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A Study on Curvature Scale Space

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ABSTRACT: Advancement in digital technologies have resulted in large amount of images. Hence there a huge demand in retrieving desired images. In order to retrieve an image, the image has to be described or represented by certain features. Shape is an important visual feature of an image. Searching for images using shape features has been an important field of study. There are many shape representation and description techniques in the literature. In this paper, we review one of the important shape descriptor techniques named curvature scale space. The CSS extracts the shape feature of the image and represents them as curvature maxima points. We discuss implementation procedure of this technique, its variants and discuss their advantages and disadvantages.

KEYWORDS: Shape feature, image retrieval, CSS, curvature maxima.

I. INTRODUCTION

When real world objects are digitized and transformed into various image formats, the amount of images that are created using these advanced and ease of use technologies becomes available in huge amounts that are spread across various large repositories such as Internet, databases etc. Hence there is an urgent demand for effective tools to facilitate the searching and retrieval of desired images in an efficient way. 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 [1]. 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. As a result, shape properties play an important role in content based image database systems devised by computer vision researchers.

Good retrieval accuracy requires a shape descriptor be able to effectively find perceptually similar shapes from a database [2]. Perceptually similar shapes usually mean rotated, translated, scaled shapes and affine transformed shapes. The descriptor should also be able to find noise affected shapes, variously distorted shapes and defective shapes, which are tolerated by human beings when comparing shapes [3]. The property of being tolerant to noise and distortion is called robustness. Compact features are desirable for indexing and online retrieval.

Shape representation and description techniques can be generally classified into two classes of methods [4]: contour-based methods and region-based methods. The classification is based on shape features are extracted from the contour only or are extracted from the whole shape region.

II. SHAPE FEATURE EXTRACTION METHODS

There are various features of the objects such as shape, colour, texture etc. The reason for choosing shape feature for describing an object is because of its inherent properties such as identifiability, affine invariance, and reliability and occlusion invariance [5]. thus shape of the object has proved to be a promising feature based on which several image classification and retrieval operations can be performed [6]. unlike the colour and texture features of the object, the shape feature is more effective in semantically characterising the content of the image. in literature the shape descriptors has been classified into two major kinds, namely contour based and region based shape descriptors.

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A. Contour-based shape representation and description techniques:

Contour shape techniques uses only shape boundary information. There are generally two types of approaches for contour shape modelling: continuous approach (global) and discrete approach (structural). Continuous approaches do not divide shape into sub-parts; usually a feature vector derived from the integral boundary is used to describe the shape. The measure of shape similarity is usually a metric distance between the acquired feature vectors. Discrete approaches break the shape boundary into segments, called primitives using a particular criterion. The final representation is usually a string or a graph (or tree), the similarity measure is done by string matching or graph matching.

B. Region-based shape representation and description techniques:

The region based shape representation technique takes the whole region under consideration [6][7]. The region based technique is further classified into two types namely structural and global. Some of the global region based techniques are Area, Euler Number, Eccentricity, Geometric Moments, Zernike Moments [9], Pseudo-Zernike Moments, Legendre Moments, Generic Fourier Descriptor [10], Grid Method and Shape Matrix. While the different structure based techniques are Convex Hull, Media Axis and Core.

III. CURVATURE SCALE SPACE

CSS is one of the popular global and contour based shape descriptor technique that constructs a CSS image based on the input image contour. CSS image is a group of multi-scale representation of contours of the image which consists of shallow and deep concavities [11][12]. It consists of several arch shape contours, each related to a concavity or a convexity of the curve. The main advantage of this method over the others is that it is robust with respect to noise, scale and change in orientation [13]. Moreover, both feature extraction and shape matching are carried out rapidly. Hence it is used in object recognition, content based image retrieval (CBIR), shape similarity retrieval [14][15] and leaf classification [16].

In all the above said applications, the maxima of the contours have been used to represent the boundary of an object. To construct the CSS image of a digital curve, its curvature zero crossing points should be determined at different levels of smoothing [17]. In Gaussian smoothing, there will be two curvature zero crossings on every concave or convex part of the shape and as the curve becomes smoother these points approach each other. The locations of each pair of zero crossings at different levels of scale create a contour in the CSS image. At a certain level of smoothing when the segment is filled, the two points join and represent the maximum of the relevant contour. The height of this contour then reflects the depth and size of the concavity or convexity. The deeper and larger the segment, the higher the maximum.

The main problem with CSS is the presence of ambiguities of CSS matching due to the problem of shallow concavities on the shape [18]. It can be shown that the shallow and deep concavities may create the same large contours on the CSS image. Therefore, a shallow concavity may be matched with a deep one during the CSS matching. Also CSS performs poor with respect to open curves [19].

A. Steps involved in CSS:

The construction of CSS image consists of several steps as follows:

- The contour of the image is obtained using the Canny edge detector.
- The contour of the image is then convolved with the Gaussian kernel. This process is called as smoothing of the image curve.
  1. The convolution consist of two parameters such as ‘u’ is called arc length parameter and ‘σ’ is known as scale parameter.
  2. The scale parameter ‘σ’is gradually increased during convolution and the image get smoothed as ‘σ’ increases.

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3. When σ =0, the smoothed image (more details) is same as the original image and as the 'σ 'increases smoothed image gets blurred(less details).

- The final CSS image consist of many arch shaped contours which depends on the concavity (shape or inflections) of the object.
- The evolution of the curve (smoothing) stops when the number of curvature zero crossings become zero.

The figure 1 shows the steps in the smoothing of the given image contour.

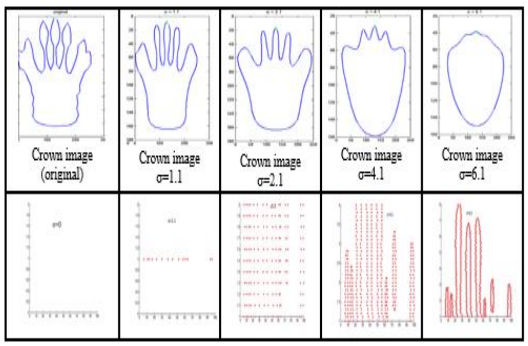

Fig. 1. Shows the various stages involved in smoothing of the image contour(crown image from MPEG7 data)

B. CSS Image:

The CSS image is a binary image which represents the contours of the image at multiple scales. Consider a parametric vector equation for a continuous curve Γ:

$$\Gamma(s) = (x(s), y(s))$$

Where *s* is the arc length of the boundary. The formula for computing the curvature function can be expressed as:

$$\mathrm{K}(s) = \frac{\dot{x}(s)\ddot{y}(s) - \ddot{x}(s)\dot{y}(s)}{(\dot{x}^2(s) + \dot{y}^2(s))^{3/2}}$$

If g(σ,μ) is a one-dimensional (1D) Gaussian kernel of width *s*, then *X*(σ,μ) and *Y*(σ,μ) represent the components of the evolved curve,

$$X(\mu,\sigma) = x(u) * g(\mu,\sigma)$$

$$Y(\mu,\sigma) = y(u) * g(\mu,\sigma)$$

Where * denotes convolution. According to the properties of convolution, the derivatives of every component can be calculated easily:

$$X_u(\mu,\sigma) = x(u) * g_u(\mu,\sigma)$$

$$X_{uu}(\mu,\sigma) = x(u) * g_{uu}(\mu,\sigma)$$

Likewise we can find *Yu*(σ,μ) and *Yuu*(σ,μ). As the exact forms of *gu*(σ,μ) and *guu*(σ,μ) are known, the curvature of an evolved digital curve can be computed easily:

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$$\mathrm{K}(\mu,\sigma) = \frac{X_u(\mu,\sigma)Y_{uu}(\mu,\sigma) - X_{uu}(\mu,\sigma)Y_u(\mu,\sigma)}{(X_u(\mu,\sigma)^2 +_u (\mu,\sigma)^2)^{3/2}}$$

The implicit function is defined by,

$$\mathrm{K}(\mu,\sigma) = 0$$

is the *CSS* image of Γ. Note that, although *s* is the normalised arc length parameter for the original curve Γ, the parameter *u* is not, in general, the normalised arc length for the evolved curve Γ_σ.

If the curvature zero crossings of Γσ during evolution is calculated, it can be displayed as points in the (μ,σ) plane [20]. Here u is an approximation of the normalised arc length and s is the width of the Gaussian kernel. In Fig 2. For every *s* there is a certain curve Γσ which in turn, has some curvature zero crossing points. As s increases, Γσ becomes smoother and the number of zero crossings decreases. When s becomes sufficiently high, Γσ will be a convex curves with no curvature zero crossing, the process of evolution can be terminated. The result of this process can be represented as a binary image called the CSS image of the curve. The small contours of the CSS image represent the minor ripples on the boundary of object and can be ignored. Every boundary is then represented by the locations of the major maxima of its CSS image contours.

C. Properties of CSS image:

The CSS image is very much robust with respect to scale, noise and change in orientation. One of the important properties of CSS is that a rotation of the object causes a circular shift on its representation, which can be determined during the matching process. And it also holds the same when the starting point is changed. Compactness is one of the important aspects of CSS, which means that a shape can be represented by about less than ten pairs of integer values without any ambiguity [21]. Another property of CSS is that it retains the local properties of the shape.

IV. VARIANTS OF CSS

Although standard CSS is used as default in MPEG7, it has its own drawbacks such as inefficient while performing with deep and shallow concavities, hence has less matching performance during image retrieval process. In order to overcome these shortcomings many variants of CSS has been proposed in literature.

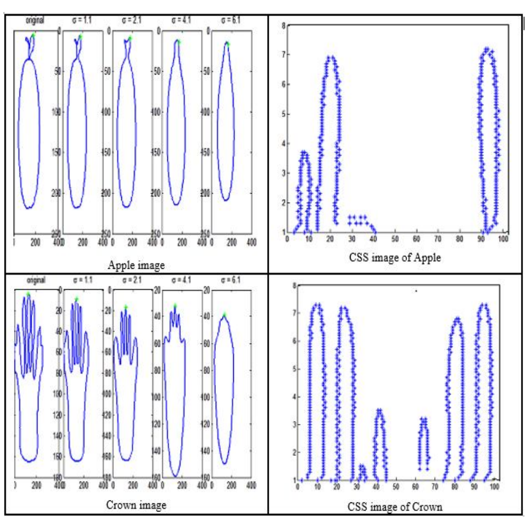

Fig. 2. (a) A boundary with shallow concavities (apple) and (b) its CSS image. (c) A boundary with curved concavities (crown) and (d) its CSS image.

A. Extreme Curvature Scale Space (ECSS):

In order to solve the problem of deep and shallow concavities of standard CSS, a shape descriptor based on Extreme Curvature scale space has been proposed [22]. While CSS uses curvature zero crossing values of the curvature, the ECSS map is created by tracking the position of extreme curvature points. Similarly to CSS descriptor, it is based on the maxima of the obtained ECSS map [23]. It is robust with respect to noise, scale and orientation changes of the shape. The ECSS has proved to be efficient shape descriptor when compared to the CSS one, especially in the case of shallow or deep concavities.

ECSS deals to overcome the disadvantage of standard CSS. A set of a multi scale curvature $\kappa(\mu,\sigma)$ that corresponds to the set of curve of shape $\{f((\mu,\sigma)/\sigma\geq 0\}$ can be defined as follows:

$$K(\mu,\sigma)=\frac{x_t(\mu,\sigma)y_{tt}(\mu,\sigma)-x_{tt}(\mu,\sigma)y_t(\mu,\sigma)}{(x_t^2(\mu,\sigma)+y_t^2(\mu,\sigma))^{3/2}}$$

Where x_t, y_t, x_{tt}, y_{tt} are respectively the first and second derivatives of x and y with respect to't'. This contributes to extrema curvature zero crossing points. As σ increases the inflection points decreases and therefore at highest scale value inflection point disappears. In order to this process we take into account only the extreme curvature points between each pair of successive zero-curvature points. The algorithm stops when the curvature zero-crossing points disappear. The final ECSS descriptors contour are composed of all maximum curvature points from the ECSS image. Hence, the peaks (i.e. the maxima) are then extracted out and sorted. Finally, the ECSS descriptors based on the ECSS image, which are like CSS descriptors based on the CSS image, are composed of all maximum points in the ECSS image.

Thus this method proposes two changes to the conventional CSS that it substitutes the use of contour extrema for curvature zero crossings and adds the value of the curvature in each extreme as an additional feature on each of the matched points. One of the great benefits to integrate the curvature characteristic for descriptor ECSS is to distinguish between shape with shallow and with deep concavities.

B. Direct Curvature Scale Space (DCSS):

DCSS is one of the efficient variants of CSS that is used in corner detection technique [24][25]. Direct Curvature Scale Space (DCSS) is defined as the CSS that results from convolving the curvature of a planar curve with a Gaussian kernel directly.

Let $\varphi(s)$ be the function of the planar curve. The curvature function of the curve is expressed as $\kappa(s)=\varphi(s)$. The DCSS constructs the image by convolving $\kappa(s)$ directly with the Gaussian kernel $g(s,\sigma)$. The convolved curvature function $\kappa(s,\sigma)$ is given by $\kappa(s,\sigma)=\kappa(s) * g(s,\sigma)$. It can be shown that:

$$K(s,\sigma)=\int_{-\infty}^{+\infty}K(u)g(s-u,\sigma)du=\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{+\infty}K(u)e^{-\frac{(s-u)^2}{2\sigma^2}}du$$

To determine corners at a given scale σ, all the locations that have maxima absolute curvature,$|\kappa(s,\sigma)|$, including the positive maxima and negative minima have to be solved. A DCSS image is then constructed using $\max_{s,\sigma}|\kappa(s,\sigma)|$, where 's' denotes the arc length of the contour. The DCSS image of a given curve provides information on its corner locations at varying scales. There are two models that can be used to investigate the properties of DCSS image. The single corner called Γ model is used to show the consistent behaviour of the line patterns in the DCSS image. The double corner such as END and STAIR model show the interaction between a pair of neighbouring corners with respect to scale. Though DCSS is sensitive to noise the hybrid approach of DCSS/CSS can be effectively used to overcome it. To detect corners on a curve, a tree is constructed from its DCSS or hybrid CSS/DCSS image. Then the model properties are considered to parse the tree organization and corners are detected in a multi-scale.

C. Affine Resilient Curvature Scale Space (ARCSS):

CSS based corner detectors use arc-length as parameterized curvature [26][28]. And hence they are not robust to affine transformations since the arc length of the curve does not remain invariant under affine transformations. However, the affine-length of a curve is relatively invariant to affine transformations. Thus affine resilient corner

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detectors were proposed. In this approach canny edge detector is used to extract the edges from the grey scale images. By this method the local maxima of absolute curvature is accepted as corner. False corners are eliminated by comparing each curvature maximum with its two neighbouring minima based on the assumption that the curvature of a corner point should be at least double the curvature of a neighbouring minimum. The following procedure is used in ARCSS:

1) Find edge image using the canny edge detector.
2) Extract edges from the edge image:
    i) Fill gaps if they are within a range and select long edges,
    ii) Find T-junctions and mark them as T-corners.
3) Parameterize each edge with its affine-length.
4) For each parameterized edge, compute absolute curvature at an appropriate scale and determine corners by comparing the curvature maxima to the corresponding curvature threshold of edge in the neighbouring minima.
5) Track the corners down to the lowest scale considering a small neighbourhood to improve localization.
6) Remove multiple occurrences of same corners.

When compared experimentally with CSS and ECSS corner detector, ARCSS out performs it. While CSS missed some true corners and ECSS introduced weak corners, ARCSS detectors left of few true corners and introduced few weak corners. This is because while the ARCSS detector uses the affine-length parameterization, the CSS and ECSS detectors use the arc-length parameterization. Also ARCSS is more immune to noise than its counterparts.

V. PERFORMANCE ENHANCEMENTS TO CSS

Though CSS is used as standard shape descriptor for indexing large databases, it preforms poor in cause of open curves and suffers from concavity problems. Hence there are several papers that tried to improve the performance of CSS. We shall discuss those below.

Stephan Kopf et al. have placed a method for better shape classification by improving the CSS algorithm [29]. In their work they have addressed the problem of concave and convex curves of the object. It is found that CSS performs poor in representing convex curves, so first CSS for concave curve is computed and then a second shape called mapped shape with additional features is created. Now the original shape is mapped to new shape, so that convex segments become concave segments. Similarly Jinye Peng et al have proposed a shape classification approach based on histogram representation of CSS for increased performance [30]. In this method histograms are constructed and similarity matching is done.

Alan K. Mackworth et al have come up with a method for enhancing the performance of CSS while matching curves of similar shapes [31]. Though standard CSS image generation involves convolution of normalized arc-length based curve with Gaussian kernel, the convoluted curve is not normalized and therefore unsuitable for matching purpose. Thus the proposed method re- parameterizes the convolved curve with its normalized arc length when computing the CSS image. This approach is called as Renormalized CSS. This method is proved to have efficient curve matching capabilities.

VI. CONCLUSIONS

In this paper, shape representation using CSS is studied. It has been proven that CSS performs well for indexing images and retrieving it from large databases. CSS is found to be robust with respect to noise, scale etc., CSS is found to be more efficient than others because feature extraction and shape matching can be carried out simultaneously and rapidly. Moreover the variants of CSS that have been discussed have found to be much more effective for the applications such as shape retrieval, object recognition and corner detection. Although CSS is used as a standard technique, it has some of the drawbacks such as poor performance with deep and shallow concavities of the shape and failing to address the problem of open curves present in the given shape.

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