ISSN 2321-807X
Volume 13 Number7
Journal of Advances in chemistry

# IMAGE FUSION FOR MULTIFOCUS IMAGES USING SPEEDUP ROBUST FEATURES

*Ajitha T, **Kesavan Nair N
* Assistant Professor ,Department of CSE,St. Xavier's Catholic College of Engineering, Nagercoil, Tamilnadu.
E-mail : ajita2162@yahoo.co.in
** Professor, Electrical and Electronics Engineering, CSI Institute of Technology, Thovalai, Tamilnadu
E-mail : kesavannairn2011@gmail.com

## ABSTRACT

The multi-focus image fusion technique has emerged as major topic in image processing in order to generate all focus images with increased depth of field from multi focus photographs. Image fusion is the process of combining relevant information from two or more images into a single image. The image registration technique includes the entropy theory. Speed up Robust Features (SURF), feature detector and Binary Robust Invariant Scalable Key points (BRISK) feature descriptor is used in feature matching process. An improved RANDOM Sample Consensus (RANSAC) algorithm is adopted to reject incorrect matches. The registered images are fused using stationary wavelet transform (SWT).The experimental results prove that the proposed algorithm achieves better performance for unregistered multiple multi-focus images and it especially robust to scale and rotation translation compared with traditional direct fusion method.

## Indexing terms/Keywords

Image Fusion, SIFT, SURF, SWT, DWT

## 1. INTRODUCTION

Multi-focus image fusion provides a promising way to extend the depth of defocused images by combining multiple images with diverse focuses into a single focused one. Now a days, multi-focus image fusion technique has been widely used in machine vision, targeting, object recognition, medical imaging and military affairs. Images are an integral part of our day today life. The SURF provides better computation speed and illumination invariance. The SURF algorithm consists mainly of two steps: the first is the detection of points of interest and the second is the creation of descriptors for each of these points. The response of both steps are blended together using the optimum image fusion rule. Here, the fusion process takes place using Discrete Wavelet Transform (DWT) [11]. The first factor is the dimension of the descriptor for a given point of interest. The dimension is affected by the number of descriptor sub-regions which consequently affects the matching time and the accuracy. SURF performance has been investigated and tested using different dimensions of the descriptor. The second factor is the number of sample points in each sub-region which are used to build the descriptor of the point of interest. SURF performance has been investigated and tested by changing the number of sample points in each sub-region where the matching accuracy is affected. It retains most of the advantages for image fusion, but has much more complete theoretical support. The wavelet fusion has obvious superiority over existing methods. However, it is often applied to the case of two images previously and rarely used in the multi-focus micro-image sequence fusion an algorithm of multi-focus image fusion based on wavelet transform is presented, considering the features of micro-image and the multi-resolution theory of the wavelet analysis. In addition, performance of the spatial domain and wavelet-based algorithms is compared, their advantages and disadvantages analyzed, and their features and applicable areas obtained. SURF is a detector and a descriptor for points of interest in images where the image is transformed into coordinates, using the multi-resolution pyramid technique. It is to make a copy of the original image with Pyramidal Gaussian or Laplacian Pyramid shape and obtain image with the same size but with reduced bandwidth. Thus a special blurring effect on the original image, called Scale-Space is achieved. This technique ensures that the points of interest are scale invariant. In short, SURF adds a lot of features to improve the speed in every step. Analysis shows it is 3 times faster than SIFT while performance is comparable to SIFT. SURF is good at handling images with blurring and rotation, but not good at handling viewpoint change and illumination change. The task of finding point correspondences between two images of the same scene or object is part of many computer vision applications. In this paper an image fusion scheme for combining two or multiple images with different focus points to generate an all-in focus image. Adjusting the coordinates of images to be fused, the source images are registered in image registration step. Secondly, Wavelet based algorithm is used to fuse the reference images. Now a day's image fusion has become an important sub-area of image processing. For one object or scene, multiple images can be taken from one or multiple sensors. Image fusion technique provides a promising way to solve this problem by combining two or multiple images of the same scene that are taken with diverse focuses into a single image in which all the objects within the image are in focus.

## 2. METHODS

The method of characterization ability using discrete wavelets or Gabor wavelet transformation is illustrated through an example of image fusion. The spatial domain based method[3] which directly fuse the source images into the intensity value. The category is the transformed domain based method which fuse images with certain frequency or time frequency transform. The fusion methods in the spatial domain can be summarized as

$$I_{F=} F\ (I_1, I_2, \ldots\ldots, I_k)$$

The simplest fusion method in spatial domain takes the pixel-by-pixel average of the source images. It is used to reduce the contrast. The Discrete Cosine Transform [1] domain provides efficient output. It reduces the complexity and decomposed images into series of waveform. Existing DCT based methods are suffering from some undesirable side effects like blurring or blocking artifacts which reduce the quality of the output image. The drawback in this method leads to undesirable side effect including blurring. The Pyramid method [10] provides good visual quality of an image for multi focus images. The drawback is the contrast pyramid could not retain sufficient information from its source images. Morphological Pyramid creates many false edges. The Robust principal component analysis RPCA [6] technique is used to decompose the source images into principal and sparse matrices. RPCA decomposition domain, the new fusion scheme is flexible to adopt different types of features that are suitable for a variety of fusion tasks, such as combination of remote sensing images. While fusing medical images or remote sensing images the noise will be present on the input devices. Also it was less affected by the thermal cross over. BRISK Methodology [7] achieves comparable quality of matching at much less computation time. It also exploits the speed savings process. The drawback is expense of computational cost. Wavelet based image fusion [9]. A wavelet-based image fusion (WIF) approach combined with the recently developed PCA denoising method. Wavelet-based schemes perform better than standard schemes, particularly in terms of minimizing color distortion. Schemes that combine standard methods with wavelet transforms produce superior results than either standard methods or simple wavelet-based methods alone. The results from wavelet-based methods can also be improved by applying more sophisticated models for injecting detail information. The drawback of this method is statistically insignificant. The Discrete Wavelet Transform (DWT) [11] provides good quality fused images. It also provide better signal to noise ratio. The drawback of this is to produce image with shift variance and additive noise. The Stationary Wavelet Transform (SWT) provides good result at level2 decomposition. The drawback of this method is, it is time consuming method compare to DWT and implementation is difficult.

# 3 OVERVIEW

## 3.1. SURF (SPEEDED UP ROBUST FEATURES)

As for the different methods of stitching, image registration fall broadly into three methods: gray information based, transform domain based and feature based. Among them, the feature-based image stitching technology is widely used because it has the quality of high time efficiency, maximum matching accuracy and good robustness. Point feature is an important feature of the image in a various image features; it has the benefits of rotational invariance, not varying with changes in light conditions and high speed. The common feature points are Harris corner detection, SIFT (Scale- Invariant Feature Transform) and SURF (Speeded Up Robust Features). For all above features has compared the commonly used local invariant features and found SURF feature detection is more effective than other feature detection. We propose a fast stitching method based on SURF. It can be majorly divided into four steps: feature points extraction, feature points matching, determining the transformation relationship and image fusion.

The use of SURF features improved the result for many uploaded image sets, especially when the images were taken further apart. The previous procedure using Harris corners and normalized cross correlation of image windows has problems matching such wide-baseline images. Furthermore, the DoG detector combined with SIFT description failed on some image sequences, where SURF succeeded to calibrate all the cameras accurately. They presented a fast and rotation invariant interest point detector and descriptor. The important speed gain is due to the use of integral images, which drastically reduce the number of operations for simple box convolutions, independent of the chosen scale. The high repeatability is advantageous for camera self-calibration, where an accurate interest point detection has a direct impact on the accuracy of the camera self-calibration and therefore on the quality of the resulting 3D model. The most important improvement, however, is the speed of the detector. Even without any dedicated optimizations, an almost real-time computation without loss in performance was achieved, which represents an important advantage for many on-line computer vision applications. Our descriptor, based on sums of Haar wavelet components, out performs the state-of-the-art methods. It seems that the description of the nature of the underlying image intensity pattern is more distinctive than histogram-based approaches. The simplicity and again the use of integral images make our descriptor competitive in terms of speed. Moreover, the Laplacian-based indexing strategy makes the matching step faster without any loss in terms of performance. Experiments for camera calibration and object recognition highlighted SURF's potential in a wide range of computer vision applications. In the former, the accuracy of the interest points and the distinctiveness of the descriptor showed to be major factors for obtaining a more accurate 3D reconstruction, or even getting any 3D reconstruction at all in difficult cases.

### 3.1.1. Points

Point features can be used to find a sparse set of corresponding locations in different images, often as a pre-cursor to computing camera pose, which is a prerequisite for computing a denser set of correspondences using stereo matching. Such correspondences can also be used to align different images, e.g., when stitching image mosaics or performing video stabilization. They are also used extensively to perform object instance and category recognition. A key advantage of key points is that they permit matching even in the presence of clutter (occlusion) and large scale and orientation changes.

There are two main approaches to finding feature points and their correspondences. The first is to find features in one image that can be accurately tracked using a local search technique such as correlation or least square. The second is to independently detect features in all the images under consideration and then match features based on their local appearance. The former approach is more suitable when images are taken from nearby viewpoints or in rapid succession (e.g., video sequences), while the latter is more suitable when a large amount of motion or appearance change is expected, e.g., in stitching together panoramas establishing correspondences in wide baseline stereo or performing object recognition.

### 3.1.2. SURF Feature point detection

SURF is a feature point extraction algorithm and it is three times faster than commonly SIFT algorithm and the overall performance is much better than SIFT algorithm. SURF feature point extractions include feature detection and feature points description. Generally SURF involves three steps: establishing integral image, building scale-space image and positioning feature points. The main reason obtain of integral image is that it is used to accelerate the convolution between original images and box filters with different sizes in the process of SURF feature detection.

### 3.1.3. Interest point detection

The SIFT approach uses cascaded filters to detect scale-invariant characteristic points, where the difference of Gaussians (DoG) is calculated on rescaled images progressively. In SURF, square-shaped filters are used as an approximation of Gaussian smoothing. SURF uses a blob detector based on the Hessian matrix to find points of interest. The determinant of the Hessian matrix is used as a measure of local change around the point and points are chosen where this determinant is maximal.

### 3.1.4. Feature descriptors

After detecting the features (key points), we must match them, i.e., determine which features come from corresponding locations in different images. In some situations, e.g., for video sequences or for stereo pairs that have been rectified the local motion around each feature point may be mostly translational. It can be used to directly compare the intensities in small patches around each feature point. Because feature points may not be exactly located, but this can be time consuming and can sometimes even decrease performance. In most cases, however, the local appearance of features will change in orientation, scale, and even affine frame between images. Extracting a local scale, orientation, and/or affine frame estimate and then using this to resample the patch before forming the feature descriptor is thus usually preferable. Even after compensating for these changes, the local appearance of image patches will usually still vary from image to image. How can we make the descriptor that we match more invariant to such changes, while still preserving discriminability between different (non-corresponding) patches

## 3.2. IMAGE FUSION

Image fusion is the process in which two or more images are blended together to form an image holding all the common as well as complementary information from each of the original images. The fusion process also produces a higher spatial resolution image free from all volatile blurring effects. Pixel level image fusion techniques are mostly stirred by blurring effect and usually time consuming due to large number of computations. We have opted for wavelet base multi resolution analysis technique mitigating all issues due to pixel level fusion. The original image is passed through high pass and low pass filters so as to get the detail and approximate components. Again, the down sampling operation takes place followed by the next filtering stage to generate the low-low (LL), low-high (LH), high-low (HL), high-high (HH) image sub band components. Here, we have implemented the Haar-wavelet decomposition for better subjective analysis. The fusion rule for this process is Maximum selection scheme to extract only the dominant sub- band components. The generalized discrete wavelet based image fusion process flow is depicted. The fusion of responses from scale invariant feature transform algorithm and speeded-up robust features based algorithm regenerates a panoramic image having the best features of both the algorithms. The topics covered include the following: a system overview of the basic components of a system designed to improve the ability of a pilot to fly through low-visibility conditions such as fog; the role of visual sciences; fusion issues; sensor characterization; sources of information; image processing; and image fusion. The registered image and the reference image at level N using a wavelet basis in SWT to obtain approximation coefficients and detail coefficients. The focused regions will be get from the registered image. Then reference image and registered image is fused using undecimated (Stationary) wavelet transformation. Image fusion which improve the spatial resolution, geometric precision, classification accuracy and enhance the visual interpretation..The fused image contain salient information from each source images .Fusion method using a morphology based measure in a quad-tree structure to against pixel misregistration.

## 4 PROPOSED SCHEME

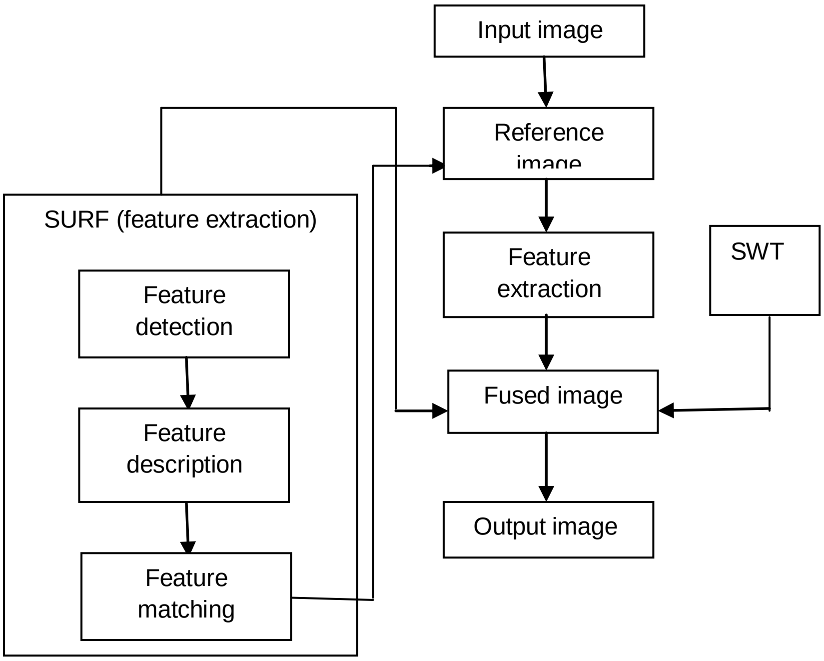


**Fig 1: Architecture Diagram**

## 4.1Reference image

Each multi-focus image has different focus region. At first a reference image is choose from the input image based on the entropy value. Image entropy is measured by

$$E = \sum_{i=0}^{255} -p_i \log(p_i)$$

$$P_i = N_i / N$$

Although any image to be fused can be considered as reference image. An image that has middle information amount, and other images can be matched with it successfully. In information theory, entropy is a measure of the uncertainty in a random variable. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as SUM (p.*log2(p)).Where p contains the histogram counts returned from imhist.

## 4.2 Registration image

In registration the features are detected, decrypted and matching process will take place. The registered image which are mainly used to sort the minimum error.

## 4.3. Feature Extraction

The reference image feature is detected based on the SURF with second order Gaussian derivative. For the detected feature the feature description is made to find the pixel coordinates. The feature matching is made with the help of Euclidean distance. The DetectSurffeature is used to find the blob features. It manipulates and plot SURF features. The DetectSurffeature is more advance than the open Surf feature

## 4.4. Fused image

The registered image and the reference image at level N using a wavelet basis in SWT to obtain approximation coefficients and detail coefficients. Second we can get the focused regions in each registered image. Finally, the reference image and registered image is fused using undecimated (Stationary) wavelet transformation.

# 5 EXPERIMENTAL RESULT

## 5.1. Efficiency and repeatability

The proposed image fusion method was applied to 9316 pairs of multi-focus images which can be downloaded from website. The images was processed on a computer with an Intel Core i5-3210M 2.5GHZ processor and 4.0 GB RAM.

$$\text{MathRate} = \frac{\text{Number of cleaned matched points}}{\text{Max Number of matched points}(a->b, b->a)}$$

Where the number of cleaned matched points is the remaining feature points after feature matching process. SURF detector with BRISK descriptor are much better in efficiency, which is approximately half of SURF detector with SURF descriptor. The experimental results show that the proposed method is robust to noise.

## 5.2. Multiply image sequence

The Discrete Wavelet Transform algorithm is the most popular and effective algorithm among the various kind of fusion algorithms.

## 5.3. Fusion images with scale and rotation translation

Two set of real images with scale and rotation translation. Feature matching process is done firstly. The traditional direct fusion algorithm cannot settle the problem of scale translation. We compared four kind of fusion methods using some coefficients selection rule, including SWT with haar wavelet bassist with sym5 wavelet basis, traditional WT with haar wavelet basis and traditional WT with sym5 wavelet basis. Haar wavelet basis only have one finite support, and sym wavelets are a general term for a series of near symmetrical and support wavelets, so sym5 wavelet basis can keep the signal non-distorted. It preserves more details. The fusion result of proposed method displayed is more distinct and without ghost effect.

## 5.5. Results:

### 5.5.1. Choosing an image

Choose an input image from the directory. The input image contains multiply multifocused images. Here the neuron image was choosen as an input image.


Fig 2 Choosing an image


Fig 3 Reference image

### 5.5.2. Reference image selection:

The entropy value is calculated to select the reference image from the input image.

### 5.5.3. Matching images with reference image:

To select the number of features from the input image. Each image are compared with the reference image using the speed up robust features (surf).

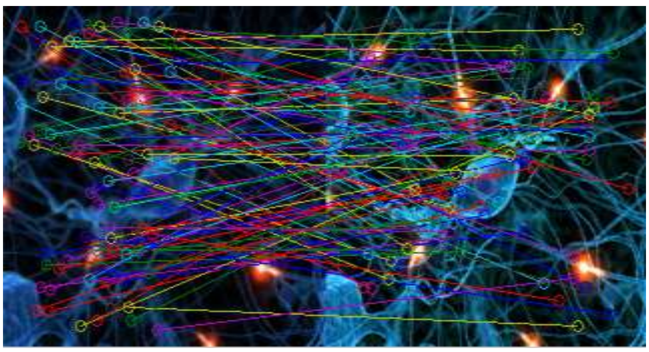

**Fig 4 Examples for comparing images with reference image**


**Fig 5 Registered images**

### 5.5.4. Registered image:

The best matches in the input images should be registered as registered image.

### 5.5.5. Stationary wavelet transforms:

This method provides good result at level 2 of decomposition.


**Fig.6:SWT images**

## 6 CONCLUSION

The Feature points and descriptor points are matched by using the SURF and RANSAC algorithms. The results will be quite nice. Using the RANSAC algorithm it will reject the incorrect matches and give better result. The proposed method improves the overall performance.

## REFERENCE

[1] Phamila, Y.A.V. and Amutha, R., 2014. Discrete Cosine Transform based fusion of multi-focus images for visual sensor networks. *Signal Processing*, *95*, pp.161-170.

[2] Redondo, R., Šroubek, F., Fischer, S. and Cristóbal, G., 2009. Multifocus image fusion using the log-Gabor transform and a multisize windows technique. *Information Fusion*, *10*(2), pp.163-171.

[3] Yang, B. and Li, S., 2010. Multifocus image fusion and restoration with sparse representation. *IEEE Transactions on Instrumentation and Measurement*, *59*(4), pp.884-892.

[4] Wang, Z., Ma, Y. and Gu, J., 2010. Multi-focus image fusion using PCNN. *Pattern Recognition*, *43*(6), pp.2003-2016.

[5] Li, Y. and Verma, R., 2011. Multichannel image registration by feature-based information fusion. *IEEE Transactions on Medical Imaging*, *30*(3), pp.707-720.

[6] Wan, T., Zhu, C. and Qin, Z., 2013. Multifocus image fusion based on robust principal component analysis. *Pattern Recognition Letters*, *34*(9), pp.1001-1008

[7] Leutenegger, S., Chli, M. and Siegwart, R.Y., 2011, November. BRISK: Binary robust invariant scalable keypoints. In *Computer Vision (ICCV), 2011 IEEE International Conference on* (pp. 2548-2555). IEEE.

[8] Cao, L., Jin, L., Tao, H., Li, G., Zhuang, Z. and Zhang, Y., 2015. Multi-focus image fusion based on spatial frequency in discrete cosine transform domain. *IEEE Signal Processing Letters*, *22*(2), pp.220-224.

[9] Wei, H., Viallon, M., Delattre, B.M., Moulin, K., Yang, F., Croisille, P. and Zhu, Y., 2015. Free-breathing diffusion tensor imaging and tractography of the human heart in healthy volunteers using wavelet-based image fusion. *IEEE transactions on medical imaging*, *34*(1), pp.306-316.

[10] Burt, P. and Adelson, E., 1983. The Laplacian pyramid as a compact image code. *IEEE Transactions on communications*, *31*(4), pp.532-540.

[11] Shensa, M.J., 1992. The discrete wavelet transform: wedding the a trous and Mallat algorithms. *IEEE Transactions on signal processing*, *40*(10), pp.2464-2482.