

Texture and Region Based Segmentation for Image Object Detection

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Abstract— The number of digital images rapidly increases, and it becomes an important challenge to organize these resources effectively. As a way to facilitate image categorization and retrieval, automatic image annotation has received much research attention. Considering that there are a great number of unlabelled images available, it is beneficial to develop an effective mechanism to leverage unlabelled images for large-scale image annotation. Nowadays, locations of images have been widely used in many application scenarios for large geo-tagged image corpora. As to images which are not geographically tagged, we estimate their locations with the help of the large geo-tagged image set by content-based image retrieval. We first construct a graph model according to image visual features. A multi label classifier is then trained by simultaneously uncovering the shared structure common to different labels and the visual graph embedded label prediction matrix for image annotation. We show that the globally optimal solution of the proposed framework can be obtained by performing generalized Eigen-decomposition. The dominant spectral components of this graph lead to simultaneous pixel-wise alignment of the images and saliency-based synchronization of 'soft' image segmentation.

Index Terms— annotation; retrieval; geo-tagged; classifier.

I. INTRODUCTION

Traditional image retrieval techniques are mainly based on manual text annotation. Given the rapid increase in the number of digital images, manual image annotation is extremely time-consuming. Furthermore, it is annotator dependent. Content-Based Image Retrieval (CBIR) promises to address some of the shortcomings of manual annotation. Many existing CBIR systems rely on queries that are based on low-level features. One of the main challenges in CBIR is to bridge the semantic gap between low-level features and high-level contents. For example, consider an image of a mountain: in low-level terms, it is a composition of colours, lines of different length, and different shapes; in high-level terms, it is a mountain. If users want to search for mountain images, they need to specify the low-level features such as green texture or they could enter the keyword mountain.

Automatic image annotation, whose goal is to automatically assign the images with the keywords, Has been an active research topic owing to its great potentials in image retrieval and management systems. Image annotation is essentially a typical multi-label learning problem, where each image could contain multiple objects and therefore could be associated with a set of labels. Since generally it is tedious and time-consuming for humans to manually annotate the keywords in the object/region level for data collection, instead the keywords are usually labeled in the image level, which makes the automatic image annotation problem even more challenging. The image annotation problem has been extensively studied in recent years. The popular algorithms can be roughly divided into three categories: classification-based methods, probabilistic modeling-based methods, and Web image related methods.

II. AUTOMATIC IMAGE ANNOTATION

Main idea of Automatic Image Annotation (AIA) is to capture semantic content of images to provide better means to organize and search on image database. It is mapping from the visual content information to the semantic context information automatically. It is best case in terms of efficiency and time but more error prone. But AIA is difficult task because visual content to be analyzed depend on many factors such as shooting conditions, instances of objects, lighting condition, resolution of camera, and the background clutters. State of the art automatic image annotation systems can be analyzed and grouped from various point of views.

III. PROPOSED WORK

The proposed solution was initially to extract the primitive features of a query image and compare them to those of database images. The image features under consideration were color, texture and shape. Thus, using matching and comparison algorithms, the color, texture and shape features of one image are compared and matched to the corresponding features of another image. This comparison is performed using color, texture and shape distance metrics. In the end, these metrics are performed one after another, so as to retrieve database images that are similar to the query. The salient region matching using feature extraction is given below:

a) *Colour*

Colour is a property that depends on the reflection of light to the eye and the processing of that information in the brain. We use Colour every day to tell the difference between objects, places, and the time of day. Usually, colours are defined in three dimensional Colour spaces. These could either be RGB (Red, Green, and Blue), HSV (Hue, Saturation, and Value) or HSB (Hue, Saturation, and Brightness). The last two are dependent on the human perception of hue, saturation, and brightness.

b) *Texture*

Texture is that innate property of all surfaces that describes visual patterns, each having properties of homogeneity. It contains important information about the structural arrangement of the surface, such as; clouds, leaves, bricks, fabric, etc. It also describes the relationship of the surface to the surrounding environment. In short, it is a feature that describes the distinctive physical composition of a surface.

Texture properties include coarseness, contrast, directionality, line-likeness, regularity and roughness. The most popular statistical representations of texture are:

- Co-occurrence Matrix
- Tamura Texture
- Wavelet Transform

c) *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 representations can be generally divided into two categories:

- Boundary-based, and
- Region-based.

d) *Gaussian Smoothing*

Gaussian blur is also known as Gaussian smoothing is the result of blurring an image by a Gaussian function. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen, distinctly different from the bokeh effect produced by an out-of-focus lens or the shadow of an object under usual illumination. Gaussian smoothing is commonly used with edge detection. Most edge-detection algorithms are sensitive to noise and the 2-D Laplacian filter, built from a discretization of the Laplace operator, is highly sensitive to noisy environments. Using a Gaussian Blur filter before edge detection aims to reduce the level of noise in the image, which improves the result of the following edge-detection algorithm.

e) *Gradient*

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. In graphics software for digital image editing, the term gradient or color gradient is used for a gradual blend of color which can be considered as an even gradation from low to high values, as used from white to black in the images to the right.

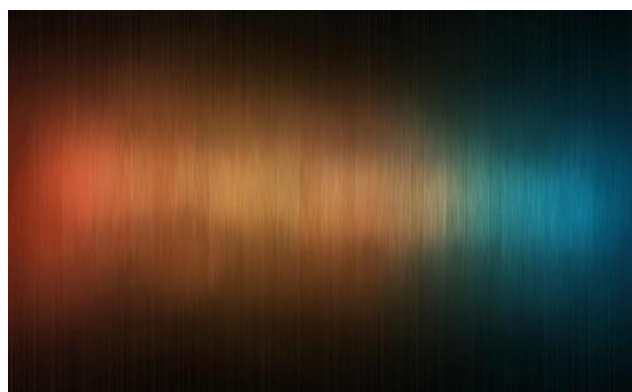


Fig. 1 Color Gradient

The gradient of an image is given by the formula,

$$\nabla f = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (1)$$

Where,

$\frac{\partial f}{\partial x}$ is the gradient in the x direction

$\frac{\partial f}{\partial y}$ is the gradient in the y direction.

IV. COARSE AND FINE SEGMENTATION

Edges are boundaries between different textures. Edge also can be defined as discontinuities in image intensity from one pixel to another. The edges for an image are always the important characteristics that offer an indication for a higher frequency. Detection of edges for an image may help for image segmentation, data compression, and also help for well matching, such as image reconstruction and so on.

V. REGION-BASED SEGMENTATION

The main goal of segmentation is to partition an image into regions. Some segmentation methods such as "Thresholding" achieve this goal by looking for the boundaries between regions based on discontinuities in gray levels or color properties. Region-based segmentation is a technique for determining the region directly.

The first step in region growing is to select a set of seed points. Seed point selection is based on some user criterion (for example, pixels in a certain gray-level range, pixels evenly spaced on a grid, etc.). The initial region begins as the exact location of these seeds.

The regions are then grown from these seed points to adjacent points depending on a region membership criterion. The criterion could be, for example, pixel intensity, gray level texture, or color. Since the regions are grown on the basis of the criterion, the image information itself is important. For example, if the criterion were a pixel intensity threshold value, knowledge of the histogram of the image would be of use, as one could use it to determine a suitable threshold value for the region membership criterion.

VI. RESULTS AND OBSERVATIONS

The human visual system can distinguish hundreds of thousands of different Colour shades and intensities, but only around 100 shades of grey. Therefore, in an image, a great deal of extra information may be contained in the Colour, and this extra information can then be used to simplify image analysis, e.g. object identification and extraction based on Colour.



Fig. 2 Input images

It converts an RGB Colour map to an HSV Colour map. Each map is a matrix with any number of rows, exactly three columns, and elements in the interval 0 to 1. The columns of the input matrix M , represent intensity of red, blue and green, respectively. The columns of the resulting output matrix H , represent hue, saturation and Colour value, respectively.

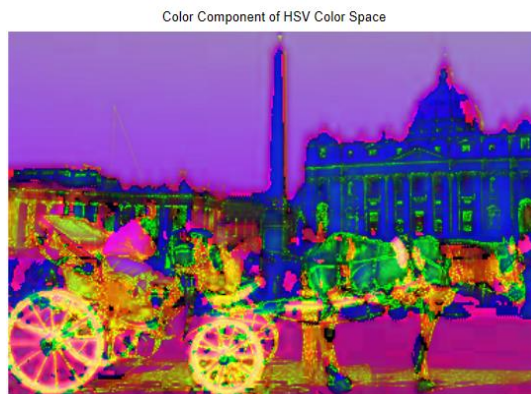


Fig.3 HSV

The Gaussian smoothing operator is a 2-D convolution operator that is used to 'blur' images and remove detail and noise. In this sense it is similar to the mean filter, but it uses a different kernel that represents the shape of a Gaussian ('bell-shaped') hump.



Fig. 4 Gaussian smoothing

The gradient of an image measures how it is changing. It provides two pieces of information. The magnitude of the gradient tells us how quickly the image is changing, while the direction of the gradient tells us the direction in which the image is changing most rapidly. To illustrate this, think of an image as like a terrain, in which at each point height is given, rather than intensity. For any point in the terrain, the direction of the gradient would be the direction uphill. The magnitude of the gradient would tell us how rapidly our height increases when we take a very small step uphill.



Fig.5 Magnitude of gradient vector

An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image texture gives us information about the spatial arrangement of Colour or intensities in an image or selected region of an image.



Fig. 6 Texture mapping

Where an edge based technique may attempt to find the object boundaries and then locate the object itself by filling them in, a region based technique takes the opposite approach, by (e.g.) starting in the middle of an object and then “growing” outward until it meets the object boundaries.

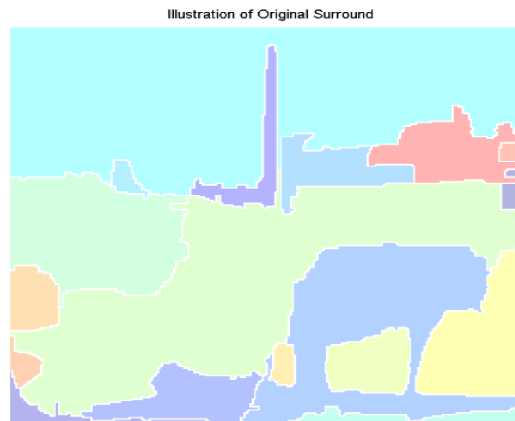


Fig. 7 Illustration of original surround

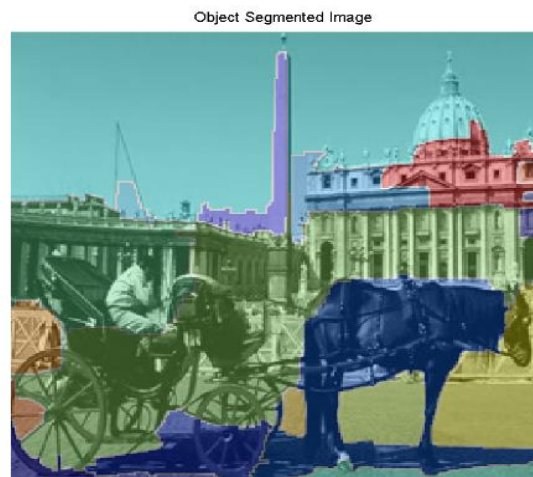


Fig. 8 Segmented images

VII. CONCLUSION AND FUTURE WORK

In this paper, a new scheme is developed for ambiguous image representation by using bags of instances: 1) each image is first partitioned into a set of image regions by using multiple segmentations are integrated to obtain more meaningful image regions (image instances) for object detection 2) each image region is treated as one instance; and 3) multimodal visual features are extracted from each image instance to characterize its various visual properties more sufficiently. By partitioning the images into bags of instances, our ambiguous image representation framework can provide multiple advantages: 1) it can provide a good foundation to automatically identify the correspondences between multiple labels (given at the image level) and the image instances (image regions); 2) it can provide a natural way to tackle the issue of multiple labels explicitly in the instance space, e.g., different image instances may relate to different labels; and 3) it is able to characterize the appearances of the objects effectively by integrating multiple segmentation results. In our current implementations, we have extracted the following region-based visual features: 12-bins Colour histogram, top three dominant colours, nine-bin edge histogram, region shapes, region size and location of its centre in an image, and Tamura textures. Each type of these visual features (i.e., one particular feature subset) is used to characterize one certain type of the visual properties of the image instances, and a suitable base kernel is designed for each type of visual features for characterizing one certain type of the visual similarity contexts between the image

instances. To avoid the issue of image segmentation for feature extraction while providing the object information at certain accuracy level, four grid resolutions are alternatively used for image partition and feature extraction is used.

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