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# Stationary Wavelet Transform Image Fusion and Optimization Using Particle Swarm Optimization

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***Abstract:*** *The complementary nature of imaging sensors of different modalities all brought a great need of image fusion to extract relevant information images. Image fusion using Stationary wavelet transform (SWT) and optimize parameter using particle swarm optimization (PSO) has been implemented and demonstrated in PC MATLAB. In this paper selected images are fused and results obtained are tabulated. The objective of proposed algorithm was to maximize the total number of pixel in the edges to improve the resolution of edges details, thus being able to visualize more details in the images. In proposed algorithm, entropy is taken as selection criteria in stationary wavelet decomposition and PSNR is applied as the fitness function on particle swarm optimization to the data set The performance of proposed algorithm is measured by peak signal to noise ratio (PSNR), entropy, mean square error (MSE), standard deviation, (STD) etc.*

***Keywords:*** *Image fusion, Particle Swarm optimization, peak signal to noise ratio, entropy, Stationary Wavelet Transform.*

## I. Introduction

In computer vision, multisensory image fusion is technique to extract relevant information from two or more source images into single fused image that contains great quality feature often means highest spatial or higher spectral resolution as well as more reliable and accurate informative as compared to any of the source image. Generally, Image fusion methods can be classified into two categories -Direct image fusion and Multi - resolution image fusion that is based on pixel level fusion method [1]. It is often divided into three levels depending on the stage at which fusion takes place, namely: pixel level, feature level and decision level of representation. Pixel fusion is the lowest –level fusion, which analyzes and integrates the information before the original information is estimated and recognized. Feature fusion is done in the middle level, which analyzes and deals with the feature information such as edge, contour, direction obtained by pretreatment and feature extraction. Decision fusion is the highest –level fusion, which points to the actual target. Before fusion, the data should be procured to gain the independent decision result, so the information lose cannot be avoided and at the same time the cost is high [3].

Image fusion is necessary techniques in some cases where it is not possible to obtain an image that contain all important objects in focus due to limited focus depth of optical lenses in CCD devices. Consequently, resultant image will not be in focus everywhere. Image fusion process is required to achieve all objects in focus so that all focused objects are selected. In recent years, image fusion has been widely used in medical field, military operation, in satellite etc. [5].In addition, an increasing number of applications, such as feature detection, change monitoring and land cover classification; often demand the highest spatial and spectral resolution for the best accomplishment of their objectives. In response to those needs, image fusion has become a powerful solution providing a single image with simultaneously the multispectral content of the source image and an enhanced spatial resolution [6].

The complementary nature of imaging sensors of different modalities, all brought a great need of image fusion to extract relevant information from medical images. The significance of fusion process is important for multisensory images as single sensor images provides only specific information; thus it is not feasible to get all the requisite information from image generated by single sensor in imaging [8].This paper utilizes stationary wavelet transform (SWT) to fuse the different multisensory general images and optimize the results using Particle Swarm Optimization (PSO).The proposed algorithm is tested on number of selected images and results obtained are tabulated.

Richa gupta et.al fused the multisensory images by wavelet packet based method with genetic algorithm as an optimization algorithm [5]. However, the discrete wavelet transform (DWT) is lack of translation variant property. S.S Bedi et.al fused the images by using hybrid of wavelet and curvelet fusion rule [4] where the image undergoes fusion twice using efficient fusion technique provide improved result. This method is complex and required good fusion technique for better results.

# II. Proposed fusion approaches

## 2.1 Stationary Wavelet Transform (SWT)

Wavelet Transform is basically used in feature detection of MRI, signal de-noising, pattern recognition and brain image classification. Richa gupta et.al fused the multisensory images by wavelet packet based method with genetic algorithm as optimization algorithm [5]. However, the discrete wavelet transform (DWT) is lack of translation variant property which can be nullified by using stationary wavelet transform (SWT). In SWT, even if the signal is shifted, the transformed coefficient will not change and also performs better in de-noising and edge detecting. In contrast to DWT, SWT can be applied to any arbitrary size of images rather than size of power of two and has shown better fusion performance in medical and other images.

SWT is similar to DWT is more commonly known as “algorithm a trous” [9] in French meaning “with holes” which refers to inserts zeros in the filter for up sampling the filter and suppressing the down sampling step of the DWT [7].As with DWT, First the filters is applied to the rows and then the columns as results four images are produced (one approximation and three horizontal, vertical and diagonal detail images.

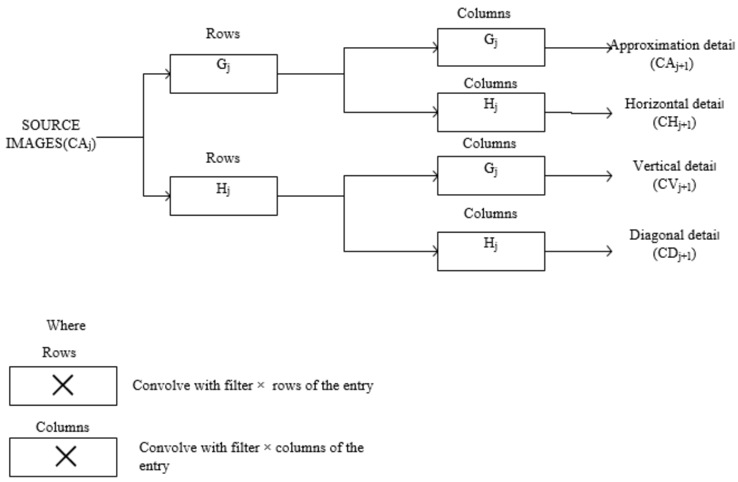



**Figure 1** Decomposition steps for two dimensional SWT

Translation invariance of is achieved by removing the down samples and up samples in the DWT and up sampling the coefficients by the factor of $2^{j-1}$ in the jth level of the algorithm. Therefore, The SWT is redundant technique as the output of each level of SWT contains the same number of samples as input and improves the resolution of edges details with three groups of wavelet coefficients [7].

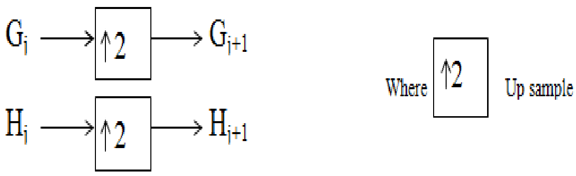



**Figure 2** Final Computation

## 2.2 Particle Swarm Optimization

Particle Swarm Optimization is population based stochastic optimization algorithm, introduced by Dr. James Kennedy and Dr. Russell Eberhart in 1995.Particle swarm optimization is inspired by social behavior of bird flocking and school of fish and swarming theory in particle [10] and used to solve various problems in telecommunication, robotic, military and medical application [11]. In computer language, the swarm is similar to a population (set of particles) while each particle represents a potential solution [12].Unlike other approaches of evolutionary algorithms, the particle Swarm Optimization uses neither mutation nor crossover. To find the best solution PSO uses local and global information [13-14].

In PSO process, initially a group of random particles are considered and particle’s fitness function is evaluated .Each particle moves with a adaptive velocity as given in equation (1) in search space and update its position by keep track of previous best position called pbest (position best) based on best experience of the particle itself and its neighbors or globally the whole swarm called gbest (globally best).

$$V_i = wV_{i-1} + C_1 * rand(.) * (pbest - X_i) + C_2 * rand(.)(gbest - X_i) \quad (1)$$
$$X_i = X_{i-1} + V_i \; (2)$$
$$w = \frac{1}{gen.Num} \; (3)$$

Where $V_{i-1}$, $V_i$, $X_i$ are previous velocity, modified velocity and position of particle i respectively.$C_1$ and $C_2$ are cognitive and stochastic coefficients that influence particle velocity. rand is a random number ranges between 0 &1.gen. Num is current generation number.

This algorithm then searches for optimum results through a series of generation. The location of best position of search space it has ever visited is stored in pbest and the best fitness function achieved during any generation is stored in gbest. The update process is repeated until the maximum number of generation is reached or specified fitness function is achieved as shown in Fig 3.

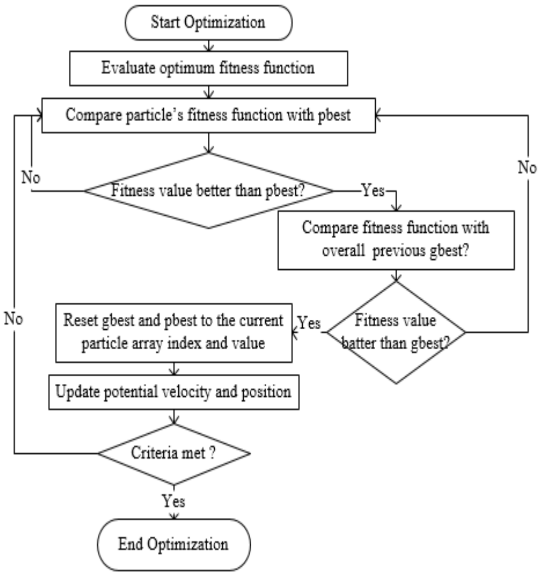



**Figure 3** Flow diagram of particle swarm optimization

## III. Proposed algorithm

In our proposed algorithm we have first register source images to assure that the corresponding pixels are aligned. After that SWT is applied to decompose images into wavelet transformed images. The transform coefficients of different portions are performed with a certain fused rule. Apply optimization on transformed images by using particle swarm optimization (PSO).The fused image is constructed by performing an inverse stationary wavelet transform (SWT). The whole process is shown in Fig. 4.

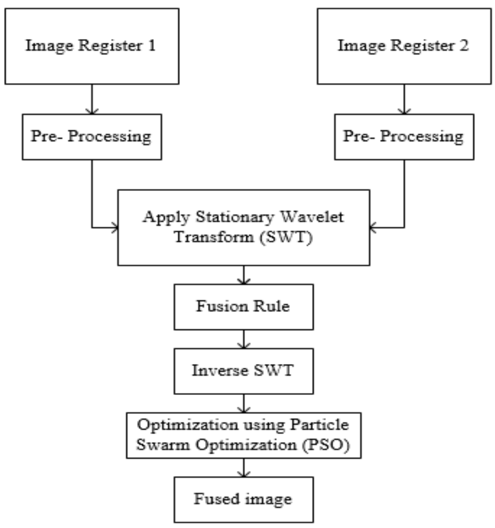



**Figure 4:** Proposed algorithm

## IV. Objective evaluation for image fusion

The quantitative evaluation parameters are as follow [5]. The parameter evaluated mainly peak signal to noise ratio, mean square error, mutual information etc.

### 4.1 Peak Signal to Noise Ratio

PSNR will be high when the fused and source images are alike. Higher value means better fusion. It is computed as:

$$PSNR = 10\log_{10}\left(\frac{L^2}{RMSE}\right) \quad (4)$$

Where L is the number of gray level in the image
Where $I_x(i,j)$ =source image
$I_f(i,j)$=fused image.

### 4.2 Standard Deviation

It is known that standard deviation is composed of the signal and noise parts and it is more efficient in the absence of noise. It measures the contrast in the fused image. An image with high contrast would have a high standard deviation.

$$\sigma^2 = \frac{1}{N-1}\sum_i^n (x-\mu)^2 \qquad (5)$$

Where µ= number of pixels.

### 4.3 Mutual Information

Larger value of mutual information indicates better image quality. The best possible value is 0.

$$MI = \sum_{i=1}^{M}\sum_{j=1}^{N} h_{I_x I_f}(i,j)\log_2\left(\frac{h_{I_x I_f}(i,j)}{h_{I_x}(i,j)h_{I_f}(i,j)}\right) \qquad (6)$$

Where $I_x$=original image and $I_f$=fused image.

### 4.4 Mean Square Error

It computed as the mean absolute error of the corresponding pixels in source and fused image. The value is given relative to the mean value of the original image. The ideal value is 0.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|I_x(i,j) - I_f(i,j)\right| \qquad (7)$$

### 4.5 Entropy

Entropy is defined as amount of information contained in an image. Shanon was the first person to introduce entropy to quantify the information. Entropy is sensitive to noise and other unwanted rapid fluctuation. If entropy of the fused image is higher than parent image then it indicates that the fused image contains more information. Using the entropy, the information content of a fused image $I_f$ is

$$He = -\sum_{i=0}^{L} h_{I_f}(i)\log_2 h_{I_f}(i) \qquad (8)$$

### 4.6 Variance

Variance filter is basically used to determine the edge detection and to find how each pixel varies from the neighboring pixel. It is computed as:

$$\sigma^2 = \frac{\sum(x-\mu)^2}{N} \qquad (9)$$

X=Source image, µ= mean of the population and N=number of source images.

## V. Results and Discussion

This section contains the qualitative and quantitative analysis of the fused images taken from the proposed algorithms.

### 5.1 Data Set

The proposed algorithm is tested on three multisensory general images. All the images are of same size i.e. 256*256.Evaluation parameter play vital role in measuring the quality of image obtained from proposed fusion algorithm. The objective of proposed algorithm was to maximize the total number of pixel in the edges thus being able to visualize more details in the images. The parameter evaluated mainly entropy, peak signal to noise ratio (PSNR), mean square error (MSE), mutual information (MI), standard deviation (STD) and variance etc.

### 5.2 Qualitative and quantitative analysis

Source images and qualitative analysis results for data set using SWT-PSO is shown in fig 5, while the quantitative results are outlined in table 1. In proposed algorithm, entropy is taken as selection criteria in stationary wavelet decomposition and PSNR is applied as the fitness function on particle swarm optimization to the data set.

**Table 1:** Resultant Fused Images Using Swt-Pso

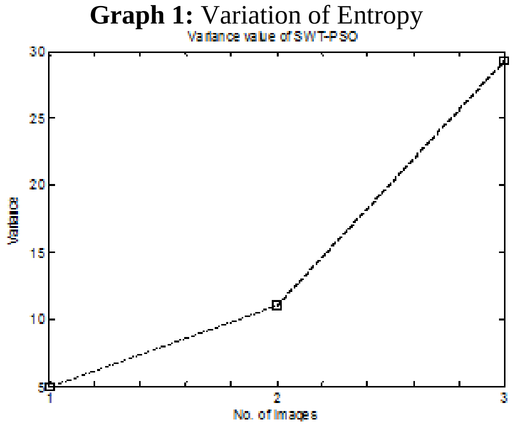
| Image | Source image 1 | Source image 2 | SWT- PSO fused image |
|---|---|---|---|
| Image 1 |  |  |  |
| Image 2 |  |  |  |
| Image 3 |  |  |  |

**Table 2:** Quantitative Analysis of SWT-PSO

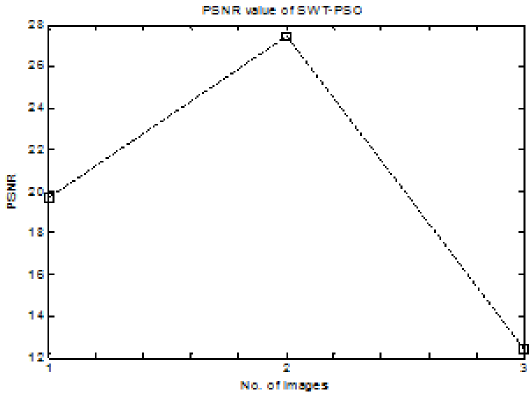
| Parameter | Entropy | Variance | PSNR | MI | MSE | STD |
|---|---|---|---|---|---|---|
| Image 1 | **22.21** | 5.00 | **19.70** | 0.68 | 0.69 | 0.22 |
| Image 2 | **21.10** | 11.01 | **27.46** | 2.30 | **0.12** | 0.27 |
| Image 3 | **17.60** | 29.33 | 12.40 | 0.63 | 3.73 | 0.54 |

Graph of results for given image data set are shown below

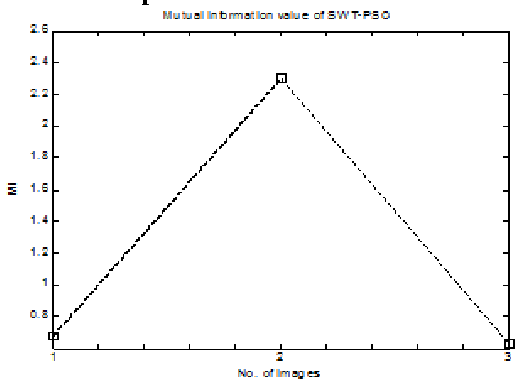
**Graph 1:** Variation of Entropy



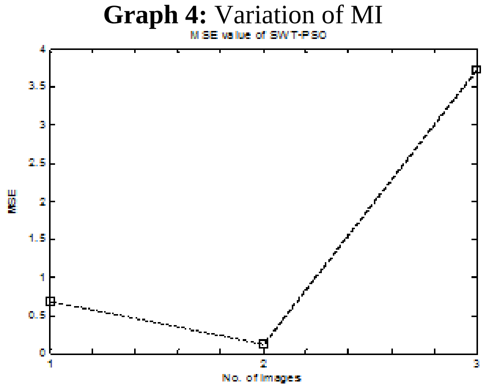
**Graph 2:** Variation of Variance



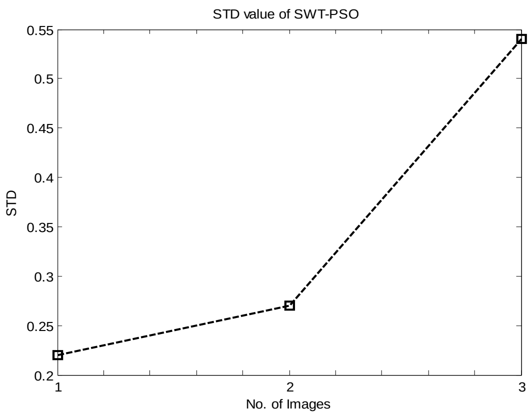

**Graph 3:** Variation of PSNR



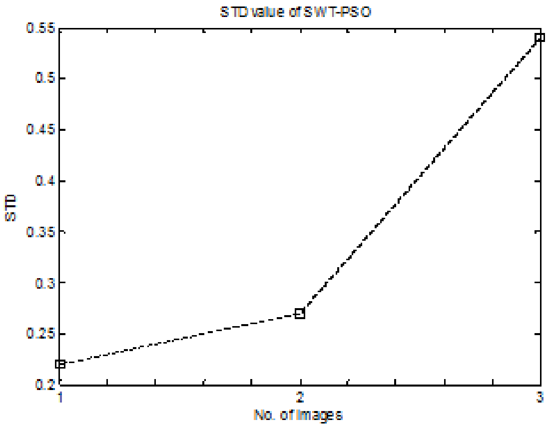

**Graph 4:** Variation of MI




**Graph 5:** Variation for MSE



**Graph6:** Variation for STD




## VI. Conclusion

In this paper, three multisensory images are fused using stationary wavelet transform and real coded particle swarm optimization (PSO) is applied for image enhancement. In proposed algorithm, entropy is taken as selection criteria in stationary wavelet decomposition, corresponding value of entropy found are 22.21, 21.10, 17.60 and PSNR is applied as the fitness function on particle swarm optimization to the data set, found that values of PSNR are 19.70, 27.46 and 12.40 for image 1, image 2 and image 3 respectively. By applying PSNR as the fitness function to the data set, it is observed that PSNR has high value by de-noising the images implying that present work is capable of giving good quality fused image with more informative contents. Hence, this proposed work is very much useful for number of images.

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