An Enhanced Multi Focus Image Fusion Algorithm through Guided Filters using Quadtree

Seema Mishra [1], Vipin Verma[2], Prof. B.P.S. Sengar[3]

[1]M.Tech Scholar, Department of Computer Science & Engineering, All Saints' College of Technology, Bhopal (M.P), India
[2]Assistant Professor, Department of CSE, All Saints' College of Technology, Bhopal (M.P)
[3]Head of Department Computer Science, All Saints' College of Technology, Bhopal (M.P)

---***---

Abstract:- The purpose of multi-focus image fusion is integrating the partially focused images into one single image which is focused everywhere. To achieve this purpose, we propose a new quadtree-based algorithm for multi-focus image fusion. In this work, an effective quadtree decomposition strategy is presented. According to the proposed decomposition strategy, the source images are decomposed into blocks with optimal sizes in a quadtree structure. And in this tree structure, the focused regions are detected by using a new weighted focus-measure, named as the sum of the weighted modified Laplacian. Finally, the focused regions could be well extracted from the source images and reconstructed to produce one fully focused image. Moreover, the new weighted focus-measure performs better than the commonly used focus-measures on the detection of the focused regions, since it is sensitive to the homogeneous regions. The proposed algorithm is simple yet effective, because of the Quadtree decomposition strategy and the new weighted focus-measure. To do the comparison, the proposed algorithm is compared with several existing fusion algorithms, in both the qualitative and quantitative ways. The experimental results show that the proposed algorithm yields good results.

Keyword: Multi-focus image fusion, Quadtree decomposition strategy, Quadtree structure, weighted focus-measure, Sum of the weighted modified Laplacian.

I. INTRODUCTION

In scientific microscopic imaging or in a general photograph, a single image usually cannot represent all objects of interest, since an optical system is limited by depth of field [1]. Multi-focus image fusion is considered a good solution to this problem as it is suitable for generating a single image from multiple source images and is aimed at providing a more accurate description of certain objects, or a combination of information, to meet a particular human or machine perception requirement [2]. Meanwhile, multi-focus image fusion is also a hot research topic since many proposed multi-focus image

fusion methods have been efficiently applied in various fields such as remote sensing and medical imaging. During the last few decades, a large number of image fusion methods with various fusion frames have been proposed [3] that can be applied to multi-focus image fusion. More recently, various image fusion methods have been proposed [4], mostly concerning transform domain or spatial domain methods. In this paper, we mainly examine multi-focus image fusion.

For transform domain methods, the source images are first decomposed into different transform coefficients, and then these coefficients are fused by certain fusion rules. The fused image is then obtained by reconstructing the fused coefficients. Under this framework, multi-scale transform-based fusion methods are the most commonly applied in this group with the development of multi-scale theories. A variety of multi-scale transforms

have been presented and applied in image fusion mainly containing pyramid decomposition [3], discrete wavelet transform , dual-tree complex wavelet transform (DTCWT) [5]. In addition, independent component analysis [4], robust principal component analysis [14], morphological component analysis [5], sparse representation (SR) and multi-scale transform and sparse representation (MST-SR) methods have also been discussed and they share one common trait: fusion in the transform domain, which may change the intensity values and produce some artificial contours and may lead to undesired artifacts introduced in the fused result.

BASIC METHODS OF IMAGE DATA FUSION

The images get in the environment of ubiquitous computing, because of the complexity and their stronger relationship of image information itself, incomplete and inaccuracy, unstructured as well as difficulties in modelling will occur at all layers of the process of image fusion. Artificial intelligence applies to image pervasive fusion, with the better results than traditional methods of calculation (that is, the use of precise, fixed and unchanging algorithm to express and solve the problem), can integrated with their respective advantages, compose intelligent fusion system, expand their original function. Therefore, it is a pervasive image fusion method with huge potential, the main intelligent methods as follows:-

NEURAL NETWORK

In recent years, neural network theory is a cutting-edge research field in artificial intelligence, suitable for non-linear modelling, with self-learning, self-organization, adaptive capacity, and higher accuracy, have good generality and flexibility for different object modelling, but the structure is complicated, not suitable as the steady-state model of optimization method for complex systems.

FUZZY THEORY

In recent years, fuzzy theory has begun to apply to the field of data fusion, because fuzzy theory provides an effective methods to express uncertainty and inaccuracy of in-formation, thus can establish the corresponding mathematical model to a lot of uncertainty data in data fusion issues; Meanwhile, fuzzy set theory can deal with knowledge digitally, with a way similar to the thinking of people to construct knowledge, therefore, it has a advantage of computing with clear and easy to understand.

ROUGH SET THEORY

Rough set theory has not only provided new scientific logic and research methods for the information science and cognitive science, but also provided an effective treatment technology to intelligent information processing. Rough set theory has abilities of analyzing, reasoning for incomplete data, and finding the intrinsic relationship between the data extracting useful features and simplifying the information processing, so the using of rough set theory on the image fusion is a subject worth exploring.

IMAGE FUSION CATEGORIES

Image fusion methods can be grouped into three categories: Pixel or sensor level, feature level and decision level [10].

Pixel Level

In pixel level fusion the source images are fused pixel-by-pixel followed by the information/feature extraction. To implement the pixel level fusion, arithmetic operations are widely used in time domain and frequency transformations are used in frequency domain. The main goal of pixel level fusion is to enhance the raw input images and provide an output image with more useful information than either input image. Pixel level fusion is effective for high quality raw images but not suitable for images with unbalanced quality level because information from one physical channel might be impeded by the other.

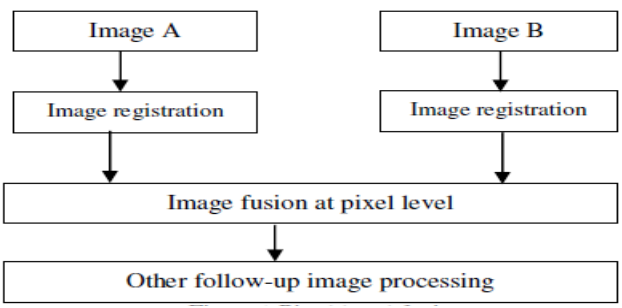

Figure 1: Pixel level fusion

Feature Level

In feature level fusion the information is extracted from each image source separately then fused based on features from input images. The feature detection is typically achieved through edge enhancement algorithms, artificial neural networks, and knowledge based approaches. Feature level fusion is effective for raw images with unbalanced quality level. It requires a feature-extraction algorithm effective for both physical channels.

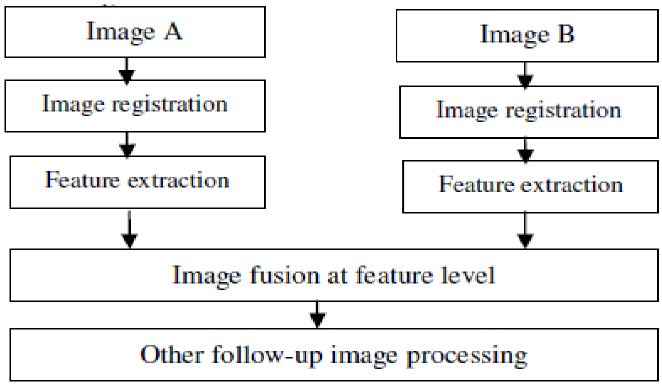

Figure 2: Feature level fusion

Decision Level

In decision level fusion information is extracted from each source image separately and then decisions are made for each input or source channel. Finally these decisions are fused to generate the final decision or image. Decision level fusion is effective for complicated systems with multiple true or false decisions but not suitable for general applications.

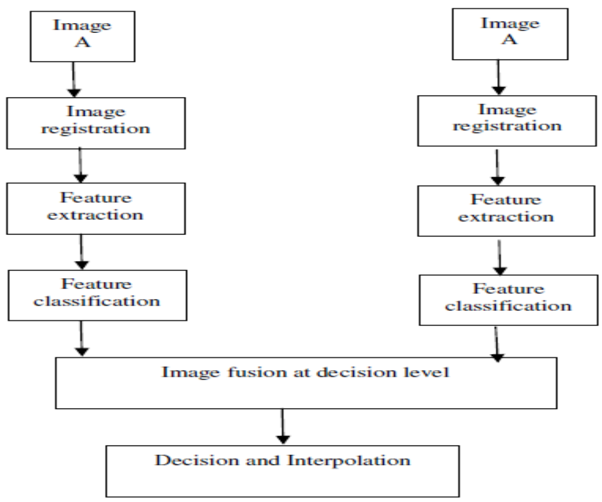

Figure 3: Decision level Fusion

II. MULTI-FOCUS IMAGE FUSION

The 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.

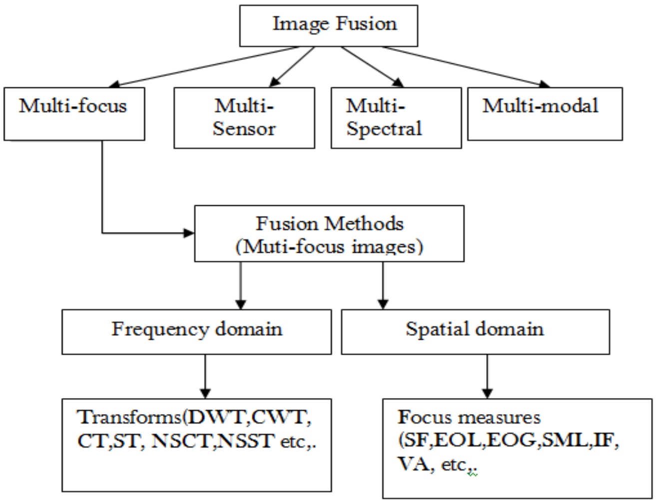

Fig.4. Methods used in multi-focus image fusion

The Figure-4 depicts the different types of image fusion and further categorization of multi-focus image fusion methods. Figure-1 gives few example images for multi-focus image fusion. The following section discusses the research work involving various frequency domain and spatial domain methods.

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.

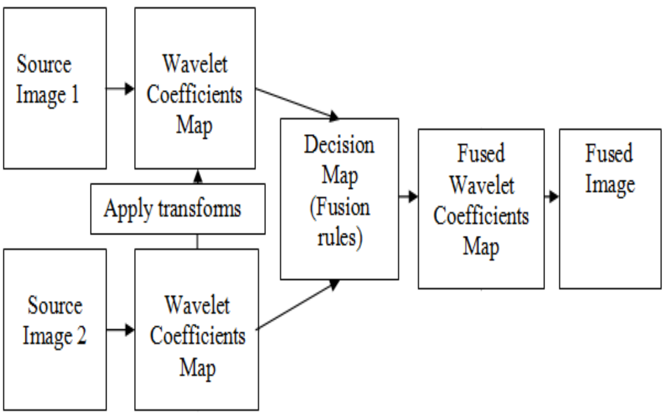

Fig.5. Frequency domain image fusion process

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.

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.

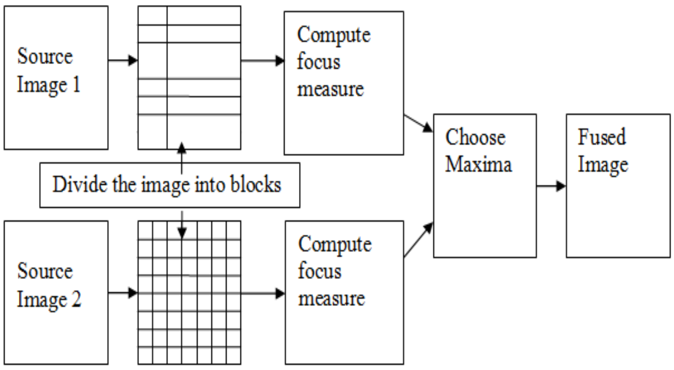

Fig.6. Spatial domain image fusion process

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.Figure-4 illustrates the spatial domain image fusion process.

Note: Guided Image Filtering Theory Guided filters have been successfully employed in many image processing applications, especially in image fusion. Some image fusion methods with guided filters have obtained positive results. A guided filter is applied to optimize the fusion weight map in these existing methods.

III. LITERATURE SURVEY

Pixel-level image fusion scheme based on steerable pyramid wavelet transform using absolute maximum selection fusion rule

In this paper Author conclude that when images are free from any noise and other when they are corrupted with zero mean white Gaussian noise. From experiments, we observed that the proposed method performs better in all of the cases. The Performance is evaluated on the basis of qualitative and quantitative criteria. The main reasons to use steerable pyramid wavelet transform in image fusion are its shift invariance and rotation invariance nature.

Optimization of Image Fusion Using Genetic Algorithms and Discrete Wavelet Transform

In this paper Author conclude that A pair of "parent" solutions is selected for breeding from the previous selection pool. A new solution is created by producing a "child" solution using crossover and/or mutation. New candidate solutions are selected and the process continues until a new population of solutions of appropriate size is generated. Given technique is more accurate and improves in the aspect of information loss which is a drawback of many other techniques. When incorporating the feature extraction technique from DWT_IF as well as the efficiency from PLGA_IF, the results improve the accuracy of the fused image which could be beneficial to weather forecasting.

Multispectral and panchromatic image fusion Based on Genetic Algorithm and Data Assimilation

In this paper Author concludes that Most of fusion algorithms for multispectral and panchromatic image such as: principal component analysis, contrast pyramid decomposition, IHS method, Brovey method, PCA method, wavelet transformation, Gaussian-Laplace pyramid, and so on, their fusion rules could not be adjusted adaptively according to the purpose of the fusion image. In order to solve this problem, data assimilation conception in meteorological field is introduced. It means that observation data and numerical simulation data are integrated to obtain more nature objective analysis results. The framework of fusion based on data assimilation and genetic algorithm for multispectral and panchromatic image was presented.

Focus Measure of Light Field image using Modified-Laplacian and Weighted Harmonic Variance

In this paper Author conclude that focus measure of light field image for different focal image fusion. We apply sum modified- Laplacian and weighted harmonic mean of variance algorithms. SML is a process to select the proper feature for region detection. While WHV algorithm decomposes in focused regions, then defocused and blurred parts will be omitted. Eventually, an all-focused image can be reconstructed. Based on the experiment results, we can analyze that the proposed method has more efficiently than other comparative methods.

Multi-focus Image Fusion Based on Image Decomposition and Quad Tree Decomposition

In this paper Author conclude that a novel multi-focus image fusion method is proposed to enhance the validity of focused regions extraction and blocking artifacts inhibition. The qualitative and quantitative evaluations have demonstrated that the proposed method can produce better fused image and significantly inhibit the blocking artifacts. But the proposed method is time-consuming for the computation of total EOG. In the future, we will consider optimizing the proposed method to reduce the computational cost and extending the developed method to the fusion of medical images.

Multi-Focus Image Fusion through Gradient-Based Decision Map Construction and Mathematical Morphology

In this paper Author conclude that a novel algorithm for multi-focus image fusion through gradient based decision map construction and mathematical morphology. The contributions of this paper are: (1) a weighted kernel based on image gradient is proposed to measure focus regions; (2) the boundaries between focus and defocus regions are adjusted by morphological operations and free boundary condition based active contour model. From the qualitative and quantitative comparisons, it can be seen that the proposed algorithm is effective for multi-focus image fusion.

IV. PROPOSED METHOD

The main requirement of the fusion process is to identify the most significant features in the input images and to transfer them without loss of detail into the fused image.

1. **Take Image 1 using imread function**
2. **Take Image 2 using imread function**
3. **Combine those images**

(a) Take dimension of images using size (img)function

NormDim = align(p1, p2);

Check if the maxDim == 2048, exit the program

4. **Initialize the step, threshold and block size(Proposed parameters)**

step = 1; T = 5; bsz = 17;

5. **Compute the modified laplacian gradients of the images**

Grads = zeros(p1, p2, num);

for kk = 1 : num

img = mImg(: , : , kk);

Grad = mlap(img, step, T, bsz);

6. First, compute the modified Laplacian gradients(Proposed Technique)

(a) pad the image suitably

domainSize = size(domain);

center = floor((domainSize + 1) / 2);

[r,c] = find(domain);

r = r - center(1);

c = c - center(2);

padSize = [max(abs(r)) max(abs(c))];

(b) Get the dimensions of the image

[M, N] = size(g);

(c) A fast way to compute the matrix operations

mat1 = gpad(step + 1 : M + step, step + 1 : N + step);

mat2 = gpad(1 : M, step + 1 : N + step);

mat3 = gpad(2 * step + 1 : M + 2 * step, step + 1 : N + step);

mat4 = gpad(step + 1 : M + step, 1 : N);

mat5 = gpad(step + 1 : M + step, 2 * step + 1 : N + 2 * step);

(d) Two components

part1 = abs(2 * mat1 - mat2 - mat3);

part2 = abs(2 * mat1 - mat4 - mat5);

result = part1 + part2;

(e) Threshold

result(result<T) = 0;

(f) Then, sum the ML gradients with local weights

result = weight(mlg, bsz);

Grads(:,:,kk) = Grad;

% Extend mImgs and Grads to maxDim(2 ^ X)

dx = ceil((NormDim - p1) / 2);

dy = ceil((NormDim - p2) / 2);

NormGrads = zeros(NormDim, NormDim, num);

NormGrads(dx + 1 : dx + p1, dy + 1 : dy + p2, :) = Grads;

% decomposition set the Default level, when not set level

if level == 0

level = log2(NormDim);

end

(g) docomposition and decision map detection

[Quadtree_Structure, d_map, maxGrad] = decomp(NormDim, NormGrads, num, level);

(h) Decision map reconstruction

d_map = d_map(dx + 1 : dx + p1, dy + 1 : dy + p2);

maxGrad = maxGrad(dx + 1 : dx + p1, dy + 1 : dy + p2);

% First Filter: Open and Close morphilogical filtering

Iter = 1;

d_map = marph(d_map, num, Iter);

% Second Filter: Fiter small blocks inside

smallsz = p1 * p2 / 40;

d_map = blocking(d_map, num, smallsz);

7. Image Fusion initialize the fusion image

fimg = zeros(p1,p2);

(a)Firstly, fusing the defined part, copied directly according to the decision map

for ii = 1 : num

fimg = fimg + mImg(:,:,ii) .* (d_map == ii);

end

(b) Secondly, fusing the non-defined part, copied by maximum selection method

max_tag = zeros(p1, p2, num);

img_tag = zeros(p1, p2);

(C) Find the pixels with the maximum gradients from each gradient map

for ii = 1 : num

tag = (Grads(:,:,ii) == maxGrad);

max_tag(:,:,ii) = tag;

img_tag = img_tag + tag .* ii;

end

(d)The nonpart images and maximum selection

non_part = (d_map < 1);

nonImgs = mImg;

part1 = zeros(p1,p2);

for ii = 1 : num

nonImgs(:,:,ii) = nonImgs(:,:,ii) .* non_part;

part1 = part1 + nonImgs(:,:,ii) .* max_tag(:,:,ii);

end

(e)Finding the positions where more than one Grad(i) have the maxGrad

max_num = sum(max_tag, 3);

% The sigle and multiple positions

single_num = (max_num == 1);

multi_num = 1 - single_num;

% If there are more than one image grad(i) equal to maxGrad

part2 = sum(nonImgs, 3) ./ num;

% As to the whole nonpart

nonPart = part1 .* single_num + part2 .* multi_num;

8. Extend images

(a)Extend mImgs and Grads to maxDim(2 ^ X)

dx = ceil((NormDim - p1) / 2);

dy = ceil((NormDim - p2) / 2);

NormGrads = zeros(NormDim, NormDim, num);

NormGrads(dx + 1 : dx + p1, dy + 1 : dy + p2, :) = Grads;

(b) decomposition set the Default level, when not set level

if level == 0

level = log2(NormDim);

end

(c)docomposition and decision map detection

[Quadtree_Structure, d_map, maxGrad] = decomp(NormDim, NormGrads, num, level);

(d)Decision map reconstruction

d_map = d_map(dx + 1 : dx + p1, dy + 1 : dy + p2);

maxGrad = maxGrad(dx + 1 : dx + p1, dy + 1 : dy + p2);

(e)First Filter: Open and Close morphological filtering

Iter = 1;

d_map = marph(d_map, num, Iter);

(f)Second Filter: Fiter small blocks inside

smallsz = p1 * p2 / 40;

d_map = blocking(d_map, num, smallsz);

(g)Image Fusion initialize the fusion image

fimg = zeros(p1,p2);

(h)Firstly, fusing the defined part, copied directly according to the decision map

for ii = 1 : num

(a) (b)

Figure1: a) front clock focus image

b) back clock focus image

(a) (b)

Figure 2: a) back flower focus image

b) front flower focus image

Table 1: Image SSIM and ESSIM value

Image	SSIM	ESSIM
Clock	0.9834	0.9988
Pepsi	0.9834	0.9948
flower	0.9927	0.9995
OpenGL	0.9802	0.9919
lab	0.9906	0.9931
disk	0.9834	0.9983

Table 2:- Gradient similarity metrics

Image sets	Contrast pyramid	DWT	SIDWT	De's algorithm	QT Based	Proposed Method
Clock	0.9735	0.9751	0.9819	0.9778	0.9762	0.9834
Disk	0.9725	0.9755	0.9757	0.9725	0.9774	0.9834
Flower	0.9648	0.9669	0.9645	0.9607	0.9671	0.9927
Lab	0.9807	0.9818	0.9831	0.9813	0.9834	0.9906
OpenGL	0.9556	0.9642	0.9662	0.9592	0.9608	0.9802
Pepsi	0.9852	0.9854	0.9822	0.9860	0.9862	0.9834

Table 3:- Edge base similarity matrices

Image sets	Contrast pyramid	DWT	SIDWT	De's algorithm	QT Based	Proposed Method
Clock	0.6880	0.6619	0.7003	0.7384	0.7373	0.9988
Disk	0.6849	0.6503	0.6822	0.7340	0.7383	0.9983
Flower	0.6444	0.6222	0.6583	0.6821	0.6962	0.9995
Lab	0.6910	0.6616	0.6839	0.7442	0.7470	0.9931
OpenGL	0.6946	0.6784	0.7058	0.7289	0.7308	0.9919
Pepsi	0.7548	0.7293	0.7445	0.7847	0.7847	0.9948

V. CONCLUSION

The potential of a guided filter in image fusion has been proved in previous image fusion papers. In this paper, we propose a new multi-focus image fusion method with a guided filter. In the proposed algorithm, the guided filter is first used to obtain the difference images of the source images to identify the salient feature maps, and then the initial decision map is defined with a mixed focus measure combined with two efficient focus measure descriptors. Finally, the final decision map is obtained by refining the initial decision map with a morphological filter and a guided filter in turn. The proposed method is compared with nine representative fusion methods in terms of both visual perception and objective metrics. Experimental results demonstrate that the proposed fusion method can be competitive with or even outperform some state-of-the-art methods. However, the question to extend the proposed method to other image fusion fields such as remote sensing image fusion and medical image fusion is a future research direction. quadtree decomposition strategy and also present a new weighted focus-measure, thus the focused regions could be detected from the source images in a quadtree structure, effectively and precisely. And the detected focused regions could be well extracted from the source images and reconstructed to produce the fusion image.

REFERENCES

[1] J. Alonso, A. Fernández, G. Ayubi, and J. Ferrari, "All-in-focus image

reconstruction under severe defocus," Opt. Lett. 40, 1671–1674 (2015).

[2] R. Van de Plas, J. Yang, J. Spraggins, and R. Caprioli, "Image fusion of mass spectrometry and microscopy: a multimodality paradigm for molecular tissue mapping," Nat. Methods 12, 366–372 (2015).

[3] P. Burt and E. Adelson, "The Laplacian pyramid as a compact image code," IEEE Trans. Commun. 31, 532-540 (1983).

[4]Y. Jiang and M. Wang, "Image fusion with morphological component analysis," Inf. Fusion 18, 107–118 (2014).

[5] C. Mi, L. IDe-ren, Q. Qian-qing, and J. Yong-hong, "Remote Sensing Image Fusion Based on Contourlet Transform," MINI-MICRO SYSTEMS, vol. 27, pp. 2052-2055, 2006.

[6] D. Batchelder, J. Blackbird, P. Henry, and G. MacDonald, "Microsoft Security Intelligence Report -Volume 17," Microsoft Secur. Intell. Rep., vol. 16, pp. 1–19, 2014.

[7] Li, J. T. Kwok, and Y. Wang. (2010, April) Using the Discrete Wavelet Frame Transform to Merge Landsat TM and SPOT Panchromatic Images.[Online].Available: http://www.cs.ust.hk/~jamesk/papers/if02.pdf, 2002

[8] Z. Yunfeng, Y. Yixin, F. Dongmei, "Decision-level fusion of infrared and visible images for face recognition," Control and Decision Conference (CCDC), pp. 2411 - 2414, 2008.

[9] W. Huang, Z. Jing, Evaluation of focus measures in multi-focus image fusion, Pattern Recogn. Lett. 28 (4) (2007) 493–500.

[10] W. Huang, Z. Jing, Multi-focus image fusion using pulse coupled neural network, Pattern Recogn. Lett. 28 (9) (2007) 1123–1132.