A Novel Approach of Curvature Based Heat Diffusion for Shape Based Object Recognition

M. Radhika Mani, G. P. S. Varma, Potukuchidm, and C. Satyanarayana

***Abstract*—Diffusion geometry plays a vital role in shape analysis and object recognition. It evokes from propagation of heat on the object surface. This derives the intrinsic or invariant features of the surface. The heat kernel signature (HKS) based on heat diffusion suffers with the problem of scale sensitivity. This is resolved by the scale invariant heat kernel signature (SIHSK). It involves the Fourier descriptors for providing scale invariance property. This method considers only orthogonal features. The present paper has extended this by considering the curvature properties to SIHSK viz., curvature heat diffusion method with SIHSK (CSIHSK). The proposed method adopted the Modified Euclidean distance for shape similarity measure and is experimented over three standard databases. The results prove the efficiency of the proposed method than that reported for other descriptor of concurrent interests.**

***Index Terms*—LOB operator, eigen modes, eigen values, heat kernel, fourier transform.**

I. Introduction

Currently, the content based image retrieval is an upcoming era in the image processing and pattern recognition. This becomes effective with the shape based object recognition techniques. So, in the present scenario, more focus is on robust shape representation and description techniques which are invariant to scale, translation, rotation, and deformations [1]. For this, a proficient shape descriptor (signature) is needed for representing the shape surface. With the notable shape signature, the object of one class should be prominently distinguished from another class of objects.

With respect to the conceivable image information, the shape based representation methods are classified in to two categories, either following contour based or content based [2] recognition of regions. The contour based representation involves the evaluation of various descriptors positioned on the contour of the object, while content based representation requires evaluation of descriptors positioned over the entire content. However, both of these representations independently adopt spatial or transform domain [3] or structural or global approaches [3] to enrich the quality. Zhang *et al*. [3] reviewed various techniques of shape representation and description. In content based shape representation, description of the object is carried out by their 'moments' as they able to reflect the geometrical aspect of object. Moment Invariants [4], Zernike Moments [5], [6], Krawtchouk moments [7], Chebyshev moments [8, 9] represent some other types of popular moments used for region based descriptors. The regional shape representation methods include the procedures viz., the medial axis transform [10]-[12], grid method [13], generic Fourier transform [14], convex hull [14], shock graph [17] and shape matrix [16] etc.

The geodesic geometry [18]-[20] are used for describing the shape by inelastic deformations. The internal distances and Laplacian transforms are incorporated to extend the inelastic deformations [21]-[24]. Recently, heat diffusion is becoming popular in the intrinsic geometry. It is applied on the shape surface to observe the heat diffusion equation. The diffusion geometry is observed to be approximately similar to scale space based object recognition methods [10]. The time distances (diffusion distances) are utilized in the diffusion geometry [25], [26]. The description of the shape includes the feature vector computed from the shape surface [24].

The heat diffusion [26], [27] is becoming popular because of its invariance property among various characteristics except scaling. The heat diffusion involves the usage of heat kernel signature and Laplacian of Beltrami operator (LOB). The LOB operator is used to compute the eigenfunctions and eigenvalues of the given surface. To overcome the scale sensitivity to the heat diffusion, the scale invariant kernel signature (SIHSK) is proposed [28]. The SIHSK describes the shape feature vector with Fourier descriptors. This approach is capturing the orthogonal basis of the shape surface with LOB operator with invariant feature vector. This invariance is achieved through the Laplacian transformation properties that depend on the surface metrics only. Though it is efficient, it suffers with some disadvantages i.e. shape bends of the surface are not represented by SIHKS. In this, the curvature of the surface is also represented by the orthogonal basis only. To overcome this, the eigenmodes and spectra are replaced by the LOB operator. In this, LOB is replaced by the modified Dirichlet energy. The eigenfunctions and eigenmodes of the Hessian are computed as the deformation energy. Hildebrandt *et al.* [29] has used the described approach and computed vibration and feature signatures and vibration distance is used in the shape similarity process. Though, it is advantageous than the SIHSK, but the computation process in complex.

In the wake of the necessity to conceive the curvature information, to overcome this problem, the SIHSK method needs a simple method to include the curvature of the eigenmodes and eigenfunctions of LOB operator. Hence, the

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authors intend to propose a novel curvature based SIHSK (CSIHSK) by computing the LOB operator on the polar transformation of the surface. The paper is organized in 4 sections as follows. Introduction to heat diffusion based shape description methods and recent developments in this field are briefed in Section I. Section II involves the details of methodology implemented. The results of experiments and their discussion are depicted in Section III with comparing conclusions in Section IV.

II. Results and Discussions

Presently, a novel scheme for object recognition process designed to use Curvature based Scale Invariant Heat Kernel Signature (CSIHSK) signature is proposed. The proposed system consists of four successive steps viz.,

1) Shape representation with contour
2) CSIHSK signature construction
3) Shape description by using Fourier Transform and
4) Shape similarity and ranking, respectively.

The first step contains the contour representation of the shape surface. This is sampled to finite no. of representation points by Equal Arc Length sampling (EAL) [30] method. Then, in the next step the proposed CSIHSK signature is defined as a diffusion kernel with diffusion operator. The Heat diffusion on the surface is computed as the heat propagation on the surface and is given by (1).

$$\left(\Delta_X + \frac{\partial}{\partial t}\right)u = 0 \tag{1}$$

where, Δ_X represents the positive semi definite Laplace Beltrami Operator (LOB)

The heat kernel is represented by (2).

$$K_{X,t}(x,z) = \sum_{i=0}^{\infty} e^{-\lambda_i t}\varphi_i(x)\varphi_i(z) \tag{2}$$

where, λ represents the eigenvalues and φ represents the eigenfunctions of LOB operator satisfying $\Delta_X \varphi i = \lambda i \varphi i$.

The heat kernel signature is derived by computing heat kernel as given in (3).

$$K_{X,t}(x,x) = \sum_{i=0}^{\infty} e^{-\lambda_i t}\varphi_i^2(x) \tag{3}$$

To handle the sensitivity problem with HKS, the Scale invariant heat Kernel Signature (SIHKS) is introduced. In this, X' represents the scaled shape and β represents the scaling factor. In this, every shape point should be sampled logarithmically in time ($t=\alpha\tau$). Then the multiplicative constant ($\beta 2$) will be removed. In the SIHSK process, the LOB operator is applied on the orthogonal basis only. This will not capture the sharp bends in the shape surface. To overcome this, the present paper proposes a novel and simple approach called Curvature based Scale Invariant heat Kernel Signature (CSIHSK) method. In the proposed method, the rectilinear coordinates of the given shape surface is replaced by the polar transformation. The angular representation is always efficient than the Cartesian coordinate representation for capturing the curves or bends in the shape. The CSIHSK is clearly explained by (4).

$$K_{X,t}(R,\theta) = \sum_{i=0}^{\infty} e^{-\lambda_i t}\varphi_i(R\sin\theta)\varphi_i(R\cos\theta) \tag{4}$$

During the third stage in the proposed CSIHKS, the Fourier transformation is used to derive the feature vector. The Fourier transformation is given by (5).

$$FD_n = \frac{1}{N}\sum_{t=0}^{N-1} s(t)\times e^{\left(\frac{-j2\pi nt}{N}\right)} \tag{5}$$

where, $s(t)$ represents KX, $t(R, \theta)$ and N represents the length of the CSIHSK signature.

To further improve the quality of CSIHSK signature, three global descriptors (GD) are augmented to the proposed signature feature vector. The GD feature vector {S, C, A} contains the measures of solidity, circularity and aspect ratio.

The last step of object recognition i.e. shape toning process is comprised of the similarity measurement of test object feature vector with the training sample feature vector. Generally, distance measures are used to evaluate the similarity. The present paper proposes a new distance measure as given in (6).

$$D(TE,TR) = \sum_{i=0}^{M} \frac{e^{TE_i - TR_i}}{\left(TE_i + TR_i\right)^6} \tag{6}$$

where TE represents the test shape feature vector, TR represents the trained shape feature vector and M represents the length of the feature vector.

The performance of various object recognition schemes reported [31] so far employ different measures. Among them, precision and recall are considered to be important measures; Further, they can quantify the similarity measurement. Precision (P) and Recall (R) measures are defined by;

$$P = \frac{x}{y} \tag{7}$$

$$R = \frac{x}{groupsize} \tag{8}$$

where x denotes the true recognition results, y denotes the total recognized result and groupsize denotes the maximum true recognition result.

The Average Precision value for each recall is also computed. This value is affirmatively classified to fall into two categories viz., Low Recall (LR), High Recall (HR). The Average Precision for Low Recall (APLR) denotes the average precision for recalls less than or equal to 50. In contrast, the Average Precision for High Recall (APHR) represents the average precision for recalls greater than 50.

The presently proposed shape descriptor is then can be compared with four standard descriptors viz., Angular Radial Transform Descriptor (ARTD) [32], Moment Invariant Descriptor (MID) [32], Zernike Moment Descriptor (ZMD) [33] and Curvature-Scale-Space-Descriptor (CSSD) [33] to testify its efficiency. The performance for the present curvature based technique is compared with the Feature size of 35 for ARTD (n<3, m<12), 6 for MID, 34 for ZMD (order from 2 to 10). But, the CSSD feature size is varied from one image to another, because of the apparent variation in number of the peaks.

III. Results and Discussions

The proposed Curvature based Scale Invariant Heat Kernel Signature (CSIHSK) is applied on the MPEG CE-1 Set B database [34]. It is noticed that the Set B database characteristically includes rotated, scaled, skewed and defected shapes. Set B has seventy groups i.e. each group having twenty images making up to a sum of 1400 images. During the first stage, the contour of the object shape is extracted and by using EAL method, the no. of representation points is sampled to 128. Then during the second stage, the CSIHSK signature is constructed with considering the angular or curvature measurement of each and every representative point of the shape. In the third stage, the Fourier transformation is applied on the proposed signature and the first six coefficients are used to form the feature vector of the proposed CSIHSK descriptor. The proposed method feature vector is extended by including the GD features. During the final stage, the proposed new distance measure is used for shape similarity and ranking.

The proposed CSIHSK descriptor performance is measured by APLR and APHR values. The performance measure of proposed and different popular methods is compared and given in the Table- I. From the table I, it is clear that the SIHSK is giving superior performance results when compared with other standard descriptors (ARTD, MID, ZMD, and CSSSD). The SIHSK descriptor increases the performance measure of the APLR than APHR. Further, the SIHSK performance measure is improved by the proposed CSIHSK descriptor with the inclusion of GD features (CSIHSK+GD). The proposed CSIHSK+GD is increasing both the APLR and APHR values.

TABLE I: APLR and APHR Results of Various Descriptors Using Set B Database

	Avg. Precision		
	APHR	APLR	Average
SIHSK	80.63	49.47	65.05
CSIHSK+GD	83.46	52.01	67.74
ARTD	82.10	45.69	63.90
MID	79.54	44.50	62.02
ZMD	82.56	45.62	64.09
CSSD	78.61	41.81	60.21

The Precision-Recall (PR) plot of the SIHSK and CIHSK+GD is depicted in Fig. 1. From this Figure, it is clear that the proposed curvature based SIHKS descriptor is improving the precision measure at each recall measure.

The PR plots for these six descriptors with set B are presented in Fig. 2. The Fig. 2 reveals that all the six descriptors are yielding considerable enhancements to the precision measure on the Set B database corresponding low recalls. At high recalls, the proposed descriptor is found to result for improved precision measure when compared with other standard descriptors. The proposed descriptor is found to increase the precision measure marginally at low recalls i.e. for less than or equal to 50, where as it is significantly increase the precision at high recalls i.e. for greater than 50.

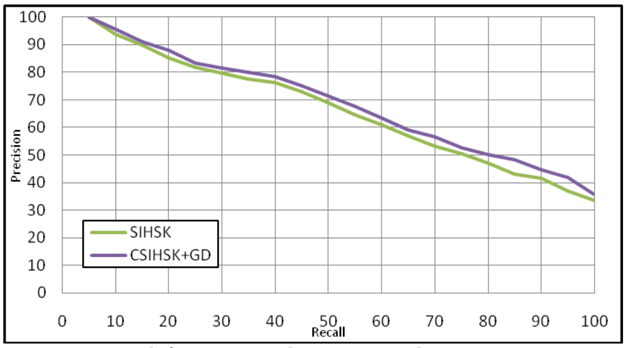


Fig. 1. PR graph for SIHSK and CIHSK+GD descriptors using set B database.

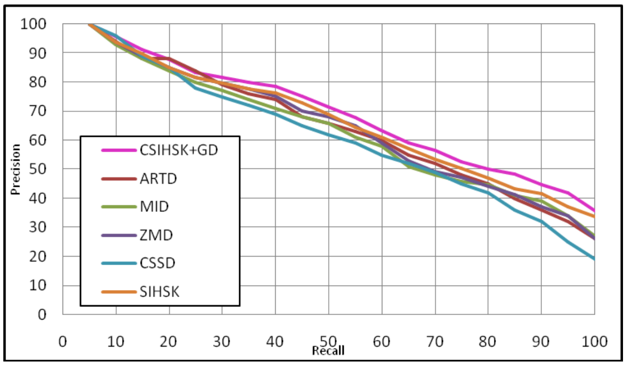
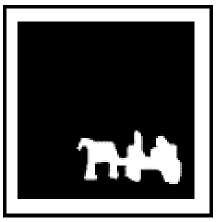


Fig. 2. PR graph for various descriptors using set B database.

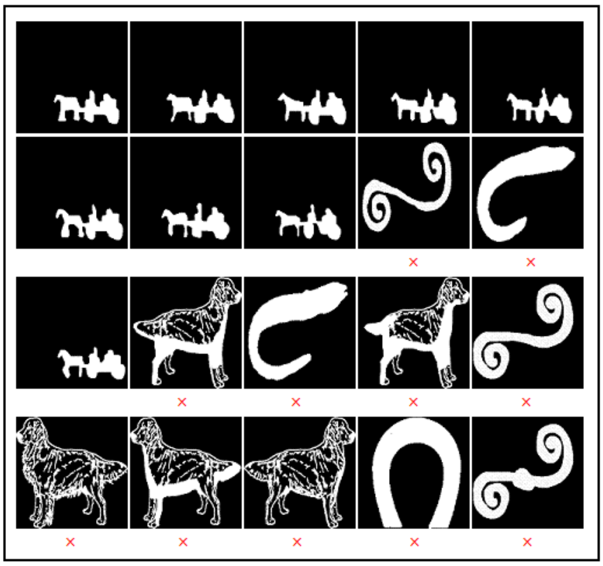
For the Set-B database, the accuracy for the recognized results corresponding to top 20 images is illustrated in Fig. 3. Among various standard descriptors, the ZMD is proved to be superior to other descriptors. So, the recognition result of proposed descriptor is compared with the ZMD result. The Fig. 3(a) shows Carriage6 image from Set B used as the query image. The Fig. 3(b) shows the recognition result of ZMD and Fig. 3(c) shows the recognition result of proposed CSIHSK+GD descriptor. The rate of dissimilar images in recognition result of ZMD is reduced in the recognition result of proposed CSIHSK+GD descriptor.

IV. Conclusions

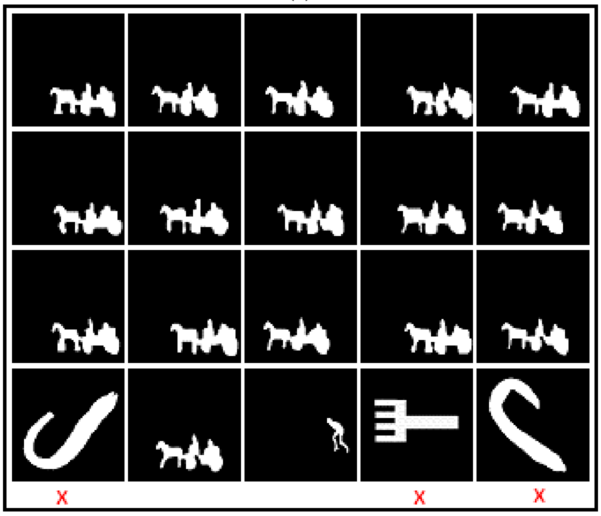
- A simple curvature based method relying on using LOB operator with polar transformation of surface can be proposed for the shape representation and description.
- Inclusion of angular variables in object recognition techniques enhances the performance.
- Consideration of global descriptors in the proposed signature performs better than of the original signature.



(a)



(b)



(c)

Fig. 3. Retrieval results of carriage6 query image from set B database (a) Query image (b) ZMD recognition results (c) Proposed CSIHSK+GD recognition results.

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