

# International Journal of Advance Research in Computer Science and Management Studies

Research Article / Survey Paper / Case Study

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## *Improve the Quality of Multispectral Bands using Different Fusion Techniques*

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*Abstract: Image fusion is the process of combining the panchromatic band with the multispectral bands to form a fused image that retains the spatial information from the high resolution panchromatic image and the spectral characteristics of the lower resolution multispectral image. Many techniques such as Local mean, matching, wavelet, PCA, Brovey have been adopted in this research. Spatial and spectral qualities can be evaluated by relying on metric performance data such as (MSE, RMSE, CC ERGAS, RASE). World view-2 satellite images for multispectral and panchromatic image in 2m and 0.5m spatial resolution respectively were used to perform this research.*

*Keywords: image fusion, wavelet, PCA, Brovey, local mean matching.*

### I. INTRODUCTION

In image processing the need for Image Fusion is increasing mainly due to the increased number and variety of image acquisition techniques. Image Fusion is defined as the process of combining substantial information from several sensors using mathematical techniques in order to a single composite image that will be more comprehensive and thus, more useful for a human operator or other computer vision tasks [1]. Current technology in imaging sensors offers a wide variety of information that can be extracted from an observed scene. Images which have been acquired using different sensor modalities exhibit diverse characteristics, such as type of degradation, salient features, texture properties etc. Representative examples of available sensors are radar, sonar and other acoustic sensors, infrared and thermal imaging cameras, seismic, magnetic, LIDAR and other types of sensors. Multi-sensor information is jointly combined to provide an enhanced representation in many cases of experimental sciences. The automated procedure of conveying all the meaningful information from the input sensors to a final composite image is the goal of a fusion system, which appears to be an essential pre-processing stage for a number of applications, such as aerial and satellite imaging, medical imaging, robot vision and vehicle or robot guidance [2]. There are a number of applications in remote sensing that require images with both high spatial and spectral resolutions. The fusion of the multispectral and panchromatic images, or pan-sharpening, provides a solution to this by combining the clear geometric features of the panchromatic image and the color information of the multispectral image. In this research different pan-sharpening techniques will be examined and explored various metrics that can be used to judge the image quality of the fused image. We will be working with images from world view-2 with high spatial resolution 0.5 m for panchromatic and 2m for multispectral.

## II. METHODOLOGY

Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. In this research local mean matching, principle component analysis (PCA), Brovey and wavelet fusion techniques have been adopted to get high resolution image combine from the panchromatic and multispectral image, the using images have been captured by worldwiew-2 with spatial resolution .5m for panachromatic and 2m for multispectral as shown in figure (1), six quality metric were used to compare between the adaptive fusion techniques.

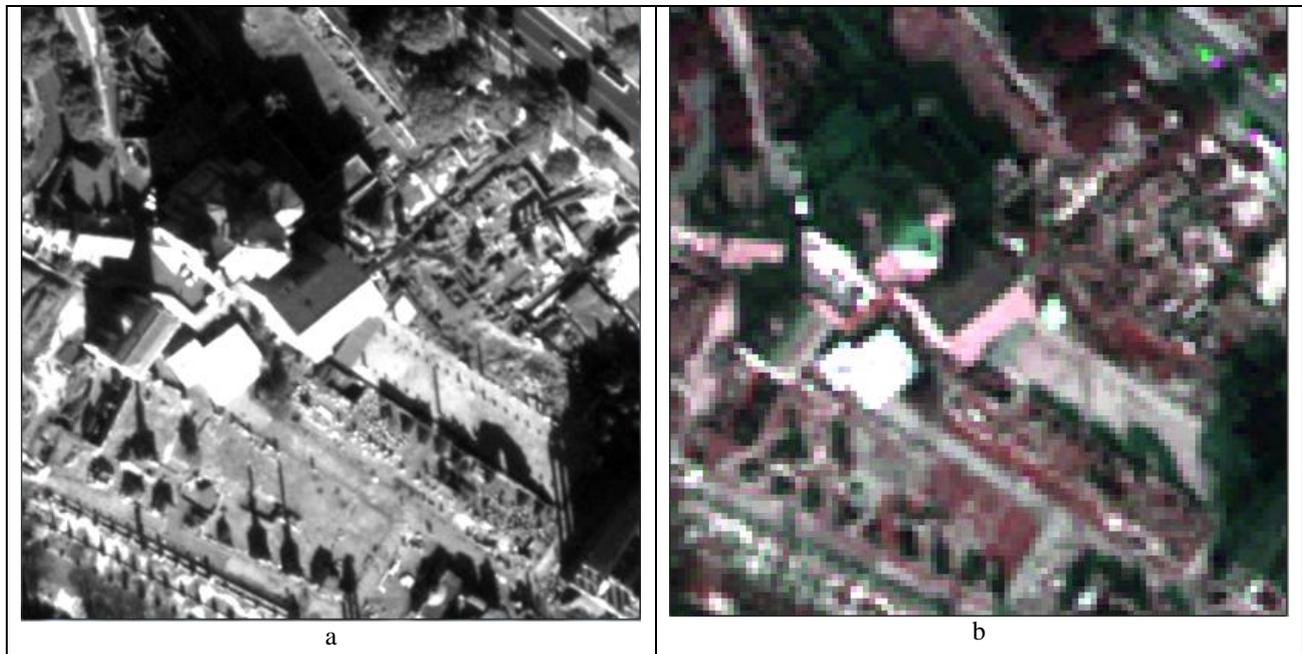


Fig 1: a. panchromatic with 0.5m resolution b. RGB 3,2,1 of the original multispectral image with 2 m resolution by WV-2 sensor.

## III. FUSION TECHNIQUES

The fusion methods can be listed as follow:

### A. The local Mean Matching (LMM) Algorithm

$$F_{k(i,j)} = P_{(i,j)} \times \frac{\bar{M}_{k(i,j)(w,h)}}{\bar{P}_{k(i,j)(w,h)}} \quad (1)$$

Where  $F_{k(i,j)}$  is the fused image,  $P_{(i,j)}$  and  $M_{k(i,j)}$  are respectively the high and low spatial resolution images at pixel coordinates  $(i, j)$   $\bar{M}_{k(i,j)(w,h)}$  and  $\bar{P}_{k(i,j)(w,h)}$  are the local means calculated inside the window of size  $(w, h)$  [3].

### B. Brovey Transform

Brovey transform (BT), also known as color normalized fusion, is based on the chromaticity transform and the concept of intensity modulation. It is a simple method to merge data from different sensors, which can preserve the relative spectral contributions of each pixel but replace its overall brightness with the high spatial resolution image. As applied to three MS bands, each of the three spectral components (as RGB components) is multiplied by the ratio of a high-resolution co-registered image to the intensity component I of the MS data.[4] the mathematical algorithm for the Brovey method [4].

$$F_i = \frac{M_i}{\sum_{j=1}^N M_j + C} \times P \quad (2)$$

$F_i$ : fused image

$M_i$ : multispectral band to be fused,  $P$ : panachromatic band,  $\sum_{j=1}^N M_j$ : sum of all multispectral bands

### C. The Wavelet

Transform decomposes the image into low-high, high-low, high-high spatial frequency bands at different scales and the low-low band at the coarsest scale. The L-L band contains the average image information whereas the other bands contain directional information due to spatial orientation. Higher absolute values of wavelet coefficients in the high bands correspond to salient features such as edges or lines. With these premises [5], propose a selection based rule to perform image fusion in the wavelet transform domain. Since larger absolute transform coefficients correspond to sharper brightness changes, a good integration rule is to select, at every point in the transform domain, the coefficients whose absolute values are higher [6]. This idea is represented in Figure (2).

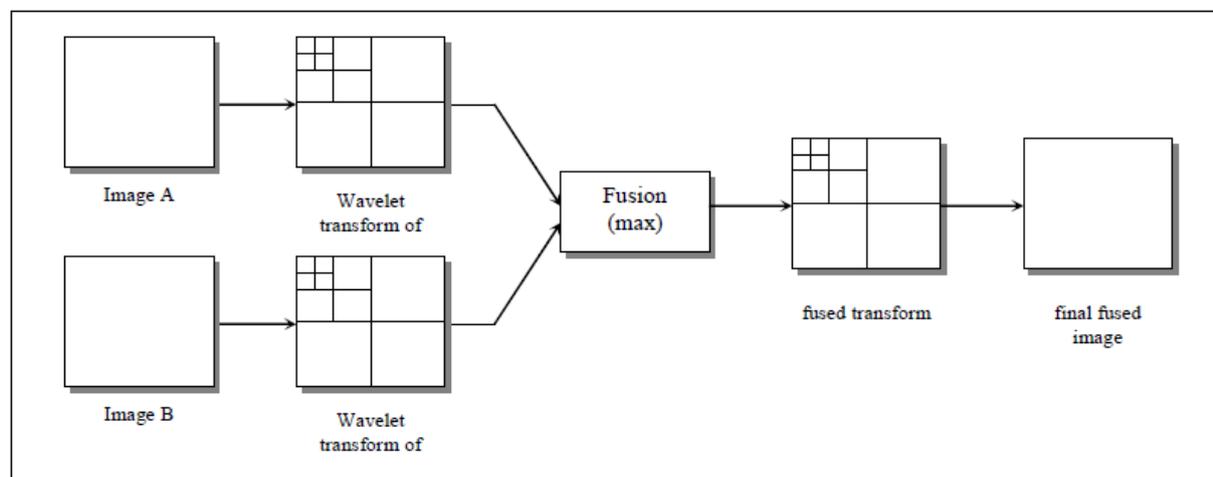


Fig.. 2: Wavelet fusion scheme

### D. Principle Component Analysis (PCA)

In general, the first principal component PC collects the information that is common to all the bands used as input data in the PCA, i.e., the spatial information, while the spectral information that is specific to each band is picked up in the other principal components [7]. This makes PCA a very adequate technique when merging MS and PAN images. In this case, all the bands of the original MS image constitute the input data. As a result of this transformation, we obtain noncorrelated new bands, the principal components. The PC is substituted by the PAN image, whose histogram has previously been matched with that of PC. Finally, the inverse transformation is applied to the whole dataset formed by the modified PAN image and the PC, obtaining that way the new fused bands with the spatial detail of PAN image incorporated into them [8].

## IV. IMAGE QUALITY METRICS

In the case of pan-sharpening it necessary to compare the colors of the small low resolution image to the ones of the larger high resolution sharpened image. Furthermore, the human eye seems to be much more sensitive to shapes than to color, which shows that in general spectral quality is much harder to see than spatial quality. There are many ways for measuring the fidelity "quality" of images [9].

### 1. Root Mean Squared Error (RMSE):

RMSE measures the difference between values that are fused and the actual value. It is an objective evaluation measure requiring a reference image. The formula for RMSE is

$$RMSE = \sqrt{\frac{\sum_x \sum_i (A_i(x) - F_i(x))^2}{n \times m \times d}} \quad (3)$$

In this formula  $x$  is the pixel and  $(i)$  is the band number. Also  $n$  is the number of rows,  $m$  is the number of columns and  $d$  is the number of bands.

## 2. The relative average spectral error (RASE)

RASE is Expressed as a percentage characterizes the average performance of the method of image fusion in the spectral bands [10]. The formula is given by:

$$RASE = \frac{100}{M} \sqrt{\frac{1}{N} \sum_{i=1}^N RMSE^2(B_i)} \quad (4)$$

In the formula for RASE,  $M$  is the mean radiance of the  $N$  spectral bands ( $B_i$ ) of the original MS bands.

## 3. ERGAS “Erreur Relative Globale Adimensionnelle De Synthèse”:

ERGAS is calculates the amount of spectral distortion in the image. The formula for ERGAS is given by:

$$ERGAS = \frac{h}{l} \sqrt{\frac{1}{N} \sum_{n=1}^N \left( \frac{RMSE_n}{\mu_n} \right)^2} \quad (5)$$

Where  $\frac{h}{l}$  the ratio between pixel sizes of Pan and MS is,  $\mu_n$  is the mean of the  $n$ th band, and  $N$  is the number of bands. [11,12].

## 4. Correlation Coefficient (CC)

The correlation coefficient is a very popular statistical method for measuring the similarity of two datasets. The CC is in a range from minus one to one while values close to one indicate a high similarity and values close to minus one an inverse relationship. Formula for the correlation between two images A and B is [9]

$$CC(A, B) = \frac{\sum_i \sum_j (A_{ij} - \bar{A})(B_{ij} - \bar{B})}{\sqrt{(\sum_i \sum_j (A_{ij} - \bar{A})^2)(\sum_i \sum_j (B_{ij} - \bar{B})^2)}} \quad (6)$$

Where A is the multispectral image and B is the fused image,  $i, j$  is pixel coordinates.

## V. RESULT AND DISCUSSION

The fusing techniques have been used to enhance the spatial resolution of multispectral image captured by worldwiew-2 (2m) by combining it with high resolution panchromatic image with spatial resolution (0.5m). The original image can be shown in figure(1), while the result fused images can be shown in figure (2), all the criteria fidelity between the original multispectral image and fused image can be listed in tables (1) &(2). Where it can be easy to see the comparison between the fusing images performed by different fusion techniques. Subjectively, the fusing image using brovey and PCA same to be very good and have high spatial resolution than wavelet and local mean matching. But objectively and by use some criteria it is can be noticed that inversely relation between the correlation coefficient CC and the relative average spectral error RASE, local mean matching and wavelet give high CC and low RASE than Brovey and PCA, that is mean that the fusion method used allows a high-quality transformation of the multispectral content when increasing the spatial resolution. As well as mege image using wavelet and brovey give low CC and high RASE indicate that the analyzed image-fusion procedure tends to modify the spectral information of the initial ultispectral image.

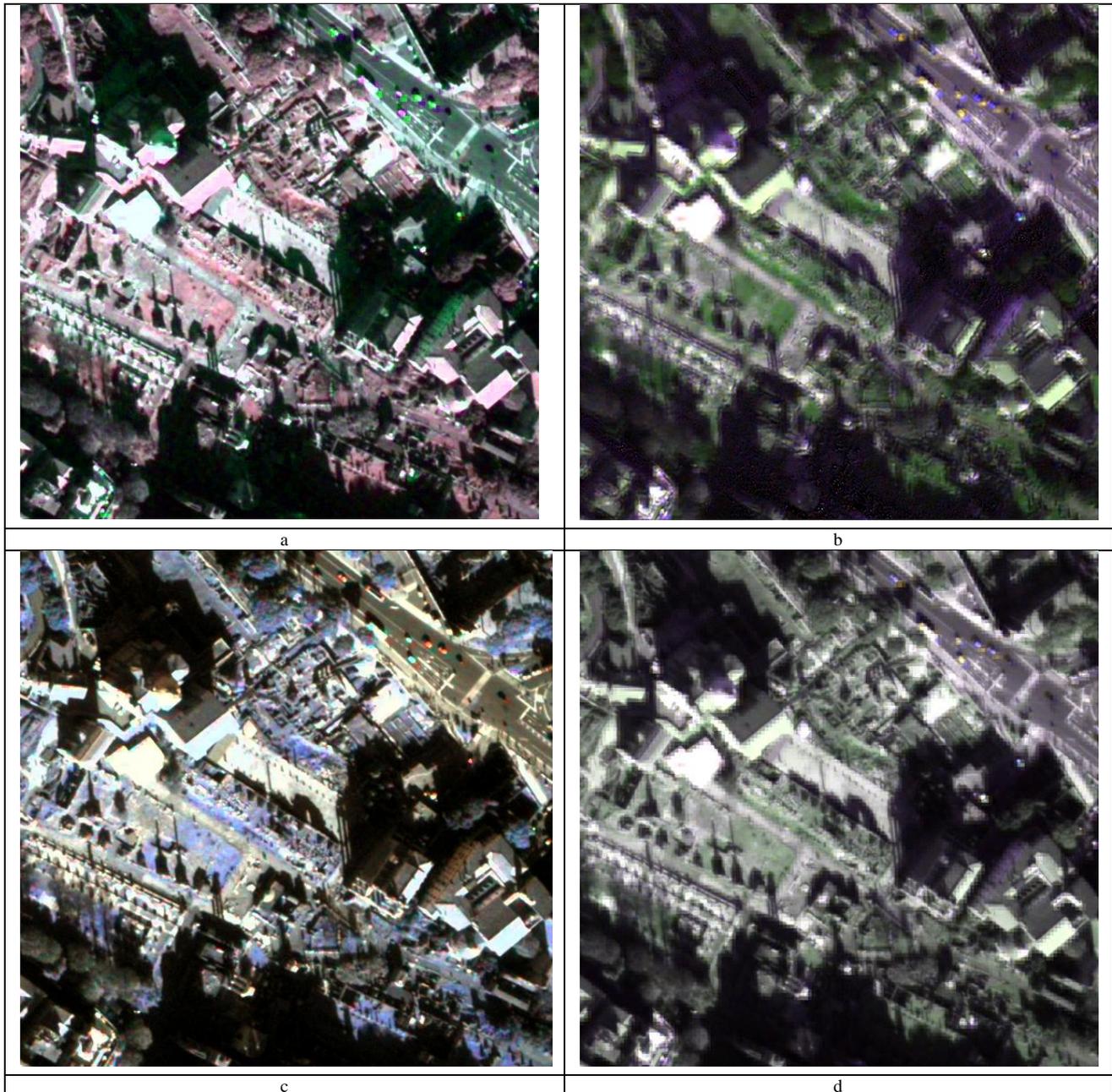


Fig. 3: The results of fused image using a) PCA b) Local mean matching c) Brovey d) wavelet.

Table (1) show the fidelity (MSE, RMSE, PSNR) criteria of fusing image

Fusing Techniques	MSE	RMSE	PSNR
Local mean matching	48.9662	6.9976	31.2318
wavelet	39	6.2798	32.1719
PCA	72.09	8.49	29.5519
Brovey	79.605	8.9222	29.1214

Table (2) show the fidelity(CC, ERASE, RASE) criteria of fusing image

Fusing Techniques	CC	ERGAS	RASE
Local mean matching	0.96	2.332	8.042
wavelet	0.92	1.810	13.446
PCA	0.73	2.240	14.692
Brovey	0.77	2.418	14.137

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