International Journal of Electrical and Electronic Engineering & Telecommunications

ISSN 2319 – 2518 www.ijeetc.com
Vol. 4, No. 2, April 2015

Research Paper

A COMPARATIVE STUDY OF FEATURE DETECTION METHODS

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This paper presents the methods of extracting distinctive invariant features from the set of images. These methods are useful for image stitching of multiple images. In this work, we formulate that SIFT is an efficient image stitching algorithm amongst the SURF, SUZAN and HARIS. SIFT is used to extracts image features which are invariant to image scale and rotation and provides best matching across the change in 3D viewpoint, addition of noise, and change in illumination (Russol Abdelfatah and Haitham Omer, 2013). The result of simulation demonstrates the efficiency of our method (Manjusha Deshmukh and Udhav Bhosle, 2011).

Keywords: Image matching, Invariant features

INTRODUCTION

Images are an integral part of our daily lives. Image stitching is the process of combining multiple photographic images or small video footage to produce a single image. Stitched images are used in applications such as interactive stitched viewing of images, architectural walk-through, multi-node movies and other applications associated with modeling the 3D environment using images acquired from the real world. Due to the limited FOV using multiple cameras. Image stitching is one of the methods that can be used to exploit and remove the redundancy created by the overlapping FOV. Hence the need of image stitching becomes important.

Various algorithms are available for feature extraction and registration. SIFT-RANSAC are very stable methods and also reduce the time and computational complexity. Among the local descriptors compared, SIFT features generally perform the best. SIFT is a corner detection algorithm which detects features in an image which can be used to identify similar objects in other images. Scale Invariant Feature Transform (SIFT) is one of the most active research subjects in the field of feature matching algorithms at present. It extracts image features from a set of reference image, stores in database and individually compares each feature to match new image. This algorithm can dispose of matching problem

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with translation, rotation and affine distortion between images and to a certain extent is with more stable feature matching ability of images which are shot from random different angles. RANdom Sample And Consensus (RANSAC) algorithm is used for featured-based image registration applications. RANSAC is a resampling technique that generates candidate solutions by using the minimum number observations (data points) required to estimate the underlying model parameters.

This paper introduces us to different methods used for image stitching.

RELATED WORK

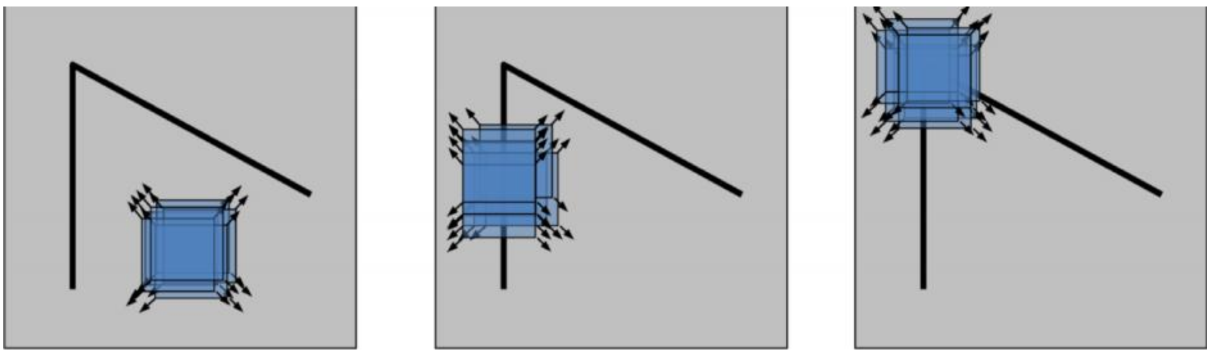
A lot of research is available on feature detection and matching. The available work explains about the various methods that can be used to detect and match the features amongst the set of images.

The Harris corner detector has been widely used for many other image matching tasks. While these feature detectors are usually called corner detectors, they are not selecting just corners, but rather any image location that has large gradients in all directions at a predetermined scale. Corner detection is good for obtaining image features for object tracking and recognition. The basic idea is that we should easily recognize the point by looking through a small window. Shifting a window in any direction should give a large change in intensity. Corners detection is the key step in the image processing, and the Harris comer detector is based on the gray scales of images, much sensitive to the change of the image scale.

The Harris corner detector is a popular feature point detector due to its strong invariance to Schmid *et al.* (2000): rotation, scale, image noise and illumination variation and. The Harris corner detector is based on the local auto-correlation function of a signal; where the local auto-correlation function measures the local changes of the signal. The Harris corners extracted removed most noised points, and the utilization factor of the image was increased, the calculation time is decreased, and the image was high recurrence rate and stable.

The algorithm used for Harris corner detector is:

Figure 1: Harris Corner Detection



Flat Region: No change in all direction

Edge: No change along the edge direction

Corner: Significant change in in all direction

1. Compute partial derivatives from intensity image
2. Compute A, B and C from the image
3. Compute corner response
4. Find local maxima in the corner response

Properties of Harris corner detector

1. Rotationally invariant.
2. Partially invariant to affine intensity change
3. Non-invariant to image scale However, there is multi-scale harris detector
4. Computationally demanding
5. Still sensitive to noise
6. Good localization only occurs at L-junctions

Speeded-Up Robust Features (SURF)

It has been our goal to develop both a detector and descriptor that, in comparison to the state-of-the-art, are fast to compute while not sacrificing performance. In order to succeed, one has to strike a balance between the above requirements like simplifying the detection scheme while keeping it accurate, and reducing the descriptor's size while keeping it sufficiently distinctive.

Our fast detector and descriptor, called Speeded-Up Robust Features (SURF), was introduced. It is built on the insights gained from this previous work. SURF's detector and descriptor are not only faster, but the former is also more repeatable and the latter more distinctive. SIFT and SURF algorithms employ slightly different ways of detecting features (Yang Zhan-Long and Guo Bao-Long, 2008). We focus on scale and in-plane rotation-invariant detectors and descriptors. These seem to offer a good compromise between feature complexity and robustness to commonly occurring photometric deformations. Skew, anisotropic scaling, and perspective effects are assumed to be second order effects, that are covered to some degree by the overall robustness of the descriptor. Note that the descriptor can be extended towards affine-invariant regions using affine normalisation of the ellipse, although this will have an impact on the computation time. Extending the detector, on the other hand, is less straightforward. Concerning the photometric deformations, we assume a simple linear model with a bias (offset) and contrast change (scale factor). Neither detector nor descriptor use colour information.

SUSAN

The SUSAN edge finder has been implemented using circular masks (sometimes known as windows or kernels) to give isotropic responses. Digital approximations to circles have been used, either with constant weighting within them or with Gaussian weighting. As the SUSAN principle does not require edge direction to be found for enhancement to take place, a reliable method of finding it from the USAN has been developed. The direction of an edge associated with an image point which has a non zero edge strength is found by analyzing the USAN in one of two ways, depending on the type of edge point which is being examined

SIFT isn't just scale invariant. You can change the following things, and still get good results:

☐ Scale

| Rotation

- Illumination
- | Viewpoint

Here is an example:

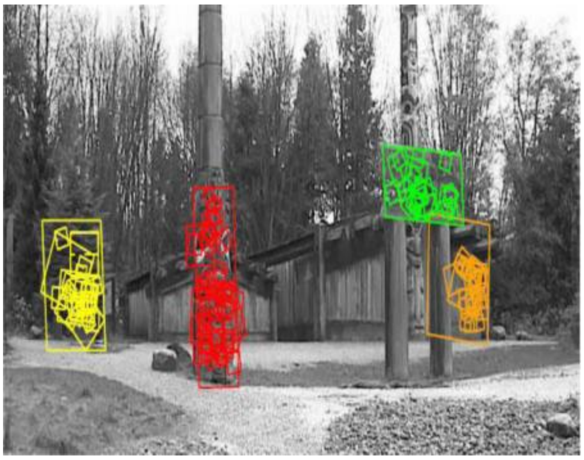
Figure 2: Objects to be Matched

And we want to find these objects in this scene:

Figure 3: Finding Given Objects in These Scenes

Here is the result:

Figure 4: Result of SIFT



Now that's some real robust image matching going on. The big rectangles mark matched images. The smaller squares are for individual features in those regions. Note how the big rectangles are skewed. They follow the orientation and perspective of the object in the scene.

The Scale Invariant Feature Transform (Manjusha Deshmukh and Udhav Bhosle,

2011) can detect and extract feature points which are invariant to changes in illumination, image noise, rotation, scaling, and small changes in viewpoint. After features are extracted from images, the initial matching process can begin. Feature vectors from one image are compared to those from the other image in pairs. To give robustness, feature vectors from the other image which are within a certain similarity threshold are preserved. As a result, bad matches appear. In some cases one feature point in the first image may match two different feature points in thesecond image according to this method.

The SIFT algorithm has four major phases:

Constructing a Scale Space: This is the initial preparation. You create internal representations of the original image to ensure scale invariance. This is done by generating a "scale space".

LoG Approximation: The Laplacian of Gaussian is great for finding interesting points (or key points) in an image. But it's computationally expensive. So we cheat and approximate it using the representation created earlier.

Finding Keypoints: With the super fast approximation, we can find the key points. These are maxima and minima in the Difference of Gaussian image that we calculate in step 2.

Get Rid of Bad Key Points: Edges and low contrast regions are bad keypoints. By eliminating these the algorithm becomes efficient and robust.

Assigning an Orientation to the Keypoints: An orientation is calculated for each key point. This effectively cancels out the effect of orientation, making it rotation invariant.

Generate SIFT Features: Finally, with scale and rotation invariance in place, one more representation is generated. This uniquely identify features. Input image Output Image

Following example shows the matched features using SIFT method.

Figure 5: Input Image

Figure 6: Output Image

Table 1: Comparison of Methods

Methods	SIFT	SURF	SUSAN	Harris Corner
Core idea	SIFT uses a cascading filtering approach. Where the Difference of Gaussians, DoG, is calculated on progressively downscaled images	a distribution of Haar wavelet responses within the interest point neighbourhood	Usage of a mask to count the no. of pixels having same brightness of the centre pixel	Calculates eigenvalues and eigenvectors of a small region
Detected features	Entire image	Entire image	Edges and corners	Edges and corners
No. of features detected	More	Moderate	Less than Harris corner	More than SUSAN
Type of images	Texture based images	Texture based images		
Time Cost	Better	Best	Less	Better
Scale	Best	Good	No	No
Rotation	Best	Common	No	No
Image Blur	Best	Good	Good	Worse
Illumination	Common	Best	Common	Good
Affine	Good	Good	Worse	Better
Computational speed	Moderate	Good	Moderate for corners	Good for corners
performance	Good	Good	Moderate for corners	Good for corners
Sensitivity to noise	Moderate	Most	More	Less
Type of images	Texture based images	Texture based images		
Time Cost	Better	Best	Less	Better

CONCLUSION

SIFT is used to extract distinctive invariant features from images that can be invariant to image scale and rotation. From our work, we conclude that the features detected by using SIFT helps to stitch images in an accurate way. The SIFT feature ensures smooth transformation between Images with different illumination and orientation and it can also overcome the difficulty of matching in vertical direction. High accuracy and better effect are obtained from the method based on SIFT features in image stitching. It is found that the SIFT has detected more number of features compared to SURF. SIFT shows its stability in all the experiments except for time, because it detects so many keypoints and finds so many matches. Among the local descriptors compared, SIFT features generally perform the best. Because of the unreliability of many algorithm such as the algorithm based on area and based on feature pattern, the algorithm based on SIFT features is of importance. From our analysis it was found that SIFT Key point features are highly distinctive and invariant to image scaling and rotation. It provides correct matching in images when subjected to noise, viewpoint and illumination changes.

We can also conclude that SIFT is a simple, yet powerful, technique that can be used for feature detection, registration and matching.

ACKNOWLEDGMENT

I would particularly like to thank Prof. Nishikant B Surwade, who has suggested numerous improvements to both the content and presentation of this paper and whose own work on Digital Image Processing has contributed to this approach. In addition, I would like to thank Dr S S Sonavane (Director, Dr D Y Patil School Of Engineering) and Prof. B K Shiragapur (HOD of E & TC Department, Dr D Y Patil School of Engineering) for their valuable suggestions.

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