Image Similarity Measurement using Shape Feature

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ABSTRACT
In this paper, we describe an incipient method for image retrieval predicated on the local invariant shape feature, designated scalable shape context. The feature utilizes the Harris-Laplace corner to locat the fix points and coinside scale in the animal and flower image. Then, we utilize shape context to explain the local shape. Correspondence of feature points is achieved by a weighted bipartite graph matching algorithm and the homogeneous attribute between the query and the indexing image is presented by the match cost. The practical results show that our method is efficient than shape context and SIFT for the animal and flower image retrieval.

General Terms
Recognition and representation.

Keywords
Local invariant shape feature, key points, graph matching.

1. INTRODUCTION
Animal and flower is one of the most popular images in history. It is well-relished by children and adults for its comic characters and the concise drawing style. The animal and flower images as secondary products are now all over the internet, and the customer have a strong force on to find the animal and flower image by retrieval, however, few efforts have been made on animal The animal and flower images as secondary products are now all over the cyber world, and the customer have a vigorous demand to find the animal and flower image by retrieval, however, few efforts have been made on animal and flower image retrieval [10,9,11].

Roughly verbalizing, there are mainly two quandaries lying on the content predicated animal and flower image retrieval. Firstly, they appearance of the animal and flower image changes from time to time, when utilized in different applications, such as advertisement, poster and operating system themes and what is main content in the animal and flower image is still not clear. Secondly, most of the ecumenical features utilized in the Content Predicated Image Retrieval (CBIR) will fail to localize the kindred image patch in the local part of the whole image, even when the image patch is equipollent to the query.

Nowadays, with the rapid development of Internet and multimedia technology, image data has a sharp expansion, in order to find the intriguing images expeditiously and accurately, the content-predicated image retrieval (CBIR for short) technology is utilized. Image has sundry innate features which reflect its content such as color, texture, shape, and spati features etc. Image retrieval predicated on shape content remains a more arduous task than that predicated on other visual features. Shape is one of the most rudimentary and consequential characteristics, shape descriptors should be invariant to translation, rotation and scaling of the object on the substructure of distinguishing different objects. Shape descriptors are broadly categorized into two groups: contour-predicated and region-predicated techniques. Utilizing just one kind of feature information may cause inaccuracy compared with utilizing more than two kinds of feature information. Therefore many image retrieval systems use lots of feature information like color, shape, texture and other features.

There are an abundance of shape predicated features that have been utilized for the retrieval of curve structure. To designate a few, Fourier descriptor [1], wavelet descriptor [4] and curvature feature [5] are studied, and they performance well for the retrieval of the objects outline. However, they cannot used to describe the inner structure of the shape. Chin explain invariant moment [2] and Teague explain the Zernike moment [6], both of them can be utilized for describe the shape, but they are sensitive to the noise and the interference from the background. S. Belongie studied [7] a feature designated Shape Context (SC), which sanctions quantifying the shape kindred attribute between curvilinear structures, and is utilized in digit apperception, silhouette kindred attribute-predicated retrieval. The rudimental conception of SC is to model the differenciation of other curve pixels relative to the culled pixel.

We define the curves in the image as the main content, and study a local feature designated Scalable Shape Context (SSC) predicated on the SC feature. Firstly, we extracted both the edge and the lines in the animal and flower image. Then, Harris-Laplace corner detector is employed to localize the points and corresponding scale in the animal and flower image. The scale of each key point is utilized as a reference scale by SC to describe the curvilinear structure around the key points so that feature can be extracted at a consistent scale among images. There are two methods. First method is curve extraction .Second method is feature extraction, in.The H (∏) presents the shape homogeneous attribute between the query and the test image local region. We can give a indexing by sorting the kindred attribute this is a weighted bipartite matching quandary, which can be solved efficiently.

2. METHODS
We extracted both the edge and the lines in the animal and flower image. Then, Harris-Laplace [3] corner detector is employed to locat the key points and corresponding scale in the animal and flower image. The scale of each key point is utilized as a reference scale by SC to describe the curvilinear structure around the points so that the feature can be extracted at a fix scale among images. The features we formulate the matching between the animal & testing animal and flower image as a weighted bigraph matching quandary and then find the optimal matching. The sum of the edge weight of the bigraph presents the kindred attribute between the query and indexing image.

Following methods are utilized for image retrieval:

2.1 Curve Extraction

There are mainly two type of curve in the image: one is the edge caused by the astronomically immense uniform regions and another is the thick lines, called embellishment lines. We extract these two types of lines together to present the shape in the image.

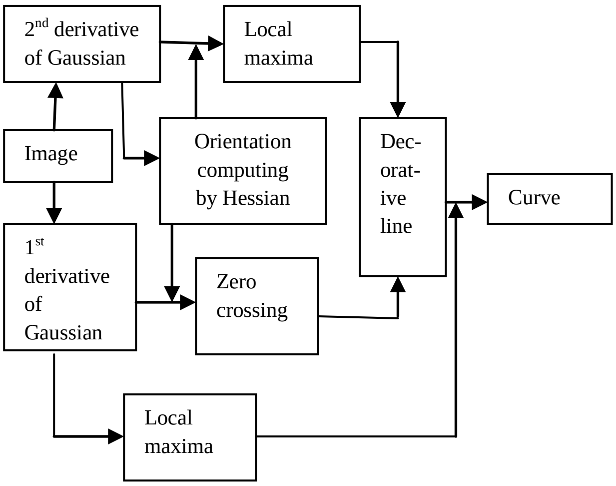


Fig 1: Flow chart of curve extraction in image

Firstly, the direction of the second derivative of Gaussian is gained by computing the Hessian matrix's eigenvector corresponding to the most sizably voluminous Eigen value. Secondly, the local maxima of the second derivative of Gaussian of the image are extracted. Then the zero-crossing pixels along the direction are gained to verify the decorative line. Determinately, we get the local maximum of the first derivative of Gaussian to get the edge. To consummate the picture, the obtained edge together with the decorative lines, we can get both of the two types of curve. To evaluate the performance of image rotation, we used images with a rotation angle of approximatively 45 degrees which presents the most arduous case. we comparing the descriptors computed for standard Harris points. For that points image patches are fine-tuned to a size of 21x21 pixels and σ=3.3 for Gaussian derivative. We can visually perceive that SIFT steerable filters and cross correlation obtain the results. The detection rates are smaller for scale invariant Harris-Laplace points. However, the ranking of the detectors remains equipollent. The best results are obtained by the SIFT descriptor followed by cross correlation and steerable filters. Note that for a 0.9 probability of correct detection the probability of erroneous match is about 4 times lower for steerable filters than for moment invariants. The error in scale estimation in point localization and in estimating the orientation angle. In Harris the scale and therefore the patch size remains fine-tuned. The only noise emanates from the in precision of the localize and from the angle estimation. We descry that these errors have low impact on descriptors than he scale error which occurs in the case of Harris-Laplace. An error is introduced, if the culled scales are not identically tantamount, which can transpired due to noise. It avails the encoder to cull exemplar and the decoder to renovate skipped regions with our edge- predicated in painting. Extracted edges do not require representing consummate and perpetual topological properties of an image because our purport is not to segment or recuperate an object. Discontinuous edges can likelywise play the role of assistant information scheme but taking the topological properties into account in edge extraction will make edges more consequential in terms of low-level vision. Therefore though there are many mature implements available to extract edges from images, the topology-predicated algorithm presented in adopted in our system to extract assistant information. The algorithm presents good results specially on extracting intersection edges. According to this method an input image is first smoothed by a two-dimensional isotropic Gaussian filter so as to eschew noise.In decorative line detection unlike authentic video which contains just edges between regions of different color, cartoons withal often contain drawn decorative lines, with minute but finite width. The former matching to a high color gradient, while the latter are categorically drawn by artists to convey structure, kinetics' or other artistic designation. Some decorative lines are located within regions while others may accentuate region boundaries. Relatively used edge detectors like the canny edge detector are not suited to decorative line detection-such detectors would find two edges one on either side of the decorative line, leading to the decorative line being considered as a small region. Furthermore, edge detectors lead to results with gaps so to engender connected decorative lines as narrow regions, we would require either an edge-linking method, or a flood-filling method which could ignore gaps of a certain size. To eschew such issues, we detect decorative lines discretely from edges utilizing a specialized approach.

2.2 Feature Extraction

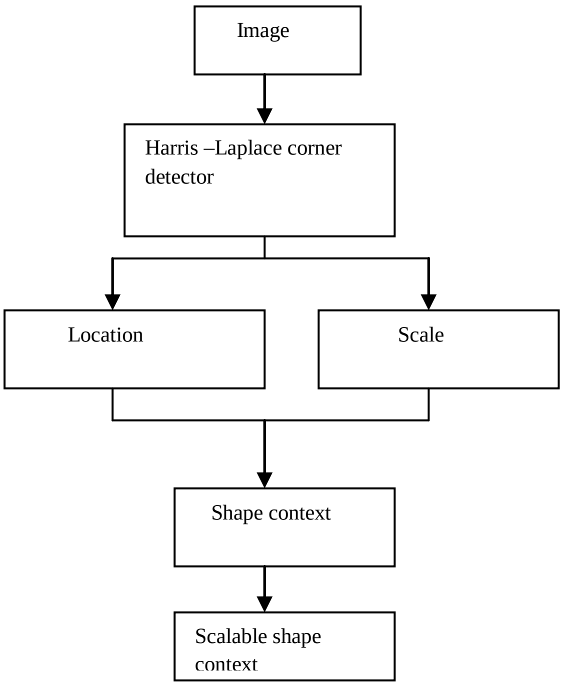


Fig 2: Flow chart of SSC extraction

Shape context can describe the distribution of the nearby curve pixels, is a compact and rotation invariant feature, but not invariant to the scale transmitting.

We find that the main content of the animal and flower image is the curve, and the intersection points of the different curve often provide more information than different part of curve. Therefore, it is a consequential to local the SC feature on this point with certain invariant scale. Motivated by this, we study a feature predicated on Harris-Laplace corner detector and the Shape Context. Harris-Laplace corner detector is inclined to detect the intersection point and give the reference scale. Afterwards, we utilize the Shape Context to describe the curve near the corner, with the corner location as the reference point and the corresponding scale as the reference scale. To detect corners in multi-scale, the following matrix be habituated to scale have changes to make it independent of the image resolution.

$$\mu(\mathrm{x}, \sigma_{1,}\, \sigma_{D,}) = \begin{bmatrix} \mu_{11} & \mu_{12} \\ \mu_{21} & \mu_{22} \end{bmatrix} \qquad (1)$$

$$= \sigma_\rho^2 g(\sigma_1) * \begin{bmatrix} L_x^2(x,\sigma_D) & L_x(x,\sigma_D)L_y(x,\sigma_D) \\ L_y(x,\sigma_D)L_x(x,\sigma_D) & L_y^2(x,\sigma_D) \end{bmatrix}$$

with

$$L_x(x,\sigma_D) = \frac{\partial}{\partial_x} g(\sigma_D) * I(x) \qquad (2)$$

$$g(\sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \qquad (3)$$

Where σ_1 is a smooth filter, σ_D is differentiation scale. I(x) is given image x, y are direction to σ_D.

The Matrix which describes the gradient distribution in a local nearest of a point. The Harris corner of scale can be localized by finding the local maxima in the Harris measure :

$$R = \det\left(\mu(x,\sigma_{1,}\sigma_D)\right) - \alpha trace^2\left(\mu(x,\sigma_{1,}\sigma_D)\right) \qquad (4)$$

Eventually, we verify each the scales if the local maxima of certain scale is addiditionaly also the maxima in the scale-space. The fix center is scale at which Harris measure R reaches its maxima over scales. it is clear that the corner usually arise at the intersection or junction of two curves, which satiate with our requirement .Suppose a reference point (a Harris corner) as P_i,i ϵ (1,2,…m), $P_i \; \epsilon \; R^2$, and curve pixels as l ϵ(1,2,..M), $Pixel_i \epsilon R^2$ the Harris corners scale is s , we utilize bins that are uniform in log polar square space, with12 bins for the an-gular direction and 5 bins for the polar direction, with radius $S^*2^t, t = \epsilon(0,1,..4)$. S is relative stable over images so that shape context can be computed in a fix scale to be invariant to the scale transmuting from image to image. We compute the histogram h_i as follows.

$$h_i(k) = pixel \neq P_i : (pixel - P_i) \epsilon bin(k) \qquad (5)$$

Descriptors are very different techniques for describing local image regions have been developed. The simple descriptor is a vector of image pixels. The cross-correlation measure can then be habituated to compute a homogeneous attribute score between two regions. However the high dimensionality of a description increases the computational intricacy of apperception.

2.3 Similarity Measurement

Let $C_{ij} = C\left(p_i, q_j\right)$ denote the matching cost between two feature points. We use the x^2 test statistic to compute C_{ij} .

$$C_{ij} = C\left(p_i, q_j\right) = \frac{1}{2}\sum_{k=1}^{k} \frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)} \qquad (6)$$

Where $h_i(k)$ and $h_j(k)$ denote the K-bin normalized histogram at p_i and q_j respectively. x^2 test is a measure for the independence. If the features p_i of and q_j are different C_{ij} will be relatively large and if the features of p_i and q_j are the same C_{ij} will reach a minimum of 0.

3. RESULT

We construct an animal and flower database. The images are Horse, Elephant, Rose etc collected from internet. Each class of character contains 80 images with different position, angle and background. The dataset contain one character image as the query image to evaluate the effectiveness of different feature.

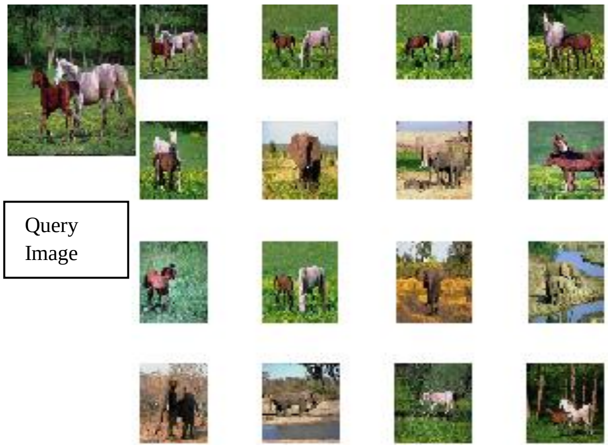


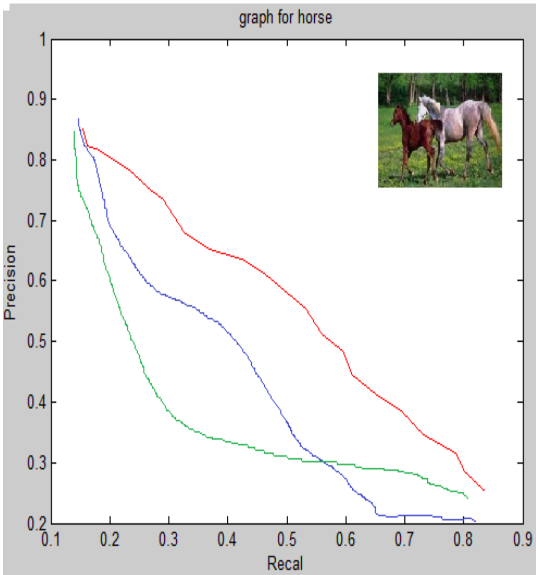
Fig 3: The result of the query image

To evaluate the proposed method, we make use the Precision-Recall (PR) curve to capture the trade off between accuracy and noise as the cost threshold varies.

$$\mathrm{P} = \frac{\text{true positive detected pixels}}{\text{all the detected pixels}}$$

$$\mathrm{R} = \frac{\text{true positive hit}}{\text{all pixels on the human labeled contour}}$$

Final result is shown in fig.4.

e 

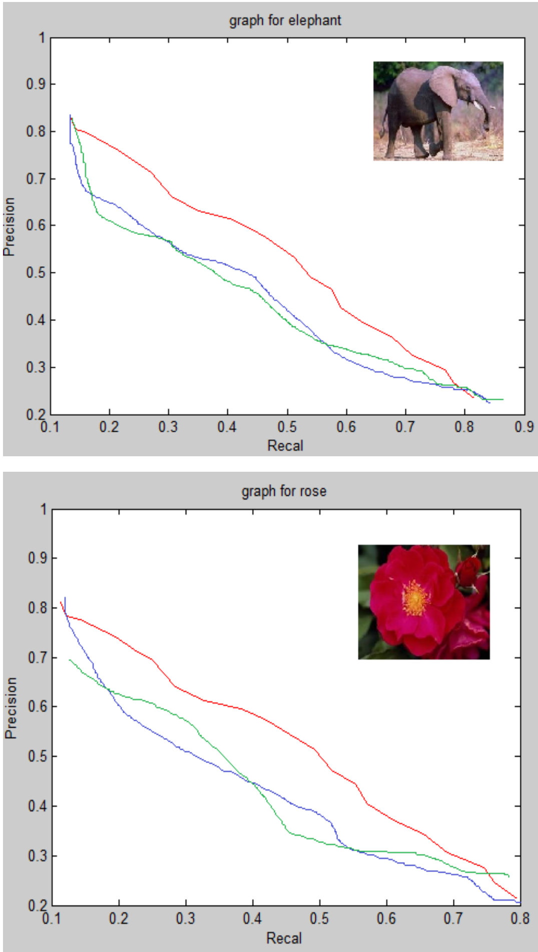


Fig 4: Result for retrieval of images. Red line shows SSC, blue line shows SC, green line shows SIFT.

4. CONCLUSION

We study how one character image as the standard query image to evaluate the effectiveness of different feature by using weighted bipartite graph matching algorithm. Also we make PR curve to study how SSC mehod is more efficient than SC, SIFT mehods.

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