

A Comparative Analysis of Image Stitching Algorithms Using Harris Corner Detection And SIFT Algorithm.

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Abstract

A technique of combining several overlapping images from the similar viewpoint into a bigger one without thrashing of information is known as an image stitching. In line of image stitching the literature shows the use of a variety of angles or corners keypoints recognition algorithms used. The most universally used methods are the Harris corner detection method and the Scale Invariant Feature Transform (SIFT) method.[1] In this paper, using similar keypoints matching scheme a comparative study is performed for the Harris corner detection algorithm and the image sifting SIFT algorithm. This comparative study presents a new approach for Photo Stitching of MRI images of the spinal cord to explore the effectiveness of Scale Invariant Feature Transform (SIFT) for keypoint matching. Because of the limitations of MRI scanners, whenever Patient undergoes spinal cord examination, three different images Cervix, thoracic and lumbar vertebrae with overlap are produced. For diagnostic purpose, it is desired to have single flawless image of entire spinal cord.

This article aims at generating single flawless image of spinal cord from three different images having several overlap. For comparison and simulation sample C-T-L images of a patient have been used. The algorithms were compared with the number of corners detected, the number of corresponding match keypoints pairs and time required for matching keypoints. From the simulation results, it was observed that the SIFT method is more effective in image stitching

Keywords: Image stitching, SIFT, Harris corner detection

Introduction

Image stitching is the method that combines various images to structure a single image with a broad field of vision. To figure one exclusive image it fundamentally combines more than two dissimilar images that is called panorama. Panoramic images can be created in a variety of manners. [18]

The purpose of the stitching is to increase the resolution of the image as well as the field of vision. A camera is normally

proficient of capturing films contained by the span of its visualization only; it cannot take a big picture with all details mounted in a solitary frame. This problem leads to the use of the panoramic camera and use of these types of cameras increases the overall costing. Panoramic imagery solves this problem by combining images taken different sources in a single image. The soaring resolution film mosaics produced using Image stitching algorithms. And it is used to produce the current digital images, maps and satellite images. Image stitching provides an adaptable and viable alternative to a panoramic camera. In this article, the focus is on the image stitching of spinal cord MRI Images.

Magnetic resonance imaging (MRI) was built-up in 1980s and enhanced the doctor's capability to distinguish between normal and abnormal structures of the spine and assist in diagnosis. The Doctor needs some spatial information from MRI scan that is the position of the spine, the stature of the disc, vertebral body configuration and irregularities, etc.

MRI Scanners which has capacity 3 Tesla that cannot scan the whole body in solitary stroke. The majority MRI Scanners in India are 0.2 to 3 Tesla. Accordingly these are unable to obtain a complete view of the body at once. Even though a small number of MRI scanners in the world which have capacity 4 Tesla and more than that can capture full picture at a one stroke. But the cost of these scanners is uneconomical. This provoked me to use an image stitching on images obtained by MRI scanners available. And generate a full vision of the interested body part.

Anatomical details

One of the fundamental sciences of medicine that deals with the study of the basic structure of body parts is the Human anatomy. The most important structure between the body and the brain is the spinal cord. The central nervous system is constituted the brain and spinal cord together. The human spinal cord is sheltered by the bone spine which consists of bones called vertebrae. There are five subdivisions of the spinal cord analogous to the diverse grouping of vertebrae, as shown in Fig.1.

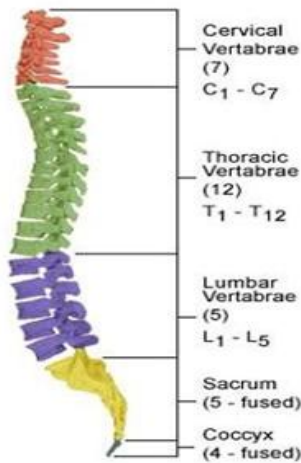


Figure 1: segments of spinal cord

Methodology

We have to detect the keypoints of each image in order to stitch two images. We use Harris corner detector and the SIFT for keypoint detection, which is explained as follows:

Harris corner detector

In 1988 Harris C and Stephens MJ anticipated the Harris corners detection algorithm. This is a still image-based algorithm used for the communal edge and edge detector. The realistic amounts of corner functions are extracted that gives a better quantitative measurement using a steady operator. In the image a local detection window is designed. With a minute quantity of shifting the window is shifted in diverse directions. And the average dissimilarity in intensity is determined. As a corner keypoint the midpoint of the window is take out. By considering the intensity values in a minute window the point can be effortlessly predicted. A huge change in emergence can be given by moving the window in either direction. [4]

To identify the corner keypoints The Harris corner detector is used. It will not show Change of intensity in all directions on moving the window if it is a flat region. It will not show change in intensity alongside the edge direction if an edge section is found. But there will be a considerable change in intensity in every direction if we find a corner. For determining the flat region, edge or corner the Harris Corner Detector gives a mathematical approach. Harris corner technique which is invariant to rotation and variant to scale detects more features. By the following equations these can be described.

$$E(u,v) = \sum_{x,y} w(x,y) [I(x+u,y+v) - I(x,y)]^2 \quad (1)$$

- The difference between the original and the moved window is E
- Displacement of the window in the x direction is u

- Displacement of the window in the y direction is v
 - The window at position (x, y) is w (x, y).
- Make sure that only the desired window is used because it acts like a mask.

- The intensity of the image at a position (x, y) is I.
- The intensity of the window moved I (x + u, y + v).
- The intensity of the original is I (x, y).

It needs to find the windows that produce a high value E. To do this, we need high valued terms in to square brackets. Using the Taylor series we develop this term.

$$E(u,v) = \sum_{x,y} [I(x,y) + uI_x + vI_y - I(x,y)]^2 \quad (2)$$

We introduced this equation into matrix form,

$$E(u,v) = [u \quad v] \left(\sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix} \quad (3)$$

Subsequent to that rename the summed-matrix. And situate it to be M:

$$M = \sum w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \quad (4)$$

So we can say that, Harris corner defined as the maximum in local area and which can be given by the following formula:

$$R = \text{Det}(M) - k \text{Trace}(M)^2 \quad (5)$$

Where,

$$\text{Det}(M) = \lambda_1 \lambda_2 \quad (6)$$

$$\text{Trace}(M) = \lambda_1 + \lambda_2 \quad (7)$$

The SIFT descriptor

In 1999 the David G Lowe first introduced the SIFT. SIFT stands for Scale Invariant Feature Transform. With the scaling, rotation or refinement transformation the SIFT algorithm is very invariant and robust for the characteristic or feature matching. We use the SIFT features to find matching keypoints between two successive images. The SIFT algorithm can be explained with main steps such as:

- 1) Detection of the extrema of the scale space.
- 2) Accurate keypoint localization.
- 3) The orientation assignment.
- 4) The key point descriptor.

Scale space extrema detection

By progressively blurring the original image Scale space is constructed. After that the original image is reduced to half size. Next blurred out images are generated again then the same process is repeated. Mathematically, the convolution of input image and Gaussian operator as given in Eq(8) results in blurring of images. Expression of Gaussian blur is given in Eq(9) which gives blurred image when applied to each pixel in image. With a Gaussian mask we initially construct the image pyramid by continuous smoothing. Difference Gaussian

which is DoG pyramid of the image will be obtained by subtracting the smoothed adjacent images. [17]The expression for DOG pyramid is given in Eq(10).

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (8)$$

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (9)$$

G: The Gaussian blur operator.

L: The blurred image.

I: Input image.

σ : The scale parameter.

x, y: The location coordinates of pixels in image.

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \quad (10)$$

$$= L(x, y, k\sigma) - L(x, y, \sigma)$$

The local extrema which is maxima or minima of Difference of Gaussian pyramid is determined by using the locations of feature points. A 3 x 3 neighborhood area is considered around region of each pixel. First in the same scale the center pixel is compared with its 8 neighboring pixels. Further it is compared with its 9 consequent neighbors from the superior scale and 9 corresponding neighbors from the inferior scale if it is found an extrema. If it is not extrema then it is discarded. This reduces calculations significantly rather than comparing each pixel directly with 26 neighboring pixels. [3]

Accurate keypoint localization

The initial result of this algorithm assumes that at the center of the sampling point there is the location of the keypoint. Nevertheless, it is not the correct maximum position of the keypoint. So that we require 3D quadratic function to fit the local sampling points in order to determine the actual location, that is, the sub-pixel precision level of the maximum value. Shifting of the Taylor expansion of the space scale function is done so that the original is at the sampling point.

$$D(X) = D + \frac{\partial D^T}{\partial X} X + \frac{1}{2} X^T \frac{\partial^2 D}{\partial X^2} X \quad (11)$$

At the sampling point and $x = (x, y, \sigma)$, D along with its derivative is estimated. From this point T is the offset. By taking the derivative of this function with respect to x and fixing it to zero, the location from the extremum, \hat{X} is determined.

$$\hat{X} = -\frac{\partial^2 D^{-1}}{\partial X^2} \frac{\partial D}{\partial X} \quad (12)$$

The keypoints having a low contrast or which are poorly located on one edge are eliminated in this step. We evaluate the value $D(\hat{X})$ with threshold for the search for points of low contrast. By substituting two equations above, we have: \hat{X}

$$D(\hat{X}) = D + \frac{1}{2} \frac{\partial D^T}{\partial X} \hat{X} \quad (13)$$

This point will be excluded if the value of D (x) is less than a threshold. We use the reality that in these cases there is a huge

principle curvature across the edge but a miniature curvature in the perpendicular direction in the difference of Gaussian function in order to eliminate extrema which is poorly localized. H which is a 2x2 Hessian matrix is computed at the location. To find the curvature scale of the key point is used. The ratio of the curvature of the principle can be confirmed proficiently using these formulas.

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \quad (14)$$

$$\frac{(D_{xx} + D_{yy})^2}{D_{xx}D_{yy} - (D_{xy})^2} < \frac{(r+1)^2}{r} \quad (15)$$

The keypoint is removed from the contender list if inequality in above equation (15) fails.

Keypoints orientation assignment

A foremost orientation is assigned to each feature based local image gradient after the stable features are determined. This gives the rotation invariance characteristics. The gradient magnitude $m(x, y)$ and orientation $\theta(x, y)$ are computed for each pixel (x,y) of the region around the feature location. This is given in Eq (16) and Eq (17).

$$m(x, y) = \sqrt{((L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2)} \quad (16)$$

$$\theta(x, y) = \tan^{-1}((L(x, y+1) - L(x, y-1)) / (L(x+1, y) - L(x-1, y))) \quad (17)$$

For each feature point from the weighted magnitude and orientation of each pixel around the feature point an orientation histogram is created.

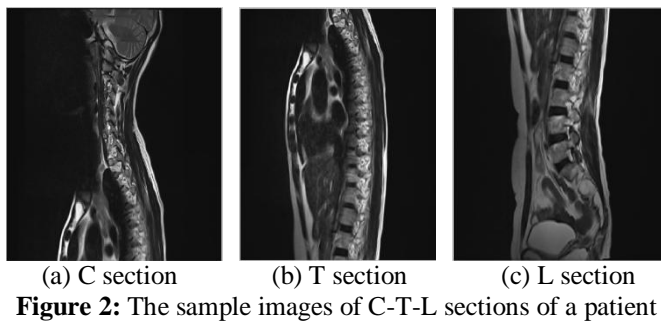
Keypoint Descriptor

The m x m region about the keypoint is conked out into n x n windows where $n < m$. Gradient magnitudes are weighted by appropriate Gaussian window and orientations are calculated inside each n x n window. Also these are put into an 8 bin histogram. This is done on all the windows in order to obtain n x n x 8 dimensional vector which is SIFT descriptor. In order to achieve illumination invariance the descriptor is normalized to unit length. Using the feature vector a keypoint is exclusively identified.

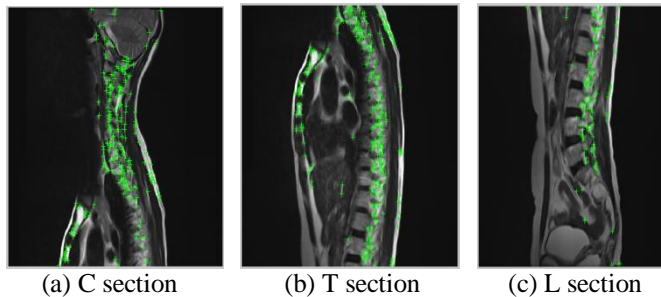
Results

In turn to execute the comparison of Harris corner detection and SIFT method testing has been executed using Matlab R2013a. The testing has been performed on a sample of C-T-L images of a patient. The sample images of patient 1 are shown in Fig. 2. The difference between two different images can be seen from the figures and the complication of the stitching problem.

We discover first the equivalent keypoints from both pairs of images to be stitched from the C-T-L sections of spine using Harris comer detection method which is shown in Fig. 3

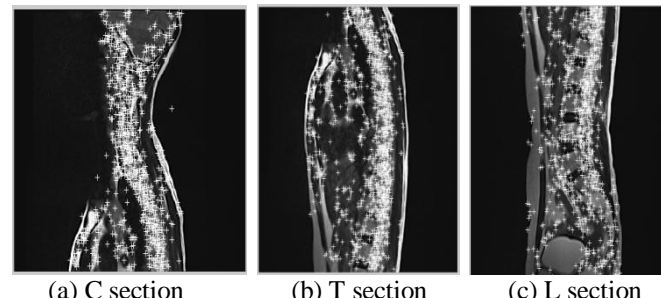


(a) C section (b) T section (c) L section
Figure 2: The sample images of C-T-L sections of a patient



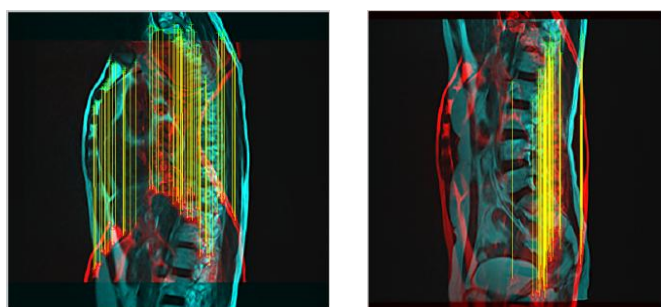
(a) C section (b) T section (c) L section
Figure 3: The keypoints detected for images of C-T-L sections of a patient using Harris Corner detection method

After that, we discover the equivalent keypoints from both pairs of images to be stitched from the C-T-L sections of spine using SIFT method which is shown in Fig. 4

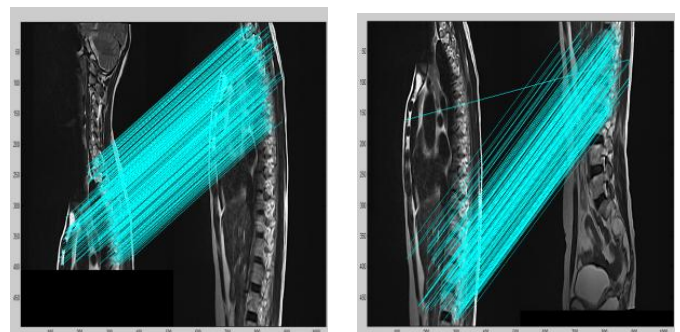


(a) C section (b) T section (c) L section
Figure 4: The keypoints detected for images of C-T-L sections of a patient using SIFT method

Finally, after detection of keypoints the matching of keypoints is done. From the set of detected keypoints the perfectly matched keypoints are extracted and matched using Harris corner detection and SIFT both algorithms. Matching of keypoints using Harris corner detection is shown in Fig. 5. And matching done by SIFT is shown in Fig. 6.



(a) C-T section match (b) T-L section match
Figure 5: The keypoints matching of images of C-T-L sections of a patient using Harris corner detection



(a) C-T section match (b) T-L section match
Figure 6: The keypoints matching of images of C-T-L sections of a patient using SIFT

Table 1: Results of image stitching using SIFT algorithm

Sample Pair	Keypoints detected		Matched keypoints	Elapsed time in sec
	C section	T section		
1	C section	T section	C-T section	C-T section
	919	1190	377	0.244994
2	T section	L section	T-L section	T-L section
	1190	899	268	0.281067

The number of keypoints detected and number of keypoints exactly matched for C-T, T-L sections using the SIFT method are tabulated in Table 1. These detected SIFT features keypoints have been used for matching. For case, in Table 1 it is seen that for sample pair 1, 919 keypoints (C) and 1190 keypoints (T) have been detected. 377 keypoints have matched. Hence, these 377 keypoints will be overlapped to get a stitched image.

Table 2: Results of image stitching using Harris corner detection algorithm

Sample Pair	Keypoints detected		Matched keypoints	Elapsed time in sec
	C section	T section		
1	C section	T section	C-T section	C-T section
	212	319	68	0.065511
2	T section	L section	T-L section	T-L section
	319	132	42	0.014630

The numbers of keypoints detected and number of keypoints exactly matched for C-T, T-L sections using the Harris corner method are tabulated in Table 2. These detected Harris corner features have been used for matching. For case, in Table 2 it is seen that for sample pair 1, 212 keypoints (C) and 319 keypoints (T) have been detected. 68 keypoints have matched. From this it is clear that keypoints detected are not so relevant to be matched for stitching.

Conclusion

In this research we have executed keypoints matching for image stitching using two keypoints detection methods that are Harris corner detection and SIFT. We have thrash out the detailed algorithms of these two methods. From the results, we can see that the number of keypoints detected using Harris corner detection are less than that of SIFT algorithm. Also the keypoint matching done using SIFT algorithm is superior to Harris corner detection algorithm.

SIFT algorithm is more vital and robust than Harris corner detection algorithm. The matching keypoint point from Harris detection can be obtained with high elapsed time and is very difficult to get highly correct and exact match keypoint. Where using SIFT features we can get high exactness and robustness match keypoints. We get probable keypoint matches for SIFT algorithm founded on extracting invariant scale features, than to for Harris corner detection algorithm. SIFT can give better performance compared with Harris corner detection method for exact keypoints matching used for image stitching of MRI C-T-L sections of human spine.

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