

Image fusion using Teaching Learning Based Optimization

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ABSTRACT

Image fusion is one of the techniques in Image processing. In this paper, we are going to propose a Image fusion method based on Teaching Learning Based Optimization. Taking two multifocused images, we are going to divide them into blocks then contrast visibility of the two image blocks then is calculated. TLBO algorithm performed to obtain optimal coefficients and fused image is acquired finally using Optimal Coefficients. For different set of multi focus images, different quantities measured are calculated. Then the results of proposed method are compared with existing Particle Swarm Optimization.

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Introduction

Image fusion can be described as the process of combining two or more multifocused images to acquire an output image with more clarity and information content.

There are different types of Image Fusion techniques: Multi view Fusion, Multimodal Fusion, Multi temporal Fusion and Multi focus Fusion. Multi focus image Fusion can be obtained by combining the images of same scene which creates a resultant image with all the objects in the image to be in focus. Image Fusion process takes place in two domains: Spatial Domain and Transformed Domain. If the pixel values are directly integrated on the fusion process then it is spatial domain. But in transformed Domain, input images are transformed to exploit information at different resolutions using Pyramid decomposition or Wavelet decomposition.

In an image, at different resolutions some physically relevant features are observed. A means to exploit this fact is provided by Multi-Scale or Multi-resolution [1-2]. The resultant transformed image is again fused using any fusion operation. Then by taking inverse form fused image can be obtained.

Image Fusion can be performed in three different levels of information which includes Pixel level, Decision Level and Feature Level [3-4]. Pixel Level image fusion is the simplest fusion where fusion operation is directly performed on pixel intensities. In Pixel Level image Fusion, the mean or max of the pixel values of registered images is calculated. But these techniques have some undesired effects like smoothening of Sharp edges or blurring effect on the image. For feature level image fusion, input images should be segmented first into different regions, then the features of each region is calculated. The detection and classification of different objects in input images is done by Decision level image fusion and then fused image is obtained using any of the fusion algorithms. To perform Image Fusion, different techniques like PCA based image fusion [5], laplacian pyramid image fusion [6], DWT based image fusion and wavelet transform based image fusion. But each technique has certain disadvantages like not

providing information about sudden intensity changes, edges are smoothed out, reducing contrast of the images. So, there is a need to overcome disadvantages.

Particle Swarm Optimization:

Particle Swarm Optimization is one of the optimization techniques used for continuous problems. It is developed by J. Kennedy et al., [7]

PSO is inspired by the societal behaviour of bird flocking, fish schooling nature/ PSO these days have been used in different areas such as image processing, sensor networks, neural networks etc. PSO is used in image processing for finding an optimal block size of fused image [8].

As PSO is inspired by birds, each bird is called a particle. Every particle has its own solution. At first, the velocity and position of the particle is determined randomly in the search space. Each bird has its own fitness value which is evaluated using fitness function. Every particle alters its position by moving forward on the basis of path followed by it and by neighborhood. Velocity and Position of the each particle is updated every time using the equations.

$$v_b^a(t+1) = w * v_b^a(t) + c1 * r1 * (p_b^a - x_b^a(t)) + c2 * r2 * (g^a - x_b^a(t)) \quad (1)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (2)$$

Where $a=1, 2 \dots A$, $b=1, 2 \dots B$. A is the number of dimensions of the particle and B is the population size. w is the inertia, g is the global best position of the particle, p is the particle best position. v and x are the velocity and position update of the particle. $c1$ and $c2$ are the constants that deal with cognitive and social behaviour of the particle. $r1$ and $r2$ are the random values ranging between 0 and 1.

As the frequent updation of velocity and position of the particle at every time takes place, the particles can go out of the search space sometimes. So, to avoid this problem maximum velocity parameter v_{max} is calculated. If the new velocity of the particle is greater than the v_{max} then its velocity is set to v_{max} .

$$v_{pq}(t+1) = \begin{cases} v'_{pq}(t+1); v_{pq}(t+1) < v_{\max} \\ v_{\max}, q; \text{otherwise} \end{cases} \quad (3)$$

Where q is the qth dimension of the particle p. Value of v_{max} should be kept large to encourage exploration while v_{max} is kept smaller to encourage exploitation.

Teaching Learning based Optimization:

Teaching Learning Based Optimization (TLBO) is a one of the global optimization method based on population proposed by Rao et al [9, 10]. It also uses population of solutions to proceed to global solution just like other methods [11]. It also used for parameter optimization in mechanical engineering, casting [12] etc. TLBO can be used in image processing for finding optimal coefficients for fusion of images [13].

Population in TLBO is described as group of learners. The different design variables are comparable to the subjects offered by Learners which are different. The learners result is comparable to fitness. TLBO working is divided into 'Teacher Phase' and 'Learner Phase'. Learning from the teacher is termed as 'Teacher Phase' and learning through interaction with learners is 'Learner Phase'.

Teacher Phase

The mean parameter is calculated here. It is denoted by M^l of each subject of learners at generation G is given as

$$M^l = [m_1^l, m_2^l, \dots, m_j^l, \dots, m_N^l] \quad (4)$$

The algorithm moves forward by shifting the mean of learners towards its teacher in Teacher Phase. A random weighted differential vector is formed to obtain a new set of improved learners using current mean and desired mean values and adding to existing population of learners.

$$X_{new(i)}^l = X_{(i)}^l + rand * (X_{Teacher}^l - T_F M^l) \quad (5)$$

Where T_F is the teaching factor. Value of T_F is decided randomly with equal probability as

$$T_F = round[1 + rand(0,1)\{2-1\}] \quad (6)$$

Experimentally, it is said that algorithm performs better if the value of T_F is between 1 or 2.

Learner Phase

Mutual interaction tends to increase the knowledge of the learner. The random interaction improves the learners knowledge. For One learner X^g_(i) another learner is randomly selected. The ith parameter of matrix in learner phase is given as

$$X_{new(i)}^l = \begin{cases} X_{(i)}^l + rand * (X_{(i)}^l - X_{(r)}^l) & \text{if } (f(X_{(i)}^l) < f(X_{(r)}^l)) \\ X_{(i)}^l + rand * (X_{(i)}^l - X_{(r)}^l); & \text{otherwise} \end{cases} \quad (7)$$

The algorithm terminates after MAXITE Iterations finally. By Optimal Coefficients we are going to obtain a fused image.

Proposed method Algorithm

- Step1:** Take two multifocused images as inputs.
- Step2:** Divide these two images into blocks of equal size
- Step3:** Calculate Contrast visibility for each image block using the formula

$$VI = 1/(m * n) \sum_{(i,j) \in B_k} \frac{|I(i,j) - \mu_k|}{\mu_k} \quad (8)$$

Continue this step for each block of two images

Step4: Performing TLBO algorithm to find Optimal Coefficients of the image.

Step5: With these Optimal Coefficients we are going to obtain Fused Image.

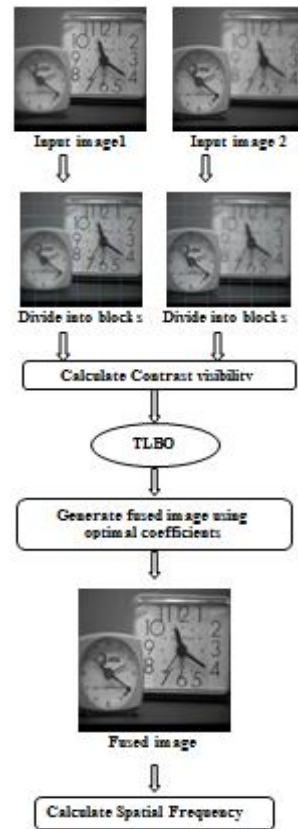


Fig1. Block diagram for proposed method.

Step6: Now for fused image calculate the Spatial Frequency value using the formula

$$SF = \sqrt{(RF)^2 + (CF)^2} \quad (9)$$

where

$$RF = \sqrt{\frac{1}{m * n} \sum_{i=1}^m \sum_{j=2}^n [F(i,j) - F(i,j-1)]^2} \quad (10)$$

$$CF = \sqrt{\frac{1}{m * n} \sum_{i=2}^m \sum_{j=1}^n [F(i,j) - F(i-1,j)]^2} \quad (11)$$

Experimental results

Experimental results are carried out by using different natural images like clock image, pepsi image and Remote Sensing image.

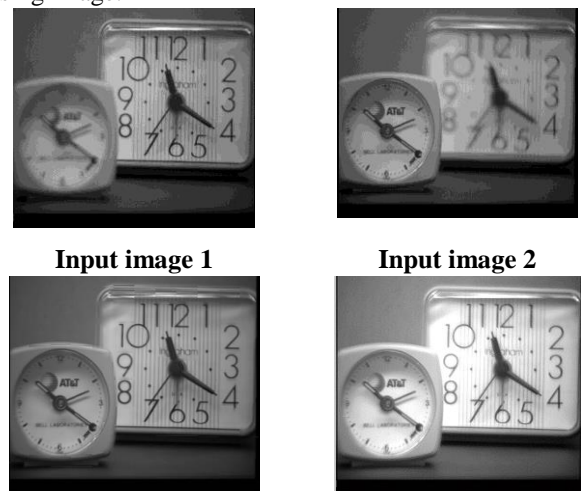
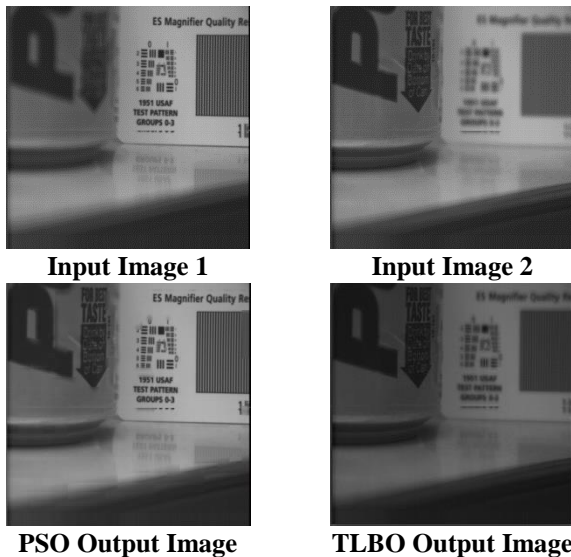


Fig 2. Clock Image.

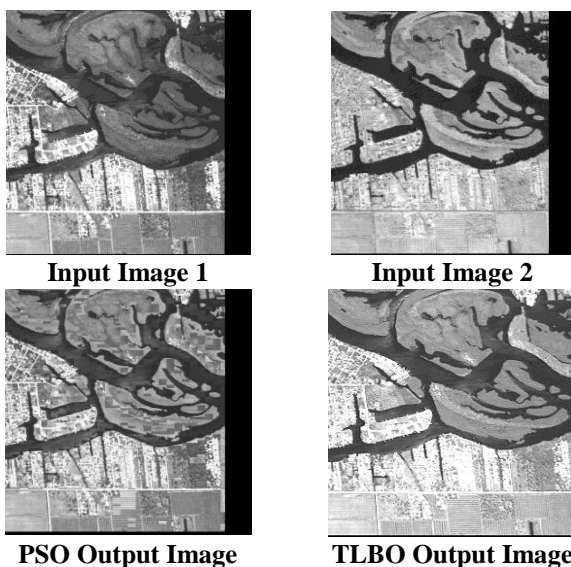
Table1. Calculation of Performance measures for the input images with PSO and TLBO.

| Fusion method | SF | PSNR | MSE | E | MI |
|---------------|-------|-------|------|------|------|
| PSO | 9.96 | 7.50 | 1.15 | 0.32 | 3.90 |
| TLBO | 14.63 | 61.71 | 0.04 | 7.66 | 0.60 |

Where SF= Spatial Frequency, PSNR= Peak Signal to Noise Ratio, MSE= Mean Square Error, MI= Mutual Information, E= Entropy

**Fig 3. Pepsi Image.****Table2. Calculation of Performance measures for the Pepsi input images with PSO and TLBO.**

| Fusion method | SF | PSNR | MSE | E | MI |
|---------------|-------|-------|------|------|------|
| PSO | 13.24 | 7.96 | 1.03 | 0.49 | 2.12 |
| TLBO | 7.65 | 66.10 | 0.01 | 6.58 | 0.03 |

**Fig 4. Remote Sensing Image.****Table3. Calculation of Performance measures for the input images with PSO and TLBO.**

| Fusion method | SF | PSNR | MSE | E | MI |
|---------------|-------|-------|------|------|------|
| PSO | 31.96 | 5.33 | 1.90 | 0.62 | 2.13 |
| TLBO | 33.31 | 59.87 | 0.06 | 7.33 | 1.01 |

Conclusion

This paper presents the optimal block size for the fusion of multifocus images by one of the global optimization technique Teaching Learning Based Optimization. Here, for a fixed number of iterations, algorithm is run and Optimal Coefficients are obtained. So, finally final fused image can be acquired. The obtained results are compared with Particle Swarm Optimization with respect to different quantitative measures. The difference between the quantitative measures shows that the proposed method has more accuracy than the existing method.

References

- [1] I. De and B. Chanda, A simple and efficient algorithm for multifocus image fusion using morphological wavelets, *Signal Processing*(2006), pp.924-936.
- [2]T.Tirupal, B.Chandra Mohan, S.Srinivas Kumar, Multifocus Medical Image Fusion based on Fractional Lower Order Moments and Modified Spatial Frequency, *International Conference on Advances in Biotechnology, BIOTECH-2015*, pp.145-154.
- [3] G. Pajares and J. M. Cruz, A wavelet-based image fusion tutorial, *Pattern Recognition* (2004), vol.37, no.9, pp.1855-1872.
- [4] T.Tirupal, B.Chandra Mohan, S.Srinivas Kumar, Image Fusion of Natural, Satellite, and Medical Images using Undecimated Discrete Wavelet Transform and Contrast Visibility, *National Conference on Recent Advances in Electronics & Computer Engineering*, RAECE-2015, 2015.
- [5] A. Toet, Image Fusion by a ratio of low pass pyramid, *Pattern recognition letters*, vol.9, no.4, pp.245-253, 1989
- [6] 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, pp.338-352, 2008.
- [7] J. Kennedy and R. Eberhart, Particle swarm optimization, *IEEE International Conference on Neural Networks* (1995), Perth, Australia.
- [8] Abdul Basit Siddiqui, M. Arfan Jaffar, Ayyaz Hussain and Anwar M. Mirza, Block-Based pixel level multi-focus image fusion using particle swarm optimization, *International Journal of Innovative Computing, Information and Control ICIC* ISSN 1349-4198 Volume 7, Number 7(A), pp. 3583- 3596, 2011
- [9] R.V. Rao,V.J. Savsani, D.P.Vakharia, Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems, *Comput. Aided Des.* 43 (2011) 303–315.
- [10] R.V.Rao,V.J. Savsani, D.P. Vakharia, Teaching-learning-based optimization: an optimization method for continuous non-linear large scale problems, *Inf. Sci.* 183 (2012) 1–15.
- [11] Suresh Chandra Satapathy, Anima Naik and K Parvathi” A teaching learning based optimization based on orthogonal design for solving global optimization problems” in *Springer Open Journal* (2013).
- [12] R.V.Rao,V.J. Savsani,D.P. Vakharia,Parameters optimization of selected casting processes using teaching-learning-based optimization algorithm, *Elsevier* (2014)
- [13] Haiyan Jin, Yanyan Wang, A fusion method for visible and infrared images based on contrast pyramid with teaching learning based optimization, *Elsevier* (2014).