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Effective Method of Image Retrieval Using Markov Random Field with Hough Transform

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Abstract— The emergence of multimedia technology and the rapidly expanding image collections on the database have attracted significant research efforts in providing tools for effective retrieval and management of visual data. The need to find a desired image from a large collection. Image retrieval is the field of study concerned with searching and retrieving digital image from a collection of database .In real images, regions are often homogenous; neighboring pixels usually have similar properties (shape, color, texture) Markov Random Field (MRF) is a probabilistic model which captures such contextual constraints. Hough Transform method is used for detecting lines in binary images. Spatially extended patterns are transformed to produce compact features in a parameter space. The main advantages of using the HT is, it treats each edge point independently this means that the parallel processing of all points is possible which is suitable for real-time applications.

Keywords: *Feature Extraction, Similarity Measures, Image Retrieval.*

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I. INTRODUCTION

Image retrieval is the field of knowledge that deals with the representation, storage and access to image items. The remote sensing image processing and analysis have been an active research topic in the geosciences field [1]–[2] in recent decades. Local and holistic features are two types of descriptors for representing images. Local features are particularly capable of attending to local image patterns or textures, whereas holistic features describe the overall layouts of an image. One drawback of the two features is that the retrieved images often look alike but may be irrelevant to the query because remote sensing images often represent large natural geographical scenes that contain abundant and complex visual contents [7]. Directly combining different feature vectors into one vector is not a good idea for improving image retrieval accuracy because the feature characteristics and the algorithmic procedures are dramatically different [9]. The objective in Markov random field problem is to minimize the sum of the deviation cost function and a penalty function that grows with the distance between the values of related pairs— separation function. We discuss Markov random fields problems in the context of a representative application—the image segmentation problem. In this problem, the goal is to modify color shades assigned to pixels of an image so that the penalty function consisting of one term due to the deviation from the initial color shade and a second term that penalizes differences in assigned values to neighboring pixels is minimized. The Hough transform can efficiently detect straight or transformed lines which exist partially in images, even in images with noise. In particular, it simplified the complex problem of detecting straight lines in images into finding the maximum local value from the two-dimensional Hough arrangement through conversion of the parameter coordinate system planes. In this way, the Hough transform (HT) converts a global detection problem in the image space into an easier local peak detection problem in the parameter space.

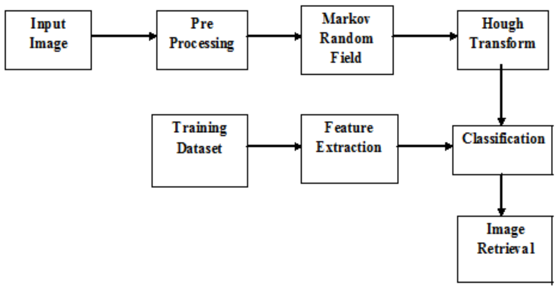

Fig block diagram of image retrieval

II. RELATED WORK

In this section, the related work about feature extraction, image retrieval, and similarity measure metrics, in the following.

A. Feature Representation and Fusion

Over the last two decades, a variety of feature descriptions has been proposed. They are generally divided into two categories: Markov Random Field and Hough Transform. In MRF the problem of image segmentation the image is transmitted and degraded by noise. The goal is to reset the values of the colors to the pixels so as to minimize the penalty for the deviation from the observed colors, and furthermore, so that the discontinuity in terms of separation of colors between adjacent pixels is as small as possible. In Hough Transform introduced an efficient method for detecting lines in binary images. Spatially extended patterns are transformed to produce compact features in a parameter space. In this way, the Hough transform (HT) converts a global detection problem in the image space into an easier local peak detection problem in the parameter space. To describe the working of the HT algorithm, the slope-intercept parameterization and the voting scheme are summarized.

Clearly, combining local and holistic cues at the feature level makes it difficult to preserve the efficiency and scalability. By combining the complementary advantages offered by both MRF and Hough Transform can enhance the overall retrieval precision.

B. Similarity Measure Approaches

Similarity measure is often used on the extracted features to identify the images similar to the query. The shape similarity can easily be defined by means of a distance measure (the Euclidean distance).The Euclidean distance can simply be described as the ordinary distance between two values. The Euclidean distances between the feature vectors P=(p1,p2,…..pn) and Q=(q1,q2,…..qn) is expressed by

$$D=\sqrt{\sum_{k=1}^{n}(p_k\text{-}q_k)}^2$$

C. Image Retrieval

In this section, the subjects of image matching and retrieval related to our paper. In a content based image retrieval system was presented, which aimed at classifying and retrieving oceanic structures from satellite images. In semantic matching of multilevel image scenes was utilized to retrieve. In the authors described a content-based shape retrieval of objects from a large-scale satellite images. Ferecatu and Boujemaa developed an active relevance feedback solution based on support vector machines using weighted histograms as descriptors. In a support vector machine approach was employed to recognize land

cover information corresponding to spectral characteristics.

III. IMAGE FEATURE DESCRIPTORS

In this section, The procedure for extracting Markov Random Field and Hough Transform descriptors.

3.1 Markov Random Field

This class of problems is also known as the metric labeling problem. The unifying ideas in using MRFs for vision are the following:

1. Images are dissected into an assembly of nodes that may correspond to pixels or agglomerations of pixels.
2. Hidden variables associated with the nodes are introduced into a model designed to “explain” the values (colors) of all the pixels.
3. A joint probabilistic model is built over the pixel values and the hidden variables.
4. The direct statistical dependencies between hidden variables are expressed by explicitly grouping hidden variables; these groups are often pairs depicted as edges in a graph.

The motivation for constructing such a graph is to connect the hidden variables associated with the nodes.

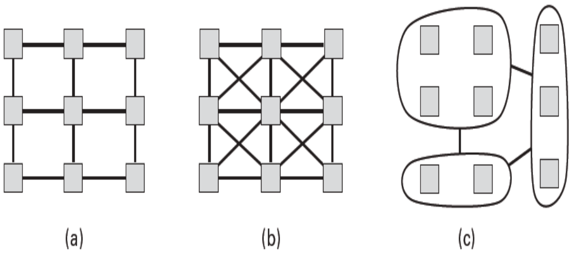

Fig Graphs for Markov models in vision. (a) Simple 4-connected grid of image pixels. (b) Grids with greater connectivity can be useful—for example, to achieve better geometrical detail (see discussion later)—as here with the 8-connected pixel grid. (c) Irregular grids are also useful. Here a more compact graph is constructed in which the nodes are super pixels—clusters of adjacent pixels with similar colors.

3.1.1 Markov Chains:

The Simplest Markov Models In a Markov chain a sequence of random variables X = (X1,X2, . . .) has a joint distribution specified by the conditionals P(Xi |Xi−1,Xi−2, . . . , X1). The classic tutorial example is the weather, so that Xi ∈ L = {sunny, rainy}. The weather on day i can be influenced by the weather many days previous, but in the simplest form of Markov chain, the dependence of today’s weather is linked explicitly only to yesterday’s weather. It is also linked implicitly, as a knock-on effect, to all previous days. This is a first-order Markov assumption, that

P(Xi | Xi−1,Xi−2, . . . , X1) =
P(Xi | Xi−1)……………………….. (1.1)

This is illustrated in figure 1.2. The set of conditional probabilities P(Xi | Xi−1) is in fact a 2×2 matrix. For example: An interesting and commonly used special case is the stationary Markov chain, in which the matrix
Mi(x, x’) = P(Xi = x | Xi−1 = x’) …...(1.2)

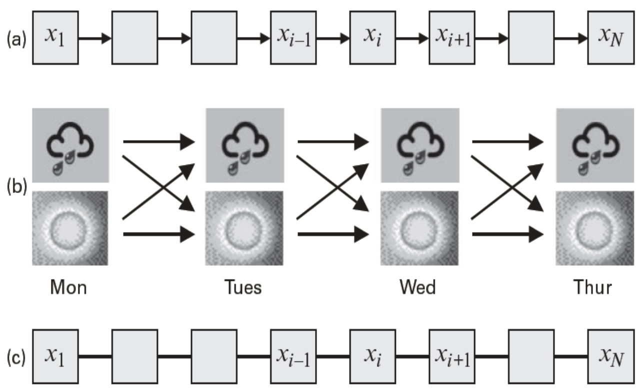

Fig. A simple first-order Markov chain for weather forecasting. (a)A directed graph is used to represent the conditional dependencies of a Markov chain. (b) In more detail, the state transition diagram completely specifies the probabilistic process of the evolving weather states. (c)A Markov chain can alternatively be expressed as an undirected graphical model; see text for details.

3.2. Hough Transform

In this way, the Hough transform (HT) converts a global detection problem in the image space into an easier local peak detection problem in the parameter space. To describe the working of the HT algorithm, the slope-intercept parameterization and the voting scheme are summarized [9].

1. Build a parameter space with a suitable quantization level for line slope m and intercept c
2. Create an accumulator array A(m,c)
3. Set A(m,c) = 0,
4. Extract image edges using Canny detector
5. For each pixel on the image (xi,yj) (mk,ci)edges verifying equation:

   Ci = -xi*mk+yj

   Increment: A(mk,ci)=A(mk,ci)+1.
6. Find the local maxima in A(m,c) that indicate the lines in the parameter space.

xcos θ +ysin θ =1

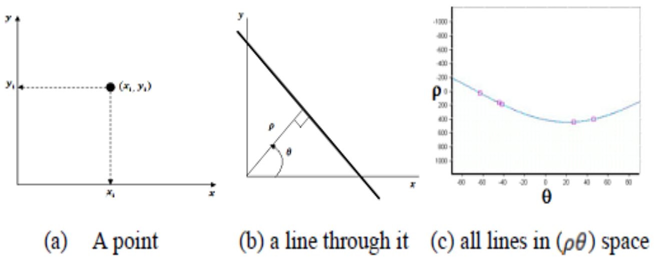

Fig. A point-to-curve transformation in (ρ,θ) parameterization

3.2.1. HT-BASED INDEXING

Retrieval is performed by tasking a sample drawing as an input. Given the sample image, the task is to find all database images similar to the query image. A feature vector is generated from the query image, and this feature vector is used for the matching. The selection of the features is the key part of the indexing scheme. The size of the feature vector should be small enough to be stored compactly and processed efficiently, but it should also representative so that then images can be differentiated from each other on the basis of their feature vectors[10], [11]. Apply Hough transform for the indexing as it gives scale independent global description of the spatial image content. In Hough Transform, global features are sought as sets of individual points over the whole image. In the simplest case the features are straight line segments. In the case of binary images, the line detection algorithm can be described as follows:

1. Create the set *D* of the black pixels in the image.
2. Transform each pixel in *D* into a parametric curve in the parameter space.
3. Increment the cells in the accumulator matrix *A* determined by the parametric curve.
4. Detect local maxima in the accumulator array. Each local maximum may correspond to a parametric curve in the image space.
5. Extract the curve segments using the knowledge of the maximum positions.

3.2.2. Generating feature vector

That the accumulator matrix is denoted by *A*, and each row in corresponds to one value of ρ, and each column to one value of θ. The procedure for generating the feature vector from the accumulator matrix. initially extract only the most significant information by thresholding the matrix using a threshold value *T* (step 1). Next, shrink the threshold accumulator matrix to one-dimensional θ-vector by summing up the remaining

coefficients in each column (step 2). Thus, only the angular information of the matrix will be used. Finally, normalize the feature vectors according to the mean value of the components of the vector (steps 3 and 4).

3.2.3. Translation and scale invariant matching

The usage of only the angular information (θ-vector) has several advantages. First, the matching is independent of the spatial location of the lines and therefore the method is translation and scaling invariant by its nature. This is verified by the fact that every line has the same θ-value independent of scaling and translation of the image. The angular information can be sufficient for separating different image types [12]. For example, drawing of buildings consists mainly of 45° and 90° angles. Then approximate the dissimilarity of the images by calculating the distance of their feature vectors. Let us assume that we got feature vector *D* for database image and feature vector *S* for sample query image (both of size *N*). The distance is calculated

$$\mathrm{D} = \sum_{j=1}^{N} (\mathrm{Dj} - \mathrm{Sj})2$$

Here d=0 coincides to absolutely similar images and $d=d_{max}$ coincides to images with no similarities found. An important advantage of the simplicity of the formula is its speed. This is highly desired property for searching from large image database.

IV. IMAGE DESCRIPTORS

The basis of any content-based image retrieval technique. In a broad sense, features may include both text-based features (key words, annotations) and visual features (color, texture, shape, etc.).

A.COLOR

Color is a perception that depends on the response of the human visual system to light and the interaction of light with objects. Color is one of the most widely used visual features in visual image retrieval. The key issues in color feature extraction include the color space, color quantization, and the choice of similarity function. Each pixel of the image can be represented as a point in a 3D color space. To describe an image by its color features, and first determine the color space to use.

a. Color space

There are a number of different color spaces currently used for the representation of images in the digital world. Choosing an appropriate color space for the implementation of an image retrieval system is not only important to the production of the accurate results, but to the accurate representation of color in the way the human visual system perceives it. There are a number of color spaces in use of which some of the most commonly used are:

1. RGB

The most popular color space is RGB which stands for Red-Green-Blue these are the additive primary colors. By this added to produce more or less any color in the visible spectrum. This space is device dependant and perceptually non-uniform. This means that a color relative close together in the RGB space may not necessarily be perceived as being close by the human eye. For a monitor the phosphor luminescence consists of additive primaries and can simply parameterize all colors via the coefficients (α, β, γ), such that $C = \alpha R+\beta G+\gamma B$. The coefficients range from zero (no luminescence) to one (full phosphor output). In this parameterization the color coordinates fill a cubical volume with vertices black, the three primaries (red, green, blue), the three secondary mixes (cyan, magenta, yellow), and white as shown in Fig 2 .

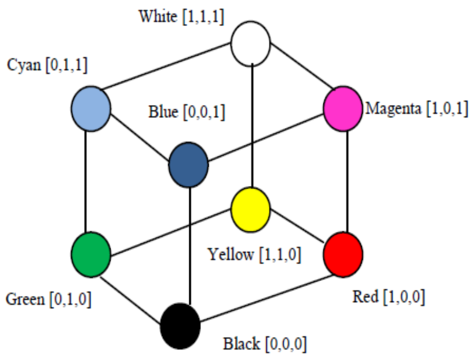

Fig 2: RGB Color space

2. HSV

Colors in the HSV color space are defined in terms of three constituent components; Hue, Saturation and Value. Hue is the type of color (red, blue, etc), saturation is the vibrancy of the color (the lower the saturation the more grayness is present) and the value is the brightness of the color. RGB coordinates can be easily translated to the HSV coordinates by a simple formula.HSV is perceptually uniform so colors close in value are also perceived close by the human eye.

B.TEXTURE

a. Definition

The Texture is defined as the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. It is a natural property of virtually all surfaces, including clouds, trees, bricks, hair, and fabrics. It contains important information about the structural arrangement of surfaces and their relationship. Fig,3 shows a few types of texture

Fig 3. Examples of Texture

b. Methods of representation

Texture representation methods can be classified into three categories:

Statistical techniques characterize texture using the statistical properties of the gray levels of the pixels comprising an image. Normally, in images, there is periodic occurrence of certain gray levels. The spatial distribution of gray levels is calculated.

Structural techniques characterize texture as being composed of texels (texture elements). These texels are arranged regularly on a surface according to some specific arrangement rules.

Spectral techniques are based on properties of the Fourier spectrum and describe global periodicity of the grey levels of a surface by identifying high-energy peaks in the Fourier spectrum.

C. SHAPE

a. Definition

Defining the shape of an object is often very difficult. Shape is usually represented verbally or in figures, and people use terms such as elongated, rounded etc. Computer-based processing of shape requires describing even very complicated shapes precisely and while many practical shape description methods exists, there is no generally accepted methodology of shape description. Shape is an important visual feature and it is one of the primitive features for image content description. It contains all the geometrical information of an object in the image which does not change generally change even when orientation or location of the object are changed. Some simple shape features are the perimeter, area, eccentricity, symmetry, etc.

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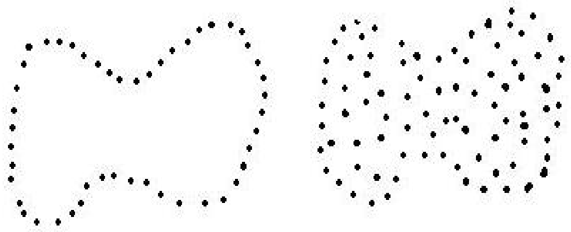
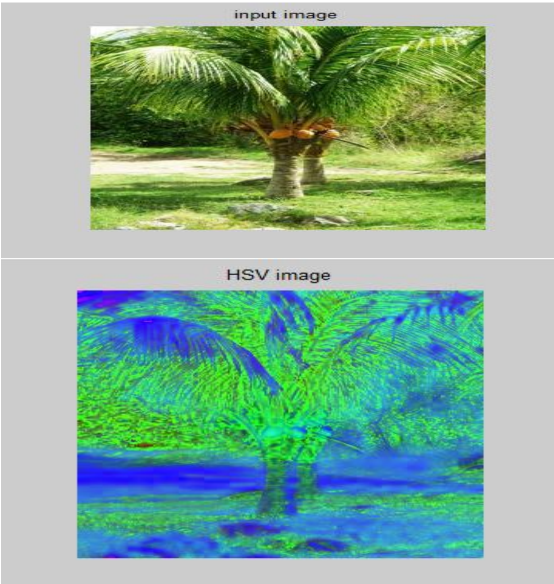
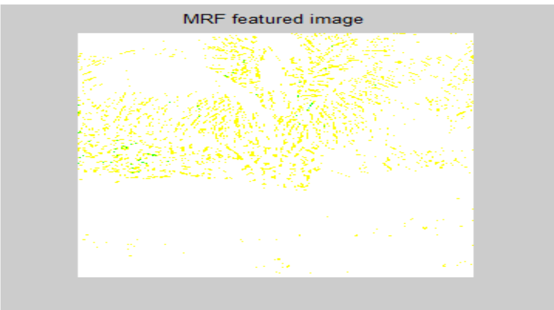
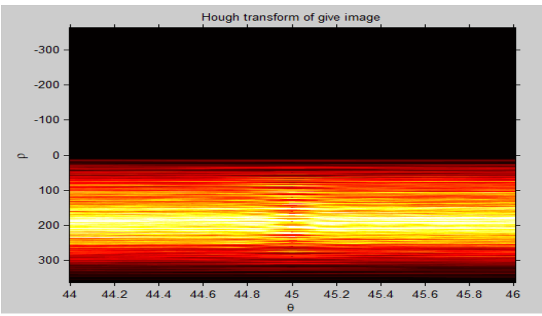


Fig 4: Boundary-based & Region-based shape representations

V SIMULATION RESULT







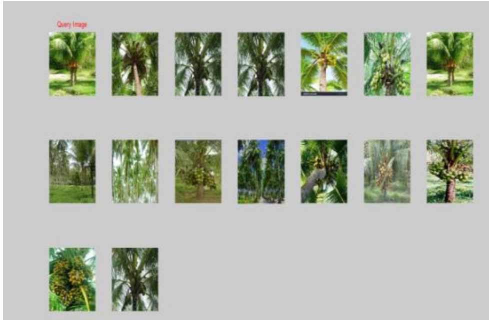


Fig. (a) sample input image (b)RGB to HSV converted image (c)corresponding MRF image (d)Hough transform image (e)similarity measurement images.

VI CONCLUSION

Rapid growth of remote sensed information generates a new research challenges in processing, transferring, archiving, and retrieving of these huge amounts of data. Existing methods share some common issues; the main important is that they are not adapted to all types of categories. In this paper, we have implemented in sequential, the segmentation algorithm is highly parallel due to the local nature of the MRF model. Thus, a parallel implementation can further improve the computing speed. Hough transform scheme, generalized Hough transform has been presented. This is robust parametric estimation and clustering method even though image is distorted by noise and discretization. By selecting various feature and feature composition function, it is applicable for various applications. From the tests, it appeared that this stage can greatly improve the retrieval process by boosting its performances even for basic features. Thus, associated to multi scale representation of color features descriptors, this will permit to better take into account objects of different sizes and shapes present in images.

VI FUTURE WORK

The future scope of novel image retrieval is based on block truncation coding (BTC) with Gabor wavelet Co-occurrence matrix. BTC can be used for grayscale as well as for color images. The average precision and recall rate of all queries are considered for performance analysis. To achieve the better results modified SVM will be taken for classification.

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