Modified gain intervention refinement filter and multiobjective particle swarm optimization based local detail enhancement technique

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Abstract: Image enhancement plays an important role in improving the quality of the poor image. Most of existing image enhancement approaches suffer from the problems of color distortion, edge preservation, and halo artifacts. In this paper, an effective local image enhancement technique for remotely sensed images is proposed to enhance the spectral details. The proposed technique utilizes Particle Swarm Optimization (PSO) to enhance the spatial information of the image. Also, PSO based enhancement will be followed by the modified gain intervention refinement filter, to reduce the gradient reversal artifacts and halo artifacts. More distinctively, the proposed PSO based enhancement utilizes the sigmoid function and the local histogram to maximize the spatial information. The proposed technique is compared with some well-known image enhancement approaches. The comparative analysis has clearly proven that the result produced by proposed technique has natural contrast and rich spectral details without introducing halo and gradient reversal artifacts.

Keywords: Remote sensing images, Gain intervention filter, Particle swarm optimization, Local detail enhancement.

1. Introduction

Remotely sensed images are used in various fields of research [1]. One of the primary issue associated with remotely sensed images is their poor resolution, which may occur due to the higher distance among the satellite camera and the earth [2]. Several image enhancement methods have been proposed so far in order to enhance the visibility of given digital image [3]. An effective enhancement technique is proposed to improve the global contrast and the local details [4]. Dominant brightness level analysis and adaptive intensity transformation based enhancement can overcome the over-enhancement problem [5]. A new hybrid intensity transfer function based enhancement can effectively distinguish details in the whole image automatically and greatly enhances the overall contrast in various images [6]. A novel controlled random sampling strategy for the spectral-spatial technique is implemented to reduce the color distortion technique [7].

Image enhancement approaches are divided among spatial and transform domain techniques [8]. The histogram equalization is found to be well-known image enhancement technique, which is also divided into local and global categories [9]. Nowadays remote sensing images are widely used in an application like surveillance environment, hazardous environment, military and agricultural etc [10]. The unfocused environment decreases the contrast as well as the quality of remote sensing images by hiding the details [11]. So, in remote sensing images, the main focus is to improve the contrast by which the images are used for both visual perceptions as well as further processing [12]. Image enhancement by using transform domain techniques prevent artifacts and enhances the visible contents in the more promising way [13]. To overcome the issue of in excess of enhancement, the enhanced and input images are averaged by utilizing a weighting operation. The weighting operation has the ability to manage the visibility enhancement level of segments with dissimilar luminance into the actual image dynamically [14].

The standard histogram equalization uses visible intensities to enhance the content of given image, but some time leads to over enhancement issue if the image has higher or lower set of intensities [15]. Several
techniques have been introduced in order to limit the issue of over-enhancement, which is done by altering the existing definition of histogram equalization. An image enhancement using adaptive gamma correction smoothes the fluctuant occurrence by weighting distribution and improve the visibility of image automatically [16]. The adaptive gamma correction may lose information in brighter segments of given image. The local histogram equalization is proficient of achieving high contrast, but some time may produce an enhanced image. Local histogram equalization based techniques are demand additional multiplications than global histogram equalization based methods [17]. Also, it faces the contrast overstretching and noise improvement issues [18]. A common enlightenment normalization technique for numerous remote sensing images has introduced. That technique basically improves brightness in the gradient domain as well as equalizes the singular value to regulate illumines [19]. On the other hand, contrast with particulars has not clearly emphasized while this algorithm mainly contains the enlightenment consistency.

This paper has proposed a novel technique for improving the visibility of remotely sensed images. The proposed method produces efficient results by using PSO based image enhancement. The PSO can automatically extract the local atmospheric light and roughly eliminate the atmospheric veil of local detail enhancement. Thus proposed technique can easily handle the issue of over-enhancement and color distortion. Also to reduce the halo and gradient reversal artifacts the proposed technique utilizes gain intervention filter as post-processing technique.

The rest of this letter is organized as follows. PSO and gain intervention filter based image enhancement technique is discussed in Section II. In Section III, the performance metrics of image enhancement are given. To verify the effectiveness of the proposed technique, visual and quantitative results are carried out on remotely sensed images in Section IV. In Section V conclusion along with suitable future directions are presented.

2. Proposed Technique

Consider a Remotely sensed image I of size R x S with a range of \([u_{\text{min}}, u_{\text{max}}]\), where \(u_{\text{min}}, u_{\text{max}}\) are the elements of minimum and maximum correspondingly. The major aim is to enhance global contrast resultant image \(F_{\text{global}}\) with enhanced image \(v_{\text{min}}, v_{\text{max}}\). The existing histogram equalization produces over enhanced results if it comes up with high peaks in histogram of image the destination allocation function for generate the result should be modified to ignore this issue. The sigmoid function which has features of compression and smoothness is used to avoid the issue of saturation artefacts and over enhancement. Thus an enhanced allocation function \(c\) is created as

\[
c(m) = \text{Sig} (m) (1+g(m))
\]  
(1)

Where \(g\) is the standardized histogram; \(m = 1,2,\ldots,M\); and \(M\) is the gray levels integer in the actual image \(I\).

Sigmoid function (Sig) is adjusted as

\[
\text{Sig}(m) = \frac{1}{1+e^{-\left(m-\frac{1}{2}\right)}} - \frac{1}{2}
\]  
(2)

![Figure 1: Histograms of the zemu glacier- Sikkim](image)
This justification ensures the least of the improved image be equal to 0. The allocation function \( c \) is additionally normalized to

\[
c(m) \leftarrow c(m) / \sum_{q=1}^{m} c(q)
\]

and uniform allocation function \( C \) is calculated by \( c(m) = \sum_{q=1}^{m} c(q) \) (4), the new gray levels \( d(m) \) are computed by using \( c(m), v_{\text{min}}, \text{and } v_{\text{max}} \).

\[
d(m) = L_c(m) (v_{\text{min}}, v_{\text{max}}) + v_{\text{min}}
\]

Where \( L \) rounds the value to the least close integer. Eventually, with the help of lookup table based histogram equalization method, \( F_{global} \) global contrast improved image is produced. Figure 1 is showing the benefit of the Sig(m) function over the histogram equalization and the actual image's histogram. In figure 1(c) the histogram of the Sig (m) function is shown which has better intensity modification than histogram of the histogram equalization technique shown in figure 1(b).

### 2.1 Local detail Enhancement

To improve both local details and global contrast in the remotely sensed images, the cosine values of global contrast enhancement remotely sensed an image and again modified.

For the two-dimensional image 2-D, DCT transform domain technique is to produce the coefficients. These coefficients \( B \) of size \( R \times S \) are computed by

\[
B(e, f) = j_e j_f \sum_{k=0}^{R-1} \sum_{l=0}^{S-1} F_{global}(k,l) \cos \frac{\pi (2k+1)e}{2R} \cos \frac{\pi (2l+1)f}{2S}
\]

(6)

Where \( 0 \leq k, e \leq R - 1, 0 \leq l \leq S - 1 \), \( j_e \) and \( j_f \) are calculated by

\[
j_e = \begin{cases} \frac{1}{\sqrt{R}}, & e = 0 \\ \frac{1}{\sqrt{R}}, & 1 \leq e \leq R - 1 \end{cases} \quad (7) \quad j_f = \begin{cases} \frac{1}{\sqrt{S}}, & f = 0 \\ \frac{1}{\sqrt{S}}, & 1 \leq f \leq S - 1 \end{cases}
\]

(8)

The noteworthy point that minimum absolute values of \( B \) signify the minimum energy mechanisms, that is details and textures. Furthermore, \( B(0,0) \) is the maximum energy element that explains the value of mean in an image. Low energy parts should be modified to highlight the local details, while high energy portions should be preserved to ignore any important or notify change.

The thresholding algorithm is modeled to modify the cosine values \( B \) by

\[
B'(e, f) = \begin{cases} B(e, f) \text{ if } |B(e, f)| > 0.01 * B(0,0) \\ \epsilon B(e, f), \text{otherwise} \end{cases}
\]

(9)

Where \( \epsilon > 1 \) is used to control the local detail improvement level. After testing our improved method to 50 images, 0.01 is actual value to distinct the low and high energy parts. Over enhancement occurs only when \( \epsilon \) has a large value. Hence \( \epsilon \) is calculated as:

\[
\epsilon = \sqrt{\frac{SD(F_{global}) - SD(I)}{2^T - 1}}
\]

(10)

Where \( T \) is the image bit depth, \( D(F_{global}) \)and \( SD(I) \) are the standard deviations of the previously improved image \( F_{global} \) and the actual image I correspondingly. If the value is greater distinction between \( F_{global} \) and I that means high local detailed image is obtained. At last, the improved image is obtained from inverse DCT transform.
2.2 Particle Swarm Optimization (PSO) Based Enhancement

Image enhancement is found to be a challenging issue because each image requires different enhancement parameters. Therefore, selecting optimistic parameters for each image in an efficient way is found to be NP-hard problem. Therefore, evolutionary optimization approaches are required to enhance the images in a more efficient way. PSO is a well-known heuristic technique, founded from lessons on food aggregation of birds. In recent years, many researchers have utilized PSO solve many problems in the computational theory. In PSO, each choice is called as a “particle”. Particles are coexisting and shall be optimized. That is because each particle should “fly” towards an optimistic outcome in search domain, depends upon its own knowledge to discover the optimistic result [20]. Potential outcomes, the image enhancement factors, are symbolized by using particles in the problem domain and are directed to fly as per adaptively evaluated velocities. PSO is utilized in those areas where gradient or derivative kinds of optimization methods are hard to execute. The standard PSO is mostly represented by,

\[ \omega^m \vartheta^m_n + C_1^m \left( w^\vartheta_n - w^m_n \right) + C_2^m \left( w^\vartheta_n - w^m_n \right) = \vartheta^m_{n+1} \quad (11) \]

\[ w^m_{n+1} = w^m_n + \vartheta^m_{n+1} \quad (12) \]

where \( w^m \) define \( m^{th} \) outcome, \( \omega^m \) represent inactivity weigh values, \( \vartheta^m_n \) represents the velocity, \( C_1^m, C_2^m \) are gains of uniform random values ranges from \([0, C_{max1,2}]\), \( w^\vartheta_n \) is the global optimistic so far from entire set of particles also called optimistic. Also \( w^\vartheta_n \) is the population optimistic also called poptimistic. Particles values are updated, based upon their previously known values. The PSO initiate itself by using \( N \) particles which are developed randomly with particle \( w^\vartheta_0 \) and velocities \( \vartheta^m_0 \). The entire PSO procedure will be repeated till the stopping criteria met.

The behavior of PSO can be examined by doing an investigation by utilizing the control theory. The assurance on optimization outcome may be evaluated from an indication of awareness of particles in neighborhoods of group-optimistic particle \( w^\vartheta_n \). The attitude adopted should deal with dilemma of convergence of possible outcomes to optimal outcome. The position error of a particle is represented by

\[ P^m_{n+1} = w^\vartheta_n - w^m_n \quad (13) \]

From (2), the position error and velocity is defined in state space form as

\[ \begin{bmatrix} P^m_{n+1} \\ \vartheta^m_{n+1} \end{bmatrix} = \begin{bmatrix} 1 - C_2 - \vartheta \\ C_1 + C_2 \end{bmatrix} \begin{bmatrix} P^m_n \\ \vartheta^m_n \end{bmatrix} + C_2 \begin{bmatrix} 1 \\ -1 \end{bmatrix} (w^\vartheta_n - w^m_n) \quad (14) \]

\[ S_n+1 = b \sigma n + R \delta n \quad (15) \]

where \( S_n = P_n + 1, \vartheta_n + 1 \) is \( w^\vartheta_n - w^\vartheta \), and \( A, B \) are self-explanatory.

It turns out to be understood that the condition for convergence involves \( P_n \to 0 \) and \( \vartheta_n \to 0 \) as time \( n \to 0 \). When optimistic outcome is established \( w^\vartheta \) turn out to be constant and \( w^m \) leads to \( w^\vartheta \) if the structure is stable system. The steadiness of a discrete control organization can be determined by restricting the magnitude of Eigen values \( \gamma 1,2 \) of the system matrix \( A \in \mathbb{R}^{2,2} \) to be less than unity, i.e.

\[ \gamma 1,2 \leq \sqrt{2} (\gamma^2 + (\omega - C_1 - C_2) + \omega^2) \quad (16) \]

By utilizing the random numbers \( C_1 \) and \( C_2 \) as \( C_{1,2} \) take the probable values from a standardized allocation, the coefficients turnout to be \( C_1 = 1 \) and \( C_2 = 1 \). It corresponds to a entire feedback of inconsistency of particle locations from preferred outcome at \( w^\vartheta \). The Eigen values can be evaluated from

\[ \gamma 1,2 = \frac{1}{2} (\omega - 1) (\omega + 1 + \sqrt{4 + (\omega - 1)^2} \quad (16) \]

It can be represented, therefore that \( \omega < 1 \) with \( C_1 \) and \( C_2 = 2 \) will assure steadiness for the organization, hence particle will come together to \( w^\vartheta \). For example, \( \omega = 0.2 \) leads to \( \gamma 1,2 = -0.4 \pm m \times 0.2 \) it provides a...
reasonable convergence velocity. In addition, without actual information of outcome landscape, a consistent allocation is selected for the gain factors on $C_1, C_2$, the foundation of principle of maximum entropy.

2.3 Proposed PSO Based Image Enhancement

It is found that the PSO technique maintains two centers of desirability, namely, the global optimistic $w^g_n$ and the particle optimistic outcome $w^p_n$. In the optimization problem formulated in this work, that is, optimization of the scalar gamma-factor there are $\hat{y}^m_n \rightarrow m^m_n$ are two contradicting objectives including i) preservation of brightness values and ii) maximization of information content in actual image. To handle these objectives a modification is done with standard PSO is.

$$g^m_n+1 = w^m_n, g^m_n + c^m_1(y^w_n, y^m_n) + c^m_2(H^w_n - H^m_n)$$

(17)

$$w^m_n+1 = w^m_n + \hat{y}^m_n$$

where $\hat{y}^w_n, H^w_n$ are the optimistic outcomes obtained based on the values of the average intensity and information content? Each par $H^w_n$ is used to provide a temporal gamma factor for contrast enhancement and the average intensity with the information content calculated as the objective function. The optimistic result for these two objectives are formulated as

$$\hat{y}^m_n = \{y^w_n | (k^m_n - M^w_n < |k^m_n - M^w_n|), K^w_n K_n \neq i\}$$

(18)

$$\hat{y}^H_n = \{y^w_n | H^m_n > H^w_n, K_n \neq i\}$$

(19)

where average brightness values $k^m_n, k^w_n, M$ are evaluated by using (4), superscript represents actual image, and $H^w_n$ is entropy calculated by using (5). To judge the viewer’s console, preservation of average brightness value may be preferable to maximization of information values. In this case, unlike weighted sum technique, there is no requirement for user to identify weights of fitness function in PSO. The optimistic gamma-factor $\hat{y}^m_n$ stored along with its fitness value and compared with values which are calculated in successive iterations. If a good outcome is evaluated, the gamma factor is updated. After last iteration $\hat{y}^m_n$ is utilised to enhance the visibility of image.

3. Gain Intervention Refinement Filter

The gain intervention refinement filter [22], is utilized in order to evaluate and remove various artifacts (i.e. gradient reversal artifacts and halo artifacts) of the enhanced image using proposed PSO based enhancement technique. Also, gain coefficients have the ability to preserve information of every mask as its depth edges. Thus, the gain intervention filter improves the accuracy of image enhancement process, with the low computational load. The gain coefficient $g$ can be calculated as in Eq. (20).

$$g = \frac{\sum_{x,y} d(x, y)}{|d|}$$

(20)

Where $I^m = \min_c I_c(x, y)$, and $|I^m|$ and $|d|$ represent the total number of pixels in $I^m$ and $d$, respectively: $d(x, y)$ is the difference at position $(x, y)$ among the minimum intensity $I^m(x, y)$ of trichromatic components within each pixel $(x, y)$ in the image and PSO based enhanced image $I^d(x, y)$, which can be calculated as in equation (21).

$$d(x, y) = I^m(x, y) - I^d(x, y)$$

(21)

$g$ is utilized to estimate the intensity and preserve the inherent information of every mask. Therefore, the improved $t(x, y)$ without blocking artefacts can be evaluated as:

$$t(x, y) = (1 - I^m(x, y)) + gp$$

(22)

Finally, we employ the gain coefficient to approximate the intensity of the PSO based enhanced image and keep the intrinsic information of each patch. Hence, the refined image without artifacts can be yielded ad in Eq. (22). Where $p$ is the predefined calibration factor.
4. Performance Metrics

In real time applications, ground truth images are not given. Then it becomes difficult to measure the effectiveness of the given algorithm. In case of image enhancement techniques, a natural image has more contrast compared to the image with poor visibility. Therefore, contrast gain (CG) and Percentage of saturated pixels (PSP) can be effective parameters for evaluating the best image enhancement technique.

4.1. Contrast gain (CG)

CG for image enhancement techniques should be a positive value. A higher value of CG indicates that given image enhancement technique is more effective than others. It is described as the average contrast difference among low resolution and enhanced image [21]. Let \( C_{hf} \) and \( C_{hi} \) are average contrast of enhanced and low resolution image respectively, then CG can be evaluated as in Eq. (23).

\[
C_g = C_{hf} - C_{hi}
\]  
(23)

Let an image of size \( K \times L \) be represented by \( I_{mg}(p, q) \). Then, mean contrast \( A_c \) can be calculated as in Eq. (24).

\[
A_c = \frac{1}{K \times L} \sum_{p=1}^{K} \sum_{q=1}^{L} I_{mg}(p, q)
\]  
(24)

4.2. Percentage of saturated pixels (PSP)

CG should not be so high that the pixels of the haze-free image become saturated. Therefore, along with the high CG, it is also required to calculate the PSP. PSP can be calculated as in (25).

\[
PSP = \frac{S_p}{K \times L}
\]  
(25)

Where \( S_p \) represents the number of pixels that are saturated either completely black or white, after the enhancement technique but were not in the input image. Lower the value of \( S_p \), proves the effectiveness of the image enhancement technique.

5. Experimental results

In order to obtain the objectives of this paper, we have designed and implemented the Fu et al. [16], Zhang et al. [19], Xiao et al. [17], Lidong et al. [18] and proposed technique in MATLAB 2014b tool with the help of image processing toolbox. The experiments are performed on the Intel Core i5 processor with 8GB RAM and 2GB graphics card. Five well known remotely sensed images from Remote Sensing and Landsat dataset [20] are taken for performance evaluation purpose. However proposed technique is not limited to these remotely sensed images only. We can also apply the proposed technique on other images such as underwater, roadside images for better results. Figure 2(a), 3(a), 4(a), 5(a) and 6(a) shows the actual images, used for experimental purpose. Figures 2(b), 3(b), 4(b), 5(b) and 6(b) shows the results of the Fu et al. [16]'s technique. Figures 2(c), 3(c), 4(c), 5(c) and 6(c) outcomes of the Zhang et al. [19]'s technique. Results of the Xiao et al. [17]'s approach are shown in figures 2(d), 3(d), 4(d), 5(d) and 6(d). The outcomes of the Lidong et al. [18]'s approach are depicted in the figures 2(e), 3(e), 4(e), 5(e) and 6(e). The results of the proposed techniques are shown in the figures 2(f), 3(f), 4(f), 5(f) and 6(f).

5.1. Visual analysis

As demonstrated in Figure 2(b), 3(b), 4(b), 5(b), 6(b), 2(c), 3(c), 4(c), 5(c) and 6(c), the information have been considerably improved in enhanced remotely sensed image using the Fu et al. [16] and Zhang et al. [19]'s techniques respectively, but colors are distorted in the global and local regions. Therefore the spectral distortion has occurred.
Although edge sharpening leaves much to be preferred, the conserved spectral information is appropriate in Xiao et al. [17]'s algorithm. The colors have distorted, and edges are not sharpened sufficiently in Lidong et al. [18]'s approach. Therefore, the enhanced remotely sensed image by Lidong et al. [18]'s technique has minimum spectral information than Xiao et al. [17]'s technique and poor spatial information than Fu et al. [16], Zhang et al. [19]'s algorithm. As it is clear from Figure 2(f), 3(f), 4(f), 5(f) and 6(f), colors of the enhanced images are more similar to that of the actual image in the proposed method, and the edges of the enhanced images have been sharpened significantly than other methods. Thus the image provided by the proposed technique has lesser artifacts as compared to other techniques, also the enhanced images seem more natural.
Figure 4: Experimental results of gangotri glacier-uttarkhand (a) Input image, (b) Fu et al. [16], (c) Zhang et al. [19], (d) Xiao et al. [17], (e) Lidong et al. [18] and (f) Proposed technique.

Figure 5: Experimental results of siachen glacier-j & k (a) Input image, (b) Fu et al. [16], (c) Zhang et al. [19], (d) Xiao et al. [17], (e) Lidong et al. [18] and (f) Proposed technique.
Figure 6: Experimental results of zemu glacier- Sikkim (a) Input image, (b) Fu et al. [16], (c) Zhang et al. [19], (d) Xiao et al. [17], (e) Lidong et al. [18] and (f) Proposed technique

5.2. Quantitative analysis

In addition to the visual observation, we have also evaluated the quantitative analysis. We have compared the proposed technique with Fu et al. [16], Zhang et al. [19], Xiao et al. [17] and Lidong et al. [18] using different quality metrics. The normal necessity for an image enhancement technique involves all logical information coming from source images to be protected. Meanwhile, the following reformulation of merged images should not be delayed because of surplus object introduction. Popular metrics for objective evaluation are CG and PSP because reference images are not available.

Table 1 and 2 are showing the quantitative analysis of the well-known remotely sensed image [16] when Fu et al. [16], Zhang et al. [19], Xiao et al. [17], Lidong et al. [18] and proposed technique are applied on them.

Table 1: Comparative analysis of contrast gain ($\Omega$)

<table>
<thead>
<tr>
<th>Method</th>
<th>Image 1</th>
<th>Image 2</th>
<th>Image 3</th>
<th>Image 4</th>
<th>Image 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fu et al. [16]</td>
<td>1.3636</td>
<td>0.9425</td>
<td>1.1505</td>
<td>1.0227</td>
<td>0.9827</td>
</tr>
<tr>
<td>Zhang et al. [19]</td>
<td>1.4373</td>
<td>0.9897</td>
<td>1.2753</td>
<td>1.1611</td>
<td>1.1923</td>
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<tr>
<td>Xiao et al. [17]</td>
<td>1.5847</td>
<td>1.1929</td>
<td>1.3501</td>
<td>1.3922</td>
<td>1.3285</td>
</tr>
<tr>
<td>Lidong et al. [18]</td>
<td>1.6950</td>
<td>1.2474</td>
<td>1.4698</td>
<td>1.4326</td>
<td>1.5496</td>
</tr>
<tr>
<td>Proposed</td>
<td><strong>1.7554</strong></td>
<td><strong>2.4954</strong></td>
<td><strong>1.7824</strong></td>
<td><strong>1.6174</strong></td>
<td><strong>1.8333</strong></td>
</tr>
</tbody>
</table>

Table 2: Comparative analysis of percentage of saturated pixels ($\tau$)

<table>
<thead>
<tr>
<th>Method</th>
<th>Image 1</th>
<th>Image 2</th>
<th>Image 3</th>
<th>Image 4</th>
<th>Image 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fu et al. [16]</td>
<td>0.2879</td>
<td>0.2659</td>
<td>0.3851</td>
<td>0.2133</td>
<td>0.3494</td>
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<td>Zhang et al. [19]</td>
<td>0.1930</td>
<td>0.2183</td>
<td>0.2901</td>
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<td>0.2545</td>
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<td>Xiao et al. [17]</td>
<td>0.1732</td>
<td>0.1944</td>
<td>0.1896</td>
<td>0.1442</td>
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<td>Lidong et al. [18]</td>
<td>0.1492</td>
<td>0.1765</td>
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<td>0.1189</td>
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<tr>
<td>Proposed</td>
<td><strong>0.1264</strong></td>
<td><strong>0.1646</strong></td>
<td><strong>0.1143</strong></td>
<td><strong>0.1152</strong></td>
<td><strong>0.1029</strong></td>
</tr>
</tbody>
</table>
Table 1 and 2 are also showing the analysis of the CG and PSP respectively. The mean improvement in CG is 0.47 and mean reduction in PSP is 0.07. This proposed technique is more effective than other techniques such as enhancement techniques proposed by Fu et al. [16], Zhang et al. [19], Xiao et al. [17] and Lidong et al. [18].

Table 3: Comparative analysis of execution time (ET) in minutes

<table>
<thead>
<tr>
<th>Method</th>
<th>Image 1</th>
<th>Image 2</th>
<th>Image 3</th>
<th>Image 4</th>
<th>Image 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fu et al. [16]</td>
<td>1.9856</td>
<td>1.8539</td>
<td>2.1365</td>
<td>2.4299</td>
<td>2.0464</td>
</tr>
<tr>
<td>Xiao et al. [17]</td>
<td>3.5958</td>
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<tr>
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<td>2.8973</td>
<td>2.7048</td>
<td>2.9874</td>
<td>3.2808</td>
</tr>
</tbody>
</table>

We have run the simulation 10 times and find out the average execution time analysis, also called the speed of the algorithm. Because speed varies a little bit every time. Table 3 demonstrates the speed analysis. The mean execution time of the proposed technique for given set of images is 2.36 minutes. The Fu et al. [16] which has efficient speed than other techniques have taken 2.02 minutes to accomplish the work. This proposed technique is more effective than that of Zhang et al. [19], Xiao et al. [17] and Lidong et al. [18] in terms of execution time. But takes more time than Fu et al. [16]'s techniques. But for satellite images speed can be relaxed for many applications.

Table 4: Effect of various parameters on contrast gain and saturated pixels

<table>
<thead>
<tr>
<th>$p$</th>
<th>$\Omega$</th>
<th>$\tau$</th>
<th>$\chi_0$</th>
<th>$\Omega$</th>
<th>$\tau$</th>
<th>$c$</th>
<th>$\Omega$</th>
<th>$\tau$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.1274</td>
<td>0.0591</td>
<td>0.1</td>
<td>0.2035</td>
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5.3 Sensitivity analysis

Subsequent section describes the effect various parameters on proposed technique. For efficient dehazing results have set the response factor ($p$) within the range of $[0.7, 0.95]$. We have taken this range by doing the experiments on several images. It has been found that any value of $p \leq 0.7$ results in image with lesser contrast when it is compared with other techniques. Also any value of $p \geq 0.95$ will increase the number of saturated pixels. Table 4 shows the effect of $p$, $\chi_0$ and $c$ using the proposed technique by considering the building image. It is found that any value of $p \leq 0.7$ results in image with lesser contrast gain ($\Omega$) when compared with other technique. Also, any value of $p \geq 0.95$ will increase the number of Percentage of saturated pixels ($\tau$). In the same way, it is found that any value of $\chi_0 > 0.1$ results in an image with lesser contrast when compared with other technique. Also any value of $c \leq 0.9$ will increase the number of saturated pixels.
6. Conclusion
This paper has proposed a novel technique for improving the visibility of remotely sensed images. The proposed method produces efficient results by using PSO based image enhancement. The PSO can automatically extract the local atmospheric light and roughly eliminate the atmospheric veil of local detail enhancement. Thus proposed technique can easily handle the issue of over-enhancement and color distortion. Also to reduce the halo and gradient reversal artifacts the proposed technique utilizes gain intervention filter as post-processing technique. The proposed technique is tested on the well-known remotely sensed images. Comparative quantitative analysis of the proposed with Fu et al. [16], Zhang et al. [19], Xiao et al. [17], Lidong et al. [18] has clearly demonstrated that it has better structural detail, spatial resolution, and rich spectral information. Also, the proposed technique has lesser halo and gradient reversal artifacts when compared with other techniques. Thus, it is more suitable for real-time applications.

References


