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Multi-Sensor Image Registration for Remote Sensing under Scale Invariant Feature Transformation

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Abstract

Image registration deals with establishing correspondence between pictures of an equivalent scene or object. A picture registration rule ought to handle the variations introduced by the imaging system capturing the scene. Scale Invariant Feature remodel (SIFT) is a picture registration rule supported native options in a picture. Compared to the previous registration algorithms, SIFT is a lot of sturdy to variations caused by changes in size, illumination, rotation, and viewpoint of the pictures. As a result of its performance, the rule is wide studied, modified, and with success applied in several image and video primarily based applications, within the domains akin to drugs, industry and defense. This paper is associate outcome of in depth study on the state-of-art image registration algorithms supported SIFT. However, directly applying SIFT to remote sensing image registration usually ends up in a really variety of feature points or key points, however, a tiny low number of matching points with a high warning rate. We tend to argue that this is often because of the actual fact that spatial data is not thought about throughout the SIFT-based matching method. This paper proposes a way to enhance SIFT-based matching by taking advantage of neighborhood data. The planned methodology generates a lot of correct matching points because the relative structure in numerous remote sensing pictures area unit virtually static.

Keywords: *Registration, multi-sensor, SAR, optical, matching, SIFT, RMSE*

INTRODUCTION

IMAGE registration is wide employed in several fields corresponding to laptop vision, medical imaging, military, and remote sensing. For a try of pictures (a reference image and a detected image), the

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most objective of image registration is to search out an optimized transformation from the detected image to the reference image in order that the remodeled image is as similar as attainable to the reference image. Up to date, variety of image registration ways is planned. Area-based ways focus a lot of on the images' grey areas than on the images' feature areas. This sort of ways finds the matching info by shrewd the utmost similarity of intensity patterns between the perceived image and, therefore, the reference image with a such that similarity metric, to illustrate, sequent similarity detection algorithmic program, cross-correlation, cross-power spectrum, and mutual info (MI) whereas feature-based ways ask for the correspondence between the images' feature areas wherever options should be salient, distinct, and stable, which may be vital regions (forests, lakes, and fields), curves (region boundaries, coastlines, roads, and rivers), or points (region corners, line intersections, and points on curves with high curvature) [1, 2]. Although, the implementation details of feature-based methods may be different in one or more aspects, most of them involve the following four steps.

Feature Detection

With a certain feature detecting algorithm, two sets of features are detected from the reference image and the sensed image, respectively [3–5].

Feature Matching

A certain similarity function is used to evaluate the matching degree of any two features from the sensed image and the reference image, respectively, and a queue of feature correspondences is calculated.

Transformation Parameter Estimation

With a specific transformation parameter estimation algorithm such as random sample consensus (RANSAC), progressive sample consensus (PROSAC), and so on, the values of transformation parameters are estimated.

Transformation and Resampling

Based on the estimated parameters and a selected interpolation algorithm, the sensed image is resampled and aligned to the coordinated system of the reference image. Compared to the area-based strategies, feature-based strategies area unit a lot of wide applied thanks to their blessings. The area based strategies notice correspondences within the image area, whereas the feature based strategies notice correspondences within the feature area

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that represents data at the next and abstract level. If there is complicated distortion between the pictures to be aligned, the computation quality or the search area of the area-based algorithms will increase nonlinearly with the transformation quality. The feature-based methods can overcome this drawback because their search space is proportional to the number of features detected from the images. Also, the selected features sometimes are invariant to the changes of the image's geometric and radiometric conditions, presence of noise, and the changes in the target scene. Therefore, this type of method is suitable for the situations where illumination changes are expected or multi sensor analysis is demanded [6, 7].

SIFT WORKING

SIFT may be a standard selection forautomatic management purpose generation thanks to its scale and rotation unchangeableness properties. Normally, the SIFT methodology is thought to come up with matching feature points distributed over a full vary of positions and scales of the photographs. Multi-spectral image registration involves an excellent deal of illumination variation and may contain similar objects across the image which ends up in a very only a few range of properly matched management points. Lowe did not think about the neighborhood relationship of feature points within the abstraction area of the photographs because the methodology was targeted at object retrieval wherever the locations, poses, and abstraction relations of the objects to be retrieved may be quite totally different in two pictures. On the contrary, within the case of remote sensing image registration, we have a tendency to assume in most cases that the spacial relationship of the objects inside a picture does not expertise a big amendment inside another image subject to native affine distortions. For instance, Li, Yi, and Vural instructed modifications to SIFT for higher matching accuracy by imposing scale and orientation restrictions. What makes the spacial relationship a lot of necessary is that similar feature descriptors are also found in several locations, adore from buildings with similar shapes, that is common in remote sensing pictures. Thus, imposing a location restriction in feature purpose matching is that the underlying principle of the technique we have a tendency to propose during this paper. In the case of monomodal image registration, feature-based methods work well, but when they face multimodal images, even some multitemporal images, their performances may be problematic. Multimodal images

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refer to images acquired by different sensors/scanners or the photographs taken in different wavelengths [8, 9]. Due to different physical characteristics of various sensors, the relationships among intensity values of corresponding pixels are often intricate. Specifically, multiple values of pixel intensity in one image may correspond to a single value in another image, and the features of one image may partially appear or even disappear at all in the other one. Such problems will degrade the correct rate of feature matching when feature-point-based algorithms are applied. The correct matching rate of the matched feature points calculated by the SURF algorithm is very low, sometimes even below 20%. Too many mismatches cause the algorithm of the subsequent step, which is to calculate the transformation parameters, such as least median of squares and RANSAC, to be inefficient, sometimes even to fail to estimate the parameters of the selected transformation model [10, 11].

Therefore, it is necessary to explore new approaches to over-come the problems mentioned earlier. The purpose of this paper is to develop a new method that not only can effectively identify the CCs from the candidate ones but also is independent from and robust and invariant to image transformation and illumination changes. In the feature match step, the descriptors are usually calculated from the gray values within a selected window around the feature point, while the information of local transformation is always ignored. Also, in the subsequent step, such information is usually not fully utilized. From the viewpoint of information theory, if the transformation information is included, better performance can be achieved.

The standard way of applying SIFT to image registration is as follows. The SIFT algorithm at first detects a set of feature points or keypoints in scale-space by applying a difference-of-Gaussian (DoG) filter to a pyramid of Gaussian smoothed and resized images. Feature points with low contrast and located at edges are discarded. Then, a 128- element feature descriptor is generated for each feature point using statistics of the gradient directions which are scale and rotation invariant. These descriptors are used to find matching points by calculating the ratio of the Euclidian distance between every feature point in the images to be registered. These matched feature points are used to determine the parameters of the transformation model between the images. As we mentioned above, in multi-

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sen in multi-sensor remote sensing images, the spatial relationship between objects remains approximately the same. Thus, if we can find the matching position of a feature point, we can predict the matching position of the neighboring feature points. Note that each feature point is associated with a scale and an orientation via SIFT, so from a pair of matched feature points the scale difference for surrounding points can be predicted. SIFT matching is applied to images A and B. The bold line shows a pair (a, c) of matched featured points in the two images. The dotted line shows the best match e of another feature point b in image A, while the correct match should be point d. In the proposed technique, e is not selected as a matched feature point for b because the spatial distance between points c and e is too large. Feature points a and c are matched while the counterpart for neighboring feature point b cannot be decided because the SIFT descriptors for points d and e are almost equally different from the SIFT descriptor of point b. This drawback is created worse by the actual fact that heaps of comparable descriptors are found in typical remote sensing pictures. The thought to unravel this drawback is as follows. Still considering the instance in Figure one, assume points a and c are already matched with high confidence that the match is correct. We will predict that the feature points around a (shown within the circular window) is found around c. So, for purpose b we tend to solely search the neighborhood of purpose c for an identical descriptor, which ends during a correct match at purpose d. This method is iterated to recover a lot of matching feature points and thence a a lot of correct registration.

EXISTING SYSTEM

The points in the target and the reference images were identified. The identified points were sorted based on the quality function and the correspondence of the pixels. The values were arranged in queue satisfying the condition:

$k1 < k2 \rightarrow q\ (gfk1) \geq q\ (gfk2)$ where $gfk1, gfk2 \in GM$.

The elements of GM can be categorized into two types

$GIN = \{gfk|gfk \in GM, pk, f\ (pk) \leq \xi, k=1, 2, . . . ,N1\}$

$GIN = \{gfk|gfk \in GM, pk, f\ (pk) > \xi, k=1, 2, . . . ,N2\}$

Where ξ is a given threshold and f (pk) is the correct corresponding feature point of pk in the sensed image calculated by transformation f-the real transformation between the two images. We call any correspondence in GIN a CC and any

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correspondence in GIN an incorrect correspondence (ICC). In the literature, inliers and outliers are also used to denote CCs and ICCs, respectively. In the sequel, we use inlier and CC and outlier and ICC, interchangeably. Suppose that GMh is a subset that contains h correspondences with the highest quality from GM, where h is a given integer. DSτ = {gfk1, gfk2, gfk3, . . . , gfk} is a duality sample composed of correspondences. If the correspondences within a duality sample are all inliers, then the sample is called an uncontaminated sample; otherwise, it is called a contaminated sample. In this paper, we also call an uncontaminated sample a correct sample and a contaminated sample an incorrect sample. Specifically, for l = 3,

DTτ = {gfk1, gfk2, gfk3} = {(pk1, pk1), (pk2, pk2), (pk3, pk3)},
which contains three correspondences. We also call it a duality triple because it consists of two corresponding triples (Tτ, Tτ), where Tτ = (pk1, pk2, pk3) and Tτ = (pk1, pk2, pk3). Therefore, a set of duality triples whose elements are composed of three correspondences from GMh can be denotedas
DT = {DTτ = {gfk1, gfk2, gfk3}| gfk1, gfk2, gfk3 ∈ GMh, k1 ~= k2 ~= k3, τ = 1, 2, . . . , Ch3}, where Ch 3 is the number of possible duality triples.
For l = 4, DTτ = {gfk1, gfk2, gfk3, gfk4} = {(pk1, pk1), (pk2, pk2), (pk3, pk3), (pk4, Qpk4)} is also called a duality quadruple because it contains two corresponding quadruples (Qτ, Qτ), where Qτ = (pk1, pk2, pk3, pk4) and Qτ = (pk1, pk2, pk3, pk4).

With the help of the algorithm of calculating the statistic information of correspondences from the HTAR, a robust estimator named HTSC is proposed. The major advantage of the HTSC algorithm lies in that it can effectively find out the correct duality samples (e.g., duality triples or duality quadruples) from the candidates. In HTSC, the following MI-based similarity function SMf is used:

$$\begin{aligned} SM^f &= MI(S, R, \hat{\theta}, \eta) \\ &= H\left(X^{S^f}\right) + H(Y^R) - H\left(X^{S^f}, Y^R\right) \\ &= -\sum_{x \in X^{S^f}} p(x)\log_2 p(x) - \sum_{y \in Y^R} p(y)\log_2 p(y) \\ &\quad + \sum_{x \in X^{S^f}} \sum_{y \in Y^R} p(x,y)\log_2 p(x,y). \end{aligned}$$

The intensity of the regions that are similar in both the reference and the target images were obtained. The obtained matching pixel regions and the feature points identified the images were transformed using Affine transformation process. The transformation process computes the image pixels that are similar

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in both reference and the target image. The pixels were identified based on the Euclidean distance between the detected points in the images.

DISADVANTAGES

The process is intensity based and the transformation of the images requires complex mechanisms. The accuracy of the process measured shows that the process is affected due to the physical disturbances in the images. The computation time of the process is increased due to the employment of a large amount of complex algorithms.

PROPOSED SYSTEM

The image pixel values and the objects located in the pixels were different in the reference and the target image. The reference image has mainly intensity variations and object location difference. The registration process transforms the target image as the reference image which helps in remote sensing process.

1. The input reference image and sensed image are preprocessed by applying gaussian filter. The feature points are extracted from the preprocessed image using SIFT algorithm.
2. The feature points refer to the location of the image pixels present in the images that have the same coordinate vales in different orientations. The extracted feature points were the same for the different images. Correspondence is established between features detected in the sensed and the reference image.
3. The correspondence process refers to the matching of the pixels. The reference and the clustered regions were clustered.
4. The clustering process is employed in both target and the reference image. The clustered portions in both the reference and the target portions which are in common are identified. The identification of the correct matching pixels will give the pixels that are needed to be modified in the sensed image.
5. The sensed image is transformed similar to the target image by means piecewise transformation of the pixels from the sensed image to the reference image is employed.
6. Performance is analyzed by measuring the accuracy and the error rate. The error rate gives the rate of number of pixels modified in the sensed image corresponding to the target image.
7. The error rate is the rate of number of pixels modified in the sensed images corresponding to the target image.

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8. The proposed method has overcome difficulties in the existing complex HSTC and other methods and the accuracy is also improves in the proposed process.

In preprocessing unnecessary noises in the images were eliminated. An unnecessary noise refers to the unwanted pixels in the images. Pre-processing methods use a small neighborhood of a pixel in an input image to get a new brightness value in output image. Such pre-processing operations are also called filtration. The derivative of the images is calculated. The calculated values give the changes in the color and the gray scale values of the image which indicates the information's in the image. The laplacian function calculates the edges in the images based on the derivative values. The values are then arranged in order in a matrix format. The values in a particular circle region are first chosen. The values in the chosen region were dilated. In the dilation process the values are compared and the values that have the lowest values are combined. Then, the values that having the minimum values are then removed. The resulting points are saved as the HRL points. The obtained HRL points are then used along with the image in order to find the main orientation points in the image. The edges of the histogram points were calculated and for the calculated values derivative values are calculated so that the obtained points were more optimized to get the exact edge values. The obtained values are shifted based on the particular angles to optimize the obtained values more clearly. Then the optimal values are selected from the given set of values based on the gradient calculation and max value and max intensity value calculation. Finally, the calculated values are padded with the image pixels and their corresponding ids were obtained and then the values are saved as the main orientation points. The reference and the target images were clustered. The clustering process is employed using Fuzzy C Means approach. The initial assumptions for means are made for the calculation of the mean value. The degree of membership functions were identified in the clusters. The fuzzy mean is calculated and the values for the members in the clusters were replaced by the calculated fuzzy mean at the instant. The process is repeated till the means values obtained does not change. The process is applied iteratively and the whole image is clustered. Regions in the images that are having different intensities were clustered to a particular region. The images pixels that were commonly detected in the both

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clustering images were obtained. The obtained pixels along with the detected keypoint locations in the images were obtained. The pixel values within the identified regions were identified. The image pixels in the reference image are replaces by the target image pixels. The performance of the process finally measured.

ADVANTAGES

The proposed process can able to detect the feature points in an accurate even if the intensity variations in the images were high. The SIFT matching points were more exact for all the type of images. The performance of the process is measured by calculating PSNR value and MSE value. The performance measures obtained through PSNR and MSE shows that the proposed method has better performance compared to the existing HSTC method for image registration process. The process is computationally effective and the performance of the process is also improved [12, 13].

OBTAINED RESULT

Table 1: *PSNR and RMSE.*

Image	PSNR	RMSE
1	24.9569	0.3817
2	24.9342	0.4321
3	24.973	0.5432
4	25.0765	0.4321
5	24.8651	0.3421

Table 2: *RMSE and Accuracy.*

Image	RMSE	Accuracy
1	0.3817	96.6183
2	0.4321	97.5679
3	0.5432	96.4568
4	0.4321	98.5679
5	0.3421	96.6579

Table 3: *Key Points, RMSE and Accuracy.*

Image	Key Points	RMSE	Accuracy
1	3710	0.3817	96.6183
2	3976	0.4321	97.5679
3	3870	0.5432	96.4568
4	3869	0.4321	98.5679
5	3976	0.3421	96.6579
Mean		0.4262	96.6183

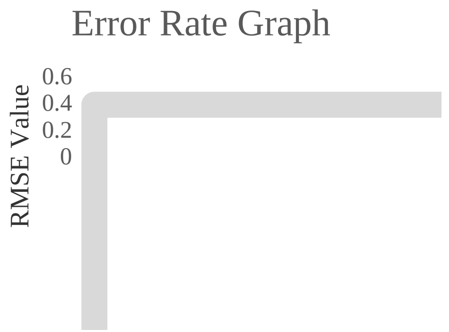

Fig. 1: *Error Rate Graph.*

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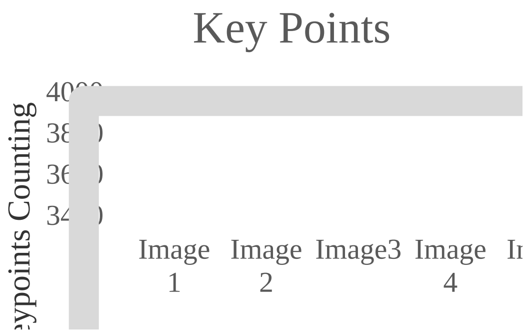

***Fig. 2:** Key Points.*

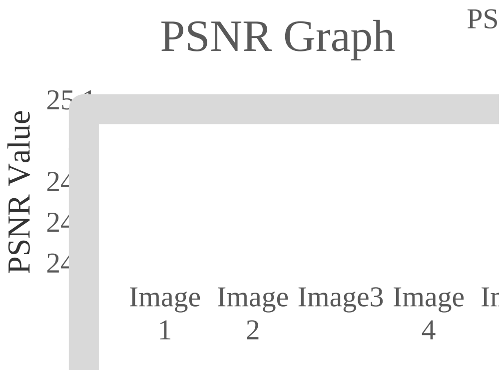

***Fig. 3:** PSNR Graph.*

CONCLUSION

An image registration process that registers the images based on the extracted SIFT feature points is proposed. The proposed approach is improved compared to the existing HSTC based image registration. Satellite images are collected from different sensors. The image pixel values and the objects located in the pixels were different in the reference and the target image. The reference image has mainly intensity variations and object location difference. The registration process transforms the target image as the reference image which helps in remote sensing process. The input reference image and sensed image are preprocessed by applying gaussian filter. The feature points are extracted from the preprocessed image using SIFT algorithm. The feature points refer to the location of the image pixels present in the images that have the same coordinate vales in different orientations. The extracted feature points were the same for the different images. Correspondence is established between features detected in the sensed and the reference image. The correspondence process refers to the matching of the pixels. The reference and the clustered regions were clustered. The clustering process is employed in both target and the reference image. The clustered portions in both the reference and the target portions which are in common are were identified. The identification of the correct matching pixels will give the pixels that are needed to be modified in the sensed image. The sensed image is transformed similar to the target image by means piecewise transformation of the pixels from the sensed image to the reference image is employed. Performance is analyzed by measuring the accuracy and the error rate. The error rate gives the rate of number of pixels modified in the sensed image corresponding to the target image. The error rate is the rate of number of pixels

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modified in the sensed images corresponding to the target image. The proposed method has overcome difficulties in the existing complex HSTC and other methods and the accuracy is also improves in the proposed process.

REFRENCES

1. L. Brown. A survey of image registration techniques. *ACM Comput. Surv*. 2012; 24(4): 325–376p.
2. J. Maintz, M. Viergever. A survey of medical image registration. *Med. Image Anal.* 2013; 2(1): 1–36p.
3. B. Zitova, J. Flusser. Image registration methods: A survey. *Image Vis. Comput*. 2013; 21(11): 977–1000p.
4. Y. Heo, K. Lee, S. Lee. Robust stereo matching using adaptive normalized cross-correlation. *IEEE Trans. Pattern Anal. Mach. Intell.* 2011; 33(4): 807–822p.
5. G. Tzimiropoulos, V. Argyriou, S. Zafeiriou, et al. Robust FFT-based scale-invariant image registration with image gradients. *IEEE Trans. Pattern Anal. Mach. Intell.* 2014; 32(10): 1899–1906p.
6. S. Leprince, S. Barbot, F. Ayoub, et al. Automatic and precise orthorectification, coregistration, and subpixel correlation of satellite images, application to ground deformation measurements. *IEEE Trans. Geosci. Remote Sens*. 2014; 45(6): 1529–1558p.
7. S. Suri, P. Reinartz. Mutual-information-based registration of TerraSAR-X and Ikonos imagery in urban areas. *IEEE Trans. Geosci. Remote Sens*. 2010; 48(2): 939–949p.
8. D. Loeckx, P. Slagmolen, F. Maes, et al. Nonrigid image registration using conditional mutual information. *IEEE Trans. Med. Imaging*. 2014; 29(1): 19–29p.
9. D. Lee, M. Hofmann, F. Steinke, et al. Learning similarity measure for multi-modal 3D image registration. *In Proc. IEEE CVPR*. 2009; 186–193p.
10. G. Rohde, A. Aldroubi, B. Dawant. The adaptive bases algorithm for intensity-based nonrigid image registration. *IEEE Trans. Med. Imaging*. 2012; 22(11): 1470–1479p.
11. V. Mandava, J. Fitzpatrick, D. Pickens. Adaptive search space scaling in digital image registration. *IEEE Trans. Med. Imaging*. 2013; 8(3): 251–262p.
12. T. Bin, A. Lei, C. Jiwen, et al. Subpixel edge location based on orthogonal Fourier-Mellin moments. *Image Vis. Comput*. 2014; 26(4): 563–569p.

Page 1-12 © MAT Journals 2016. All Rights Reserved

13. A. Rajwade, A. Banerjee, A. Rangarajan. Probability density estimation using isocontours and isosurfaces: Application to information theoretic image registration. *IEEE Trans. Pattern Anal. Mach. Intell*. 2009; 31(3): 475–491p.

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