Multiband Pan Sharpening Using Correlation Matching Fusion Method

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ABSTRACT:

Multiresolution Sensor Fusion, also known as Panchromatic Sharpening, is a very important task in Geospatial Image Processing. It involves enhancing a scene image to produce the highest resolution available, while preserving spectral quality provided by low-resolution channels. A robust Pan Sharpening method also minimizes distortions and artifacts resulting from transformations applied during the process. In this article, we present Correlation Matching Fusion (CMF) algorithm, a novel Pan Sharpening method addressing the issues above. To reduce spectral distortions, CMF operates in Principal Component space of the multiband image. It preserves spatial features by performing optimal monotonic piecewise linear match at the fusion stage. Satellite imagery that includes data bands outside visible range (e.g., Near and Far Infrared) provides an additional challenge as these bands are usually not correlated with other bands. The CMF algorithm provides a multi-band solution by enhancing correlation of these bands and the rest of the data. The method demonstrated good performance on several data sets, including WorldView-3, WorldView-2, Pleiades and GeoEye-1 imagery.

1. INTRODUCTION

Multiresolution Sensor Fusion, also known as PAN Sharpening, is applied to Multispectral (MS) and Panchromatic (PAN) geospatial images of the same terrain. It produces PAN Sharpened (PS) Multispectral image at the highest resolution available, which is usually the resolution provided by PAN sensor. Generally speaking, PAN sharpening produces an image at the highest resolution available (Spatial Quality, Objective 1) while preserving all spectral characteristics of the MS image (Spectral Quality, Objective 2). More importantly, it keeps artifacts resulting from the PAN Sharpening process to a minimum (No Artifacts, Objective 3).

These objectives are not in agreement with each other. For example, replacing each of the multispectral bands with PAN will meet Objective 1. However, it will likely alter spectral characteristics of MS, scoring very low on the Objective 2 scale. At the same time, leaving the MS image unmodified scores very high on Objective 2, while contributing nothing to Objective 1. Also, some of the existing methods discussed in this paper work reasonably well with regards to objectives 1 and 2, but leave easily noticeable artifacts and thus fail to meet Objective 3. This issue is very common to methods that apply filtering and/or wavelet decomposition. In our experiments, image analysts were able to easily identify artifacts resulting from application of Gaussian kernel or wavelets.

Additionally, it should be noted that quality of PS is very subjective and depends on the application domain. Ultimately, it is for domain experts to decide which of the objectives take precedence and which artifacts are most important to control.

In this work, we present Correlation Matching Fusion, an algorithm specifically designed to address the challenges above.

2. RELATED WORK

Pan Sharpening has been an active area of research for the last few decades. Several practical solutions exist.

The Synthetic Variable Ratio (SVR) method is based on the following decomposition (Zhang, 1999)

$$PS_i = \frac{MS_i}{\sum MS_i} \ast PAN$$  \hspace{1cm} (1)

Where $MS_i$ is multispectral band $i$, $PS_i$ is PS band $i$ and PAN is panchromatic image. Due to this specific choice of nonlinearity in this decomposition, SVR method and its variants are very sensitive to noise in low intensity settings (where $\sum MS_i$ approaches zero).

Variational Wavelet PAN Sharpening (VWP) method is based on a completely different approach. It seeks to minimize an energy functional in order to optimize both spectral and spatial quality of the PS image by performing wavelet-based fusion (Moeller, 2009). The energy functional is given by:

$$E(u) = E_g + E_s + E_a$$  \hspace{1cm} (2)

Where $E_g$ is geometry-based term, $E_s$ controls spectral quality and $E_a$ is an “alternative” energy term, enforcing both the spatial quality and the wavelet fusion quality.

While this method rests on solid theoretical foundations taking its roots in Calculus of Variations, the specific choices of coefficients inside each of the energy terms seem to be arbitrary and likely scene-dependent, making its results difficult to duplicate.
HSV/HSI/LAB methods (Padwick et al., 2010, Tu et al., 2004), belong to a wide field of color space transform methods of PS. They are based on applying one of the color space transforms to the original MS image, substituting one of the resulting components (usually, the “Intensity” one) with PAN and then performing inverse color space transform. Some of the variants also use High Pass Filtering or Wavelet decomposition to substitute only the high frequency portion of PAN. Methods belonging to this family of methods usually perform very well in practice. It should be noted that the result varies depending on the specific choice of a color space. A High Pass filter or a Wavelet-based decomposition, if used, may improve spatial quality, but usually introduces easily identifiable artifacts. Finally, while color space transforms are only defined in RGB space, attempts have been made to generalize these methods for data sets that include invisible (IR) bands (Padwick et al., 2010).

Orthogonal transform-based methods (GS, QR, PCA) take the color space/component substitution idea one step further, while making it applicable to multiband data sets (Aiazzi et al., 2006). They apply orthogonal decompositions to the MS image to identify substitution component(s):

\[
MS = Q * R = [Q_{1}Q_{2}Q_{3}] * \begin{bmatrix}
R_{11} & R_{12} & R_{13} \\
R_{21} & R_{22} & R_{23} \\
R_{31} & R_{32} & R_{33}
\end{bmatrix}
\]  

(3)

Without loss of generality, we assume here that our MS image is 3-band, and therefore our R matrix is 3x3.

Here, Q is an orthogonal matrix having the same dimensions as the original image, and R is a method-dependent projection matrix. One possible choice of R comes from GS orthogonalization process (Hazewinkel, 2001). Once the GS process is completed, \( Q_{1} \), \( Q_{2} \) and \( Q_{3} \) represent the new bands of the original MS image. The band that “resembles” PAN, the most (for example, \( Q_{1} \)) gets substituted with PAN:

\[
Q_{1} = S(Q_{1}, PAN)
\]

(4)

Then, inverse transform is applied:

\[
PS = Q' * R = [Q'_{1}Q'_{2}Q'_{3}] * \begin{bmatrix}
R_{11} & R_{12} & R_{13} \\
R_{21} & R_{22} & R_{23} \\
R_{31} & R_{32} & R_{33}
\end{bmatrix}
\]

(5)

where \( Q' \) represents orthogonalized MS having \( Q_{1} \) substituted with PAN.

It should be noted that this process, as formulated here, does not guarantee good spatial quality. Specifically, the coefficients of \( Q_{1} \), namely, \( R_{11}, R_{12} \) and \( R_{13} \) may be very low resulting in PS being dominated by low frequency components coming from \( Q_{2} \) and \( Q_{3} \). Our experiments with orthogonal transform-based family of methods confirm that sufficient sharpness is only achieved when:

\[
\begin{align*}
|R_{11}| & \gg \max(|R_{21}|,|R_{31}|) \\
|R_{12}| & \gg \max(|R_{22}|,|R_{32}|) \\
|R_{13}| & \gg \max(|R_{23}|,|R_{33}|)
\end{align*}
\]  

(6)

As it turns out, the GS algorithm is just one of the many orthogonalization schemes possible.

Karhunen–Loève transform (KLT) is another orthogonalization scheme. KLT transform gives rise to PCA algorithm, which is widely used in practice for a variety of tasks (Jolliffe, 2002). Unlike GS, PCA orders \( Q_{1}, Q_{2} \) and \( Q_{3} \) in the order of decreasing variance of the projection. It can be shown that if MS bands are correlated (which is usually the case for visible bands) and PCA is used for orthogonalization, conditions (6) are satisfied.

In PCA notation, the formulas above become:

\[
MS = [MS_{1}MS_{2}MS_{3}] = PC \ast T = [PC_{1}PC_{2}PC_{3}] \ast \begin{bmatrix}T_{11} & T_{12} & T_{13} \\
T_{21} & T_{22} & T_{23} \\
T_{31} & T_{32} & T_{33}\end{bmatrix}
\]

(7)

Where MS is a 3-band multispectral image written as a matrix with band vectors stored in matrix columns, PCs are principal components of MS (PC vectors are stored in columns as well) T is the score (projection) matrix.

The substitution process is described by:

\[
PC_{1}' = P(PC_{1}, PAN)
\]

(8)

And inverse PCA transform is described by:

\[
PS = PC'*T = [PC_{1}'PC_{2}'PC_{3}'] \ast \begin{bmatrix}T_{11} & T_{12} & T_{13} \\
T_{21} & T_{22} & T_{23} \\
T_{31} & T_{32} & T_{33}\end{bmatrix}
\]

(9)

where \( PC' \) represents PCA-transformed MS, having \( PC_{1}' \) substituted with PAN.

3. CORRELATION MATCHING FUSION (CMF) ALGORITHM

The CMF Algorithm capitalizes on PCA decomposition and its ability to extract the dominant linear component of a multiband scene. CMF operates in PC space by extracting \( PC_{1} \), the top PC of a multiband image.

3.1 PCA Transform and Its Properties

PCA can be viewed in the context of a color space family of methods: it relies on an orthogonal color space model, with intensity being modeled by \( PC_{1} \) and color being modeled by the rest of the PCs.
PCA has the following useful property: if between-band correlation is high and correlation matrix $X$ approaches

$$X = corr(MS, MST) \approx \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$  \hspace{1cm} (10)$$

Then, for coefficients in (9), the following holds:

$$\begin{cases} |T_{11}| \gg \max(|T_{21}|, |T_{31}|) \\
|T_{12}| \gg \max(|T_{22}|, |T_{32}|) \\
|T_{13}| \gg \max(|T_{23}|, |T_{33}|) \end{cases}$$  \hspace{1cm} (11)$$

This means that if the bands of MS are highly correlated, PAN (and high spatial resolution content therein) will dominate the resulting PS image.

### 3.2 Monotone Piecewise Linear Match

The component substitution phase is defined by $P(PC_3, PAN)$ in formula (8).

To control spectral quality at component substitution phase in CMF algorithm, $P(PC_3, PAN)$ performs a monotone piecewise linear match. It applies piecewise linear transform to PAN so the result matches $PC_3$ as closely as possible (see Figure 1 below). It can be shown that the closer the match is, the better is the spectral quality of the resulting image.

![Figure 1. Matching PC-1 and PAN](image)

In fact, if $P(PC_3, PAN) = PC_1$, the spectral quality is perfect. The piecewise linear regression is formulated in such a way that:

1. Characteristic points of the MS image are preserved: zero intensity point of MS maps to zero intensity point of PS, and the maximum intensity point of MS maps to maximum intensity point of PS.
2. The regression is strictly monotonic. This choice prevents feature degradation when different intensity levels of MS map to the same intensity levels of PS.
3. The total number of linear pieces (3) is chosen empirically as a tradeoff between spectral and spatial quality.

We seek to optimize each linear piece $\{L_i\}_{i=1}^3$ of (12):

$$P(x) = \begin{cases} L_1(x) & t_0 \leq x < t_1 \\
L_2(x) & t_1 \leq x < t_2 \\
L_3(x) & t_2 \leq x \leq t_3 \end{cases}$$  \hspace{1cm} (12)$$

We do this in order to minimize the following norm:

$$F = \|PC_1 - P(PAN)\|^2 = \sum_{i=1}^n (PC_{1i} - S(PAN_i))^2$$  \hspace{1cm} (13)$$

Here, $i$ iterates over all pixels of the scene.

Each piece of the piecewise linear regression, $\{L_i\}_{i=1}^3$, is a linear function:

$$L_i(x) = (gain_i)x + bias_i \hspace{0.5cm} t_{i-1} \leq x < t_i$$  \hspace{1cm} (14)$$

The choice of

$$\{(gain_i > 0)\}_{i=1}^3$$

ensures that regression (12) is strictly monotonic. Additional restrictions are obtained by connecting $L_1$, $L_2$, and $L_3$ together. We shall also respect boundary conditions at $t_0$ and $t_3$:

$$\begin{cases} L_1(t_0) = L_2(t_0) \\
L_2(t_2) = L_3(t_2) \\
L_3(t_3) = \min(PC_1) \\
L_3(t_3) = \max(PC_1) \end{cases}$$  \hspace{1cm} (16)$$

We use the Restricted Least Squares method (Mikhail, 1982) to minimize $F$ given restrictions (15) and (16) to obtain

$$\{gain_i, bias_i, t_0, t_2\}_{i=1}^3$$  \hspace{1cm} (17)$$

These eight parameters uniquely define our piecewise linear transformation $P(x)$ that we apply to PAN before substitution.
3.3 Providing a Multiband Solution

So far, we have been dealing with visible bands of a multiband image (for example, R, G, and B bands of a multiband image). In our experiments, they are highly correlated. Introducing data from other parts of the spectrum poses another challenge. These data bands are not correlated with visible bands, so the combined data no longer satisfy conditions (10) and (11).

As extraordinary times warrant extraordinary measures, we introduce an extra correlation step in the algorithm. Equation (7) becomes

\[ MS = PC * T * E^{-1} \]  \hspace{1cm} (18)

Without loss of generality, assume that our MS image is 4-band and consequently both T and E are 4x4 matrices.

E is a linear transform. It is formulated to increase correlation of bands in the image without altering the statistics of the individual bands.

The specific choice of E that worked well in practice was:

\[ E = \begin{bmatrix} 1 & 0 & 0 & 0.25 \\ 0 & 1 & 0 & 0.25 \\ 0 & 0 & 1 & 0.25 \\ 0 & 0 & 0 & 0.25 \end{bmatrix} \]  \hspace{1cm} (19)

It is formulated to make \( MS_4' \) correlated with other band.

3.4 Putting it all together

Inverting (18), we get

\[ PC = MS * E * T^{-1} \]  \hspace{1cm} (20)

Here, \( MS = [MS_1 MS_2 MS_3 MS_4] \) is multispectral image in column notation, E comes from (19), \( T \) is PCA score matrix and \( PC = [PC_1 PC_2 PC_3 PC_4] \) are PCs of \( (MS * E) \), in column notation as well.

Then, the step by step algorithm is as follows:

1. (Correlation) Compute \( MS' = MS * E \) to ensure \( MS_4 \) is correlated with \( MS_{1:3} \)
2. Compute PCA decomposition of \( MS' \) as defined in (20)
3. (Matching) Optimize functional \( F(PC_1, PAN) \) in formula (13) to obtain parameters \( \{g_{\text{gain}_i}, b_{\text{bias}_i}, t_1, t_2\}_{i=1}^4 \) (17) that define \( P(x) \)
4. Compute \( PC'_i = P(PAN) \) and perform substitution \( PC' = [PC'_1 PC'_2 PC'_3 PC'_4] \)
5. (Fusion) Compute PS image \( PS = PC' * T * E^{-1} \) using (18)

4. RESULTS

CMF Algorithm was evaluated on several multiband scenes coming from several different sensors across varying terrain types.

4.1 WorldView-3 Sensor

WorldView-3 data included 3-band (RGB) and 4-band (RGBN) scenery centered on Melbourne, Florida, shown in Figures 2 and 3. The terrain is a mix of subtropical greenery, suburban neighborhoods, and various bodies of water:

![Figure 2](image1)

Figure 2. In these settings, CMF performed consistently well in terms of both spectral and spatial quality.

![Figure 3](image2)

Figure 3. WorldView-3 data was used to compare RGB solutions derived from 3-band and 4-band input data.

WorldView-3 data was also used to evaluate a 4-band solution. Figure 4 represents a false color image using NRG band order, N being near-infrared band.

![Figure 4](image3)

Figure 4. Good spatial and spectral quality match in the areas where N-band is correlated with the rest of the bands.

4.2 WorldView-2 Sensor
WorldView-2 imagery was used to evaluate algorithm performance in desert settings. See Figure 5.

4.3 More Results

Additional experiments were performed on data provided by GeoEye-1 and Pleiades sensors.

Figure 6 shows some of the results obtained. They demonstrate good spectral and spatial quality and near complete lack of artifacts.

5. CONCLUSION

Correlation Matching Fusion (CMF) Algorithm provides a multiband PS solution. It demonstrates good spectral and spatial quality of results. The artifacts (both spectral and spatial) are kept to a minimum.

6. REFERENCES


7. ACKNOWLEDGEMENTS

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