MULTISPECTRAL IMAGE ENHANCEMENT BASED ON FUSION AND SUPER-RESOLUTION

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ABSTRACT

A principally new technique for fast fusion of multiresolution satellite images with minimal colour distortion is presented in the paper. This technique allows multispectral image reconstruction with resolution higher than resolution of the panchromatic image. It is based on combination of a method for super-resolution image reconstruction and an algorithm for image fusion based on global regression. Super-resolution image reconstruction is based on simultaneous processing of several multispectral images to reconstruct a panchromatic image with higher resolution. This method is near optimal in a minimum mean squared error sense of image restoration.

1. INTRODUCTION

Image fusion or pan-sharpening is performed in order to increase resolution of multispectral images utilizing the panchromatic image information. Resolution of sharpened images is limited by resolution of a panchromatic image. For example, Landsat 7ETM+ provides panchromatic images with resolution 15m and multispectral with 30m. Therefore, resolution of the sharpened multispectral images is two times higher than original one. The Brovey transform [1] and IHS fusion [2] methods are point type methods, fast and applicable for images of the large size. PCA and wavelet-based fusion methods [3] are of global and local operator type and computationally expensive.

In satellites launched after 1999, sensitivity range of the panchromatic image sensor is usually extended to cover nearest infrared range. It is made in order to increase resolution of the registered panchromatic image, but the former fusion methods cause significant color distortion [4].

We develop a principally new technique for multispectral image fusion with resolution higher than resolution of the original panchromatic image and with minimization of color composition distortion of the fused images. Two tasks are to be solved in order to achieve the higher resolution: super-resolution panchromatic image reconstruction and multispectral image fusion.

To solve the first task one can use reconstruction of a panchromatic image from color images by demosaicing algorithm [5] either super-resolution image reconstruction [6, 7]. Our solution is based on the method, which is near optimal in a minimum squared error (MSE) sense of image restoration [8]. This method allows theoretical quality evaluation and can be developed for super-resolution image reconstruction from several images [9].

The solution of the second task may be based on an algorithm of multiresolution image fusion. We select a fusion algorithm based on the linear regression. The algorithm is of point type (i.e. fast) and provides minimal color composite distortion.

The reconstructed panchromatic and original panchromatic images were compared using the structural similarity index (SSI) [10].

Quality of fused images was evaluated by the Euclidean norm (L2) of the histogram difference of the original and the fused images, correlation, RMSE, square error of the difference image (SEDI).

2. IMAGE RESTORATION METHOD

The optimal solution of Fredholm’s integral equation of the first kind may be used for image resolution increase [11]. The solution restores a continuous representation of digital images. Note, that images are registered by a focal plane array (FPA).

2.1 Model of image formation

Information about optical properties of the original ideal image \( Z(\xi, \eta, \lambda) \) is transmitted into an optical system. This system is characterized by a point spread function (PSF) \( K(x, y, \xi, \eta, \lambda) \). The optical system projects a panchromatic image \( f(x, y, \lambda) \) onto the FPA. This process can be described by a linear equation [11, 12]

\[
  f(x, y, \lambda) = \int_{-\lambda_{\alpha}}^{\lambda_{\beta}} \int_{-\lambda_{\gamma}}^{\lambda_{\delta}} Z(\xi, \eta, \lambda) K(x, y, \xi, \eta, \lambda) d\xi d\eta, 
\]

where \( S_1, S_2 \) are the integration limits, \( (\xi, \eta) \) are Cartesian coordinates of a point in the plane of image \( Z(\xi, \eta, \lambda) \), \( \lambda \) – the wavelength of light, \( (x, y) \) are the coordinates of point in the plane of the registered image \( f(x, y, \lambda) \). For clarity, the images with different spectral bands and light wavelengths in Equation (1) will be labeled below by \( f(x, y, \lambda_p, p) \), where \( p = 0, \ldots, P \), \( \lambda_p = \lambda_0, \lambda_1, \ldots, \lambda_P \). The spectral photosensitivity function \( \text{Sen}(x, y, \lambda) \) of an FPA element can be nonuniform [13]. In the paper was shown how to measure the function. On the other hand, the fill fac-
tor of FPA may be known from the manufacturer and this helps to describe the function.

Registration of the ideal image $Z(\xi, \eta, \lambda)$ can be described by Fredholm’s integral equation. For the image $f(i, j, p)$ registered by FPA the equation is

$$
\int_{-S_1}^{S_1} \int_{-S_2}^{S_2} Z(\xi, \eta, \lambda) K_{ij}(i, j, \xi, \eta, \lambda, p) d\xi d\eta = f(i, j, p) + \gamma(i, j, p) = F(i, j, p),
$$

where

$$
K_{ij}(i, j, \xi, \eta, \lambda, p) = \int_{-S_1}^{S_1} \int_{-S_2}^{S_2} Sen(x, y, \lambda) K(x, y, \xi, \eta, \lambda, p) dx dy,
$$

$F(i, j, p)$ – signal registered by an FPA $(i, j)$ element with area $A_{ij}$, $\lambda_p$ – the light wavelength for image $p$, $\gamma(i, j, p)$ – error of the signal (additive noise).

The signal $F(i, j, p)$ can be represented as

$$
F(i, j, p) = \int_{-S_1}^{S_1} \int_{-S_2}^{S_2} Sen(x, y, \lambda) f(x, y, \xi, \eta, \lambda, p) dx dy + \gamma(i, j, p).
$$

Hence, the function $K$ (PSF) in (3) can be written as

$$
K(x, y, \xi, \eta, \lambda, p) = \begin{cases} 
K(x, y, \xi, \eta, \lambda, p) = 0, \\
K(x, y, \xi, \eta, \lambda, p) = 1, \\
\cdots \cdots \\
K(x, y, \xi, \eta, \lambda, p) = P.
\end{cases}
$$

### 2.2 Solution of the integral equation

Solution of Equation (1) is an ill-posed problem. According to the theory of regularization, small errors (noise) $\gamma(i, j, p)$ can lead to huge dispersion in solution of the equation. However, it is possible to build an approximated solution with regularized properties. Solving Equation (2) this approximated solution converges to Equation (1) if power of noise converges to zero. Additional conditions are required because uniqueness of solution can be violated. Let us consider an approximated stabilized solution (for small changes in an image; variance of the solution is a monotone and non-decreasing function of noise power). It is possible to find the average value over the set of squared errors of restoration. Then the solution can be represented as decomposition on arbitrary orthonormalized system of basic functions $\psi_k(\xi, \eta, \lambda)$:

$$
Z(\xi, \eta, \lambda) = \sum_{k=1}^{n} c_k \psi_k(\xi, \eta, \lambda), |c| < S_1, |p| < S_2,
$$

where $c_k$ – decomposition coefficients. In this case the initial image $Z$ and noise are non-correlated.

In comparison to the Wiener method, the main advantage of the presented image restoration method is calculation of the MSE for small number of pixels in the initial image. This fact is very important for reconstruction of image registered by FPA [12]. Values of an electrical signal $F(i, j, p)$ are used for restoration $Z(\xi, \eta, \lambda)$ of the ideal continuous image $Z$ of a scene. An algorithm described in [8] was adopted for this restoration. This algorithm is fast (an image with $10^5$ pixels is processed on Intel 2.4 GHz for less than 10 sec), but in comparison with blind image restoration methods (e.g. [14]) has a disadvantage – the PSF is to be known.

An image restoration filter $Q(\xi, \eta, i, j, p, \tilde{\beta})$ can be calculated by equations described in [9], [13]. The stabilizing parameters $\tilde{\beta} = (\tilde{\beta}_1, \tilde{\beta}_2, \ldots)$ [11] are used for the filter calculation:

$$
Q(\xi, \eta, i, j, p, \tilde{\beta}) = \frac{\sum_{n=1}^{\infty} d_{nn}(\tilde{\beta}) \varphi_n(i, j, p) \sum_{i=1}^{\infty} d_{nn}(\tilde{\beta}) \varphi_n(\xi, \eta)}{\beta_n + \sum_{i=1}^{\infty} d_{nn}(\tilde{\beta}) \varphi_n(i, \varphi_n)},
$$

where $(\varphi, \varphi_n) = \sum_{i=1}^{\infty} \varphi(i, j) \varphi_n(i, j)$ are scalar multiplication of images of basis functions, $G$ is number of functions of object decomposition, $m = 1, 2, \ldots, G$, $I \times J$ is the number of pixels, $d_{nn}(\tilde{\beta})$ are recurrently calculated coefficients

$$
\begin{align*}
&d_{nn}(\tilde{\beta}) = \sum_{n=1}^{\infty} d_{nn}(\tilde{\beta}), \\
&\beta_n + \sum_{i=1}^{\infty} d_{nn}(\tilde{\beta}) \varphi_n(i, \varphi_n),
&l = 1, 2, \ldots, n-1; n = 2, 3, \ldots;
\end{align*}
$$

Summation is made over all sampling points of an image $F(i, j, p)$ for the original image super-resolution reconstruction

$$
Z^*(\xi, \eta, \lambda) = \sum_{i,j,p} F(i, j, p) Q(\xi, \eta, i, j, p, \tilde{\beta})
$$

Knowledge of the PSF (Equation (5)) is required for restoration based on different spectral images. Bilinear interpolation is used in order to resize the spectral images.

**Image restoration algorithm:**

- **Step 1.** Enter images $F(i, j, p), p = 0, 1, \ldots P$. Enlarge the images by interpolation.

- **Step 2.** Set parameters of the FPA: fill factor or $Sen(x, y, \lambda)$, SNR, enter values of the PSF $K(x, y, \xi, \eta, \lambda, p)$ for every image.

- **Step 3.** Calculate a filter $Q(\xi, \eta, i, j, p, \tilde{\beta})$ and reconstruct an image $Z^*$ by Equation (9).

### 3. MULTISOLUTION IMAGE FUSION USING GLOBAL REGRESSION

Among the fusion algorithms those based on regression less distort the image colors. Hill et al. proposed an algorithm for multisolution image fusion [15]. The algorithm calculates local regression in a sliding window with size $n \times n$ ($n=5$ in [15]) between degraded and scaled pansharmonic and the
spectral image. Such degradation is performed to match the resolution of the spectral image. Entitle the degraded panchromatic image as \( \text{Pan}^{\text{deg}} \) and the scaled as \( \text{Pan}^{\text{low}} \). Local regression analysis between the image \( \text{Pan}^{\text{low}} \) and the spectral image \( \text{Mult} \), is calculated by

\[
\text{Mult}_j = A_j + B_j \times \text{Pan}^{\text{low}} + E_j,
\]

where \( A_j, B_j \) – the matrices of local regression parameters for the \( j \)-th spectral image, \( E_j \) – the matrix of residuals, \( \text{Pan}^{\text{low}} \) – the degraded and scaled down panchromatic image. The spectral image \( \text{Mult}_j \) and the matrix \( B_j \) are resized to the size of the panchromatic image by interpolation (entitle results as \( \text{Mult}_j^\text{hpf} \) and \( B_j^\text{hpf} \)).

The spectral image with high resolution is calculated by

\[
\text{Mult}_j^\text{hpf} = \text{Mult}_j^\text{hpf} + B_j^\text{hpf} (\text{Pan} - \text{Pan}^{\text{deg}}),
\]

where \( \text{Mult}_j^\text{hpf} \) – high resolution spectral image. This algorithm is a local type algorithm, computationally expensive. Keeping the matrix \( B_j^\text{hpf} \), which size is equal to the size of the panchromatic image, is costly in memory.

Values of the local regression parameters \( (B_j) \) for images of red, green and blue spectrums were compared with values of the global linear regression between panchromatic and spectral images. Distribution of the local regression parameters \( (B_j) \) of Landsat 7 ETM+ images was analyzed. Median values of \( (B_j) \) for all spectral images and \( B \)-coefficients of the global linear regression are very close.

Since, the median values are close to the coefficients of the global regression (0.7085 and 0.7008 for the red spectrum, 0.8633 and 0.8457 for the green spectrum, 1.0116 and 0.9954 for the blue spectrum), the global regression may be applied for multisresolution image fusion instead of the local regression. Note that water and cloud areas have local regression coefficients bigger than one. Fusion based on the local regression preserves the color composite. There is no visual difference between the local regression and global regression fusion. Therefore, the difference between the fusion results can be determined only by quantitative analysis.

Algorithm for multiresolution image fusion based on global regression

\textbf{Input data.} R, G, B – the spectral images of red, green and blue color ranges, \( \text{Nir} \) – the near infrared image, \( \text{Pan} \) – the panchromatic image.

\textbf{Step 1.} Separately for the \( R,G,B \) and \( \text{Pan} \) images assign zero values for the pixels representing cloud, water and shadow areas. The mask for those areas can be calculated by the following formulas

\[
\text{Mask}(1..M,1..N) = 1, \quad \text{then}
\]

\[
\text{Mask}(B > T_B) = 0,
\]

\[
\text{Mask}((\text{Nir} < T_{\text{Nir}}) = 0,
\]

where \( M,N \) – the size of the image, \( \text{Mask} \) – the mask with zero pixels representing water, shadow and cloud areas, \( T_B \) and \( T_{\text{Nir}} \) – the thresholds for the \( B \) and the \( \text{Nir} \) images. The thresholds \( T_B \) and \( T_{\text{Nir}} \) were fixed by values 200 and 40 for Landsat 7 ETM+ image fusion. The thresholds \( T_B \) and \( T_{\text{Nir}} \) were calculated experimentally.

\textbf{Step 2.} Degrade the panchromatic image \( \text{Pan} \) by a low-pass filter (3×3 average filtering, for example), entitle the result as \( \text{Pan}^{\text{deg}} \). Scale down \( \text{Pan}^{\text{deg}} \) to the size of the spectral image by interpolation (entitle result as \( \text{Pan}^{\text{low}} \)).

\textbf{Step 3.} Calculate the global regression coefficients

\[
\begin{align*}
R &= a_R + b_R \times \text{Pan}^{\text{low}} + E_R, \\
G &= a_G + b_G \times \text{Pan}^{\text{low}} + E_G, \\
B &= a_B + b_B \times \text{Pan}^{\text{low}} + E_B,
\end{align*}
\]

where \( a_R, a_G, a_B, b_R, b_G, b_B \) – the parameters of the global regression for the \( R,G,B \) images and the panchromatic image \( \text{Pan}^{\text{low}} \), \( E_R, E_G, E_B \) – the matrices of residual values.

\textbf{Step 4.} Perform spatial scaling of the \( R,G,B \) images to the size of the panchromatic image by bilinear interpolation. Entitle the results as \( R^*, G^*, B^* \).

\textbf{Step 5.} Increase the resolution of the spectral images by

\[
\begin{align*}
R^* &= R^* + b_R \times (\text{Pan} - \text{Pan}^{\text{deg}}), \\
G^* &= G^* + b_G \times (\text{Pan} - \text{Pan}^{\text{deg}}), \\
B^* &= B^* + b_B \times (\text{Pan} - \text{Pan}^{\text{deg}}),
\end{align*}
\]

where \( R^*, G^*, B^* \) – the spectral images with increased resolution. The resolution is increased by image detail addition.

\textbf{Step 6.} Set to 0 or 255 the values of the \( R^*, G^*, B^* \) images, which are less than 0 or more than 255, respectively.

The spatial scaling at Step 4 is performed for resizing of spectral images to the size of the panchromatic image and does not increase resolution. At Step 5 we improve the intensity values of every multispectral image.

Downsampling of the \( R,G,B,\text{Pan}^{\text{low}} \) images can be performed in order to reduce the time of the global regression calculation. Downsampling may be realized by keeping every \( d \)-th sample pixel starting with the first.

4. Algoritms Evaluation

Fragments of Landsat 7 ETM+ multispectral images were employed in all the experiments. The size of the original spectral images is \( 400 \times 400 \), the original panchromatic image size is \( 800 \times 800 \).

4.1 Image restoration results

Simultaneous super-resolution image reconstruction from several spectral images have enhanced quality of the panchromatic image (spatial resolution is increased and noise is reduced). The size of the restored panchromatic image is \( 1600 \times 1600 \) pixels.

An example of super-resolution image reconstruction using multispectral images is shown in Figure 1. Figures 1 \((a)\) and \((b)\) illustrate fragments of red spectrum image and original panchromatic image. Figure 1 \((c)\) presents interpolated image of red spectrum. Figure 1 \((d)\) presents interpolated panchromatic image. Figure 1 \((e)\) presents image reconstructed using multispectral image and near infrared image. Figure 1 \((f)\) present result of super-resolution image reconstruction.
reconstruction from multispectral, near infrared and panchromatic images.

4.1.1 Quality assessment of image restoration results
The restored image was compared with interpolated spectral and interpolated panchromatic images by calculation of correlation, RMSE, square error of the difference image (SEDI) and structural similarity (see Table 1). The restored image has bigger correlation with interpolated NIR image than with other spectral images. While the rest measures have similar values, utilization of the NIR image for better Pan image restoration is desirable.

<table>
<thead>
<tr>
<th>Image Type</th>
<th>Correlation</th>
<th>RMSE</th>
<th>SEDI</th>
<th>SSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interpolated Pan (Figure 1 d)</td>
<td>0.988</td>
<td>18694</td>
<td>4.15</td>
<td>0.88</td>
</tr>
<tr>
<td>Interpolated R (Figure 1 c)</td>
<td>0.143</td>
<td>42481</td>
<td>13.33</td>
<td>0.59</td>
</tr>
<tr>
<td>Interpolated G</td>
<td>0.231</td>
<td>52519</td>
<td>24.19</td>
<td>0.56</td>
</tr>
<tr>
<td>Interpolated B</td>
<td>0.390</td>
<td>40564</td>
<td>16.76</td>
<td>0.62</td>
</tr>
<tr>
<td>Interpolated NIR</td>
<td>0.949</td>
<td>45185</td>
<td>11.01</td>
<td>0.60</td>
</tr>
</tbody>
</table>

4.2 Image fusion results
Visual and quantitative analyses were carried out on fusion results. Spectral images of visible spectrum obtained from Landsat 7 ETM+ were employed in our experiments. The size of the original spectral images is 400 × 400, the size of the restored panchromatic image is 1600 × 1600 pixels. Results of the presented algorithm were compared with the Brovey, IHS and local regression fusion. The restoration of the panchromatic image employed spectral images of visible spectrum, near infrared and panchromatic image.

Figure 2 presents a) a fragment of original multispectral image of visible spectrum, (b) original panchromatic image, (c) the multispectral image scaled up by interpolation, (d) interpolated results of the IHS fusion, (e, f) the IHS and global regression fusion with super-resolution image reconstruction. Resolution of the fused images in Figure 2 (e, f) is 4 times higher than resolution of the original multispectral image (a), and 2 times higher than resolution of the panchromatic image (b).

4.2.1 Visual analysis
All the discussed algorithms increase the spatial resolution, but the Brovey and IHS fusion methods heavily distort the color composite. There is no visual difference and color distortion between the local and global regression fusion results, but the local regression fusion adds noise near edges and in homogeneous areas in the resulting image.

4.2.2 Quantitative analysis
The Euclidean norm (L2) of the histogram difference of the original and the fused images, correlation, RMSE, square error of the difference image (SEDI) were used in the quan-
tative analysis. The fused images were scaled down to the size of the source multispectral images by bilinear interpolation. The ideal values for all the measures are 0, but the ideal value for correlation is 1, respectively. Table 2 presents the results of image fusion by the Brovey, IHS, local and global regression fusion. Size of the original multispectral image is 400 × 400 pixels. Size of the fused images evaluated in Table 2 is 1600 × 1600 pixels. The best values in the tables are indicated by bold font.

The numerical measures illustrate that fusion based on the local and global regression outperform widely used the Brovey and IHS fusion methods. Calculation time of the global regression fusion is less than calculation time of the Brovey fusion and comparable to the IHS fusion.

Experiments were carried out in MATLAB R14.

Table 2 – Numerical evaluation of the fusion methods. The original Landsat 7 ETM+ multispectral image size is 400 × 400, the fused image size is 1600 × 1600 pixels.

<table>
<thead>
<tr>
<th>Method</th>
<th>L2 hist. norm (R,G,B)</th>
<th>Correlation (R,G,B)</th>
<th>RMSE (R,G,B)</th>
<th>SEDI (R,G,B)</th>
<th>Consumed time, s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brovey Fusion</td>
<td>31045</td>
<td>0.5294</td>
<td>7654</td>
<td>9.9783</td>
<td>16.171</td>
</tr>
<tr>
<td></td>
<td>32443</td>
<td>0.3384</td>
<td>12144</td>
<td>10.0945</td>
<td></td>
</tr>
<tr>
<td></td>
<td>42114</td>
<td>0.0189</td>
<td>12247</td>
<td>14.0574</td>
<td></td>
</tr>
<tr>
<td>IHS Fusion</td>
<td>162152</td>
<td>0.1101</td>
<td>21578</td>
<td>16.3232</td>
<td>13.844</td>
</tr>
<tr>
<td></td>
<td>162610</td>
<td>0.0889</td>
<td>25116</td>
<td>9.91</td>
<td></td>
</tr>
<tr>
<td></td>
<td>164330</td>
<td>0.1409</td>
<td>29445</td>
<td>7.8131</td>
<td></td>
</tr>
<tr>
<td>Local regression</td>
<td>3328</td>
<td>0.9858</td>
<td>1151</td>
<td>1.9249</td>
<td>77.703</td>
</tr>
<tr>
<td></td>
<td>2643</td>
<td>0.9851</td>
<td>704</td>
<td>1.1786</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4258</td>
<td>0.9738</td>
<td>744</td>
<td>1.2391</td>
<td></td>
</tr>
<tr>
<td>Global regression</td>
<td>3372</td>
<td>0.9858</td>
<td>1157</td>
<td>1.9376</td>
<td>15.578</td>
</tr>
<tr>
<td></td>
<td>2785</td>
<td>0.9851</td>
<td>704</td>
<td>1.1855</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4604</td>
<td>0.9744</td>
<td>739</td>
<td>1.2348</td>
<td></td>
</tr>
</tbody>
</table>

5. CONCLUSION

We presented a principally new technique for multispectral image fusion with minimization of color composite distortion and resolution of the fused images higher than resolution of the original panchromatic image. This was done in two stages: first, we apply super-resolution panchromatic image reconstruction using the original multispectral and panchromatic images; second, multispectral images are fused using the reconstructed panchromatic image.

Such approach allows us to increase resolution of the fused images 2–4 times higher than the original panchromatic image resolution without loss of acuteness and color composite distortion.

Super-resolution image reconstruction presented in the paper is based on a new algorithm developed by the authors. The restoration is carried out utilizing multispectral and panchromatic images. Resolution of the restored panchromatic image is higher than the original.

A new algorithm for multispectral image fusion based on the global regression is presented in the paper. The algorithm preserves color composite, it is fast and of point type. Visual and quantitative analyses proved advantage of image fusion based on the global regression. The calculation time of the algorithm is comparable with the time of the IHS and Brovey transform fusion.

The IHS and global regression fusion provide the same image acuteness but the IHS fusion heavily distorts color palette. Super-resolution image reconstruction with the IHS fusion can be employed for visual image analysis.

REFERENCES


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