

An Improved Image Fusion Technique Based On Texture Feature Optimization Using Wavelet Transform and Teacher Learning Optimisation Technique (TLBO)

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Abstract— Feature based image fusion is most popular area of research in the field of image fusion. The image fusion used lower content of image feature. The lower content of image feature such as color texture and dimension. The very important component of image are texture feature. the extraction and processing of texture feature used various transform function such as wavelet transform function Gabor transform function and many more signal based transform function. In the process of image fusion process requires two and more image for the process of fusion. This dissertation proposed a feature based image fusion technique. The feature based optimization technique also used feature optimization and feature selection process. The feature selection and feature optimization used Teacher learning based optimization technique. The Teacher learning based optimization technique select the optimal texture feature of both image original image and reference image. The reference and original image find the optimal feature sub set for the estimation of feature correlation. Our experimental result shows performance Better instead of WT and HBT transform method of image fusion. Our proposed method increased the value of PSNR and IQI. The improved value of IQI shows that the proposed method is very efficient and better for the process of image fusion. The proposed scheme used for the purpose of wall crack detection.

Keywords- image fusion, feature optimisation, TLBO

I. INTRODUCTION

Image fusion is the process of combining multiple images in to a single image to improve the information content of the resulting image. The researchers have proposed various image fusion schemes in the spatial as well as transform domains with different fusion rules such as pixel averaging, weighted average, maximum value selection, region energy, region variance and so forth. Several fusion approaches using multi scale transform such as the discrete wavelet transforms (DWT), the Laplacian pyramid, the contrast pyramid and the FFT have been presented in literature. However, multi- resolution transform based techniques do not allow image adaptive representation of local features and results in suboptimal image fusion [1]. Image fusion is emerging as a vital technology in many are such as military, surveillance and medical applications. To obtain an image that simultaneously contains the outline of scene as well as special objects for the convenience of human visual perception or for further image-processing tasks, image fusion can be used to integrate the information provided by individual sensors. During the past two decades, many image fusion methods are developed. According to the stage at which image information is integrated, image fusion algorithms can be categorized into pixel, feature, and decision levels[4,5]. The pixel-level fusion integrates visual information contained in source images into a single fused image based on the original pixel information. In the past decades, pixel-level image fusion has attracted a great deal of research attention. Generally, these algorithms can be categorized into spatial domain fusion and

transform domain fusion [6,7]. A dual-tree complex wavelet transform (DT-CWT) is used to segment the features of the both types of input images, such as jointly and separately, to produce a region map. Characteristics of each region are calculated and a region-based approach is used for fusion the images, region based in the wavelet domain. Other fusion methods are based on saliency measurement, local gradient and edge fusion. Pixel based algorithms concentrate on increasing image contrast whereas region based algorithms provide edge enhancement and feature extraction. Fusion can be performed on pixel, feature or decision level[15]. PCA is a classical de- correlation technique in statistical signal processing and it is pervasively used in pattern recognition and dimensionality reduction, etc. This paper we proposed a feature based image fusion technique. The proposed technique based on feature optimization technique using optimization algorithm. The above section discuss introduction of image fusion. In section II we describe Gabor wavelet transform. In section III discuss teacher learning optimisation (TLBO). In section IV discuss proposed methodology for image fusion. In section V discuss Experimental result and finally conclude in section VI.

II. FEATURE EXTRACTION

Feature extraction technique is important phase of image fusion technique [5]. In fusion image basically three types of features are color, texture and dimensions. Feature extraction can be defined as the act of mapping the image from image space to the feature space. Now days, finding good features that effectively represent an image are still a difficult task [9]. In this section discuss a features are used for fusion image from the raw image. Features basically represent the visual content. Visual content can be further divided into general or domain specific. Here used wavelet transform for extraction process. Texture analyzers implemented using 2-D Gabor functions produce a strong correlation with texture data in fusion image [3]. Gabor functions are Gaussian modulated by complex sinusoids. In the two dimensions they take the form:

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi jWx\right) \dots\dots\dots (1)$$

A dictionary of filters can be obtained by appropriate dilatations and rotations of $g(x,y)$ generating function: $g_{mn}(x,y) = a^{-m}g(x',y')$ where $m=0,1,\dots,S-1$

$$x' = a^{-m}(x\cos\theta + y\sin\theta), y' = (-x\sin\theta + y\cos\theta) \dots\dots\dots (2)$$

where $\mu = n^{1/4}/K$, K the number of orientations, S the number scales in the multi resolution, and $a = (U_h/U_l)^{1/S-1}$ with U_l and U_h the lower and upper center frequencies of interest. Compact representation needs to be derived for learning and classification purposes. Given an image $I(x, y)$, its Gabor wavelet transform is then defined as:

$$W_{mn}(x, y) = \int I(x, y) g_{mn}^* (x - x_1, y - y_1) dx_1 dy_1 \dots\dots\dots (3)$$

Where* represents the complex conjugate. Mean μ_{mn} and the standard deviation σ_{mn} of the magnitude of the transform coefficients are used to represent the image.

$$\mu_{mn} = \iint |W_{mn}(x, y)| dx dy$$

$$\text{And } \sigma_{mn} = \sqrt{\iint (|W_{mn}(x, y)| - \mu_{mn})^2 dx dy} \dots\dots\dots (4)$$

Then a feature vector is constructed using μ_{mn} and σ_{mn} as feature components:

$$f = [\mu_{00} \sigma_{00} \mu_{01} \sigma_{01} \dots \mu_{mn} \sigma_{mn}] \dots \dots \dots (5)$$

As result, we obtain a numerical vector of 30 dimensions for 6 orientations and 5 scales changes. Also note the texture feature is computed only for rectangular grid as it is difficult to compute the texture vector for one arbitrary region. The extracted texture feature generates a feature matrix for optimisation process.

III TEACHER LEARNING BASED OPTIMIZATION

This optimization method is based on the effect of the influence of a teacher on the output of learners in a class. It is a population based method and like other population based methods it uses a population of solutions to proceed to the global solution[15]. A group of learners constitute the population in TLBO. In any optimization algorithms there are numbers of different design variables. The different design variables in TLBO are analogous to different subjects offered to learners and the learners' result is analogous to the 'fitness', as in other population-based optimization techniques. As the teacher is considered the most learned person in the society, the best solution so far is analogous to Teacher in TLBO [21]. The process of TLBO is divided into two parts. The first part consists of the "Teacher phase" and the second part consists of the "Learner phase". The "Teacher phase" means learning from the teacher and the "Learner phase" means learning through the interaction between learners. In the sub-sections below we briefly discuss the implementation of TLBO.

Following are the notations used for describing the TLBO

N: number of learners in class i.e. "class size"

D: number of courses offered to the learners

MAXIT: maximum number of allowable iterations

The population X is randomly initialized by a search space bounded by matrix of N rows and D columns. The jth parameter of the ith learner is assigned values randomly using the equation

$$x_{(i,j)}^0 = x_j^{min} + rand \times (x_j^{max} - x_j^{min}) \dots \dots \dots (1)$$

where rand represents a uniformly distributed random variable within the range (0, 1), x_{min j} and x_{maxj} represent the minimum and maximum value for jth parameter. The parameters of ith learner for the generation g are given by

$$X_{(i)}^g = [x_{(i,1)}^g, x_{(i,2)}^g, \dots \dots \dots x_{(i,j)}^g \dots \dots \dots x_{(i,D)}^g] \dots \dots \dots (2)$$

III.1 Teacher phase

The mean parameter M^g of each subject of the learners in the class at generation g is given as

$$M^g = \left[m_1^g, m_2^g, \dots \dots \dots m_j^g \dots \dots \dots m_D^g \right] \dots \dots \dots (3)$$

The learner with the minimum objective function value is considered as the teacher X_g Teacher for respective iteration. The Teacher phase makes the algorithm proceed by shifting the mean of the learners towards its teacher. To obtain a new set of improved learners a random weighted differential vector is formed from the current mean and the desired mean parameters and added to the existing population of learners.

$$X_{new}^g(i) = X^g(i) + rand \times (X_{Teacher}^g - TFM^g) \dots \dots \dots (4)$$

TF is the teaching factor which decides the value of mean to be changed. Value of TF can be either 1 or 2. The value of TF is decided randomly with equal probability as,

$$T_F = round[1 + rand(0,1)\{2 - -1\}] \dots \dots \dots (5)$$

Where TF is not a parameter of the TLBO algorithm. The value of TF is not given as an input to the algorithm and its value is randomly decided by the algorithm using Eq. (5). After conducting a number of experiments on many benchmark functions it is concluded that the algorithm performs better if the value of TF is between 1 and 2. However, the algorithm is found to perform much better if the value of TF is either 1 or 2 and hence to simplify the algorithm, the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria given by Eq. (5). If Xnew is found to be a superior learner than Xg in generation g, then it replaces inferior learner Xg in the matrix.

III.2 Learner phase

In this phase the interaction of learners with one another takes place. The process of mutual interaction tends to increase the knowledge of the learner. The random interaction among learners improves his or her knowledge. For a given learner Xg, another learner Xr is randomly selected (i ≠ r). The ith parameter of the matrix the learner phase is given as

$$X_{new}^g(i) = \begin{cases} x_i^g + rand \times (x_i^g - x_r^g) & \text{if } f(x_i^g) < f(x_r^g) \\ x_i^g + rand \times (x_r^g - x_i^g) & \text{otherwise} \end{cases} \dots \dots \dots (6)$$

III.3 Algorithm termination

The algorithm is terminated after MAXIT iterations are completed.

IV PROPOSED METHODOLOGY

In this section discuss the proposed methodology of feature based image fusion technique based on wavelet transform function and Teacher Learning based optimization, the feature of transform function passes through feature selection process. The feature selection process used Teacher Learning based optimization technique. The Teacher Learning based optimization selects the optimal feature of given texture feature matrix. Fusion process is done if the correlation coefficient factor estimate the value of correlation is zero. The proposed model process divide into two section first section deals with initially take host image and reference image passes through wavelet transform function for feature extraction after the feature extraction applied optimization task done by Teacher Learning based optimization. Steps for feature extraction input the host and reference image.

The Wavelet transform function for feature extraction have to be apply separately F(x)=I(x,y) is host image and reference image is F1(x)=I1(x1,y1) M(F)= F(x) ×G(x) The convolution in host image is performed through transform function here M (F) stored the texture feature matrix of host image. Then a feature vector has to construct as feature components using μmn and σmn:

$$f = [\mu_{00} \sigma_{00} \mu_{01} \sigma_{01} \dots \mu_{mn} \sigma_{mn}] \dots \dots \dots (1)$$

We obtain a numerical vector of 60 dimensions for 10 orientations and 6 scales changes. This moment feature value stored in M (F) matrix. N (F) =F1(x) ×G(x).The convolution is perform through transform function in host image here (F) stored the texture feature matrix of host image. Then a feature vector is constructed using μ1mn and σ 1mn as feature components:

$$f = [\mu_{100} \sigma_{100} \mu_{011} \sigma_{01} \dots \mu_{1mn} \sigma_{1mn}] \dots \dots \dots (2)$$

We obtain a numerical vector of 60 dimensions for 10 orientations and 6 scales changes. This moment feature value stored in N (F) matrix.

1. Both the feature mortises are convent into feature vector and pass through Teacher Learning based optimization.
2. Step two used here Teacher Learning based optimization for classification of pattern Transform data to the format of an SVM that is X is original data R is transform data such that $X_i \in R^d$ here d is dimension of data. Conduct scaling on the data $\alpha = \sum_{i=1}^m \sum_{j=1}^n \text{sim}(X_i, X_j) \cdot m * k$ here α is scaling factor and m is total data point and k is total number of instant and sim find close point of data. Consider the RBF kernel $K(x; y) = \exp(-(\delta - c)^2 / (r^2))$ this is kernel equation of plane. Cross-validation to 2nd the best parameter is used C and the best parameter is used as C and to train the whole training set as feature components $R_o = \alpha \frac{1}{p} \sum_{i=1}^p \min(x_i - y_i)$ where R_o is learning parameter of kernel function. For both image pattern of similar and dissimilar pattern have to generate.
3. Estimate the correlation coefficient of both patterns using person's coefficient. Estimate the attribute for feature correlation as $\text{Rel}(a, b) = \frac{\text{cov}(a, b)}{\sqrt{\text{var}(a) \times \text{var}(b)}}$ Here a and b the pattern of host image and reference image. The total value of MSE is checked by estimated correlation coefficient data

$$x(t) = w_0 + \sum_{j=1}^{\text{total data}} w_j \exp\left(-\frac{(\text{total} - x_j)}{\sigma^2}\right)$$

Relative feature difference value can be created using

$$R_c = \sum_{k=1}^r \sum_{i=1}^m (h_i - h)(e_{ik} - e_t) \text{ If the value of relative pattern difference is } 0$$

4. fusion process is done
5. Calculate PSNR value of fused image
6. Calculate IQI value of fused image
7. Calculate fusion MSER of fused image.

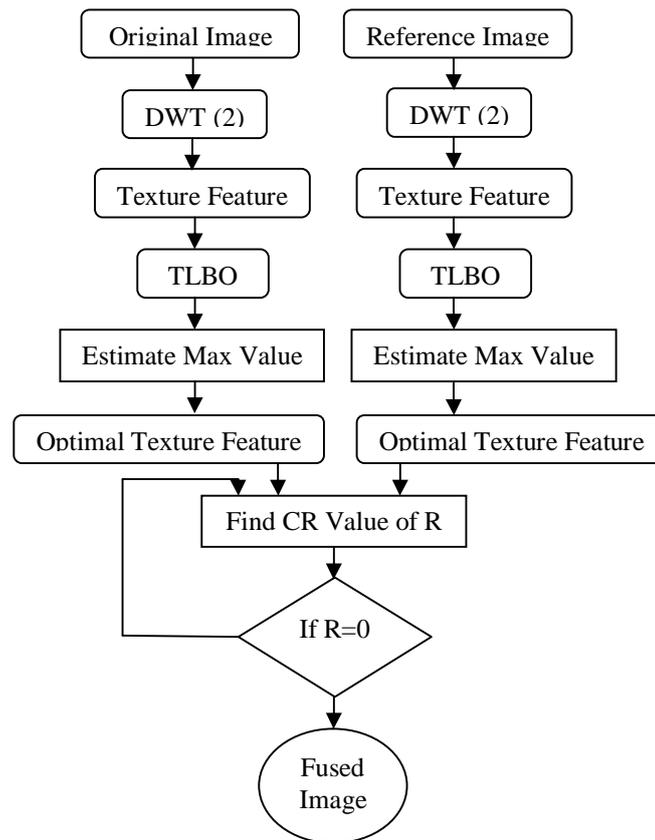


Figure 1. proposed model for feature based image fusion

V. EXPERIMENTAL RESULT ANALYSIS

In this section some of experimental results of our work on feature optimisation Image Fusion are discussed. Input image database is taken in different environment through a digital camera, the multi focused environment is generated using different light effects. In the proposed method, the first wavelet decomposition of the input source images is performed up to level second using discrete wavelet transform.

Evaluation parameter

For the Evaluation of experimental process used some standard parameter. There are different types of distortion assessment approaches or object quality. The fused images are evaluated, by considering the following parameters into consideration. Root Mean Square error (RMSE) [8], The root mean square error (RMSE) between each unsharpened MS band and corresponding sharpened band can also be computed as a measure of spectral fidelity. It is responsible for measuring the amount of change per pixel due to the processing. The RMSE between a fused image R and the reference image F is given by[9]

$$E1 = \sqrt{\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (R(i, j) - F(i, j))^2}$$

There are different approaches to construct reference image using input images. We used the following procedure to compute RMSE in our experiment. First, RMSE value E1 is computed between source image A and fused image F.

$$E1 = \sqrt{\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (I1(i,j) - F(i,j))^2}$$

Similarly E2 is computed as RMSE between sources image B and fused image F.

$$E2 = \sqrt{\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (I2(i,j) - F(i,j))^2}$$

Then the overall RMSE value is obtained by taking the average of E1 and E2.[11]

$$RMSE = \frac{(E1+E2)}{2}$$

Smaller RMSE value indicates good fusion quality. Peak Signal to Noise Ratio PSNR can be calculated by using the formula[12].

$$PSNR = 20 \log_{10} \left[\frac{L^2}{MSE} \right]$$

Where MSE is the mean square error and L is the number of gray levels in the image. Image Quality Index IQI measures the similarity between two images (I1 & I2) and its value ranges from -1 to 1. IQI is equal to 1 if both images are identical. IQI measure is given by [14].

Where the mean values of images I1 and I2 is denoted by x and y, and denotes the variance of I1, I2 and covariance of I1 and I2.

$$IQI = \frac{m_{ab}}{m_a m_b} \frac{2xy}{x^2 + y^2} \frac{2m_a m_b}{m_a^2 + m_b^2}$$

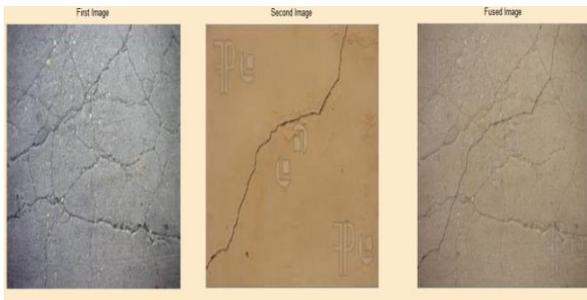


Figure 2. shows that two input image of wall cracks in same mode of initial crakes and final cracks and fused both cracks with HBT technique.



Figure 3. shows that two input image of wall cacks in same mode of initial crakes and final cracks and fused both cracks with WT technique.



Figure 4. shows that two input image of wall cracks in same mode of initial crakes and final cracks and fused both cracks with optimized fused feature technique.

Table 1. shows that comparative result analyses of transform function with optimization technique.

METHOD	MSER	PSNR	IQI
HBT	8.172	7.215	1.982
WT	12.894	9.935	1.975
Proposed	14.950	10.934	1.969

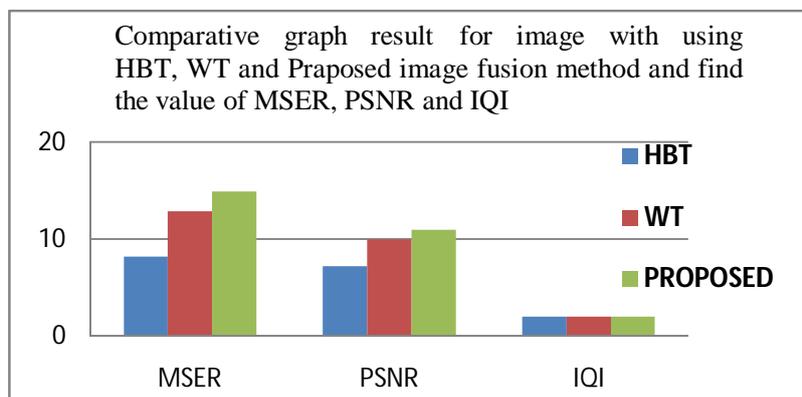


Figure 5. Graph that shows the comparative result graph for input image with using HBT, WT and Proposed image fusion method and find the value of MSER, PSNR and IQI.

CONCLUSION AND FUTURE WORK

In this dissertation proposed a feature based image fusion technique for the improvement of quality of image of distorted and damage image. The process of proposed algorithm used wavelet transform function for the feature extraction process. The wavelet transforms function extract the lower content of texture feature. The lower content of texture feature used for the process of feature optimization process. The feature optimization process done by TLBO algorithm. Teacher learning based optimizations dynamic population based optimization technique. The correlation coefficient factor estimates the relation of original image and reference image. If the value of correlation is 0 then image are fused. If the value of relation is not equal to zero the estimation factor recall. Measure the quality of fused image measures is considered. These measures play an important role in various Image Processing applications. Goal of image quality assessment is to supply quality metrics that can predict perceived image quality automatically.

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