Jurnal
Teknologi

Full Paper

ADAPTIVE CHEBYSHEV FUSION OF VEGETATION IMAGERY BASED ON SVM CLASSIFIER

Article history
Received
1 February 2015
Received in revised form
24 March 2015
Accepted
1 August 2015

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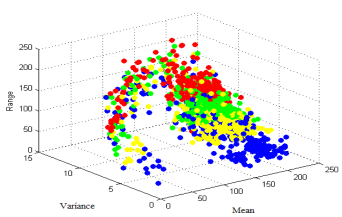
Graphical abstract



Abstract

A novel adaptive image fusion method by using Chebyshev polynomial analysis (CPA), for applications in vegetation satellite imagery, is introduced in this paper. Fusion is a technique that enables the merging of two satellite cameras: panchromatic and multi-spectral, to produce higher quality satellite images to address agricurtural and vegetation issues such as soiling, floods and crop harvesting. Recent studies show Chebyshev polynomials to be effective in image fusion mainly in medium to high noise conditions, as per real-life satellite conditions. However, its application was limited to heuristics. In this research, we have proposed a way to adaptively select the optimal CPA parameters according to user specifications. Support vector machines (SVM) is used as a classifying tool to estimate the noise parameters, from which the appropriate CPA degree is utilised to perform image fusion according to a look-up table. Performance evaluation affirms the approach's ability in reducing the computational complexity to perform fusion. Overall, adaptive CPA fusion is able to optimize an image fusion system's resources and processing time. It therefore may be suitably incorporated onto real hardware for use on vegetation satellite imagery.

Keywords: Image fusion, Chebyshev polynomials, remote sensing

1.0 INTRODUCTION

Vegetation is defined as plant life that are to be found in a particular region or habitat, and is seen as an essential factor in a nation's agricultural industry. The successful harvesting of crops, for example, is heavily dependent on farmers selecting a suitable geographical location. This in turn is influenced by aspects such as moisture, latitude, elevation above sea level, length of the growing season, solar radiation, temperature regimes, soil type and drainage conditions, topographic aspect and slope, prevailing winds, salt spray and air pollutants.

To this end, early researches in the field have led to the application of remote sensing (RS) to classify the various types of vegetation for agricultural purposes [1-2]. This comprise components like satellite imagery, airphotos from UAV's, chemical properties and physical properties such as surface texture, roughness and slope characteristics. Further, the fusion of multimodal and multi-temporal RS imagery has been implemented in recent years to enhance the visual quality of image data and consequently aid the classification process. One such method is to fuse Panchromatic (PAN) satellite images, which offer high spatial resolution and sharp, detailed scenery, with the equivalent Multi-spectral (MS) images which boasts high colour/spectral resolution. The successful merging of these modalities provides a 'best of both worlds' output image of higher quality for classification.

Problems tend to arise in real-life RS applications as the data are prone to corruption by noise. This may include sensor-level noise that are prevalent within the satellite cameras and sensors, or it may consist of transmission-based noise experienced during data

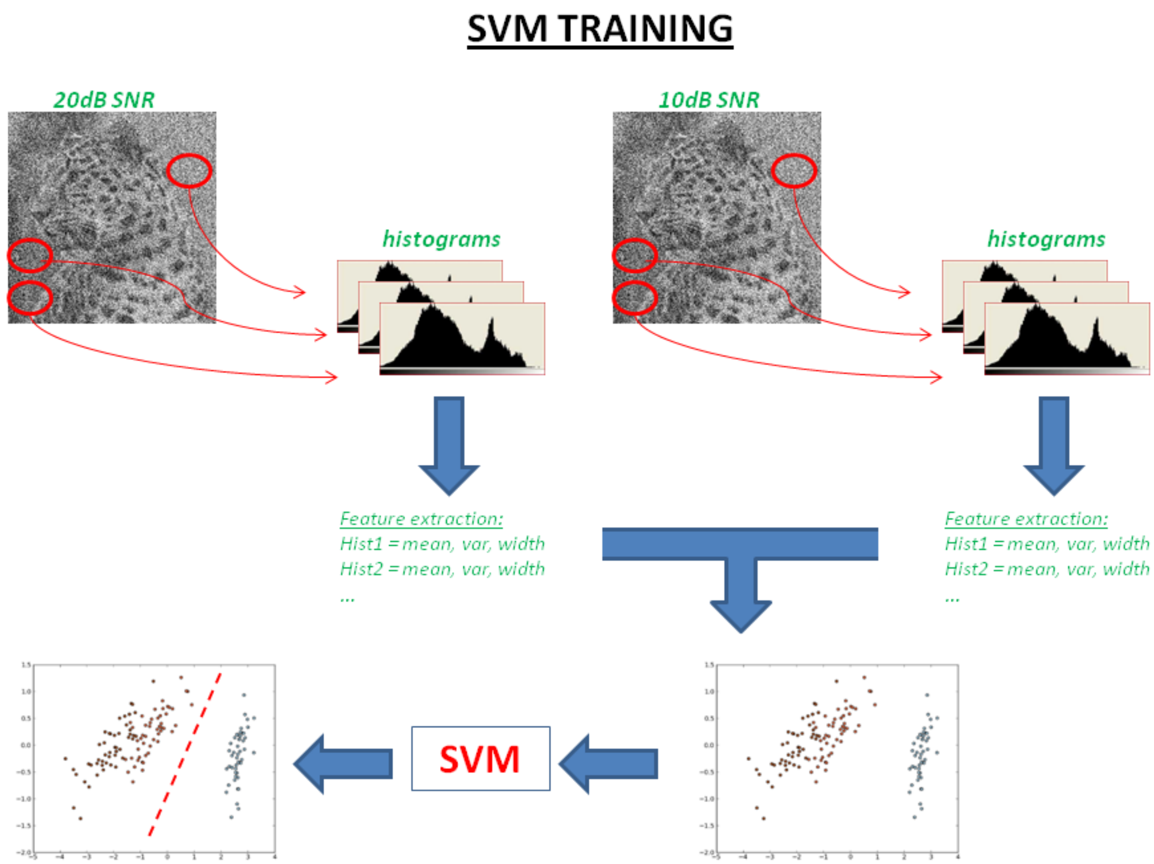


Figure 1 SVM Training Example

transmission from satellite to ground. Overall, noise components from these two sources can be combined and may generally be modelled as Gaussian [3]. Image fusion methods have been developed taking into consideration the problem of noise, such as pyramid and wavelet-based approaches and independent component analysis (ICA) [4]. In 2010 a fusion scheme using bi-variate Chebyshev polynomials as basis functions was proposed for image fusion and performed favourably over other algorithms, especially in medium to heavy noise presence [5]. Chebyshev polynomials analysis (CPA) works on the basis of low-pass signal approximation. As noise tend to occupy the higher frequency spectrum, using lower order polynomials can absolve those noise at a cost of signal accuracy during approximation.

Developments of CPA fusion however were largely restricted to a heuristical approach, where a fixed set of basis functions are used to fuse images regardless of their noise level. An obvious disadvantage of this is the lack of optimisation, less efficiency and higher computational complexity [3]. It should have been sufficient, for example, to use n = 5 orders for an image with 25dB SNR – where lower orders mean less calculations, and lower processing time. On the other hand, a 15dB SNR image may require as much as n = 13 orders for adequate processing. We therefore propose an adaptive approach to CPA fusion that automatically estimates the SNR level, hence negating any need for a reference (non-noisy or ground truth) image. Using this approach, we may tailor specific polynomial orders to be applied on certain levels of noisy images, thereby optimising the algorithm.

Section two describes the literature behind our approach and its motivations. In section three, the methodology of adaptive CPA fusion is discussed. Section four shows the performance evaluation results while section five concludes our work.

2.0 RESEARCH BACKGROUND

2.1 Vegetation Imagery

Interpreting vegetation data based on satellite imagery is a key part of the agricultural industry. From it, researchers are able to comprehend the flora species native to an area and the influences behind

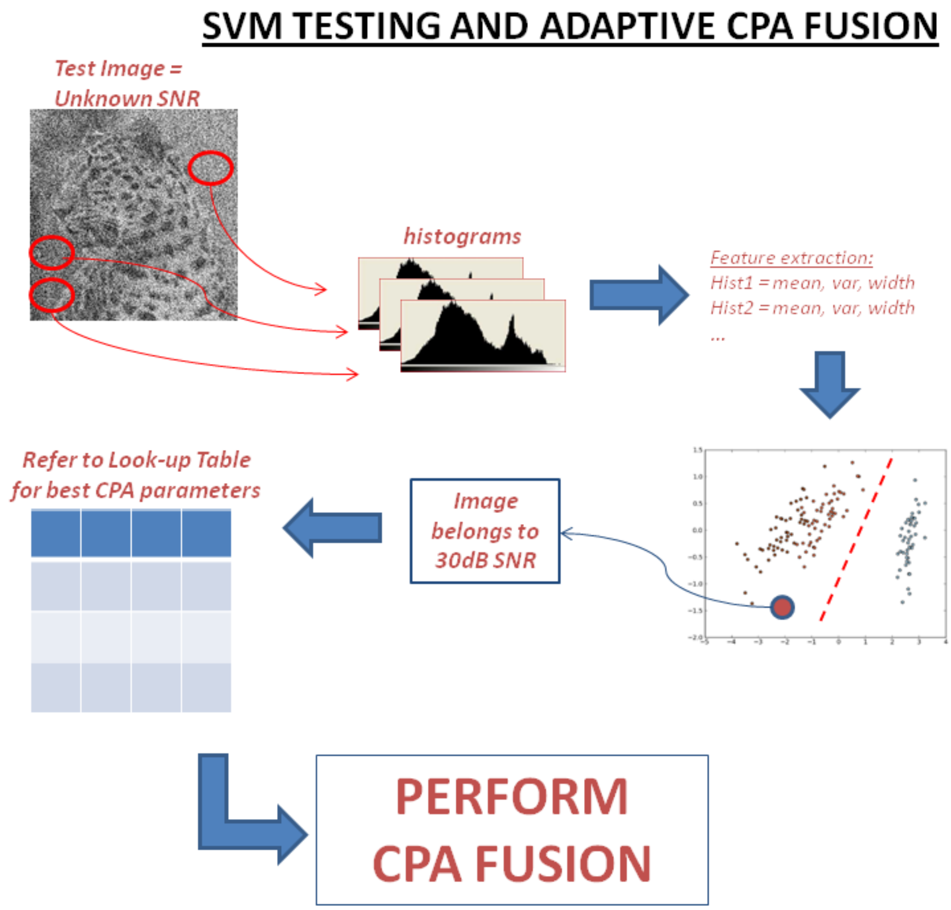


Figure 2 SVM testing and subsequent adaptive CPA fusion

their growth and distribution. Conversely, the reflectance quality of RS images may be affected by several factors: brightness, which is derived from a weighted sum of all spectral colour bands and constitutes the principal variation in soil reflectance; greenness, related to the amount of green vegetation in a scene; and moisture.

On a smaller scale, the visual quality of flora as seen from RS are influenced by factors such as the leaf's structure, age, water status, mineral stresses and health. Each leaf also differs by the typical spectral features recorded for leaf pigments, cell structure and water content. Further, the length of electromagnetic wavelengths captured by RS cameras affect the amount of reflection that occurs. For instance, the density of the tree canopy may affect the scattering of the wavelengths. A lower reflectance occurs in the visible colour spectrum i.e. 400-700nm as more light are absorbed by the leaf pigments. Moreover, the blue (450nm) and red (670nm) wavelengths comprise the two main absorption bands that absorb two main pigments of the leaf [6].

2.2 Remote Sensing Tools for Vegetation Image Analysis

The complex nature of vegetation imagery, as noted above, has necessitated the use of remote sensing tools for analysis [7]. RS is an area that has been of paramount importance to the nations technological advancements, with contributions towards global positioning system (GPS), lithography, urban planning in addition to vegetation and agriculture. Furthermore, in recent times application of RS has been hugely aided by image fusion [8]. This entails that various camera sensors are fused by signal processing techniques to achieve a higher quality composite image, which better facilitates decision making or further processing.

Remote sensing (RS) applications are concerned with the acquisition of geo-spatial images using aerial photography by satellites and airborne sensors, such as SPOT, QuickBird, IKONOS and IRS. RS aims to deliver high quality geographic images in terms of both spatial and spectral resolutions. Developing a high performance sensor camera to perform such tasks is unfeasible due to factors such as the radiation energy absorbed by the sensor and the limited data transfer rate from satellite platform to ground. Rather, signal processing methods are utilised to achieve similarly high quality results, in lieu of an expensive sensor camera [3].

One of the most important aspects of RS, in which fusion plays an integral part, is pan-sharpening [10]. This entails that the acquired data of a given scene comprise two modalities: a PAN image depicting the scene in a high spatial resolution but in a single frequency, and an MS image that captures the landscape in a multitude of spectral resolutions across the wavelength spectrum though at 1:4 the spatial resolutions of PAN. Fusion offers a practical and cost effective method to aid in distinguishing wavelength spectrum though at 1:4 the spatial resolutions of PAN, by means of injecting the detailed spatial resolutions of PAN into a resampled version of multispectral images using methods such as the wavelet transform.

2.3 Image Fusion of PAN and MS Images

Image fusion is a branch of digital signal processing and refers to the process of merging salient information from two or more source images to generate a higher quality output. The efficiency of fusion performance inadvertently depends on the fusion method, which comprises numerous transform-based approaches [11]. Classical fusion techniques in RS applications also include the intensity-hue-saturation (IHS) method in which the red-green-blue (RGB) coloured domain of the original MS imagery is transformed into IHS to obtain a better separation of colour for fusion with PAN images, though it often produces spectral degradation. Others include the principal component analysis (PCA), in which the MS image is decorrelated into several components.

Fusion occurs by replacing the first/principal MS component with the PAN image, coupled with the Brovey transform that multiplies each MS band by the PAN image, and finally by the division of each product by the sum of the MS bands. However these methods tend to ignore the need for high quality outputs of spectral information, which has proven essential in applications such as lithology and soil and vegetation analysis. High pass filtering (HPF) or modulation (HPM) of PAN inputs added to multispectral images are able to overcome this drawback. More recently, given the conciliatory nature of RS fusion between spatial resolution of PAN and spectral resolution of MS images, wavelet-based fusion techniques were found to be better equipped to handle this trade-off [9,12].

2.4 Chebyshev-Based Denoising

An approach utilising a bivariate separable approximation of classical Chebyshev polynomials has been successfully implemented in image fusion. The advantage of the CPA method, compared to the aforementioned algorithms above, is its robustness in adverse noise conditions due to the polynomials' intrinsic smoothing property. CPA was found to perform favourably well in general image fusion fields such as surveillance, medical imaging and multifocal digital camera applications [3]. An extension to the work was proposed in 2011 which involves a hybrid fusion scheme between CPA and ICA based on regional saliency [13].

A notable critique of CPA is its heuristical approach; a fixed set of basis functions are usually used to fuse images regardless of their noise level. This enables users to attain higher levels of fusion quality results but at reduced efficiency. In contrast, methods such as ICA and empirical mode decomposition (EMD) employ adaptive denoising in their fusion schemes. While this necessitates the estimation of noise information before it is suppressed, the benefit entails that the algorithm parameters may consequently be customised to fit the degree of noise. The immediate advantage of this is the efficient use of system cost and complexity.

Therefore, a modified CPA that enables adaptive fusion is desired. In this research the CPA algorithm is tweaked to include the training and classification of noise levels. In other words, machine-learning principles are utilised to allow customised fusion parameters for filtering varying degrees of noise components. Support vector machines (SVM) were chosen as the classification tool, from which the SNR classification may be implemented based on a lookup table. This effectively absolves the need for a reference (ground truth) image, thus mimicking imaging systems in the real world where signals are often corrupted by noise and a reference image does not tend to exist.

3.0 ADAPTIVE CPA FOR FUSION

3.1 Chebyshev Polynomial Theory

One-dimensional Chebyshev Polynomials, written mathematically as $T_n(x)$ can be defined via the recursive equation

$$T_0(x) = 1;$$
$$T_1(x) = x;$$
$$T_{n+1}(x) = 2xT_n(x) - T_{n-1}(x)$$

whereby their properties have been explained in [14]. For one-dimensional signal approximation, the polynomials can be used to estimate a given signal $f(x)$:

$$\tilde{f}(x) = \sum_{n=0}^{N-1} a_n T_n(x)$$

where $\tilde{f}(x)$ is the approximation, and an a coefficient on n which was proven to have the following form:

$$a_n = \frac{2}{\pi} \sum_{x=-1}^{1} (1-x)^{-\frac{1}{2}} f(x) T_n(x)$$

The Chebyshev polynomials are sorted based on order. A finite order n used in CPA expansion enables basic signal features to be retained while more complex polynomials can be omitted. The concept of CPA can be generalised to other signal decomposition approaches such as Fourier and wavelets whereby a finite number of bases are acquired and used to adequately represent a signal.

A separable extension of 1D CPA, similar to the discrete cosine transform (DCT), was subsequently introduced for use on image signals, called two-dimensional separable Chebyshev Polynomials. Its definition and properties are given below [5]:

$$\tilde{f}(x,y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} a_{m,n} T_m(x) T_n(y)$$

and the coefficient $a_{m,n}$ is given by

$$a_{m,n} = \frac{4}{\pi^2} \sum_{x=-1}^{1} \sum_{y=-1}^{1} (1-x)^{-\frac{1}{2}} (1 - y)^{-\frac{1}{2}} f(x,y) T_m(x) T_n(y)$$

For corrupted images, Gaussian noise components tend to mostly occupy the higher frequency spectrum. Incidentally, as higher order polynomials comprise of high frequency components, the idea therefore is to limit the CPA order so as to remove noise components at a cost of also removing high energy information – including edges and strong texture. CPA approximation effectively acts as a low-pass filter that eliminates unwanted noise at the expense of lower signal accuracy. To extend this useful feature to fusion applications, comparisons are made between image coefficients as done in [15].

3.2 Support Vector Machines

The SNR of an incoming test image may be estimated from a classification technique known as support vector machines (SVM) [17], [18]. It is a supervised machine learning algorithm that enables the binary classification of data by essentially maximising the distance between two categories. The SVM algorithm maps statistical data as points in space based on their features; thereafter the algorithm is trained to draw a line that divides data into two classes. The attraction of this method is the line is designed to maximise the distance or width separating the classes.

Having achieved this, new data mapped in space shall be automatically categorised into either class. Subsequently, classification of multiple classes can be easily achieved by cascading the SVM algorithm through a number of iterations.

In this paper, SNR classes are divided into 30, 20, 15 and 10dB. The steps involved in SVM training and testing are as follows:

1) Since this is a concept study, using a basic binary (one-to-one or cascading one-to-all) SVM classifier suffices. Though we acknowledge that more advanced SVM types, like the multi-class SVM, may be employed instead to obtain further improved results. we shall first train it to classify between images of 30dB and 20dB. Other iterations would follow similar steps (30dB and 15dB, 30dB and 10dB, 20dB and 15dB and so on). Extract 100 patches of size 100x100 pixels from both 30dB and 20dB images. Choose from various parts of the image, though it is best to select patches from plain or low edge regions. The rationale is that high frequency noise components would be more distinguishable in plain areas, and therefore more easily estimated.
2) Obtain the histogram for each patch from both images. From these, relevant features to be incorporated the SVM algorithm are extracted. The effectiveness and accuracy of SVM is highly dependent on the number of samples, s and number of features, N. In our experiment we identified features to be the histogram mean, variance and intensity range. We now have two sets of feature data, which should differ accordingly between images of 30dB and 20dB.
3) which maps them into an N-dimensional space and calculates the best regressional fit to classify between 30dB and 20dB.
4) A test image of unknown SNR is provided. Patches and features are extracted similar to the above, then fed into the algorithm. The output classifies this image into either 30dB or 20dB.
5) Having obtained the class, a look-up table is then referred to determine the Chebyshev polynomial order required for fusion. Overall, this process ensures an optimal use of resources whilst obtaining the best possible score for a particular image noise scenario.

Figures 1 and 2 shows an example of SVM, and subsequently fusion, being implemented on a noise corrupted image. In turn, the scatter plot in SVM space for our data can be seen in Figure 3.

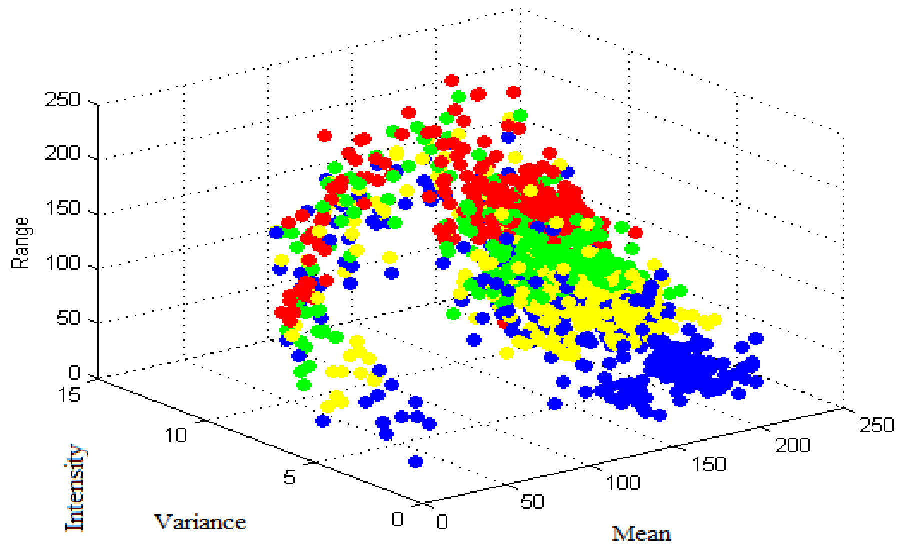


Figure 3 Scatter plot for remote sensing image with different levels of noise

4.0 RESULT AND ANALYSIS

The fusion results can be evaluated through the Petrovic objective fusion metric [16]. The metric calculates the amount of edge information that has been transferred from the input images into the fused output, thus giving a bounded score between 0.00 and 1.00. In this work, we take a step further to efficiently calculate the best fit of polynomial order according to the appropriate noise level. Regression analysis via SVM is first performed onto a set of fusion image datasets at varying noise levels to estimate their SNR class. Then, we devise a look-up table to match the appropriate CPA specification for a particular SNR. The table lists Petrovic scores for each various noise levels and polynomial orders respectively. It serves as a reference on which experimental fusion scenarios can base their selection of parameters.

The look-up table was created using noise-corrupted images to reflect real RS conditions whereby the transmission of data is prone to noise. Incremental Gaussian noise was added to a set of input images, ranging from 30dB to 5dB in order to represent the various degrees of image corruption. Two grayscale PAN and MS images (taken from the standard image fusion dataset [19]) were obtained as inputs, from which the fusion will generate a composite output image via polynomial orders n = 3; 5; 7; 9; 11; 13; 15; 17 and 21. For CPA, 7 x 7 overlapping windows/patches were used. Overlapping is performed by a shift of one pixel per iteration. For the sake of brevity, the method utilises the max-abs fusion rule [4].

All fusion outputs are assessed by the Petrovic metric. The scores are recorded in Figure 4, which constitutes our look-up table. For testing, an input image set comprising an arbitrary SNR is considered. The SNR value is estimated via SVM; from there, a suitable order is selected.

Table 1 displays the confusion matrix, showing the results of SVM. The matrix describes the accuracy of adaptive CPA for each noise condition, i.e. how well it correctly classifies the noise level as opposed to the other noise levels. For instance, 30dB SNR has been correctly predicted 63.34% of the time, compared to it being incorrectly predicted (or confused) as 20dB (18.33%), 15dB (13.33%) or 10dB (5.00%). As can be seen, the approach manages to achieve an average accuracy of 77.92% throughout all SNR levels involved. The score is acceptable, though somewhat limited mainly due to only three features - mean, variance and intensity range being used for SVM. Improved accuracy may be achieved with more features in place.

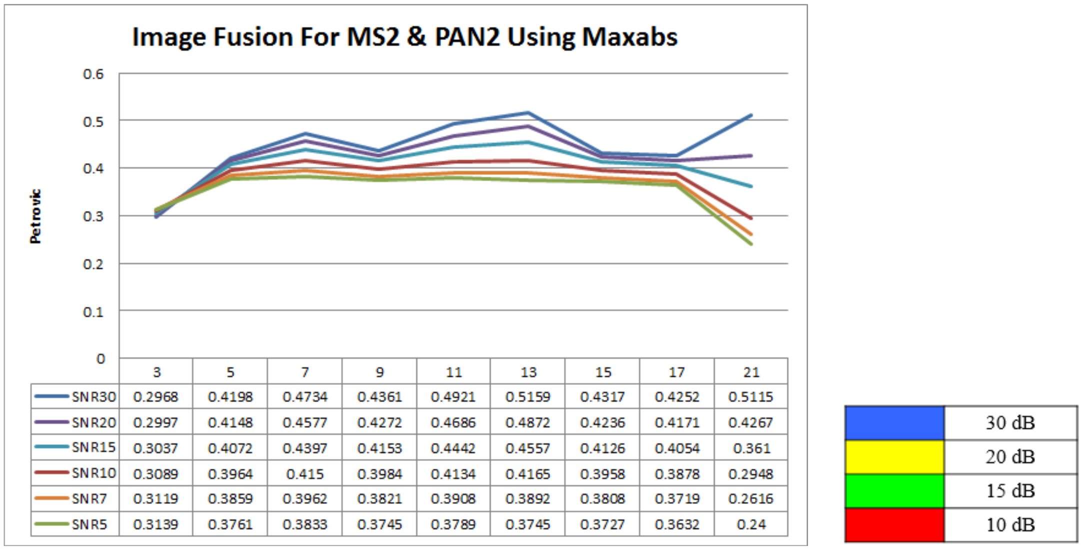


Figure 4 Fusion scores for various SNR and polynomial orders

Table 1 Confusion matrix of SVM results

	30dB	20dB	15dB	10dB
30dB	63.34	18.33	13.33	5.00
20dB	1.67	68.33	20.00	10.00
15dB	1.67	5.00	81.67	11.66
10dB	0.00	0.00	1.67	98.33

Figure 6 displays the results for a multi-spectral (MS) and panchromatic (PAN) fusion scenario.The aim of image fusion is to capture the regions of interest denoted in the PAN image (circled red), whilst suppressing its dark background and prioritise the brighter and more detailedbackground from the MS image. Two noisy fusion scenarios are presented – 30dB uses n = 13 whereas n = 5 suffices for 5dB. It can be seen that both scenarios are able to attain their objective through optimised use of resources.

The approach allows for different parameters to be tailored adaptively, according to specific requirements. The degree of polynomial order is controlled by the user and the noise level for an input image may be calculated from the equation above, whereas the range of adequate Petrovic score can be determined in advance. For a clear image input with an SNR of 30dB, if we set the acceptable visual image quality to be 0.4 in the Petrovic scale then n = 7 orders shall suffice. If 0.5 is set, then n = 11 x 13 will be appropriate. The scores in the graph tend to degrade along with the decrease in SNR, though not always in proportion. For a low SNR of 7 or 5dB the scores oscillate around the 0.38 mark regardless of order number. Hence for very noisy conditions, it makes sense to limit the number of orders thereby reducing computational redundancy. Another interesting thing to note is when using n = 21 orders, in some cases thescores tend to drop rather than increase. This means that a polynomial order of around n = 13 is optimal for low noise conditions.

Figure 5 displays the elapsed processing time for each order. The benchmark test was performed on the MATLAB R2013a platform, using Windows XP OS running on a 3.00GHz Intel Core2Duo CPU. As can be seen, higher orders require more processing due to high computational complexity. Selecting n = 5 over n = 13 orders on low SNR scenarios, for instance, saves 2,112s of processing time which translates to a speed-up of almost 6 times in efficiency rate.

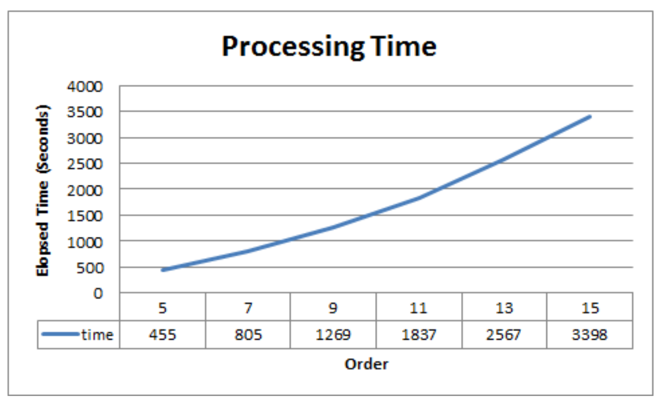


Figure 5 Processing time for different polynomial orders

5.0 CONCLUSION

A novel approach of deriving adaptive CPA fusion for vegetation RS imagery has been presented in this paper. The research is borne from requirements in vegetation-based image data which require enhancement for the purpose of classification. Fusion-based Pan-sharpening is an established tool used in RS to achieve that aim, where in this study adaptive Chebyshev polynomials are used as basis functions for signal approximation in a highly efficient manner. SVM is utilised to train and estimate the SNR parameters of a noisy image scenario, from which the suitable coefficients of CPA are chosen in order to optimise processing time. Performance evaluation via a look-up table affirms the approach's ability in reducing computational complexity for RS images affected by noise.

This study is a first application of the method and serves to prove the concept rather than getting the best results, therefore a comparative analysis with other techniques is not within the scope. However, our limitations are readily acknowledged. The accuracy of SVM should improve with the use of multi-class SVM, as well as the extraction of more pertinent features to maximise the distance between classes. Suggestions to this may be to use wavelet or histogram-of-gradients (HOG) based features rather than conventional histograms. Also, alternative classication tools such as artificial neural network (ANN) and fuzzy logic may be implemented for better accuracy and faster implementation

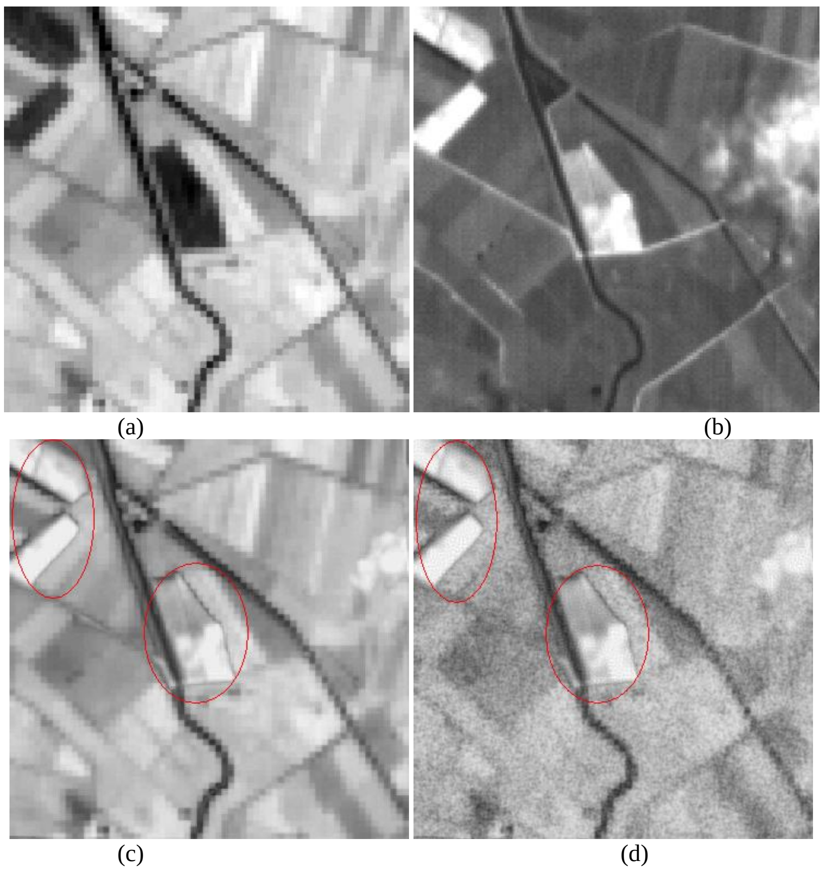


Figure 6 Result of RS image fusion showing (a) Multi-spectral input, (b) Panchromatic input, (c) Low noise (SNR 30dB) fused output and (d) High noise (SNR 5dB) fused output

Acknowledgement

The research was made possible by the fundings of the Ministry of Higher Education (MOHE) Malaysia and Universiti Teknologi Malaysia (UTM) under the Research University Tier 1 Grant (vote 12H72).

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