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A New Pan-Sharpening Method Using Joint Sparse FI Image Fusion Algorithm

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Abstract— Recently, sparse representation (SR) and joint sparse representation (JSR) have attracted a lot of interest in image fusion. The SR models signals by sparse linear combinations of prototype signal atoms that make a dictionary. The JSR indicates that different signals from the various sensors of the same scene form an ensemble. These signals have a common sparse component and each individual signal owns an innovation sparse component. The JSR offers lower computational complexity compared with SR. The SparseFI method does not assume any spectral composition model of the panchromatic image and due to the super-resolution capability and robustness of sparse signal reconstruction algorithms, it gives higher spatial resolution and, in most cases, less spectral distortion compared with the conventional methods. Comparison among the proposed technique and existing processes such as intensity hue saturation (IHS) image fusion, Brovey transform, principal component analysis, fast IHS image fusion has been done. The pan-sharpened high-resolution MS image by the proposed method is competitive or even superior to those images fused by other well-known methods. In this paper, we propose a new pan-sharpening method named Joint Sparse Fusion of Images (JSparseFI). The pan-sharpened images are quantitatively evaluated for their spatial and spectral quality using a set of well-established measures in the field of remote sensing. The evaluation metrics are ERGAS, Q4 and SAM which measure the spectral quality.To capture the image details more efficiently, we proposed the generalized JSR in which the signals ensemble depends on two dictionaries.

Keywords— JSparseFI, Compressed sensing, image fusion, multispectral(MS) image, panchromatic (PAN) image, remote sensing, sparse representation.

INTRODUCTION

"Pan Sharpening" is shorthand for "Panchromatic sharpening". It means using a panchromatic (single band) image to "sharpen" a multispectral image. In this sense, to "sharpen" means to increase the spatial resolution of a multispectral image. A multispectral image contains a higher degree of spectral resolution than a panchromatic image, while often a panchromatic image will have a higher spatial resolution than a multispectral image. A pan sharpened image represents a sensor fusion between the multispectral and panchromatic images which gives the best of both image types, high spectral resolution AND high spatial resolution. This is the simple why of pan sharpening. Pan-sharpening is defined as the process of synthesizing an MS image at a higher spatial resolution that is equivalent to the one of the PAN image. Pan-sharpening should enhance the spatial resolution of MS image while preserving its spectral resolution. Pan-sharpening continues to receive attention over years. Most of this paper is concerned with the how of pan sharpening. First, a review of some fundamental concepts is in order.

A) Multispectral Data

A multispectral image is an image that contains more than one spectral band. It is formed by a sensor which is capable of separating light reflected from the earth into discrete spectral bands. A color image is a very simpleexample of a multispectral image that contains three bands. In this case, the bands correspond to the blue, green and red wavelength bands of the electromagnetic spectrum. The full electromagnetic spectrum covers all forms of radiation, from extremely short- wavelength gamma rays through long wavelength radio wave.In Remote Sensing imagery, we are limited to radiation that is either reflected or emitted from the earth, that can also pass through the atmosphere to the sensor.The electromagnetic spectrum is the wavelength(or frequency) mapping of electromagnetic energy, as shown below.

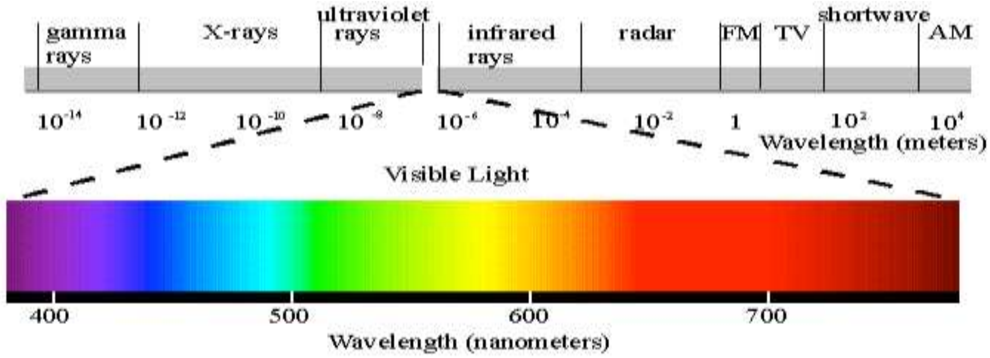

Fig. 1 : Electromagnetic spectrum

Electro-optical sensors sense solar radiation that originates at the sun and is reflected from the earth in the visible to near-infrared (just to the right of red in the figure above) region. Thermal sensors sense solar radiation that is absorbed by the earth and emitted as longer wavelength thermal radiation in the mid to far infrared regions. Radar sensors provide their own source of energy in the form of microwaves that are bounced off of the earth back to the sensor. A conceptual diagram of a multispectral sensor is shown below.

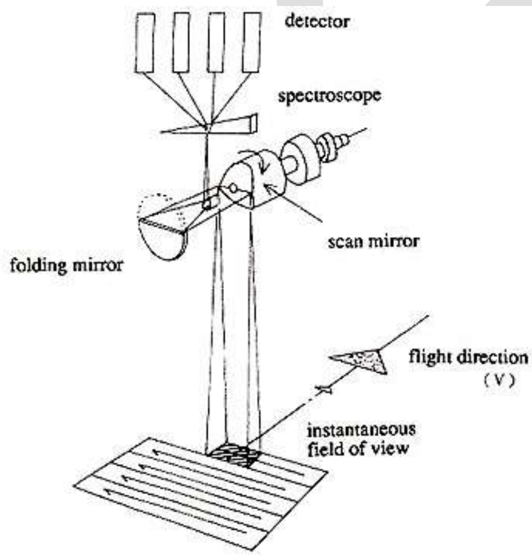

Fig. 2: Simplified diagram of a multispectral scanner

In this diagram, the incoming radiation is separated into spectral bands using a prism. We have all seen how a prism is able to do this and we have seen the earth's atmosphere act like a prism when we see rainbows. In practice, prisms are rarely used in modern sensors.Instead, a diffraction grating which is a piece of material with many thin grooves carved into it is used. The grooves cause the light to be reflected and transmitted in different directions depending on wavelength. You can see a rough example of a diffraction grating when you look at a CD and notice the multi-color effect of light reflecting off of it as you tilt it at different angles. After separating the light into different "bins" based on wavelength ranges, the multispectral sensor forms an image from each of the bins and then combines them into a single image for exploitation.Multispectral images are designed to take advantage of the different spectral properties of materials on the earth's surface. The most common example is for detection of healthy vegetation. Since healthy vegetation reflects much more near-infrared light than visible light, a sensor which combines visible and near-infrared bands can be used to detect health and less healthy vegetation. Typically this is done with one or more vegetation indices such as the Normalized DifferenceVegetation Index (NDVI) defined as the ratio of the difference of the red and near-infrared reflectance divided by the sum of these two values. Some typical spectral signatures of vegetation, soil and water are shown below,

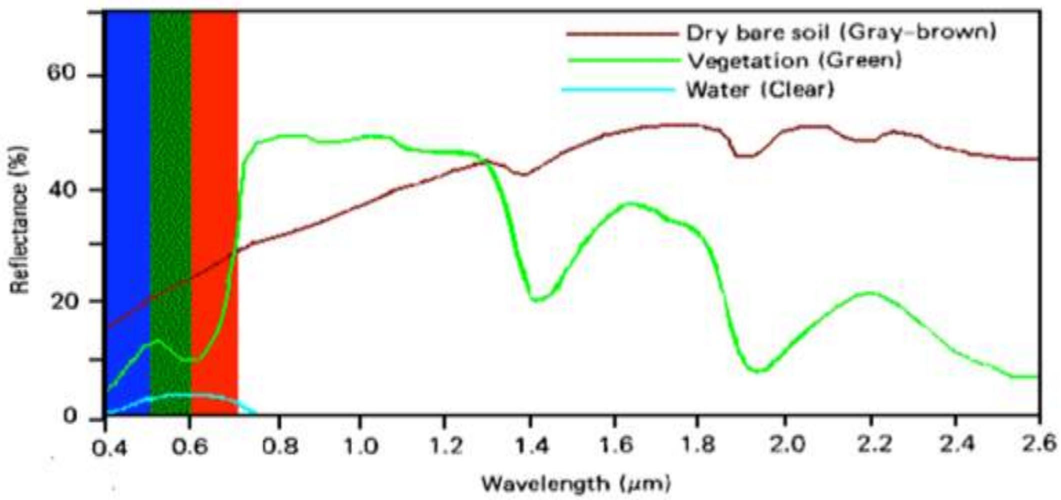

Fig. 3: Reflectance spectra of some common materials. Red, Green and Blue regions of the spectrum are shown. Near-IR is just to the right of the Red band. Ultraviolet is to the left of the Blue band.

These are only representative spectra. Each type of vegetation, water, soil and other surface type havedifferent reflectance spectra, and outside of a laboratory, these also depend on the sun's position in the sky and the satellite's position as well.When there are more bands covering more parts of the electromagnetic spectrum, more materials can be identified using more advanced algorithms such as supervised and unsupervised classification, in addition to the simple but effective band ratioand normalization methods such as the NDVI.Remote View has several tools which take advantage of multispectral data including the Image Calculator for performing NDVI and other indices and a robust Multispectral Classification capability which includes both supervised and unsupervised classification. This paper however is focused on the Pan Sharpening tools within Remote View.

B) Panchromatic data

In contrast to the multispectral image, a panchromatic image contains only one wide band of reflectance data. The data is usually representative of a range of bands and wavelengths, such as visible or thermal infrared, that is, it combines many colors so it is "pan" chromatic. A panchromatic image of the visible bands is more or less a combination of red, green and blue data into a single measure of reflectance. Modern multispectral scanners also generally include some radiation at slightly longer wavelengths than red light, called "near infrared" radiation.

Panchromatic images can generally be collected with higher spatial resolution than a multispectral image because the broad spectral range allows smaller detectors to be used while maintaining a high signal to noise ratio.
For example, 4-band multispectral data is available from QuickBird and GeoEye. For each of these, the panchromatic spatial resolution is about four times better than the multispectral data. Panchromatic imagery from QuickBird-3 has a spatial resolution of about 0.6 meters. The same sensor collects the nearly the multispectral data at about 2.4 meters resolution. For GeoEye's Ikonos, the panchromatic and multispectral spatial resolutions are about 1.0 meters and 4.0 meters respectively. Both sensors can collect co registered panchromatic and four-band (red, green, blue and near-infrared) multispectral images.

The developments in the field of sensing technologies multisensor systems have become a reality in a various fields such as remote sensing, medical imaging, machine vision and the military applications for which they were developed. The result of the use of these techniques is an increase of the amount of data available. Image fusion provides an effective way of reducing the increasing volume of information while at the same time extracting all the useful information from the source images. Multi-sensor data often presents complementary information, so image fusion provides an effective method to enable comparison and analysis of data. The aim of image fusion, apart from reducing the amount of data, is to create new images that are more suitable for the purposes of human/machine perception, and for further image- processing tasks such as segmentation, object detection or target recognition in applications such as remote sensing and medical imaging. For example, visible-band and infrared images may be fused to aid pilots landing aircraft in poor visibility.

A remote sensing platform uses a variety of sensors. Of the fundamental ones are panchromatic (PAN) sensor and Multi-Spectral (MS) sensor. The PAN sensor has a higher spatial resolution. In other words, each pixel in the PAN image covers a smaller area on the ground compared to the MS image from the same platform. On the other hand, the MS sensor has a higher spectral resolution, which means that it corresponds to a narrower range of electromagnetic wavelengths compared to the PAN sensor. There are several reasons behind not having a single sensor with both high spatial and high spectral resolutions. One reason is the incoming radiation energy. As the PAN sensor covers a broader range of the spectrum, its size can be smaller while receiving the same amount of radiation energy as the MS sensor. Other reasons include limitation of on-board storage capabilities and communication bandwidth.

I. DIFFERENT METHODS TO PERFORM PAN-SHARPENING

A) IHS Image Fusion: **-**IHS is one of the most widespread image fusion methods in remote sensing applications. The IHS transform is a technique where RGB space is replaced in the IHS space by intensity (I), hue (H), and saturation (S) level. The fusion process that uses this IHS transform is done by the following three steps.

1) First, it converts the RGB space into the IHS space (IHS transform).
2) The value of intensity I (= (R + G + B)/3) is replaced by the value of PAN.
3) Then retransformed back into the original RGB space

B) PCA Method: **-**The PCA technique is a decorrelation scheme used for various mapping and information extraction in remote sensing image data. The procedure to merge the RGB and the PAN image using the PCA fusion method is similar to that of the IHS method. The fusion process that uses this PCA is done by the following three steps.

1) First, it converts the RGB space into the first principal component (PC1), the second principalcomponent (PC2), and the third principal component (PC3) by PCA
2) The first principal component (PC1) of the PCA space is replaced by the value of the PAN image.
3) The retransformed back into the original RGB space (reverse PCA)

C) Brovery Transform (BT):- BT is a simple image fusion method that preserves the relative spectral contributions of each pixel but replaces its overall brightness with the high-resolution PAN image

II. SPARSEFI ALGORITHM FOR IMAGE FUSION

Pan-sharpening requires a low-resolution (LR) multispectral image Y with N channels and a high-resolution (HR) panchromatic image X_0 and aims at increasing the spatial resolution of Y while keeping its spectral information, i.e ,generating an HR multispectral image X utilizing both Y and X_0 as inputs. The Sparse FI algorithm reconstructs the HR multispectral image in an efficient way by ensuring both high spatial and spectral resolution with less spectral distortion.It consists of three main steps:

1) Dictionary learning
2) Sparse coefficients estimation
3) HR multispectral image reconstruction

A) Dictionary Learning

The HR pan image X_0 is low-pass filtered and down sampled by a factor of F_{DS} (typically 4–10) such that its final explored spread function is similar to the original image. The resulting LR version of X_0 is called Y_0. This Y_0 is combined with the co registration of the different channels that is required, anyway. The LR pan image Y_0 and the LR multispectral image Y are tiled into small, partially overlapping patches Y_0 and Y_k, where k stands for the k^{th} channel and k =1,...,N. All the LR patches Y_0 with pixel values arranged in column vectors form the matrix D_l called the LR dictionary. Likewise, the HR dictionary D_h is generated by tiling the HR pan image X_0 into patches X_0 of FDS times the size as the LR pan image patches, such that each HR patch corresponds to an LR patch. These image patches are called "atoms" of the dictionaries.

B) Sparse Coefficients Estimation

Sparse coefficients are estimated according to the atoms having least number of PAN patches in the LR dictionary. The atoms in the dictionary are orthogonal because they can exhibit infinite number of solution. In this step an attempt has been made to represent each LR multispectral patch in the particular channel as a linear combination of LR PAN patches. These are referred as the atoms of the dictionary represented by the coefficient vector.

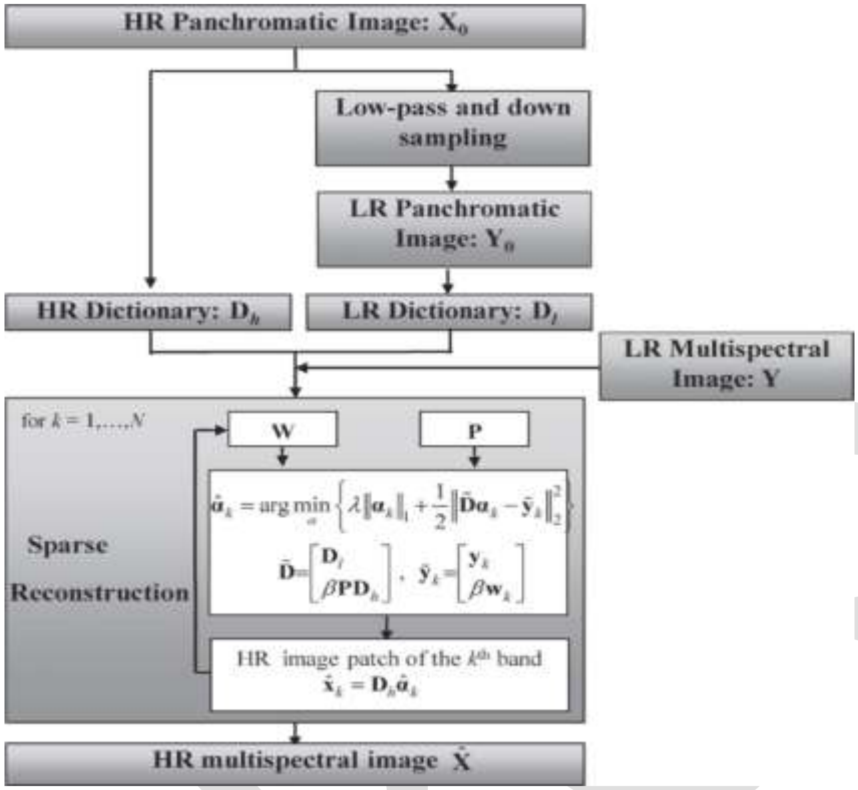

Fig 4:Flow chart of sparse FI method

C)HR Multispectral Image Reconstruction

Since each of the HR image patches X_k is assumed to share the same sparse coefficients as the corresponding LR image patch Y_k in the coupled HR/LR dictionary pair, i.e., the coefficients of X_k in D_h are identical to the coefficients of Y_k in D_l, the final sharpened multispectral image patches X_k are reconstructed by,

$$X_k = D_h \,\hat{}\, \alpha_k.$$

The tiling and summation of all patches in all individual channels finally give the desired pan-sharpened image X.

III. PROPOSED METHOD

Recently sparse signal representation of image patches was explored to solve the pan-sharpening problem for remote sensing images. Although the proposed sparse reconstruction based methods lead to motivating results, yet none of them has considered the fact that the information contained in different multispectral channels may be mutually correlated. In this paper, we extend the Sparse Fusion of Images (SparseFI, pronounced “sparsify”) algorithm, proposed by the authors before, to a Jointly Sparse Fusion of Images (JSparseFI) algorithm by exploiting these possible signal structural correlations between different multispectral channels. This is done by making use of the distributed compressive sensing (DCS) theory that restricts the solution of an underdetermined system by considering an ensemble of signals being jointly sparse. The given SparseFI algorithm works as stated as above. In this we tried to improve the parameters which decide the sparsity of the image which is to be fused. The main focus is on improving the clarity of the image. Although number of algorithms have been developed but this method has shown better performance than others. The main aspect to worry about is the down sampling factor and the patch size with a regularization parameter.

IV. A SPARSE REPRESENTATION AND COMPRESSED SENSING

The development of image processing in the past several decades reveals that a reliable image model is very important. In fact, natural images tend to be sparse in some image. This brings us to the sparse and redundant representation model of image.Compressed sensing mainly includes sparse representation, measurement matrix and reconstruction algorithm. Where, the sparse representation is the theory basis of the compressed sensing theory. The sparse representation denotes that fewer coefficients can better describe the main information of the signal. Most actual signals are nonzero. Most coefficients have small values in certain transform base (such as: wavelet basis), while less coefficients which bear most information of the signal have large values. The CS theory shows that the more sparse of the signal, the much accurate of the reconstruction signal. So the suitable transformation base can guarantee the sparsity and independence of coefficient, and guarantee the reconstruction precision of the compressed sensing while reducing the compression measurements.

At present, the common transforms are the Fourier Transform, Discrete Cosine Transform, Wavelet Transform etc. This paper proposed a novel image compressed sensing image fusion algorithm based on joint sparse representation. In order to reduce the computational burden, this study firstly constructed the joint sparse matrix. On the basis of analyzing the relationship of the reconstruction and fusion quality, the images are fused by the maximum absolute value fusion rule and reconstructed by the minimum total variation method. Consider a family of signals$\{x_i, i=1,2,...,g\}$, $x_i \in R^n$. Specially, in this paper, each such signal is assumed to be a $\sqrt{n}\times\sqrt{n}$ image patch, obtained by lexicographically stacking the pixel values. Sparse representation theory supposes the existence of a matrix $D \in R^{n\times T}$, n <<T, each column of which corresponds to a possible image. These possible images are referred to as atomic images, and the matrix D as a dictionary of the atomic images. Thus, an image signal x can be represented as $x = D\alpha$. For overcomplete D ($n \ll T$), there are many possible α satisfying $x = D\alpha$. Our aim is to find the α with the fewest nonzero elements. Thus, the α is called the sparse representation of x with dictionary D. formally, this problem can be obtained by solving the following optimization problem:

$$\alpha = \mathrm{argmin}\,\alpha_{0,}$$

Where α_0 denotes the number of nonzero components in α. In practice, because of various restrictions, we cannot get x directly; instead, only a small set of measurements y of x is observed. The observation y can be represented as

$$y = Lx$$

Where $L\in R^{k\times n}$ with k<n is interpreted as the encode process of the CS theory, where L is a CS measurement matrix. The CS theory ensures that under sparsity regularization, the signal x can be correctly recovered from the observation y by

$$\min \alpha 0$$

In this paper, we propose one remote sensing image fusion method from the perspective of compressed sensing. The high-resolution PAN and low-resolution MS images are referred as the measurements y. The matrix L is constructed by the model from the high- resolution MS images to the high-resolution PAN and low resolution MS images. Thus, the sparse representation α of the high-resolution MS images corresponding to dictionary D can be recovered from measurements y according to the sparsity regularization, and the high-resolution MS images are constructed by

$$x = D\alpha.$$

In fact, when the coefficients are sufficiently sparse, this problem can be replaced with minimizing the α_0.

V. PROPOSED IMAGE FUSION SCHEME

A) IMAGE FORMATION MODEL

Remote sensing physics should be carefully considered while designing the pan-sharpening process. Let $X^{high}{}_p$ and $Y^{low}{}_p$, p =1,..., P, represent the p^{th} band of the high-resolution and low-resolution MS images, respectively, where P denotes the number of bands of the MS images. The observed low- resolution MS images are modeled as decimated and noisy versions of the corresponding high-resolution MS images, as shown in Fig. 5.

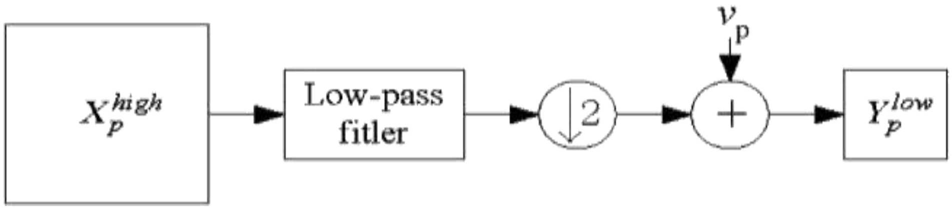

Fig 5: Relationship between a single low-resolution MS band and its corresponding high-resolution version

In fact, intensity of the low-resolution image is due to integration of light intensity that falls on the charge-coupled device sensor array of suitable area compared to the desired high- resolution images, so the low-resolution intensity can be seen as neighborhood pixels' average of the high-resolution intensities corrupted with additive noise. The relationship between X^{high} p and Y^{low} p is written as

$$Y^{low}_p = MX^{high}_p + V_P$$

Where M is the decimation matrix and V_p is the noise vector.

In fact, the PAN image usually covers a broad range of the wavelength spectrum; whereas, one MS band covers only a narrow spectral range. Moreover, the range of wavelength spectrum of the PAN modality is usually overlapped or partly overlapped with those of the MS bands. This overlapping characteristic motivates us making the assumption that the PAN image is approximately written as a linear combination of the original MS images

$$Y^{PAN} = \sum p\, w_p X^{high}_p + V_p$$

WhereW_p is the weight and V_p is the additive zero-mean Gaussian noise.

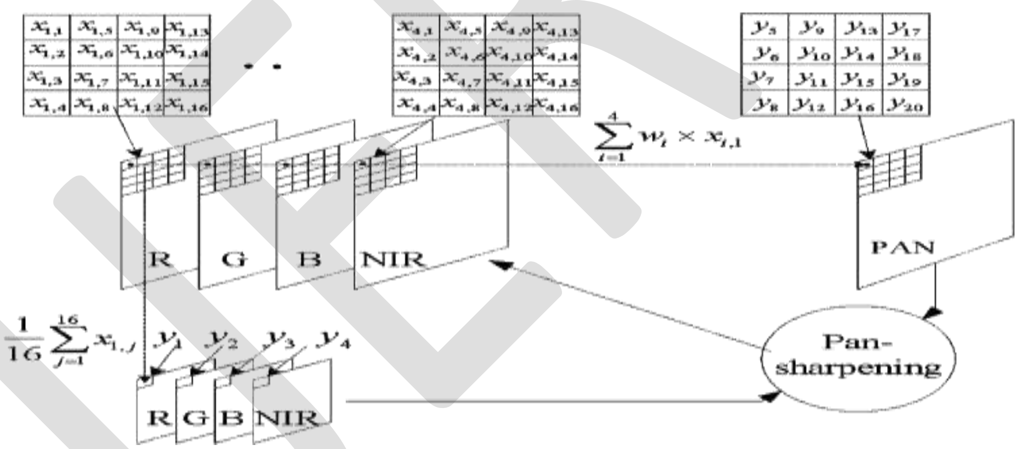

Fig. 6: Remote sensing image formation model.

However, we should note that the linear relationship between the PAN and the MS image is only approximated by the linear model because of the complexity of physics, atmospheric dispersion, and so on. We consider a pan-sharpening case with four spectralbands: 1) Red (R); 2) green (G); 3) blue (B); 4) and near infrared (NIR), and the decimation factor from high to low spatial resolution is four. Let $x = (x_{1,1},...,x_{1,16},...,x_{4,1},...,x_{4,16})^T$ represent the high spatial resolution MS image patch and $Y_{MS} = (y1,y2,y3,y4)^T$ is the vector consisting of the pixels from the low-resolution MS images shown in Fig.6.

Then, we can write

$$Y_{MS} = M_{1x} + v_1$$

VI. COMPRESSIVE SENSING AND IMAGE FUSION

Compressive sensing enables a sparse or compressible signal to be reconstructed from a small number of non-adaptive linear projections, thus significantly reducing the sampling and computation costs. CS has many promising applications in signal acquisition, compression, and medical imaging. In this paper, we investigate its potential application in the image fusion.As far as a real-valued finite-length one-dimensional discrete-time signal x is concerned, it can be viewed as a R^N space $N \times 1$ dimensional column vector, and the element is $x[n]$, $n = 1, 2, \ldots, n$. If the signal is sparse K, it can be shown as the following formula:

$$X = \psi s$$

Whereψ is the $N \times N$ matrix and s is the coefficient component column vector of dimension $N \times 1$.

When the signal x in the base of ψ has only non-zero coefficients of $K << N$ (or greater than zero coefficients), ψ is called the sparse base of the signal x. The CS theory indicates that if the signal x's (the length is N) transform coefficient which is at an orthogonal basis ψ is sparse (that is, only a small number of non-zero coefficients can be obtained), if these coefficients are projected into the measurement basic ϕ which is irrelevant to the sparse base ψ, the $M \times 1$ dimensional measurement signal y can be obtained. By this approach, the signal x's compressed sampling can be realized.

The advantage that the joint sparse theory has is that the data obtained via the projection measurement is much smaller than the conventional sampling methods, breaking the bottleneck of the Shannon sampling theorem, so that the high-resolution signal acquisition becomes possible. The attraction of joint sparse theory is that it is for applications in many fields of science and engineering and has important implications and practical significance, such as statistics, information theory, coding theory, computer science theory, and other theories.

Compared with the traditional fusion algorithms, the joint sparse FI based image fusion algorithm theory has shown significant superiority the image fusion can be conducted in the non-sampling condition of the image with the joint SparseFI technique, the quality of image fusion can be improved by increasing the number of measurements, and this algorithm can save storage space and reduce the computational complexity

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CONCLUSION

The paper put forward a fusion algorithm based on the compressed sensing having joint sparse representation. Compared with the traditional methods, the proposed CS based joint SparseFI image fusion algorithm can preserve the image feature information, enhance the fused image, space detail representation ability and improve the fused image information. The experiment proves that the approach in this paper is better than the SparseFI algorithm, wavelet transform and Laplace pyramid decomposition, etc. In this paper, a novel pan-sharpening method based on CS technique is presented. Based on the PAN and MS images generation model, we referred the pan-sharpening problem.

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