IMPROVING ARTIFICIAL NEURAL NETWORK PERFORMANCE BY USING TEMPORAL-SPECTRAL FEATURES FOR AGRICULTURAL CROP CLASSIFICATION

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Abstract: A method for improving artificial neural network performance by using multi-temporal, multi-spectral and multi-source remotely-sensed data as features for classifying agricultural crops is described. The procedure characterizes all the pixels in a scene by considering their intensity values as a function of time of imaging and spectral waveband. An analytical surface is interpolated through these data points, which may be irregularly spaced. Two fitted function interpolation methods were used to generate and parameterize the analytical surfaces. Then, the surface coefficients were input to two different supervised classifiers (Maximum Likelihood and Artificial Neural Network algorithms). Results show that classification accuracy is significantly improved in comparison with the use of any single-date image. Classification accuracies in excess of 87% were achieved. The advantages of the methodology described in this paper is that it takes account of the reflectance spectra at different points in the growing season, and that the time periods between images, as well as the wavebands, need not be the same at each date. Thus, the procedure can handle data from sensors such as SPOT HRV and Landsat TM. In addition, the use of coefficients to represent the analytical surfaces significantly reduces the amount of data processing, whilst maintaining information reliability.

Keywords: image classification, multitemporal classificatios, multi-source classification, neural networks.

1. INTRODUCTION

Remote sensing has been used to provide input data by aerial measurements for many agricultural applications, including monitoring crop production and yield forecasting from very early days [Steven et al., 1997]. Many companies and governments require a forecast to plan their processing requirements and marketing. Although remote sensing is already an established forecasting tool for agricultural applications, traditional methods (e.g., aerial photographs) are not able to cover enough samples, or wide enough areas. Therefore, it is important for crop yield forecasting to expand its boundaries to incorporate images from orbiting platforms, since these kinds of images can provide a much better statistical sample for large areas. Thus, crop yield prediction by satellite observation could become a commercial reality.

Before one can apply a forecasting model to particular crops, it is necessary to separate them from all other cover types. This identification process is referred to as classification. Although there are many classification strategies available, problems remain in getting the best accuracy performance from a given classification method. The classification strategy and its parameters may be inadequate; or, the features used in the classification process may not be well-suited to the technique of crop identification, thus causing a lower accuracy performance; or perhaps, the available spatial resolution and temporal frequency of the data is not matched to the expected accuracy.

For practical applications, it is essential that classification systems be robust and exhibit good generalisation. Although the range of image processing techniques has been greatly expanded, from classical statistical approaches to neural network methods, there is no single classification algorithm capable of deriving generic products from remotely sensed data. The performance of these algorithms is strongly

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dependent upon data selection and on the efforts devoted to the design phase. Therefore, researchers must seek alternative methods for achieving improved generalisation performance.

Efficient crop management practices require accurate and rapid information about crop distributions. Commonly, multispectral remotely sensed images are used to distinguish crop types on the basis of their spectral properties [Mather, 1999]. However, such analysis involving single-date images has the drawback that, since maximum discrimination between different crop types occurs at different stages in the growth cycle, not all differences are incorporated in the procedure. Moreover, different crop types represented in the area under study may be at different stages of growth. In addition, the temporal 'profile' of the spectral reflectance curve of each crop is not taken into account. Such profiles may be of considerable value in discriminating between crop types, which may be difficult to distinguish at certain points in the growth cycle. Furthermore, results derived from data obtained by different sensors may not be comparable due to differences in spectral and spatial characteristics. Finally, since agricultural crops are dynamic, it is often useful to observe their development over time (e.g., crop yield estimation). A solution is to use multitemporal images for crop monitoring [Badhwar et al., 1982]. For most current multitemporal classification techniques, a correspondence of time to growth state is established for each possible crop category that minimises the smallest difference between the given multispectral-multitemporal vector and the category mean vector indexed by growth state [Haralick et al., 1980]. These techniques, however, are fairly inaccurate since only relatively few static spectral and temporal 'snapshots' contribute to crop identification. That is, images with specific spectral wavebands acquired on specific dates are used, rather than images with entire spectral and temporal continua. Using the latter may increase crop classification accuracy since they contain more information than the former [Labin and Strahler, 1994].

This paper demonstrates a method for improving artificial neural network performance by using the spectral-temporal signatures of remotely sensed images as features for classifying agricultural crops. Per-pixel classifications are performed using multispectral, multitemporal and multisource data, whereby analytical surfaces representing the spectral and temporal continua of each feature (pixel) are interpolated and their coefficients are used as discriminating variables.

2. STUDY AREA AND DATA SET

The study area was located near the town of Littleport in Cambridgeshire, eastern England. This area was approximately at mean sea level with gently undulating topography. The agriculture of the region was characterized by rotational crop plantation techniques.

Eight remotely sensed images acquired throughout the 1994 summer growing season were used for analysis. These included four Landsat TM images (11 June, 27 June, 20 July, 14 August) and four SPOT HRV images (13 May, 28 June, 30 July, 14 August). Only six spectral wavebands of Landsat TM imagery were used since the thermal infrared band (band 6) was omitted from analysis. In addition, local farmers' Field Data Printouts for 1994 were collected and used to generate a ground reference data set.

All images were geometrically registered to the British National Grid. For each image, registration was performed using 17 ground control points and nearest neighbor re-sampling, since this technique maintained the original pixel values [Jensen, 1986]. In each case, the root-mean-square error associated with registration was less than 0.5 pixels.

Atmospheric correction was performed to account for atmospheric differences between multitemporal images. Initially, image digital numbers were corrected to radiance using information supplied with the image data files [Teillet and Fedosejevs, 1995]. Radiance was then converted to apparent reflectance (recorded at the sensor) and finally to surface reflectance. The final step used an inversion of the 5S (Simulation of the Satellite Signal in the Solar Spectrum) model [Tanré, 1990].

3. THE SPECTRA-TEMPORAL RESPONSE SURFACES (STRS) MODEL

[Badhwar et al., 1982], [Badhwar, 1984], [Haralick et al., 1980], [Lambin and Strahler, 1994] and [Ortiz et al., 1997] consider the problem of characterizing the temporal dimension but none utilizes the method proposed by [Vieira et al., 1998, 2000], involving the use of the spectra-temporal response surfaces (STRS), which provide for the generalisation in time of spectral reflectance properties of agricultural areas. The type and sequence of procedures used in the generation and potential use of the STRS representations are outlined in **Figure 1**.

The STRS approach is based on a view of multi-band and multitemporal imagery from different sources represented in a three-dimensional space, the axes of which are time (*x*), spectral waveband (*y*) and reflectance (*z*). Measurement from a number of different sensors in the optical wavebands can be plotted in this space. A bivariate polynomial of the form: $z = F(x,y)$, where $F()$ indicates a polynomial function of some order, is generated for each of the crop types in the area of study. Two methods were used in order to generate the fitted surfaces: polynomial trend surface analysis (PTS) and collocation (COL), since fitted function interpolation can impose a prescribed general behavior on the surface to override aberrant, anomalous, or noisy data. [Watson, 1999] and [Lam, 1983] give comprehensive reviews on these interpolations methods and [Mather, 1976] reviews polynomial trend surfaces.

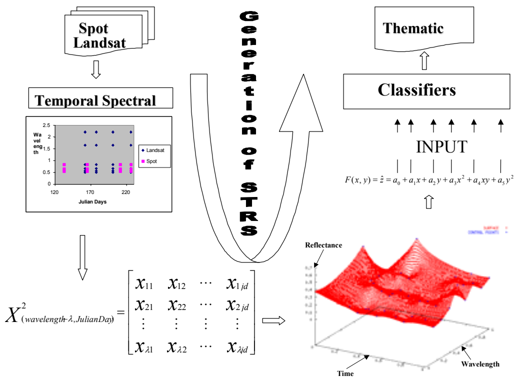

Figure 1. An outline of the methodology followed in this study to generate the STRS representations

These analytical functions are then parameterized and their coefficients, rather than the pixel values in each spectral band, are used as input features in the image classification process.

4. METHODOLOGY

4.1. Sampling Techniques and Classification Phase

From the co-registered and radiometrically corrected image set, two independent sample sets (total 1440 pixels) were selected using stratified random sampling technique and representing the six most common cover types in the study area: Potatoes, Sugar beet, Wheat, Fallow, Onions, and Peas. Each sample has 120 patterns per class (total 720 pixels). One sample (selected at random) was used to training the classifier and the other one was reserved for validating the methodology.

The image acquisition dates were expressed in the form of Julian days (x-axis) and the spectral dimensions (y-axis) were characterized by their medial waveband values computed in the form of wavelengths. Thus, the spectral bands were labeled using the medial wavelength values of 0.458, 0.56, 0.66, 0.83, 1.645, 2.215 – given to the six available TM channels (except the thermal infrared TM band 6) - and 0.545, 0.645, 0.84 – given to the three HRV channels respectively.

The radiometric properties are expressed in the form of reflectance values along the z-axis. Furthermore, for each pixel, 36 three-dimensional control points were generated (4 TM images with 6 bands plus 4 SPOT HRV images with 3 bands). It is important to mention that the values along the x, y and z axes are scaled into the interval between 0 and 1, sometimes referred to as normalization, before the interpolation phase.

Initially the control points were used to fit a surface using a Polynomial Trend Surface as described earlier. Although a surface order of 7 (36 coefficients) explained over 99% of the sum of squares, using a surface order of 3 (10 coefficients) experimentally proved to be enough to characterize the analytical surfaces. Then, the same control points were used to fit a surface using the Collocation Interpolator. As the interpolated coefficients show different magnitudes on their values, they were again scaled collectively to the interval between 0 and 1 before the training and test phases. One pixel example of the PTS and Collocation analytical surfaces is shown in **Figure 2** (a to b) for several crops.

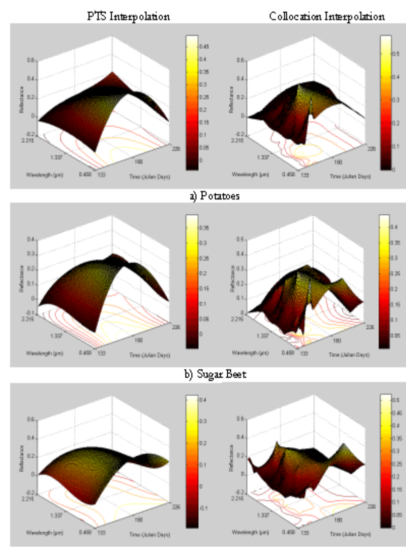

Figure 2. Analytical surfaces and contours for several crops.

According to [Vieira et al., 2000] the Maximum Likelihood (ML) classifier is the algorithm that best combines classification accuracy and computational economy when these coefficient are used as input to the classification process. Therefore, a supervised classification was performed using the Maximum Likelihood (ML) algorithm developed by [Mather, 1999] and adapted to classify 3D surface coefficients.

For the purposes of comparison, a single-date image (Landsat TM, acquired on 27th June 1994) was used to perform a standard classification in order to compare the results of this multitemporal and multisource method against a classification based on a single-date image. For each pixel, the six reflectance values are considered together and therefore generate a six dimensional vector, to be used as input to the supervised classifiers: Maximum Likelihood (ML), and two variants of an Artificial Neural Network (ANN and ANNT).

Both artificial neural network architectures chosen are multilayer perceptrons using the backpropagation algorithm [Benediktsson et al., 1990; Bischof et al., 1992; Civco, 1993]. The only difference between the models is in the input layer. The first ANN model was implemented having one pixel per spectral band in the input layer. Therefore, this neural network had 6 nodes in the first layer. The input nodes in the ANNT model represented a 3 by 3 window of pixel data from each band of the image (total 54 nodes in the input layer) as the input [Paola, 1995]. This input modification takes local texture information into account.

All neural networks configurations tested had an output layer with 6 nodes, corresponding to the 6 general crop classes. The number of hidden layers and the number of hidden nodes were found using a building up procedure. This method, described by Hirose et al. (1991) , begins with a small network composed of an input and an output layer, which are defined respectively by the number of discriminating variables and the number of classes involved in a given problem, with just one neurone in the hidden layer. The criterion for adding neurones to the hidden layer is based on the behaviour of the error during the training phase.

As the main interest in this algorithm is the minimisation of the global error, it is expected that the error will evolve to small values during training. Therefore, if after a number of cycles (e.g., 100 cycles) when the error does not decrease by more than one percent of its previous value, a new hidden unit is added and the connection weights are randomly re-initialised over the previously-defined interval. This process is repeated until the network converges to an acceptable global error value. With the above algorithm, the number of hidden units can only increase. In some cases, the number of hidden units becomes rather large, hence a counter-strategy is used. Once the network performance is judged to be satisfactory, the most recently added hidden unit is removed until the network no longer converges. The last network to converge is then taken as the optimum choice. The learning rate and momentum were set initially at 0.2 and 0.9 respectively. The learning rate was reduced during the training to 0.1 after 1000 epochs.

For this second experiment, two sample sets were selected using stratified random sampling based on the reference image (ground truth), which was generated in the same scale and projection system as the remotely sensed data. Each sample has also 120 patterns per class (total 720). One sample set was used to train the classifiers and another independent sample set was reserved to assess the accuracy of the classification.

4.2. Accuracy Assessment

In order to perform a systematic investigation of the relative (improvement of accuracy) cost involved in the incorporation of the temporal dimension into the crop classification process, standard accuracy measures derived from a confusion matrix were computed, using an independent test data set based on the Field Data Printouts. The measures based on the confusion matrix were overall accuracy, individual class accuracy, producer's accuracy and user’s accuracy. The calculations associated with these measures are described in standard textbooks (e.g., [Mather, 1999]). The Kappa coefficient, conditional Kappa for each class, and test Z statistics, all of them widely used statistics derived from the contingency matrix, were also computed [Congalton and Green, 1999].

In addition, a pairwise test statistic for evaluating the significance of the classifiers (represented here by their respective confusion matrices), was calculated utilizing the Kappa coefficients. These results are summarized in form of a *significance matrix*, in which the major diagonal elements indicate if the respective classification result is meaningful. In this single confusion matrix case, the Z value can be computed using the formula $Z = Ka \big/ \sqrt{\mathrm{var}(Ka)}$, where Z is standardized and normally distributed and *var* is the large sample variance of the Kappa coefficient K. If $Z \geq Z_{\alpha/2,}$ the classification is significant better than a random classification, where $\alpha/2$ is the confidence level of the two-tailed Z test and the degrees of freedom are assumed to be infinity. On the other hand, the off diagonal elements give an indication, again if $Z \geq Z_{\alpha/2}$, that the two independent classifiers are significantly different. The formula used to test significance of the difference of the two independent Kappa coefficients is: $Z = \left|Ka_1 - Ka_2\right| \big/ \sqrt{\mathrm{var}(Ka_1) + \mathrm{var}(Ka_2)}$, where the Ka_1 and Ka_2 are the two Kappa coefficients in comparison [Congalton and Green, 1999].

5. RESULTS AND DISCUSSIONS

Classification accuracies for six agricultural crops using the six multispectral bands of a single-date TM Landsat image, Polynomial Trend Surface (PTS) and Collocation as input features into three supervised classification algorithms - maximum likelihood (ML), artificial neural networks (ANN) and artificial neural network texture (ANNT) are presented in **Table 1**. Individual classification accuracy for each crop (Conditional Kappa * 100), overall accuracy, the value of the Kappa coefficients and their variances, and test Z statistic are reported in this table. These accuracies were calculated from an independent dataset (720 patterns). The pixels received the label of the output class having the highest probability.

Table 1. Classification accuracies for six agricultural crops using Single-Date LANDSAT Image, Polynomial Trend Surface (PTS) and Collocation (COL)) and three classification algorithms - maximum likelihood (ML), artificial neural networks (ANN) and artificial neural network texture (ANNT). The table shows individual classification accuracy for each crop (Conditional Kappa * 100), overall accuracy, the value of the Kappa coefficients and their variances, and test Z statistic. If the absolute value of the test Z statistic is greater than 1.96, the result is significant better than a random classification at the 95% confidence level. These accuracies were calculated from an independent dataset test (720 patterns).

INTERPO.	LANDSAT(27/06/94)			STRS	
CLAS/MET	ML	ANN	ANNT	PTS-ML	COL-ML
Potatoes	64.5	66.8	71.9	95.9	94.9
Sugar Beet	53.8	57.9	58.6	73.8	75.3
Wheat	70.9	75.6	95.5	89.3	92.8
Fallow	80.4	81.8	79.7	70.8	63.3
Onions	84.9	89.7	88.0	95.9	97.8
Peas	53.5	67.9	80.8	93.0	100.0
OVERALL(%)	72.9	77.6	81.7	87.4	87.2
Kappa	0.675	0.732	0.780	0.848	0.847
Variance	0.000394	0.000347	0.000299	0.000219	0.000222
Z	33.99	39.28	45.09	57.27	56.88

As the absolute value of the test Z statistic is greater than critical value of 1.96, all the classification results are significant better than a random classification at the 95% confidence level. Moreover, it is noteworthy that the level of accuracy was gradually improved by employing on the single-date Landsat image the different classifiers: ML (72.9%), ANN (77.6%) and ANNT (81.7%) respectively. However, the overall performance level attained with the features generated using the STRS (i.e., the PTS and Collocation coefficients) as input features to ML classifies were considerably greater (by 5.7%) than those obtained by a single-date image. The ML classifier, when compared to ANN classifier, is the algorithm that best combines classification accuracy and computational economy when these coefficients are used as inputs to the classification process [Vieira et al., 2000]. Oddly, fallow (or set-a-side) is the only individual category for which the accuracy was decreased using PTS and Collocation features. Therefore, it could be concluded that using these features, the ML classifier is confused by some residual patterns of crops growing in the field from the previous crop rotation, which sometimes happens on fallow land.

The lower performance achieved with ML classifier using only the TM multispectral bands is believed to be due in part to a non-linear separability of the classes under study and to a magnitude of training data set inconsistent with the design properties and assumptions of the supervised maximum likelihood algorithms. Moreover, for some of the crops (e.g., sugar beet and potatoes, or onions and peas) the multispectral profiles for that date are not very well separated. Even so, the neural models produce a satisfactory performance on the same data set. Furthermore, the separability of the classes are considerably improved when the local spatial variance of individual pixels is implicitly taken as input to the neural network model by employing a 3 x 3 window as implemented in the ANNT algorithm.

Table 2 provides the computed Z values for a pairwise statistical test in order to check the significance of the improvements on the classification accuracy. The classification accuracy obtained using the STRS approach (PTS and Collocation using ML algorithm) were found to be significantly improved in relation to the individual classifiers ML, ANN and ANNT, in which only a multispectral single-date image was used as discriminate variables (see yellow pair, Z > 1.96 at 95% of confidence level). This demonstrates a need to utilise the STRS approach if one is to achieve the highest accuracies possible in crop discrimination. Moreover, there is no significant difference between the performance of the ML using PTS or Collocation coefficient as input features (see blue pair, Z = 0.05 < 1.96). Therefore, it could be concluded that, for this data set, these two sets of feature variables may ‘work together’ because they produce approximately equal classifications.

Table 2. Results of Kappa Analysis for comparison among the classifiers. The table also presents the Kappa coefficients and variance for each classifier. The Z values (in major diagonal and off diagonal elements) were computed using formula as describe in subsection 4.2.

CLASSIF	ML	ANN	ANNT	TSA	COL
KAPPA	0.675	0.732	0.78	0.848	0.847
VAR	0.000394	0.000347	0.000299	0.000219	0.000222
ML	34.01				
ANN	2.09	39.30			
ANNT	3.99	1.89	45.11		
TSA	6.99	4.88	2.99	57.30	
COL	6.93	4.82	2.94	0.05	56.85

As expected, the use of neural network models significantly overcomes the performance of the ML classifier using a single date Landsat TM image. However, the results indicate that there are no significant differences in performance between the ANN and ANNT algorithms (Z = 1.89 < 1.96) at the same confidence level.

6. CONCLUSIONS

A method for improving artificial neural network performance by using multi-temporal, multi-spectral and multi-source remotely-sensed data as features for classifying agricultural crops has been shown to be effective in identifying general agricultural crop classes over an area in East Anglia (UK). Classification accuracies in excess of 87% were achieved, even though parts of some of the images are covered by clouds. The basic assumption of the method, that different crops have different spectral-temporal trajectories, has been used in earlier studies. However, the methods used to characterize the spectral reflectance changes over a growing season using a spectral-temporal surface represents a promising new approach, for several reasons. First, the method can deal with multi-sensor data, as the spectral bands measured at each date do not need to be the same. Second, data points obscured by clouds can be filtered out throughout the interpolation and parameterization procedures of the analytical surfaces. Third, the overall spectral variation of a given crop class over the growing season is captured by a set of coefficients, which are fewer in number than the training data pixels and hence produce computationally more efficient classifiers.

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