Histogram Driven Fusion of Set of Images Using Multi-thresholding and Optimization for WSN

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Abstract— **The recent developments of the Wireless Sensor Network (WSN) with low power cameras have made the possibility of transferring the raw images to the remote areas at any time. As a result, the energy consumption during computation is more. To alleviate this problem, a mechanism called image fusion using histogram-based multi-thresholding with entropy and optimization technique is proposed in this paper. Here, the impact of the blurred effect over the images is also reduced to some extent by averaging the pixels using the entropy. But the entropy affects the computational complexity of the proposed fusion algorithm during the identification of the optimal thresholds. Hence, the optimization technique named improved harmony search algorithm is used to maximize the entropy with less computational time. Finally, by comparing the threshold values of each input images, the set of optimal thresholds create the approximate histogram of the fused output. In this paper, the selection of the number of thresholds decides the computational complexity and the quality of the proposed fusion algorithm. From the simulation results, without compromising the performance metrics and the quality of the image, the number of bits required for representing the proposed fused output is very less compared to that of the other standard image fusion methods.**

Keyword- Entropy, Multi-thresholding, Optimization, Fusion, Harmony Search Algorithm

I. INTRODUCTION

The extension of the Wireless Sensor Network (WSN) with camera nodes and microphones are called as Wireless Multimedia Sensor Network (WMSN). The emerging WMSN have the potential to transfer the still images and videos of the particular environment area through the sensor network for various applications like remote sensing, animal tracking and intruder detection for military based applications etc [1][2]. Due to the usage of more number of less expensive low power cameras in WMSN, several images of the scene are captured with a different focus on objects. But the sensor devices are always constrained in terms of storage capacity, battery life and limited bandwidth. Hence, to transmit the details of all the captured images for different applications, a technique called image fusion is utilized to combine the important features of the multiple captured images into single one. Generally, the resultant fused image requires less memory space for storage and less energy consumption during transmission. Further, it contains required information with better image quality for further processing [3].

In particular, image fusion [4] algorithm extracts information from the source images such that the fused image provides better information for human or machine perception as compared to any of the input images. Image fusion process can take place at different levels namely at pixel, feature, region and symbolic levels [5]. In common, these fusion methods are broadly categorized into two groups, including spatial domain fusion and transform domain fusion. Spatial domain techniques are carried out directly on the source images. Weighted average method [6] is the simplest spatial domain approach. However, this method leads to several undesirable side effects like reduced contrast and loss of information. On the other hand, each source image is first decomposed into a sequence of multi-scale coefficients in transform domain [7]. Then, depending upon the amount of information contained by the each input image coefficients, the fusion is performed. Various fusion rules are then employed in the selection of these coefficients which are synthesized via inverse transforms to form the fused image [8]. The above mentioned two different image fusion categories have a number of perceived advantages, however, as on date, no any single fusion approach is sufficient to fulfill all the requirements of the WMSN without any drawbacks i.e. each fusion method is more or less limited by some constraints. Thus, some of the existing fusion approaches are integrated with the optimization algorithms to address complex problems which in turn lead to improving the accuracy of fusion results.

In this paper, an image fusion using histogram-based multi-level thresholding and optimization algorithm is proposed for different image sets. The main contribution of the method lies in the selection of optimal thresholds from the source images by using entropy and optimization algorithm. Here, the use of optimization algorithm is to identify the best thresholds of source images. The integration of optimization algorithm and the selection of the number of thresholds in image fusion provide less computation time which in turn reduces the amount of energy consumption. Also, it can preserve more details from source images and thus the quality of the fused images is improved. In this method, the selection of the number of thresholds in multi-thresholding determines the quality of the fused image. If the number of thresholds is increased then the accuracy of the proposed image fusion is more than that of the existing techniques.

The rest of the paper is organized as follows: Section II deals with the various concepts so far used in image fusion algorithm. Section III discusses the detailed working principle of the proposed image fusion technique. Section IV describes the several performance metrics used to evaluate the image fusion. Section V demonstrates the analysis of the simulation results and comparison of the proposed with the existing techniques and finally, the research work is concluded in Section VI.

II.   RELATED WORK

Over the years, numerous image fusion approaches have been developed and employed for different sensor based applications. Out of these, the transform-based image fusion algorithms are very popular than that of the spatial based fusion approaches. In this regard, Hu Li et.al [9] introduced the Discrete Wavelet Transform (DWT) as a fusion tool in image fusion algorithm. But the fused output is not perfect because of its shift invariant property. So, Gurpreet Singh [10] has presented an enhanced version of the DWT to improve the quality of the fused output with less computational complexity. Later, discrete stationary wavelets and curvelet transform are proposed to improve the image quality [11][12]. Though these proposed wavelets enhanced the quality of the image and are having less number of convolution measurements, it requires more memory space for computation. Therefore the above image fusion algorithms are not satisfied one of the attributes of the WMSN.

As a result, Discrete Cosine Transform (DCT) is incorporated with the fusion algorithm to offer less number of mathematical implementations and also it requires very less amount of energy to process the image. But the averaging of DCT of input images for obtaining the fused output causes a blurring and blocking artifact [13]. This can be rectified by using the statistical characteristics such as mean, variance and contrast in DCT domain for image fusion [14]. Recently, instead of calculating the mean and variance, Asnath et.al [15] have proposed an energy efficient image fusion technique especially designed for visual sensor network by using Alternating Current (AC) coefficients of DCT and consistency verification only. Therefore, the efficiency of the fusion performance is improved significantly by using the DCT with the higher valued AC coefficients. Followed by Asnath, Liu Cao et.al [16] have modified the DCT based image fusion algorithm for WMSN further by considering the spatial frequency of the corresponding blocks from the source images. The blocks with the larger spatial frequencies are only taken into account to compose the image fusion.

At the same time, some of the researches concentrated on another approach called integration of optimization algorithm on image fusion. From the literature survey, there are lot of optimizations such as Genetic Algorithm (GA) [17], Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithms [18] are easily adopted with the transform based image fusion as well as with the different levels of the spatial based image fusion techniques. The latest versions of the wavelet based fusion algorithms with optimization algorithm are excellent in image quality and have no block artifacts, but, in general, they are complicated and more time to consume during implementation in WMSN. Hence, the usages of the wavelet based fusion rules with optimization are not practically applicable for WMSN. Hence, the researchers are further motivated by utilizing the spatial domain based fusion technique for sensor-based applications. For example, Veysel Aslantas and Emre Bendes [19] have appended the differential evolution based optimization algorithm in the region based multisensor image fusion to improve the image quality.

Apart from that, Li-Ying Yang [20] has introduced the particle swarm optimization in pixel based image fusion to enhance the image fusion. But they have not satisfied all the requirements of the WMSN based image fusion because of their global optimization characteristics and low convergence. To solve this, another method of optimization based image fusion called bio-geography optimization based multi-focus image fusion is proposed by Ping Zhang et.al [21]. In this technique, the precision of the optimization is improved by adapting the chaotic search. The combination of the fusion techniques with optimization presented so far is to satisfy the energy consumption of the WMSN either by reduce the mathematical implementations or selecting the less number of blocks from each input image for the fusion process. Hence, in this paper an attempt is made to develop the efficient image fusion algorithm using less number of mathematical computations as well as selecting less number of samples from each input image; a detailed discussion of the proposed image fusion method is explained in the following section.

III.   PROPOSED METHOD

This paper mainly concentrates on the histogram based multi-thresholding as a major part in the selection of important features during image fusion. To enhance the image quality and reduce the computation time of the fused image significantly, the local based search optimization called improved harmony based search algorithm is appended with the proposed histogram based multi-thresholding. For explaining the concept of the proposed algorithm, only two input images are considered for the fusion process. But the proposed algorithm can be extended for fusion of more than two images. In this algorithm, a global and objective property of the histogram and Shannon entropy are used for choosing optimal thresholds from the gray-level histogram of an each input image. By comparing the optimal threshold values, the fusion is obtained.

To understand the concept of the proposed image fusion algorithm more precisely, it is necessary to give the brief introduction of the concept of multi-thresholding, Shannon entropy, and the optimization algorithms namely DE and Improved Harmony based Search Algorithm (IHSA). Finally the working principle of the proposed image fusion algorithm is explained with the flowchart.

A. Histogram based Multi-Thresholding

It is used to determine more than one threshold values by using the histogram to divide pixels into several groups called bins [5]. Let L gray levels are to be assumed in a given image I and these gray levels are in the range *0,1,2........L-1*. The threshold value *(G)* [22][23] of each level are obtained by using the following equations,

$$G_0 = \{(x, y) \, \epsilon \, I \mid 0 \leq f(x, y) \leq t_1\text{-}1\} \qquad (1)$$

$$G_1 = \{(x, y) \, \epsilon \, I \mid t_1 \leq f(x, y) \leq t_2\text{-}1\} \qquad (2)$$

$$G_2 = \{(x, y) \, \epsilon \, I \mid t_2 \leq f(x, y) \leq t_3\text{-}1\}............ \qquad (3)$$

$$G_k = \{(x, y) \, \epsilon \, I \mid t_k \leq f(x, y) \leq L\text{-}1\} \qquad (4)$$

Where *f(x, y)* is the gray level of the point *(x, y)* and t_i *(i=1,2.....k)* is the ith threshold value and k is the number of the thresholds. Selecting more than few optimal threshold values for multi-level thresholding requires a high computational cost. This problem is suppressed in the most efficient way by utilizing the entropy with optimization technique.

B. Shannon Entropy

Shannon entropy [24] is the first developed entropy as a measure of uncertainty. The expected value of the information contained *H(x)* using Shannon entropy is expressed in Eq. (5),

$$H(x) = -\sum\nolimits_{i=0}^{n} p(x_i) * \log_2 p(x_i) \qquad (5)$$

Where *P(x_i)* is the probability of the occurrence of an element x_i and n is the total number of states.

C. Differential Evolution Based Optimization

The proposed image fusion method makes use of the DE or IHSA as an optimization algorithm to construct a fused image in which the regions of source images are emphasized optimally. In that, the DE is a well-known population-based, heuristic and evolutionary optimization algorithm that is proposed by Price and Storn [25]. Before implementing the DE as optimization for further processing, certain control parameters of DE have to be determined initially like Generation size (G), Population size (P), scaling factor (F) and Crossover constant (CR). The main steps to be followed for implementing the DE are,

- Set the initial control parameters of the DE,
- Create initial population,
- Mutation and crossover,
- Selection,
- Repeat the last two steps until stopping conditions are satisfied.

D. Improved Harmony Search based Optimization Algorithm

The selection of the optimization algorithm for energy constrained sensor based fusion techniques is based upon their implementation and mathematical computations. In that way, HSA is a very good match for the proposed fusion algorithm. HSA [26] is a music-inspired algorithm used to mimic the behavior of music orchestra when they search for a better state of harmony. It provides a good balance among local based algorithms and population-based algorithms to reach a suitable balance between exploration and exploitation. Though HSA has many impressive advantages but poor in convergence rate. Hence the performance of HSA is improved by modifying the parameters such as Harmony Memory Considering Rate (HMCR), Pitch Adjusting Rate (PAR), BandWidth (BW). The parameter settings of the IHSA [27] is formulated as follows,

$$PAR = PAR_{MIN} + \frac{PAR_{MAX} - PAR_{MIN}}{NI} \times gn \tag{6}$$

$$HMCR = HMCR_{MAX} - \left[\frac{(HMCR_{MAX} - HMCR_{MIN}) \times gn}{NI} \right] \tag{7}$$

$$BW = \begin{cases} \dfrac{BW_{MAX}}{1 + K\left(\dfrac{i}{NI}\right)^2}, i < \dfrac{NI}{2} \\[4mm] BW_{MIN}, i \geq \dfrac{NI}{2} \end{cases} \tag{8}$$

Where gn is a current generation number and $k = \ln\dfrac{BW_{MAX}}{BW_{MIN}}$
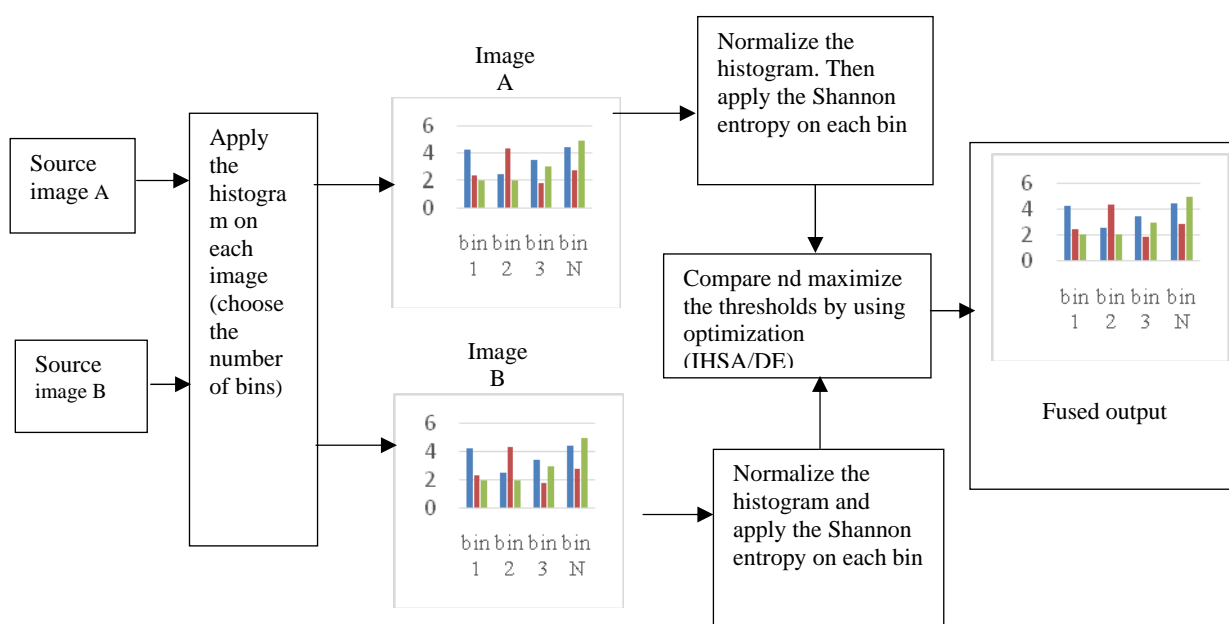
E. Working principle

Fig. 1. Block Diagram of the Proposed Method

Fig.1 illustrates the general working principle of the proposed image fusion algorithm. To obtain the fusion of multiple images, the input images are first partitioned into a number of bins using the histogram concept. After the separation of each input image into a number of bins, the probability of the pixels from each bin is averaged by using the shannon entropy. Although the entropy provides the better result in terms of grouping the pixels, the time required to process the pixels is more and also the average of pixels is not accurate. To improve the probability of the entropy, the proposed fusion algorithm is tested with two different optimization algorithms namely DE and IHSA.

Out of that, the usage of DE based optimization with shannon entropy provides better results than that of the other existing optimization techniques such as GA, PSO, and ACO in terms of time complexity and image quality. But, the reduction in computation time is not enough to save energy consumption for sensor-based applications. Hence, to construct the fused image, the optimal thresholds of input images are selected and the variation of thresholds are measured by combining the fast and effective optimization algorithm called IHSA with Shannon entropy. The number of thresholds with greater values is selected to get the precise threshold value. Hereafter, the working principle of the proposed fusion algorithm is discussed by using the optimization algorithm IHSA and the overall working steps are summarized as follows,

Step 1: The size of the two input images must be checked before using the fusion algorithm. If it is same, then the fusion rule is applied on both images. The number of required thresholds (NT) is initialized to construct the fused image.

Step 2: By using the histogram, divide the input images into a number of non-overlapping bins according to their pixel values and NT.

Step 3: The initial parameters such as HMCR, BW, PAR and Harmony Memory (HM), Number of Improvisations (NI) of the IHSA based optimization is defined.

Step 4: The solution vectors *x(i)* are randomly generated and stored in an HM. Here *i* is varied from *1 to n*

Step 5: To obtain the appropriate threshold value, the Shannon entropy (H) is applied on each bin to average the pixels from each bin of the input images.

Step 6: To construct the fused image, the HM is updated by comparing the pixel values of the bin from first input image to the bin value from the second input image. The threshold value of the first input image is included in the HM if it is better than the second input image threshold value; otherwise, the old value is retained in HM.

Step 7: Repeat the step 4 until maximum iteration NI is reached. Finally, the best threshold values are obtained by maximizing the two input images and the results are stored to form a fused image. The mean values of the each bin from the input images are also taken as a reference to enhance the fused output image.

IV. PERFORMANCE ANALYSIS

Assessing the quality of the fused images is essential before directly using them for real-world applications. As suggested by definitions of image fusion, the features with fine details of the source images are selected and combined through the fusion scheme, and hence uncertainties such as spatial and spectral distortions may be introduced into the fused image. Therefore, quality assessment should be performed by applying various metrics to evaluate the quality of the fused results. In general, quality assessment metrics can be performed through qualitative and quantitative analyses. Qualitative assessment refers mainly to visual interpretation of the fused image by comparing the similarity of features (e.g., geometric pattern, size, color, and others) in the fused image with those in other relevant images. The major advantage of qualitative assessment is its simplicity due to the lack of numerical models, but it is subjective and depends largely on the experience of the operators and viewing conditions. In contrast to the qualitative analysis, quantitative analysis can more intuitively report the exact accuracy level of the fused images by using a variety of statistical indicators as quality measures. In the past decades, numerous performance parameters are adopted to evaluate the performance and accuracy of image fusion methods. Some of them are mentioned in Table-1[28][29].

TABLE 1. Evolution Parameters of Image Fusion Algorithm

No.	Evolution Parameter	Formula
1.	Average Pixel Intensity (API): Measures an index of contrast	$API = \dfrac{\sum_{i=1}^{m}\sum_{j=1}^{n} f(i,j)}{mn}$ where f(i,j) is pixel intensity at (i,j) and image size is m×n.
2.	Standard Deviation (SD): Square root of the variance	$SD = \sqrt{\dfrac{\sum_{i=1}^{m}\sum_{j=1}^{n}(f(i,j)-API)^2}{mn}}$
3.	Average Gradient (AG): It measures a degree of clarity and sharpness	$AG = \dfrac{\sum_i \sum_j \left((f(i,j)-f(i+1,j))^2 + (f(i,j)-f(i,j+1))^2\right)^{1/2}}{mn}$
4.	Entropy (H): To measure the amount of information present in the image	$H = -\sum_{i=0}^{n} P(x_i)\log_2 p(x_i)$
5.	Mutual Information (MI): It gives the overall mutual information between source images and fused image	$MI = MI_{AF} + MI_{BF}$ where, $MI_{AF} = \sum_k \sum_l P_{AF}(k,l)\log_2\left(\dfrac{P_{AF}(k,l)}{P_A(k)P_F(l)}\right)$ $MI_{BF} = \sum_k \sum_l P_{BF}(k,l)\log_2\left(\dfrac{P_{BF}(k,l)}{P_{AB}(k)P_F(l)}\right)$
6.	Spatial Frequency (SF): It measures the overall information in the region of an image	$SF = \sqrt{RF^2 + CF^2}$ where, $RF = \sqrt{\dfrac{\sum_i \sum_j (f(i,j)-f(i,j-1))^2}{mn}}, CF = \sqrt{\dfrac{\sum_i \sum_j (f(i,j)-f(i-1,j))^2}{mn}}$

7.	Petrovic metric($Q^{AB/F}$): Total information transferred from source images to fused image	$$Q^{\frac{AB}{F}} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(Q^{AF}(i,j)W^{A}(i,j)+Q^{BF}(i,j)W^{B}(i,j)\right)}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(W^{A}(i,j)+W^{B}(i,j)\right)}$$ where, Q^{AF}, Q^{BF}-Edge information preserve values $W^{A}(i,j)$, $W^{B}(i,j)$ -weighted importance factors
8.	Fusion Symmetry (FS): It shows how much symmetric the sensor images with the fused image.	$$FS = 2 - \left| \frac{MI_{AF}}{MI} - 0.5 \right|$$

V. RESULTS AND DISCUSSION

The simulations are carried out with MATLAB2014 using a various standard set of images such as multi-focus, medical and multi-sensor images. For demonstrating purpose, the comparison of proposed fusion method for different threshold levels is done only for 3 set of images namely multi-focus (disk), medical (MRI) [30] and multi-sensor from Berkley dataset [31]. The proposed fusion algorithm using different optimization algorithms namely DE and IHSA is compared with the standard Discrete Cosine Harmonic Wavelet Transform (DCHWT) and Dual-Tree Complex Wavelet Transform (DTCWT) based image fusion with respect to quantitative and qualitative analysis. To understand the behavior of the proposed method, all the source images of different datasets are analyzed up to maximum threshold levels. Before getting into the simulation, it is necessary to choose the parameters of the optimization algorithms. The choice of DE parameters listed in Table-2 is into consideration as inferred from the paper [32]. As inferred from the literature survey [27] [33], the parameters of the IHSA used in the simulation are also mentioned in Table 2.

TABLE 2

Parameters of DE		Parameters of IHSA	
Parameter	value	**Parameter**	Value
Differential weight(F)	0.5	HMS	100
Crossover probability(CR)	0.95	PAR	0.9
Population size(P)	50	HMCR	0.95
Lower and upper bound	[0,255]	BW	[0,1]

It is very easy to find out instantly the maximum amount of information transferred from the source images to fused image and also the artifacts developed after fusion by using visual analysis. Here the first analysis is conducted over the three different sets of images as shown in Fig.2 by varying the number of thresholds of the proposed algorithm to construct the fused image. Through the results, it is observed from the figures 3 to 5, the DE and IHSA based proposed image fusion technique produced similar results for all set of images.

Multi-focus image A	Medical image A	Multi-sensor image A
Multi-focus image B	Medical image B	Multi-sensor image B
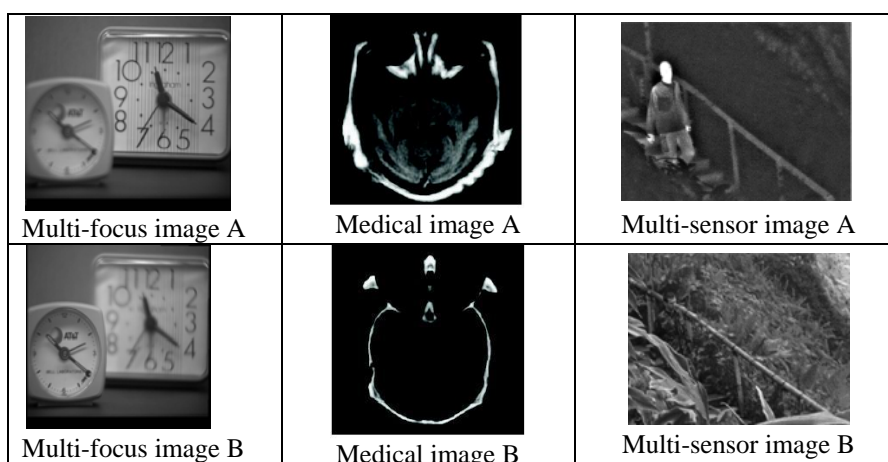
Fig.2 Different set of input images

Fig.3 Multi-focus fused output of the proposed fusion algorithm using IHSA and DE for different threshold levels

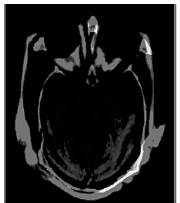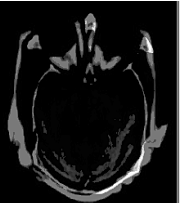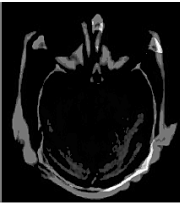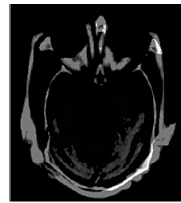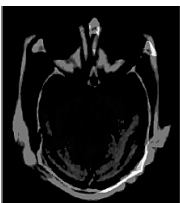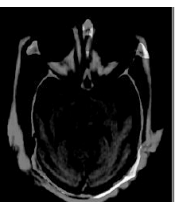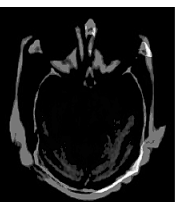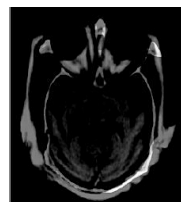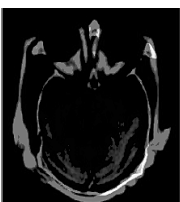Fig.4 Medical fused output of the proposed fusion algorithm using IHSA and DE for different threshold levels

Fig.5 Multi-sensor (Berkley Dataset) fused output of the proposed fusion algorithm using IHSA and DE for different threshold levels

DCHWT output	DTCWT output	Proposed with DE (NT=40)	Proposed with IHSA (NT=40)
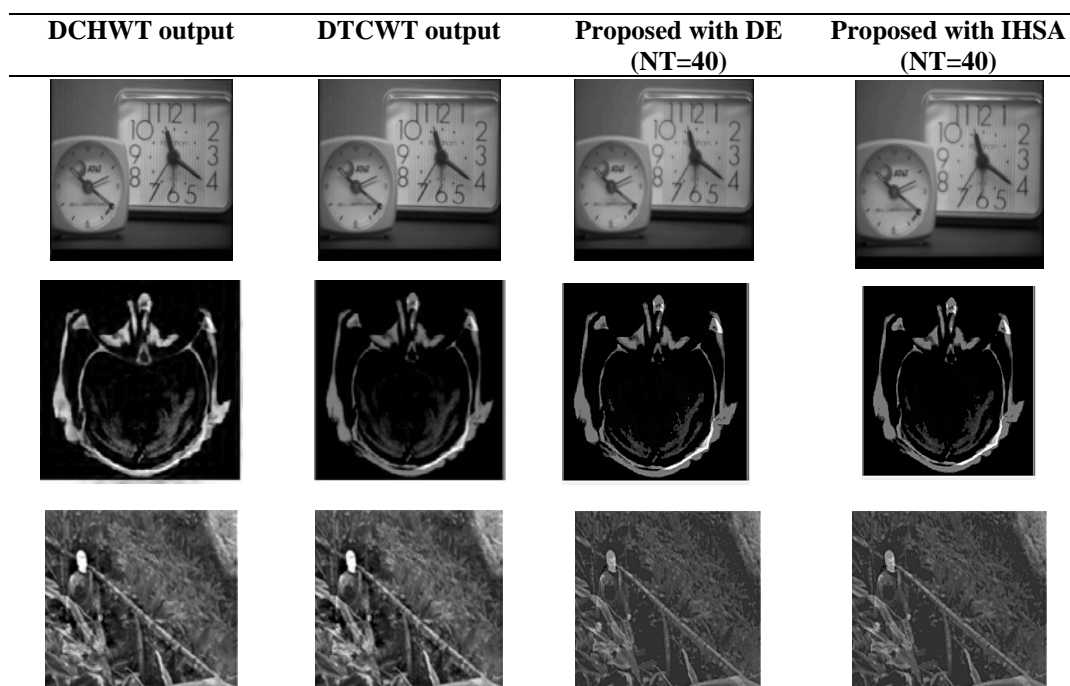
Fig.6 Qualitative comparison of the proposed with the existing fusion algorithms

The proposed fusion algorithm for different optimization algorithm achieves better image quality for the number of thresholds more than 40 with less energy consumption. The qualitative analysis of the proposed method illustrates that the fused image can be constructed effectively without accessing all the pixels of the input images. The second analysis is focused on the comparison of the proposed algorithm with the existing fusion algorithms, the fusion result of the various fusion algorithms and the proposed technique is shown in Fig.6. The DCHWT based image fusion algorithm yields better results than that of other methods. But, when it comes to the sensor images, the fused output of the proposed algorithm contains more useful information that corresponds to less number of thresholds.

A.   Quantitative Analysis

The parameters mentioned in section 4 are used as a performance metrics to verify the quality of the proposed fusion algorithm. In practical, higher the values of the performance metrics, better the quality of the output fused image. The following tables indicates that the proposed fusion algorithms with optimization algorithm IHSA and DE obtain the higher evaluation values compared to that of the existing region-based DTCWT and DCHWT approaches, except for the "medical" images .Table-4 shows the various fusion parameter results for different set of images. The metrics show that employing the IHSA optimization with the proposed fusion method leads to the best results among all other fusion models. In fact, due to the actual definitions of these metrics as mentioned in the previous section, Piella and Petrovic metrics generally correlate well with the results of visual analysis. However, it is also noted that these metrics are based on edges and consequently, fused images containing significant artefacts such as ringing introduced by the transform (DTCWT, DCHWT) can sometimes be in advertently rated high by the metrics but look inferior perceptually. In terms of computational complexity, the proposed method is less expensive than that of the existing fusion algorithms.

TABLE 4. Performance Measure of existing and proposed fusion algorithm

Input image: Multi focus disk pair

Image Fusion	API	SD	AG	H	MI	FS	CC	$Q^{AB/F}$	Time(s)
DTCWT	96.46	48.99	7.147	6.009	5.754	**1.998**	0.963	0.539	6.31
DCHWT	97.012	45.866	**7.459**	7.279	6.093	1.937	0.9799	**0.8915**	13.856
Proposed (MLT)	96.82	48.23	6.58	**7.94**	6.134	1.986	**0.989**	0.816	3.65
Proposed+DE	96.79	49.62	6.11	6.99	6.675	1.994	**0.989**	0.734	19.75
Proposed+IHSA	**97.56**	**49.624**	6.012	7.052	**6.725**	1.995	0.988	0.756	**1.996**

Input image: Medical image pair

Image Fusion	API	SD	AG	H	MI	FS	CC	Q^{AB/F}	Time(s)
DTCWT	27.241	23.54	10.2	3.389	2.03	1.53	0.695	0.635	4.412
DCHWT	**38.652**	44.0615	8.439	**6.587**	2.108	1.725	0.675	0.826	3.29
Proposed(MLT)	31.26	55.69	11.58	6.39	2.26	1.798	0.729	0.805	2.964
Proposed+DE	31.69	**56.97**	13.147	5.65	**2.328**	1.802	**0.743**	0.709	18.74
Proposed+IHSA	30.726	56.62	**13.75**	5.97	2.16	**1.824**	0.706	0.796	**2.374**

Input image: Multi sensor image pair

Image Fusion	API	SD	AG	H	MI	FS	CC	Q^{AB/F}	Time(s)
DTCWT	107.11	13.23	5.36	5.99	1.96	1.537	0.532	0.598	7.39
DCHWT	107.38	**16.83**	5.29	6.049	2.231	1.879	**0.67**	**0.724**	10.31
Proposed(MLT)	107.26	14.52	6.58	6.572	3.091	1.895	0.652	0.629	3.98
Proposed+DE	107.48	14.98	**7.609**	**6.801**	3.093	1.857	0.6114	0.636	17.33
Proposed+IHSA	**107.95**	15.86	7.36	6.68	**3.69**	**1.927**	0.619	0.642	**2.503**

VI.   CONCLUSION

In this paper, a histogram-based image fusion framework using entropy and optimization scheme is developed. In the histogram based methodology, the local statistical characteristics of images have been employed in order to drive the multi-thresholding process. Then, the salient information contained in the histogram bins is modeled by using shannon entropy. Though the entropy has the advantage of grouping the pixels to reduce the overall size of the image, it is found that there is a possibility of more computation time. To solve this, the optimization algorithm called IHSA is proposed to maximize the Shannon entropy and also find the optimal thresholds from the set of input images. Finally, the group of optimal thresholds determines the fused output. The efficiency of this proposed fusion scheme over existing techniques is discussed by conducting the simulation on a different set of images such as multi-focus, multi-sensor, and medical images. The simulation results confirm that the proposed image fusion method based on the optimization outperforms previously proposed image fusion approaches using wavelets. In the future, the research work will concentrate on the development of incorporating hybrid based optimization to enhance the fusion performance. Further, an interesting direction for future work could be the extension of the proposed fusion scheme to the case of multiple color input images.

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