Image Fusion based on Sparse Sampling Method and Hybrid Discrete Cosine Transformation

Hien Dang, K. Martin Sagayam, P. Malin Bruntha, S. Dhanasekar, A. Amir Anton Jone, G. Rajesh

Abstract— Image fusion is a mixture of several images to a merged image ensuing more informative than other input images which have been used in recent years. Image fusion based on Discrete Cosine Transformation (DCT) is dealt in this work. Generally, in image fusion, several images of the same scene are given as input and one image with higher quality is obtained as output. When compared to Nyquist theorem, compressed sensing theory offers an improved result. DCT yields better quality and it requires less storage and low cost amongst the many techniques.

Index Terms— Image fusion, compressive sensing, principal component analysis, discrete cosine transformation, sparse sampling, nyquist theorm, low pass filter, fused image.

1 Introduction

ACQUIRING and renovating are essential in every signal processing system and sampling theorems between continuous and discrete domains. Image fusion based on DCT can provide better performance than fusion based on other multi-scale methods. The multi-sensor data fusion has become an intense research area in recent years [1-2]. Cosine transform provides good localization in both frequency and space domain. With the increasing of remote sensing image fusion algorithm, the real-time of fusion faces challenges [3-5].

Remote sensing using satellite is one of the powerful mechanisms to monitor the surface of the earth, atmosphere by providing importance coverage and mapping. The term "remote sensing" is generally used in electromagnetic techniques [6-9]. The consistent and periodic view of the planet earth is being provided by the remote sensing systems which are employed on satellites. The remote sensing systems provide a broad range of spatial and temporal resolutions in order to support various applications. Many images are being taken by the satellites and their frequency bands are in the visual and non-visual range [10-11]. Multispectral image (MS) is a collection of various bands of the same scene which are obtained by a sensor. A colour image is formed with the mixture of three bands allied in a RGB colour system. The information content will be increased by the combination of spectral band of a colour image. If not, it is tedious to differentiate the images since various targets may look alike. Either single multispectral sensor or multiple sensors which are operating at various frequencies could be used to acquire different bands of frequencies [12-13].

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2 Related Work

2.1 Compressive Sensing (CS)

Compressive sensing otherwise known as sparse sampling is a method generally used to reconstruct a signal, by finding a better outcome for vague signals. Compressive sensing is one of the techniques that have received more interest in sampling procedures [14-17]. Compressive sensing has advantages of redundancy of signals and reconstruction of the image. The performance of this algorithm is ranked both computably and conditionally [18-20].

2.2 Discrete Cosine Transformation (DCT)

Using DCT, frequency components of a given signal can be obtained. Since it has good energy compaction, it is normally adopted in image processing and compression applications. DCT fuses images through weighted coefficient, recover the fusion image by recognition algorithm [21-24]. DCT based image fusion are more suitable and time-saving in the real-time application. Thus we achieve better clarity images.

DCT also described in low frequency and high frequency where it allows low-frequency substances and discards high frequency. Many images are compressed by JPEG standard format which uses Discrete Cosine Transform (DCT) which is one of the main applications [25-26].

3 Problem Definition

Recent survey papers have been provided overviews on developments and current status of remote sensing in the field of image processing [2-4]. Remote sensing satellite techniques deal with acquisition, processing, analysis and usage of data from space platform and satellites [28].

Effect of Clouds

In many applications, remote sensing plays a key role. It has high quality performance in repetitive measurement in scene analysis, detection of landscape ecological change etc [29]. Out of many applications, the remote sensing images are used to extract the information of the landscape. But these images are highly prone to noise due to the fact that the most of the earth's surface is shrouded by clouds. This is one of the major causes of blurred satellite images.

Effects of atmosphere

The atmosphere attenuates and distorts the signal coming from the earth surface to the remote sensing sensor. The gasses and aerosols present in the atmosphere scatter, observe and emit radiant energy. The atmosphere is transparent in certain narrow regions of the visible, infrared and microwave regions. It is practically opaque in the ultraviolet and hence it is not suitable for remote sensing. The main source of electromagnetic energy reaching the earth is a sun. The maximum irradiance of the sun occurs for different wavelength of the earth and atmosphere. The atmospheres scatter, absorbs or emit radiant energy.

The Rayleigh or molecular scattering is dominant in the visible and near-ultraviolet regions and increases with the inverse power of the variant [10-13]. There are some molecular energy that scatters and has absorption bands that can influence atmospheric absorption even when in trace quantities. Water vapor also has a prominent role in absorption. Infrared cloud image can give a lot of information. The temperature of the cloud can be estimated from the infrared radiation and hence the altitude.

Data Fusion

Data fusion is the process of combining many images using some fusion algorithms. In order to improve the resolution of image in spatial and temporal characteristics, data fusion can merge dissimilar and complementary data. This process will lead to obtain exact data [27]. The satellites which cover earth provide data which encompasses different regions of the electromagnetic spectrum at various resolutions in terms of spatial, temporal and spectral. Data fusion is an emerging area which can be used to handle multi-source data. The fused images carry more information because different data with its own characteristics are combined. Optical sensors in RADAR generate many data and these data can be combined using this data fusion technique. But the problem is optical images may resonate with the spectral information of the object. Moreover, the intensities of RADAR are sensitive to the roughness of the target and vertical characteristics. Also, the optical images are affected by the electromagnetic waves' carrier frequency [5-7]. In general, the optical images prone to the geometric distortions. Henceforth, it is much needed to combine various images which are obtained by the same or different sensors to eliminate distortions, noises and to get accurate images of the region of interest.

4 Proposed Work

The proposed framework consist of image datasets, discrete cosine transformation, low pass filtering, PCA, compressive sensing, inverse cosine transformation and fused image are shown in Fig 1. Each blocks are explained in subsections.

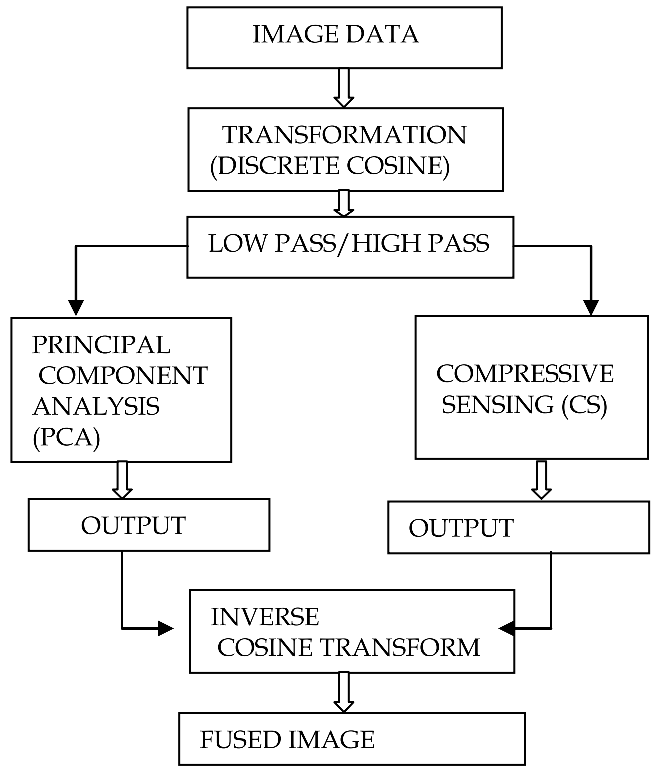


Fig. 1 Framework of the proposed work

Discrete Cosine Transform (DCT)

Nowadays, image data are extensively obtainable. These large number of data obtained from different processes are tremendously large. Hence, storing the image data or transmitting them require high cost. To mitigate this problem, data compression techniques are adopted. One such data compression technique is Discrete Cosine Transform (DCT).

Using DCT, noteworthy compression ratio can be achieved. However, there will losses of accuracy while reconstructing the image. In videophone application, such loss can be endured. In this paper, DCT as a compression technique in remote sensing images is employed.

Low pass filter

Low pass filter is an ideal filter used for blurring process, to 'smoothen' the averaging the value of neighbour pixel to improve the intensity level. The resultant data is replaces all values through the source pixel values from the image. This repeats for all values of pixels still it gets refined final output. Each pixel is independent of noise, but it cannot be tolerate to the minimum level. It can supressed by gradually applying by an ideal filter for individual pixel level for enhancing the quality of image. It brings out faint details that can be smoothen by the filtering to reduce the noise level.

High pass filter

High-pass filter is used to improve the intensity level of an input image with good resolution. It provides more precise filtering than the low-pass filter. The working principle of high pass and low pass filtering works in same fashion, but differs with convolution operator. If there is no variation in intensity level, no changes has been occur. But if any one of the pixel is high intense than neighbouring pixels, then it improves the quality of image each if it magnifies.

Even low-pass filtering smoothen the noise level of input image, high-pass filtering magnifies the noise level of input content. Since the input data consist of too noisy content, it can overwhelm with the source content [9-11]. High-pass filtering can significantly improve image content by sharpening without loss of any information.

Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is used to transform multi-variant data with correlated to uncorrelated variable. It is one of the significant methods used in statistical approach for dimensionality reduction or de-correlation operation. Image analysis deals with PCA, since it more emphasize on determination of object orientation for selection through Eigen vector properties. It used to extract high redundant feature values from the input data.

It emphasizes on the standards of data for exploratory data analysis and predictive approach. It is mathematically defined as orthogonal linear transformation into a new coordinate system in different coordinate systems. Let us consider data matrix X, with zero empirical mean has to transformed into *p*-dimensional vector of weight coefficients $w_{(k)} = (w_1,\ldots, w_p)_{(k)}$ that mapped into each row vector $X = x_{(i)}$ where i=1,…,n to a new vector $t_{(i)} = (t_1,\ldots,t_l)_{(i)}$ given by

$$t_k(i) = x(i).w(k) \text{ for } i = 1,\ldots,n \text{ and } k = 1,\ldots, l \quad (1)$$

$$w_n = \arg max \left\{ \frac{w^T X^T X w}{w^T w} \right. \quad (2)$$

Compressive Sensing (CS)

Compressive sensing is one of the most predominant tools for acquiring and reconstructing an input signal [30]. It is also known as sparse sampling or compressive sampling. It emphasize on two main problems are compression capability and lack of complexity. Cosine transform is used to decompose the original data into multi data. The fused image is recovered by two criteria are, sparsity and incoherence.

The orientation field and iterative field are used in Lagrangian multiplier as shown below:

$$\lambda_H^k = \lambda_H^{k-1} + \gamma_H(H^k - \nabla d_h^k) \quad (3)$$

$$\lambda_V^k = \lambda_V^{k-1} + \gamma_V(V^k - \nabla d_v^k) \quad (4)$$

$$\lambda_P^k = \lambda_P^{k-1} + \gamma_P(P^k - \nabla x_p^k) \quad (5)$$

$$\lambda_Q^k = \lambda_Q^{k-1} + \gamma_Q(Q^k - P^k d_h^k) \quad (6)$$

Inverse Discrete Cosine Transform

Inverse DCT reconstructs a sequence from its DCT. Using normalization method, inverse DCT is multiplication of transformed sequence and 2/(N-1). It produced more accurate original data than other transformation technique.

Fused Image

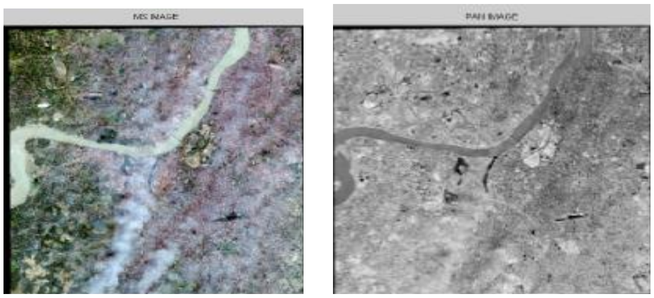
Image fusion algorithm is used to divide non-overlapping blocks of N x N using DCT coefficients for each block. Fusion rule is used to get fused data using DCT coefficient. Inverse transform is used to get the fused block. Repeat this procedure until gets the fused image.

5 Result and Analysis

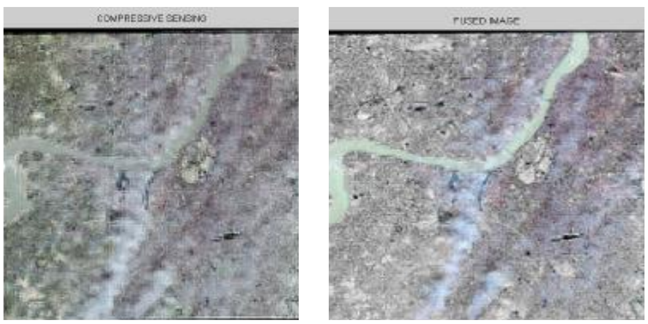
The true information and natural color preservation is very much necessary for any kind of image fusion method. Fusion performance is mainly assessed using subjective and objective metrics. However, subjective tests may be accurate if it recognize correctly, and consume less time. Hence, the performances of different multi-sensor image fusion methods are evaluated as a function of their generated objective metrics. An objective fusion test should be,

- The perceptual features are extracted from the input data.
- Ability to measure fusion process as accurate as possible from the input data.

The performance measures are determined based on the edge information of the source images that are transferred into the fused images. Hence all objective metrics are range between 0 to 1. It can be derived using objective evaluation methods; a few parameters are entropy (E), standard deviation (SD), root mean square error (RMSE), peak signal to noise ratio (PSNR), mutual information (MI).



(a) first image (b) second image



(c) PCA with CS (d) Hybrid DCT fused image

Fig. 2: Fused images of leaf with their fusion techniques

This mthod shows the significant output of each stage, the performance evaluation has shown for leaf image in table 1.

6 CONCLUSION

The Proposed algorithm presents Hybrid DCT Digital image fusion algorithm. This method exploits strength of the DCT to obtain better image quality of fused image. It has lower standard deviation and higher PSNR compared to existing technique. In this work, the image fusion algorithm is proposed to fuse the MS images and the Pan image. It is used to combine by cosine transform and sparse representation. Cosine transform and fusion rule is used to characterize into the low- and high- frequency sub-images from the input images. To get the better local information and spatial contents from the image, sparse sampling representation is used. Thus, it reduces the spectral distortion in the fused image.

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ANNEXURE

The following are the formulae of performance matrices are given below:

Metric 1: $Q^{AB/F}$

$$Q^{AB/F} = \frac{\sum_{\forall m,n} Q^{AF}(m,n)\omega_A(m,n) + Q^{BF}(m,n)\omega_B(m,n)}{\sum_{\forall m,n} \omega_A(m,n) + \omega_B(m,n)}$$

Metrics 2: Entropy

$$E_n = \sum_{i=0}^{N} p(i)\log_2 p(i)$$

Metrics 3: Standard Deviation

$$SD = \sqrt{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(I(i,j)-\bar{I})^2}$$

Metrics 4: Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{MN}\sum_{i=0}^{M}\sum_{j=0}^{N}(R(i,j)-F(i,j))^2}$$

Metrics 5: Peak signal to noise ratio (PSNR)

$$PSNR = 20\log_{10}\left(\frac{L^2}{\frac{1}{MN}\sum_{i=0}^{M}\sum_{j=0}^{N}(R(i,j)-F(i,j))^2}\right)$$

Metrics 6: Mutual Information (MI)

$$MI_F^{AB} = MI_{FA}(f;a) + MI_{FB}(f;b)$$

Table 1: Performance measures of geographical position of England

Image of geographical position of England				
Metrices	**PCA**	**CS**	**PCA with CS**	**Hybrid DCT fused image**
$Q^{AB/F}$	0.6415	0.6511	0.6621	**0.7023**
Entropy	7.3559	7.4369	7.3978	**7.4523**
Standard Deviation	42.8713	45.0531	44.0766	**46.0123**
RMSE	5.5956	6.2399	6.5997	**3.2132**
PSNR	40.6863	40.2130	39.9695	**42.3241**
Mutual Information	4.0143	3.5807	0.9244	**4.5675**

The hybrid DCT based sparse sampling methods produced better than other methods such as PCA, CS and PCA with CS. This method exploits strength of the DCT to obtain better image quality of fused image. It has lower standard deviation and higher PSNR compared to existing technique the image fusion algorithm is proposed to fuse the MS images and the Pan image by combining the cosine transform and sparse representation.