

Fusion of Local and Global Features with Stationary Wavelet Transform For Efficient Content Based Image Retrieval

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ABSTRACT:

This paper has a further exploration and study of visual feature extraction. According to the HSV (Hue, Saturation, Value) color space, the work of color feature extraction is finished, the process is as follows: quantifying the color specimen non-equal intervals, constructing one dimension feature vector and representing the color feature by cumulative histogram. Similarly, the work of texture feature extraction is obtained by using gray-level co-occurrence matrix (GLCM) or color co-occurrence matrix (CCM). Through the quantification of HSV color space, we combine color features and GLCM as well as CCM separately. Depending on the former, image retrieval based on multi-feature fusion is achieved by using normalized Euclidean distance classifier. Through the image retrieval experiment, indicate that the use of color features and texture based on CCM has obvious advantage. Color correlogram for content based image retrieval characterizes not only the color distribution of pixels but also the spatial correlation of the pair of colors. Color not only reflect the material of the surface but also varies considerably with the change of the illumination. The orientation of the surface and the viewing geometry of the camera.

1.1 Introduction:

Digital image processing is electronic data processing on a 2-D array of numbers. The array is a numeric representation of an image. A real image is formed on a sensor when an energy emission strikes the sensor with sufficient intensity to create a sensor output. An image may be defined as a two-dimensional function, $f(x, y)$, where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point.

When x , y , and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. A digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, pels, and pixels. Pixel is most widely used to denote the elements of a digital image. Images play the single most important role in human perception. Humans are limited to the visual band of the electromagnetic (EM) spectrum, imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate on images generated by sources that humans are not accustomed to associating with images. These include ultrasound, electron microscopy, and computer-generated images. Thus, digital image processing encompasses a wide and varied field of applications. Digital image processing is the use of computer algorithms to perform image processing on digital images. Digital image processing has the same advantages over analog image processing as digital signal processing has over analog signal processing it allows a much wider range of algorithms to be applied to the input data, and can avoid problems such as the build-up of noise and signal distortion during processing. Image processing is a subclass of signal processing concerned specifically with pictures. Improve image quality for human perception and/or computer interpretation.

1.2 Fundamental Steps in Digital Image Processing

1.2.1 Image Acquisition

An image is captured by a sensor (such as a monochrome or color TV camera) and digitized.

If the output of the camera or sensor is not already in digital form, an analog-to-digital converter digitizes it. Generally, the image acquisition stage involves preprocessing, such as scaling.

1.2.2 Image Enhancement :

Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image. A familiar example of enhancement is when we increase the contrast of an image because “it looks better.” To bring out detail is obscured, or simply to highlight certain features of interest in an image.

1.2.3 Image Restoration:

Image restoration is an area that also deals with improving the appearance of an image. Image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation. Enhancement, on the other hand, is based on human subjective preferences regarding what constitutes a “good” enhancement result. Improving the appearance of an image tend to be based on mathematical or probabilistic models of image degradation.

1.2.4 Image Compression:

Image Compression deals with techniques for reducing the storage required saving an image, or the bandwidth required transmitting it. Although storage technology has improved significantly over the past decade, the same cannot be said for transmission capacity. This is true particularly in uses of the Internet, which are characterized by significant pictorial content. Image compression is familiar to most users of computers in the form of image file extensions, such as the jpg file extension used in the JPEG (Joint Photographic Experts Group) image compression standard.

1.2.5 Image Segmentation:

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes. Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique. The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. The desired edges are the boundaries between such objects. Segmentation methods can also be applied to edges obtained from edge detectors. Lindeberg and Li developed an integrated method that segments edges into straight and curved edge segments for parts-based object recognition, based on a minimum description length (MDL) criterion that was optimized by a split-and-merge-like method with candidate breakpoint obtained from complementary junction cues to obtain more likely points at which to consider partitions into different segment.

2.1 Image retrieval :

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. A large amount of research has been done on automatic image annotation. Additionally, the increase in social web applications and the semantic web have inspired the development of several web-based image annotation tools. The first microcomputer-based image database retrieval system was developed at MIT, in the 1980s, by Banireddy Prasad, Amar Gupta, Hoo-min Toong, and Stuart Madnick.

2.2 Search methods

2.1.2 Image search:

It is a specialized data search used to find images. To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images “similar” to the query. The similarity used for search criteria could be meta tags, color distribution in images, region/shape attributes, etc. Image meta search - search of images based on associated metadata such as keywords, text, etc.

Content-based image retrieval (CBIR) – the application of computer vision to the image retrieval. CBIR aims at avoiding the use of textual descriptions and instead retrieves images based on similarities in their contents (textures, colors, shapes etc.) to a user-supplied query image or user-specified image features. List of CBIR Engines - list of engines which search for images based image visual content such as color, texture, shape/object, etc.

2.2.2 Data Scope:

It is crucial to understand the scope and nature of image data in order to determine the complexity of image search system design. The design is also largely influenced by factors such as the diversity of user-base and expected user traffic for a search system. Along this dimension, search data can be classified into the following categories:

- Archives - usually contain large volumes of structured or semi-structured homogeneous data pertaining to specific topics.
- Domain-Specific Collection - this is a homogeneous collection providing access to controlled users with very specific objectives. Examples of such a collection are bio-medical and satellite image databases.
- Enterprise Collection - a heterogeneous collection of images that is accessible to users within an organization’s intranet. Pictures may be stored in many different locations.
- Personal Collection - usually consists of a largely homogeneous collection and is generally small in size, accessible primarily to its owner, and usually stored on a local storage media.
- Web - World Wide Web images are accessible to everyone with an Internet connection. These image collections are semi-structured, non-homogeneous and massive in volume, and are usually stored in large disk arrays.

7.1 Feature extraction of the HSV color

7.1.1 Image Retrieval:

Image retrieval is nothing but a computer system used for browsing searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval use some method of adding metadata by captioning, Keywords or the descriptions to the images so that the retrieval can be performed. Manual image annotation is time consuming, expensive and laborious. For addressing this there has been a large amount of research done on automatic image annotation. It is crucial to understand the scope and nature of the image data in order to determine the complexity of the image search system design. The design is also largely dependent on the factors. And some of the factors include archives, Domain specific collection, Enterprise collection, Personal collection and web etc.,

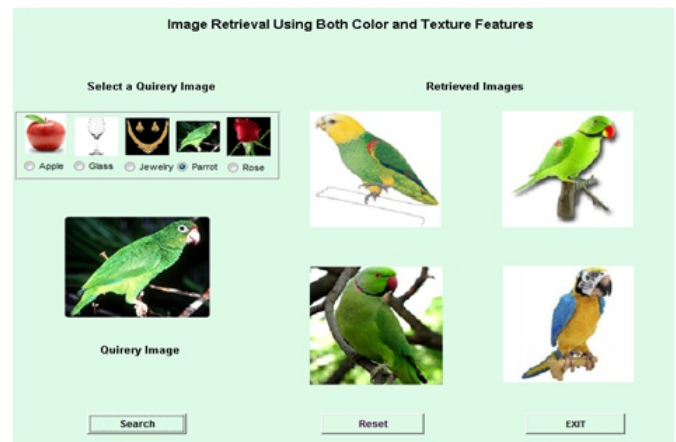
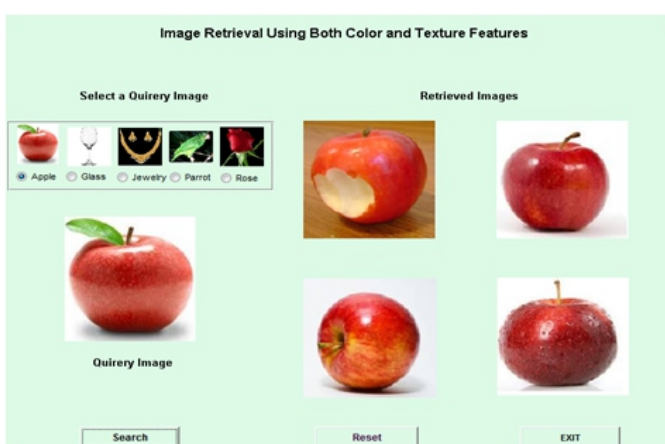
Invention of the digital camera has given the common man the privilege to capture his world in pictures, and conveniently share them with others. one can today generate volumes of images with content as diverse as family get-togethers and national park visits. Low-cost storage and easy Web hosting has fueled the metamorphosis of common man from a passive consumer of photography in the past to a current-day active producer. Today, searchable image data exists with extremely diverse visual and semantic content, spanning geographically disparate locations, and is rapidly growing in size. All these factors have created innumerable possibilities and hence considerations for real-world image search system designers.

As far as technological advances are concerned, growth in Content-based image retrieval has been unquestionably rapid. In recent years, there has been significant effort put into understanding the real world implications, applications, and constraints of the technology. Yet, real-world application of the technology is currently limited. We devote this section to understanding image retrieval in the real world and discuss user expectations, system constraints and requirements, and the research effort to make image retrieval a reality in the not-too-distant future. An image retrieval system designed to serve a personal collection should focus on features such as personalization, flexibility of browsing, and display methodology. For example, Google’s Picasa system [Picasa 2004] provides a chronological display of images taking a user on a journey down memory lane.

Domain specific collections may impose specific standards for presentation of results. Searching an archive for content discovery could involve long user search sessions. Good visualization and a rich query support system should be the design goals. A system designed for the Web should be able to support massive user traffic. One way to supplement software approaches for this purpose is to provide hardware support to the system architecture. Unfortunately, very little has been explored in this direction, partly due to the lack of agreed-upon indexing and retrieval methods. The notable few applications include an FPGA implementation of a color-histogram-based image retrieval system [Kotoulas and Andreadis 2003], an FPGA implementation for sub image retrieval within an image database [Nakano and Takamichi 2003], and a method for efficient retrieval in a network of imaging devices [Woodrow and Heinzelman 2002].

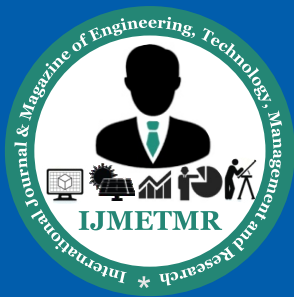
Discussion. Regardless of the nature of the collection, as the expected user-base grows, factors such as concurrent query support, efficient caching, and parallel and distributed processing of requests become critical. For future real-world image retrieval systems, both software and hardware approaches to address these issues are essential. More realistically, dedicated specialized servers, optimized memory and storage support, and highly parallelizable image search algorithms to exploit cluster computing powers are where the future of large-scale image search hardware support lies.

Simulation results:



REFERENCES:

1. Rui, Y., Huang, T.S., Mehrotra, S. [Sharad], "Retrieval with relevance feedback in MARS", In Proc of the IEEE Int'l Conf. on Image Processing, New York, pp. 815-818, 1997.
2. H. T. Shen, B. C. Ooi, K. L. Tan, "Giving meanings to www images" Proceedings of ACM Multimedia, pp. 39-48, 2000.
3. B S Manjunath, W Y Ma, "Texture feature for browsing and retrieval of image data", IEEE Transaction on PAMI, Vol 18, No. 8, pp.837-842, 1996.
4. Y. Rui, C. Alfred, T. S. Huang, "Modified descriptor for shape representation, a practical approach", In: Proc of First Int's workshop on Image Database and Multimedia Search, 1996.
5. Cao LiHua, Liu Wei, and Li GuoHui, "Research and Based on Multiple Dominant Colors", Journal of Computer Research & Development, Vol 36, No. 1, pp.96-100, 1999.
6. J. R. Smith, F. S. Chang, "Tools and Techniques for Color Image Retrieval", Symposium on Electronic Imaging: Science and Technology-Storage and Retrieval for Image and Video Database IV, pp. 426-237, 1996.
7. W. Y. Ma, B. S. Manjunath, A comparison of wavelet transform features for texture image annotation, Proceedings of the 1995 International Conference on Image Processing (Vol.2)-Volume 2, p.2256, October 23-26, 1995



8.F. Liu and R.W. Picard, "Periodicity, Directionality, and Randomness: World Features for Image Modeling and Retrieval," MIT Media Lab Technical Report no. 320, Mar. 1995.

9.M. Lades , J. C. Vorbruggen , J. Buhmann , J. Lange , C. von der Malsburg , R. P. Wurtz , W. Konen, Distortion Invariant Object Recognition in the Dynamic Link Architecture, IEEE Transactions on Computers, v.42 n.3, p.300-311, March 1993 [doi>10.1109/12.210173]

10.A. C. Bovik , M. Clark , W. S. Geisler, Multichannel Texture Analysis Using Localized Spatial Filters, IEEE Transactions on Pattern Analysis and Machine Intelligence, v.12 n.1, p.55-73, January 1990 [doi>10.1109/34.41384]

11.Jianchang Mao , Anil K. Jain, Texture classification and segmentation using multiresolution simultaneous autoregressive models, Pattern Recognition, v.25 n.2, p.173-188, Feb. 1992 [doi>10.1016/0031-3203(92)90099-5]

12.G. M. Haley , B. S. Manjunath, Rotation-invariant texture classification using modified Gabor filters, Proceedings of the 1995 International Conference on Image Processing (Vol. 1)-Volume 1, p.262, October 23-26, 1995

13. J. G. Daugman, High Confidence Visual Recognition of Persons by a Test of Statistical Independence, IEEE Transactions on Pattern Analysis and Machine Intelligence, v.15 n.11, p.1148-1161, November 1993 [doi>10.1109/34.244676]