COLOUR IMAGE REPRESENTION OF MULTISPECTRAL IMAGE FUSION

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ABSTRACT

The availability of imaging sensors operating in multiple spectral bands has led to the requirement of image fusion algorithms that would combine the image from these sensors in an efficient way to give an image that is more perceptible to human eye. Multispectral Image fusion is the process of combining images optically acquired in more than one spectral band. In this paper, we present a pixel-level image fusion that combines four images from four different spectral bands namely near infrared(0.76-0.90um), mid infrared(1.55-1.75um),thermal- infrared(10.4-12.5um) and mid infrared(2.08-2.35um) to give a composite colour image. The work coalesces a fusion technique that involves linear transformation based on Cholesky decomposition of the covariance matrix of source data that converts multispectral source images which are in grayscale into colour image. This work is composed of different segments that includes estimation of covariance matrix of images, cholesky decomposition and transformation ones. Finally, the fused colour image is compared with the fused image obtained by PCA transformation.

KEYWORDS

Multispectral image fusion, cholesky decomposition, principal component analysis, Grayscale image.

1. INTRODUCTION

The deployment of multiple number of sensors operating in different spectral bands has led to the availability of multiple data. To educe information from these data there is a need to combine all data from different sensors. This can be accomplished by image fusion algorithms. Image fusion have been analysed from past twenty years. The main objective of image fusion is to generate a fused image from a number of source images that is more informative and perceptible to human vision. The concept of data fusion goes back to the 1950's and 1960's,with the search for methods of merging images from various sensors to provide composite image which could be used to identify natural and man-made objects better. Burt [1] was one of the first to report the use of Laplacian pyramid techniques in binocular image fusion. Image fusion is a category of data fusion where data appear as arrays of numbers which represents brightness, intensity, resolution and other image properties. These data can be two dimensional, three dimension or multi-dimensional. The aim of image fusion is to reduce uncertainty and minimize redundancy in the final fused image while maximizing the relevant information. Some of the major benefits of image fusion are: wider spatial and temporal coverage, decreased uncertainty, improved reliability, and increased robustness of the system.
Image fusion algorithms are broadly classified into three levels: Low, mid and high levels. These levels sometimes are also referred to as pixel, feature and symbolic levels. In pixel level, image is fused pixel by pixel manner and is used to merge the physical parameters. The main advantage of pixel level is that the original measured quantities are directly involved in the fusion process. Also it is more simple, linear, efficient with respect to time and easy to

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implement. This fusion technique can also detect undesirable noise which makes it more effective for image fusion. Feature level need to recognise the object from various input data sources. Thus the level first requires the extraction of features contained in the various input images. These features can be identified by characteristics like size, contrast, shape or texture. The fusion in this level enables the detection of useful features with higher confidence. Fusion at symbol level allows information to be efficiently merged at higher level of abstraction. Here the information is extracted separately from each input data sources and decision is made based on input images and then fusion is done. This project mainly deals with the pixel level fusion technique because of its linearity and simplicity.

In remote sensing applications, fusion of multiband images lying in different spectral bands of the electromagnetic spectrum is one of the key areas of research. A convenient method for this is to reduce the image set dimensionality to three dimension set, which can be displayed as red, green, blue channels. Human vision also functions similarly. The visible spectrum of light entering each point of eye is converted into 3 component perceived colour, as captured by Large, medium and small cones which roughly corresponds to RGB. Also human eye can distinguish only few levels of Grayscale but can identify thousands of colour on RGB colour scale. This core idea s used to yield final colour image with maximum information from the data set and enhanced visual features compared to the source multispectral band images. In this work a different approach called VTVA(Vector valued Total Variation Algorithm)is tried that controls the correlation between colour components of the final image by means of covariance matrix.

1.1. RGB COLOUR SPACE

All colour spaces are three-dimensional orthogonal coordinate systems, meaning that there are three axes (in this case the red, green, and blue colour intensities) that are perpendicular to one another. This colour space is illustrated in figure 1. The red intensity starts at zero at the origin and increases along one of the axes. Similarly, green and blue intensities start at the origin and increase along their axes. Because each colour can only have values between zero and some maximum intensity (255 for 8-bit depth), the resulting structure is the cube. We can define any colour simply by giving its red, green, and blue values, or coordinates, within the colour cube. These coordinates are usually represented as an *ordered triplet* - the red, green, and blue intensity values enclosed within parentheses as **(red, green, blue).**

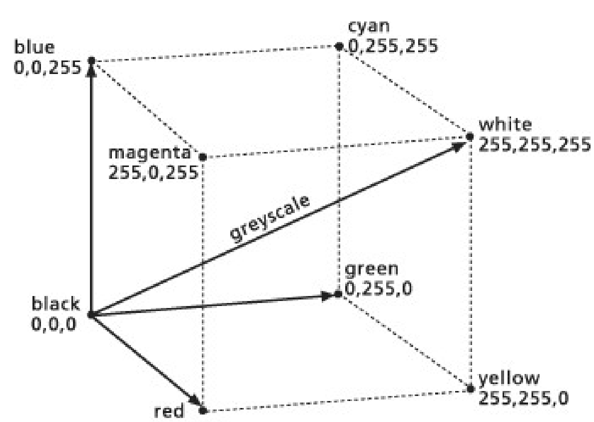

Figure 1. Data distribution before transformation

1.2. COLOUR PERCEPTION

This project displays a fused colour image which allows the user to obtain not only the information but also pleasant image to human eye. There are two types of receptor in the retina of human eye namely rods and cones. Depending on RGB colour space the cones are classified into short, medium and large cones. For same wavelength medium and large cones have same sensitivity, while the short cones have different level of sensitivity.

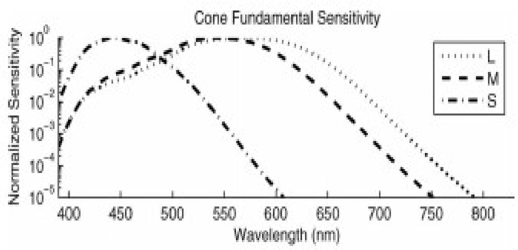

Figure 2. Spectral sensitivity of S-cone, M-cone and L-cone

The response to this is obtained by sum of product of sensitivity to that of spectral radiance of light. Figure 2 shows the spectral sensitivity curve for three cones.The spectral sensitivity of S-cones peak at approximately 440 nm, M-cones peak at 545 nm and L-cones peak at 565 nm after corrected for pre-retinal light loss, although the various measuring techniques result in slightly different maximum sensitivity values

1.3. CHOLESKY DECOMPOSITION

Every symmetric positive definite matrix A can be decomposed into a product of unique lower triangular matrix R and its transpose.

ie: $A=RR^T$ (1)

where R is called the cholesky factor of A and can be interpreted as generalised square root of A. The cholesky decomposition is unique when A is positive definite.

2. SURVEY OF RELATED RESEARCH

We examine some of the salient features of related research that has been reported. These works in image fusion can be traced back to mid eighties. Burt[2] was one of the first to report the use of Laplacian pyramid techniques. In this method, several copies of images was constructed at increasing scale, then each copy was convolved with original image. The advantages of this method was in terms of both computational cost and complexity. In 1985, P.J.Burt et.al and E.H.Adelson in[3] analysed that the essential problem in image merging is pattern conservation that must be preserved in composite image. In this paper, authors proposed an approach called Merging images through pattern decomposition. At about 1988, Alexander Toet et. Al proposed composite visible/thermal-infrared imaging apparatus[4]. R.D. Lillquist et. al in [5] presented a , Composite visible/thermal-infrared imaging apparatus Alexander Toet et al(1989),introduced ROLP(Ratio Of Low Pass) pyramid method that fits models of the human visual system. In this approach, judgments on the relative importance of pattern segments were based in their local luminance contrast values[6]. Alexander Toet et. al in [7], introduced a new approach to image fusion based on hierarchical image decomposition. This approach produced images that appeared to be more crispy than the images produced by other linear fusion scheme. H. Li et.al in [8] presented an image fusion scheme based on wavelet transforms. In this paper, the fusion took place in different resolution levels and more dominant features at each scale were preserved in the new multiresolution representation. I. Koren et.al in 1995,proposed a method of image fusion using steerable dyadic wavelet transform[9], which executed low level fusion on registered images by the use of steerable dyadic wavelet transform. Shutao Li et.al in [10], proposed pixel level image fusion algorithm for merging Landsat thematic mapper (TM) images and SPOT panchromatic images. V.S. Petrovoic et.al in [11] introduced a novel approach to multi resolution signal level image fusion for accurately transferring visual information from any number of input image signals, into a single fused image without the loss of information or the introduction of distortion. This new Gradient fusion reduced the amount of distortion, artifacts and the loss of contrast information. V.Tsagaris et.al in 2005 came up with the method based on partitioning the hyperspectral data into subgroups of bands[12]. V. Tsagaris and V. Anastassopoulos proposed Multispectral image fusion for improved RGB representation based on perceptual attributes in [13]. Q. Du, N. Raksuntorn, S. Cai, and R. J. Moorhead, et al in 2008, investigated RGB colour composition schemes for hyperspectral imagery. In their paper, they proposed to display the useful information as distinctively as possible for high-class seperability. The work also demonstrated that the use of data processing step can significantly improve the quality of colour display, whereas data classification generally outperforms data transformation, although the implementation is more complicated [14].

3. IMAGE FUSION METHOD

There are various methods that have been developed to perform image fusion. The method focussed in this paper is principal component analysis and VTVA. In this section, the necessary background information for VTVA method is provided. Also, the introduction to Principal Component Analysis (PCA) and the drawbacks of using PCA to get colour image are also discussed.

3.1. Principal Component Analysis for Grayscale

Principal Component Analysis is a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables called principal components. These components captures as much of variance in data as possible. The principal component is taken to be along the direction with the maximum variance. The second principal component will be orthogonal to the first. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. These principal components are then multiplied with the source images and added together to give the fused image. The PCA is also known as Karhunen-Loeve transform or the Hotelling.

3.2. Principal Component Analysis for Colour

Most of the Natural color images are captured in *RGB*, The main reason is that *RGB* does not separate color from intensity which results in highly correlated channels. But when PCA is used to obtain color image the results are very poor. This is due to the reason that PCA totally decorrelate the three components. The entropy and standard deviation for final fused image also decreases. Thus the in this paper another method (VTVA) is used to get colour image by fusing grayscale images.

3.3. Vector valued Total Variation Algorithm

The Idea of this method of image fusion is not to totally decorrelate the data but to control the correlation between the color components of the final image. This is achieved by means of the covariance matrix. The method distributes the energy of the source multispectral bands so that the correlation between the RGB components of the final image may be selected by the user and adjusted to be similar to that of natural color images. For example, we could consider the case of calculating the mean correlation between red–green, red–blue, and green–blue channels for the database of a large number of natural images (like the Corel or Imagine Macmillan database)as in [6]. In this way, no additional transformation is needed.

This can be achieved using a linear transformation of the form

$$Y = A^T X \tag{2}$$

Where X and Y are the population vectors of the source and the final images, respectively. The relation between the covariance matrices is

$$\begin{aligned} Cy &= E\,[YY^T] \\ &= E[A^T X.X^T A] \\ &= A^T\, E[XX^T]\, A \\ C_y &= A^T\, C_X\, A \end{aligned} \tag{3}$$

(4)

Where Cx is the covariance of the vector population X and Cy is the covariance of the resulting vector population Y. The choice of the covariance matrix based on the statistical properties of natural color image makes sure that the final colour image will be pleasing to human eye. Both the matrices Cx and Cy are of same dimension. If they both are known then the transformation matrix A can be evaluated using the cholesky factorization method. Accordingly, a symmetric positive definite matrix can be decomposed by means of upper triangular matrix Q so that,

$$S=Q^T.Q \tag{5}$$

Using the above mentioned factorization Cx and Cy can also be written as,

$$\begin{aligned} C_x &= Q^T{}_x\,.Q_x \\ C_y &= Q^T{}_y\,.Q_y \end{aligned} \tag{6}$$

thus (6) becomes,

$$Q^T{}_y\,.Q_y = A^T Q^T{}_x\,.Q_x\, A = (Q_x A)^T Q_x A \tag{7}$$

Thus,

$$Q_y = Q_x.A \tag{8}$$

and the transformation matrix A is

$$A = Q_x^{-1}.Q_y \tag{9}$$

This transformation matrix A implies that the transformation depends on the statistical properties of the origin multispectral data set. Also, in the design of the transformation, the statistical properties of the natural colour images are taken into account. The resulting population vector Y is of the same order as the original population vector X, but only three of the components of vector Y will be used for colour representation.The evaluation of the desired covariance matrix Cy for the transformed vector is based on the statistical properties of natural colour images, and on requirements imposed by the user.

The relation between the covariance matrix and the correlation coefficient matrix R_y is given by,

$$C_y = \sum R_y \sum^T \tag{10}$$

Where,

$$\Sigma = \begin{bmatrix} \sigma_{y1} & 0 & 0 & & 0 \\ 0 & \sigma_{y2} & 0 & 0 & . \; 0 \\ 0 & 0 & \sigma_{y3} & 0 \; . & 0 \\ . & . & . & . & . \; . \\ 0 & 0 & 0 & 0 \; . & \sigma_{yk} \end{bmatrix}$$

is the diagonal matrix with the variances (or standard deviations) of the new vectors in the main diagonal and

$$R_y = \begin{bmatrix} 1 & r_{RG} & r_{RB} & . \; 0 \\ r_{RG} & 1 & r_{GB} & . \; 0 \\ r_{RB} & r_{GB} & 1 & . \; 0 \\ . \;\; . & . \;\; . & . & . \\ 0 & 0 & 0 \; . & 1 \end{bmatrix}$$

is the desired correlation coefficient matrix.

3.4. VTVA Algorithm

The necessary steps for the method implementation are summarized as follows.
1) Estimate the covariance matrix Cx of population vectors X.
2) Compute the covariance matrix Cy of population vectors Y , using the correlation coefficient matrix Ry and the diagonal matrix Σ.
3) Decompose the covariance matrices C_x and C_y using the Cholesky factorization method in (6) by means of the upper triangular matrices Q_x and Q_y, respectively.
4) Compute the inverse of the upper triangular matrix Q_x, namely, Q^{-1} x .
5) Compute the transformation matrix A in (9).
6) Compute the transformed population vectors Y using (2).
7) Scale the mapped images to the range of [0, 255] in order to produce RGB representation.

For high visual quality, the final color image produced by the transformation must have a high degree of contrast. In other words, the energy of the original data must be sustained and equally distributed in the RGB components of the final color image. This requirement is expressed as follows:

$$\sum_{i=1}^{k} \sigma_{x_i}^2 = \sum_{i=1}^{3} \sigma_{y_i}^2 \qquad (11)$$

with $\sigma_{y1} = \sigma_{y2} = \sigma_{y3}$ approximately. The remaining bands should have negligible energy (contrast) and will not be used in forming the final color image. Their variance can be adjusted to small values, for example, $\sigma_{yi} = 10^{-4}\sigma_{y1}$, for i =4,...,K.

4. APPLICATIONS

Remote sensing technique have proven to be powerful tool for monitoring the earth's surface and atmosphere. The application of image fusion can be divided into Military and Non Military applications. Military applications include Detection, location tracking, identification of military entries, ocean surveillance, etc. Image fusion has also been extensively used in Non military applications that include interpretation and classification of aerial and satellite images

5. EXPERIMENTAL PROCEDURES AND RESULTS

The multispectral data set used in this work consists of 7multispectral bands images acquired from Landsat Thematic Mapper (TM)sensor. The size of each image is 850 x 1100 pixels. The average orbital height for these images is 700km and spatial resolution is 30meters except the band 6 which is 90meters. The spectral range of sensor is depicted in table 1.

Table 1. Spectral range of data

BAND	SPECTRAL RANGE(µm)
Near infrared	0.76-0.85
Mid infrared 1	1.55-1.75
Thermal infrared	10.4-12.5
Mid infrared 2	2.08-2.35

The experiments conducted in this work aim to compare the performance criteria of PCA(grayscale), PCA(Colour) and VTVA . Fusion was performed using four grayscale images. Parameters namely, entropy, standard deviation, number of levels and mean for PCA and VTVA were examined.

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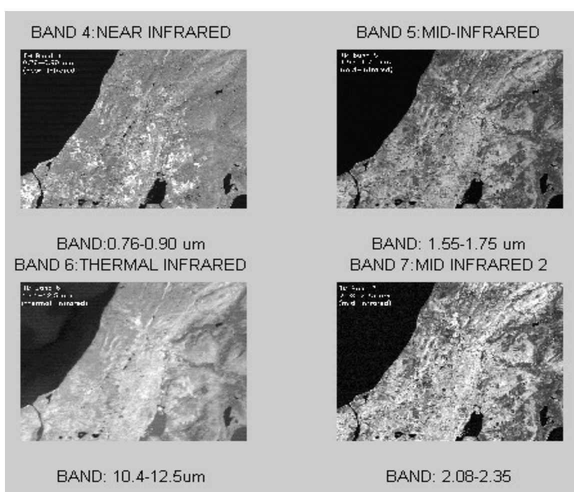

Figure 3. Detailed image (a)band 4 Near infrared (b)band 5 Mid infrared1 (c)band 6 Thermal infrared (d) band 7 Mid infrared 2

The input grayscale source images are shown in figure 3. The image in figure 4 is derived from the PCA analysis. This fused image as seen is more clear and contains more information when compared with the input source images.

Figure 4. Fused Grayscale image using PCA

Fusion result shown in figure 5 shows the fused image obtained when PCA is used to get colour image.

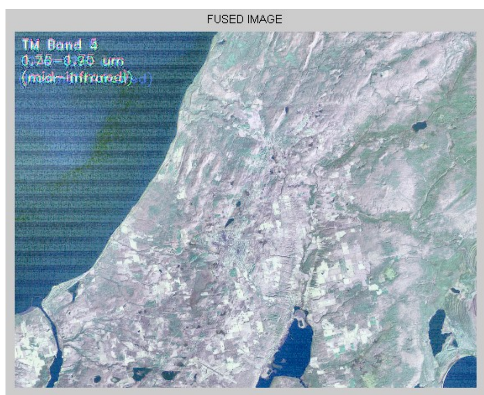

Figure 5. Fused Colour image using PCA

In this figure it can be seen that the fused image is having some colour components but the amount of information is too low. This happens because the PCA technique totally decorrelates the three colour components. But a good natural colour image has a lot of correlation between them.

Finally, the image in figure 6 shows the fused colour image obtained using VTVA method. This method converts input grayscale images into a colour image with more information and contrast than compared to PCA

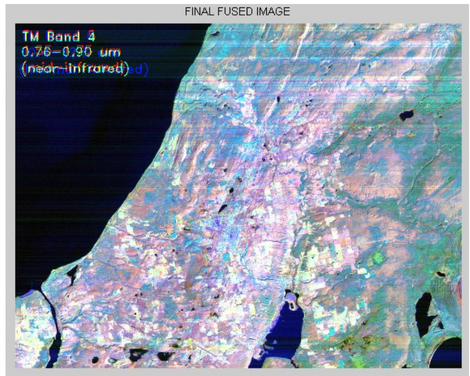

Figure 6. Fused Colour image using VTVA

This colour image has lot of correlation between the three colour components and thus the image has more information and contrast.
The values given in table 2 shows the comparison between the parameters namely entropy, standard deviation, mean and number of levels present in the input and final fused method.

Table 2. Parameter Comparison

IMAGES	ENTROPY	STANDARD DEVIATION	MEAN	NO. OF LEVELS
Image 1	6.9310	65.7602	119.1191	**256**
Image 2	7.0911	67.1405	94.8459	256
Image 3	7.2474	70.4155	142.1532	256
Image 4	7.7525	76.0397	119.8504	256
PCA(Grayscale)	7.5036	62.4518	119.1782	253
PCA(coloured)	17.5470	46.4458	84.4458	145
VTVA	17.9930	74.7853	139.54	573169

These values when compared proves that the fused image obtained using VTVA has got more information, contrast and more number of levels than compared to PCA. Also, the comparison proves that fused colour image obtained by using VTVA has more number of levels than fused grayscale image obtained by using PCA. Thus to fuse the grayscale source images and transform into colour, VTVA is the best method.

6. CONCLUSIONS

In this paper we tried to fuse four grayscale images from different spectral bands that can be fused to get more information using Principal Component Analysis method. In this paper it is concluded that PCA cannot be used to get final colour image. But when these images are fused using VTVA the final fused image obtained is found to be more pleasant to human eye. As well as this fused image has hot more information and contrast than compared to other method. Also, the work in this paper shows that the fused colour image has more number of levels which means more combinations of colours are present. But the grayscale image have maximum 256 gray levels only.

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