ASSESSMENT OF THE METHOD-INHERENT DISTORTIONS IN WAVELET FUSION

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ABSTRACT:
This paper investigates how different aspects of the wavelet transform, such as the selection of a particular wavelet filter and choosing between the decimated and undecimated version of the decomposition scheme, affect the overall performance of satellite image fusion. Using data, which were acquired in the visible and near infrared wavelength spectrum, experiments were carried out, in which the performances with respect to the different standard wavelets, fusion rules and sub-pixel misalignments were compared. It has been shown that choosing an inappropriate wavelet or decomposition scheme can significantly decrease the quality of the resulting fused product. Based on the conducted experiments, recommendations on choosing a particular wavelet transform to produce satisfactory fusion results are given.

1. INTRODUCTION

Various techniques for image fusion have been proposed in recent years (Ranchin, 2003; Núñez, 1999; Li, 1995; Aiazzi, 2002), whereby the majority of methods employ multiscale representations, i.e. the original data is first decomposed into successive levels of details and approximations before the actual fusion is carried out. A well-known decomposition approach is the discrete wavelet transform (DWT). Many authors agreed that the choice of an appropriate transform plays a significant role in the performance of image fusion (Zhang, 1999; Chibani, 2003; Rockinger, 1997; Muhammad, 2002). It has been long recognised that the properties of wavelet functions such as orthogonality, symmetry, support width and regularity affect the performance of the algorithms related to different image processing problems. Thus, these characteristics provide important objective parameters, which affect the quality of the results. As to image fusion of remotely sensed data, our literature review shows that the choice of a particular wavelet filter is often based on guessing, hence, the best possible performance is not guaranteed. The aim of this paper is to emphasise different aspects of the wavelet transform related to the highlighted image fusion problem, namely the choice of different wavelet filters as well as the decimated and undecimated version of the transform. For an in-depth analysis a series of experiments was conducted and the findings quantitatively and qualitatively summarised.

2. FUSION METHOD

Although this study focuses on the selection of the wavelet transform as the parameter of fusion performance, a few popular fusion rules have been implemented to assess the performances of different combinations of transforms and rules. The selected fusion rules, which only have an impact on the detail coefficients, are:

- **Full detail substitution:** All high-frequency components of the low-resolution data are replaced by the details taken from the high-resolution image.

- **Maximum absolute selection rule:** The absolute value of the wavelet coefficient is considered as a salience measure. Therefore, choosing the coefficient with the largest absolute value increases subtle information in the fused image.
- **Maximum absolute selection rule with consistency verification:** The maximum absolute value of the wavelet coefficients within a neighbourhood is used as an activity measure associated with the central pixel. Firstly, two activity maps are generated (one for each image to be fused). Then, based on a maximum activity selection, a preliminary binary decision map is created. Afterwards consistency verification is applied to the map using a majority filter. Fused detail coefficients are obtained based on the new decision map. For further details refer to the results of Li (1995).

3. TEST DATA

The experiments were carried out using an IKONOS dataset showing the city of San Diego since urban regions contain a high degree of high-frequency data which are more significantly distorted in the multispectral bands. The original dataset consists of four multispectral bands with a spatial resolution of 4×4 m and one panchromatic high resolution band with a resolution of 1×1 m.

For the assessment of the fusion performance the imagery that was degraded to a lower spatial resolution was used. After the fusion the synthesised multispectral bands have the same spatial resolution as the original non-degraded counterparts, which serve as references for the quality evaluation. The original multispectral image **XS** with the size of 1260×1252 pixels was spatially degraded by a factor of four using bicubic resampling. Then the intermediate product was resampled to the original resolution using nearest neighbour interpolation. The result is a new set of multispectral bands $\mathbf{XS}^{\mathbf{low}}$ with the simulated spatial resolution of 16×16 m but with a ground projected pixel size of 4×4 m. To obtain the corresponding panchromatic image, the original band **P** (5040×5008 pixels) was degraded to the size of $\mathbf{XS}^{\mathbf{low}}$ using bicubic resampling. Hence, the resulting image $\mathbf{P}^{\mathbf{low}}$ has a spatial resolution of 4×4 m. Corresponding square patches of 512×512 pixels were extracted from the $\mathbf{XS}^{\mathbf{low}}$ and $\mathbf{P}^{\mathbf{low}}$ scenes to carry out the fusion experiments.

4. WAVELET TRANSFORMS

Two major versions of the wavelet transformation were tested: classic two-dimensional discrete wavelets transform (DWT) and its undecimated equivalent (UDWT). We employed a shift-invariant undecimated wavelet transform which was first used for image fusion by Rockinger (1997). Since the main properties of the corresponding filters and decomposition scheme remain the same for the chosen DWT and UDWT, we believe that the difference in performance between these two transforms is due to the decimation of the signal after each decomposition step in the case of the decimated version of the transform (subject to the selection of the same filters). Thus, decimation can be seen as an independent parameter with respect to the fusion performance.

4.1. Filters

A variety of standard wavelets was used in the experiments which are summarised in Table 1. It is worthwhile mentioning that although regularity, smoothness and the number of vanishing moments are not directly related, wavelets tend to be more regular (and therefore smoother) as the number of vanishing moments increases. For a more detailed discussion about the relation of regularity, smoothness and vanishing moments refer to the work of Da Silva (1996).

Table 1: Wavelets properties

Wavelet Name	Short Name	Orthogonality / Biorthogonality	Support Width *)	Symmetry	Vanishing Moments **)
Biorthogonal	BiorNr.Nd	No / Yes	2Nr+1, 2Nd+1	Yes	Nr
Daubechies	DbN	Yes / Yes	2N–1	Far from	N
Coiflets	CoifN	Yes / Yes	6N–1	Near from	2N
Symlets	SymN	Yes / Yes	2N–1	Near from	N

*) For the biorthogonal wavelets the two values indicate the support width of the reconstruction and the analysis functions, respectively.

**) For the biorthogonal wavelets the value represents the number of vanishing moments for the analysis wavelet.

5. EXPERIMENTS

Three experiments were carried out, which are described here together with the results and discussions. Based on the resolution of the images ($\mathbf{p}^{low}$ four times more highly resolved than $\mathbf{xs}^{low}$), the second level of decomposition was used in all experiments as the deepest level.

5.1. Testing Different Wavelet Transforms

In this experiment the image $\mathbf{xs}^{low}$ was fused with $\mathbf{p}^{low}$ using the "full details substitution" rule. The fusion was performed for all wavelets presented in Table 1 using both decimated and undecimated transforms. Then the fusion performance was evaluated by calculation the RMS between the corresponding products and the reference image. The results for the DWT are shown in Figure 1a, while Figure 1b represents the performance of the UDWT. Note that only the Bior1.x family of biorthogonal wavelets is depicted in Figure 1a and Figure 1b. The performance of the other selected biorthogonal filters is shown separately in Figure 1c and Figure 1d. For the sake of compactness the presentation of the results is limited to the red band.

As can be seen from Figure 1a, in case of the decimated transform the RMS for almost all filters lies within the interval of 10 and 11 values per pixel. A considerable decrease in performance is shown by Bior1.3 and Bior1.5 wavelets (the RMS is around 12.2 and 12.4 values per pixel, respectively). This can be explained by the low regularity of the reconstruction function, i.e. for both wavelets the reconstruction function is highly non-smooth. Another outlier can be identified from Figure 1.c: for the Bior3.1 wavelet the RMS jumps to nearly 14.5 values per pixels. This wavelet is characterised by the highly non-regular decomposition function. However, the smoothness of wavelet functions has long been recognised as an important property for image processing applications (Da Silva, 1996). For example, choosing a rough synthesis functions produces blocking-like artefacts in the final image (Strang, 1996). Other properties of the filters such as orthogonality, symmetry and length were found to have little effect on the fusion performance for the DWT case.

Using the UDWT instead of the DWT helps to decrease the RMS by 2-3 values per pixel on average as can be seen from Figure 1c and Figure 1d. Moreover, the outliers, which occurred in the DWT, do not longer exist and the whole performance picture is more systematic. The RMS increases slowly with the order of the wavelets, which is directly related to the effective length of the filter. The best performances in this experiment have been shown by the shortest filters in conjunction with the undecimated transform.

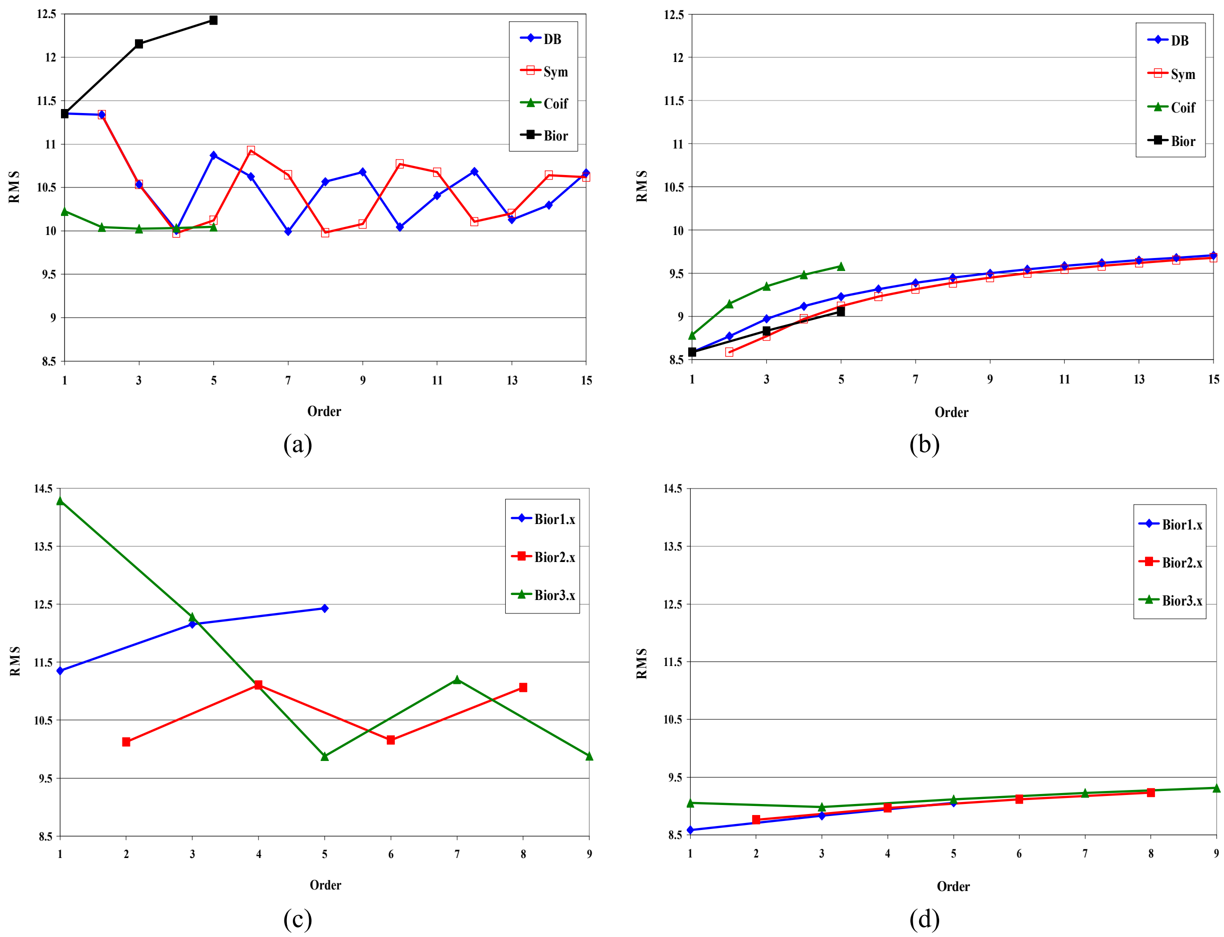


Figure 1: Fusion performance for different wavelets: (a) DWT, (b) UDWT, (c) Biorthogonal families DWT, (d) Biorthogonal families UDWT

Keeping in mind that the calculation of the RMS over the entire image is often not an objective representation of the fusion performance, a new quality measure method was employed to assess the difference in performance for different wavelets more accurately (Buntilov, 2004). In this method, the whole scene of the original image is divided into three regions characterised by spatial variability, and the fusion evaluation is performed for each particular region type independently. It is reasonable to define three different regions: homogeneous areas, highly heterogeneous regions with a high degree of variability of the spatial features, and areas with moderate salience. In the original algorithm, the RMS between fused and original image is used as a measure of spectral distortions and the alterations in the gradient of the image as spatial changes. Here, since the reference image is available, it is used for the region classification and for comparison with the fused product. Table 2 shows the performance of the DWT for two biorthogonal wavelets: Bior1.5 and Bior3.5 (in case of UDWT the performance is almost identical). The first wavelet was chosen because it has shown a significant decrease in performance if used with the DWT. The Bior3.5 wavelet has similar properties of the analysis filter, but its reconstruction function is smoother and therefore more suitable for image processing applications. Although the RMS error values for these two cases differ only in about 2.5 values per pixel (from Figure 1c), one can see from Table 2 that for highly heterogeneous regions the difference is more significant and constitutes about 4.5 values per pixel. This is an expected behaviour since the regions with high variability of spatial data are more easily distorted by the image fusion process than the homogeneous ones. Other regions have also larger distortions if processed with a non-smooth wavelet, though the difference in performance between Bior1.5 and Bior3.5 is not as significant as in the other cases.

Table 2: Fusion performance for different image regions

Regions	Filter	Spectral changes Values per pixel	Spatial changes Values per pixel
Homogeneous	Bior 1.5 / Bior 3.5	9.11 / 7.17	6.36 / 4.48
Highly heterogeneous	Bior 1.5 / Bior 3.5	18.44 / 13.98	10.55 / 7.64
Mid-heterogeneous	Bior 1.5 / Bior 3.5	11.51 / 9.35	7.03 / 5.15

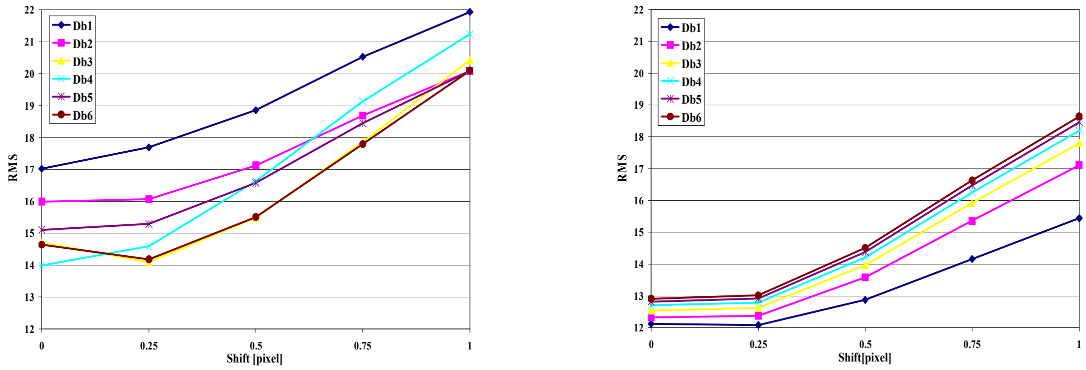
5.2. Testing Different Fusion Rules

To find out if any specific parameter of the wavelet transform bears influence on the performance of the fusion rule algorithm, we followed the same procedures as in the first experiment but incorporating all the fusion rules described in Section 2. Similar graphs as in Figure 1 were plotted for each fusion rule case. However, it was found that none of the implemented rules changes the overall performance, i.e. the regularities in the performance, which were observed in the first experiment exist both for DWT and UDWT after applying above mentioned fusion rules.

5.3. Sub-Pixel Misalignment

It is usually required that the two image sets are perfectly co-registered to each other before the fusion takes place. In practice, fusion often deals with images coming from different scanners, thus a small misalignment is possible, depending on the registration algorithm. To create a new set of $\mathbf{p}^{low}$ images, the scene of $\mathbf{P}^{low}$ was shifted in the horizontal direction by one, two, three and four pixels. Due to the resampling described in Section 3 the resulting new set of $\mathbf{P}^{low}$ images is misaligned with respect to $\mathbf{XS}^{low}$ by ¼, ½, ¾ and one pixel(s), respectively. Then the same square patches as in Section 3 were selected from the new set of panchromatic images to fuse them with $\mathbf{xs}^{low}$. Note that each fusion case of $\mathbf{xs}^{low}$ and shifted version of $\mathbf{p}^{low}$ has its own reference image, which is the corresponding sub-scene of the shifted version of **XS**.

The results for Daubechies wavelets are shown in Figure 2. The RMS inside the highly heterogeneous areas is plotted versus the sub-pixel shift. These areas were selected for the analysis as they suffer the most from the degradation during the fusion of two slightly misregistered images.



(a) (b)

Figure 2: RMS in highly heterogeneous regions versus misalignment: (a) DWT, (b) UDWT

Shifting by more than a quarter of a pixel always results in a decreased performance for both the DWT and the UDWT. Raw satellite image data are usually co-registered within at least ¼ pixels of accuracy, therefore the interval of 0-0.25 pixels shifting is the most important for practical considerations. As can be seen from Figure 2a and Figure 2b neither the DWT nor the UDWT exhibit large instabilities within this interval. In the 0-0.25 pixel shifting range, the differences of RMS values for a given filter do not exceed one value per pixel and are almost negligible for the DWT and UDWT, respectively. Thus, it can be concluded that if a particular filter provides satisfactory performance if the images are perfectly registered, then it preserves its performance in case of real-world misregistered satellite data for both the DWT and the UDWT, assuming that the misalignment is within the highlighted range. As in the first and the second experiments, we can also see that omitting the decimation helps to decrease the RMS values essentially. In spite of the image misregistration, again short filters can be used to achieve the best performance in case of undecimated transform, which is consistent with the results of the first two experiments.

6. CONCLUSIONS

This paper analysed the different aspects of the wavelet transform as applied to image fusion in remote sensing. As a result, a few recommendations, which are valid in case of using simple fusion rules and in the presence of small misalignments of the images, can be derived from the results of the conducted experiments:

- Wherever it is possible, it is recommended to avoid decimation of the wavelet coefficients and to use the UDWT instead of the DWT. In all experiments described above, the undecimated transform always outperformed the DWT regardless of the used filter.
- If the decimated transform is preferable for some reason (e.g. if computation time plays an important role), then using a wavelet which is regular enough guarantees satisfactory results. Other properties of the wavelets such as symmetry, orthogonality and support width were found to have little influence on the fusion performance in case of the DWT.
- Short filters were found to produce the best results if the UDWT is used. Although it is difficult to draw a clear distinction between "short" and "long" filters, the length of more than eight taps (corresponds to the fourth order Daubechies wavelet) can be considered as excessive.

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