Improved Registration of Infrared Images using EOH descriptor

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Abstract Feature based image registration involves overlaying two images of the same area by extracting features, matching and computing geometric transformation. Multi modal image registration is useful in a variety of applications as the unique information contained in diverse images can be combined. Descriptors proposed for multimodal image matching such as EOH (edge-oriented histogram), LGHD (Log Gabor histogram), can address the photometric variation between the visual and infrared images better than conventional image descriptors such as SIFT. However the invariance of such descriptors to geometric variations such as scale, rotation is poor. To address the geometric variations in addition to photometric variations, the region around the feature point is pre-processed using scale and rotation information of detector before deriving the descriptor. Different data sets composed of images obtained in visible light and infrared spectra images, and IR images containing variations to compare scale, rotation, noise, blur etc. to the performance with those of state-of-the-art algorithms.

Keywords: Multi-modal image matching, EOH, LGHD, Key point error, Ground truth homography

1 Introduction

Image registration is the process of transforming different images of the same scene into one coordinate system. Change in images could be because of acquisition from different sensors (Multimodal Analysis), times (Multi-temporal Analysis), depths (Model Registration), or viewpoints (Multi-View Analysis). Registration is widely used across multiple domains and applications such as image stitching [1], change multi-spectral image registration is gaining popularity due to availability of wide variety of image capturing sensors. For instance, images created by different medical diagnostic modalities, MRI and SPECT[6] are used to visualize and localize a tumor in an image or multispectral satellite images of the earth's surface are compared to see how a river has migrated or how an area is flooded. However finding similar features between such images is challenging due to intense radiometric variations in addition to geometric distortions [7]. The form of the work reported in this paper is to register visual and infrared images using feature based method. Conventionally two major categories of image registration exist which are: area based, feature based. Area based methods employ similarity measures such as normalized cross correlation, mutual information and optimize a function to find the control points. In feature based method, interest points like Harris corners, scale invariant features, speed-up robust features etc., are first extracted from images [8]. The features are matched based on the similarity or dissimilarity metrics, such as Euclidean, Cosine etc. In this paper, In section 2 image registration and matching for multi-modality images are reviewed. The approach that was proposed is presented in Section 3. Evaluation of registration performance across various descriptors presented in Section 4.

2 Related Work

Feature based image registration typically has feature detection, feature matching, mapping function design, image transformation and re-sampling. Key point extraction and descriptor computation techniques have been widely applied in computer vision or pattern recognition. Though SIFT [9] and its variants have been widely used for matching similar spectral images, they fail to effectively address large photometric variations of multi spectral images.

Table 1: Literature Survey

Paper	Images	Features used for comparison	Similarity	Evaluation
[19]	remote sensing, multi sensor images	SIFT, LoG, Harris corner detector Edge detection: Canny, phase convergence model anisotropic directional derivatives (ANDD) based Edge strength map(ESM)	Normalized mutual information based registration method(NMI)	Root mean square error[RMSE], precision
[20]	Remote sensing images, Visual-NIR, Visual-LWIR, multi spectral images	Descriptors : SURF, SIFT, NGSIFT EOH, LGHD, MFD, HODM, HOSM	Euclidean distance	precision, recall, F1-score, computation time
[21]	Remote sensing images	Detector: Laplace, canny, Phase congruency, Descriptor: SIFT, SAR-SIFT, SURF, PSOSIFT, RIFT, RSCJ, LDSR, GLPM	Euclidean distance	RMSE, no. of correct matches, time
[18]	Remote sensing images (Visible, in-frared)	Detector: MMPC-lap, Harlap, DoG, MSER, Descriptor: LHOPC, SURF, ASIFT, DAISY	Euclidean distance	Precision, Recall from matches
[17]	Multi spectral images, Visible (RGBNIR, RGB-LWIR)	Detector: FAST, Descriptor: LGHD, SIFT, MFD, EOH, SURF	Euclidean distance	computation time, precision, recall, F1-score
[16]	Visible-SWIR,LWIR,NIR	SIFT-SIFT, SIFT-GISIFT, FAST-SIFT, Harris-SIFT, HarrisGISIFT	Euclidean Dis-tance	Repeatability, Precision, Recall, Matching ratio
[6]	RGB-depth, RGBLWIR, RGB-NIR, Flash-No Flash	SIFT, EHD, PCEHD, GSIFT, LGHD	Euclidean Dis-tance	Resulting matching, precision
[14]	Six types of multi modal image data sets are selected*	RIFT Descriptor, SIFT,FAST Detector	Euclidean Dis-tance	No of correct matches, Success rate, RMSE, ME

*optical-optical, infrared-optical, SAR-optical, depth-optical, map-optical and day-night

To address such variations, descriptors based on orientations of edges have been proposed. The EHD descriptor [13] describes the spatial edge distribution around a point computing an orientation histogram of 80 bins. Region around each interest

point is divided into 16 smaller sub-regions (4x4) and for each sub-region, an orientation histogram of 5 bins is computed using the strongest pixel value for one of 5 oriented sobel filters (horizontal, vertical, 35 degrees, 135 degrees and non-oriented). The edge-oriented histogram (EOH)[10] similar to EHD computes descriptor vector using only edge points of the region around key point[11]. LGHD (Log-Gabor Histogram Descriptor)[12] is proposed for matching pair of images with non-linearity in variations, such as significant illumination change, cross spectral modal image pairs and cross spectral image pairs. The Log-Gabor Histogram Descriptor (LGHD)[14], describes local patches in a similar way to EHD but describes the neighborhood of feature points using log-Gabor filters of multiple scales and orientations. Later RIFT [15] has been proposed to increase the invariance of LGHD descriptor towards rotation deformation.
Table1 lists some of the research proposed in the area of multi modal/multi spectral image matching. It can be observed that the focus of most of the approaches is to address radiometric variations of the images. Hence, conventional feature detectors used for similar image matching such as SIFT, FAST are combined with descriptors modified for cross spectral image matching.

3 Proposed Approach

Feature based Image registration pipeline involves Key point detection, descriptor computation, matching corresponding key points of the images and computing transformation matrix. Features are detected from the given input image pairs using detector SIFT and features are described using descriptors using EOH. However to handle the geometric variations between the images, each patch extracted from SIFT is pre-processed using rotation information of the key point. Fig 1 shows the details. From the image, key points are detected and for each key point a patch of size 100 x

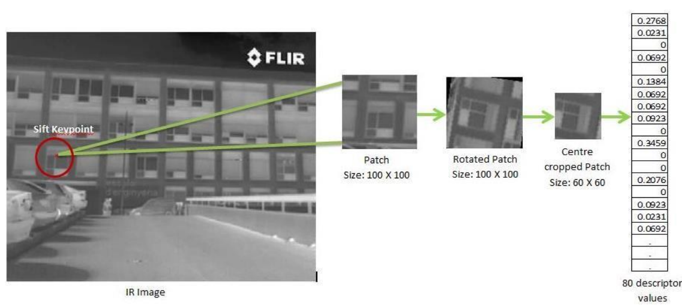


Fig. 1: Patch Extraction, Rotation and Preprocessing

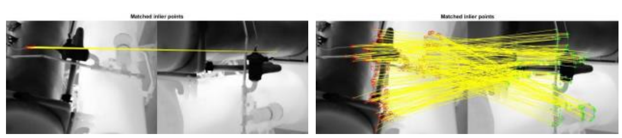
100 is extracted. The extracted patch is rotated by an angle corresponding to the key point. From the rotated patch the center cropped patch will be identified with size 60 X 60. From this patch, EOH descriptor computes 80 values. The matching technique finds nearest key points by using nearest neighbor matching with euclidean distance in the descriptor space. Appropriate transformation of reference and target images is estimated using RANSAC (Random Sample Consensus), which

detects the inliers from the corresponding feature points. Quality of registration is evaluated using the following measures:

- **Key-point error:** The matched key points of source image are transformed using the ground truth homography matrix to the target image. Euclidean distance between transformed matched points of source image and target image matched key points is known as key point error. However, groundtruth information is not available for 100 VS/LWIR images (dataset-I) and hence it is generated for a more accurate evaluation. Ground truth is generated manually by selecting key points from both images and from these key points ground truth homgraphy matrix is estimated.
- **Number of True positive matches:** The matched key points of source image are transformed using the ground truth homography matrix. A match is considered true positive if the distance between transformed match point and the corresponding matched key point of target image is less than 3 pixels.
- **InlierRatio:** The ratio of number of inliers to the total number of matches. A high value of this ratio indicates that the correspondences made between the feature points are mostly useful.

4 Experimental Results

Evaluation Dataset Two data sets are used for evaluation:
- Dataset-I: consists of 100 VS/LWIR pairs available through website (http://www.cvc.uab.es/adas/projects/simeve/) [10]
- Dataset-II: A new infrared image database of 53 images with ground truth having deformations like viewpoint, rotation, blur, down sampling, noise, scale from (http://www.csc.kth.se/atsuto/dataset.html)[15].



Matches without patch rotation ::::: | ::::: Matches with patch rotation

Fig. 2: Matches between two IR images which vary by rotation angle 80 deg

Fig 3 shows the ground truth key point error and number of matched points for EOH with rotation against EOH, LGHD, Daisy of Visual and Infrared (100)images of Dataset-I. It can be observed that number of matches is more and error in most cases

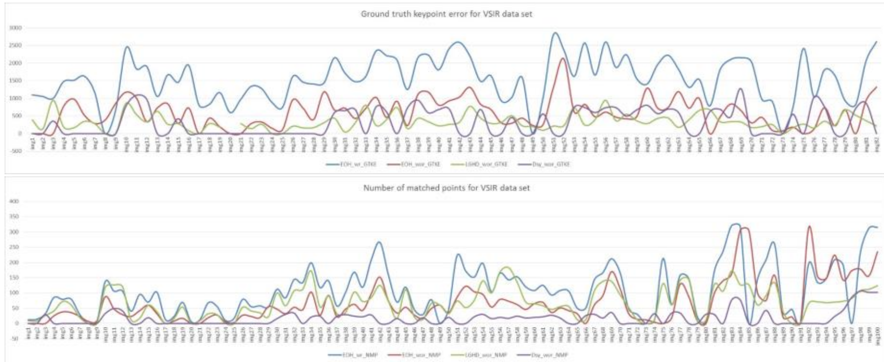


Fig. 3: Comparison of EOH with pre processing against EOH, LGHD, Daisy on Dataset I

is either similar or less for proposed approach. Hence pre processing of patch does not affect the performance of descriptor in the case of multi spectral images, in this case visual and IR images. To test the geometric invariance, results are generated for 18 rotation varying image pairs of Dataset II using proposed approach (EOH_WR), EOH, LGHD and DAISY. Fig 4 shows the comparison of four approaches in number of matched points, Inlier ratio, Ground truth keypoint error, and true positive matches for 18 rotation varying images in Dataset II. It can be observed that the proposed approach improves the performance quite considerably in this case.

The proposed pre processing of patch is implemented in LGHD descriptor also. Fig 5 shows number of true positives and inlier ratio across 10 images which vary by Blur from Dataset 2 with rotation of patch and without rotation for LGHD-SIFT.

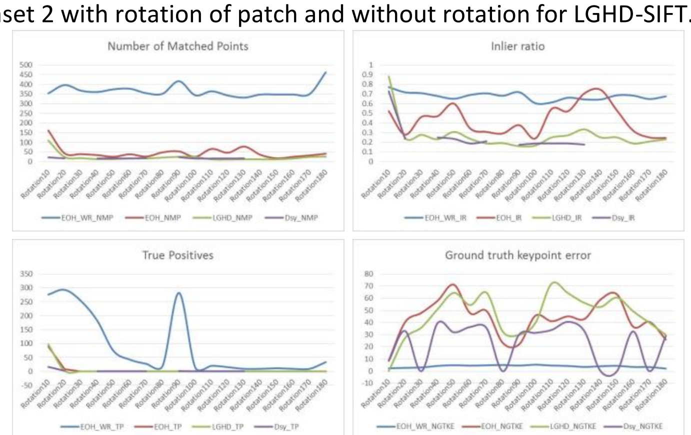


Fig. 4: Comparison of EOH with patch pre processing against EOH, LGHD and Daisy

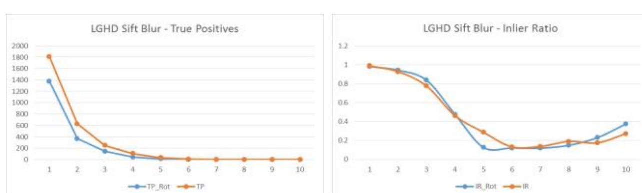


Fig. 5: Comparison of LGHD with patch pre processing and without on Blur varying images of Dataset II

5 Conclusion

Registration of infrared and visual images is challenging due to the inherent differences in the characteristics of images. Widely used feature descriptors such as SIFT fail to address such variations in intensity values. Descriptors such as EOH, LGHD have been proposed to address matching of visual and IR images. However such descriptors are not robust to geometric variations like rotation and scale. To improve the performance, scale and rotation information of key point detector is incorporated in descriptor computation by pre-processing the patch before computing EOH or LGHD. Experiments are carried out on a dataset of IR images with geometric variations. Performance of various descriptors is compared using objective evaluation measures computed from the ground truth. Results indicate that proposed approach greatly enhances the matching and registration performance of the algorithms.

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