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Pansharpening – Simple Approaches and their Evaluation

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Summary: Fusing data of different resolution and possibly of different sensors has been already addressed for a long time. With the development of high-resolution optical satellite systems, fusion techniques became more important with the task to fuse low-resolution multispectral with high-resolution panchromatic data of the same sensor. Therefore the requirements with respect to consistency and maintaining the spectral properties increased. Older simple approaches – simple with respect to implementation within toolboxes of image processing and remote sensing software packages – often fail to fulfil this requirement mainly because properties of the data are not taken into account. Spectral consistency was not required for the intended application. This led to the development of more sophisticated and complex approaches. Nonetheless the simple approaches may provide data for visualisation with just a few improvements. In this contribution simple pansharpening approaches and improvements are discussed and applied. The results are quantitatively evaluated based on the criterion proposed by Wang & Bovik (2002) already adapted to four channels by Alparone et al. (2004), but here extended to image data with arbitrary number of channels.

Zusammenfassung: *Panschärfung – Einfache Ansätze und ihre Bewertung.* Nicht erst seit der Verfügbarkeit hochauflösender Satellitendaten sind zahlreiche Verfahren für die Fusion von Daten unterschiedlicher Auflösungen entwickelt worden. Stand zu Beginn der Entwicklungen häufig die Fusion von Daten unterschiedlicher Sensoren zur Visualisierung im Vordergrund, so liegt der Schwerpunkt der Entwicklungen heute auf der Fusion der multispektralen und der panchromatischen Daten von hochauflösenden Sensoren wie QuickBird. Hierdurch ergeben sich andere Anforderungen an die Verfahren hinsichtlich der spektralen Konsistenz der pangeschärften Daten. Einfache Verfahren – hinsichtlich Realisierung innerhalb einer Toolbox von Bildverarbeitungs- oder Fernerkundungssoftware – wie das Verfahren nach Brovey genügen diesen Anforderungen in der Regel nicht, da sie oftmals nicht die Eigenschaften der Eingangsdaten berücksichtigen. Dies führte zur Entwicklung von komplexeren Verfahren, jedoch können einfache Verfahren durch geringe Modifikationen verbessert werden, so dass auch sie zu spektral konsistenteren Ergebnissen führen. In diesem Beitrag werden einige einfache Verfahren zur Panschärfung und deren Modifikationen vorgestellt. Die Ergebnisse werden anschließend quantitativ bewertet. Diese Bewertung erfolgt auf der Grundlage des von Wang & Bovik (2002) vorgeschlagenen Bewertungsmaßes. Dieses ist von Alparone et al. (2004) auf der Basis von Quaternionen für Daten mit vier Kanälen angepasst worden und wird hier für Daten mit beliebiger Anzahl von Kanälen verallgemeinert.

1 Introduction

High-resolution remote sensing systems often do not only register multispectral but also panchromatic data. Due to physical and technical reasons, the panchromatic data provides higher geometric resolution than the multispectral. This limitation with respect to the multispectral channels' geometric resolution led to the development of a number of approaches for fusing the panchromatic with the multispectral data in order to provide multispectral im-

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ages with the same geometric resolution as the panchromatic. These pansharpening approaches have been categorised by Zhang (2004) into four groups: (1) approaches based on arithmetic combination of the multispectral channels with the panchromatic channel, (2) approaches based on IHS-transformation, (3) approaches based on principal component analysis, and (4) approaches based on frequency analysis or wavelets. All approaches lead to an improvement of the multispectral data with respect to its geometric visual interpretability, but they often also lead to colour shifts and distortions in the pansharpened channels. In particular approaches based on transformation and substitution like IHS or based on arithmetic combination like Brovey are often regarded as inferior to more complex approaches. In part this is due to the fact that some of the simple approaches were originally designed to fuse data of different types (e. g., optical and RADAR data) from different sensors for visualisation only and not to fuse optical data from one sensor with the requirement to deliver spectrally consistent data. On one hand spectral distortions are due to the used approach, on the other they depend on the used input data itself. In both cases sometimes quantities are combined which are either not meaningful physical quantities for combination or not similar and of different ranges.

In this contribution the focus is on pansharpening as data fusion of low-resolution multispectral with high-resolution panchromatic data using simple approaches based on arithmetic combinations, on transformation and substitution, and linear filtering, which can be easily implemented in common toolboxes of standard image processing / remote sensing packages. In Section 2 some of these simple approaches are discussed and improvements as well as new approaches based on the lessons learned from the discussion are proposed. Results of pansharpening for a number of these approaches and an evaluation of these results are given in Section 3 followed by conclusions and an outlook. Computationally more complex approaches as, e. g., (Zhang 2002) based on estimating signal characteristics by adjustment are not included. Nevertheless, the used criterions allow a comparison with the results of Alparone et al. (2007).

2 Pansharpening and Evaluation Approaches

The intention of this section is neither to give an overview on the state of the art of sophisticated pansharpening approaches nor their evaluation – for both aspects please refer to Data Fusion Contests of IEEE (cf. Alparone et al. 2007). The aim is to provide the principal ideas of simple pansharpening techniques which can be easily implemented in common image processing toolboxes and furthermore to outline their limitations and possible improvements. Therefore descriptions of the applied approaches are given in the next section. The subsequent section is dedicated to a short discussion of aspects of quality evaluation performed in Section 3.

2.1 *Approaches for Pansharpening*

(Zhang 2004) categorised pansharpening approaches into four different groups depending on their principle concept as stated in Section 1. Here a slightly different categorisation is proposed keeping the number of groups. These groups are (1) arithmetic combinations, (2) colour space transformations, (3) orthogonal transformations, and (4) frequency analysis. The first and the last group are the same as given by Zhang (2004). The second group consists of colour-space transformations including the IHS-transformation. The third group comprises orthogonal transformations including the principal component transformation (PCT). A joint characteristic of the approaches of group (2) and (3) is the inherent component substitution. In the following the considered simple approaches are described in sequence of the given categorisation above. C_i denotes the i-th low-resolution multispectral channel, C_{pan} the high-resolution panchromatic channel, and $C_{i.pansh}$ the i-th pansharpened multispectral channel. For IKONOS and QuickBird the range of the panchromatic channel covers the ranges of the multispectral channels. Therefore the physically meaningful assumption

$$C_{pan} \propto \sum_{j}^{n} w_j C_j + e_s \tag{1}$$

with n = 4, wi > 0 and the constant es about the data is valid. This assumption is also used by Kalpoma & Kudoh (2007) and Aiazzi et al. (2007). From this assumption follows the existence of a linear transform to map the panchromatic channel to the weighted sum. An example for such a linear transformation is histogram matching based on the means and the standard deviations of the histograms. For approaches based on component substitution the high-resolution channel and the component to be substituted have to be similar, thus

$$C_{pan} \propto C_{sub} + e_{sub} \qquad (2)$$

with $e_{sub} = const.$ and high correlation between the two channels is required.

In the following the considered simple approaches, namely the Brovey transformation, IHS based approaches, approaches based on orthogonal transformations and an approach based on linear filtering are presented.

The **Brovey transformation** is applicable for an arbitrary number of multispectral channels and performs an arithmetic combination of the multispectral channels with the panchromatic channel according to

$$C_{i.pansh} = \frac{C_i}{C_{MSI}} C_{pan} \qquad \text{with } C_{MSI} = \sum_j^n C_j \qquad (3)$$

This transform is likely to lead to colour shifts and distortions. The reason for this is the fact that the computed mean intensity c_{mSI} and the panchromatic channel C_{pan} are not spectrally consistent. In order to overcome this problem (cf. Weidner & Müller 2006) we may first compute a weighted sum of the channels

$$C_{wMSI} = \sum_j^n w_j C_j \qquad (4)$$

With the assumption given in (1) the weights can be set according to the ranges of the single channels as a rough approximation leading to a higher spectral correspondance of the computed intensity and the panchromatic channel. This processing may be improved by modelling of the weights using the spectral response of the sensors (Otazu et al. 2005) or by adjustment (Kalpoma & Kudoh 2007, Aiazzi et al. 2007). Besides the use of the weighted mean the panchromatic channel can be linearly transformed by histogram matching based on the computed intensity channel. At the end of processing the computed pansharpened channels $C_{i.pansh}$ can be linearly transformed via histogram matching with respect to the input channels C_i.

The principal idea of **IHS-transformation-based pansharpening** is to transform RGB-data into the IHS colour space, substitute the intensity I by the panchromatic channel C_{pan} and transform this data back to the RGB colour space. In order to achieve acceptable results an approximate spectral consistency with respect to (2) of the two channels involved in substitution is required, but often not fullfilled. As example let us consider the first three channels of the IKONOS or QuickBird systems. The computed intensity I may differ severely from the panchromatic channel in particular within vegetation areas. In order to solve this problem the panchromatic channel may be reduced by the near infrared fraction. Still the IHS transform is designed for three channels only leading to the question how to incorporate $n > 3$ into the procedure. An adaption as given in (Tu et al. 2004) is necessary.

Approaches relying on **Principal Component Transformation** (PCT) are applicable for an arbitrary number of multispectral input channels. They are based on a forward transformation of the data which yields the principal components, the substitution of the first component PC_1 by the panchromatic channel C_{pan}, and the inverse transformation of the data. The transformation matrices are computed based on the input data and are orthogonal. As within all transformation based approaches the question arises whether the computed channel to be substituted corresponds to the panchromatic channel according to (2). An indicator is the shape of the histogram or more strictly the correlation. If it does not correspond, a histogram matching does not improve the quality of results. Furthermore the data dependence may lead to quite different results for different data sets.

The **Ohta transform** was proposed by Ohta et al. (1980). It is an orthogonal transformation as pre-processing step for the segmentation of RGB images with the transformation matrix

$$T_{Ohta} = \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/2 & 0 & 1/2 \\ -1/4 & 1/2 & -1/4 \end{pmatrix} \tag{5}$$

This matrix approximated the matrices of eigenvectors derived for a set of RGB images, thus a similar approach to the tasselled-cap transformation described below. The sequence of the channels is symmetric, i. e., that either RGB or BGR can be used yielding the same results having in mind that the second row may be multiplied by -1. The transformation was designed for RGB images. Thus it is not directly applicable for data sets of other dimensionality.

Originally the **Tasselled-Cap Transformation** was proposed by Kauth & Thomas (1976) for Landsat data. (Horne 2003) determined a tasselled-cap transformation matrix for IKONOS imagery as mean of PC transformations leading to the transformation matrix

$$T_{TCAP} = \begin{pmatrix} 0.326 & 0.509 & 0.560 & 0.567 \\ -0.311 & -0.356 & -0.325 & 0.819 \\ -0.612 & -0.312 & 0.722 & -0.081 \\ -0.650 & 0.719 & -0.243 & -0.031 \end{pmatrix} \tag{6}$$

This tasselled-cap transformation is an orthogonal transformation. The transformation matrix is not derived for each data set separately, but in advance based on a number of data sets. Similar to PCT pansharpening approaches the first component is substituted by the panchromatic channel, followed by an inverse transformation.

Based on the discussion of approaches above an **Orthogonal Transform** (OrthT) is proposed. The principal idea is to design a transformation for which the resulting first component $OrthT_1$ is spectrally similar to the panchromatic channel C_{pan} and thus allowing a meaningful substitution followed by the inverse transformation yielding the pansharpened channels. This transformation can be applied to data of arbitrary dimensionality with the assumption in (1). For QuickBird data with four channels

$$T_{OrthT} = \begin{pmatrix} t_1 & t_2 & t_3 & t_4 \\ t_4 & t_3 & -t_2 & -t_1 \\ t_3 & -t_4 & -t_1 & t_2 \\ t_2 & -t_1 & t_4 & -t_3 \end{pmatrix} \quad \text{with} \quad t_i = \frac{w_i}{\sum_j^4 w_j} \tag{7}$$

is such a transformation matrix. The first row of the transformation matrix consists of the normed weights for the single channels C_i, thus the first component is C_{wMSI} according to (4). Keeping in mind that we just want to define a transformation which is applicable for pansharpening, the other rows are computed based on the first row with the condition that the rows form an orthogonal base and therefore the transformation matrix is orthogonal like in the PC, tasseled-cap and Ohta transformations. The transformation matrix is not unique, because after a multiplication of rows or cols with a scalar the orthogonality is still fulfilled, but uniqueness is not required, only orthogonality.

The next approach is **Pansharpening based on linear filter** (PanshLapl). In this approach a high-pass filter – the Laplace filter – is applied to the panchromatic channel C_{pan} and the result is fused with the multispectral channels C_i. Therefore it belongs to the group of frequency analysis based approaches. This approach is motivated by the observation that the Laplace filterered image Δ is given by the difference of the Gaussian smoothed image G and the original image I

$$\Delta = G - I \tag{8}$$

which is quite closely related to (Thomas et al. 2008). Although approaches like (Tu et al. 2004) and (Aiazzi et al. 2007) are motivated differently, they use (8). As pre-processing a weighted mean C_{wMSI} according to (4) of the multispectral channels C_i is computed and the high-resolution panchromatic image is adopted using histogram matching. This step is in accordance with the Gram-Schmidt pansharpening described in (Aiazzi et al. 2007) and is motivated by the fact that the intensities may differ by a linear stretch leading to poor approximation of the Laplace values with respect to the multispectral information. For the computation of the Laplace image the smallest filter

$$\Delta_{3x3} = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \tag{9}$$

is applied which is sensitive to noise. Therefore the adopted high-resolution image is smoothed by a selectable filter. Rewriting (8) and replacing G by the low-resolution multispectral channels C_i and the original image by $C_{i.pansh}$ yields

$$C_{i.pansh} = C_i - \Delta \tag{10}$$

where Δ is computed based on the high-resolution panchromatic channel, thus the Laplace is subtracted from the single multispectral channels directly. An alternative is given by subtracting the Laplace from the computed mean C_{wMSI} and compute the pixel values of the pansharpened multispectral channels by

$$C_{i.pansh} = C_i \frac{C_{wMSI} - \Delta}{C_{wMSI}} \tag{11}$$

2.2 *Approaches for Evaluation*

Wang & Bovik (2002) proposed an index which measures the similarity between two images. It is defined as

$$\rho_{WB} = \frac{4\sigma_{AB}\mu_A\mu_B}{(\sigma_A^2 + \sigma_B^2)(\mu_A^2 + \mu_B^2)} \tag{12}$$

where μ_A and μ_B denote the means, $\sigma_A{}^2$ and $\sigma_B{}^2$ the variances and σ_{AB} the covariance of the images. For explanation it can be rewritten to

$$\rho_{WB} = \frac{\sigma_{AB}}{\sigma_A\sigma_B} \cdot \frac{2\mu_A\mu_B}{\mu_A^2 + \mu_B^2} \cdot \frac{2\sigma_A\sigma_B}{\sigma_A^2 + \sigma_B^2} \tag{13}$$

The first term in (13) is the correlation coefficient. The range of this term is [−1.1], the best value 1. The second term measures a linear shift of the image means. Its range is [0.1] and the best value is 1 achieved only if $\mu_A = \mu_B$. The third term measures a difference in image contrast and has a range of [0.1]. It is 1 only if $\sigma_A = \sigma_B$. Therefore ρ_{WB} is in the range of [−1.1]. Its best value 1 for two images with $\mu_A = \mu_B$, $\sigma_A = \sigma_B$, and $\rho_{AB} = 1$. ρ_{WB} is less than zero, if the correlation is negative, and $\rho_{WB} = -1$ only if $\mu_A = \mu_B$, $\sigma_A = \sigma_B$, and $\sigma_{AB} = -1$, thus an image B is an inverted and shifted version of image A.

Although often used to evaluate the results of pansharpening only, ρ_{WB} may be also used to check the similarity of those channels involved in substitution. This similarity is a prerequisite for simple approaches to yield acceptable results. The first condition is that the means of the two images are approximately the same. Therefore the second term in (13) is approximately 1 and the equation simplifies to

$$\rho_{WB} \approx \frac{\sigma_{AB}}{\sigma_A\sigma_B} \cdot \frac{2\sigma_A\sigma_B}{\sigma_A^2 + \sigma_B^2} \tag{14}$$

If similar variances $\sigma_A{}^2 \approx \sigma_B{}^2$ are assumed the equation reduces to

$$\rho_{WB} \approx \frac{\sigma_{AB}}{\sigma_A^2} \tag{15}$$

indicating that ρ_{WB} is proportional to the correlation coefficient in this case. Both conditions can be satisfied by histogram matching. Examples based on the multispectral data shown in Fig. 1 are given in Tab. 1. The table compiles the quantity ρ_{WB} and the correlation coefficient between the panchromatic channel shown in Fig. 2 and the channels or components to be substituted without and with applied histogram matching. Obvious are the low correlation of the panchromatic channel with the first principal component PC_1 and the high correlation with the first component of the orthogonal transformation $OrthT_1$. In this case the weights are 0.2 for the first three channels and 0.4 for the near-infrared channel.

A review of evaluation approaches (cf. Weidner & Müller 2006) shows that single components of (13) are used as only criterion or as one among others. The correlation coefficient is used by Sanjeevi et al. (2001), Aiazzi et al. (2003), Garzelli et al. (2005), and Chibani (2006) for the evaluation of their pansharpening approaches, the difference of means by Hsu & Burke (2003) and Laporterie Dejean

Tab. 1: ρ_{WB} and correlation – panchromatic channel and channels to be substituted – without and with histogram matching.

Channel used for substitution	ρ_{WB}	corr
1. principal component (PC1)	0.00	0.70
1. principal component (PC1) after histogram matching	0.70	0.70
1. component of tasselled cap transformation (TCAP)	0.70	0.89
1. component of tasselled cap transformation (TCAP) after histogram matching	0.89	0.89
1. component of orthogonal transformation (OrthT)	0.86	0.90
1. component of orthogonal transformation (OrthT) after histogram matching	0.90	0.90

et al. (2003), and contrast related quantities by Vijayaraj et al. (2004) and Nikolakopoulos (2005). Alparone et al. (2004) generalised the index of (Wang & Bovik 2002). This generalised index is used in (Alparone et al. 2007) besides two other measures – SAM and ERGAS. Their generalisation is based on the use of quaternions and thereby restricted to evaluate results of images with $n = 4$ channels. We therefore propose to generalise the index of (Wang & Bovik 2002) by

$$\rho^*_{WB} = \frac{4tr(\Sigma_{AB})\left|\underline{\mu}_A\right|\left|\underline{\mu}_B\right|}{(tr(\Sigma_A)+tr(\Sigma_B))(\left|\underline{\mu}_A\right|^2+\left|\underline{\mu}_B\right|^2)} \tag{16}$$

where $\underline{\mu}_A$ denotes the vector of mean values of data set A, $|\underline{\mu}_A|$ the length of the vector, Σ_A the covariance matrix of A, and Σ_{AB} the covariance matrix of the data sets to be compared. Instead of the quantity Q4 proposed by Alparone et al. (2004), (16) is not restricted to four channels. For the special case ($n = 4$) it is equivalent to the index proposed by Alparone et al. (2004). Zhang (2008) questioned the outcome of the comparison of pansharpening approaches presented by Alparone et al. (2007). He argues that the quantities are not fully meaningful for quality assessment giving a counter example based on linear transformed data sets using visual inspection and the results of ISODATA clustering. These results are the same for all transformed data sets, although the quantity Q4 indicates differences in quality. These differences for Q4 are due to different signal means and variances caused by the linear transformations, whereas the clustering is not sensitive and thereby the results are not influenced by these transformations. Nonetheless other subsequent processing and classification algorithms may be sensitive. Thus using ρ_{WB} or its generalisation as criterion imposes harsher requirements.

Within all the above mentioned approaches the quality measures are computed based on the entire image, although the results of pansharpening may differ in homogeneous and non-homogeneous image regions. Therefore, (Perko 2004) – focussing on images from digital aerial cameras – proposed to distinguish between these regions. Accordingly the similarity index of (Wang & Bovik 2002) is computed for the entire image, the homogeneous and the non-homogeneous image regions to evaluate the results of pansharpening. Evaluation of the spatial content of the pansharpened image as in (Wang et al. 2004) or (Buntilov & Bretschneider 2007) is not considered in this contribution. The index ρ_{WB} according to (12) is applied for the evaluation of each channel in order to show differences in the results. Furthermore ρ^*_{WB} as given in (16) and SAM are taken into account, the later for comparison with (Alparone et al. 2007).

3 Results

For the evaluation of the approaches different QuickBird data sets are used. A detailed analysis is presented for a subset of an urban scene (dataset A) including building and larger vegetation areas. Fig. 1 displays the original multispectral data resampled to the same pixel size as the panchromatic channel (cf. Fig. 2). Figs. 4 to 8 display the results of pansharpening. For some of the approaches different alternatives for processing exist and are evaluated (cf. Tab. 2).

Fig. 1: Original multispectral data.

Fig. 5: PCT.

Fig. 2: Panchromatic data.

Fig. 6: TCAP2.

Fig. 3: Non-homogeneous regions (edges).

Fig. 7: OrthT2.

Fig. 4: BROV4.

Fig. 8: PanshLapl2.

Tab. 2: List of applied approaches.

BROV1	Brovey without histogram matching
BROV2	Brovey with histogram matching I: C_{pan} to C_{wMSI}
BROV3	Brovey with histogram matching II: $C_{i.pansh}$ to C_i
BROV4	Brovey with histogram matching I+II
TCAP1	Tasselled cap transformation without histogram matching
TCAP2	Tasselled cap transformation with histogram matching: C_{pan} to $TCAP_1$
PCT	Principal component transformation with histogram matching: C_{pan} to PC_1
OrthT1	Orthogonal transformation without histogram matching
OrthT2	Orthogonal transformation with histogram matching: C_{pan} to $OrthT_1$
PanshLapl1	according to (10)
PanshLapl2	according to (11)

A visual inspection of the results – paying attention to same visualisation conditions – indicates that the *PCT* transform leads to a colour shift in particular for the vegetation areas. *BROV4* and *Orth2* yield similar results. The best results are obtained from *TCAP2* and *PanshLapl2*. All – except *PCT* – exhibit colour distortions at object edges. With respect to this effect *PanshLapl* yields the best results although they appear to some degree noisier than the result of *TCAP2* due to the inherent Laplace.

The evaluation using ρ^*_{WB} for the entire image, the non-homogeneous regions as shown in Fig. 3, and the homogeneous regions is given in Tab. 3. For this evaluation the original multispectral data is taken as reference. Analysing the results in detail yields the importance of pre-processing by histogram matching. The impact is, e. g., visible for the different alternatives of pansharpening according to Brovey. Note that the approaches are already improved with respect to the original procedure, where the ratio of the panchromatic channel and the computed intensities according to (3) is used for which $\rho^*_{WB} = 0.90$ without (*BROV1*) and $\rho^*_{WB} = 0.94$ with histogram matching (*BROV4*). For the result of *PCT* $\rho^*_{WB} = 0.86$ – the worst result of all – and clearly verifies the visual impression. The best re-

Tab. 3: Evaluation based on ρ^*_{WB} for dataset A.

Approach	ρ^*_{WB}	$\rho^*_{WB\,(nh)}$	$\rho^*_{WB\,(h)}$
BROV1	0.90	0.84	0.94
BROV2	0.94	0.89	0.96
BROV3	0.93	0.87	0.96
BROV4	0.94	0.89	0.97
PCT	0.86	0.82	0.87
TCAP1	0.94	0.90	0.96
TCAP2	0.94	0.89	0.96
OrthT1	0.93	0.87	0.96
OrthT2	0.94	0.90	0.96
PanshLapl1	0.97	0.93	0.99
PanshLapl2	0.97	0.93	0.99

Tab. 4: Evaluation based on *SAM* for dataset A.

Approach	*SAM*	$SAM_{(nh)}$	$SAM_{(h)}$
BROV1	0.00	0.00	0.00
BROV2	0.00	0.00	0.00
BROV3	1.91	2.04	1.86
BROV4	0.47	0.50	0.46
PCT	5.17	5.53	5.01
TCAP1	2.41	2.98	2.17
TCAP2	1.92	2.47	1.68
OrthT1	2.44	2.90	2.24
OrthT2	1.47	2.10	1.19
PanshLapl1	0.97	1.76	0.62
PanshLapl2	0.00	0.00	0.00

Tab. 5: Evaluation for datasets B – D for selected approaches.

Approach	Dataset B		Dataset C		Dataset D	
	ρ^*_{WB}	SAM	ρ^*_{WB}	SAM	ρ^*_{WB}	SAM
BROV1	0.90	0.00	0.98	0.00	0.95	0.00
BROV2	0.95	0.00	0.98	0.00	0.95	0.00
BROV3	0.94	1.48	0.98	1.12	0.96	0.95
BROV4	0.96	0.68	0.98	0.46	0.96	0.68
PCT	0.76	10.98	0.94	3.94	0.92	2.21
TCAP1	0.96	2.05	0.98	2.90	0.95	2.58
TCAP2	0.96	1.65	0.99	1.16	0.97	1.11
OrthT1	0.94	1.70	0.98	1.28	0.96	1.30
OrthT2	0.96	1.17	0.98	1.06	0.96	1.16
PanshLapl1	0.98	1.01	0.99	0.68	0.98	0.73
PanshLapl2	0.98	0.00	0.99	0.00	0.98	0.00

sults are obtained using the approaches based on linear filtering (*PanshLapl*).

An evaluation based on SAM (optimal value is zero) yields a totally different ranking of the approaches. The reason for this is the fact that ρ^*_{WB} puts harsher requirements on the results of pansharpening than SAM and thus should be preferred as a general measure. The results also indicate those pansharpening approaches – e. g., Brovey without any histogram matching or the approach based on linear filtering according to (11) – which do not change the spectral angle and thus should be used if this angle is important for further processing.

The evaluation was also performed for other datasets. Dataset B and C are taken from the same QuickBird scene, but with different image content: dataset B comprises a forested and an industrial area, dataset C comprises forested areas, fields and a larger river. The last dataset D is taken from a scene showing rural and lagoon areas in Benin. The results for these datasets compiled in Tab. 5 support the results discussed for dataset A. Moreover, the data dependence of the principal component based approach is clearly obvious. For some approaches the results slightly differ for the used datasets, only for the approaches based on linear filtering the results are almost the same.

4 Conclusions

In this contribution we focussed on simple approaches for pansharpening and their evaluation. We showed that some of these approaches can be easily improved by pre-processing in order to yield spectrally consistent data. The improvements of the results have been shown using known quantities for the evaluation of pansharpening results. In order to cope with data of arbitrary dimensionality we generalised the quality measure of (Wang & Bovik 2002). Although the visual and quantitative evaluations based on the generalised similarity measure are quite consistent the question arises which quantity should be used. As an example the SAM has been computed yielding a different ranking. In our opinion this question can not be answered uniquely, because requirements of the applications vary depending on the further analysis. Nonetheless we consider the generalised similarity indices more appropriate than other quantities, because they entail more demanding conditions on the similarity than others. Thus the pansharpened data that passes the quality assessment will be suited for a larger range of applications.

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