Fusion Based Spectral Enhancement of Hyperspectral Images in Remote Sensing

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ABSTRACT: In this paper, a new fusion based spectral enhancement of hyperspectral images is proposed. This method is designed to create a fused image with a special technique for fine-tuning. Fusion-based methods provide similar images without over- or underexposed any pixels. It contains spatial smoothness constraints for weight vectors. The solution of the optimum fusion-based approach is obtained from the modified Euler-Lagrange equation. The visual presentation and several results confirm the effectiveness of the fusion-based technique.

Keywords: Image Fusion, Enhancement, Remote sensing Image, Optimization, Visualization, Hyperspectral Image.

1. INTRODUCTION

In recent years, remote sensing technology has developed rapidly. It is successfully used in quality control, medical diagnosis, anomaly detection, remote sensing and forensic applications [1]-[3]. Often, a single image cannot provide complete information about a particular location, and multiple images of the same location are captured to provide additional information. Image fusion is the process of combining information from two or more scenes into a composite image that is more informative for visual perception [4]. However, depending on the needs of the remote sensing application, different images can be generated from the same set of input data. Fusion of remote sensing images is frequently used in many applications such as uncertainty reduction, improved classification and better visualization [5]. Image compositing results for remote viewing images are grayscale or RGB images that can be viewed on a standard tristimulus display. In remote sensing, hyperspectral images are one of the most important and frequently occurring data with multiple bands. It works by measuring the reflectivity of the field, obtained by a combination of continuous narrow hyperspectral sensors. This hyperspectral sensor array is tuned to cover a wide range of wavelengths in the visible and infrared spectrum. Due to its stability, accuracy and detailed information in many fields, the investigation of remote sensing images has recently attracted attention [6]. [7]-[8] uses fusion-based methods to refine remote sensing images for better visualization. The optimization process described in this document finds the best fusion parameters to improve the performance of remote sensing images. Visualizing hyperspectral scenes quickly and efficiently can be an important step before using remote sensing processing algorithms. This visualization provides a quick overview of hyperspectral data across multiple categories and eliminates redundancy in remote data access. A number of data-based distant fusion techniques have been proposed in [9]. However, most of these techniques are temporary image compositing techniques. Pixel-based techniques create composite images from input image bands. However, from a better point of view, this fusion image does not reflect the properties of the fusion image. In this paper, a new method is proposed to combine hyperspectral data. The suggested method is to find the optimal weight that produces the most output images. In this model, the original image is combined with α-mat for each group. Fusion zones are divided into three zone groups. Combine all group groups to get the output color combination. This article presents an Alpha matting model that optimizes contrast and contrast for better hyperspectral image contrast and clarity. Therefore, it must have the necessary costs to reduce the consequences of linking images. The thesis was prepared as follows. The preparation process is described in Chapter II. Part III describes experiments on various materials and Part IV presents the results.

2. ALPHA MATTING FUSION BASED APPROACH

Alpha matting fusion method developed a new hyperspectral image correction method using the alpha matting model of hyperspectral bands. The objective function relies on improving contrast and sharpness to optimize the variance and bias parameters. In general, hyperspectral images have a wide bandwidth and can be based on two concepts, the area between the dynamic range and the average gray value, resulting in poor contrast and low sharpness. In the proposed plan, parametric entropy is used to create an all-purpose value function to improve contrast and increase sharpness and avoid punitive terms for over-smoothing. The solution of the multi-objective cost function called α-mat is obtained by changing the Euler-Lagrange equation. Calculate the α-mat function weight for each group. Then, the original image is combined with α-mat for each group. Fusion zones are divided into three zone groups. Combine all group groups to get the output color combination. The mat based fusion method finds the best fusion weight method to produce the maximum output image by increasing the contrast and sharpness of the output image and reducing color distortion. A block diagram representation of standard alpha matting for multiple images is shown in Figure 1.1.
2.1 Computation of α-matte

Fusion of hyperspectral images is a fusion of pixels at available wavelengths. Different fusion processes produce different weights, called α-mat. Let \( I \) be a three-Dimensional array whose dimensions \( (X \times Y \times B) \) are discrete locations \( B \) of the hyperspectral images.

Let \( g(x, y) \) be the large merged image of dimensions \( (X \times Y) \) created using a pixel-based fusion technique, i.e. a linearly combined sampled wavelength response at every pixel location and is given by

\[
g(x, y) = \sum_{k=1}^{B} \alpha_k(x, y) i_k(x, y)
\]  

(1.1)

where \( i_k(x, y) \) represents the pixel at location \( (x, y) \) in the \( k^{th} \) band of the hyperspectral image, and \( \alpha_k(x, y) \) is the value of α-matte for the pixel which acts as the weight for fusion. The weights \( \alpha_k(x, y) \) should satisfy the following conditions:

(i) At any given pixel, the sum of all the weights should be equal to 1, i.e.

\[
\sum_{k=1}^{B} \alpha_k(x, y) = 1, \quad \forall(x, y)
\]  

(1.2)

(ii) The weights should not be negative, i.e.

\[
\alpha_k(x, y) \geq 0, \quad \forall(x, y)
\]  

(1.3)

It provides sufficient conditions for the fusion image to be non-negative. Therefore, during the fusion process, the input hyperspectral data is assumed to be normalized \( 0 \leq i_k(x, y) \leq 1, \forall(x, y) \). The projection area of satellite images varies in band. The reflectance response of a satellite image varies largely throughout the bands. The fusion algorithm maps pixels from a wide dynamic range to a narrow range for the imaging system.

Remote sensing applications prefer a small amount of electrical disturbance. Two strategies are used: (i) map pixels to the region between different gray values. This helps bring the overexposed and underexposed areas around the middle area. (ii) Map the pixels to the average gray value of the input data. This will help approximate the average density of the input data so the fused image will have bias and therefore less electrical distortion. If the first idea is accepted, the weight is calculated so that the pixels in the merged image are closer to the gray level in the center. Therefore, the concept can be defined as optimization in Equation (1.4) where the objective function is to calculate α-matte with maximized entropy \( \Psi_1 \) of the combined output image.
\[
\psi_1(\alpha) = -\int_{x} \int_{y} g(x, y) \log \left( \frac{g(x, y)}{m_y e} \right) dxdy
\]

where \( m_y \) is the mid region. In the second strategy, instead of using \( m_y e \) in the denominator, \( m_y e \) is used where \( m_y \) is the mean of the entire hyperspectral data. The output image from strategy one has poor contrast. Therefore, maximizing entropy does not produce a sharper fused image. Hence the optimization function should be corrected to maintain the balance between entropy maximization and contrast of the fused image. Therefore, another objective function \( \psi_2 \) is introduced to produce high contrast fused image by maximizing the variance.

\[
\psi_2(\alpha) = \frac{1}{XY} \int_{x} \int_{y} \left( \frac{\int_{x} \int_{y} g(x, y) dxdy}{XY} \right)^2 dxdy
\]

\( \psi_1 \) and \( \psi_2 \) are opposite in nature because \( \psi_1 \) pulls the distinct pixels towards the mean, while \( \psi_2 \) pushes away the pixels from the mean. It is also seen that the adjacent pixels exhibit higher degree of spatial correlation which may introduce smoothing in the image. Excessive smoothing blurs the edges and washes away the minor features. Therefore, penalty term \( \psi_3 \) is taken as the cost function which enforces smoothness in the fusion weights (i.e. \( \alpha \)-mate).

\[
\psi_3(\alpha) = \int_{x} \int_{y} \sum_{k=1}^{B} \left( \alpha_k^2(x, y) + \alpha_k^2(x, y) \right) dxdy
\]

Therefore, the final objective function is constructed by considering \( \psi_1, \psi_2 \) and \( \psi_3 \) as

\[
J(\alpha) = -\psi_1(\alpha) - \lambda_v \psi_2(\alpha) + \lambda_s \psi_3(\alpha)
\]

subject to \( \alpha_k(x, y) \geq 0, \forall k \) satisfying the non-negativity and unitary properties. \( \lambda_v \) and \( \lambda_s \) are the scalars that weigh the relative importance of the variance and smoothness terms respectively. The fused image is obtained from the solution of the objective function. The solution for this can be adopted into a cost function with the help of Lagrange multiplier. For the computation solution, a set of auxiliary variables \( w \) is introduced where \( w \) is the positive square root of \( \alpha \)-mate. Thus, the original weights are replaced as, \( \alpha_k(x, y) = \Delta w_k^2(x, y) \), \( \forall (x, y) \) and the constraint and the cost function are also modified in terms of \( w \). Similarly, \( \psi_1 \) and \( \psi_2 \) are also modified by replacing \( \alpha \) by \( w^2 \). For \( \psi_3 \), the smoothness terms of \( w_k \) are an explicit constraint to ensure the smoothness in the actual weights \( \Delta w_k^2 \). The normalization constraint is added explicitly to ensure that for every pixel, the addition of the weights is equal to unity. This constraint is calculated after modifying the weights to a square term as

\[
\sum_{k=1}^{B} w_k^2(x, y) = 1
\]

The constraint given in Equation (1.2) requires that the weights to be chosen are such that they lie on the hyperplane in the first quadrant. The constraint in Equation (1.8) requires the auxiliary variables to lie in a unit hypersphere so that a unity norm constraint can be easily enforced externally while solving the optimization problem. The solution to the optimization problem is given by using modified Euler Lagrange method. The vector notations are adopted as follows. Let \( i(x, y) \in R^B \) denote a vector consisting of \( B \) bands at the location \((x, y)\) across the image cube. \( W^2(x, y) \in R^B \) denotes the defined weight vector for the same location. This vector is an element-wise product of the vector \( W(x, y) \in R^B \) which is given below

\[
W^2(x, y) = \{w_k(x, y)w_k(x, y), \forall k\}
\]

\[
= W(x, y) \bullet W(x, y)
\]

where \( \bullet \) is an element-wise product operator. Using the vector notations, the resultant fused image \( g(x, y) \) can be denoted in the
form of a dot product of the input data vector \( \hat{i}(x, y) \) at the corresponding pixel location \((x, y)\) with the defined weight vector \( w^2(x, y) \) at the same spatial location, i.e.

\[
g(x, y) = \hat{i}(x, y) \cdot w^2(x, y) = \hat{I}^T(x, y)w^2(x, y) \tag{1.10}
\]

The cost function is given by

\[
J(w) = \int_\mathbb{R} (\hat{I}m^2) \left( \log \left( \frac{\hat{I}m^2}{\hat{I}m^2_{ref}} \right) - \frac{1}{XY} \left[ \hat{I}m^2 \Sigma s_j w^2_{mat} \right] \right) dy \quad \text{(1.11)}
\]

\( m \) is the index of iteration, and \( \mu \) is the Lagrangian multiplier for the unity norm constraint. For an efficient computation, the argument \( x \) and \( y \) of the functions are omitted. The solution for the previous equation is obtained using a corresponding modified Euler-Lagrange equation as follows:

\[
\frac{\partial J}{\partial w} - \frac{\partial}{\partial x} \left( \frac{\partial J}{\partial w_x} \right) - \frac{\partial}{\partial y} \left( \frac{\partial J}{\partial w_y} \right) = 0 \tag{1.12}
\]

where \( J(w, w_x, w_y) \) is integrand in Equation (1.11). On simplification, Equation (1.12) becomes

\[
s_{\max} = \frac{w_{\max}^2}{4\Delta_y} \left\{ \sum w_{\max} \left[ 1 + \log \left( \frac{\hat{I}m^2_{\max}}{\hat{I}m^2_{\min}} \right) \right] - \log(0.5e) - 2\Delta_y \left[ \hat{I}m^2_{\max} \Sigma s_j w_{\max} \right] \right\}
\]

\[
t_{\max} = \frac{w_{\max}^2}{4\Delta_y} \left\{ \sum w_{\max} \left[ 1 + \log \left( \frac{\hat{I}m^2_{\max}}{\hat{I}m^2_{\min}} \right) \right] - \log(0.5e) - 2\Delta_y \left[ \hat{I}m^2_{\max} \Sigma s_j w_{\max} \right] \right\}
\]

Hence the optimization problem is solved. The resultant fused image is expected to be centered on mean radiometric value of the entire bands and has a greater contrast. After computing the \( \alpha \)-mate by using the above solutions, the original image bands are fused with the \( \alpha \)-mate of each image band.

### 2.2 Computation of Bands for Fusion

The proposed method sorts the fused image bands based on spatial information. Spatial information computes the information content present in each band.

The spatial information \( E \) of an image is given as

\[
E = -\sum_{i=1}^{N} P(I_i) \log_2 \left( \frac{P(I_i)}{P(I)} \right) \tag{1.14}
\]

where \( I_i \) denotes the possible gray value. The arranged spectral bands are split into three groups of nearly equal bands and spatial information. Each group is clubbed into a single color channel using the \( \alpha \)-mate of each band, and the fusion is made separately based on the expression given below.

\[
f_1(x, y) = \sum_{i=1}^{B_1} \alpha_{k_1}(x, y) i_{k_1}(x, y)
\]

\[
f_2(x, y) = \sum_{k_2=B_1}^{B_2} \alpha_{k_2}(x, y) i_{k_2}(x, y)
\]

\[
f_3(x, y) = \sum_{k_3=B_2}^{B_3} \alpha_{k_3}(x, y) i_{k_3}(x, y)
\]

where \( f_1(x, y) \) is the first group of fused bands, and \( B_1 \) is the number of bands in the first group. \( f_2(x, y) \) is the second group of fused bands, and \( B_2 \) is the number of bands. \( B_3 \) is the number of bands in the third group \( f_3(x, y) \). Each of the three groups is assigned Red, Green and Blue channels. The task of colors is not directly related to the actual wavelength of these primary colors, and hence several pseudo-color schemes are used to present the result in an enhanced manner. Thus, the resultant image represents the collective spectral response of the scene for a better visualization of the scene contents. The matting technique has been able to provide the image with a reasonably high amount of spatial information and contrast, suitable for human observer.

### 2.3 Visualization of Hyperspectral Images
The fused R, G and B channels are individually enhanced using histogram equalization. The main idea of histogram equalization is to reassign the pixel values to make the distribution uniform. The histogram of each band is calculated as the probability of occurrence of a pixel of level \( i \) in the image as

\[
P_x(i) = P(x = i) = \frac{n_i}{n}, \quad 0 \leq i \leq L
\]

where \( L \) is the total number of levels in the image, \( n \) is the total number of pixels in the image, and \( P_x(i) \) is the image’s histogram for a pixel value \( i \) normalized to [0, 1]. The cumulative distribution is calculated as

\[
cdf_x(i) = \sum_{j=0}^{i} P_x(j)
\]

The fused image is transformed using the transformation function

\[
cdf_x(k) = cdf_y(T(k))
\]

where \( k \) lies in the range [0, \( L \)], since the transformation \( T \) maps the level in the range [0, 1]. To map the values onto their original range, the following transformation is applied to the result. The transformed image is given as follows:

\[
f' = f.(\max\{i\} - \min\{i\}) + \min\{i\}
\]

where \( i \) is the intensity value of the image \( f \).

The enhanced images are assigned to RGB channels to form a composite image. Hence the proposed technique provides good quality visualization from a low contrast hyperspectral data.

### EXPERIMENTAL RESULTS AND COMPARISON

In this section, experiments for evaluation of Alpha Matting algorithm are presented and compared with existing techniques like UCNMF, Gram Schmidt, optimization-based approach and KNN matting method. To demonstrate the performance of the Alpha matting algorithm, experiments are carried out on AVIRIS datasets. This section presents the quantitative results of applying the Alpha matting algorithm to hyperspectral images.

#### 3.1 Quantitative Evaluation

In the quantitative assessment of the fused images, University of Pavia and Cuprite are processed using the proposed algorithm and analyzed. The datasets are analyzed in spectral aspects. The performance measures used for spectral aspects are correlation coefficient, \( Q\text{-Average} \), relative dimensionless global error in synthesis, spectral angle mapper, spectral information divergence, spectral discrepancy, and the parameters entropy, average gradient and fusion factor are used for evaluating the proposed method in spatial aspect.

##### 3.1.1 Spectral aspect

The spectral information in different hyperspectral images is determined using SD, \( Q\text{-Avg} \) and CC. The lower value of SD represents better spectral retaining property. Similarly, the lower values of RMSE, SAM, SID and ERGAS indicate best spectral property. The quantitative assessment of the proposed method on various datasets is given in Tables 1.1-1.2.

#### Table 1.1Quantitative comparison of various techniques in University of Pavia dataset with different spectral quality measures
Table 1.2  Quantitative comparison of various techniques in Cuprite dataset with different spectral quality measures

<table>
<thead>
<tr>
<th></th>
<th>University of Pavia</th>
<th>Cuprite</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_s$</td>
<td>$\lambda_c$ = 90</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>95</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>105</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Gram Schmidt method involves initial fusion process with a synthetic low resolution panchromatic image followed by orthogonal decomposition and finally inverting the decomposition. The CC and Q_avg are high when compared to the UCNMF method which results in a little high spectral information. The RMSE and ERGAS present in the Gram Schmidt technique are also high when compared to the existing techniques which results in inobvious color distortion. Hence this method’s results are good compared to UCNMF method, but the performance is not good while compared with the proposed method.

In the optimization-based approach, the objective function involves maximizing the contrast with minimal saturation. Though this approach improves the contrast, it introduces spectral distortion when compared with the proposed method. The RMSE and ERGAS values show a considerable reduction in spectral distortion when compared with the previous two methods. Hence this method shows reduced value of SD, SID and SAM, thus reduced spectral distortion when compared with the previous two existing methods. This optimization-based approach shows good results when compared to the previous two methods, but the performance is reduced when compared to the proposed method.

The KNN matting method provides a non-local matting model which involves multiple layer extraction spectrally that results in reduced spectral distortion, but limits their performance in case of overall contrast and sharpness. The performance measures like RMSE and ERGAS have been reduced to very small value when compared to the existing methods, which infers that it results in reduced spectral distortion. Further, the spectral information present in the KNN matting method also increases when compared to the existing methods while considering the values of CC and Q_Avg. Thus, this method shows a better result when compared to the existing methods in spectral aspects, but degraded performance when compared to the proposed method.

Even though the spectral behaviour of KNN matting model is better, in order to improve the overall contrast and sharpness, an objective function is developed to optimize the parameters so that the overall contrast and sharpness get improved, which results in best spectral information while calculating the performance measures like CC and Q_Avg.

Hence the spectral distortion is much reduced in the proposed method while calculating the performance measures like RMSE and ERGAS when compared to the existing techniques. Thus, the proposed method outperforms the existing methods in all spectral aspects of the performance measures for various datasets.

3.1.2 Effect of Regularization Parameter

The performance of the proposed algorithm on this hyperspectral image with different values of variance is quantitatively evaluated using the divergence parameter as shown in Table 1.3.

Table 1.3  Quantitative comparison results of different regularization Parameter in the proposed method for different datasets

From the above table, it can be viewed that the alpha matting model is robust to contrast, when compared to the existing algorithms. In the proposed method an objective function which optimizes the divergence and variance is adopted, so that the overall contrast and sharpness is improved. To further evaluate the performance of alpha matting algorithm with other existing algorithms, the alpha matting algorithm is applied to the real hyperspectral images in AVIRIS dataset. Two datasets of hyperspectral images have been considered to prove the betterness of the proposed alpha matting algorithm.
CONCLUSION
This paper explains a new alpha matting model which enhances the hyperspectral images and provides high spatial information with reduced spectral distortion when compared with other recent methods, as the spectral bands are rearranged based on entropy. Also, the contrast and sharpness are improved by solving the modified Euler Lagrange optimization function. The quantitative results demonstrate that the proposed technique performs better when compared to the existing methods.

REFERENCES