# HKSD for deformation measurement of nonrigid biological tissues from MR images

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Due to the nonlinear deformation of nonrigid and nonuniform tissues, it is challenging to accurately measure the displacements of feature points distributed on the inner parts, boundaries, and separatrices of tissue layers. To address this challenge, we propose a feature point matching technique called HKSD to measure MR 2-D slice deformation of nonuniform and nonrigid biological tissues. Finally, we describe patches based on the Heat Kernel Signature (HKS). We apply Gaussian function as weigh to noise 2D image. The experimental results showed that the proposed HKSD method outperformed the single SURF and SIFT methods.

Keywords: Feature point; Matching; Nonrigid; Image

### Introduction

It is a wisdom to extract and match feature points of magnetic resonance (MR) images in Euclidean spaces [1-5]. In this paper, we propose a feature points matching technique (HKSD) using Riemannian spaces; we apply our technique to measure MR 2-D slice deformation of nonuniform and nonrigid biological tissues.

Recently, there has some new ways to interpret and analyze image [6, 7, 8, 9, 10], such as Riemannian manifolds. These ways are non-Euclidean geometry. Also, heat diffusion theory has shown effectiveness in 3D shape analysis and recognition. In [11], they used heat diffusion theory to describe local features of deforming and scaling surfaces, and introduced a novel feature point descriptor named DaLI to non-rigid image transformations and illumination changes.

Drawing inspiration from the DaLI [11], we propose a feature points matching technique (HKSD) using Riemannian spaces; we apply our technique to measure MR 2-D slice deformation of nonuniform and nonrigid biological tissues. We show how to embed 2D surfaces into 3D space, and how to describe patches based on the Heat Kernel Signature (HKS). Meanwhile, to increase robustness against 2D and intensity noise, we use multiple such descriptors in the neighborhood of a point, and weigh them by Gaussian function.

#### **Related Works**

Extraction and matching of the feature points, which should be robust against the change in illumination, scaling, rotation, and noise or slight distortion, is one of the most important methods used to detect the correspondences between the images. In the literature [12-24], a wide variety of feature point detectors and descriptors have already been proposed. Harris [14] proposed famous corner detector, which is based on the eigenvalues of the second-moment matrix, and this detector is not scale-invariant. Another famous detector is Scale Invariant Feature Transform (SIFT) approach, proposed by Lowe [12], [15], [16]. This approach approximated the Laplacian of Gaussian (LoG) by a Difference of Gaussians (DoG) filter. Florack [18] proposed moment invariants, but in [17], author pointed out SIFT outperforms other feature descriptors. Actually, There have some other well-known methods such as PCA-SIFT (Principle Component Analysis-SIFT) [13] and the GLOH (Gradient location-orientation histogram)[16], these methods are various refinements on the SIFT scheme. In [19], SURF (Speeded-UP Robust Feature) proposed by Bay, this scheme is more repeatable, distinctive, and robust than SIFT. However, SIFT and SURF is not invariant to general deformations [13], [21].

In [22], a nonrigid point matching algorithm RPM (robust point matching) propsed by Chui, this method can estimate the correspondence and nonrigid transformations between the two point-sets at the same time. Ling and Jacobs proposed GIH (Geodesic-Intensity Histogram) [23], which is a geodesic distance based deformation descriptor. However, this method assumed the deformation along different directions is isotropic. In [24], Tian used Hilbert scanning to reduce complexity. However, this scheme would be disabled when a point is located in the subdivision line of Hilbert scanning.



# Methods

#### Feature point detection

First, we need extract a large number of feature points in the MR images welldistributed. In this study, we adopt the Difference of Gaussian (DoG) operator to extract a number of feature points from a given deformed tissue and original tissue images respectively.

In what follows, we describe how to apply the DoG operator to generate a set of image features in three steps.

Firstly: We need identify potential interest points. We use a difference-of-Gaussian function.

Secondly: Through calculate the Laplacian value of each key point found above, eliminating some low contrast points.

Finally: we use orientation to represent a key point, as a descriptor. We compute gradient magnitude and orientation to select Gaussian smoothed image, and form an orientation histogram. According the histogram, assign orientation to the key points.

Now, we need embed a image patch in a 3D space. A point of interest p is a center in a 2D image patch S. Based on the diffusion geometry theory, mapping of the patch S to a 3D Riemannian manifold M(f:  $S \rightarrow P$ ).We use follow function:

f: 
$$x \to (x, y, \alpha S(x)) \forall x \in P$$
 (1)

where S(x) is the pixel intensity at  $x = (x, y)^T$ , and  $\alpha$  is a parameter which controls the amount of gradient magnitude preserved in the descriptor.

#### Deformation invariant descriptor

Based on heat diffusion equation, we can character each patch S:

$$(\Delta N + \frac{\partial}{\partial t})\mathbf{v}(x,t) = 0,$$
 (2)

Where  $\Delta N$  is the Laplace-Beltrami operator. We called L(x,y,t) which is a heat equation heat kernel. We use this equation represent the amount of heat between two points at some time t. We also use follow equation to express heat kernel for a compact manifold M [25,26]:

$$L(x, y, t) = \sum_{i=0}^{\infty} g^{-\lambda_i t} \ell_i(x) \ell_i(y), \quad (3)$$



Where  $\{\lambda_i\}$  and  $\{\ell_i\}$  are the eigenvalues and eigenvectors of  $\Delta N$ . Actually, this equation (3) is equation (2)'s expansion. So, according to the equation (3), we describe a point **s** on *M* using the Heat Kernel Signature:

$$HKS(s,t) = L(s,s,t) = \sum_{i=0}^{\infty} g^{-\lambda_i t} \ell_i^2(s), \quad (4)$$

It is isometrically-invariant, and adequate for capturing both the local properties of the shape around  $\mathbf{s}(\text{when } t \rightarrow 0)$  and the global structure of M (when  $t\rightarrow\infty$ ).

But, the heat kernel may be unstable along the spatial domain, because when the shapes are irregular, the HKS of neighboring points are very similar. So, this HKS is sensitive to some 2D coordinates of keypoints. In this paper, we introduce a Gaussian function, this function is the distance to the center of the patch. Thus, we define the following Deformation Invariant descriptor:

$$SP(\mathbf{s},t) = [HKS(x,t) \cdot G(x;\mathbf{s},\delta)]_{\forall x \in S}, \quad (5)$$

where  $G(\mathbf{x}; \mathbf{S}, \delta)$  is a 2D Gaussian function, **S** is mean and  $\delta$  is standard deviation.

#### Handling in-plane rotation and scaling

Actually, SP descriptor is not designed for rotation and scaling. We designed Gaussian function is for the 2D noise, so we need all the pixels in the patch and their spatial relations.

In order to handle this situation, during the matching process we will consider several rotated and scaled copies of the descriptors. Therefore, given SP(s1) and SP(s2) we will compare them based on the following metric:

$$d(\mathbf{s}_1, \mathbf{s}_2) = \arg\min\left\| \left| T_{\theta_i, s_j} (SP(\mathbf{s}_1)) - SP(\mathbf{s}_2) \right| \right\| \qquad (6)$$
$$\theta_i, s_j$$

where  $\|\cdot\|$  denotes the L<sub>2</sub> norm and  $T_{\theta_i, s_j}(SP(s))$  rotates and scales SP(s) by

an angle  $\theta_i$  and a scale parameter  $s_j$ , respectively. These parameters are chosen among a discrete set of values  $\theta$  and s.

#### **Experiments**

We compared the methods of SIFT, SURF, and HKSD experimentally. The initial and deformed MR images of volunteers' calves are shown in Figure 1.



The images are taken by the 0.5T open MRI device, of which the FOV is  $24 \times 24$ cm. The distance between two adjacent slices is 2mm. For the SIFT and SURF methods, each of the image pyramids consisted of 3 octaves, with every octave having 4 levels with different scales. After the feature points were extracted, the NN/SCN (the ratio of the nearest and second nearest neighbors) of SURF distance was adopted to match the feature points of the initial and the deformed MR images.



Figure 1. Calf push (CalPush)

Table 1 show that compared with SIFT and SURF, HKSD significantly improves the number of correctly matched pairs. In this example, HKSD increases the correctly matched pairs of SIFT and SURF by 21% and 20%, respectively. The results confirm that our HKSD is capable of offering accurate deformation measurements of no rigid deformed tissues.

Table 1. comparison of Experimental Results of Four Methods

MR image	Method	NM	NCM	NWM	Ratio(%)
CalPush	SIFT	63	18	45	28.57
	SURF	66	14	52	21.21
	HKSD	63	47	16	74.95

NM: Number of the matched pairs; NCM: Number of correctly matched pairs; NWM: Number of incorrectly matched pairs; Ratio: matching accuracy.

## Conclusion

In this study, we proposed a feature point matching scheme called HKSD to offer MR 2-D slice deformation measurements. We carried out three phases in the development of HKSD. First, we used DoG detector and SIFT descriptor to extract the feature points. Then, embed 2D surfaces into 3D space. Finally, we embedded Riemannian manifolds into the familiar HKSD space and use HKS described the spatch.

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