Histogram Generation from the HSV Color Space

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INTRODUCTION

Digital image databases have seen an enormous growth over the last few years. However, since many image collections are poorly indexed or annotated, there is a great need for developing automated, content-based methods that would help users to retrieve images from these databases. In recent times, a lot of attention has been paid to the management of an overwhelming accumulation of rich digital images to support various search strategies. In order to improve the traditional text-based or SQL (Structured Query Language)-based database searches, research has been focused on efficient access to large image databases by the contents of images, such as color, shape, and texture. Content-based image retrieval (CBIR) has become an important research topic that covers a large number of domains like image processing, computer vision, very large databases, and human computer interaction (Smeulders, Worring, Santini, Gupta & Jain, 2000). Several content-based image retrieval systems and methods have recently been developed.

QBIC (Query By Image Content) is one of the first image retrieval systems developed at IBM (Niblack et al., 1993). Color, texture, and shape features are combined to represent each image in this system. The VisualSeek system, developed at the Columbia University, is an image retrieval system based on visual features (Chang, Smith, Mandis & Benitez, 1997). The NeTra system is a prototype image retrieval system, which uses color, texture, shape, and spatial location information as features to retrieve similar images (Ma & Manjunath, 1997). Some of the other popular CBIR systems are MARS (Ortega et al., 1998), Blobworld (Carson, Thomas, Belongie, Hellerstein & Malik, 1999), PicToSeek (Gevers & Smeulders, 2000), and SIMPLIcity (Wang, Li & Wiederhold, 2001).

An analysis of these systems reveals that all of them give a lot of importance on the image color for retrieval. In fact, color is always considered to be an important attribute, not only in content-based image retrieval systems, but also in a number of other applications like segmentation and video shot analysis. In color-based image retrieval, there are primarily two methods: one based on color layout (Smith & Chang, 1996) and the other based on color histogram (Swain & Ballard, 1991; Wang, 2001). In the color layout approach, two images are matched by their exact color distribution. This means that two images are considered close if they not only have similar color content, but also if they have similar color in approximately the same positions. In the second approach, each image is represented by its color histogram. A histogram is a vector whose components represent a count of the number of pixels having similar colors in the image. Thus, a color histogram may be considered to be a signature extracted from a complete image. Color histograms extracted from different images are indexed and stored in a database. During retrieval, the histogram of a query image is compared with the histogram of each database image using a standard distance metric like the Euclidean distance or the Manhattan distance. Since color histogram is a global feature of an image, the approaches based on color histogram are invariant to translation and rotation, and scale invariant with normalization.

Color histograms may be generated using properties of the different color spaces like RGB (Red, Green, and Blue), HSV (Hue, Saturation, and Intensity Value), and others. In this article, we give an overview of the different histogram generation methods using the HSV color space. We first present a brief background of the HSV color space and its characteristics, followed by the histogram generation techniques for various applications.

BACKGROUND

A color space or a color model is a specification of a coordinate system and a subspace within that system where a single point represents a distinct color value. There are several well-known color spaces that are used to represent the pixels of an image. This representation is used for image analysis like extraction of color histograms. Each color space has its own merits and demerits depending on the application and hardware specification where it is going to be used. RGB, CMY, CMYK, and HSV are some of the popular color spaces. The RGB color space contains three color components, namely red, green and blue, each of which appears in its primary spectral components. Devices that deposit colored pigments on paper use CMY color space, and the representation of this color space is with the secondary colors of light, which are Cyan, Magenta, and Yellow. CMYK (Cyan, Magenta, Yellow, Black) color space is similar to CMY but is used to produce true black color, which is muddy-black in the CMY color space.

The HSV (Hue, Saturation, Value) color space, on the other hand, closely corresponds to the human visual perception of color. The HSV color space can be represented as a three-dimensional hexacone, where the central vertical axis represents intensity which takes a value between 0 and 255 (Shapiro & Stockman, 2001). Hue is defined as an angle in the range $\pi[0,2]$ relative to the red axis with red at angle 0, green π at 2/3, blue π at 4/3, and red again π at 2. Saturation is the depth or purity of color and is measured as a radial distance from the central axis to the outer surface. For zero saturation, as we move higher along the intensity axis, we go from black to white through various shades of gray. On the other hand, for a given intensity and hue, if the saturation is changed from zero to one, the perceived color changes from a shade of gray to the most pure form of the color represented by its hue. When saturation is near zero, all pixels, even with different hues, look alike and as we increase the saturation towards one, they tend to get separated out and are visually perceived as the true colors represented by their hues. Thus, the effect of saturation may be considered as that of introducing visual shadows on the image for any given value of hue and intensity.

The HSV model is an ideal tool for developing image and video processing algorithms based on color descriptions. A number of histogram generation methods from the HSV color space have recently been proposed for different applications. We next describe some of these approaches.

HISTOGRAM GENERATION FROM THE HSV COLOR SPACE

The HSV color space in general, and the HSV color histogram in particular, plays an important role in image analysis. A color histogram can be used in image retrieval, segmentation, video shot detection, color and intensity-based clustering, place recognition for topological localization, person identification and authentication using biometric techniques, as well as in many other applications.

For image retrieval applications, an HSV color histogram can be generated using an approach similar to the RGB color space. The hue scale is divided into eight groups, saturation scale is divided into two groups, and the intensity scale is divided into four groups. By combining each of these groups, we get a total of 64 cells to represent a 64-component HSV color histogram. The reason for having a different number of groups for the three scales is that, of the three axes, hue is considered to be the most important, followed by intensity, and finally, saturation. For the H, S, and V combination of values, the corresponding histogram component is determined. The respective histogram component is updated by one for each pixel having the corresponding color combination. An efficient indexing of the histograms can enhance the performance of a CBIR application to a great extent. Smith and Chang (1996) exploit this idea in their color set approach. This method extracts spatially localized color information and provides efficient indexing of the color regions. The large single color regions are extracted first, followed by multiple color regions. They utilize binary color sets to represent the color content as a color histogram. The H and S dimensions are divided into N and M bins, respectively, for a total of N×M bins (Ortega et al., 1998). Each bin contains the percentage of pixels in the image that have corresponding H and S colors for that bin. Intersection similarity is used as a measure to capture the amount of overlap between two histograms.

From the properties of the HSV color space, it is observed that for low values of saturation, a color is approximated by a gray value specified by the intensity level while for higher saturation, the color is approximated by its hue. This captures the human visual properties effectively and can be used to generate a histogram for image retrieval applications (Sural, 2003; Sural, Qian & Pramanik, 2002). The saturation threshold that determines this transition is once again dependent on the intensity. Thus, the value of saturation projected onto the hue and intensity plane is useful for the extraction of color information. A threshold function can be used to determine if a pixel should be represented by its hue or by its intensity in the color histogram. For an intensity value of zero, all the colors are considered as black, whatever their hue or saturation may be. On the other hand, with increasing values of intensity, the saturation threshold that separates hue dominance from intensity dominance goes down. This approach treats the pixels as a distribution of “colors” in an image where a pixel may be of a “gray color” or of a “true color.” The histogram is a logical combination of two independent histograms—one for the true colors and one for the gray colors. One drawback of this approach is that for saturation values near the threshold, a pixel is neither a true color pixel nor a gray color pixel. In order to capture the fuzzy nature of human visual perception of color, there is a need for using a soft threshold to determine the dominant property of a pixel. In the soft threshold approach, two

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