Image Stitching for Chest Digital Radiography Using the SIFT and SURF Feature Extraction by RANSAC Algorithm

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Abstract. Image stitching is one of the branches of computer vision. It combines two or more images for a scene to acquire a high-resolution panoramic image. An invariant local function often uses to stitch two images together. Since the flat plate of a digital radiography (DR) system does not cover all parts of the body, the whole bone structure image cannot seize in a single scan. To solved this problem, image stitching is broadly utilized by medical systems to stitch DR images, which can be helpful for scoliosis or lower extremity deformities in the diagnosis, and pre-operative planning are of great importance. In this paper, the stitching and retrieval of medical images planned. To conquer the background noise in medical images, and improve the recovery of quality and stitching rapidity of medical images, a random sample consensus (RANSAC) algorithm is useful to stitching the images of Chest digital radiography by scale-invariant feature transform (SIFT) and speeded-up robust features (SURF) feature extraction. Down-sampling utilizes to lessen the size of the images and reduction the measure of calculation. In the interim, the phase correlation is engaged to discover the overlapping region. After feature matching and perspective transformation, the stitched image is gotten dependent on the homography. At last, experimentation has finished showing the presentation.

Keywords: Image stitching; Chest digital radiography; SIFT and SURF feature extraction; RANSAC algorithm; Warp perspective image.

1. Introduction

Digital Radiography (DR) is a form of x-ray imaging, where innovative x-ray sensors are utilized instead of customary photographic film. Preferences incorporate time efficiency through bypassing chemical care and the ability to deliberately move and improve images. The computerized portrayal of radiographs gives a few preferences for the health system [ⁱ]. However, there are still difficulties for DR techniques, for example, (1) prior changes of the camera’s limits; (2) usage of help to reduce camera shaking when capturing images; (3) post-version (cutting, grayscale, rotation, and so on) of caught pictures [²]. Here the accentuation ought to be put on the limited size of the detector because usually, DR frameworks with enormous detectors or plates are over the top expensive. A trade-off is made that a vast field of view (FOV) is gained by a few exposures and the image is produced by image stitching utilizing
these exposures. For this very explanation, the target of the current examination has been to build up a reproducible, easy to use and low-cost process for the setting that the flat panel detector is with the limited size [3]. Particularly, chest radiographs, for example, DR is commonly used in physical assessment, by using a straightforwardness scanner related with an image stitching programming exceptionally created by the current undertaking group, using which parts of an image are automatically combined. Medical image stitching is practically identical to the making of a panorama photo of a scene using a few images of that scene [4]. The two central points for the image stitching procedure are: (i) the stitched image should be almost close as reasonable to enter images. (ii) It should be not easy to perceive seams of a stitched image.

Image stitching has two principal parts- image matching and image blending. The former is utilized to identify the movement connection among two or more rent images. There are two techniques, direct technique and feature detection technique, to match images. In the former technique, a reasonable assessment of photos needed to be stitched is finished. It is not a fast method to use since it requires an inordinate best picture. The feature based technique basically separates the unmistakable aspects from each image to shape these features. Two algorithms are used for feature detection- SIFT and SURF. To begin with, we find focuses on the images utilizing SIFT or SURF, followed by RANSAC to find the specific matches that consider the homography matrix. Then blend the utilization of picking blending procedures to dispense with the stitched crease and brightening hugeness.

2. Proposed Methods

Image stitching for chest digital radiography is proposed. The proposed work utilizes SIFT and SURF feature extraction tailed by the RANSAC algorithm. Fig. 1 shows the general system architecture.

3. Image Stitching Techniques

3.1. Image Pre-processing

Image pre-processing is the initial step expected to set up the image. In the paper, the proposed technique utilizes grey-level images. Load the grayscale chest digital radiography image pre-processing technique is uses to improve the image quality and prepare it for additional processing by removing noise and undesired parts in the image. To converts RGB values to a single grayscale intensity.

3.2. SIFT

David G. Lowe proposed a scale-invariant feature transform algorithm. It has unique features, such as rotation, affine transformation, scale invariance, blur image, viewpoint change, and noise immunity. The SIFT features are robust in image scale and rotation[5] and incompletely invariant to change in illumination and 3D camera perspective. The features are exceptionally unmistakable to make sure a
single feature to be matched in high probability against a big feature database. SIFT features detection consists of four following steps:

3.2.1. Scale Space Extrema Detection. This step discovers useful points which doesn’t change with scale and orientation. It is finished using the Difference of Gaussian (DoG) function. The external points are examined for all the image areas and scales. The DoG function is convolved with the image to obtain $D(x, y, \sigma)$, the DoG image, which is shown in Fig. 2 (a):

![Figure 2. (a) Structure of DoG image and (b) Maxima and Minima identification of DoG images [4].](image)

It can be formulated as:

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) \ast I(x, y),$$

(1)

where $G(x, y, \sigma)$ and $k$ are Gaussian function and a fixed factor, respectively. The DoG function is desired to Laplacian of Gaussian (LoG) since it is very easy to compute and the value could be a very close estimate to LoG [6]. David G. Lowe has consequent the connection between LoG images and DoG images:

$$G(x, y, k\sigma) - G(x, y, \sigma) \approx (k - 1)\sigma^2 \Delta^2 G$$

(2)

This demonstrates that DoG and LoG are varied only by a fixed factor $k - 1$.

Scale-space detection, initial authorize the key points, location and scale presented in Fig. 2 (b), the local maxima and minima of the DoG images set up by contrasting each sample point with its eight neighbors in the current of the image and nine neighbors in the scale above and beneath. In the 2D circumstance, we have to think about 3 DoG images in every octave, so we need to fabricate 4 different scale images [7].

3.2.2. Key Point Localization. This progression plays out an itemized fit to close data for location, scale, and the ratio of principal curvatures so that we can expel the focuses with low contrast localized along the edge [6]. After dependability estimation, the interest points are chosen as key points. The $2 \times 2$ Hessian matrix which is used to determine primary curvatures expressed as:

$$H = \begin{pmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{pmatrix}$$

(3)

It relies upon the second subsidiary of the DoG.

3.2.3. Orientation Assignment. At least one orientation to each key point allocated by neighborhood image gradient directions and in this way, it is not variant to the rotation of images. Gradient magnitude and orientation, expressed as $m(x, y)$ and $\theta(x, y)$ respectively, are processed for $L(x, y)$, the image sample at a specific scale [8], which can be calculate as:

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

(4)
\[ \theta(x, y) = \tan^{-1} \frac{L(x, y + 1) - L(x, y - 1)}{L(x + 1, y) - L(x - 1, y)} \]  

A key point descriptor is allocated to the orientation to make it invariant to the operation of image rotation.

### 3.2.4. Key Point Descriptor
In the above steps, the location, scale and orientation of each key point is decided. In this step, we make a profoundly particular descriptor for each key point that is invariant to illumination change or a 3D perspective. Around a key point, a window is selected to create the vectors for feature. The vector of descriptor for every part including 4×4 is characterized using 8 orientations so that the vectors of 128 component features are acquired, a number that looks like a decent understanding between data conservation and decrease in dimensions \[8\].

### 3.3. SURF
The Speeded-Up Robust Features (SURF) based method is created by Herbert Bay. It turned out to be famous for computing speed. This algorithm additionally founded on a scale-space idea. SURF technique of feature recognition has created to defeat the disadvantage of SIFT, for example, making matching algorithms quicker by the production of the low dimensional feature vector. Without down-sampling, it creates a stack to reestablish a similar resolution. Here, the nearby maxima evaluated utilizing the Hessian matrix (H). The Hessian matrix of an image at any point \( (x, y) \) in an image \( I \), the Hessian matrix \( H(x, \sigma) \) can be characterized as:

\[
H(x, \sigma) = \begin{pmatrix}
L_{xx}(x, \sigma) & L_{xy}(x, \sigma) \\
L_{yx}(x, \sigma) & L_{yy}(x, \sigma)
\end{pmatrix}
\]  

Thus, \( L_{xx}(x, \sigma) \) characterizes to the convolution of center point \( X \) with the Gaussian filter \( \frac{\partial^2 g(\sigma)}{\partial x^2} \) \[9\].

In SURF box-type filter guess is utilized rather than the Gaussian filter to upgrade computing speed. The multi-directional box filters appear in Fig. 3. To generate the mass reactions, \( D_{xx}, D_{yy} \) and \( D_{xy} \) at that point, the Hessian determinant, for example, \( \det(H_{\text{approx}}) \) is processed in the following equation:

\[
\det(H_{\text{approx}}) = D_{xx}D_{yy} - w(D_{xy}^2)
\]  

Here, weight function \( w \) is utilized to validate the energy for the Gaussian portion and its estimation \[8\]. SURF descriptor demonstrates the apportioning of force contained in the interest point neighborhood. In both of the directions, x and y, Haar wavelet reactions are resolved to obtain interest point with rotation-invariance. Every descriptor is determined proficiently and communicated in all the dimensions of 64. Therefore, the roundabout neighborhood of range 6s is involved \[8\].

![Figure 3. (a,b,c) Multidirectional box filter \[4\] and (d) Haar-wavelet response in x and y direction \[4\].](image)

Gaussian weighting coefficients are converged with Haar wavelet reactions to separate the intrigue points. The Haar wavelet reactions in the vertical path (dy) and horizontal path (dx) summarized alongside the supreme estimation of the response as \[9\].
3.4. Matching Feature Points

We will get a lot of key-points and their descriptors for each image. The matching procedure utilizes the descriptor data to discover the comparing matching point on the pictures. All of the points in one image contrasted with points in another image, and the matched points are distinguished. We have countless features from the two pictures. Presently, we might want to think about two arrangements features and stick with the sets that show the great likeness. Feature matching requires a matcher object. Here, we investigate three matches: (i) Brute Force (BF), (ii) k-Nearest Neighbors (kNN), and (iii) Fast Library for Approximate Nearest Neighbors (FLANN) matcher.

Brute-Force matcher takes the descriptor of one feature in the initial set and matches every single other feature into the second set utilizing some separation figuring. Furthermore, the nearest one returns. It takes two free parameters, the initial one is a normal-type. It determines the separation estimation to be utilized by default. It is useful for SIFT, SURF, and so forth. For the descriptors which is based on binary string, such as ORB, BRIEF, BRISK, hamming distance is utilized as an estimation. The second parameter is a Boolean variable, cross-check that is false by default. It gives a steady outcome and is a decent option in contrast to the proportion test. There two vital techniques that are BF and kNN matcher.

The first one returns the best match. The second one returns $k$ best match where $k$ is determined by the client. It stacks two images on a level plane and draws lines from the first image to the second image demonstrating the best matches.

FLANN matcher contains an assortment of algorithms enhanced for quick closest neighbors search in enormous datasets and high dimensional features. It works quicker than a BF matcher for vast datasets.

3.5. Homography Using RANSAC

An iterative to fit the direct models, an emphasis based algorithm is RANSAC. Not equivalent to other direct repressors, RANSAC intended to be tough to exceptions. After we have the data of all pictures of feature matching, we can utilize this valuable data to do image matching. In the image matching stage, we are going to discover which image a neighbor of another image and discover the accurately feature matching set we required for the following stage of all feature matching set. It utilized to guess parameters for the homography of a numerical model from a lot of examining data that contains outliners iteratively. RANSAC loop includes picking 4 feature sets (randomly); figure homography $H$ (precise); calculate inliers, keep the biggest set of inliers, and lastly, it recomputed least-squares $H$ gauge on the entirety of the inliers. RANSAC expels undesirable feature points to keep only the correct feature points. After the feature points are correctly acquired, each image is correlated to them. Following this, RANSAC is adopted to them to acquire the stitched images. Therefore, the output panoramic image is obtained with best features.

4. Results and Discussion

4.1. Describe of Experimental Processing

The results to obtain from experimentation to test the exhibition of the RANSAC algorithm coding outline. The simulation has finished using Spyder (Python 3.7). In this paper, chest images have been observing. The experiment results show the proposed procedure works improved than the current methods. We have tested two feature extractors- SIFT and SURF. The experimental result shows the original image, surf image, sift image & output created stitching images of surf image, sift image, and O/P compressed the image. So the output stitching image is increasingly accurate, much vivid in looking when contrasted with the input image. As can be seen from Fig. 4 (a), it is the left chest image (2000×1820 pixels) & right chest image (2000×2230 pixels) collected from Fiji.app (ImageJ). In the first place, convert an RGB color image into a grayscale image that appeared in Fig. 4 (b), Original color image split two-color images (left color image & right color image) and Fig. 4 (c) shows the imagined picture of the original chest image.
Both SIFT and SURF are utilized for feature detection when stitching an image. SIFT is a technique not change with affine transformation, rotation and scale. It additionally gives good outcomes in a noisy environment. Comparing to SIFT, SURF has the property of illumination. It is not steady for the change of illumination and rotation. It is also extremely high in computation speed, which is three times higher than SIFT. Thus, SURF is known as a speeded-up robust feature technique. 

Firstly, stitching two images by discovering features detector of them utilizing SIFT and SURF technique is present in Fig. 5. After the feature detector with SIFT and SURF, the following stage is to match feature points Fig. 6 (a) that is attained from the two images to decide the overlap region of similarity. The matching is finishing by contrasting the feature point to the feature point. Once a set of matched feature points is gotten, the RANSAC algorithm utilized to perspective transformation parameter. RANSAC unwanted feature points and keep only correct feature points. After finding the proper feature points for the image related to them, RANSAC utilizing homography to them to attain stitched image. The warp perspective transformation method is used to expel the seam between the stitched images. By use of image warp perspective techniques, the visible seam in the stitched images is therefore separated. To get warp perspective transformation after matching feature and overlapping areas Fig. 6 (b).

Finally, we have got the panoramic stitching image with the black part Fig. 6 (c). After that, removes the black part from the panoramic stitching image, and lastly, we have got the panoramic stitching image Fig. 6 (d).

| Key Points | Left Image | Right Image | Matches Features |
|------------|------------|-------------|------------------|
| SIFT       | 1219       | 1238        | 704              |
| SURF       | 12103      | 13091       | 7067             |
5. Conclusion

Image stitching is one of the fundamental regions in advanced image processing, and it is widely used in many areas. Image stitching is utilized in clinical applications for stitching chest images. In this paper, the essential techniques and methods is investigated to stitching chest digital radiography images. It presents a proposed method utilizing SIFT and SURF techniques likewise followed homography by the RANSAC algorithm. In this paper, the focus is on getting a better stitching output image for chest digital radiography. For future, several directions could be examined in determining invariant image features. Efficient test is required for data sets in the condition of full 3D perspective and illumination changes.

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