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Wavelet Domain Dictionary Learning Approach to Pan-sharpening

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***Abstract*—Remote sensing applications gain more importance nowadays. This requires multispectral images with high visual quality. Using Pan-sharpening technique a low resolution multispectral (LRM) image and high resolution panchromatic (HRP) image are fused to obtain a high resolution multispectral (HRM) image. This paper addresses the above problem using the compressed sensing technique to improve the spatial resolution. It also incorporates the wavelet transform to significantly reduce spectral distortion. Compared to the conventional methods this technique can be applied to multispectral image bands directly. This method ensures a pan sharpened image with high spatial resolution and less spectral distortion**

.***Index Terms*—Image fusion, pan-sharpening, dictionary learning, sparse coding**.

I. INTRODUCTION

Remote sensing refers to the acquisition of information about an object without making physical contact with the object. Remote sensing applications like land-use classification, change detection, vegetationand urban studies require multispectral satellite images with high spatial resolution and less spectral distortion. But the optical remote sensors in the Earth observation satellites such as IKONOS, world view-2, Quick Bird, provide data comprising of a panchromatic image and a multispectral image. The multispectral image has a coarser spatial resolution than corresponding panchromatic image. Pan-sharpening artificially produces a HRM image by fusing HRP image and LRM image [1]. The fine spatial information from HRP image is injected into the LRM image to obtain HRM image.Pan- sharpening aims to provide an image with pleasing appearance.

Conventional pan-sharpening methods are based on Projection substitution concept which includes intensity-hue saturation (IHS) [2], principal component analysis (PCA) [3] and Gram Schmidt [4]. Another Popular algorithm is based on Brovey Transform [5]. It is based on an arithmetic combination technique. These methods improved spatial resolution of multispectral images, but caused significant spectral distortion. Another approach to pan sharpening is wavelet based fusion [6]. It adopts ARSIS concept, which extracts details from the HRP image and injects the details into LRM image. Wavelet based fusion follow two different schemes: substitutive wavelet fusion scheme, additive wavelet fusion scheme. Using this method spectral distortion is minimized

Recently a model based method based on compressed sensing [7] was proposed. It tries to explore a sparse signal representation of image patches. A degradation model from a high to low resolution multispectral image and pan image is created. It required high resolution multispectral satellite images from same type of sensor for training. Another model based method [8] uses a joint dictionary from low resolution multispectral image and its corresponding pan image. This method requires big collections of low resolution multispectral and high resolution pan image pairs. In [9] Zhu and Bamler introduced sparseFi technique to solve pan sharpening problem, which train the dictionary from the panchromatic image corresponding to the LRM image. This method uses a single large dictionary.

In this paper a new pan sharpening method, Wavelet Domain Dictionary Learning (WDL) method is proposed which combines the advantages of wavelet and compressed sensing technique. Instead of a single large dictionary in spatial domain a compact dictionary is designed for each wavelet subband.The

wavelet domain dictionary learning avoids the need of feature extraction filters, since wavelet dictionaries are structured. These dictionaries capture high frequency details well from the pan image.

The remainder of the paper is organized into five sections. In section II sparse representation and compressed sensing theory is briefly described. In section III proposed dictionary learning algorithm for fusion is described. Experimental discussion and results are included in section IV. Section V describes the conclusions arrived.

II. COMPRESSED SENSING AND SPARSE REPRESENTATION

Sparse representation over learned dictionary is based on compressed sensing theory.In 2006, Candes[10] and Donoho [11] proposed a new sparse sampling theory, namely, compressed sensing. A sparse signal is a signal that can be represented as a linear combination of relatively few base elements in a basis or an over complete dictionary. High dimensional sparse signals can be accurately recovered from a smallernumber of linear measurements .The measurement process is written as

$$y = \Phi x = \Phi \Psi \alpha \qquad (1)$$

where$x$ is the vector of the original signal, Φ is the measurement matrix,α is referred to as sparse coefficient and y is the vector of measurements. Ψ is the transform matrix or over complete dictionary that maps the sparse representation α into x. Use of measurements to recover the original signal is a reconstruction problem. Basis pursuit (BP) [12] is the most well-known problem, which views the reconstruction problem as an l1 optimization problem formed as

$$\min \lambda ||\alpha\_||1 + ||y - \Phi\Psi\alpha||_2^2 \qquad (2)$$

whereλ is called the regularization parameter.

Dictionary learning process is performed in two stages. Initially sparse coefficient is calculated using the present dictionary, called sparse coding. Then dictionary is updated based on the calculated sparse coefficients. The two steps are performed in wavelet domain. The designed dictionaries are directional since wavelet transforms effectively separates horizontal, vertical, diagonal details of given image.

III. WDL ALGORITHM FOR PAN-SHARPENING

Given a LRM image WDL algorithm calculates the sparse coefficients of its detail wavelet subbands. These sparse coefficients along with the HR subband dictionaries of pan image reconstruct corresponding HR MS wavelet subbands .It has been shown in [13] that designing multiple dictionaries is more beneficial than single dictionary. Designing a dedicated dictionary for detail subbands will help the dictionaries to inherit the important features of image.

Due to the fact that the dictionaries are built up from the pan image observing the same area, the multispectral image patches can be described by a few non-zero or significant coefficients i.e. a sparse representation in these dictionary pair. By means of an L1 norm minimization, the sparsecoefficients representing the LR multispectral image patches in the LR dictionary can be accurately reconstructed.

A. Wavelet decomposition

The HRP image is used to create the dictionary. The HRP image X_H is down sampled by factor F_{DS} .The resulting low resolution version of X_H is X_L. X_H and X_L are decomposed using undecimated wavelet transform. Level-1 approximation coefficient X_L^a and detail subbands X_L^h, X_L^v, X_L^dcorresponds to LRP image $X_L$andX_H^a,X_H^h, X_H^v,X_H^d corresponds to HRP image X_H.

B. Dictionary learning

Initially learn the three wavelet subband dictionaries D_L^h, D_L^v,D_L^d from detail subbands X_L^h, X_L^v,X_L^d. The process is repeated for HR detail subbands to obtain D_H^h, D_H^v,D_H^d .The detail subband of HRP image is tiled to patches and of LRP image by F_{DS} times less than HRP Patch size. The patches with pixel values arranged to column vector form the Subband dictionaries. There is no training for approximation band, since it carries low frequency detail which is the base of image.

C.Sparse coefficient estimation

This step attempts to represent the LRM image patch as a linear combination of pan patches. Single level wavelet decomposition is applied to LRM image to obtain approximation band $Y_L^a$and detail subbandsY_L^y (y = h, v, d). Extractpatches from detail subband $Y_L^y$and vectorise each patch by arranging it as a column vector.

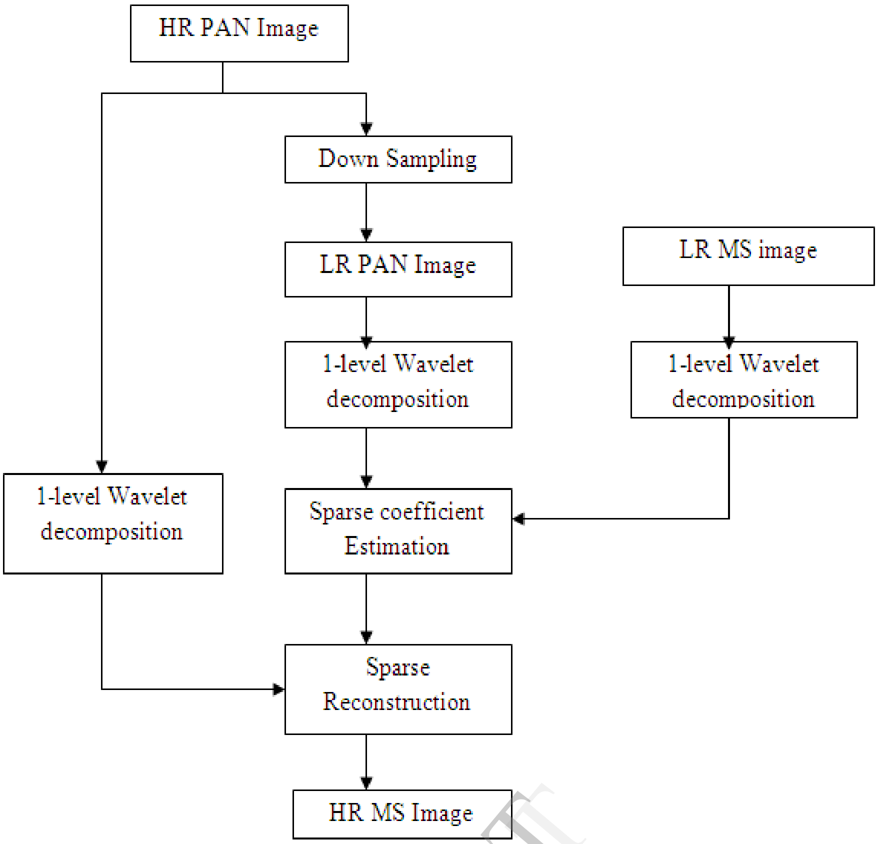

Fig 1.Block Diagram

The sparse coefficient for multispectral patch in detail subband is estimated by

$$\hat{\alpha}_y = \arg min_{\propto} \left\{\lambda \left\|\alpha_y\right\|_1 + \frac{1}{2}\left\|D_L^y \alpha_y - Y_L^y\right\|_2^2\right\} (3)$$

λ is the standard Lagrangian multiplier balancing the sparsity of the solution and fidelity of approximation to Y_L^y. In the experiments λ is chosen as 0.1. Sparse coefficient α_y is estimated using [14]which give a robust estimate of sparse coefficients.

D. Sparse reconstruction

The HR image patch is assumed to share same sparse coefficient as corresponding LR image patch in the HR/LR dictionary pair [9]. The final pan sharpened multispectral patch in a subband is

$$\widehat{Y_H^y} = D_H^y \hat{\alpha}_y (4)$$

This process is repeated for all patches. Inverse wavelet transform is applied to the reconstructed detail subbands and approximation band after interpolation.

IV. EXPERIMENTAL RESULTS

The data acquired by Worldview 2 has a panchromatic image and multispectral image having eight bands. The test site is Hvanneyri of Iceland.The resolution of pan imageis.5mand multispectral image is 2m respectively.

Inorder to have a referenceof multispectral image, down sample pan image to the resolution level of available low resolution multispectral image. The down sampling factor $F_{DS}$is chosen as 4.For quality assessment reference, down sample the input pan image to the resolution of LR multispectral image. Finally a high resolution multispectral image of same resolution level of pan image is obtained.

The image used for the experiment is from dual image dataset. The reconstructed HR multispectral image is compared with the results produced by IHS, PCA methods of pansharpening in TABLE 1. The proposed method shows more closeness to the nominal values in quality assessment.

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Fig 2 (a) Multispectral Source image

Fig 2 (d) High resolution MS image by IHS

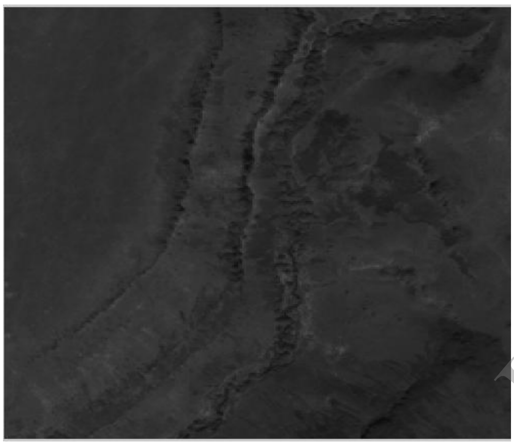

Fig 2 (b) High resolution Pan Image

Fig 2 (e) High resolution MS image by PCA

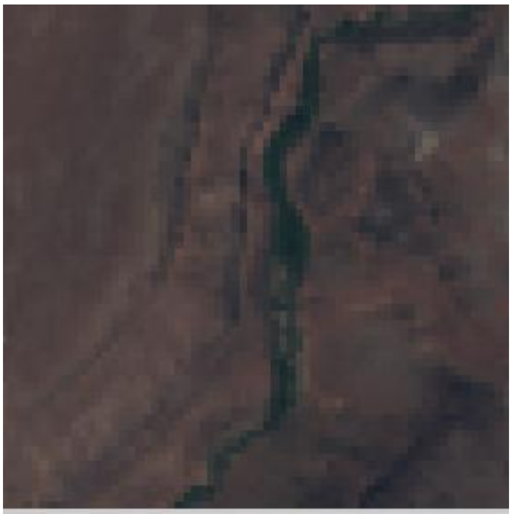

Fig 2(c) Low resolution multispectral input

Fig 2 (f) High resolution MS image by proposed WDL method

TABLE 1: QUALITY METRICES

	RMSE	SAM	ERGAS	UIQI
Nominal Values	0	0	0	1
IHS	3.4401	1.1781	2.8163	0.9907
PCA	2.5103	1.1860	2.0416	0.9877
WDL	2.2427	1.1543	1.4570	0.9998

V.CONCLUSION

In this paper novelwavelet domain dictionary learning is proposed for pan sharpening problem.The multispectral images obtained using conventional methods show severe spectral distortion. WDL method increases spatial resolution, creating less spectral distortion, thereby increasing visual quality of image. The overall quality of sharpened image is increased .The low rmse value shows that pan-sharpened image is closer to the original image.

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