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Curvature Signature Based Image Retrieval System

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Abstract:

Shape is one of the chief low level image description in Content Based Image Retrieval (CBIR).Image is a key reason in several areas. The more functional the images are being stored,the more capable the images are important for those regions to be able to regain the stored image quickly and be retrieve later,this is where content-Based Image Retrieval(CBIR) move towards in.Content Based Image Retrieval(CBIR) is a technique used for regaining similar images for given input image from an image database. CBIR aims to recover the images based on the content of a given image rather than textual data of a file name. CBIR uses the various features such as color, texture, shape etc. The shape is free of transformations like scaling, translation, rotation and flip. A good shape representation method repossess similar images irrespective of the transformation performed on a shape. Curvature is a very significant boundary feature for human to critic relationship between shapes. Even though curvature is important curve feature, there is a difficulty for using curvature as shape representation.Inorder to overcome the difficulty smooth curve function is being derived. This helps you to show the curvature signatures of a particular shape.

Key words*: Image retrieval, ontology, semantic web, shapes*

1.Introduction

With the rising popularity of the internet, the amount of digital image data accessible to users have grown in a great deal. Digital image processing stems from two principal application areas: perfection of pictorial data for human interpretation and handing out of image data for storage, program and representation for self-directed machine perception. The objective of digital image processing techniques is to visually enhance or statistically evaluate some aspect of an image not readily apparent in its original form. 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 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. Note that a digital image is self-possessed 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, pixels, and pixels. Pixel is the term most widely used to denote the elements of a digital image .Vision is the most advanced of our senses, so it is not surprising that images play the single most important role in human observation. However, unlike humans, where 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 ultra- sound, electron microscopy, and computer-generated images. Thus, digital image Processing encompasses a wide and varied field of applications. Sometimes a distinction is made by defining image processing as a discipline in which both the input and output of a process are images. We believe this to be a limiting and somewhat artificial boundary. For example, under this definition, even the trivial task of computing the average intensity of an image (which yields a single number) would not be considered an image processing operation. On the other hand, there are fields such as computer vision whose ultimate goal is to use computers to Emulate human vision, including learning and being able to make inferences and take actions based on visual inputs. This area itself is a branch of artificial intelligence (AI) whose objective is to emulate Human intelligence. There are no clear-cut boundaries in the continuum from image processing at one end to computer vision at the other.

1.1.Digital Image Processing

Digital image processing allows one to enhance image features of interest while attenuating detail irrelevant to a given application, and then extract useful information bout the scene from the enhanced image. This introduction is a practical guide to the challenges, and the hardware and algorithms used to meet them.Images are produced by a variety of physical devices, including still and video cameras, x-ray devices, electron microscopes, radar, and ultrasound, and used for a variety of purposes, including entertainment, medical, business (e.g. documents), industrial, military, civil (e.g. traffic), security, and scientific. The goal in each case is for an observer, human or machine, to extract useful information about the scene being imaged.

Often the raw image is not directly suitable for this purpose, and must be processed in some way. Such processing is called image enhancement; processing by an observer to extract information is called image analysis. Enhancement and analysis are distinguished by their output, images vs. scene information, and by the challenges faced and methods employed. Image enhancement has been done by chemical, optical, and electronic means, while analysis has been done mostly by humans and electronically.

Digital image processing is a subset of the electronic domain wherein the image is converted to an array of small integers, called pixels, representing a physical quantity such as scene radiance, stored in a digital memory, and processed by computer or other digital hardware. Digital image processing, either as enhancement for human observers or performing autonomous analysis, offers advantages in cost, speed, and flexibility, and with the rapidly falling price and rising performance of personal computers it has become the dominant method in use.

Digital image processing techniques are generally more versatile, reliable, and accurate; they have the additional benefit of being easier to implement than their analog counterparts. Specialized hardware is still Used for digital image processing: computer architectures based on pipelining have been the most Commercially successful. There are also many massively parallel architectures that have been developed for the purpose. Today, hardware solutions are commonly used in video processing systems. However, commercial image processing tasks are more commonly done by software running on conventional personal Computers.

2. Problem Models And Notation

2.1.Image Representation And Modelling

In image representation one is concerned with characteristics of the quantity that each picture -Element (also called pixel) represents. An image could represent luminances of objects in a scene, The absorption characteristics of the body tissue (x-ray imaging) , the radar cross section of a target (rador Imaging), the temperature profile of a region (Infrared imaging) , or the gravitational field in an area (in Geophysical imaging). An important consideration in image representation is the fidelity or the Intelligibility criteria for measuring the quality of an image or the performance of a processing technique. Specifications of such measures require models of perception of contrast, spatial frequencies, color and so on.

2.2.Image Enhancement

Image enhancement operations are processing techniques that serve to enhance or in some way alter the qualities of an image. Enhancement is basically a heuristic procedure designed to manipulate an image to take advantage of some psychophysical aspect of the human visual system.

In image enhancement, the goal is to attenuate certain image features for subsequent analysis or for Image display. Image enhancement is useful in feature extraction, image analysis, and visual information is play. The enhancement process itself does not increase the inherent information content in the data. It simply emphasizes certain specified image characteristics. Enhancement algorithms are generally interactive and application–dependent. The following is an example for Image Enhancement.

Figure 1: Image Enhancement

2.3.Image Restoration

Image Restoration is remodeling an image for some degradation by applying inverse processes to undo some known phenomenon in order to recover the original image. Image restoration is a cognitive estimation process in which operations are performed on an observed or measured field to estimate the ideal image that would be observed if no degradations were present in the imaging system. The aim of image restoration is to bring the image towards what it would have been if it.Following is an example for Image Restoration.

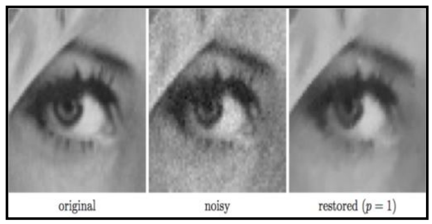

Figure 2: Image Restoration

2.4.Image Compression

It is a technique wherein, image containing tremendous amount of redundant information, can be run through algorithms that reduce the number of bits needed to represent them. Image compression is the natural technology for handling the increased spatial resolution of today's imaging sensors and evolving broadcast television standards.The Following is an example for image Compression.

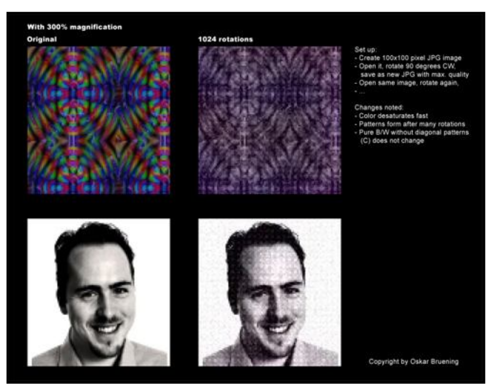

Figure3: Image Compression

3.ShapeRepresentation& Description

As information objects are digitized, more and more digital images have been generated. There is an urgent demand for effective tools to facilitate the searching of images. The goal to find a similar image (object) from large collections or from remotely distributed databases is shared not only by researchers, educators and professionals, but also by general users. Shape is an important visual feature and it is one of the basic features used to describe image content. However, shape representation and description is a difficult task. This is because when a 3-D real world object is projected onto a 2-D image plane, one dimension of object information is lost. As a result, the shape extracted from the image only partially represents the projected object. To make the problem even more complex, shape is often corrupted with noise, defects, arbitrary distortion and occlusion.

Shape representation generally looks for effective and perceptually important shape features based on either shape boundary information or boundary plus interior content. Various features have been designed, including shape signature, signature histogram, shape invariants, moments, curvature, shape context, shape matrix, spectral features etc. These various shape features are often evaluated by how accurately they allow one to retrieve similar shapes from a designated database. However, it is not sufficient to evaluate a representation technique only by the effectiveness of the features employed. This is because the evaluation ignores other important characteristics of a shape representation technique. For example, in the new multimedia application content-based image retrieval (CBIR), efficiency is envisaged as equally important as effectiveness due to the online retrieval demand. In fact, MPEG-7 has set several principles to measure a shape descriptor, that is, good retrieval accuracy, compact features, general application, low computation complexity, robust retrieval performance and hierarchical coarse to fine representation.

Good retrieval accuracy requires a shape descriptor be able to effectively 1ndperceptually similar shapes from a database. A perceptually similar shape usually means rotated, translated, scaled shapes and affinity transformed shapes. The descriptor should also be able to 1ndnoise affected shapes, variously distorted shapes and defective shapes, which are tolerated by human beings when comparing shapes. This is known as the robustness requirement. Compact features are desirable for indexing and online retrieval. If a shape descriptor has a hierarchical course to fine representation characteristic, it can achieve a high level of matching efficiency. This is because shapes can be matched at coarse level to 1rst eliminate large amount dissimilar shapes, and at 1ner level, shapes can be matched in details. A desirable shape descriptor should be application independent rather than only performing well for certain type of shapes. Low computation complexity is an important characteristic of a desirable shape descriptor.

For a shape descriptor, low computation complexity means minimizing any uncertain or ad hoc factors that are involved in the derivation processes. The fewer the uncertain factors Involved in the computationprocesses, the more robust the shape descriptor becomes. In essence, low computation complexity means clarity and stability.Many shape representation and description techniques have been developed in the past. A number of new techniques have been proposed in recent years. There are also many new shape applications in recent years. In this paper, we review and examine important shape representation and description techniques, and indicate their pros and cons. The retrieval performance and comparison results will be discussed where available. Finally, promising shape descriptors are identified according to the principles mentioned above.

3.1.Classification

Shape representation and description techniques can be generally classi1edinto two class of methods: contour-based methods and region-based methods. The classification is based on whether shape features are extracted from the contour only or are extracted from the whole shape region. Under each class, the different methods are further divided into structural approaches and global approaches. This sub-class is based on whether the shape is Represented as a whole or represented by segments/sections (primitives). These approaches can be further distinguished into space domain and transform domain, based on whether the shape features are derived from the spatial domain or from the transformed domain.

3.1.1.<u>Global Methods</u>

Global contour shape representation techniques usually compute a multi-dimensional numeric feature vector from the shape boundary information. The matching between shapes is a straight forward process, which is usually conducted by using a metric distance, such as Euclidean distance or city block distance. Point (or point feature) based matching is also used in particular applications.

3.1.1.1.Simple Shape Descriptors

Common simple global descriptors are area, circularity (perimeter2=area), eccentricity (length of major axis/length of minor axis), major axis orientation, and bending energy. These simple global descriptors usually can only discriminate shapes with large differences; therefore, they are usually used as 1lters to eliminate false hits or combined with other shape descriptors to discriminate shapes. They are not suitable to be standalone shape descriptors.

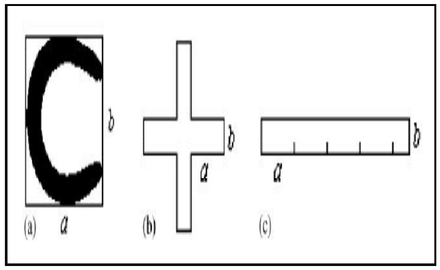

Figure 4: Shape Eccentricity And Circularity

For example, the eccentricity of the shape in (a) is close to 1 (a = b), it does not correctly describe the shape, because perceptually it is an elongated shape. In this case, circularity is a better descriptor. The two shapes in 2(b) and (c) have the same circularity (a = 2b), however, they are very different shapes. In this case, eccentricity is a better descriptor. Other simple global contour shape descriptors have been Proposed by Peura and Iivarinen . These descriptors include convexity, ratio of principle axis, circular variance and elliptic variance.

3.1.1.2.Shape Signature

A Shape signature represents a shape by a one dimensional function derived from shape boundary points. Many shape signatures exist, they include centroidal profile, complex coordinates, centroid distance, tangent angle, cumulative angle, curvature, area and chord-length. Shape signatures are usually normalized into being translation and scale invariant. In order to compensate for orientation changes, shift matching is needed to 1ndthe best matching between two shapes. Most of the signature matching is normalized to shift matching in 1-D space, however, some signature matching requires shift matching in 2-D space, such as the matching of centroidal profiles. In either case, the matching cost is too high for online retrieval. In addition to the high matching cost, shape signatures are sensitive to noise, and slight changes in the boundary can cause large errors in matching. Therefore, it is undesirable to directly describe shape using a shape signature. Further processing is necessary to increase its robustness and reduce the matching load. For example, a shape signature can be simpli1edby quantizing the signature into a signature histogram, which is rotationally invariant.

3.1.2.Structural Methods

Another member in the shape analysis family is the structural shape representation. With the structural approach, shapes are broken down into boundary segments called primitives. Structural methods differ in the selection of primitives and the organization of the primitives for shape representation. Common methods of boundary decomposition are based on polygonal approximation, curvature decomposition and curve fitting. The result is encoded into a string of the general form:

$$S = s_1, s_2, \ldots, s_n,$$

where si may be an element of a chain code, a side of a polygon, a quadratic arc, a spline, etc. si may contain a number of attributes like length, average curvature, maximal curvature, bending energy, orientation etc. The string can be directly used for description or can be used as input to a higher level syntactic analyzer. In the following we describe methods of shape representation and description using S.

3.1.2.1. Chain Code Representation

Chain code describes an object by a sequence of unit-size line segments with a given orientation. The method was introduced in 1961 by Freeman who described a method permitting the encoding of arbitrary geometric con1gurations. In this approach, an arbitrary curve is represented by a sequence of small vectors of unit length and a limited set of possible directions, thus termed the unit-vector method. In the implementation, a digital boundary of an image is superimposed with a grid, the boundary points are approximated to the nearest grid point, then a sampled image is obtained. From a selected starting point, a chain code can be generated by using 4-directional or 8-directional chain code. N-directional (N ¿8 and N = 2k) chain code is also possible, it is called general chain code.

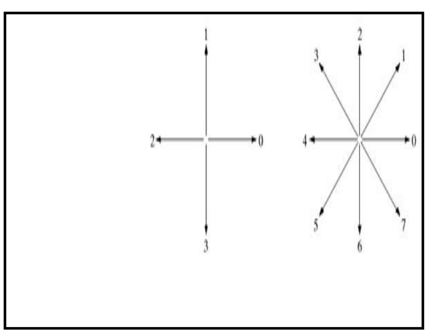

Figure 5: Directional and 8- Directional Chain Codes

4.System Analysis

4.1.Existing System

There are some well-known systems for visual information retrieval (VIR) which may be used as prototypes for a novel approach. One of them is Query by Image Content system (QBIC) provides retrieval of images, graphics and video data from online collections using image features such as color, texture, and shape for computing the similarity between images . AMORE (Advanced Multimedia Oriented Retrieval Engine) and SQUID systems provide image retrieval from the Web using queries formed by keywords specifying similar images, sketches, and SQL predicates. Although the contributions of these systems to field of VIR are important, they do not provide mechanisms to represent the meaning of objects in images.

Images are presented to a user by calculating Euclidian distance with every shape descriptor. It is a computational expensive problem. With large database this process may take minutes & hours. So to reduce the computational requirement, the images are indexed based on Color, Medial Axis, Area, Eccentricity, Euler number. These indexing parameters are bias existing system in details is an found in chapter 2.

4.2.Proposed System

Shape signature is a one dimensional function which correspond to the boundary points. Curvature is a very important boundary feature for human to match similarity between shapes. It is not surprise that many researchers use curvature for shape representation. Curvature function is given by

$$\kappa(t) = d\theta / dt$$

and the function is defined under

$$\theta(t) = \arctan \frac{y(t) - y(t-w)}{x(t) - x(t-w)}$$

where x(t) and y(t) t =0, 1, …, N-1 are called as boundary coordinates and 't' is called as the arc length. The tangent angle function can only assume values under the discreet intervals therefore discontinuities occur in this function. In order to overcome we introduce the cumulative angular function which is the net amount of angular bend between the starting and ending position of the on the shape boundary.

$$\varphi(t) = [\theta(t) - \theta(0)]\mathrm{mod}(2\pi)$$

This is continous at places where the function is multiples of 2π.

Here we use a step function and so k(t) is zero everywhere and infinite at discreet jumps at step function. This represents k(t) as a poor candidate. Therefore to use k(t) function smooth curvature function is derived. It is interesting to use Fourier reconstructed shape to derive curvature as the reconstructed shape is an rough calculation to the original shape and is smooth. The reconstructed function is used to derive the smoothed curvature *k*(*t*). Figure (a),(b) show the different curvature signatures of the apple.

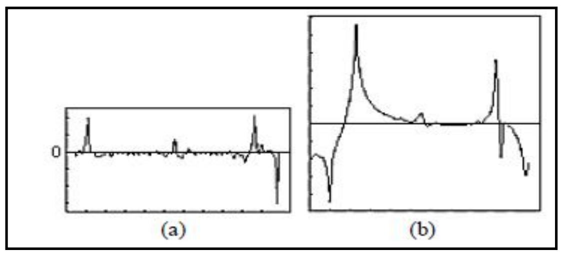

Figure 6: (a) k(t) of the apple; (b) k(t) of the apple

When the boundary points change along the shape boundary, the area of the triangle formed by the two boundary points and the center of gravity also changes. This forms an area function which can be exploited as shape representation.

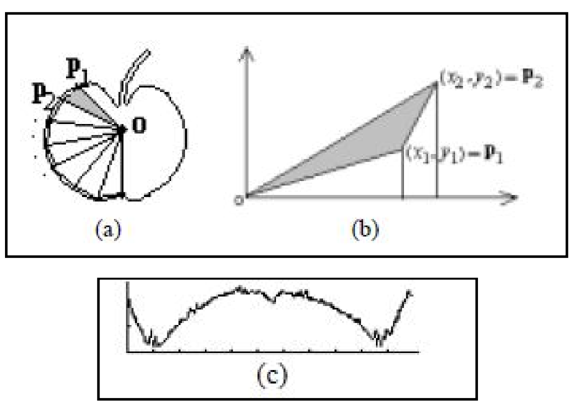

Figure 7: (a) area function of the apple; (b) area of a triangle; (c) A(t) of the apple

For the triangle formed by o, p1 and p2 its area is given by

$$A(t) = \frac{1}{2} | x_1(t) y_2(t) - x_2(t) y_1(t) |$$

For each boundary points, the area of the triangle with 5 degree angle at vertex **o** is calculated.

It has been found that $A(t)$ is very nearer to $r(t)$. However $A(t)$ is more computation expensive than $r(t)$. Because of the numerical fault in calculating angles, $A(t)$ is more rough than $r(t)$. The derivation of $A(t)$ involves more computation when compares to that of the $r(t)$. $A(t)$ is linear under affine transform, this can be exploited to produce affine invariant FDs from $A(t)$. But this linearity only works for polygon shape sampled at its vertices. For polygon shape which is sampled at every point, the $A(t)$ may not be linear under affine transform due to the change of boundary perimeter. There do not exists the sample points on the original shape where they are on the affined shape.

5.Discussion and Conclusion

This Paper represents the curvature signature based image retrieval which has all required properties,.Further it is hierarchical representation which can be easily adopted with a hierarchical based retrieval system. The proposed system is compared against a similar system and is found to be a better one as far as test database is considered. While experimentally the effectiveness of the proposed method is demonstrated, theoretically there are several questions to answered like the tangent angle functions, smooth curvature functions.

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