Adaptive Chebyshev Fusion of Vegetation Imagery based on SVM Classifier

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Abstract

A novel approach of an adaptive fusion method by using Chebyshev polynomial analysis (CPA) for use in remote sensing vegetation imagery is described in this paper. Chebyshev polynomials have been effectively used in image fusion mainly in medium to high noise conditions, though 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 computational complexity for remote sensing images affected by noise.

Keywords. Image fusion, Chebyshev polynomials, remote sensing

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 boast 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 transmission from satellite to ground. In 2010 a fusion scheme using bi-variate Chebyshev polynomials as basis functions was proposed for image fusion and has performed favourably over other algorithms, especially in medium to heavy noise presence [3]. 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 heuristic 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, efficiency and computational complexity [4]. It should be sufficient, for example, to use n = 5 orders for an image with 25dB SNR – where lower orders equate to 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) image. Using this approach, we may tailor specific polynomial orders to be applied on certain levels of noisy images, thereby optimising the algorithm.

Chebyshev Polynomials for Adaptive Fusion

The method utilizes Chebyshev polynomial approximation, an introduction of which can be found in [3]. A separable extension of one-dimensional 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 [3]:

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

where $\tilde{f}(x,y)$ is the approximated signal, M and N the image patch size while $T_m(x)$ and $T_n(y)$ refer to the Chebyshev polynomials of degree m and n respectively.
The coefficient $a_{m,n}$ is given by:

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

The fused image approximation $f_{fused}(x,y)$ is formed by fusing the two coefficients via the max-abs fusion rule, i.e. choose the coefficient with the higher absolute value [7]:

$$f_{fused}(x,y) = \sum_{m=0}^{M} \sum_{n=0}^{N} max\{a_{m,n} | b_{m,n}\} T_m(x) T_n(y)$$

The idea is to limit the CPA degree m and n so as to remove noise components, at a cost of also removing high energy information. CPA approximation effectively acts as a low-pass filter that eliminates unwanted noise at the expense of lower signal accuracy. The SNR of an incoming test image may be estimated from a classification technique known as support vector machines (SVM) [5, 6]. 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 on a hyper-plane 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 the plane 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. Here, we divide the SNR classes into 30, 20, 15 and 10dB to represent the various degrees of satellite image degradation.

Experimental Results and Discussion

Regression analysis via SVM is first performed onto a set of fusion image datasets at varying noise levels to estimate their SNR class. A look-up table is then devised to match the appropriate CPA specification for a particular SNR. Scores using the Petrovic metric [8], an established image fusion quality measure, is listed 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.

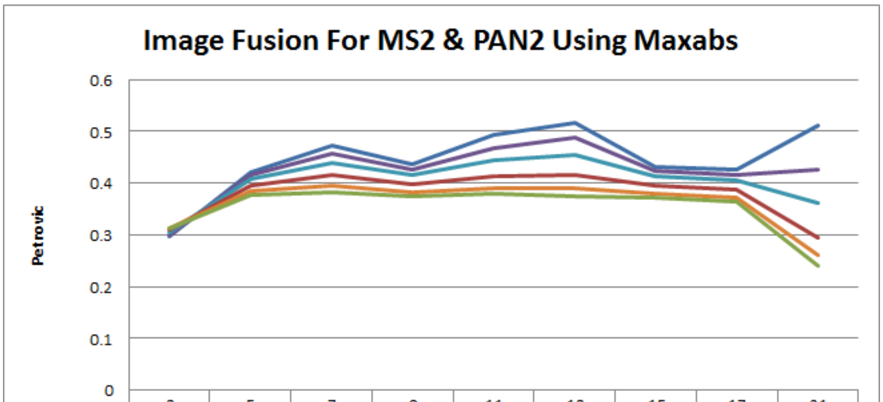
The look-up table was created using noise-corrupted images to reflect real RS conditions whereby the transmission of data is prone to noise. Incremental Gaussian noise was added to a set of input images, ranging from 30dB to 10dB in order to represent the various degrees of image corruption. Two grayscale PAN and MS images 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, 7x7 overlapping patches were used. Overlapping is performed by a shift of one pixel per iteration. All fusion outputs are assessed by the Petrovic metric. The scores are recorded in Figure 1, 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.

Using a confusion matrix, the approach manages to achieve an accuracy of 77.92%. 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 2 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 detailed background 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 or 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 the scores tend to drop rather than increase. This indicates that a polynomial order of around n = 13 is optimal for low noise conditions.

Simulations on the Matlab 2013a platform demonstrate that higher orders require more processing due to high computational complexity. Selecting n = 5 over n = 13 orders on low SNR scenarios, for instance, saves 2,112 seconds (35 minutes) of processing time which translates to a speed-up of almost 6 times in efficiency rate.



	3	5	7	9	11	13	15	17	21
SNR30	0.2968	0.4198	0.4734	0.4361	0.4921	0.5159	0.4317	0.4252	0.5115
SNR20	0.2997	0.4148	0.4577	0.4272	0.4686	0.4872	0.4236	0.4171	0.4267
SNR15	0.3037	0.4072	0.4397	0.4153	0.4442	0.4557	0.4126	0.4054	0.361
SNR10	0.3089	0.3964	0.415	0.3984	0.4134	0.4165	0.3958	0.3878	0.2948
SNR7	0.3119	0.3859	0.3962	0.3821	0.3908	0.3892	0.3808	0.3719	0.2616
SNR5	0.3139	0.3761	0.3833	0.3745	0.3789	0.3745	0.3727	0.3632	0.24

Figure 1 Fusion scores for various SNR and polynomial orders

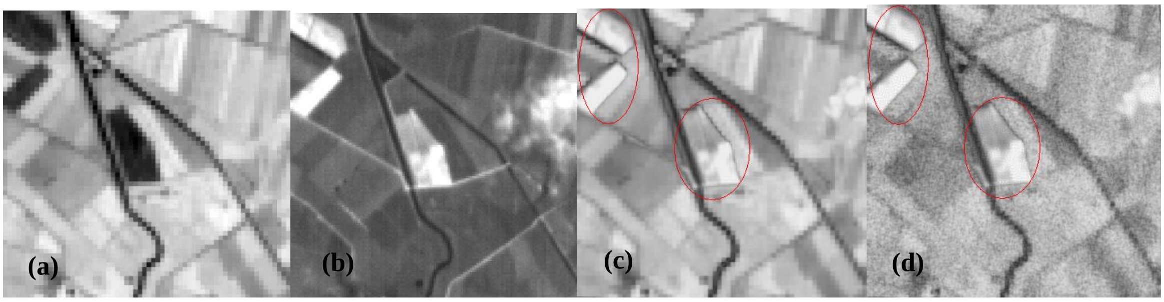


Figure 2 Result of RS image fusion showing (a) Multi-spectral input, (b) PaPanchromatic input, (c) Low noise (SNR 30dB) fused output and (d) High noise (SNR 5dB) fused output

Conclusion

A novel approach of deriving adaptive CPA fusion for vegetation RS imagery has been presented in this paper. The research is borne from specifications 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.

The limitations of the study is readily acknowledged. The accuracy of SVM should improve with the extraction of more salient 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.

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