Multi-Focus Image Fusion Methods – A Survey

*Dr. R.Maruthi1,Dr.I.Lakshmi2
1Assistant Professor, Department of Computer Science, Stella Maris College, TN,India
2Assistant Professor, Department of Computer Science, Stella Maris College, TN,India

Abstract: Multi-focus image fusion is a technique of combining two images of the same scene with diverse focuses into a single image. The single fused image has greater depth of field than each of the input images. The multi-focus image fusion technique seeks to provide an effective activity level measurement to evaluate the clarity of source images. It finds application in various fields such as remote sensing, optical microscopy, medical diagnostics, forensic and defense departments. This review article presents an exhaustive list of methods that can be applied in the multi-focus image fusion process. The applications, advantages, challenges and limitations in the fusion methods are also reviewed. The objective of this paper is to provide wide range of references for the researchers working in the area of multi-focus image fusion. This survey focuses on both current as well as classical multi-focus image fusion methods.

Keywords: Image fusion, multi-focus, fusion methods, frequency domain, spatial domain

Date of Submission: 26-01-2017
Date of acceptance: 17-08-2017

I. Introduction

Of late image fusion has become very significant area in the field of image analysis and computer vision. Image fusion is a process of integrating complementary information from multiple images of the same scene from multiple sources such as multi-sensor, multi-focus, or multi-spectral images. This resultant composite image is more precise and reliable than any unfocused input image from different sources. Scenarios in which it is not possible to capture images with all the objects in focus wherein the images are partly focused and partly defocused, a fully focused image can be obtained from the source images by the process of multi-focus image fusion. Applications of multi-focus image fusion include medical imaging, microscopic imaging, remote sensing, computer vision and robotics [5]. The advantages of image fusion include, enhanced spatial information, greater accuracy in target detection and recognition, and condensed workload and better system reliability [36]. The multi-focus fused image thus becomes more suitable for human visual perception and computer processing tasks such as segmentation, feature extraction and object recognition. United States invests around one billion dollars every year in the research of information fusion technology. This makes image fusion, a very significant research area in image processing worldwide.

A wide range of image fusion applications are in the fields of Geo Science and Remote Sensing, where the satellite images from different bands and with varied resolutions are combined to extract more useful information from the earth’s landscape. Change detection is one of the most important of the various defense related applications in image fusion, wherein images acquired over a period of time, are fused to detect changes. The rapid growth in the medical research along with the ever-growing need of imaging research for medical diagnosis and in addition the availability of multi-modal medical imagery for medical applications has paved way for integrating images from different modalities. This has made medical image fusion a novel and exciting area of research.

The existing multi-focus image fusion methods can be classified in several different ways. A common classification is to categorize the three different levels according to the stage at which the fusion takes place: pixel level, feature level and decision level[1].

- Pixel level fusion generates a fused image in which information content associated with each pixel is determined from a set of pixels in source images by employing mathematical operations such as max, average, etc.. Fusion at this level can be performed either in spatial or in frequency domain. However, pixel level fusion may lead to contrast reduction and blurring.
- Feature level fusion (also known as Object Level Image Fusion), entails the extraction of salient features namely pixel intensities, edges or textures. These features from the input images are fused in order to create additional composite features. The fused image can also be used for classification or detection.
- Decision level is a higher level of fusion, in which the source images are processed one at a time for information extraction. [156]. The extracted information is then merged by applying decision rules for better
elucidation. The feature level and decision level fusion may lead to a loss of information during the fusion process [2].

Image fusion methodology comprises of two basic stages: image registration, wherein the input images are fitted within the given spatial co-ordinates, and image fusion where the integration of images takes place. While making the assumption that the images are already registered, in this review we focus on the second stage i.e. the image fusion stage. Multi-focus image fusion is one of the emerging topics in image fusion and this survey paper provides an overview of the various multi-focus image fusion methods. The rapid development of sensor technology has made it possible to acquire several images of the same scene by providing complementary and redundant information. This is due to the fact that each image has been captured with a different sensor. On account of the limited depth of field of optical lenses in CCD devices, it is often impossible to get an image that contains all relevant objects in focus, which means if one object in the scene is in focus, another one will be out of focus (blurred)[7].

One way to solve this problem is via image fusion, in which one can take multiple pictures having diverse focus settings and fuse them to generate a single fused image with enhanced depth of field [10]. A simple microscope having optical lenses of high resolving power suffers with the issue of reduced depth of focus. As only a small part of each image is in focus, it is not possible to have a clear view of the object in a single image. This issue exists for flat images of 3D structures as it is not possible to bring all dimensions in focus in a single frame. The applications in the field of biomedicine and material science, requires both spatial resolution and depth of focus simultaneously. This can be easily achieved by the multi-focus image fusion technique.[49]

II. Multi-Focus Image Fusion Methods

Researchers have proposed various methods for the fusion of multi-focus images. Literatures also describe many algorithms and tools for the same. Based on this literature study, the process of image fusion can be categorized into - frequency (transform) domain and spatial domain methods. Frequency domain methods involve an image undergoing multiple levels of resolutions, followed by various manipulations on the transformed images whereas spatial domain methods work directly on the pixel values. Both these methods can employ either of the three fusion methods namely pixel level, feature level and decision level. The Figure-1 depicts the different types of image fusion and further categorization of multi-focus image fusion methods. Figure-2 gives few example images for multi-focus image fusion. The following section discusses the research work involving various frequency domain and spatial domain methods. Section 3 discusses methods other than these two.

![Image Fusion Diagram](image_url)

Figure-1 A Chart showing the types of image fusion and the fusion methods used in multi-focus image fusion
2.1 Frequency domain methods

Frequency domain methods initially decompose the input images into multi-scale coefficients. Thereafter, various fusion rules are employed for the selection or manipulation of these coefficients that are then synthesized via inverse transforms to form the fused image. The essential characteristic of the frequency domain methods is to avoid blocking effects in the images [3]. The frequency domain methods uses multi-resolution techniques namely pyramid transform and the wavelet transform. The different variations of pyramid approach are Laplacian pyramid (LP), the contrast pyramid, the gradient pyramid, etc. However, the pyramid based method does not bring in any spatial orientation selectivity in the decomposition process. The issue being, these methods often cause blocking effects in the fusion results. Another family of the multi-resolution fusion techniques is the wavelet based methods which employs different types of wavelet transforms in the fusion process. The Figure-3 illustrates the frequency domain image fusion process. The following section gives an overview of the different forms of wavelet based methods.
2.1.1 Wavelet based Methods

Wavelet based methods are widely employed in the area of multi-focus image fusion. Wavelet theory employs multi-resolution analysis theory and a wavelet transform is a linear tool. The issue with linear wavelets is that while decomposing the signal they do not preserve the original data. The resultant image is in low contrast on account of the low pass filtering and edge smoothening of these wavelet transform [7]. The nonlinear wavelet overcomes this drawback by employing morphological operators, lifting scheme etc., that involves division operation and thus either requires floating point arithmetic or integer arithmetic [12]. The literature describes the various methods based on wavelet such as, Discrete Wavelet Transform (DWT), Complex Wavelet Transform (CWT), Curvelet Transform (CT), Fast Discrete Curvelet Transform (FDCT), Non-Subsample Contourlet Transform (NSCT), Shearlet Transform (ST), Non-Sampled Shearlet Transform (NSST) for the fusion of multi focus images. Many wavelets based methods for the fusion of multi-focus images [4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20, 21, 22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57, 58,59,60,61,62,63,64,65,75,112,135,136,137,138,139,141,142,143,144,145,146,147,148,149,150,151,152,153,1 54,155,156,157,158,159,170,181,216,226,235,236,239] have been suggested in the literature. The details of the various transform domain methods found in the literature for multi-focus image fusion has been elaborated in Table-1. Some of the wavelet based image fusion for fusing multi-focus images has been discussed below.

2.1.2 Wavelet Transform Methods (WT)

Wavelet transform is optimal tool for one-dimensional smooth signals; however it has serious limitations in dealing with higher dimensional signals like images. This is because, it captures only limited directional information and does not preserve the vital feature of the input source images efficiently. In addition, it also introduces some artifacts and inconsistency in the fused results [35]. Wavelet transform is a tool of selection and reconstruction of the image, and fusion rules take an important part in performance of the fused image [149]. It uses various criteria[13,15,28,45,55,147,149,153,157,159] for selection of the coefficients of the focused region from the source images. A multi-focus image fusion through wavelet transform can also be achieved using various schemes such as, morphological and genetic algorithm, which combines aspects of feature and pixel-level fusion [29], data assimilation and genetic algorithm [135],edge features[136],anny filter and decision map[156], structure tensor based approach to extract local features in detail sub-bands[158], non-linear wavelet constructed with morphological wavelet[12], Multi-Wavelet Transform(MWT)[16], Pyramid Dual Tree directional Filter Bank (PDTDFB)[18], Haar function[44,160],bi-orthogonal wavelet [59], Redundant wavelet transform (RWT) [60,144], dynamic-segmented morphological wavelet fusion method (DSMF) and dynamic-segmented cut and paste fusion method (DSCP) using spectrum energy[50], lifting wavelet transform[112,141], Quaternion wavelet transform (QWT) [137], biothogonal two-dimensional wavelet transform[138], multi-wavelet, laplacian operator and regional gradient[140,142], nonseparable symmetrical wavelets[152], multi-scale top-hat transformation and morphological filters[165],etc. Researchers have suggested extensions to the classical wavelet transform that have been used for multi-focus image fusion. These extensions are discussed in the following section.

2.1.2 Discrete Wavelet Transform (DWT) Methods

DWT is a wavelet based transform wherein, the source images initially undergo transformation into their multi-resolution representations. DWT is applied on every image block with the assumption that images have focused or blurred areas rather than individual pixels. The fusion process uses fusion rules to obtain a new composite multi-resolution representation. The Maximum Selection (MS) scheme is the most prevalent fusion rule. A typical fusion scheme selects the biggest absolute wavede coefficient (clarity evaluation function) at each location from the input source images as the coefficient at the location in the fused image. Finally, the resultant fused image is reconstructed by applying an inverse DWT (IDWT). In DWT, the image signals generate a non-redundant image representation for improved better spatial and spectral localization during fused image formation in comparison to other multi-scale representations such as Gaussian and Laplacian pyramid [150]. DWT based method has been extensively used for remote sensing image fusion, medical image fusion, as well as for multi-focus image fusion [7]. DWT based fusion technique use different parameters to select the fusion co-efficient [7,8,9,51,139,143,146,148,150,169,176,238].

Many variations of DWT exist in literature. The following paragraph discusses of some of them. The DT-DWT is a modified version of the DWT and was proposed to overcome shift variance and directionality limitations of the DWT [111]. A double density dual-tree discrete wavelet transform (DT-DWT) has been applied in [5, 6, and 19,111]. DT-DWT with the fuzzy classifier using fusion operators like average operator in [5], direction value and standard deviation (SD) in [6], visual sensor networks in [17], mean squared difference between central pixel and neighborhood pixels (K-Means Clustering) in [19] local features such as energy, mean, SD and entropy in [111]. The disadvantages of Discrete Wavelet Transform (DWT), such as shift
variability and lack of directional selectivity are overcome by fusing the images using dual tree complex wavelet transform (DT-CWT)[207]. Discrete multi-wavelet transform (DMWT) is a generalized version of the scalar wavelet transform and has several advantages over it. DMWT may have simultaneously compact support, orthogonality, symmetry and vanishing moments, while all these features cannot be realized using a single wavelet. A multi-focus image fusion method based on DMWT is suggested in [155]. DWFT closely resembles the DWT, but uses an over complete wavelet decomposition by avoiding DWT’s underlying down-sampling process. Its resultant signal representation is thus both aliasing free and translation-invariant. The use of DWFT and SVM for fusing images with different focuses of the same scene in order to obtain an everywhere-in-focus image is presented in [161].

2.1.3 Curvelet Transform Methods (CT)

Curvelet has the description ability to the image edges such as curve and line characteristics [42]. In general, wavelets do not take long edges into consideration. CT employs edges as the basic element. They possess maturity, anisotropy, high directional sensitivity and thereby provide more image information and can adapt well to the image characteristic. CT can represent appropriately the edge of image and smoothness area in the same precision of inverse transforms (20). Therefore an hybrid approach combining wavelet and curvelet have been discussed in [10, 14, 20, 43, and 203,230]. The CT methods perform well than DWT methods. A fusion scheme by integrating discrete and fast discrete curvelet transforms (FDCT) is discussed in [11]. The fusion process employs CT methods using local energy (LE)[52], quaternion curvelet transform(QCT)[61].

2.1.4 Contourlet Transform Methods (CoT)

Contourlet transform (CoT) is a two dimensional image representation method which represents edges and other singularities along curves much more efficiently than other wavelet based methods. It is achieved by integrating LP and Directional Filter Bank (DFB). CoT lacks shift-invariance and causes pseudo-Gibbs phenomena around singularities due to down sampling and up sampling in both LP and DFB. According to multi-sampled rate theory, down sample on filtered image may result in low-pass and high-pass frequency aliasing. The frequency aliasing affects directional sub-bands from the high-pass sub-bands filtered by DFB. It results in information in one direction to appear in different directional sub-bands at the same time. This limits the directional selectivity of contour lets[34]. Many CoT [34,130, 131] based methods were found in the literature. Non-sampled contour let transform (NSCT) is suggested in the literature to overcome the disadvantages of CT. The problem of frequency aliasing in CoT is solved by NSCT using non sub-sampled pyramid decomposition and non sub-sampled filter banks (NSFB’s). NSCT is a fully shift-invariant form of contour let, can lead to better frequency selectivity and regularity. Various fusion schemes using non-sampled contour let transform (NSCT) has been suggested in [30,31,32,33,34,35,36,37,38,39, 40, 41, 63,95,122,123,124, 125,126,127,128,129,131,132,133,208,215].

2.1.5 Shearlet Transform Methods (ST)

Shearlet is an emerging multi-scale geometric analysis tool. It is much more efficient than the conventional multi-resolution analysis techniques as it significantly enhances the visual quality of the fused image [21]. Shearlets have rich mathematical structure similar to wavelets, which is required for multi-resolution analysis. In addition, they possess all the essential properties of other transforms. The most important advantage of ST over CoT is that they work in multiple directions. Hence researchers are widely using ST in many image processing applications such as image denoising, sparse image representation and edge detection, to name a few. However, its application in image fusion is still under study. Researcher have proposed fusion rules of larger high-frequency coefficients based on regional energy, regional variance, and absolute value, due to ST property of catching detailed information in any scale and direction. The fusion accuracy is also further improved by a region consistency check. Several different experiments were conducted to prove that fusion results based on ST achieved better fusion quality than any other methods [21, 22, 24, 26, 27].

The Non-Sampled Shearlet Transform (NSST) is the shift-invariant version of ST, which can capture 2-D geometrical structure much more effectively than those traditional MST (Multi-Scale transform). The key aspect that differentiates NSST from ST is that NSST eliminates the down-samplers and up-samplers. With the introduction of NSST in the image fusion field, more information for fusion could be obtained and the impacts of mis-registration on the fused results could also be reduced effectively than that of the NSCT. Due to the better flexible directional selectivity and shift-invariance of NSST, it is employed for image fusion process with Pulse coupled neural network (PCNN)[23], artificial neural network(ANN) models to select the fusion coefficient [25,27].
2.1.6 Stationary Wavelet Transform Methods (SWT)

Stationary Wavelet Transform (SWT) differs from DWT, in curbing the process of down-sampling thereby making it translation-invariant. A multi-focus image fusion approach based on SWT and extended Spatial Frequency Measurement (SFM) [57] and various wavelet filters belonging to orthogonal and bi-orthogonal wavelets [151] has been discussed in the literature. A multi-focus color image fusion method is implemented to perform Intensity-Hue-Saturation (IHS) transform on multi-focus color images to get intensity (I) components, and wavelet coefficients by taking SWT [237]. A multi-focus image fusion method based on the multi-scale products of lifting SWT (LSWT) and PCNN is presented in [62,242]. The unregistered images are fused based on feature detection and stationary WT is suggested in [251].

<table>
<thead>
<tr>
<th>Method</th>
<th>Strategy type</th>
<th>Fusion Mechanisms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelet</td>
<td>solitary</td>
<td>the average, greatest pixel [15], the statistical properties of the neighborhood [13], neighboring region variance weighted-average [28], spreading characteristic of the wavelet co-efficient [45], statistical sharpness measure [55], gradient [147], local standard deviation [149], maximum selection or weighted average [153], local energy [157], SML and SF [159], edge features extraction[136], structure tensor to extract local features [158], features extraction using canny filter and decision map[156], Haar function[44, 160], Bi-orthogonal wavelet[59], Redundant wavelet transform (trous algorithm)[144,60], lifting wavelet transform [112,141], Quaternion wavelet transform (QWT)[137], simple average, simple greatest pixel, simple block replace[54].</td>
</tr>
<tr>
<td>Multiple</td>
<td>morphological and genetic algorithm[29], data assimilation and genetic algorithm[135], non-linear wavelet and morphological [12],multi-wavelet transform[16], Pyramid Dual Tree directional Filter Bank (PDTDFB) and wavelet[18], RWT and local variance[154], dynamic-segmented morphological wavelet fusion method (DSMWF) and a dynamic-segmented cut and paste fusion method (DSCP) using spectrum energy[50], multi-resolution wavelet transform and Evolution strategy(MWT-ES) local area energy [138], multi-wavelet[148], laplacian operator and regional gradient[140], three channel nonseparable symmetrical wavelets[152], Laplacian mixture model, three statistical metrics such as Chi-square(C-S), Kolmogorov-Smirnov (K-S) and Kullback-Liebler (K-L) - empirical probability density functions(pdfs)[154], log Gabor transform multi-size windows[170],Gabor filter bank [181], surfacelet and PCNN[255], Self Organizing Feature Map neural networks(SOFM) and evolution strategies(ES)[177].</td>
<td></td>
</tr>
<tr>
<td>DWT</td>
<td>Solitary</td>
<td>Gaussian and Laplacian pyramid[150,51, 238], coefficient selection [7,150], maximum sharpness focus measure [8], spatial frequency [9], local phase coherence measurement[169], variance[143], image activity level measurement (local gradient) [139,146], Prewitt edge detector[148].</td>
</tr>
<tr>
<td>DT-DWT</td>
<td>Solitary</td>
<td>DWFT[5, 6,19,111,207] fuzzy classifier use fusion operators like average operator in [5], direction value and standard deviation (SD) in [6], visual sensor networks in [17], mean squared difference between central pixel and neighborhood pixels (K-Means Clustering) in [19] local features such as energy, mean, SD and entropy in [11].</td>
</tr>
<tr>
<td>CT</td>
<td>Solitary</td>
<td>CT[10, 14, 20, 43,203,230], image edges such as curve and line characteristics [42], local energy(LE)[52], quaternion curvelet transform(QCT)[61].</td>
</tr>
<tr>
<td>CoT</td>
<td>Solitary</td>
<td>Co(T)[131], HMT(hidden Markov Tree) model[130], non-negative matrix factorization [33,40], local features contrast[34,41], image decomposition model[35], local area variance [37,132], fractional differential focus measure[123], SML based local visual contrast and local log Gabor energy [124], visibility(VI) and spatial frequency(SF) [125], Y luminance component [126], region energy [127],directional multi-resolution representation [128].</td>
</tr>
<tr>
<td>ST</td>
<td>Solitary</td>
<td>Local energy[21,22,24,26], Multiple NSSST and PCNN[23,25,27].</td>
</tr>
<tr>
<td>SWT</td>
<td>Solitary</td>
<td>Spatial Frequency Measurement (SFM) [57,151], Intensity-Hue-Saturation (IHS) transform[237], feature detection[151].</td>
</tr>
</tbody>
</table>

DOI: 10.9790/0661-1904060925  www.iosjournals.org  14 | Page
Multi-Focus Image Fusion Methods – A Survey

<table>
<thead>
<tr>
<th>Other transform based methods</th>
<th>Multiple orthogonal and bi-orthogonal wavelets [151], lifting stationary wavelet transform (LSWT) and PCNN [62,242]</th>
</tr>
</thead>
</table>

2.2 Spatial Domain Methods

Spatial domain fusion method work directly on the source images, weighted average is one of the simplest spatial domain methods, which doesn’t need any transformation or decomposition on the original images. This method is advantageous because, it is simple and fit for real-time processing. The spatial domain is further improved by computing the degree of focus for each pixel or block using various focus measures [3]. Figure-4 illustrates the spatial domain image fusion process.

![Spatial domain image fusion process](image)

2.2.1 Focus Measures based Methods

A key challenge of multi-focus image fusion is the way focused regions or clearer blocks are evaluated from the source input images. A good focus measure should possess the following characteristics:

1. It should be independent of the image content;
2. It should be monotonic with respect to blur;
3. The chosen focus measure must be uni-modal, that is, it must have one and only one maximum value;
4. It should show large variation in value with respect to the degree of blurring;
5. It should have minimal computation complexity;
6. It must be robust to noise.


2.2.2 Fuzzy logic based Methods

The review of recent research shows that fuzzy logic is employed in different environments for designing a number of diverse applications including image processing. Fuzzy logic introduces a logical system quite different from the traditional logical system. During image processing if it is found that there does not exist any mathematical relations between components, fuzzy logic is employed to solve problem of uncertainty. Fuzzy image processing comprises of three major stages: image fuzzification, modification of membership values, and image de-fuzzification (if required)[73]. The increase or decrease in image fuzziness can be used in image processing tasks such as enhancement, segmentation and classification. Many applications of fuzzy logic based multi-focus image fusion techniques is presented in the literature namely simple rule based if-then system [19,73,111], pixel clarity[110] and salience map of the gradient[171], the index of fuzziness (IF)[74] etc.
Researchers have also proposed many algorithms which cannot be classified as purely spatial domain or frequency domain methods. These methods have been listed under the section other methods.

2.3 Other Multi-focus Image Fusion Methods

Multi-focus image fusion method employing weighted non-negative matrix factorization and focal point analysis is proposed in [166] for enhanced image fusion. The multi-resolution (MR) transforms are a widespread tool for image fusion and log Gabor transform using MR is presented in [170] Novel feature-level multi-focus image fusion technique is proposed in [167] which uses classification to achieve fusing of multi-focus images. The pulse coupled neural network (PCNN) model is widely used [27, 32, 38, 168, 179, 180, 255] by researchers for fusion of multi focus images. The application of artificial neural networks ([175], human visual system (HVS) and back propagation (BP) neural network [178]), SF and Genetic Search Strategies ([69], [117], [199], [200], [245], [246], [247], [248], [249], [250], [251], [252], [253], [254], [255]) have also been discussed. Some of the other techniques are Rudin-Osher-Fatemi (ROF) model in combination with Chambolle’s projection algorithm [195] and binary particle swarm optimization [183]. A weighted function (rational spline) has been used in [201] to achieve multi-focus image fusion. A fusion method using non-negative matrix factorization (NMF) and difference images is presented in [246, 247]. An algorithm based on error estimation and Partial Differential Equations for fusing multi-focus, noise corrupted images is presented in [204] to obtain an enhanced quality image. The images in diverse focuses have also been fused employing an edge information based fusion algorithm using K-mean segmentation in [210] and dynamic salient weights on discriminative edge points in [211]. Various fusion algorithms have been proposed using Spline Pyramidal Direction Filter Banks in [214], frequency selective median filter criterion in [219], adaptive Wiener filter in [233], batch digital finite impulse response (FIR) filters in [234] and cellular automata method [53].

Table-2 Spatial domain method for multi-focus image fusion

<table>
<thead>
<tr>
<th>Method</th>
<th>Strategy type</th>
<th>Fusion Mechanisms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus measures based</td>
<td>Solitary</td>
<td>spatial frequency (SF) [66, 67, 68, 69, 70, 71, 72, 73, 79, 83, 87, 115, 116, 117, 119, 120, 134, 161, 172, 173, 182, 206, 222, 226, 239], index of fuzziness [74], maximum selection and simple average methods [75], variance [76, 79, 115, 117, 118, 119, 120, 161], sum modified laplacian [76, 79, 85, 117, 213], energy measure and blurring measure [77], bilateral sharpness criterion [78, 84, 113, 114], energy of image Gradient (EGO) [79, 112, 115, 119, 120, 217, 222, 254], tenengrad measure [76, 79, 221], Energy of laplacian of image (EOL) [76, 79, 85, 112, 119, 161, 174, 191, 254], frequency selective weighted median filter [76], sum of absolute value of gray difference function (SMD) [112], pixel clarity or visibility criteria [80, 110, 225], spatial gradient [82, 164], standard deviation [83], morphological focus measures [86, 87, 88], sparse representation, and features [89, 90, 92, 93, 94, 96, 97, 99, 102], neighbor distance-sharpness measure [103], non-reference objective image fusion metric based on mutual information [104, 106], spiking cortical model-composite image quality criterion [105], structural similarity (SSIM) [108], gradient difference and intensity difference [109], visibility [115, 119, 120, 222], Edge [120, 223], pixel level measure through Pseudo wigner distribution [121], no-reference blur metric [161], focal connectivity [163], L∞ norm of image gradient, Active Central Moment (ACM) [172], Radon wigner ville based blur metri [223], blurriness measure [224], Region acutance [227], local perceived sharpness (LPS) [228], reconstruction error [229], Mutual Spectral Residual (MRS) [232], differential evolution (DE) [117], quality assessment [69], computation of point spread function (PSF’s) [245], weighted gradient focus measure [250], multispectral focus measure [252], weighted non-negative matrix algorithm [166].</td>
</tr>
<tr>
<td>Multi</td>
<td>Gabor dictionary and orthogonal matching pursuit, an algorithm for sparse representation [91, 98, 100, 101], comprehensive index-SF and Entropy [107], RMSE and fractal dimension (FD) [205], Genetic algorithm-SF [68], quad tree based algorithm using the sum of the weighted modified Laplacian [249] and sum modified laplacian (SML) [255], Gabor filter bank [181] and spatial frequency and morphological operators [173], genetic search strategies and spatial frequency [182], SF and morphological operators [173], neural networks [167], PCNN [168, 180], SF, EOL and modified PCNN [179], SF and Artificial neural networks [ANN] [175], Human visual System (HVS) and Back Propagation (BP) neural network [178], SF and Genetic Search Strategies [69, 117], compressive image fusion using clarity measures [190], hidden Markov model (HMM) [240].</td>
<td></td>
</tr>
</tbody>
</table>
Fuzzy Logic                | Simple rule based if-then system [19, 73, 111], pixel clarity [110] and salience map of the gradient [171].
III. Discussions And Conclusions

In recent years, there has been great progress in the field of multi-focus image fusion. However, existing methods are not without defects, and there is a real need for the improvement of the quality of fused images. This is due to the fact that multi-focus image fusion approaches are not dependent greatly on the application domain or on the acquisition devices, their major focus being the quality of the images. In order to assess the quality of the fused image, speed and accuracy are the two important parameters. The accuracy is also dependent on bringing the source images to common co-ordinate system (Image Registration) before the fusion process. Hence the choosing the correct image registration algorithm is very vital. Therefore researchers are directing their research towards achieving better quality of fused image through speed and accuracy. It was also observed in the literature survey that most of the prevalent multi-focus image fusion methods were in the transform domain. In addition, researchers have also proposed combinational approaches employing more than one strategy to fuse the images. In this paper the multi-focus fusion research methods have been broadly classified as frequency and spatial domain methods. Frequency domain methods have been further classified as wavelet and different variations of waveletes. Spatial domain methods are mostly based on focus measure evaluation. The frequency and spatial domain strategies have been further divided into solitary and multiple based on whether a single method has been used or multiple methods has been used. Another categorization of the methods are also listed which is neither falling under frequency domain category nor under spatial domain category. These methods have been presented in the other methods category. In conclusion, a survey on the fusion of multi-focus images using wide variety of approaches has been done. The widespread progress in multi-focus image fusion research summed up in this literature review signifies the importance of this research in improving the visualization of the images. In addition, this survey presents a broad classification of the various methods and techniques that are being used in the field of multi-focus image fusion. This survey presents a comprehensive repository to the researchers in the field of multi-focus image fusion research.

References


DOI: 10.9790/0661-1904060925 www.irosjournals.org 17 | Page
Multi-Focus Image Fusion Methods – A Survey


[26]. Jia Zhao et al., 2010, A Novel Multi-Focus Image Fusion Method Using Shearlet Transform Advanced Materials Research, 121- 122, 373.


[34]. Yi Chai, Huafeng Li, Xiaoyang Zhang, Multifocus image fusion based on features contrast of multiscale products in nonsubsampled contourlet transform domain, Optik - International Journal for Light and Electron Optics, Volume 123, Issue 7, April 2012, Pages 569-581, ISSN 0165-0114.

[35]. M. H. Ould mohamed dyla, h.tariri, Multi-focus Image Fusion Scheme using a Combination of Nonsubsampled Contourlet Transform and an Image Decomposition Model, Journal of Theoretical and Applied Information Technology 30th April 2012. Vol. 38 No.2


[41]. Xinxiang Zhou ; Dianhong Wang ; Zhijuan Duan and Dongming Li “Multi-focus image fusion scheme based on nonsubsampled contourlet transform”, Proc. SPIE 8009, Third International Conference on Digital Image Processing (ICDIP 2011), 800904 (July 01, 2011); doi:10.1117/12.896148;

[42]. Wencheng Wang, Faliang Chang, Tao Ji, , Qiang Fu; Fenghua Ren; Legeng Chen; Zhexin Xiao; and Han Dong; “Multi-focus Image Fusion Based on M-band Multi-wavelet Transform”, International Journal of Digital Content Technology and its Applications, Vol. 5, No. 1, pp. 32 – 42, 2011


Multi-Focus Image Fusion Methods – A Survey


Liqiang Guo,Ming Dai, and Ming Zhu, Multifocus color image fusion based on quaternion curvelet transform, 2012, Vol. 20, No. 19 / Optics Express 18846


Yinqie Zhang, – and Lilin Ge, Efficient fusion scheme for multi-focus images by using huring measure, Digital Signal Processing, Volume 19, Issue 2, March 2009, Pages 186-193

Jing Tian et al., Multi-focus image fusion using a bilateral gradient-based sharpness criterion, Optics Communications (Impact Factor: 1.54), 01/2011; 284(1):80-87.

Wei Huang, Zhongliang Jing, Evaluation of focus measures in multi-focus image fusion, Pattern Recognition Letters Volume 28, Issue 4, 1 March 2007, Pages 493-500


Ishita De, Bhattachor Shanda, Multi-focus image fusion using a morphology-based focus measure in a quad-tree structure, Information Fusion, Volume 14, Issue 2, April 2013, Pages 136-146.


DOI: 10.9790/0661-1904060925 www.iosrjournals.org 19
Multi-Focus Image Fusion Methods – A Survey


[100] Bin Yang; Shutao Li, Pixel-level image fusion with simultaneous orthogonal matching pursuit, Information Fusion, Volume 13, Issue 1, January 2012, Pages 10-19, ISSN 1566-2535.

[101] Mansour Nejati, Shadrokh Samavi, Shahram Shirani, Multi-focus image fusion using dictionary-based sparse representation, Information Fusion, Available online 1 November 2014, ISSN 1566-2535

[102] Hengjun Zhao, Zhaoei Shang, Yuan Yan Tang, Bin Fang, Multi-focus image fusion based on the neighbor distance, Pattern Recognition, Volume 46, Issue 3, March 2013, Pages 1002-1011, ISSN 0031-3203


[105] Rodrigo Nava ; Boris Escalante-Ramirez and Gabriel Cristóbal "Blind quality assessment of multi-focus image fusion algorithms", Proc. SPIE 7723, Optics, Photonics, and Digital Technologies for Multimedia Applications, 77230F (May 04, 2010);

[106] Hao Lu ; Zongxi Song ; Wei Gao ; Qi Wang and Jiangbo Xi, " A multi-focus image adaptive fusion method based on comprehensive index ", Proc. SPIE 9284, 7th International Symposium on Advanced Optical Manufacturing and Testing Technologies: Optoelectronics Materials and Devices for Sensing and Imaging, 92840M (September 2, 2014);


DOI: 10.9790/0661-1904060925 www.iosrjournals.org 20 | Page
Multi-Focus Image Fusion Methods – A Survey

[121] Fuping Zhong, Yaqi Ma, Huafeng Li, Multifocus image fusion using focus measure of fractional differential and NSCT, Pattern Recognition and Image Analysis June 2014, Volume 24, Issue 2, pp 234-242
[122] Yong Yang; Song Tong; Shuying Huang; Pan Lin, "Multifocus Image Fusion Based on NSCT and Focused Area Detection," Sensors Journal, IEEE , vol.15, no.5, pp.2824,2838, May 2015
[125] Li Ding; Han ChongZhao, "Multi-focus Image Fusion Using Wavelet Based Contourlet Transform and Region," Information Management and Engineering, 2009, ICIME '09. International Conference on , vol., no., pp.90,93, 3-5 April 2009
[130] Ning Ma ; Lijian Zhou, "A multiscale approach to pixel level fusion and normalized cut, Signal Processing, Volume 97, April 2014, Pages 9-20
[133] Yipeng Liu, Jing Jin, Qiang Wang, Yi Shen, Xiaojue Dong, Region level based multifocus image fusion using quaternion wavelet and normalized cut, Signal Processing, Volume 97, April 2014, Pages 9-30, ISSN 0165-1684
[135] Yu Song; Mantian Li; Qiangli Li; Lining Sun, "A New Wavelet Based Multi-focus Image Fusion Scheme and Its Application on Optical Microscopy," Robotics and Biomimetics, 2006. ROBIO '06. IEEE International Conference on , vol., no., pp.401,405, 17-20 Dec. 2006
[140] Yan Sun; Chunhui Zhao; Ling Jiang, “A New Multi-focus Image Fusion Algorithm Based on Redundant Wavelet Transform,” Information and Computing (ICIC), 2010 Third International Conference on , vol.3, no., pp.300,303, 4-6 June 2010

DOI: 10.9790/0661-1904060925 www.iomrsjournals.org 21 | Page
Multi-Focus Image Fusion Methods – A Survey


[162] Ishita De, Bhabatosh Chanda, and Buddhajyoti Chattopadhyay, “Enhancing effective depth-of-field by image fusion using morphological morphology" and Image Visualization, Volume 24, Issue 12, 2006 Pages 1278-1287


Multi-Focus Image Fusion Methods – A Survey


183. Y. Asnath Vicy Phamila, R. Amutha, Discrete Cosine Transform based fusion of multi-focus images for visual sensor networks, Signal Processing, Volume 95, 2014 First International Conference on, Pages 161-170, ISSN 0165-186X.


188. Radek Benes, Pavel Dvorák, Marcos Faundez-Zanuy, Virginia Espinoza-Duró, Jiri Meyksa, Multi-focus thermal image fusion, Pattern Recognition Letters, Volume 34, Issue 5, 1 April 2013, Pages 536-544, ISSN 0167-8655.


Multi-Focus Image Fusion Methods – A Survey


[225] Jiangyong Duan; Gaofeng Ma; Shuming Xiang; Chunhong Pan, "Multifocus Image Fusion via Region Reconstruction," Pattern Recognition (ACPR), 2013 2nd IAPR Asian Conference on , vol., no., pp.396,400, 5-8 Nov 2013


[229] Junhong Hu ; Tianxu Zhu ; Sheng Zhong and Xujun Chen "Multi-focus image fusion using adaptive Wiener filter", Proc. SPIE 6786, MIPPTR 2007; Automatic Target Recognition and Image Analysis; and Multispectral Image Acquisition, 67862U (November 15, 2007)


[232] F. Strobek ; S. Gabarda ; R. Redondo ; S. Fischer and G. Cristobal, “Multifocus fusion with oriented windows”, Proc. SPIE 5839, Bioengineered and Bioinspired Systems II, 264 (June 29, 2005);


[239] T.Wan, C.Zhab and Z.Qin, “Multifocus Image Fusion Based on Robust Principal Component Analysis” Pattern RecognitionLetters,vol.34, no.9, 2013.10

[240] Di Guo, Jingwen Yan, Xiaobo Qu, High quality multi-focus image fusion using self-similarity and depth information, Optics Communications, Volume 338, 1 March 2015, Pages 138-144


[242] Xiangzhi Bai, Yu Zhang, Fugen Zhou, Bindang Xue, Quadtree-based multi-focus image fusion using a weighted focus-measure, Information Fusion, Volume 22, March 2015, Pages 105-118, ISSN 1566-2535

[243] Zhiqiang Zhou, Sun Li, Bo Wang, Multi-scale weighted gradient-based fusion for multi-focus images, Information Fusion, Volume 20, November 2014, Pages 60-72

[244] Yan Liu, Fehong Yu, An automatic image fusion algorithm for unregistered multi-focus images, Optics Communications, Volume 341, 15 April 2015, Pages 101-113

DOI: 10.9790/0661-1904060925 www.iiosjournals.org 24 | Page

[250]. Xiaoli Zhang, Xiongfei Li, Zhaojun Liu, Yuncong Feng, Multi-focus image fusion using image-partition-based focus detection, Signal Processing, Volume 102, September 2014, Pages 64-76.


[253]. Jiangyong Duan, Gaofeng Meng, Shiming Xiang, Chunhong Pan, Multifocus image fusion via focus segmentation and region reconstruction, Neurocomputing, Volume 140, 22 September 2014, Pages 193-209.