PAPER

Automatic Scale Detection for Contour Fragment Based on Difference of Curvature

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SUMMARY Scale-invariant features are widely used for image retrieval and shape classification. The curvature of a planar curve is a fundamental feature and it is geometrically invariant with respect it the coordinate system. The curvature-based feature varies in position when multiscale analysis is performed. Therefore, it is important to recognize the scale in order to detect the feature point. Numerous shape descriptors based on contour shapes have been developed in the field of pattern recognition and computer vision. A curvature scale-space (CSS) representation cannot be applied to a contour fragment and requires the tracking of feature points. In a gradient-based curvature computation, although the gradient computation considers the scale, the curvature is normalized with respect to not the scale but the contour length. The scale-invariant feature transform algorithm that detects feature points from an image solves similar problems by using the difference of Gaussian (DoG). It is difficult to apply the SIFT algorithm to a planar curve for feature extraction. In this paper, an automatic scale detection method for a contour fragment is proposed. The proposed method detects the appropriate scales and their positions on the basis of the difference of curvature (DoC) without the tracking of feature points. To calculate the differences, scale-normalized curvature is introduced. An advantage of the DoC algorithm is that the appropriate scale can be obtained from a contour fragment as a local feature. It then extends the application area. The validity of the proposed method is confirmed by experiments. The proposed method provides the most stable and robust scales of feature points among conventional methods such as curvature scale-space and gradient-based curvature.
key words: *curvature, scale invariance, planar curve, shape description, pattern recognition*

1. Introduction

Scale-invariant features are widely used for image retrieval and shape classification. The scale-invariant feature transform (SIFT) algorithm for an image is one of the most successful techniques in content-based image retrieval and classification [1]. The SIFT algorithm is invariant with respect to an image's scaling and rotation. On the other hand, shape retrieval and classification use several features such as contour, color, region, texture, and so on. These features and descriptions are standardized in MPEG-7, also called "Multimedia Content Description Interface [2]–[4]." This paper focuses on the planar curves obtained from the contours of 2D shapes.

The curvature of a planar curve is a fundamental feature and it is geometrically invariant with respect it the coordinate system. The curvature of a continuous planar curve is scale-independent since the differential of the curve is uniquely determined. The curvature of a discrete planar curve, in contrast, is scale-dependent since the differential of the curve has one degree of freedom. For example, the differential of a discrete planar curve is derived from the convolution between the curve and a derivative Gaussian function with a standard deviation. In either curve, curvature-based feature point of multi-scale analysis varies in position. Therefore, it is important to recognize the scale in order to detect the feature point.

Scale detection for contour fragment extends the application area. For example, the shape that is not the whole is accepted as a query of CBIR. Layout of feature points is also accepted. The meaning of the layout is that feature points are extracted from not only a single shape but also plural shapes, and that distance of them can be described by the scale. For more specific situation, occlusion generally occurs in the real world. Single object boundaries are divided by another one. In this case, not a whole but a partial object boundary is obtained. Naturally, the application is not limited to the contour fragments. When plural and partial shapes become single shape, some feature points can be extracted without the influence of the composition. It is noted that a description method for feature points is out of the scope of this paper.

Numerous shape descriptors based on contour shapes have been developed in the field of pattern recognition and computer vision. Initially, Witkin et al. proposed scale-space filtering for 1D planar curves [5]. The function $f(x)$ of the planar curve is convolved with a Gaussian function, where its variance σ^2 varies from small to large. The zero-crossings of the second derivative of each convolved function are extracted and marked in the x–σ plane. The resulting plane is the scale-space image of the function. Although this technique is effective for structure detection of the planar curve, tracking, describing, and comparing feature points are complex problems.

Mokhtarian et al. introduced a curvature scale-space (CSS) representation for 2D planar curves [6]. The parametric representation of a contour shape is convolved with a Gaussian function. The zero-crossings of the curvatures from the resulting curves are extracted and marked in the t–

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σ plane, where t is a parameter. The CSS representation is essentially invariant with respect to rotation, uniform scaling, and translation of the contour. This representation was further extended and optimized during the MPEG-7 development phase [3]. In the contour shape descriptor of MPEG-7, the number of passes of a low-pass filter is nonlinearly normalized with respect to the contour length. The scale value is defined by the normalized value in order to guarantee scale invariance. Consequently, this method cannot be applied to a contour fragment. CSS approaches are continuously improved. Zhong et al. proposed Direct Curvature Scale Space (DCSS), which is defined as the CSS that results from convolving not the planar curve but the curvature of it with a Gaussian kernel [7]. Awrangjeb et al. proposed an improved CSS corner detector using not the arc-length parameterization but the affine-length parameterization [8]. These methods are also not independent to the arc-length of the whole shape or to the transformation of a partial shape.

Daliri et al. proposed a gradient-based curvature (GbC) computation [9]. According to the definition of the curvature for the planar curve—the rate of change in the tangent vector with respect to the contour length—, the derivatives of the tangent vector for the x- and y-directions should be computed. The tangent vectors of the planar curve are orthogonal to the gradient vectors, which are obtained by the convolution between an intensity image and a derivative Gaussian function. Although the gradient vectors are computed at the best scales along the contour, the curvature is normalized with respect to the contour length. The appropriate scales for the curvature are not detected.

Conventional shape descriptors cannot be applied to a contour fragment, as mentioned above. Further, in the CSS representation, the tracking of feature points is required. The SIFT algorithm solves similar problems using the difference of Gaussian (DoG), which approximates the scale-normalized Laplacian of Gaussian.

In this paper, an automatic scale detection method for a contour fragment is proposed. The proposed method detects the appropriate scales and their positions on the basis of the difference of curvature (DoC) without the tracking of feature points. In other words, instead of the Gaussian in the DoG, a scale-normalized curvature is employed for the DoC. An advantage of the DoC algorithm is that the appropriate scale can be obtained from a contour fragment as a local feature.

The remainder of the paper is organized as follows. Section 2 presents an overview of the CSS representation, the SIFT algorithm, and the gradient-based curvature. Section 3 describes the proposed automatic scale detection method. Section 4 provides several experiments and considerations. Finally, Sect. 5 presents the conclusions of this work.

2. Conventional Methods

2.1 Curvature Scale-Space

A curvature scale-space (CSS) representation detects the structure of a contour shape in multi-scale analysis [2], [4]. This representation has been successfully used for image retrieval and classification.

To create the CSS representation of the contour shape, N equidistant points are selected from the contour. The x- and y-coordinates of the selected N points are grouped into X and Y. The contour is then gradually smoothed by the repetitive application of a low-pass filter to the X and Y. As a result of the smoothing, concave parts of the contour gradually flatten out, until the contour becomes convex.

A so-called CSS image can be associated with the contour evolution process. The horizontal- and vertical-coordinates correspond to the indices of the contour points and the number of passes of the filter. Each horizontal line in the CSS image corresponds to the smoothed contour resulting from k-passes of the filter. For each smoothed contour, the zero-crossings of its curvature function are computed. Curvature zero-crossing points separate concave and convex parts of the contour. Each zero-crossing point is marked on the horizontal line.

The CSS image is characterized by peaks. The coordinate values of the prominent peak $(x_{\mathrm{css}}, y_{\mathrm{css}})$ in the CSS image are extracted. Peaks are arranged according to y_{css} value in descending order. The value of y_{css} is transformed and quantized. The transformation is nonlinear and defined by

$$\mathrm{peak} = 3.8\left(\frac{y_{\mathrm{css}}}{N^2}\right)^{0.6}, \tag{1}$$

where a peak is truncated into $[0, 1.7]$.

The CSS representation has some problems in order to detect the appropriate scales. The peak value indicates a scale of feature points, which is invariant with respect to the shape size since the number of samples is constant in our experiments. Consequently, the CSS algorithm cannot be applied to a contour fragment. The appropriate scale is also not detected. Further, curvature values are not used since feature points indicate the disappearance of concave or convex parts.

2.2 Laplacian of Gaussian

The scale-invariant feature transform (SIFT) algorithm extracts feature points from an image and describes features. The detected feature points are generally located on corners based on the gradient of intensities and they are robust to an image rotation and scale.

In order to extract an appropriate scale, the scale-normalized Laplacian of Gaussian (sLoG) operator is utilized. Since the sLoG operator has a high computation cost, it is approximated by the difference of Gaussian (DoG) operator as follows:

$$\mathrm{sLoG} \approx \frac{G(x, y, k\sigma) - G(x, y, \sigma)}{k-1}, \tag{2}$$

where k is the ratio between adjacent scales and G is a 2D Gaussian function with a standard deviation σ as the scale.

When the value of DoG is the local maximum at $\sigma = \sigma_{\max}$, the appropriate scale is defined as $\sigma_{\max}$. By downsampling the image, the computation cost of DoG is dramatically reduced. An appropriate scale is used to normalize the features. In other words, scale invariance is achieved by detecting the appropriate scale.

It is difficult to apply the SIFT algorithm to a planar curve for feature extraction. A bitmap image obtained by rasterizing the planar curve can be applied to the SIFT approach indirectly, as described in the Sect. 2.3.

2.3 Gradient-Based Curvature

Daliri et al. proposed the use of the tangent vectors along the contours for the computation of the curvature [9]. The tangent vector is orthogonal to the gradient vector. L_x and L_y are defined as the convolution between an image and the derivative Gaussian function. The local scale is determined by computing the normalized derivatives of the image as follows:

$$G_\lambda = t^{\lambda/2}\sqrt{L_x^2 + L_y^2}, \tag{3}$$

$$\lambda = \frac{1}{2}. \tag{4}$$

When the value of $G_{1/2}(t)$ is the local maximum at $t = t_{\max}$, the best scale is defined by $2\pi\sqrt{t_{\max}}$. When the value of $G_\lambda(t)$ increases monotonically, the maximum value of t is considered as the best scale. This scale can be computed for every point of the image along the contour. The gradient $G = (G_x, G_y)$ is then computed at the best scale using a 2D Gaussian function in x- and y-directions. Since the tangent vector is orthogonal to the gradient vector, the tangent vector at the best scale is defined by

$$T = (T_x, T_y) = (G_y, -G_x). \tag{5}$$

The curvature κ is related to the rate at which the tangent vector is changing with respect to the arc length s. The derivatives of the tangent vector for the x- and y-directions should be computed. This can be done by using simply the convolution of each component of the tangent vector by the first derivative of the 1D Gaussian function.

Since different shapes have different contour lengths, an adaptive σ_1 for the Gaussian function is utilized. Standard deviation σ_1 of the Gaussian function is related to the contour length,

$$\sigma_1 = \sigma_0 \frac{l}{l_0} \tag{6}$$

where l is the contour length. According to the Daliri et al., $l_0 = 200$ and $\sigma_0 = 3$ are used [9]. Having the two derivative components of the tangent vector, the value of the curvature can be computed as follows:

$$\|\kappa\| = \sqrt{\left(\frac{\partial T_x}{\partial s}\right)^2 + \left(\frac{\partial T_y}{\partial s}\right)^2}. \tag{7}$$

Unfortunately, the gradient-based curvature cannot be applied for a contour fragment. Although the tangent vector appears to be invariant with respect to the scale, the curvature depends on the contour length. The best scale for the gradient computation is not the appropriate scale for the curvature computation. The appropriate scale cannot be obtained. In our experiments, the obtained curvature values are assumed to be the scale and used for the evaluation of the scale invariance as a matter of convenience. Further, consideration to a structure of a coarse contour shape is also insufficient because multi-scale analysis is not realized.

3. Proposed Algorithm

3.1 Scale-Normalized Curvature

An automatic scale detection method, which can be applied to a contour fragment, is proposed in order to involve the scale invariance of the features. The curvature of the parametric planar curve $(x(t), y(t))$ is defined by

$$\kappa = \frac{x'y'' - x''y'}{(x'^2 + y'^2)^{3/2}}, \tag{8}$$

where x' and x'' are the first and second order derivatives of x with respect to t. The derivative is calculated by a convolution between the parametric curve and the derivative Gaussian function. The Gaussian function is defined by

$$G(t, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{t^2}{2\sigma^2}\right), \tag{9}$$

where t and σ are the parameter and standard deviation.

The proposed method defines a scale as the standard deviation. The derivative of the parametric curve depends on the scale and it is computed by

$$x' = x'[t, \sigma] = G'[t, \sigma] * x[t], \tag{10}$$

$$y' = y'[t, \sigma] = G'[t, \sigma] * y[t], \tag{11}$$

where "$*$" is the convolution operator with respect to t.

Scale-normalized curvature is realized to introduce a scale-normalization factor. It is assumed that the curvature operator is defined by

$$\widehat{C_p} = \frac{G'_x G''_y - G''_x G'_y}{(G'^2_x + G'^2_y)^{3/2}}, \tag{12}$$

where G' and G'' are the first and second derivatives of the Gaussian function. This operator can be applied to parametric curves. Now, the curvature operator is simplified in order to derive the scale-normalization factor, i.e. $y[t] =$ constant. In this case, the curvature operator is simply given by

$$\widehat{C_1} = \frac{G''}{(1 + G'^2)^{3/2}}. \tag{13}$$

The waveform of this operator is shown in Fig. 1. The four regions A_0, A_1, A_2, and A_3 have the same area. This area is employed as a scale-normalization criterion, i.e. this area remains constant whenever the scale varies. For example, one area is calculated by

$$A_2 = \int_0^{\sigma} \frac{-G''(t,\sigma)}{(1+G'(t,\sigma)^2)^{3/2}} dt = \frac{1}{\sqrt{1+2\pi e\sigma^4}}. \qquad (14)$$

The scale-normalization factor is then defined as $\sqrt{1+2\pi e\sigma^4}$. In the following section, a scale-normalized curvature based on Eq. (12) and its factor is used in order to calculate the difference between the curvature values.

It should be noted that the scale-normalization factor does not contain the contour length. The detected curvature is independent of the entire shape size. The scale-normalized curvature can then be obtained from the contour fragment as a local feature.

3.2 Difference of Curvature

By using the proposed scale-normalized curvature, a scale detection method is proposed based on the difference of curvature (DoC), which is an analogous to the difference of Gaussian in the SIFT algorithm. The procedure to construct the DoC is shown in Fig. 2. The initial planar curve is convolved with the derivative Gaussian functions of changing scale parameters σ. The curvatures of them are then calculated to obtain the set of curvature scale-space shown in the left-hand side of Fig. 2. Scale-normalized curvatures with adjacent scales are subtracted to obtain the difference of curvature shown in the right-hand side of Fig. 2. The ratio between adjacent scales is constant so that the scale is a geometrical progression.

The local maximum or minimum points are detected as feature points among the DoC. The comparison points of curvatures are shown in Fig. 3. The horizontal axis indicates the position based on the parameter t, and the vertical axis indicates the DoC. Each series corresponds to the different scale. The point (marked by x) is compared to its eight

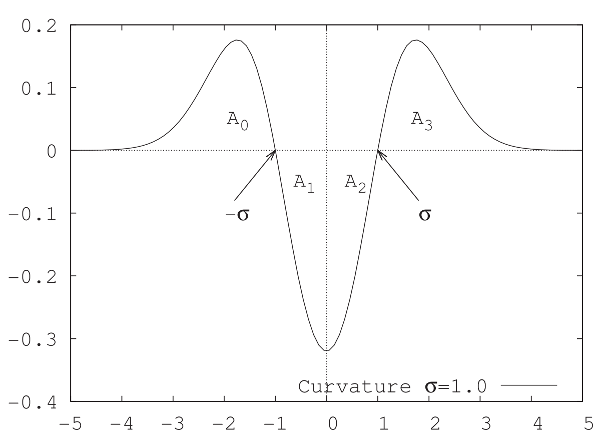

Fig. 1 Shape of curvature operator [10].

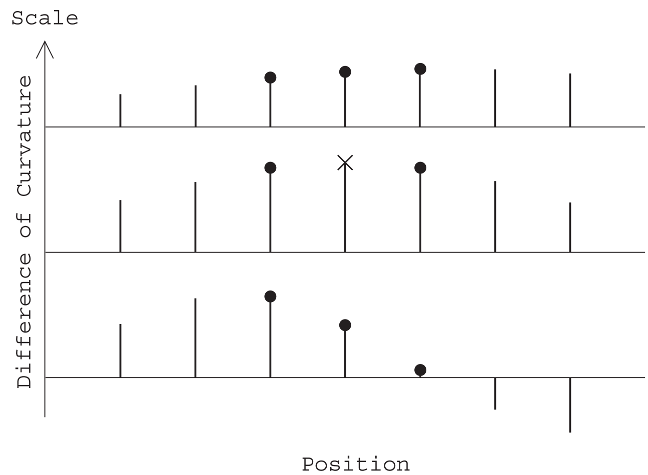

Fig. 3 Comparing points of difference of curvature.

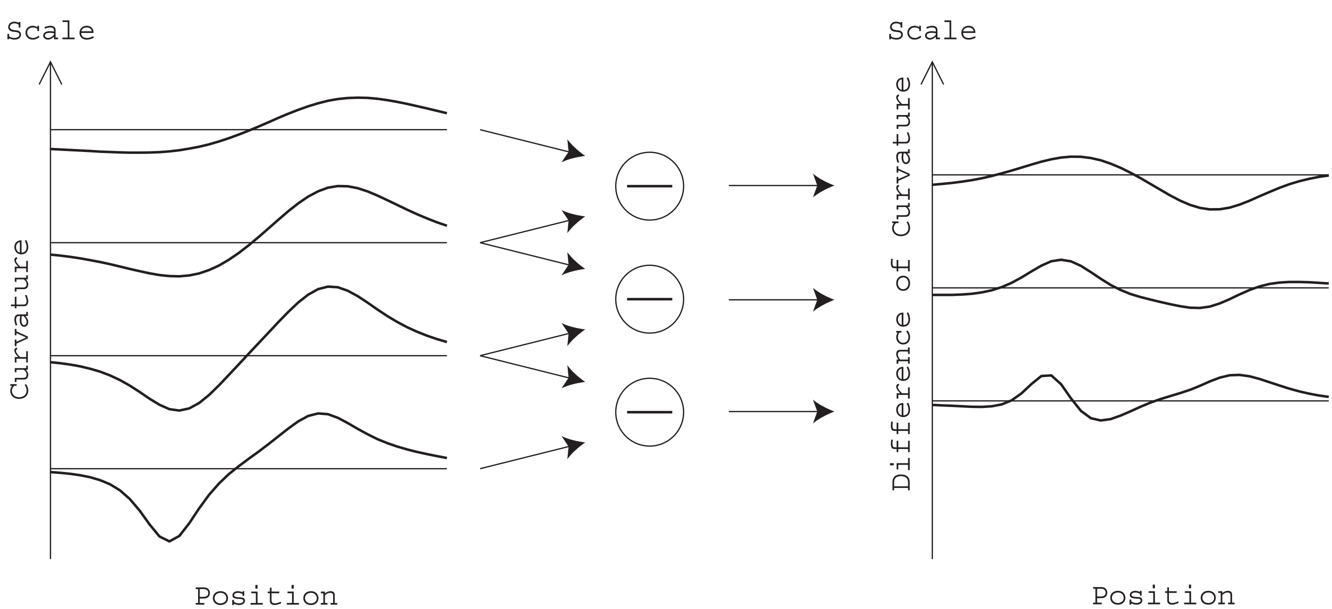

Fig. 2 The procedure to construct difference of curvature.

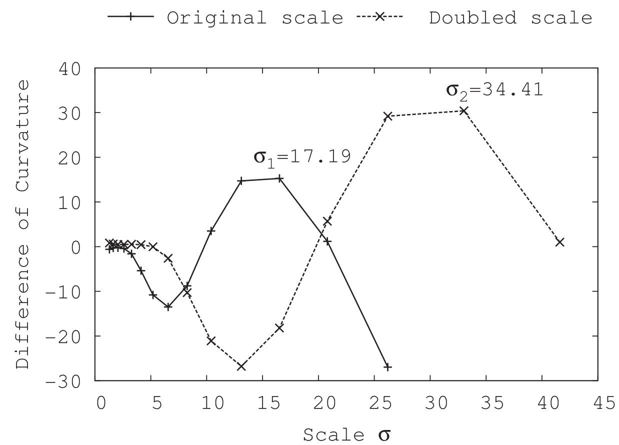

Fig. 4 An example of the detected scales from two contours that one is expanded to twice the other.

neighbors (marked by circles).

The feature point as the local maximum or minimum is refined by the interpolation of the linear function. Finally, an accurate feature point can be detected without the tracking of feature points in the DoC. An example of the proposed scale detection is shown in Fig. 4, where the ratio between adjacent scales is defined as $2^{1/3}$ from preliminary experiments. The local maximum scales are detected from two contours that one is expanded to twice the other. The values of σ_1 and σ_2 are interpolated by using three adjacent points. The value of σ_2 is twice of the value of σ_1 as expected. Additional experiments are described in Sect. 4.

In practice, the resampling or downsampling techniques have some advantages for noisy contours or large contours [1], [6]. However, the resampling technique, which is utilized in the MPEG-7 contour shape descriptor, is not used in the proposed method. A few adjustments to the positional difference caused by the resampling or downsampling techniques need a high computation cost because the computation of DoC should be performed at the same position on the difference scales.

3.3 Curvature Description with the Scale Invariance

In this paper, a description method for feature points is not specified. Since the description strongly depends on applications such as shape classification, shape retrieval, and computer vision described in Sect. 1.

Some approaches to the shape description are suggested instead. Beginning at the position of the feature point, a series of curvature is described along the contour, which is normalized by the appropriate scale of the feature point. This approach is similar to the SIFT descriptor. Another approach is to describe the relationship between two feature points. In this case, by using one of the two appropriate scales, curvature values and/or the distance between them are normalized. Feature points are extracted from the single shape but not limited to, i.e. arbitrary combinations of feature points from plural shapes are permitted.

Fig. 5 Example of test shapes; key, hammer, and apple.

4. Experimental Results and Discussion

4.1 Experimental Conditions

In this paper, we use the analogy between the difference of Gaussian on an image and the difference of curvature on a planar curve. The validity of the proposed method is confirmed by two experiments. One is the scale detection stability of the varying size of shape. The other is robustness of contour fragment.

The test sequence of shapes is a subset of MPEG-7 Core Experiment CE-Shape-1 [3]. In this paper, 70 shapes are used. Some shapes of them are shown in Fig. 5.

Two conventional methods are compared. One is the MPEG-7 contour shape descriptor that is based on the curvature scale-space. The other is the gradient-based curvature that is based on the intensity image of contour [9], [11]. In the following, these conventional methods are called CSS and GbC, whereas the proposed method is called DoC.

4.2 Scale Detection Stability

First experiment shows the scale detection stability of the varying size of shape. In this experiment, it is expected that detected scale value of feature point which is located at the same position among the given varying scales is proportion to the given scale or constant. The procedure of this experiment is described. A shape is shrunk/enlarged at different given scales in order to obtain a set of contours. A set of appropriate scale is normalized by the given scale and/or average scale value at the same position. Normalized scale values become almost 1.00. Finally, the standard deviations of the set of normalized scales are then calculated, which is defined as the stability.

The shrinkage and enlargement are performed through a vector representation, which is produced by the conventional vectorization tool [12]. This vectorization tool converts the contour obtained from the binary image into smooth Bézier curves. The scale of the Bézier curve is changed and the resulting curves are rasterized to the binary images again. The given scale value varies from 0.1 to 10.0.

The scale values detected by the proposed method (DoC) have following characteristics. The scale value is proportion to the given scale while each scale at the different position on the same shape has different value. Therefore, a set of scale value is normalized by the given scale and by the average from scale values among the given varying scales. The scale value detected by CSS is independent to a given

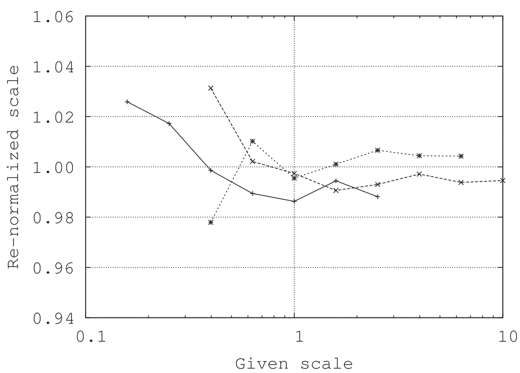

Fig. 6 The re-normalized scales detected by the proposed method (DoC).

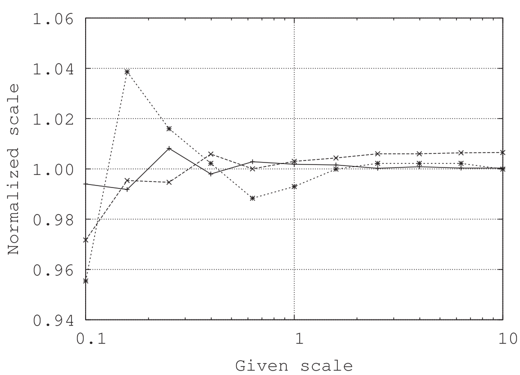

Fig. 7 The normalized scales detected by CSS.

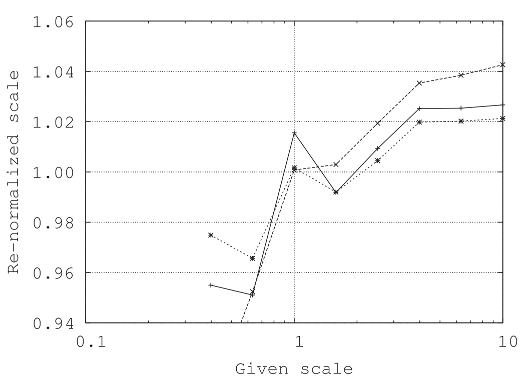

Fig. 8 The re-normalized scales detected by GbC.

scale. They are normalized by the average from the scale values among the given varying scales. The scale value detected by GbC has same characteristics to the one by DoC.

The results of normalized scale value at the same position of some feature points are shown in Figs. 6–8. The X- and Y-axis indicate the given and detected scales which are normalized. Each series indicates the set of feature points at the same position from the shapes of different given scales. The absence of points in the series implies that feature points are not detected. Further, the standard deviations of the normalized scales from 70 shapes are shown in Table 1.

These results indicate three important facts. The first is that the proposed method detects the appropriate scales

Table 1 The standard deviation of the normalized scales.

DoC	CSS	GbC
0.0396	0.0573	0.0651

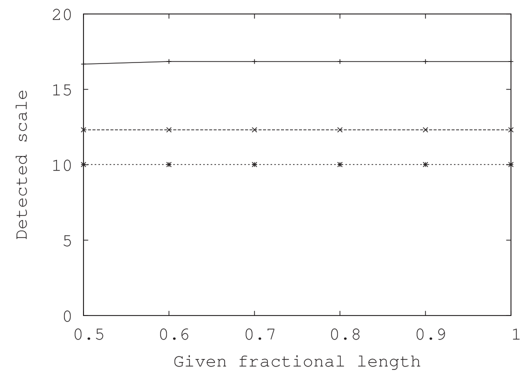

Fig. 9 The deteced scales from a contour fragment by the proposed method (DoC).

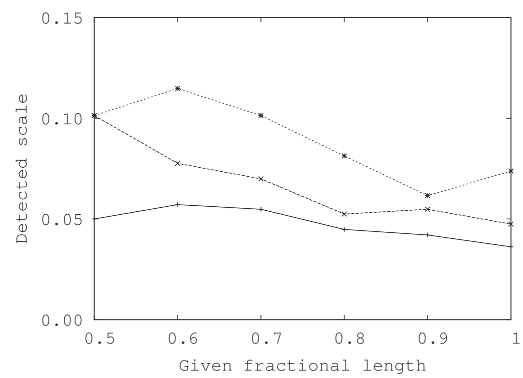

Fig. 10 The deteced scales from a contour fragment by CSS.

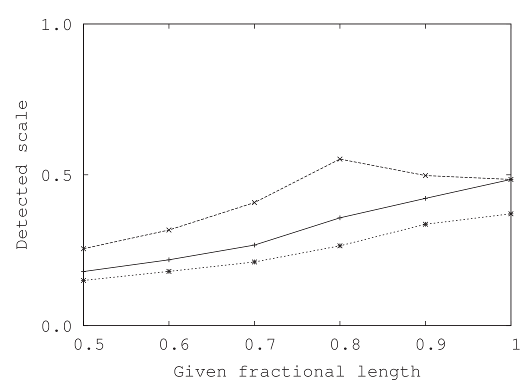

Fig. 11 The deteced scales from a contour fragment by GbC.

from shapes of different sizes without the contour length. The second is that the proposed method detects only feature points with correct scales. In other words, some of feature points detected by the conventional method have wrong scale, which is away from 1.00, where the given scale values are too small. The last is that the proposed method reduces the standard deviation of the normalized scales by 30–

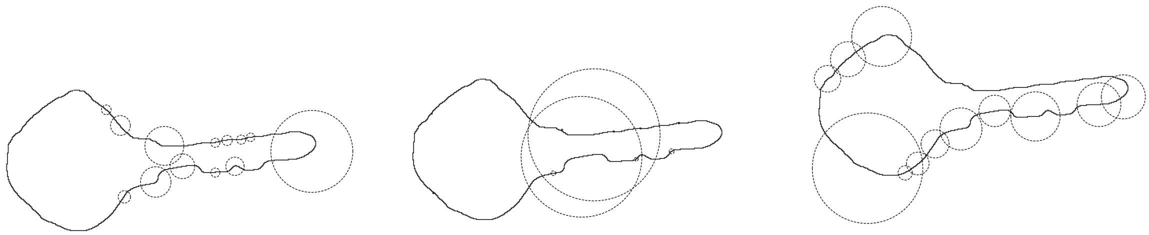

Fig. 12 Example results of the detected feature points with dotted lines and the original contour with heavy line. Detection methods are sequentially DoC, CSS, and GbC from the left.

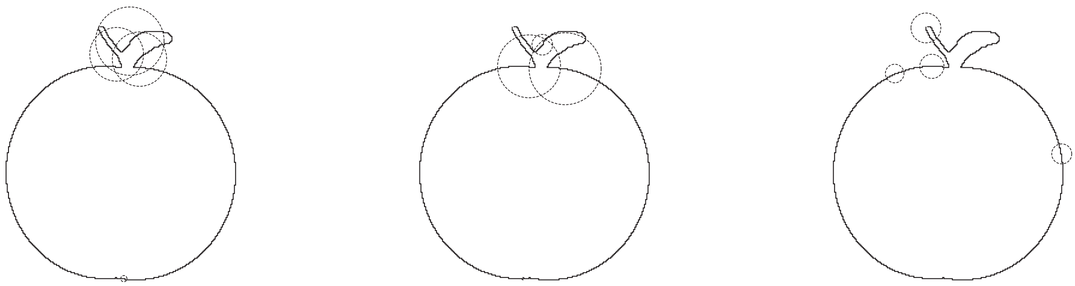

Fig. 13 Example results of the detected feature points with dotted lines and the original contour with heavy line for diverse shape. Detection methods are sequentially DoC, CSS, and GbC from the left.

40%. Consequently, the proposed method is the most stable among all methods.

4.3 Robustness for Contour Fragment

Second experiment is robustness of contour fragment. Comparing the conventional methods, which are difficult to be applied to contour fragment, a part of shape is dilated such that whole contour length becomes short. In the followings, the ratio of short length to whole length is called "fractional length." In addition, all methods are applied to the same contour fragments. For some feature points, the relation between fractional length and detected scale, which are raw data obtained by each method, are shown in Figs. 9–11.

The proposed method provides the entirely constant scale values for each feature point. On the other hand, the scales values detected by the conventional methods are varying. In the result of GbC method, detected scale values tend to be proportion to the given fractions. Whenever the detected scale values are normalized by one scale value in the same contour fragment, stability is lower than one by the proposed method.

This result indicates that the proposed method is the most robust for the contour fragment where the feature point is remained on the fragment.

4.4 Layout Characteristics of Detected Feature Points

An example of detected feature points for two shapes are show in Figs. 12 and 13. In this figure, detected scale points by three methods are drawn with dotted lines, which are superimposed on the original contour with heavy line. The radius of each circle is proportional to the detected scale, whereas the center of each circle indicates the position of the feature point.

These experiments indicate two trends. The one is that the proposed method detects feature points with varying scales, compared to the CSS method. The other is that the position of feature point does not correspond to the location where the curvature is visually large, compared to the GbC method. These detected scales can finally be used to describe the scale-invariant features of shapes.

Curvature-based feature detection methods has disadvantage to diverse shape or a part of the smooth curve. In other word, feature points are not defined when varying curvature is monotone. An example of this is shown in Fig. 13. There are no feature points on a part of the smooth curve by three methods. This observation implies that the feature of smooth curve should be characterized by other techniques.

5. Conclusion

In this paper, we propose the automatic scale detection method for a contour fragment based on the difference of curvature. The appropriate scales and their positions are detected by analogy to the difference of Gaussian in the SIFT algorithm. To calculate the differences, scale-normalized curvature is introduced. Validity of the proposed method is confirmed by the experiments. The proposed method provides the most stable scales of feature points among conventional methods such as curvature scale-space and gradient-based curvature. It is also confirmed that the proposed method is robust to the contour fragments.

Compared to a curvature scale-space method like the MPEG-7 contour shape descriptor, the proposed method as a local feature has the following advantage. The tracking of feature points in different scales is not required. The appropriate scales are detected without the contour length. Feature points can then exist on the contour fragments or the plural contours, which extends the application area.

There are many directions for further research based on the appropriate scale detection. A feature description and systematic testing are required for specific applications such as contour fragment retrieval of a contour, classification, and so on. Another direction is the analysis and definition of an appropriate scale for visually large curvatures.

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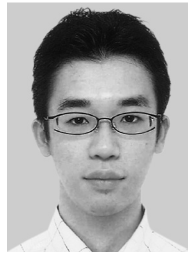

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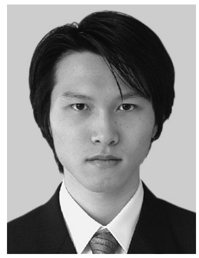

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