Estimation of weighting distribution using fuzzy memberships and wavelet transformation with PSO optimization in satellite image enhancement

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Abstract: Satellite image enhancement suffers from edge localization and distortion of detail. A novel satellite image enhancement is presented which enhance the detail as well as a quality of low-resolution satellite images. In the proposed approach, we improve and preserve the edge detail of a significant region using particle swarm optimization and fuzzy logic in the high spectral region. Further, the fusion of detail images is performed to conquer the limitation of intensity distortion and over saturation in the region using an estimation of weights. The magnitude of weights is estimated by fuzzy membership functions to extract optimal spectral information. The measure of enhancement and contrast assessment function criterion are used to examine the performance of proposed method in comparison with other two recent techniques.

Subjects: CAD CAE CAM - Computing & Information Technology; Technology; Image Processing

Keywords: satellite images; DWT; DCT; CAF

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PUBLIC INTEREST STATEMENT

Satellite images have a wide range of different applications like metrology department, disaster management and are needed to be enhanced both in terms of edges and resolution so that the enhanced image looks better in terms of various performance metrics. Thus, we need a method that extracts the useful information and performs its proper analysis, identification, classification, and processing. There are a number of existing algorithms that enhance the features of the image. But it is observed that by employing existing algorithms of the enhancement, edges are not preserved or retained. Hence, the loss or distortion of the important information of an image had occurred. For this reason, the proposed method is presented that preserves the valuable edge information as well as perform image enhancement and resulted image may be used efficiently in different analysis applications.
1. Introduction

Satellite images carrying valuable information about the Earth. The objective of information analysis is to give details about those properties which are used in different applications. The information associated with edge localization is difficult to analyze by the human visual system. The solution of the problem can be solved using enhancement technique. It provides more significant information which is useful in various applications. There is a requirement of detail information in the satellite image. Poor quality can lead to incorrect identification or inexactness of the characterization of defects. But defects are difficult to remove with conventional enhancement process. This implies that it is important to make the best use of the information obtained from available satellite image enhancement. In this case, a reliable quality enhancement technique used which combine the output of high frequency region. Generally, image enhancement methods manipulate the pixel information according to the application. There are the number of enhancement methods exist but one method is more suitable for a particular type of satellite image. Like a method is useful for the enhancement in the lower frequency region, may not be the best candidate to enhance the edge details present in the original one. In order to improve the low-resolution image, it becomes essential to use image enhancement methods that often cause the distortion in edge information. The combination of the traditional approach with preserving of edges is a challenging task.

There are different enhancement technique which may involve enhancing the shapes and structures of the satellite images (Acharya & Ray, 2005; Gonzales & Woods, 2010). These techniques can be classified in spatial and frequency domain. The frequency domain method used transforms techniques like Fourier. The spatial domain techniques operate directly on the pixel or group of pixels. These groups of pixel operation applied on the whole image. The point operation techniques like contrast stretching, gamma correction, bit plane slicing, and histogram equalization behaves nonlinearly (Bhandari, Kumar, & Padhy, 2011; Kim & Paik, 2008). Both the domain is used in discrete wavelet transform (DWT) at different frequency band. The histogram equalization along with DWT is used by Demirel and Anbarjafari (2011) and Demirel, Ozcinar, and Anbarjafari (2010). This operation loses the edge information of the enhanced image. In order to preserve the edge information a correction factor called gamma correction or power law operator is used in lower region of wavelet transform (Sharma & Verma, 2014). This value of gamma sometime enhanced the lower region but the edges of this region are not revealed. Due to the use of contrast enhancement techniques the higher frequency region shows blurring effect. Satellite images contain the information of a different region in which edge information is required to preserve.

Generally, the image obtained after enhancement suffers from the uncertainty of the edge information. Thus, researchers observed the necessity of considering the improvement of the uncertainty present in an edge of the image (Sharma & Verma, 2017; Verma, Hanmandlu, Kumar, Chhabra, & Jindal, 2011). This may achieve by utilizing the fuzzy set theory which was evolved by L.A. Zadeh in 1965, helps in dealing with imprecise information. The uncertainty in the sharpness of the image is removed by the fuzzy membership function. The membership functions consist of different parameters that characterize membership function. Since the systems based on fuzzy logic are resembled with human decision. It determines the edges whose degree of membership is non-zero. Recently, researcher combines the fuzzy technique with evolutionary algorithms to detect the edges present in captured satellite images (Hanmandlu, Verma, Kumar, & Kulkarni, 2009; Hanmandlu, Verma, Gangwar, & Vasikarla, 2009; Verma, Kumar, Hanmandlu, & Chhabra, 2012). Particle swarm optimization (PSO) is one of the mostly used heuristic algorithm to detect edges that enhances low level features from the noisy images for the recognition of simple objects (Khatami, Khosravi, Lim, & Nahavandi, 2016; Khatami, Mirghasemi, Khosravi, Lim, & Nahavandi, 2017; Mostaghim & Teich, 2003; Poli, Kennedy, & Blackwell, 2007; Verma, Hanmandlu, Sultan, & Dhruv, 2010). Most of the algorithms enhance satellite images but not consider the edge information. Moreover, it suffers from edge localization. The desired value of parameters is computed using fuzzy along with PSO in the proposed work that gives the sharpness and fixed the edges in the significant portion of the satellite image.
In the proposed method, we present a method that enhances the dynamic range of low-resolution satellite image by keeping the maximum possible edges information intact. We improve the significant portion of the contrast and edge details without distorting the satellite image. Here, we used DWT to analyze the image in spatial domain and frequency domain. The PSO-based optimal fuzzy membership functions presented that will provide more detail information of the satellite image.

The contribution of the proposed work is as follows

(i) A modified fuzzy membership function is developed to enhance the satellite image keeping maximum edge information locally.
(ii) The effective utilization of PSO optimization to obtain optimal fuzzy edge that ensures maximum entropy present in the enhanced image.
(iii) Furthermore, intensity distortion and over saturation is avoided using the estimation of weights.

The paper is organized as follows. In Section 2, DWT is used to find the details of the image and these details are improved by intensification is explaining in Section 3. The proposed approach is discussed in Section 4. The performance and the results of the proposed approach are shown in Sections 5 and 6 respectively. Finally, conclusions are drawn in Section 7.

2. Discrete wavelet transform (DWT)
When we applied enhancement operation on the satellite images then, it will distort the high-frequency component. This operation results the smoothing of image but the edge details are not fixed as a consequence of these operations. Hence, there is a need to improve the quality of the satellite image in a way that it must preserve the edges intact. In this paper, DWT has been employed to bifurcate the image into different frequency components. DWT separates the image into different subband images, namely LL (low–low-frequency subband), LH (low–high-frequency subband), HL (high–low-frequency subband), and HH (high–high-frequency subband) as shown in Figure 1. HH subband contains the high-frequency component of the image. The unquantized low-resolution image is used as the input for the proposed enhancement method. There are researchers which use the low-frequency subband images for pixel manipulation.

The LL band contains the lower frequency part of the original image. It has been found that edges of the lower part of the region being smoother. Therefore, we have been used high-frequency region or HH subband of the image, which contains high-frequency information of the original captured satellite image (Shamna, 2014). Here, we are using histogram equalized image whose edges are not preserved due to the enhancement operation. In order to preserve more edge information fuzzy-based particle swarm-based optimization proposed in HH subband, i.e. main objective is to sharpen
as well as enhanced the satellite image. Figure 2 shows the block diagram of proposed approach in which high-frequency subband is used. The lower frequency part of input satellite image and the histogram equalized LL image are highly correlated. The difference between histogram equalized image and the low-resolution input image are in their high-frequency components. This approach correct the estimated high-frequency histogram equalized components. This estimation is performed by particle swarm optimized-based edge enhancement in the high-frequency subband. The difference image consists of high-frequency components of low-resolution input image and histogram equalized image, followed by the optimally weighted combination to perform the inverse discrete wavelet transform (IDWT) process. The intermediate process of adding the difference image, containing high-frequency components, generates significantly sharper and clearer final image.

3. Edge details fuzzification and intensification

The color satellite image subband is converted into Red, Green, and Blue channel subband. The channel matrix, obtained from the spatial domain, is transformed into a fuzzy domain using histogram-based Gaussian membership function. We considered the mask of size 3x3 to detect the edges. The mask is placed at each pixel location in image at which we compute $I$ that is the sum of exponential of the negative difference between the centrally located normalized pixel intensity with all other normalized pixels intensities present in the mask. The presence of edge may be accomplished by selecting the appropriate value of threshold. But by doing this, in most cases it is observed that we do not be able to retain the shape of edges. In particular cases in which the edges has smoother profile we probably do not include, thus, wrongly discarded the presence of edge. To reduce the probability of wrong selection of noise and rejection of the present weak edges, we use Gaussian profile membership function for fuzzifying each grayscale channel subband. We construct a histogram of obtained set of values of $I$ in a selected mask i.e. hist($I$) that helps in retaining the shape of edges. The normalized probability $p$ is given by: $p(I) = \text{hist}(I)/(\text{Total number of pixels in a mask})$, where $I = 1, \ldots, 9$.

The histogram-based Gaussian membership function for fuzzification of the channel matrix is given as:
The strong edge detection is performed by finding the minimum value of \( I \) i.e. \( I_{\text{min}} \). Hence, results obtained with metric of deviation of the \( I \) from \( I_{\text{min}} \). In this method, we emphasized on the normalized value of moment in place of the variance of \( I \) which is generally used in the literature. This makes our method robust edge detection in presence of adverse edges and noise. Since, \( MF_1(I) \) involves only one parameter \( \sigma_h^2 \) and fuzzifier is given by,

\[
MF_1(I) = \exp \left( -\frac{(I_{\text{min}} - I)^2}{2 \times \sigma_h^2} \right)
\]  

(1)

Here, \( x_{\text{max}} \) is the maximum value of \( I \) and \( L \) is equal to the size of mask. There are regions in the image which suffer from edge localization. Thus, we propose a parametric fuzzy intensification operator (FINT) on fuzzy set generated by \( MF_1(I) \) to enhance the weak edge information by modifying the shape of membership function in accordance with requirement of weak edge detection. Fuzzy measures are considered to assess the strength of weak and strong edges. The fuzzy entropy used to define the objective function for optimization that gives the best selection values required for modification of membership function. The membership function for intensifier is given by:

\[
MF_2(I) = \max \left( \frac{\lambda}{1 + \left( \frac{MF_1(I) - \gamma}{\tau} \right)^{2s}}, 1, 0 \right)
\]  

(2)

Hence, by finding the optimum value of four parameters \( r, t, s \) and \( \sigma_h^2 \) using PSO getting the best possible edges information present in the satellite images. Here, we arbitrarily chosen \( \lambda \) is equal to 4. Moreover, parameter “\( r \)” represents the center and “\( t \)” and “\( s \)” controls the shape of bell of membership function. These parameters varies in such a way that it results the positive value of membership function \( MF_2(I) \) and able to extract weak edges significantly.

4. Fuzzy measures and proposed optimal edge enhancement approach

4.1. Fuzzy edge entropy

Fuzzification is the phenomenon; which improves the spatial domain edge information into the corresponding fuzzy domain information. It measures the uncertainty or randomness present in the image is characterized by fuzzy edge entropy. The maximum edge information calculates using Shannon’s theorem. This indicates the presence of uncertainty and randomness of the edge in fuzzy domain are given by,

\[
E = -\frac{1}{\ln 2} \sum_{I=0}^{L-1} (MF_2(I)) \ln(MF_2(I)) + (1-MF_2(I)) \ln(1 - MF_2(I))
\]  

(3)

The optimization of fuzzy entropy should result in the desired value of the parameters \( r, t \) and \( s \). The range of these constraints is from \( r \in (-2, 0) \), \( t \in (3, 6) \) and \( s \in (1, 3) \).

4.2. Objective function for optimization

The proposed approach uses a PSO algorithm for optimization of parameters. The parameters \( r, t \), and \( s \) defined in Equation (3) is optimized by the objective function given by

\[
J = E + \Delta
\]  

(4)
It provides the optimized value of associated with the uncertainty of edge detail. The optimized value of entropy depends on the membership values. The high values of entropy achieve when all the membership values are 0.5. Therefore, the range of $\Delta$ is 0.2–0.8. Experimentally, we choose the value of $\Delta$ is 0.5 for the pleasant images. We maximize the entropy function in such a way that details information is maximum. The value of each particle in PSO is computing according to the objective function. This means, we will be able to observe details in horizontal direction, vertical direction and in diagonal directions also. PSO is used to get an optimized fuzzy edge map, which is further de-fuzzify to get binary edge map using adaptive thresholding.

### 4.3. Particle swarm optimization

J. Kennedy and R. C. Eberhart introduced the particle swarm evolutionary technique in 1995. This algorithm recently used by different researchers as it inspired from nature. The particle gives their best position on the basis of population experience. In a multidimensional space, each particle updates their solution according to the objective function. Each particle also has memory to keep information of its previously visited space. The PSO algorithm is guided by two factors: $p_{best}$ and $g_{best}$ which depends on the movement of the particle in the local and global neighborhood. The PSO algorithm implementation can be summarized as (Poli et al., 2007).

1. **Step 1:** Initialize all particles randomly according to the solution space satisfying the computational load or iterations required to obtain the optimum solution. The particles have random positions and velocities on D dimensions in the search space and initial velocities of a particle in PSO are assigned any random value or set to zero.

2. **Step 2:** Loop: For each particle, obtain the fitness function in D variables do:

3. **Step 3:** Set the $p_{best}$ value as the maximum value between the current value and existing $p_{best}$ value.

4. **Step 4:** Identify the particle in the neighborhood with the best success so far, and assign its index to the variable $t$.

5. **Step 5:** Update the particle velocity using

$$v_{t+1}^{i} = W^{t} \cdot v_{t}^{i} + c_{1} \cdot r_{1} \cdot (p_{best}^{t} - X_{t}^{i}) + c_{2} \cdot r_{2} \cdot (g_{best}^{t} - X_{t}^{i})$$

6. **Step 6:** Update the particle position using

$$X_{t+1}^{i} = X_{t}^{i} + \left(\frac{v_{t+1}^{i}}{q}\right)$$

where $X_{t}^{i}$ is the particle position in the solution space, $v_{t}^{i}$ is the velocity of the particle motion assuming a unity time step, $W^{t}$ is the velocity control coefficient, $c_{1}$ and $c_{2}$ are the gain control coefficients, $r_{1}$ and $r_{2}$ are random values generated in the range (Gonzales & Woods, 2010).

7. **Step 7:** If a criterion (i.e. usually a sufficiently good fitness or a maximum number of iterations) is met, then terminate the loop.

### 4.4. Initialization of PSO parameters

PSO generates the range of solution called population according to the objective function given in Equation (5). Furthermore, optimal value finds in this solution space. This value governed by the local and global position of the particle given in Equations (6) and (7). The values of initial parameters are used in the proposed algorithm are as follows

(i) The number of swarms $\text{swarm\_size} = 50$.

(ii) Maximum number of iterations $\text{itr} = 80$.

(iii) Inertia weight $W^{t} = 1.0$.

(iv) Cognitive parameter $c_{1} = 2$.

(v) Social parameter $c_{2} = 2$.

(vi) Parameters $r_{1}$ and $r_{2}$ are generated randomly in the interval [0–1].

(vii) Correction factor $q = 1.3$.
4.5. De-fuzzification based on adaptive thresholding

We are using optimized parameter results in the edge map for satellite image with fuzzy membership, termed as the fuzzy edge map. The Fuzzy edge map designed a set of pixels that truly belongs to edges only. Therefore, we need to de-fuzzify the fuzzy set to a classical set of 1 and 0. Therefore, a presence of fuzzy edge set is defined which result in the binarized image. The adaptive thresholding decides the presence of an edge in the image. It allows a user to differentiate the high-intensity (membership value) edge from the smooth region which varies with intensity and not the edge in an image. The binarized edge map is obtained by adaptive thresholding which analyzing the membership value of each pixel with respect to the other neighborhood membership values. Here, the thresholding process takes edge values as the input and outputs of the binarized image. Therefore, each image pixel is judged adaptively by the localized criteria. In the context of adaptive thresholding, the value obtained as a result of threshold decision yields a particular fuzzy edge map region, hence resulting in adaptive de-fuzzification.

4.6. Fusion of brightness and edge enhanced image in higher wavelet coefficient

The Decision rule is defined to optimize weighted algorithm. We calculate the detail coefficients of the two images. The resulted information formed from the actual combination of coefficients. The optimized weighted algorithm rules has been applied on the images of the same size as the original image, where each edge value is enhanced on the basis of the source image which provides more detail information of the corresponding wavelet coefficients. The conventional approach of combining the images suffers from reduction of contrast. The proposed method used the fuzzy space to estimate the weights of the different combination. PSO maximizes the entropy function, a measure of the edge strength present in an image. This weight is based on the fuzzy membership function at which the entropy of resulted color satellite image gets maximized.

Each wavelet combination of high frequency coefficients corresponding to the source image and histogram equalized image are formed the fused image. The uncertainty in the combination based on the corresponding coefficients becomes the most important problem. In this case, we find the solution through estimation of coefficients ($\Phi(HH, A)$ and $\Phi(HH, B)$) to get the combined resulted image in image. The detail coefficient measures the energy and its information entropy coefficient which may give more importance to the resulted image. The concept behind this assumption that the strong and weak edges, which we have already detected, is to yield detail final image. The detail edge information obtained in HH domain are and. The detail information is contributed to weak and strong edges. This information is required to give enhanced image by combination of the details. We perform efficient fusion on the basis of their weight strength. The suggested fuzzy membership function measure the information at each pixel position and neglect the possibility of detecting wrong edges. Let $MF_3$ and $MF_4$ are the membership function computes the contribution of the coefficient for energy and information, respectively. The coefficient $MF_{prop}(w)$ represents the importance of the combined image,

$$MF_{prop}(w) = \text{Min}(MF_3(w), MF_4(w))$$  \hspace{1cm} (8)

$$MF_3(w) = \frac{(w \times w)}{\text{Max}_{HH}(w \times w)}$$ \hspace{1cm} (9)

$$MF_4(w) = \frac{e^{1-\text{prob}(w)}}{\text{Max}_{HH}(e^{1-\text{prob}(w)})}$$ \hspace{1cm} (10)

The fused detail coefficient $w_F$ is given by

$$w_F = \frac{\sum_{i=A}^{B} w_i \times MF_{prop}(w_i)}{\sum_{i=A}^{B} MF_{prop}(w_i)}$$ \hspace{1cm} (11)
The above equation represents the combining operator designed for high-frequency subbands. Based on this operator, the combined high-frequency components in wavelet domain can preserve all the salient features in source images and introduce as fewer artifacts or inconsistency as possible.

The inputs to the proposed algorithm are the edge information extracted from both test image and histogram equalized image. It yields an optimal weighted image on the application of designed set of fuzzy rules. In our case, the objective of the finding the optimal weights based on maximum edge information of the test and histogram equalized image of the same low-resolution image. We consider this approach which extracts information intelligently using soft computing technique of weak as well as strong edges present in the satellite image. The steps of proposed optimal edge enhancement approach are given in the proposed algorithm mentioned below.

Proposed Algorithm

Step 1: Read the low-resolution and low-contrast multi-spectral satellite image A.
Step 2: Histogram equalization is performed on Image A that yields an image B.
Step 3: DWT decomposition is performed on satellite images A and on histogram equalized image B, respectively. We obtain the corresponding coefficients Low–Low, Low–High, High–Low, High–High of low resolution satellite image A are $\Phi(LL, A)$, $\Phi(LH, A)$, $\Phi(HL, A)$, $\Phi(HH, A)$, respectively, and coefficients Low–Low, Low–High, High–Low, High–High of histogram equalized satellite image B are $\Phi(LL, B)$, $\Phi(LH, B)$, $\Phi(HL, B)$, $\Phi(HH, B)$, respectively.
Step 4: The high-frequency subband for each color satellite images $\Phi(HH, A)$ and $\Phi(HH, B)$ are bifurcated into three channels $R_A$, $G_A$, $B_A$, respectively, and $R_B$, $G_B$, $B_B$, respectively.
Step 5: Optimize parameters $r$, $t$, and $s$ using PSO and forms the fuzzy edge map for the resultant HH subbands. This band is formed by compute the objective function in given equation no 5. The maximum value of objective function preserves the edge strength present in the satellite image.
Step 6: The new color fuzzy edge map is defined on the basis of fusion using equation no 8 of three resulted in color channel of HH subband detail information $w_A$ and $w_B$.
Step 7: The detail information coefficient is combined using fuzzy membership function equation 1 and equation 3.
Step 8: Apply the inverse discrete wavelet transform (IDWT) sequentially in order to modify the higher domain coefficients using equation 11 with other all subbands.
Step 9: Finally, the enhanced satellite image has resulted.

Finally, the resulted image is reconstructed using IDWT of LL, LH, and HL band of histogram equalized image and high-frequency band obtained after the optimized combined image of high-frequency band.

5. Performance measures

To show the effectiveness of the proposed approach, we compared our statistical measures with other techniques. The performance of the enhanced image is evaluated visually and statistically. There are different statistical measures proposed in the literature. The technique like PSNR, MSE require reference image but reference image is not available for each condition. We measure our proposed approach by computing contrast assessment function (CAF) (Xie & Wang, 2010) and a measure of enhancement (EME) value (Agaian, Silver, & Panetta, 2007). These measures calculate the value for proposed image. These measures do not require any reference image. The higher the CAF and EME value better the quality of the image.

5.1. Contrast assessment function (CAF)

The CAF function are given by

$$CAF = \bar{H}^\alpha + \bar{C}^\beta$$ (12)

where $H$ is the entropy of the given image and $C$ is the contrast of the image. Here, we take $\alpha=1$ and $\beta=1/4$ for calculating the CAF value.
5.2. Measure of enhancement (EME)
The value of EME is calculated by the equation given by

\[
EME = \frac{k_1}{k_2} \sum_{l=1}^{k_1} \sum_{i=1}^{k_2} \frac{I_{\max}(k, l)}{I_{\min}(k, l) + c} \ln \frac{I_{\max}(k, l)}{I_{\min}(k, l) + c}
\]  

(13)
ge where \(k_1\) and \(k_2\) represent the total number of blocks of an input image, \(I_{\max}(k, l)\) represents the maximum value of the block present in an image, \(I_{\min}(k, l)\) gives the minimum value of the block present in an image, and \(c\) represents a small constant value which is added in the denominator part of logarithmic ratio in order to avoid dividing by zero. In this paper, we considered the 8x8 block size and \(c = 0.0001\).

| Images | Luminance \(\bar{L}\) | Entropy \(H\) | Average contrast \(\bar{C}\) | CAF |
|--------|----------------|-------------|----------------|-----|
| 1      | Test image     | 79.9986     | 6.4551         | 65.6653 | 18.3753 |
|        | Proposed approach | 98.4167    | 7.6711         | 194.7099 | 28.6551 |
|        | DWT (Demirel & Anbarjafari, 2011) | 128.3178 | 7.1251         | 93.4568 | 22.1536 |
|        | DCT (Bhandari et al., 2011) | 89.4299 | 6.6564         | 73.0664 | 19.4610 |
| 2      | Test image     | 65.4602     | 7.0769         | 99.3299 | 22.3417 |
|        | Proposed approach | 112.9181   | 7.4293         | 201.7765 | 28.0005 |
|        | DWT (Demirel & Anbarjafari, 2011) | 116.2298 | 7.4915         | 146.0859 | 26.0447 |
|        | DCT (Bhandari et al., 2011) | 85.2260 | 7.3169         | 127.5119 | 24.5875 |
| 3      | Test image     | 71.6810     | 6.6087         | 54.6698 | 17.9702 |
|        | Proposed approach | 137.1429   | 7.3670         | 216.1301 | 28.2469 |
|        | DWT (Demirel & Anbarjafari, 2011) | 172.8170 | 6.9092         | 95.3200 | 21.5887 |
|        | DCT (Bhandari et al., 2011) | 101.3466 | 7.1918         | 81.3107 | 21.5960 |
| 4      | Test image     | 39.8276     | 5.8954         | 56.0258 | 16.1292 |
|        | Proposed approach | 97.0773    | 7.6711         | 134.7808 | 26.1376 |
|        | DWT (Demirel & Anbarjafari, 2011) | 110.2186 | 6.7147         | 140.0949 | 23.1010 |
|        | DCT (Bhandari et al., 2011) | 85.5918 | 6.7959         | 144.7823 | 23.5737 |
| 5      | Test image     | 56.6508     | 6.5098         | 75.0127 | 19.1581 |
|        | Proposed approach | 109.4173   | 7.7799         | 138.2868 | 26.6788 |
|        | DWT (Demirel & Anbarjafari, 2011) | 131.7408 | 6.1716         | 134.5537 | 21.0195 |
|        | DCT (Bhandari et al., 2011) | 104.7732 | 7.0262         | 146.8237 | 24.4580 |
| 6      | Test image     | 107.9119    | 6.3510         | 68.8707 | 18.2957 |
|        | Proposed approach | 109.0543   | 7.8674         | 218.2253 | 30.2382 |
|        | DWT (Demirel & Anbarjafari, 2011) | 174.3260 | 6.8506         | 90.1928 | 21.1115 |
|        | DCT (Bhandari et al., 2011) | 118.0860 | 6.6610         | 82.7390 | 20.0893 |
| 7      | Test image     | 97.8874     | 7.0313         | 58.4979 | 19.4455 |
|        | Proposed approach | 111.2269   | 7.9427         | 111.4781 | 25.8086 |
|        | DWT (Demirel & Anbarjafari, 2011) | 152.1536 | 7.2286         | 72.3521 | 21.0824 |
|        | DCT (Bhandari et al., 2011) | 89.4299 | 6.6564         | 73.0664 | 19.4610 |
6. Experiments, results & discussions

The proposed method is used for preserving the satellite edge map in color images. It has been implemented on Intel core i3 at 2.4 GHz using MATLAB version 2014. The optimal fuzzy edge estimation algorithm is tested on 150 images obtained from NASA’s earth observatory satellite Lab images. Out of which we shows the seven satellite test images from Figure 3(i), (v), (ix), (xiii), (xvii), (xxi), and (xxv). The output of proposed images is shown from Figure 3(ii), (vi), (x), (xiv), (xviii), (xxii), and (xxvi). The proposed method compared with DWT (Demirel & Anbarjafari 2011)- and DCT (Bhandari et al., 2011)-based methods shown in Figure 3(iii), (vii), (xi), (xv), (xix), (xxiii), (xxvii), and Figure 3(iv), (viii), (xii), (xvi), (xx), (xxiv), (xxviii), respectively.

It is observed with the proposed method that it well preserved the edges and increases the significant portion of the contrast as compared with the other existing approaches. The enhanced image shown in Figure 3(ii) is observed with better edges as compared with other methods shown in Figure 3(iii) and (iv). In other state of art methods the edge information are not well preserved during the enhancement process. Those images obtained after DWT- and DCT-based methods are increases the intensity value but loose information. It has been observed from Figure 3(vi) the edges of blue color are shown but in Figure 3(vii) and (viii) these edges are not shown properly. The DWT-based method increases the brightness and sometime distort the edge detail. The proposed method improves the edge detail as well as the contrast of the image. Edge details do not lose as shown in Figure 3(x) as compared with Figure 3(xi) and (xii). The image obtained from DWT is brighter than DCT-based approach but it cannot allocate the edge detail. For the test image shown in Figure 3(xiii), the DCT-based method better than DWT as shown in Figure 3(xv) and (xvi). The DWT-based method changes the detail of the image as compare to the DCT method but proposed approach enhanced the image without changing of the details. When we visually analyzed the resulted images with our proposed method then, it will found that our method accomplish the requirement of enhancement without scarifying the detail of the image as shown in Figure 3(xviii), (xxii), and (xxvi). The difference here is to use the correction applies in higher region of DWT which preserve the edges. In the two existing approaches, the edge shows blurry due to the smoothing operation andlooses the information. But the images formed with the use of proposed work are sharper in reconstruction after IDWT. The efficient use of details overcomes the limitation of color distortion. We found the information enhances in optimal way that give more detail without saturation.

It was found the proposed algorithm gives better CAF value and EME value than other methods as shown in Tables 1 and 2. The CAF value which evaluates the intensity, entropy, and contrast value. It is clearly depicted from the Table 1 that the CAF value obtained in the proposed method is higher in comparison to the DCT- and DWT-based approaches in all seven test images. We have computed EME values for the images obtained with proposed method, DWT-based method and DCT-based method. The EME value of images obtained by employing proposed method is 14.1886, 11.9619, 12.7564, 8.5995, 9.2419, 7.7436, and 11.0726 which is clearly higher than the other two existing

| Test image | Proposed approach | DWT based method (Demirel & Anbarjafari, 2011) | DCT based method (Bhandari et al., 2011) |
|------------|-------------------|-----------------------------------------------|----------------------------------------|
| Image 1    | 14.1886           | 3.8198                                        | 4.6112                                 |
| Image 2    | 11.9619           | 7.9285                                        | 9.4718                                 |
| Image 3    | 12.7564           | 5.6743                                        | 3.4208                                 |
| Image 4    | 8.5995            | 7.8576                                        | 5.6761                                 |
| Image 5    | 9.2419            | 7.3345                                        | 3.4930                                 |
| Image 6    | 7.7436            | 4.8682                                        | 7.2640                                 |
| Image 7    | 11.0726           | 3.0337                                        | 4.6112                                 |
Figure 3. Resulted images.

(i) Test image1 (ii) proposed approach image1 (iii) DWT based image1 (iv) DCT based image1

(v) Test image2 (vi) proposed approach image2 (vii) DWT based image2 (viii) DCT based image2

(ix) Test image3 (x) proposed approach image3 (xi) DWT based image3 (xii) DCT based image3

(xiii) Test image4 (xiv) proposed approach image4 (xv) DWT based image4 (xvi) DCT based image4

(xvii) Test image5 (xviii) proposed approach image5 (xix) DWT based image5 (xx) DCT based image5

(xxi) Test image6 (xxii) proposed approach image6 (xxiii) DWT based image6 (xxiv) DCT based image6

(xxv) Test image7 (xxvi) proposed approach image7 (xxvii) DWT based image7 (xxviii) DCT based image7
approach. These tabulated results clearly indicate that the proposed approach are produced more contrast, information, and limits the saturation value.

7. Conclusion
An edge preserving satellite image enhancement method is proposed which is based on PSO and fuzzy membership functions. The sharpness of the satellite image is achieved by an optimal value of weights. These weights are calculated in the higher domain of DWT after taking the histogram equalization of the image. The limitations of histogram equalized satellite image are removed by the proposed approach. The proposed algorithm infers the following advantages:

(i) These weights are calculated in the higher domain of DWT after taking the histogram equalization of the image.

(ii) Due to the significant edge improvement which increases the color contrast in the enhanced images

(iii) The objects are easily detected used in the analysis of the satellite image. This method applied to low contrast satellite image and found that the enhanced image is visible with more detail. The visual and statistical comparison proves the effectiveness of the proposed approach.

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