A New Multi-Focus Image Fusion Techniquefor an Efficient Surveillance

Prabhishek Singh
ASET/ CSE
Amity University,
Noida, UP, India
prabhisheksingh88@gmail.com

Pramod Kumar
Department of CSE
Krishna Engineering College,
Ghaziabad, UP, India
pramodkumar.hod@krishnacollege.ac.in

Alaknanda Ashok
Director
Women Institute of Technology
Dehradun, Uttrakhand

Abstract—The paper presents a new multi—focus based image fusion method for enhancing the image processing component of the central computer system in the visual sensor network (VSN) for efficient surveillance and motion tracking. The proposed method is based on decomposing the input multi-focus images using stationary wavelet transform (SWT). The wavelet coefficients are fused on the basis of the selected threshold value. The threshold value is selected on the basis of various parameters such asloss of correlation, luminance distortion, and contrast distortion. On the basis of these parameters and residual information of the input images, the fusion of wavelet coefficients is performed. The proposed fusion approach is analyzed on the basis of qualitative and quantitative measures. It is also compared to some of the traditional and non-traditional methods. The proposed method is capable of being incorporated in the real-time application of surveillance in VSN.

Keywords—multi-focus image fusion, SWT, UIQI, surveillance, VSN.

I. INTRODUCTION

A VSN is a network where smart camera devices are spatially distributed. This network is skilled enough to process various individual images captured from different view location and fuses them to a single image which more informative and clear than the captured individual images. The network contains multiple cameras that are connected to one central computer of the VSN. These cameras are of different focal length. This feature of surveillance camera helps in acquiring the images with detailed information of all objects in the scene (near or far). The camera with the small focal length will easily and efficiently capture the objects near to camera andthe camera with the large focal length will easily and efficiently capture the objects that are far away from the camera. Through this network, the central computer will acquire multiple multi-focus images that carry mostly all the information of the scene. The system process and fuses these images into a single image that holds the complete information. VSNs are helpful in applications like surveillance, environmental monitoring and motion tracking.

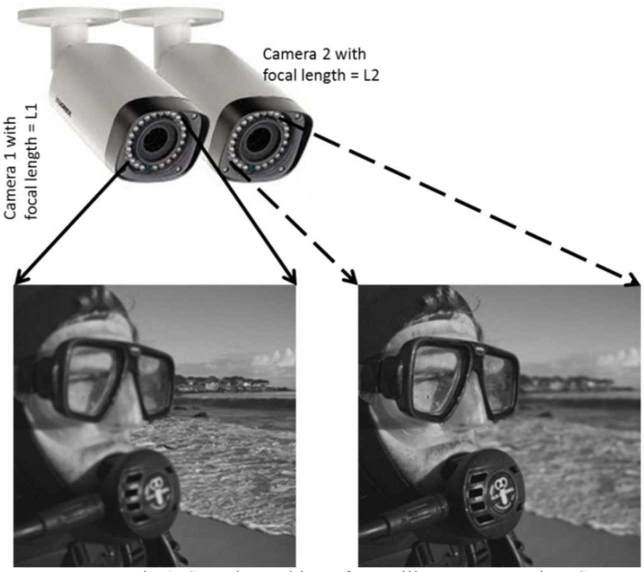

Fig 1. Sample working of surveillance cameras in VSN

Surveillance is the monitoring of behavior, activities, or other changing information for the purpose of influencing, managing, directing, or protecting people. A better surveillance can be performed using an efficient multi-focus image fusion technique inbuilt in the central computer of the visual sensor network that processes multiple multi-focus blurred images captured from the multiple surveillance cameras and fuses them to a single clean image. Figure 1 shows the working of surveillance cameras in VSN architecture, as there are two cameras with two different focal lengths L1 and L2. In the scenario, the focal length of the cameras contains the following relation: L1>L2. Therefore the objects at the large distances are clearer in image captured from the camera 1 due to large focal length while the objects nearer to the camera 2 are captured clear due to small focal length of the camera 2.

The central computer off the VSN that processes the entire captured images has unique image processing software that fuses these captured images into a single enhanced image that contains all the required information. Figure 2 shows the basic working of the central computer of the VSN architecture.

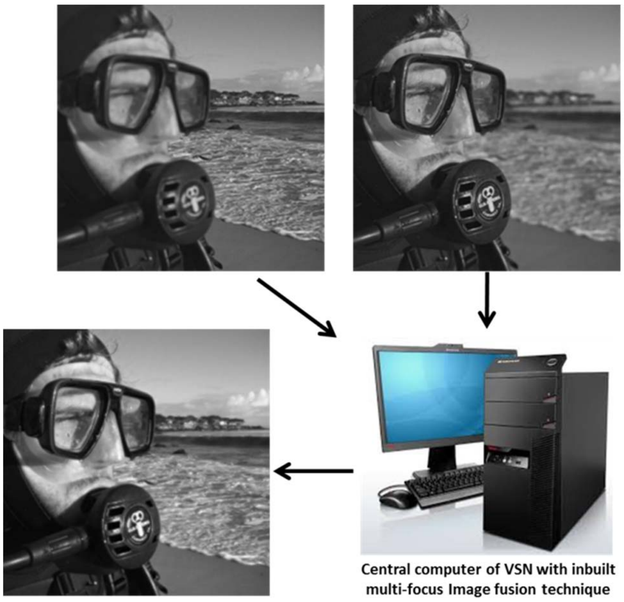

Fig 2. Multi-focus image fusion performed by the server computer of VSN

There are certain tasks that are regularly used in the multi-focus image fusion techniques like addition, max, min, average etc. The multi-focus image fusion techniques are classified into two main categories i.e. spatial and transform domain techniques [1]. Some of the most frequently used techniques in spatial domain are weighted averaging method, Principal Component Analysis (PCA) etc. The advantage of spatial domain methods is its simplicity and less time complexity [3]. The disadvantage of these methods is low fusion quality, spatial distortion, introduction of artifacts and blurring. Sometime it introduces artifacts too [2]. On other hand, the transform domain techniques are frequently used and popular. There are mainly three steps used in transform domain i.e. firstly the wavelet transform is applied on input images that converts the input images into frequency coefficients, next step is to fuse respective wavelet coefficients using some fusion rule, Lastly, these updated waveletcoefficients are transformed back to the spatial domain to obtain the fused image using inverse method. Some of the frequently used transform domain methods are Pyramid based and wavelet-based techniques like discrete wavelet transform (DWT), curvelet transform, SWT, contourlet transform etc.SametAyma, CemalKöse [3] proposed a hybrid approach for multi-focus mage fusion technique using spatial domain (PCA) and transform domain (SWT). VPS Naidu has a significant contribution in the field of image fusion. He proposed a multi-focus image fusion technique using DWT and PCA separately [4].

The article comprises of five sections. The section 1 introduces the VSN, image fusion and their major applications i.e. surveillance. The section 2 describes the terminologies used in the article. Section 3 describes the proposed method. Section 4 describes and analyses the experimental results. The Section 5 concludes the article.

II. Decomposition of Images using SWT and Fusion Rule

The proposed method applies SWT on the input images. The SWT is also called as Undecimated wavelet transform or Algorithme à trous which is specifically designed to overcome the drawback of DWT i.e. lack of translation-invariance [13], [14]. The SWT does not decimate wavelet coefficients at every transformation level as shown in the Figure 3.

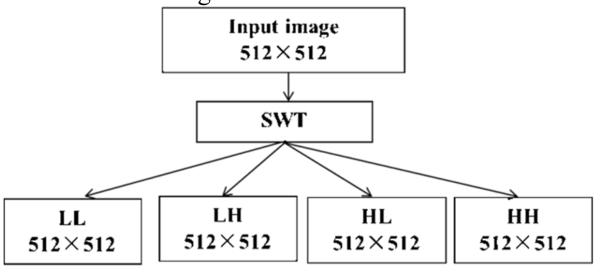

Fig 3. Frequency band decomposition using SWT

The working of SWT up to level 3 is shown in the block diagram in the Figure 4.Let x[n] is the multi-focus input image [16]. The SWT method is firstly applied on the rows and to the columns. It decomposes the x[n] into two parts i.e. approximate and detailed part [6]. The approximate part holds the average information of the input image denoted by LL. The detailed part consists of three subband i.e. horizontal, vertical and diagonal subband denoted by HL, LH and HH respectively. The LL contains the low frequency components of the image while HL, LH and HH contain the high frequency components of the image [15]. The maximum information is available in the detailed subband. If the required information is acquired till the level 1, then process stops there, but if not then approximate part is further decomposed [17]. The process continues till the target is achieved. The fusion rule is applied using approximate and detailed part of the image. Lastly inverse SWT (ISWT) is applied to reconstruct the original image using of these sub-bands [7]. In the Figure 4, g1[n] and h1[n] are wavelet coefficients at level 1. Similarly, {g2[n], h2[n]} and {g3[n], h3[n]} are wavelet coefficients at level 2 and 3 respectively [18], [19].

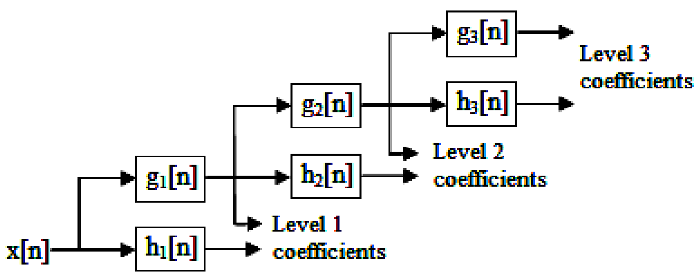

Fig 4. Block diagram of SWT up to level 3 [5]

The decomposed wavelet coefficients are fused using fusion rule that depends on the parameters like residual information, loss of correlation, luminance distortion, and contrast distortion. On decomposition the approximate component of the input images are fused using average operation as approximate component holds the residual information of the images [20]. The detailed components of the images are fused using the parameters like loss of correlation, luminance distortion, and contrast distortion and these parameters are used to decide the threshold value depending on which the fusion rule is generated. These features are analyzed using Universal Image Quality Index (UIQI) metric [21]. UIQI [8] is product of three components: degree of linear correlation, closeness of mean luminance and its range lies in between 0 and 1.

$$\mathrm{UIQI} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \cdot \frac{2\bar{x}\bar{y}}{(\bar{x})^2 + (\bar{y})^2} \cdot \frac{2\sigma_x \sigma_y}{\sigma_x^2 + \sigma_y^2} \tag{1}$$

The respective detailed parts are correlated using correlation coefficient (CC) and compared with the threshold value. On the basis of this comparison, the fusion is applied [22]. The CC is calculated using below formulation:

$$\mathrm{CC} = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right)\left(\left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)\right)}} \tag{2}$$

The CC measures that how strong the two subband are related to each other. The value of CC lies between [-1 to 1] range, where '1' specifies a strong positive relationship, '-1' specifies a strong negative relationship. A CC of '0' specifies no relationship at all.

III. Proposed Multi-Focus Image Fusion Technique

Step 1:X and Y are the input images. sym2 based SWT is applied on the X and Y up to level 1. The proposed method uses decomposition level = 1.

Step 2: On applying SWT, X is decomposed to approximate part and detailed part i.e. [LL1, LH1, HL1 and HH1] and Y is decomposed to [LL11, LH11, HL11 and HH11].

Step 3: Apply averaging operation to fuse the approximate part of the input images.

LLu = avg (LL1, LL11)

Step 4: Apply below fusion rule on all the detailed part of the X and Y.

T1 = UIQI (LH1, LH11)

CC1 = CC (LH1, LH11)

$$\mathrm{LHu} = \begin{cases} \max(\mathrm{LH1}, \mathrm{LH11}) & \text{if } (\mathrm{CC1} \le \mathrm{T1}) \\ \mathrm{avg}(\mathrm{LH1}, \mathrm{LH11}) & \text{otherwise} \end{cases}$$

The T1 and CC1 are calculated using Eq. 1 and 2 respectively. T1 is the threshold value. CC1 is the correlation coefficient between the vertical components i.e. LH1 and LH11.

Step 5: Repeat step 4 for the horizontal [HL1 and HL11] and diagonal[HH1 and HH11] component.HLu and HHu are the fused and updated coefficients.

Step 6: Apply inverse SWT.

F = ISWT (LLu, LHu, HLu, HHu)

Step 7: F is the final fused image.

IV. Numerical Experiment and Analysis

The proposed methodology is tested on many gray scale multi-focus images of size 520×520 pixels [9], [10]. The results of proposed method are compared with some standard methods. The qualitative as well as quantitative analysis is performed. The qualitative measures are edge and corner preservation, smoothness in homogeneous areas, no artifacts generation. The quantitative parameters used to assess the fused image quality are standard deviation (σ), entropy (He), spatial frequency (SF).

'σ' is the square root of variance. It measures the contrast in the fused image. The high σ indicates high contrast in the fused image which refers to high quality. It is evaluated by below Eq. 3.

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{3}$$

'He' is quality assessment parameter in order to measure the uncertainty of pixel values that can be used to illustrate the texture of the fused image. The high value of He indicates high quality of fused image. It is evaluated by below Eq. 4.

$$-\sum_i P_i \mathrm{Log}_2 P_i \tag{4}$$

'SF' is calculated by computing the row frequency (RF) and column frequency (CF) of fused image. The high value of SF indicates high quality of fused image. It is evaluated by below Eq. 5.

$$\sqrt{RF^2 + CF^2} \tag{5}$$

The standard methods with which the results of proposed method are compared are Averaging, PCA [11], and DWT [12]. The sample dataset over which the fusion results are experimented are shown in the Fig 5 to 8.

Fig 5. Dataset 1

Fig 6. Dataset 2

Fig 7. Dataset 3

Fig 8. Dataset 4

The qualitative analysis is performed in the Figure 9 to 12. These figures show the fusion results of various fusion algorithms including proposed methodology. On analyzing the Figure 9 and 10 at pixel level by zooming, it is observed that there is blurriness at the edges of the images specifically in the Figure 9. The fusion results of DWT are better than the averaging method in terms of qualitative analysis. The fusion results of PCA are even better than the DWT. In the Figure 11, there is smoothness in the uniform regions. The edge components are sharp and the brightness is bit higher. Comparatively, the PCA shows better results than DWT and averaging.

On analyzing the fusion results of proposed method in the Figure 12, it is observed that proposed method shows the best results in terms of edge preservation and smoothness. There is even no introduction of artifacts in the fusion results. On observing all the four images in the fusion results of the proposed method, it is seen that all the objects are well preserved and reconstructed. The proposed method shows the best fusion performance.

Fig 9. Fusion results of AVG method

Fig 10. Fusion results of DWT method

Fig 11. Fusion results of PCA method

978-1-7281-1253-4/19/$31.00 © 2019 IEEE

Fig 12. Fusion results of proposed method

The Table 1 to 4 presents the quantitative analysis of fusion algorithms. The best fusion results are shown in the bold. The proposed method shows the best results among the all methods in terms of all quantitative metrics. It can be seen in the tables that the quantitative values of the proposed method is much better than all other methods. It is observed from the quantitative results that the overall contrast of the fused images of proposed method is higher which makes them sharp. The overall texture is also well maintained in the proposed method results.

Table 1.Performance evaluation metrics to evaluate image fusion algorithms on dataset 1

	σ	He	SF
AVG	5.0091	0.0981	0.0320
DWT [12]	6.1631	0.1110	0.0490
PCA [11]	6.8503	0.1453	0.0512
Proposed method	**7.0086**	**0.1789**	**0.0550**

Table 2. Performance evaluation metrics to evaluate image fusion algorithms on dataset 2

	σ	He	SF
AVG	5.5134	0.1743	0.0300
DWT [12]	6.0001	0.1991	0.0374
PCA [11]	6.9812	0.2036	0.0412
Proposed method	**7.3003**	**0.2245**	**0.0514**

Table 3. Performance evaluation metrics to evaluate image fusion algorithms on dataset 3

	σ	He	SF
AVG	5.7241	0.1421	0.0481
DWT [12]	6.8201	0.1874	0.0523
PCA [11]	7.1203	0.1994	0.0600
Proposed method	**7.4563**	**0.2131**	**0.0612**

Table 4. Performance evaluation metrics to evaluate image fusion algorithms on dataset 4

	σ	He	SF
AVG	5.9756	0.1762	0.0431
DWT [12]	6.7631	0.1952	0.0534
PCA [11]	7.1392	0.2095	0.0694
Proposed method	**7.5641**	**0.2214**	**0.0712**

V. CONCLUSION

In this article, a new multi-focus image fusion technique based on wavelet transform for VSN is proposed for the better surveillance application. The proposed method uses sym2 based SWT for decomposition of images. The fusion is performed on the wavelet coefficients using averaging and maximum rule. A new rule is formulated for the fusion purpose using averaging and maximum operations. The qualitative and quantitative results show the best performance of proposed method among the compared approaches. The fused image is visually analyzed using parameters like artifacts generation; edge and texture preservation and visibility of low contrast objects. The quantitative analysis is tested by using parameters like σ, He and SF.

REFERENCES

[1] A.A. Goshtasby, S. Nikolov, Guest editorial: image fusion: advances in the state of the art, Inf. Fusion 8 (2) (2007) 114–118.

[2] C. Liu, Y. Long, J. Mao, Energy efficient multi-focus image fusion based on neighbour distance and morphology, Optik 127 (2016) 11354–11363.

[3] Samet Aymaz, Cemal Köse, “A novel image decomposition-based hybrid technique with super-resolution method for multi-focus image fusion”, Information Fusion 45 (2019) 113–127.

[4] V.P.S. Naidu and J.R. Raol, “Pixel-level Image Fusion using Wavelets and Principal Component Analysis”, Defence Science Journal, Vol. 58, No. 3, May 2008, pp. 338-352, 2008, DESIDOC.

[5] Stationary wavelet transform, Available at: https://en.wikipedia.org/wiki/Stationary_wavelet_transform

[6] Zhang, Y. (2010). "Feature Extraction of Brain MRI by Stationary Wavelet Transform and its Applications". Journal of Biological Systems. 18 (s1): 115–132. doi:10.1142/S0218339010003652.

[7] Dong, Z. (2015). "Magnetic Resonance Brain Image Classification via Stationary Wavelet Transform and Generalized Eigenvalue Proximal Support Vector Machine". Journal of Medical Imaging and Health Informatics. 5 (7): 1395–1403. doi:10.1166/jmihi.2015.1542

[8] Fabrizio argenti, alessandro lapini, and luciano alparone, A Tutorial on Speckle Reduction in Synthetic Aperture Radar Images, IEEE Geoscience and remote sensing magazine September 2013.

[9] M. Nejati, S. Samavi, and S. Shirani, "Multi-focus Image Fusion Using Dictionary-Based Sparse Representation", Information Fusion, vol. 25, Sept. 2015, pp. 72-84.

[10] Multi focus image dataset, Available at: http://mansournejati.ece.iut.ac.ir/content/lytro-multi-focus-dataset

[11] PCA based image fusion, Available at: https://in.mathworks.com/matlabcentral/fileexchange/31338-pca-based-image-fusion?s_tid=prof_contriblnk

[12] Image Fusion Based Wavelet Transform, Available at: https://in.mathworks.com/matlabcentral/fileexchange/56494-image-fusion-based-wavelet-transform

[13] Prabhishek Singh, Raj Shree, "Statistical Quality Analysis of Wavelet Based SAR Images in Despeckling Process", Asian Journal of Electrical Sciences (AJES), Volume 6 No.2 July-December 2017 pp 1-18.

[14] Prabhishek Singh, Raj Shree, "A new homomorphic and method noise thresholding based despeckling of SAR image using anisotropic diffusion", Journal of King Saud University – Computer and Information Sciences (2017), http://dx.doi.org/10.1016/j.jksuci.2017.06.006

[15] Prabhishek Singh, Raj Shree, Manoj Diwakar, "A new SAR image despeckling using correlation based fusion and method noise thresholding", Journal of King Saud University – Computer and Information Sciences (2018), https://doi.org/10.1016/j.jksuci.2018.03.009

[16] Prabhishek Singh, Raj Shree, "Importance Of DWT In Despeckling SAR Images And Experimentally Analyzing The Wavelet Based Thresholding Techniques", in International Journal Of Engineering Sciences & Research Technology, 5(10): October, 2016.

[17] Prabhishek Singh, Raj Shree, "Quantitative Dual Nature Analysis of Mean Square Error in SAR Image Despeckling", in International Journal on Computer Science and Engineering (IJCSE), Volume 9 Number 11 Nov, Page: 619-622. (2017)

[18] Prabhishek Singh, Raj Shree, "A Comparative Study to Noise Models and Image Restoration Techniques", in International Journal of Computer Applications, Volume 149 - Number 1, Year: 2016.

[19] Prabhishek Singh, Raj Shree, "Statistical Modelling of Log Transformed Speckled Image", 380 Vol. 14 No. 8 AUGUST 2016 International Journal of Computer Science and Information Security, (pp. 426-431).

[20] Prabhishek Singh, Raj Shree, "A New Computationally Improved Homomorphic Despeckling Technique of SAR Images", International Journal of Advanced Research in Computer Science, Volume 8, No. 3, March April 2017.

[21] Prabhishek Singh, Raj Shree, "Analysis and effects of speckle noise in SAR images", IEEE International Conference on Advances in Computing, Communication, Automation (ICACCA) 2016.

[22] Prabhishek Singh, Raj Shree, "A new SAR image despeckling using directional smoothing filter and method noise thresholding", Eng. Sci. Tech., Int. J. (2018), https://doi.org/10.1016/j.jestch.2018.05.009