International Journal of Enhanced Research in Management & Computer Applications, ISSN: 2319-7471
Vol. 3 Issue 5, May-2014, pp: (77-81), Impact Factor: 1.147, Available online at: www.erpublications.com

Review on color and texture feature extraction techniques

Garima Tripathi

Abstract: This paper presents a survey on the various techniques used for color and statistical texture feature extraction. The paper also discusses the use of color co occurrence matrices for feature extraction which is used for detection of plant diseases. The techniques for statistical texture analysis and color feature extraction discussed in the paper are reviewed on the basis of available literature and research carried out by authors.

INTRODUCTION

Feature extraction involves transforming the input data into a set of features which can uniquely represent an image. These set of features are also called feature vector. Visual information plays a pivotal role in our society and it will play an increasingly pervasive role in our lives [1]. The pictures or images are used in many application areas like architectural and engineering design, fashion, journalism, advertising, entertainment. Visual features of the images provide a description of their content. The content based image retrieval (CBIR) system has emerged as a promising tool for retrieving images and browsing large images databases [2].By choosing the appropriate feature extraction technique we can extract the relevant information from the input data and perform the required task .The features such as color, texture and shape [2] are used for extracting the relevant information from the input image. Feature extraction provides us methods with the help of which we can identify characters uniquely and with high degree of accuracy.

Color feature extraction techniques

Color is an important feature that makes possible recognition of images by humans. We use color to tell the difference between objects, places, and the time of day. Usually colors are defined in three dimensional color spaces. These could either be RGB (Red, Green, and Blue), HSV (Hue, Saturation, and Value) or HSB (Hue, Saturation, and Brightness).The most common technique for extracting the color features is based on color histograms of images [3]. A color histogram tells the global distribution of colors in the images. It is very easy to compute and insensitive to small variations in the images [4] [5]. There are two types of color histograms, Global Color Histograms (**GCH**s) and Local Color Histograms (**LCH**s). A GCH represents one whole image with a single color histogram. An LCH divides an image into fixed blocks and takes the color histogram of each of those blocks. LCHs contain more information about an image but are computationally expensive when comparing images. The GCH is the traditional method for color based image retrieval. However, it does not include information concerning the color distribution of the regions of an image. Thus when comparing GCHs one may get inconsistent result in terms of images [3]. There are two main drawbacks in color histogram. First, color histogram doesn't take into account the spatial information. The second is that the histogram is not unique and also not robust [6] [7]. Two different images with similar color distribution give rise to very similar histograms. Similarly, the images of the same view with different conditions of lighting create very different histograms.

To deal with the first problem, many researchers suggested the use of color Correlogram for taking into account the spatial information [8].

Correlogram is efficiently used for image indexing in content-based image retrieval. Color Correlogram [7] extracts not only the color distribution of pixels in images like color histogram, but also extracts the spatial information of pixels in the images. The auto-correlogram of image I for color Ci , distance k is given by equation 1

$$\gamma_{C_i}^{(k)}(I) \equiv \Pr[|p_1 - p_2| = k, p_2 \in I_{C_i} \mid p_1 \in I_{C_i}] \qquad \text{(eq. 1)}$$

Color correlogram integrates both color information and space information. The use of multi resolution histogram for image retrieval is suggested in [9].

Texture feature Extraction

Texture can be defined as a regular repetition of an element or pattern on a surface. . These textures give us information about the spatial arrangement of the colors or intensities in an image. Figure 1 shows three different images of regions with this intensity distribution that would be considered three different textures. The leftmost image has two big blocks:

one white and one black. The center image has 18 small white blocks and 18 small black blocks forming a checkerboard pattern. The rightmost image has six long blocks, three white and three black, in a striped pattern.

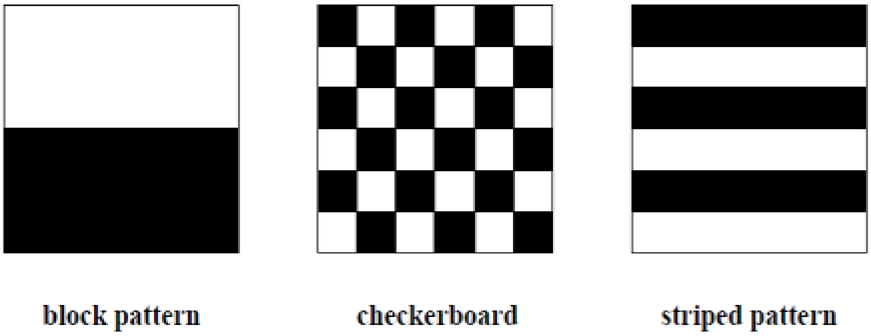

Fig 1: Three different textures with the same distribution of black and white

Texture has so many different dimensions and hence a number of techniques are used for texture analysis. We discuss some of the texture analysis techniques with examples. Mathematical procedures to characterize texture fall into two major categories: 1) Statistical and 2) Syntactic

Statistical approach to texture analysis: Statistical approaches compute different properties and are suitable if texture primitive sizes are comparable with the pixel sizes [10].These include co-occurrence matrix, spatial autocorrelation, edge density and direction and Law's Texture Energy mask [15]. Syntactic and hybrid (Combination of statistical and syntactic) methods are suitable for textures where primitive can be described using a larger variety of properties than just tonal properties, for example shape description. Using these properties, the primitives can be identified, defined and assigned a label. Statistical methods analyze the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. The reason behind this is the fact that the spatial distribution of gray levels is one of the defining qualities of texture.

Depending on the number of pixels defining the local feature, statistical methods can be further classified into first order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics [13]. The basic difference is that first-order statistics estimate properties (e.g. average and variance) of individual pixel values, ignoring the spatial interaction between image pixels, whereas second- and higher order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other. Statistical approaches yield characterizations of textures as fine, coarse etc. Thus one measure of texture is based on the primitive size, which could be the average area of these primitives of relatively constant gray level. The average could be taken over some set of primitives to measure its texture or the average could be about any pixel in the image. If the average is taken within a primitive centered at each pixel in the image, the result can be used to produce a texture image in which a large gray level at a pixel indicates, for example, that the average primitive size is large in a region around that pixel [14].

Spatial frequencies based Texture Analysis

Image texture can also be represented as a function of the tonal and structural relationships between the primitives. Tone is based mainly on pixel intensity (gray values) properties in the primitives while the structure is the spatial (location) relationship between the primitives [12]. One method of measuring spatial frequency is to evaluate the autocorrelation function of a texture. The autocorrelation function of an image can be used to assess the amount of regularity as well as the fineness/coarseness of the texture present in the image. In an autocorrelation model, texture spatial organization is described by the correlation coefficient that evaluates linear spatial relationship between primitives. We will use

$\{I(x, y), 0 \le x \le N, 0 \le y \le N-1$, to denote an N X N image with G gray levels. The autocorrelation function of an image $I(x, y)$ is defined as equation 5.1.1 given below.

$$\rho(x, y) = \frac{\sum_{u=0}^{N}\sum_{v=0}^{N} I(u,v)I(u+x,v+y)}{\sum_{u=0}^{N}\sum_{v=0}^{N} I^2(u,v)} \qquad \text{eq. 2}$$

If the texture primitives are relatively large, the autocorrelation function value decreases slowly with increasing distance, while it decreases rapidly if texture consists of small primitives. If primitives are placed periodically in a texture, the autocorrelation increases and decreases periodically with distance.

International Journal of Enhanced Research in Management & Computer Applications, ISSN: 2319-7471
Vol. 3 Issue 5, May-2014, pp: (77-81), Impact Factor: 1.147, Available online at: www.erpublications.com

Co-occurrence matrices

Spatial gray level co-occurrence estimates image properties related to second-order statistics which considers the relationship among pixels or groups of pixels (usually two).

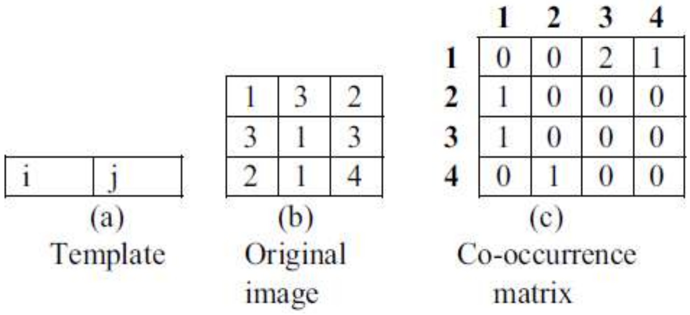

Fig 2: Co occurrence matrix

Fig 2 shows 3 X 3 image and its 4 gray level co-occurrence matrices. The number of threshold levels is 4. The 2 in the co occurrence matrix indicates that there are two occurrences of a pixel with gray level 3 immediately to the right of pixel with gray level 1. The size of co-occurrence matrix will be the number of threshold levels.

Law's texture energy measures

Image texture has a number of perceived qualities which play an important role in describing texture. Laws[15] identified the following properties as playing an important role in describing texture: uniformity, density, coarseness, roughness, regularity, linearity, directionality, direction, frequency, and phase. Laws texture energy measures determine texture properties by assessing Average Gray Level, Edges, Spots, Ripples and Waves in texture. The measures are derived from three simple vectors. L3 = (1,2,3) which represents averaging; E3 = (-1,0,1) calculating first difference (edges); and S3 = (-1,2,-1) corresponding to the second difference (spots). After convolution of these vectors with themselves and each other, five vectors result:

Level L5 = [1, 4, 6, 4, 1], Edge E5 = [-1,-2, 0, 2, 1], Spots S5 = [-1, 0, 2, 0,-1], Ripples R5 = [1, -4, 6,-4, 1] and Waves W5 = [-1, 2, 0,-2,-1]

Mutual Multiplying of these vectors, considering the first term as a column vector and the second term as row vector, results in 5X 5 Matrix known as Law's Masks. By convoluting the Law's Mask with Texture image and calculating energy statistics, a feature vector is derived that can be used for texture description.

Syntactic approaches to texture analysis

Shape chain grammars: Chain grammars are the simplest grammars usable for texture description.

1. Start a texture generation process by applying some transform rule to the start symbol.

2. Find a part of a previously generated texture that matches the left side of some transform rule. This match must be an ambiguous correspondence between terminal and non-terminal symbols of the left hand side of the chosen transform rule with terminal and non-terminal symbols of the part of the texture to which the rule is applied. If no such part of the texture is found, then stop.

3. Find an appropriate geometric transform that can be applied to the left hand side of the chosen rule to match it to the considered texture part exactly.

4. Apply this geometric rule to right hand side of the transform rule.

5. Substitute the specified part of the texture with the geometrically transformed right hand side of the chosen transform rule.

6. Continue with step (2).

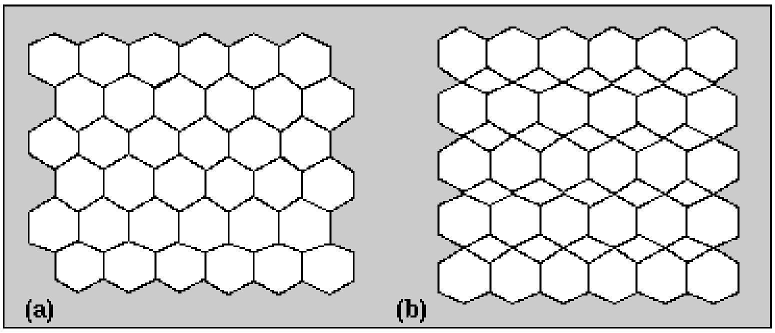

Fig 3: Hexagonal textures (a) Accepted (b) Rejected

Application of feature extraction technique

A common practice for plant scientists is to estimate the damage of plant (leaf, stem) because of disease by an eye on a scale based on percentage of affected area. Plant diseases problem can cause significant reduction in both quality and quantity of agricultural products. Automatic detection of plant leaf diseases is an essential research topic as it may prove benefits in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant leaves. The method proposed in [23] tries to identify five different plant diseases. After a preprocessing stage, a K-means clustering algorithm is applied in order to divide the image into four clusters. According to the authors, at least one of the clusters must correspond to one of the diseases. After that, for each cluster a number of color and texture features are extracted by means of the so-called Color Co-Occurrence Method, which operates with images in the HSI format. Those features are fed to a MLP Neural Network with ten hidden layers, which performs the final classification.

Summary

The method of representing color information of images in Content based Image retrieval systems is through color histograms. However it does not include information concerning the color distribution of the regions of an image. Color Correlogram extracts not only the color distribution of pixels in images like color histogram, but also extracts the spatial information of pixels in the image. There are three principal statistical approaches used in image processing to describe the texture of a region: Basic or First Order, structural or Second Order and spectral approaches. The Basic Statistical approaches yield characterizations of textures as smooth, coarse, grainy, and soon. Syntactic approaches deal with the arrangement of image primitives. They use a set of predefined texture primitives and a set of construction rules to define how a texture region is constructed with the primitives and the rules. The application of feature extraction in detecting plant diseases is also studied.

References

[1]. MPEG-7 overview (version 10)," ISO/IEC JTC1/SC29/WG11, Tech. Rep, 2004. D. Zhang and G. Lu, "Review of shape representation and description techniques," Pattern Recognition, vol. 37, pp. 1-19, 2004.
[2]. Dr.Fuhuri Long, Dr.Hongjiang and Prof.David Dagan Feng, Fundamental of content basedImage Retrieval, http:// www. cse. iitd.ernet.in/pkalra/siv864/Projects/ch0 proof.pdf, 2003.
[3]. Young-jun Song, Won-bae Park, Dong-woo Kim, and Jae-hyeong Ahn, "Content-based image retrieval using new color histogram", Intelligent Signal Processing and Communication Systems, Proceedings of 2004 International Symposium on 18-19 Nov. 2004.
[4]. J-L.Shih and L.-H. Chen, "Color image retrieval based on primitives of color moments", Vision, Image and Signal, 2005.
[5]. NicuSebe, Michael S. Lew, Arnold W. M Smeulders, "Video retrieval and summarization: editorial introduction", Computer Vision and Image Understanding, Vol. 92, No. 2-3, pp. 141-146, 2003.
[6]. P. Geetha and Vasumathi Narayanan, "A Survey of Content-Based Video Retrieval", Journal of Computer Science, Vol. 4, No. 6, pp: 474-486, Shweta Ghodeswar, B.B. Meshram, "Content Based Video Retrieval", Proceeding of
[7]. International Symposium on Computer Engineering and technology, Mandi Gobindgarh,
[8]. Punjab, 20103852, pp 111-120, 2006.
[9]. Buch P, Patel N, "Content Based Image Retrieval: A Review" in proceedings of KITE-pp 48-51,2011.
[10]. R. Datta, D. Joshi, J. Li, and J. Z. WANG, "Image retrieval: Ideas, influences, and trends of the new age," ACM Computing Surveys, vol. 40, no.2 pp 1–60,2008.
[11]. MPEG-7 overview (version 10)," ISO/IEC JTC1/SC29/WG11, Tech. Rep, 2004. D. Zhang and G. Lu, "Review of shape representation and description techniques," Pattern Recognition, vol. 37, pp. 1-19, 2004.
[12]. Laws. K.. Rapid texture identification. In SPIE Vol. 238 Image Processing for Missile Guidance, pages 376-380, 1988.
[13]. Haralick, R.M., Watson, L.: A facet model for image data. Computer Vision Graphics Image Process 15, 113–129, 1988.

[14]. A P Pentland, Fractal Based Description of Natural Scenes, IEEE transaction on Pattern Analysis and Machine Intelligence, 6:661-674, 1984.

[15]. B. Mandelbrot. The Fractal Geometry of Nature. Freeman Co, San Francisco, 1982.

[16]. K Deguchi and I Morishita, Texture Characteristics and Texture Based Partitioning using two dimensional linear estimation, IEEE Transaction on Computers 27:739- 745,1977.

[17]. A. Rosenfeld and J. Weszka, “Picture Recognition” in Digital Pattern Recognition, K. Fu (Ed.), Springer-Verlag, 135-166, 1980.

[18]. J. Daugman, “Uncertainty Relation for Resolution in Space, Spatial Frequency and Orientation Optimised by Two-Dimensional Visual Cortical Filters”, Journal of the Optical Society of America, 2, 1160-1169, 1985.

[19]. Super, B. J. and A. C. Bovik, “Localized Measurement of Image Fractal Dimension Using Gabor Filters,” Journal of Visual Communication and Image Representation, 2 pp. 114-128, 1991Vision Research, pp. 847-856, 1980.

[20]. S G Mallat, Ab theory of multiresolution signal decomposition: The wavelet representation, IEEE transactions on pattern analysis and Machine intelligence. 11:674-693, 1989.

[21]. A. Laine and J. Fan, “Texture Classification by Wavelet Packet Signatures”, IEEE Trans. Pattern Analysis and Machine Intelligence, 15, 11, 1186-1191, 1993.

[22]. C. Lu, P. Chung and C. Chen, “Unsupervised Texture Segmentation via Wavelet Transform”, Pattern Recognition, 30, 5, 729-742, 1997.

[23]. D .-M. Tsai and M. fong Chen, “Object recognition by a linear weight classifier,” Pattern Recognition Letters, vol. 16, pp. 591-600, 1995.

[24]. H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik and Z. ALRahamneh,"Fast and Accurate Detection and Classification of Plant Diseases",International Journal of Computer Applications (0975 – 8887) Volume 17– No.1, March 2011.

[25]. Dheeb Al Bashish, Malik Braik, and Sulieman Bani-Ahmad,"A Framework for Detection and Classification of Plant Leaf and Stem Diseases", 2010 IEEE.