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DWT Based Image Fusion Technique for Infrared and Visible Images Using Particle Swarm Optimization

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Abstract- Image fusion is a process of merging information available in two or more images into a single output image, called fused image. The fused image contains more features and information as compared to any of the source images. Combining information from multiple images into a single image is pre-requisite for many image processing applications. This study proposes a new technique to generate a fused image by combining features of grayscale image and infrared image. The proposed technique converts infrared source image into visual saliency map and then decomposes saliency mapped image and visible source image into frequency sub-bands using Discrete Wavelet Transform. Afterwards, it applies Particle Swarm Optimization to calculate the combined weights for each sub-band and multiply those weights with each fused sub-band. At final stage, Inverse Discrete Wavelet Transform is applied on fused sub-bands to get output image. The functioning of the proposed fusion technique is tested by applying it on three sets of images and its performance is compared with four existing techniques in the same domain using image quality assessment matrices. It is evident from comparative analysis that the proposed technique performed better, visually as well as objectively.

Keywords- Image Fusion, Region-based Image Fusion, Multi Sensor Image Fusion, Discrete Wavelet Transform, Particle Swam Optimization.

I. INTRODUCTION

Fusion of the grayscale and Infrared images is rapidly growing research area because of its effectiveness in applications such as temperature calculation, weather information, surveillance, agricultural analysis, robotics, astronomy, and biometric applications [1 – 2]. In recent years, researchers have proposed many algorithms to blend the attributes of infrared and visible images into a single but more detailed image to make use of the attributes of visible and infrared wavelengths. On the electromagnetic spectrum, infrared images have wavelength from 700nm to 1mm that is not visible to human eyes. Special camera sensors are used to capture infrared images as they possess valuable information not visible to human eye, otherwise[3].

Image fusion algorithms can roughly be grouped into three categories: pixel level image fusion algorithms, feature level image fusion algorithms, and decision level image fusion algorithms. Pixel level image fusion algorithms directly process image pixels to increase or decrease their intensity values, by a mathematically calculated factor, before fusing corresponding pixels of source images [1]. Feature-level image fusion algorithms extracts features from source images by converting each source image into coefficients using one of many mathematical techniques called transformations. Then these features are used to build decision maps or can directly be embedded into coefficients before fusing coefficients of source images. Inverse transformation is then applied on fused coefficients to get fused image [2]. Decision-level image fusion algorithms produce fused image by processing input images individually to extract information and merge extracted information at a higher level of abstraction [3].

This study proposes a simple and noise tolerant technique to fuse grayscale and infrared images by making use of DWT and Particle Swarm Optimization (PSO) methods. The proposed technique converts infrared source image into visual saliency map and then decomposes saliency mapped image and visible source image into frequency sub-bands using Discrete Wavelet Transform. It applies PSO to calculate fusion weights for each sub-band after adding together corresponding sub-bands to form a combined decomposition of sub-bands. Calculated fusion weights are then multiplied with each combined sub-band. At final stage, Inverse Discrete Wavelet Transform is applied on fused sub-bands to get fused image. To test the proper functioning of this fusion technique, we applied it on three sets of images and its output is compared mathematically with the output of four existing techniques in the same domain using image quality assessment matrices.

The rest of the paper is organized as follows; Section II describes related work, Section III defines methodology of the proposed fusion technique, Section IV presents experimental results, and Section V concludes the paper.

II. LITERATURE REVIEW

Region based image fusion technique, one of the techniques used in feature-level image fusion, has certain vantages over non-region-based techniques such as: it avoids misregistration, it is more noise tolerant and robust. Authors in [4] proposed a region based image fusion technique that built a pyramid hierarchy by using Discrete Wavelet Transformation (DWT) at each level. At first level, source image is decomposed into four frequency quadrants. At subsequent levels, first frequency quadrant is further divided into four quadrants. Piella et al. proposed another region based image fusion technique based on multi resolution decomposition [5]. Lewis et al. proposed different fusion strategies for region based and pixel based image fusion using DWT and Dual Tree Complex Wavelet Transformation (DTCWT) [6 - 7]. Nirmala used Independent Component Analysis (ICA) in combination with Support Vector Machine (SVM) to fuse multimodal images [8]. In recent studies, Neural Networks have been employed in many image fusion tasks because of their accuracy. In [9], authors proposed region-based image fusion using Pulse Coupled Neural Networks (PCNN). Huang and Jing proposed a multi-focus image fusion technique that build fusion map using focus measuring technique [10]. Yin et al. proposed infrared and visible image fusion technique that is based on Fuzzy Logic and Nonsubsampled Contourlet Transform (NSCT) [11]. To fuse infrared and visible images, researchers also proposed fusion techniques based on Directionlet Transform [12], Saliency Map [13], and Morphological Framework [14]. Information on some simple fusion techniques can be found in [15] and [16].

Wang et al. proposed Convolutional Neural Network based method for converting multi-sensors signals to construct resultant rich image [17]. Zhu et al. suggested framework to fuse different nature images using Laplacian energy and phase congruency. Non subsampled contourlet transform used to divide images into multi frequency sub-bands. Phase congruency used to blend high frequency sub-bands and weighted local energy and weighted sum of Laplacian based fusion map used to fuse low frequency sub bands [18]. Yin et al. presented Pulse Coupled Neural Network based fusion using Shearlet Transform [19]. Li proposed an algorithm for infrared and visible image fusion using deep learning fusion map [20]. Yang et al. presented structural patch decomposition-based image fusion. In this method, structural patch decomposition utilized to extract prominent structure. Then fuzzy logic based fusion map applied to fuse resultant image [21].

Many of the proposed image fusion techniques that produces good results are either complex to implement or require more processing time and power. The techniques having reduced complexity possess one or more drawbacks like noise intolerance, blueness inclusion, fusion error at corners and edges.

III. METHODOLOGY

A. Discrete Wavelet Transform (DWT)

The Wavelet Transform (WT) is most common method to decompose a signal into its subcomponents. The Discrete Wavelet Transform (DWT), a discrete version of WT, is used to decompose digital signal, like an image, into its subcomponents to easily extract noise and important features from the signal. The DWT decomposes the image into four subcomponents i.e. low- low frequency sub band (LL), contains approximation image, low-high frequency sub band (LH), contains image details in horizontal direction, high-low frequency sub band (HL), contains image details in vertical direction, and high-high frequency sub band (HH), contains image details in diagonal direction, using low pass and high pass filters [22]. 2D-DWT is a two-dimensional version of DWT, designed to process two dimensional signals, like images, effectively. Mathematical representation of 2D-DWT is given by Eq. 1 and 2.

$$ca_{i,j}(n) = \sum x(n) g_i(n - 2^i j) \tag{1}$$

$$cd_{i,j}(n) = \sum x(n) h_i(n - 2^i j) \tag{2}$$

where $ca_{i,j}$, $cd_{i,j}$, $g(n)$, and $h(n)$ represent approximation coefficient, detail coefficient, low pass filter, and high pass filter, respectively.

B. "Particle Swarm Optimization

Particle Swarm Optimization (PSO) was proposed in 1995 by Kennedy and Eberhart. Swarm Optimization is an optimization technique inspired by birds and fish patterns [23]. PSO consists of swarm population, position of particles, velocity of particle, and objective function. PSO starts with initializing the population and velocities. The velocities represented by V_N and the position of particles are represented by X_N. Particle swarm optimization deploys position and velocities of particles to detect optimize point in swarm population. Equation 3 and 4 are used to achieve position and velocities of particles, respectively.

$$V^{k+1} = V_i^k + C_P r_p \left(X_{Pbest}^k - X_i^k\right) + C_g r_g \left(X_{gbest}^k - X_i^k\right) \tag{3}$$

$$X_i^{k+1} = X_i^k + \left(V_i^{k+1}\right) \tag{4}$$

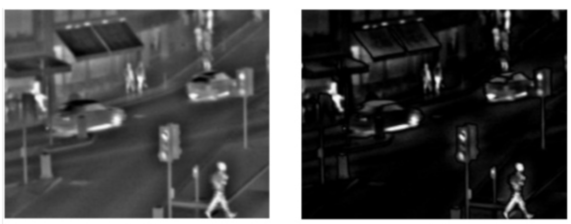
where V^{k+1} velocities of particles, X_i^k value of position of particles, C_p acceleration coefficients, C_g acceleration coefficients, X_{pbest}^k personal best of individual particle, X_{gbest}^k global best of each particle, r_p random values, and r_g random values.

C. Proposed Fusion Technique

Registering source images is mandatory requirement for any image fusion task. It is assumed that the source images supplied to the algorithm are pre-registered using any suitable image registration method. Visual representation of the proposed image fusion technique is given in Fig. 2. Following is a step by step descriptive explanation of our proposed image fusion technique.

Step 1: Read infrared and grayscale source images and convert them into double to increase the precision of the images' matrices.

Step 2: Transform infrared image into Visual Saliency Map. Saliency map changes the representation of the image into an alternate but simplified version which is easier to analyze because of its more meaningful restructured patterns [24]. Figure 1 represents input image and output image after the application of VSM method.



(a) (b)

Fig. 1. (a) Input infrared image (b) Visual saliency mapped image

Step 3: Decompose visible image and visual saliency mapped image into frequency subcomponents using DWT.

Step 4: Convert each corresponding sub-band into row vector to get combined sub-bands using the following equations.

$$LL = [LL^v_{row-vector}, LL^i_{row-vector}] \tag{5}$$

$$LH = [LH^v_{row-vector}, LH^i_{row-vector}] \tag{6}$$

$$HL = [HL^v_{row-vector}, HL^i_{row-vector}] \tag{7}$$

$$HH = [HH^v_{row-vector}, HH^i_{row-vector}] \tag{8}$$

Step 5: Take square root of combined sub-bands to avoid any possible negative values.

Step 6: To get optimal fusion weights, we applied PSO algorithm by setting swarm size equal to 100, dimension of swarm search space equal to 1, acceleration coefficients equal to 2, inertial equal to 0.9, initial velocity equal to randomly selected values between 0 and 1, initialize swarm position with pixel values, and local best position equal to current position of swarm. Initial population is evaluated using objective function, given in Eq. 9, to get current fitness value. Velocity is calculated using Eq. 10 and current position is calculated using Eq. 11. Select maximum of the current fitness value as optimal fusion weight for the corresponding sub-band. Apply this procedure on each combined sub-band to get fusion weights for LL, LH, HL, and HH sub-bands.

$$w = \frac{1}{1+e^{-z}} \tag{9}$$

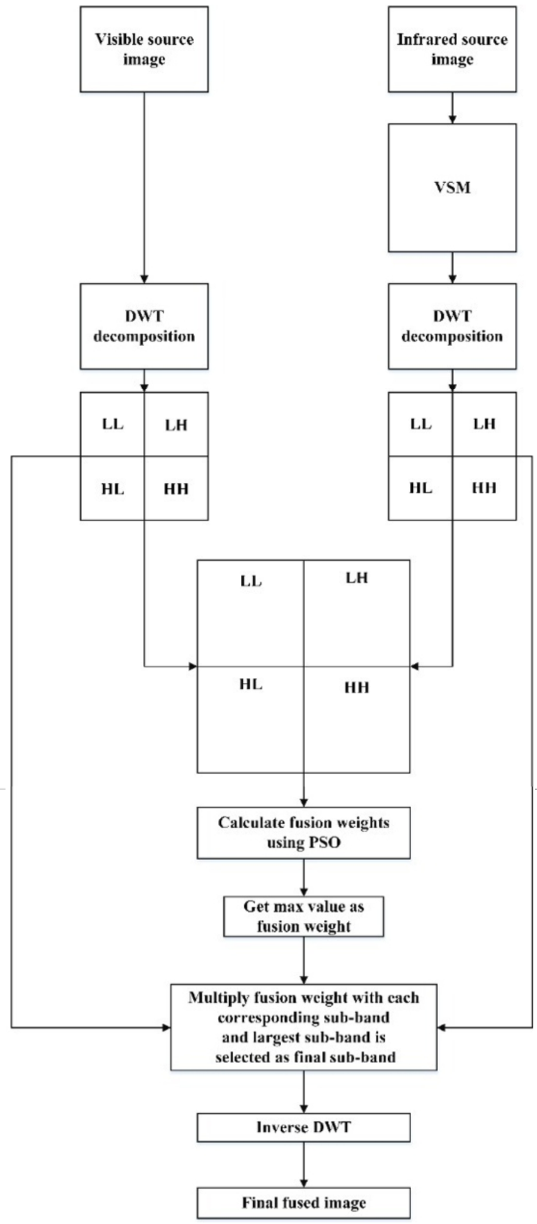


Fig. 2. Visual representation of the proposed image fusion technique

where *w* is fusion weight of corresponding sub-band.

$$v_{i+1} = x * v_i + c_1(r_1 * (\gamma - p)) + c_2(r_2 * (\beta - p)) \quad (10)$$

where x is inertia factor, $c1$ and $c2$ are acceleration coefficients, $r1$ and $r2$ are random values, γ local best position, β is global best position, and p is current position.

$$p = p + v_{i+1} \quad (11)$$

Step 7: Multiply fusion weights, calculated from each combined sub-band, with each pixel of corresponding sub-bands of step 3 and select largest pixel value as final fused sub-band using following equations.

$$F_{i,j}^{LL} = Max(w^{LL} * LL^{v}, w^{LL} * LL^{i}) \quad (12)$$

$$F_{i,j}^{LH} = Max(w^{LH} * LH^{v}, w^{LH} * LH^{i}) \quad (13)$$

$$F_{i,j}^{HL} = Max(w^{HL} * HL^{v}, w^{HL} * HL^{i}) \quad (14)$$

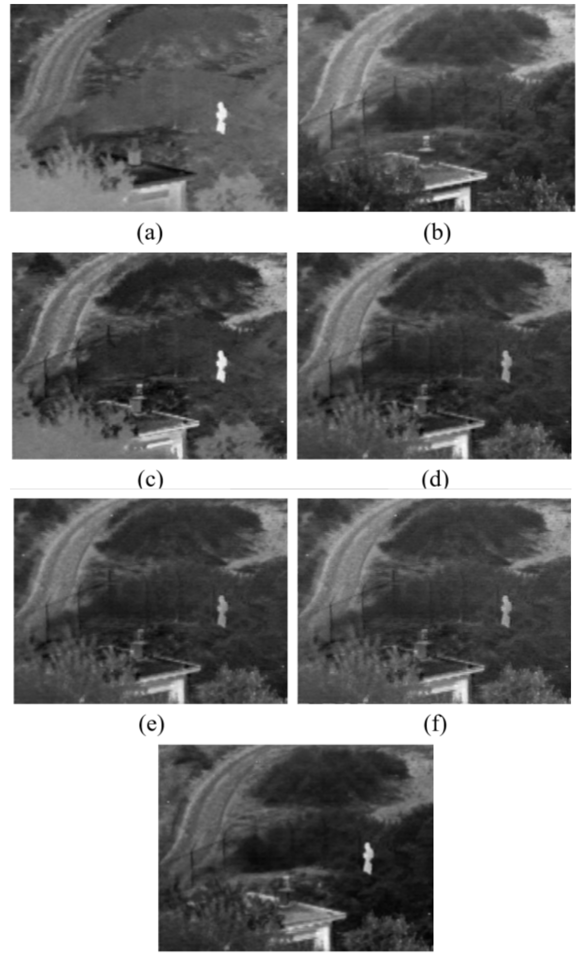
$$F_{i,j}^{HH} = Max(w^{HH} * HH^{v}, w^{HH} * HH^{i}) \quad (15)$$

Step 8: Apply Inverse DWT on fused sub-bands to get final fused image.

IV. RESULT & DISCUSSION

To evaluate effectiveness of this fusion technique, experiments were performed on three sets of images. Each set of image contains two images, one grayscale image and one infrared image, which were retrieved from freely available sources [24 - 25]. We also compared, visually and objectively, the output of our proposed fusion technique with four existing image fusion techniques. Four existing techniques that are used for comparison includes Maximum Intensity based fusion [26], Average based fusion [16], DWT based fusion [21], and Discrete Stationary Wavelet Transform based fusion [27]. For objective quality assessment, we used four image quality assessment matrices that includes Multiscale Structural Similarity Index Measure (MS-SSIM), Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE), and Entropy. Visual results of the proposed fusion technique along with visual results of exiting fusion techniques for image-set 1, image-set 2, and image-set 3 are shown in Fig. 3, Fig. 4, and Fig. 5, respectively. Objective quality assessment results of image-sets 1, image-set 2, and image-set 3 are shown in Table 1, Table 2, and Table 3, respectively.

In Fig. 3, Fig. 4, and Fig. 5, it can be observed that the Maximum Intensity fusion method produced fused image having low structural details as compared to source images whereas Average based fusion, DWT based fusion and DSWT based fusion produced almost same visual results having low intensity values for objects in comparison with source images. The proposed fusion method produced improved visual result having higher structural and color details.



(a) (b) (c) (d) (e) (f) (g)

Fig. 3. Visual results of image-set 1. (a) Infrared source image (b) Grayscale source image (c) Maximum Intensity based fusion (d) Average based fusion (e) DWT based fusion (f) Discrete Stationary Wavelet Transform based fusion (g) proposed

Checking quality of visual results is only one aspect to verify effectiveness of the algorithm. Sometimes visual results of multiple algorithms seem identical to naked eye but there are always small variations exist. These variation in results can be detect using mathematical procedures called using image quality assessment matrices. As we discussed earlier that we used four image quality assessment matrices to detect small variations in structure and color of output image. It is evident from the numerical results of quality assessment matrices for image-set, presented in Table 1, that the proposed method got highest values for MS-SSIM, PSNR, and Entropy whereas lowest for RMSE.

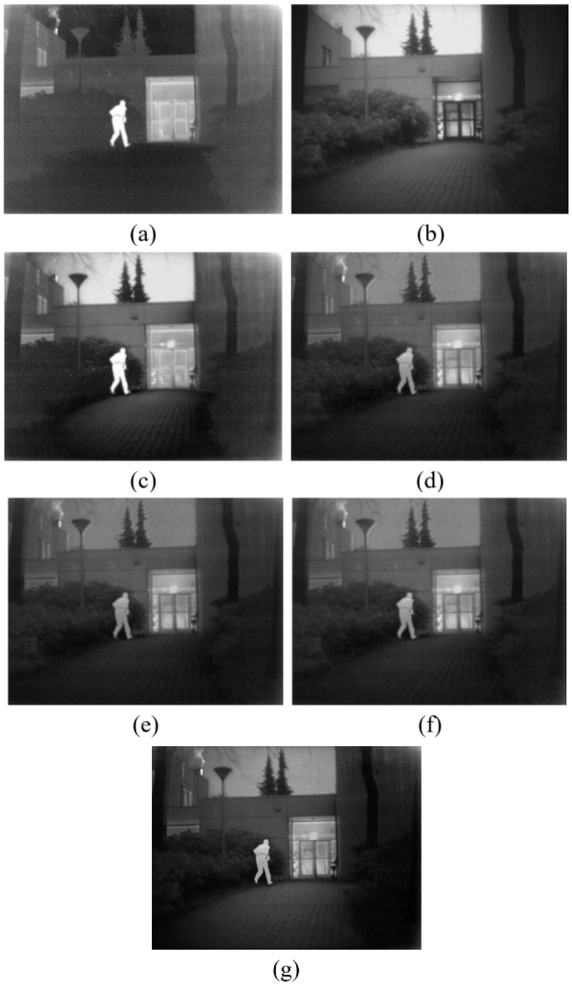
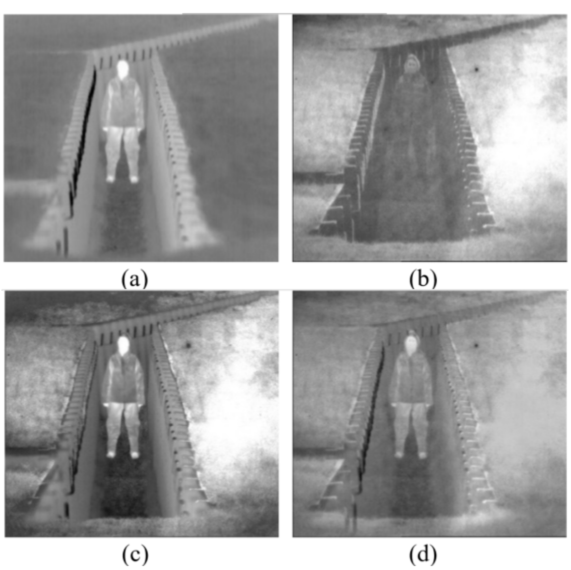


Fig. 4. Visual results of image-set 2. (a) Infrared source image (b) Grayscale source image (c) Maximum Intensity based fusion (d) Average based fusion (e) DWT based fusion (f) Discrete Stationary Wavelet Transform based fusion (g) proposed



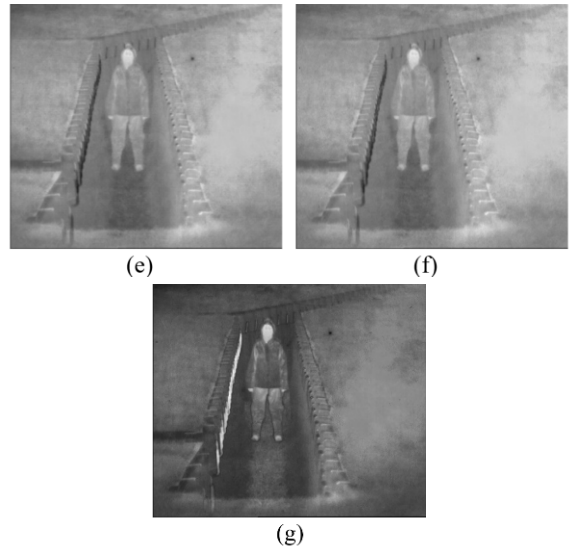


Fig. 5. Visual results of image-set 3. (a) Infrared source image (b) Grayscale source image (c) Maximum Intensity based fusion (d) Average based fusion (e) DWT based fusion (f) Discrete Stationary Wavelet Transform based fusion (g) proposed

In Table 2, results of image quality assessment matrices are presented for image-set 2. In this table, it is clear that the proposed method again got highest values for MS-SSIM, PSNR, and Entropy whereas lowest for RMSE. For image-set 3, image quality assessment results are presented in Table 3. It is evident from the results that the proposed algorithm got highest values in all matrices. These results backed our claim that the proposed method produced the fused image having better structural and color similarity with source images while having minimum error rate. Therefore, it is apparent that our proposed fusion method is a better alternative to fuse infrared and visible images.

Table 1. Objective quality assessment of image-set 1

	MS-SSIM	**PSNR**	**RMSE**	**Entropy**
Maximum Intensity Fusion	0.532	17.33	0.044	6.713
Average Fusion	0.621	19.315	0.043	6.752
DWT based Fusion	0.571	18.889	0.043	6.736
DSWT based Fusion	0.603	20.06	0.041	6.759
Proposed	0.836	25.758	0.039	7.062

Table 2. Objective quality assessment of image-set 2

	MS-SSIM	PSNR	RMSE	Entropy
Maximum Intensity Fusion	0.524	15.222	0.025	7.069
Average Fusion	0.585	15.868	0.025	6.894
DWT based Fusion	0.508	15.282	0.026	6.557
DSWT based Fusion	0.600	15.818	0.025	6.850
Proposed	0.634	20.411	0.023	7.205

Table 3. Objective quality assessment of image-set 3

	MS-SSIM	PSNR	RMSE	Entropy
Maximum Intensity Fusion	0.581	17.527	0.019	7.014
Average Fusion	0.816	17.863	0.019	6.994
DWT based Fusion	0.685	17.792	0.018	6.196
DSWT based Fusion	0.844	18.374	0.017	6.906
Proposed	0.791	26.079	0.015	7.320

IV. CONCLUSION

This study proposes a new technique to merge features of grayscale and Infrared images to get a hybrid image. The proposed technique makes use of DWT to decompose source images from spatial domain to frequency domain and PSO algorithm to find optimum fusion weights to be used in the fusion process. Working of this fusion technique is tested on three sets of images where each set contains two images; one grayscale and one infrared. The output of this technique is compared with the output of four existing image fusion algorithms from the same domain. To test the quality of output image, objective image quality assessment method is used by incorporation four of the image quality assessment matrices. Numerical values produced by image quality assessment matrices shows clear superiority of the proposed technique. Therefore, it is evident that the proposed image fusion technique is a good alternative to fuse grayscale and infrared images.

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