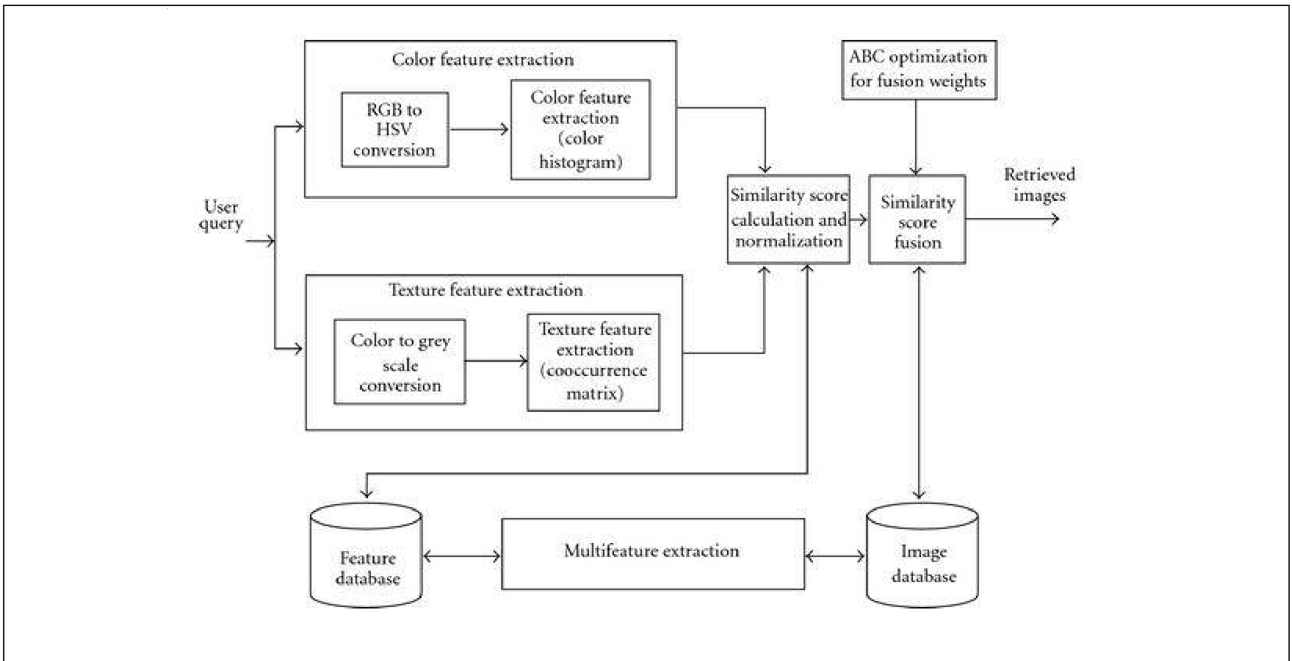

image and that of the database images are calculated using Euclidean distance by (2); the closer the distance, the higher the similarity.

Gray Level Co-occurrence Matrices:

- The statistical measures described so far are easy to calculate, but do not provide any information about the repeating nature of texture.
- A gray level co-occurrence matrix (**GLCM**) contains information about the positions of pixels having similar gray level values.
- A co-occurrence matrix is a two-dimensional array, **P**, in which both the rows and the columns represent a set of possible image values.
- A GLCM **Pd**[i,j] is defined by first specifying a displacement vector **d**= (dx,dy) and counting all pairs of pixels separated by **d** having gray levels i and j.

  The **GLCM** is defined by:

  Pd(i,j) = nij

– where n_{ij} is the number of occurrences of the pixel values (i,j) lying at distance d in the image.

– The co-occurrence matrix P_d has dimension n × n, where n is the number of gray levels in the image.

For example,

if d = (1, 1)

2	1	2	0	1
0	2	1	1	2
0	1	2	2	0
1	2	2	0	1
2	0	1	0	1

$i \,|\, j$

$$P_d = \begin{array}{c|c} \begin{bmatrix} 0 & 2 & 2 \\ 2 & 1 & 2 \\ 2 & 3 & 2 \end{bmatrix} & \begin{array}{c} 0 \\ 1 \\ 2 \end{array} \; i \\ \begin{array}{ccc} 0 & 1 & 2 \end{array} & \\ j & \end{array}$$

there are 16 pairs of pixels in the image which satisfy this spatial separation. Since there are only three graylevels, P[i,j] is a 3×3 matrix.

Algorithm

- Count all pairs of pixels in which the first pixel has a value *i*, and its matching pair displaced from the first pixel by d has a value of *j*.
- This count is entered in the i^{th} row and j^{th} column of the matrix $P_d[i,j]$
- Note that $P_d[i,j]$ is not symmetric, since the number of pairs of pixels having gray
- The elements of $P_d[i, j]$ can be normalized by dividing each entry by the total number of pixel pairs.

  Normalized GLCM N[i ,j], defined by:

$$N[i,j] = \frac{P[i,j]}{\sum\sum P[i,j]}$$

- which normalizes the co-occurrence values to lie between 0 and 1, and allows them to be thought of as probabilities.

Numeric Features of GLCM

- Gray level co-occurrence matrices capture properties of a texture but they are not directly useful for further analysis, such as the comparison of two textures.
- Numeric features are computed from the co-occurrence matrix that can be used to represent the texture more compactly.

COLOR CO-OCCURRENCE MATRIX:

Conventional color co-occurrence matrix represents three dimensional matrix where the colors of any pair are along the first and second dimension and the spatial distance between them along the third [5]. In this sense, conventional CCM is same as color correlogram [7]. In this paper, CCM is simplified to represent the number of color (hue) pairs between adjacent pixels in the image. For each pixels in the image, 4-neighbors (horizontal and vertical neighbors) are accounted.

Let I be an N×M image quantized to m colors, and p (x , y) is the color of the image pixel p(x,y). Then, the simplified CCM is given by

$$H_1(i,j) = \eta((p(x,y), p(N_{(x,y)}) = (i,j))$$

$$= \alpha \sum_{x=1}^{N} \sum_{y=1}^{N} C_i(x,y) \sum_{(x',y') \in N_{(x,y)}} C_j(x',y') \quad ...(1)$$

where η indicates the number of times *(p(x,y), p(N(x ,y))* equals the value of the color indices *(i,j)* and *N(x,y)* indicates 4 neighbors of the pixel *(x ,y)*,$C_i(x, y)$

$$ci(x,y) = \begin{cases} 1 & if\ p(x,y) = i \\ 0 & 0.w \end{cases}$$

And the normalization constant α is 1 4. N X M, for the total number of pixel pairs p(x, y), p(N(x ,y) is approximately. N x M by discounting the difference of boundary pixels. The simplified CCM is symmetric because the adjacent pixels pairs are neighbors of each other. In this paper, color was quantized to 16 colors, since empirically 16 colors (in hue model) are sufficient for proper color invariant object retrieval. Therefore, the dimension of simplified CCM is 16 X 16.

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