WAVELET-BASED FUSION OF OPTICAL AND SAR IMAGE DATA OVER URBAN AREA

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ABSTRACT:

In this paper, a fusion method is proposed, which provides an integrated map of an urban area starting from co-registered optical (panchromatic and multispectral) and SAR images. Classical Intensity-Hue-Saturation (IHS) transform based methods, or Principal Component Substitution (PCS) approaches do not take into account the contextual spatial information, and do not exploit conveniently the complementary characteristics of passive optical and radar data: they may provide interesting visual representations, but they do not guarantee definite advantages to a subsequent classification phase. The proposed method aims to generate an integrated map which selects specific information from SAR data to be injected into the optical data. This choice is application-dependent: in this paper, information related to buildings from the SAR image has been selected, since SAR point-targets strongly characterize urban areas.

1. INTRODUCTION

Multisource image fusion is probably the most difficult aspect in the integration of remote sensing image data products. In fact, while fusion is relatively straightforward when using data from the same satellite, the integration of imagery originating from different satellites carrying similar sensors, or even different sensors, is quite complicated. When dealing with urban applications, image data fusion should use efficiently the information data acquired by sensors having different spatial and radiometric resolutions.

Classical approaches of multisensor image fusion are based on multiplication techniques, Principal Component Analysis (PCA) and Brovey transform. Decision-level fusion or multisource classifiers have been also proposed (Schistad Solberg *et al.*, 1994; Schistad Solberg *et al.*, 1996). Very often the user aims to enhance application relevant features in the fused product. To this aim, wavelet multiresolution analysis has been applied successfully (Sveinsson *et al.*, 2001; Cakir *et al.*, 1999; Chibani & Houacine, 2000).

The Discrete Wavelet Transform (DWT) has been recently employed for remote sensing image fusion with very interesting results (Blanc *et al.*, 1998; Alparone *et al.*, 2001; Ranchin & Wald, 2000). Couples of subbands of corresponding frequency content are merged and the fused image is synthesized by taking the inverse transform. In particular, fusion schemes based on oversampled wavelet representations (for which decimation is not carried out) allow to decompose an image into nearly disjointed bandpass channels in the spatial frequency domain, without losing the spatial connectivity of its edges (Aiazzi *et al.*, 2002; Le Moigne *et al.*, 2001; Núñez *et al.*, 1999; Garzelli & Soldati, 2001).

In this paper, a fusion algorithm for optical (multispectral and panchromatic) and SAR images is presented. The proposed method, which exploits the properties of redundant wavelet analysis, aims to generate an integrated map which selects specific information from SAR data to be injected into the optical data. Choosing which image information should be selected is an application-dependent problem. In this work, information related to buildings derived from SAR imagery has been selected. This approach allows to preserve the spatial and spectral details of optical image data and to better characterize urban areas by means of SAR point-targets.

The proposed method (M-UDWT) is a modified version of the UDWT fusion scheme presented in (Garzelli & Soldati, 2001; Garzelli, 2002) which was designed for spatial enhancement of multispectral images by injecting spatial details of panchromatic data. In M-UDWT, the undecimated wavelet transform is also used, but the context-based criterion driving the fusion process is completely different. The method can be applied in two ways:

1. by injecting SAR point-targets into each multispectral (MS) image which has been previously spatially enhanced by the panchromatic (P) image by using the UDWT method (Garzelli & Soldati, 2001). In such a way, the fusion process can preserve as much as possible the spectral characteristics of the original MS data.
2. by integrating the SAR and the panchromatic (P) image only, thus obtaining the image result F and then substituting the original intensity of the multispectral data by F.

The second approach, which may use the IHS transform after the SAR-P integration, is a simplified approach which can be adopted when three optical bands have to be processed. In the following, more emphasis will be given to the first approach.

Section 2 briefly recalls the fundamentals of wavelet decomposition and multiresolution analysis and Section 3 reviews some recent approaches to multisource image fusion. Section 4 describes the M-UDWT algorithm and in Section 5, experimental results on multitemporal SAR images and multispectral LANDSAT data on the urban area of Pavia (Italy) are presented and discussed.

2. WAVELET MULTIRESOLUTION ANALYSIS

A multiresolution analysis with J levels of a continuous signal $f \in L^2(\mathbb{R})$ having finite energy is a projection of f on a basis $\{\phi_{J,k}, \{\psi_{j,k}\}_{j \leq J}\}_{k \in \mathbb{Z}}$.

Basis functions $\phi_{j,k}(x) = \sqrt{2^{-j}}\phi(2^{-j}x - k)$ result from translations and dilations of a same function $\phi(x)$ called *scaling* function, verifying $\int \phi(x)dx = 1$. The family $\{\phi_{j,k}\}_{k \in \mathbb{Z}}$ span a subspace $V_j \subset L^2(\mathbb{R})$. The projection of f on V_j gives an *approximation* $\{a_{j,k} = < f, \phi_{j,k} >\}_{k \in \mathbb{Z}}$ of f at the scale 2^j.

Analogously, basis functions $\psi_{j,k}(x) = \sqrt{2^{-j}}\psi(2^{-j}x - k)$ are the result of dilations and translation of the same function $\psi(x)$ called *wavelet* function, which verifies $\int \psi(x)dx = 0$. The family $\{\psi_{j,k}\}$ span a subspace $W_j \subset L^2(\mathbb{R})$. The projection of f onto W_j gives the wavelet coefficients $w_{j,k} = < f, \psi_{j,k} >$ of f representing the *details* between two successive approximations. The subspaces V_j realize a multiresolution analysis.

Eventually, a multiresolution analysis with J levels yields the following decomposition of $f \in L^2(\mathbb{R})$

$$f(x) = \sum_k a_{J,k}\tilde{\phi}_{J,k}(x) + \sum_{j \leq J}\sum_k w_{j,k}\tilde{\psi}_{j,k}(x). \qquad (1)$$

Dual functions $\tilde{\phi}(x)$ and $\tilde{\psi}(x)$ have to be defined in order to ensure a perfect reconstruction.

3. WAVELETS FOR MULTISOURCE FUSION

Wavelet approaches to multisource fusion have been proposed in (Sveinsson *et al.*, 2001; Chibani & Houacine, 2000). Wavelet multiresolution analysis is applied to enhance application relevant features in the fused product. In fact, while fusion is relatively straightforward when using data from the same satellite, the integration of imagery originating from different satellites carrying similar sensors, or even different sensors, is quite complicated and should be application dependent.

In (Sveinsson *et al.*, 2001), the transformed wavelet domain is used for feature extraction of linear features in multisource remote sensing data. The cluster-based method is an unsupervised preprocessing algorithm which computes feature-vectors to group the wavelet coefficients. Then, these feature-vectors are used to select representative wavelet coefficients, which are finally used to train a neural network classifier.

In (Chibani & Houacine, 2000), a redundant wavelet transform (RWT), namely the "à trous" algorithm, is applied to A and B input images, as shown in Figure 1, where pixel values are named $a_0(A)$ and $a_0(B)$, respectively, while w_n and a_N are the detail and approximation coefficients at level N. Each image is represented by a set of wavelet planes of the same dimensions as the input image. The fusion of these two images reduces to a simple procedure that defines the feature selection rule to apply between coefficients at each level. Subsequently, a fused image F is constructed by performing an inverse wavelet transform from the selected coefficients. The selection rule is based on the absolute amplitudes of the wavelet coefficients within a local window.

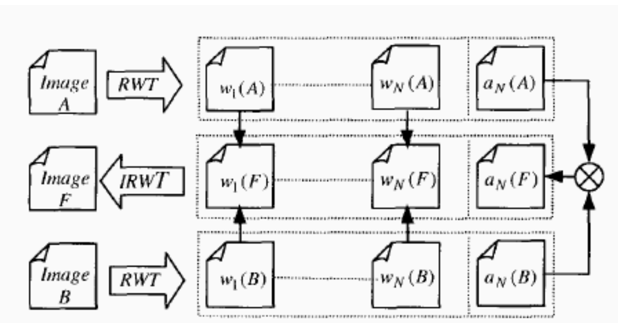

Figure 1. Scheme of the multisource image fusion algorithm proposed in (Chibani & Houacine, 2000).

4. OPTICAL-SAR FUSION

Differently from the methods described in Section 3, the proposed M-UDWT scheme adaptively exploits complementary information from optical and SAR data over urban areas: rural areas are usually efficiently represented by optical images (both spatially and spectrally), while buildings in urban areas become evident as clusters of point targets (*permanent scatterers*) in SAR images.

Figure 2 shows the schematic diagram of the M-UDWT algorithm. First, a SAR image (25m ground resolution for ERS-2) and an optical image (15m or 30m resolution for Landsat ETM, P and MS bands, respectively) both resampled to 12.5m and co-registered, are analyzed by a 1-level undecimated wavelet decomposition scheme. Spatial details HL, HH, LH of the optical image are retained in the fused image. The low-resolution part (LL) of the fused image is selected from SAR data and conveniently scaled only for the regions for which the ratio between SAR and optical is greater than twice the average ratio over the whole image. Otherwise, the original LL data (large scale information) of the optical image is transferred to the fused image F. In such a way, point targets and other urban scatterers from SAR image are injected and spatial details from PAN image are retained.

5. EXPERIMENTAL RESULTS AND CONCLUSIONS

Landsat 7 P and MS images, and a Radarsat SAR image (C band HH-polarized intensity image, acquired on 20 October, 2000) of Pavia (Italy) have been considered for experiments.

First each MS band has been spatially enhanced by the P data by applying the UDWT algorithm (Garzelli & Soldati, 2001). After registration, at 12.5m resolution, with the SAR data, each resulting image has been considered as the input (optical image) in the scheme of Fig.2. The integration of P and SAR has been also performed for comparisons. Figure 3 reports the original SAR data (Fig.3a), the original P image (Fig.3b), a color composite (R=B5, G=(B4+B3)/2, B=(B2+B1)/2) of the original MS data (Fig.3c) and the fusion results (Fig.3d and 3e).

Figure 3d shows that the method allows to inject the information related to spatially-correlated points characterized by high scattering coefficients in the SAR image to the panchromatic data. This injection occurs over strong scatterers in the urban area, while the fusion process is ineffective on streets, rural areas, or other vegetated areas (city parks, or forests). Hence, the spatial details of the panchromatic data are highly preserved.

Figure 3e shows the result of the M-UWDT fusion applied to all MS bands available. The same conclusions can be drawn about the capability to inject "urban" information without affecting the spatial resolution of the optical data - which has been previously enhanced by means of the UDWT algorithm. Further work is needed to demonstrate the impact of the proposed fusion method on a subsequent classification phase. The results obtained in terms of classification accuracy with respect to unconditioned multisensor classification and in terms of urban sprawl analysis are very promising.

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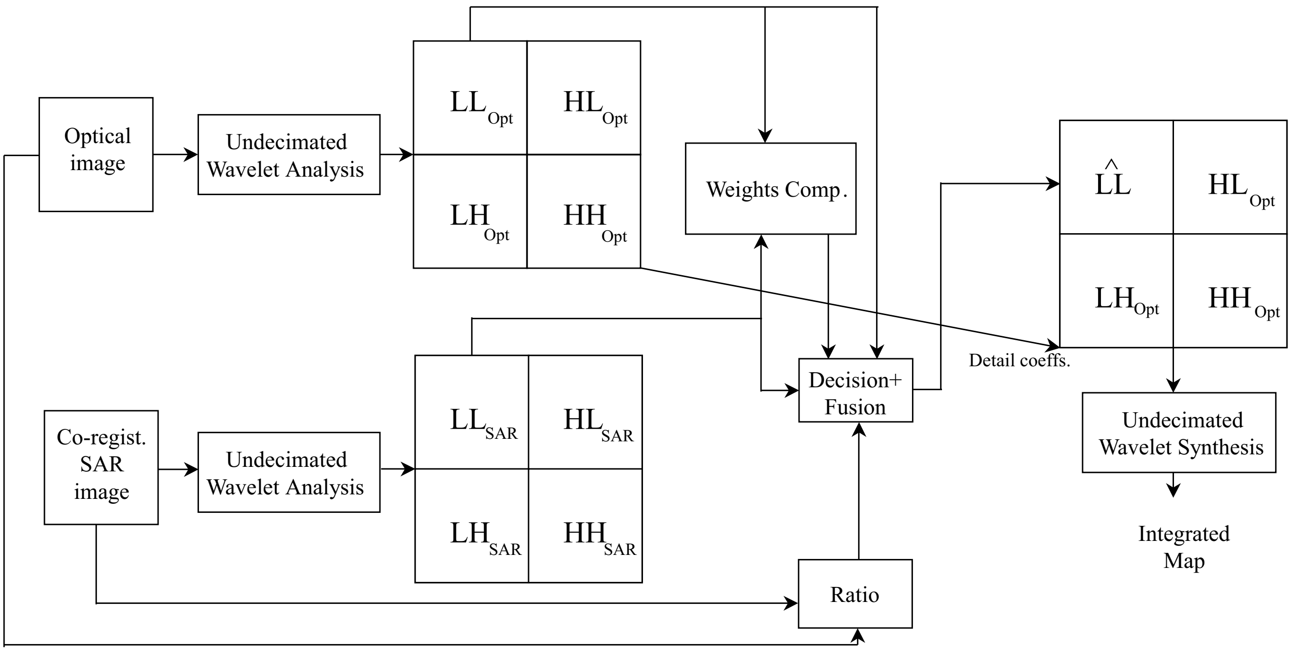

Figure 2. Scheme of M-UDWT.

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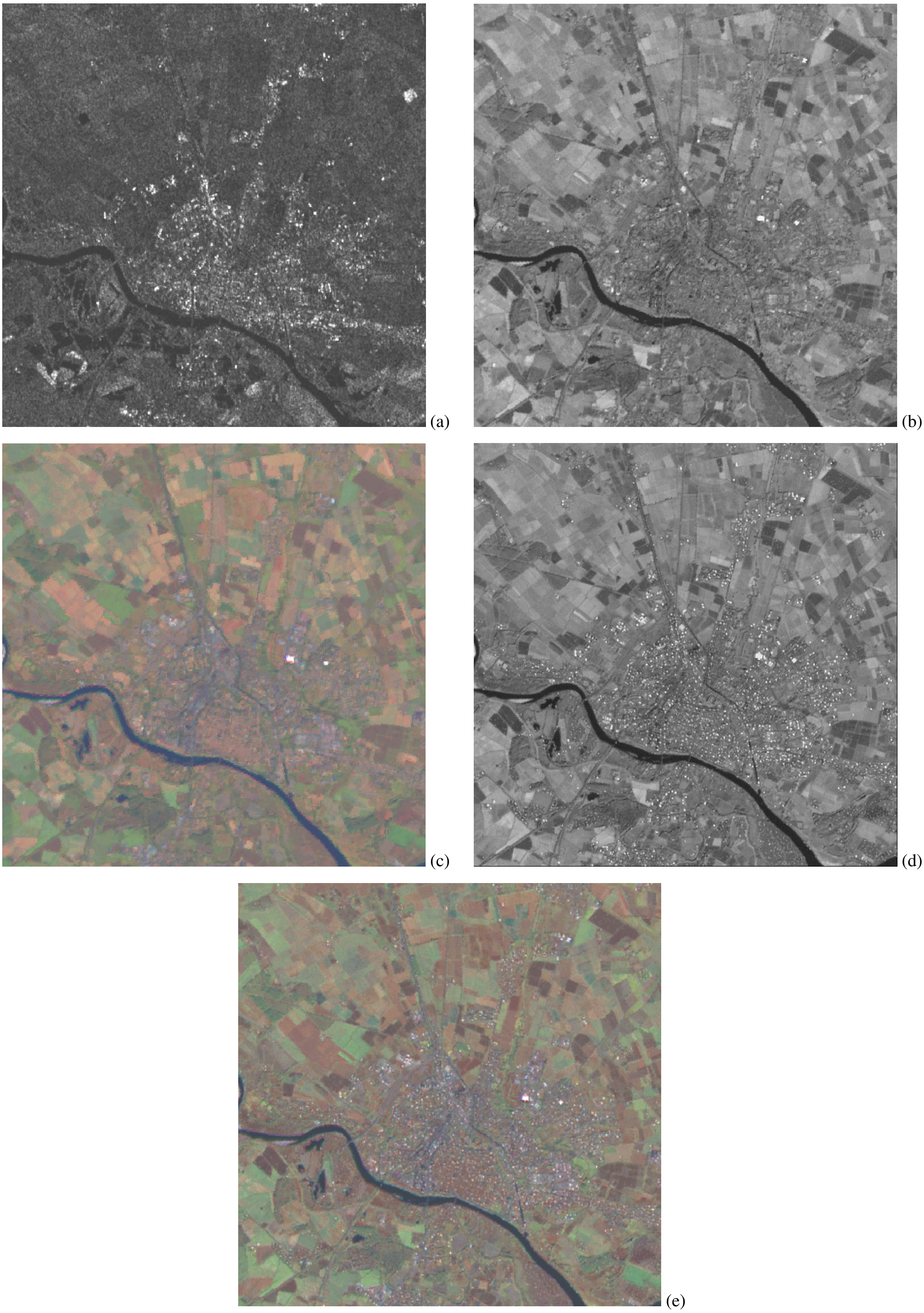

Figure 3. (a): Radarsat image, Pavia, Italy; (b): Landsat 7 panchromatic image; (c): Color composite (R=B5, G=(B4+B3)/2, B=(B2+B1)/2) of original MS data; (d): Integrated map P+SAR; (e): Color composite of integrated MS+SAR data;.