Per-Pixel Uncertainty For Change Detection Using Airborne Data

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Biography

Remote sensing scientist, Environment Agency (1999-). Currently part-time Ph.D. student at Southampton University. Research interests: classification, uncertainty, change detection.

Introduction

The 1992 European Council Habitats Directive (92/43/EEC) requires that the extent and condition of a variety of ecologically important habitats be reported on a six yearly basis. Remote sensing provides one approach by which these requirements may be carried out and could also provide monitoring to assess the impact of management practices on protected sites. An essential part of any monitoring program would be to determine where land cover change is taking place. However, operational methods of carrying out this monitoring using remote sensing are currently not in place. There is therefore a need to refine aspects of remote sensing techniques, particularly in the field of change detection.

The purpose of this paper is to develop methods of deriving the data for input to a change detection model and apply these methods to a sand dune test site near Southport, UK.

Change Detection

There are a number of approaches for change detection, but the most widely used for detecting thematic change is post-classification change analysis. The change detection process is subject to a number of errors at each stage of the data gathering and classification process and these errors may be subject to complex interactions as the change process is modelled. As errors are passed from source to derived data, the errors are modified such that the characteristics of the error may be amplified or suppressed. Errors within the final change surface could be as a result of errors in the sensors, ground data, classifiers and misregistration or due to a lack of spectral separability of classes used. Though there are a number of sources of error within change detection process, these errors manifest themselves in two major forms: thematic and misregistration errors. In order to model the errors, estimates need to be made of their magnitude.

Error modelling may be carried out at the global, scene level or on a per-pixel basis. In this study there is a requirement to know where change is taking place and so global methods are not suitable as they will not provide the spatial context of change.

Uncertainty

It is impossible to quantify the actual error on a per-pixel basis, and so the focus of any error study must be on the probability of error or the uncertainty inherent in the stages involved in the change detection process. Therefore, the uncertainty in each stage must be quantified and the propagation of errors through the change detection process modelled.

Thematic uncertainty

Neural network classifiers have been used to generate per-pixel thematic uncertainty measures (de Bruin and Gorte, 2000). The most commonly used network in remote sensing is the multi layer perceptron (MLP). A variety of measures derived from MLP activation levels have been used as indicators of membership on a per-pixel basis (Foody, 2000).

The probabilistic neural network (PNN) proposed by Specht (1990) may also be used to generate per-pixel thematic uncertainty measures. The PNN is a non-parametric Bayesian approach to classification that directly estimates probability density functions (PDFs) of the classes used. The generation of PDFs by PNNs allows the network outputs to be interpreted directly as posterior probabilities.

Geometric and misregistration uncertainty

Misregistration of the data sets used in change detection is likely to have a complex, spatially dependant function on the errors within the output layer. Even sub pixel misregistration errors can result in large change errors (Roy, 2000). Commonly used measures of geometric and misregistration error, such as root mean square (RMS) error do not consider the spatial function of these errors. One approach to determining the spatial function of misregistration would be to estimate misregistration at points across a scene and interpolate. This approach would be valid in a relatively static habitat or where known areas remain the same. However, in an environment where change is taking place, positional errors may be difficult to estimate if references points are not known to be static. These errors may be increased in coastal environments, where in many cases the greatest change occurs at the seaward side of the habitat, the area where there are least reference points. This means that extrapolation would be required, resulting in an increased probability of error in the estimates of misregistration.

A sensor dependant alternative approach would be to automatically geometrically correct the imagery using navigational data from instrumentation onboard the platform. If estimates can be made of the uncertainties of the navigational data, a geometric model may be generated using navigational uncertainty and a digital surface model (DSM) to provide measures of geometric uncertainty. This negates the need for fixed reference points on the ground for geocorrection and geometric error assessment. In the study site used in this research there are no obvious features that may be used for geocorrecting or assessing the accuracy of geocorrection.

Experimentation

1m spatial resolution ITRES Compact Airborne Spectrographic Imager (CASI) multispectral data and Optech Light Detection and Ranging (LIDAR) digital surface data were gathered over Ainsdale Nature Reserve, Southport, UK in 2001 and 2002. For both flights, ground data for classification training and accuracy assessment were also collected within 3 weeks.

The LIDAR x,y,z points were resampled to a 2m raster grid. The CASI data were geocorrected using ITRES automated geocorrection software using post processed differential GPS (dGPS), Applanix POS AV inertial measurement unit (IMU) attitude data and the LIDAR DSM.

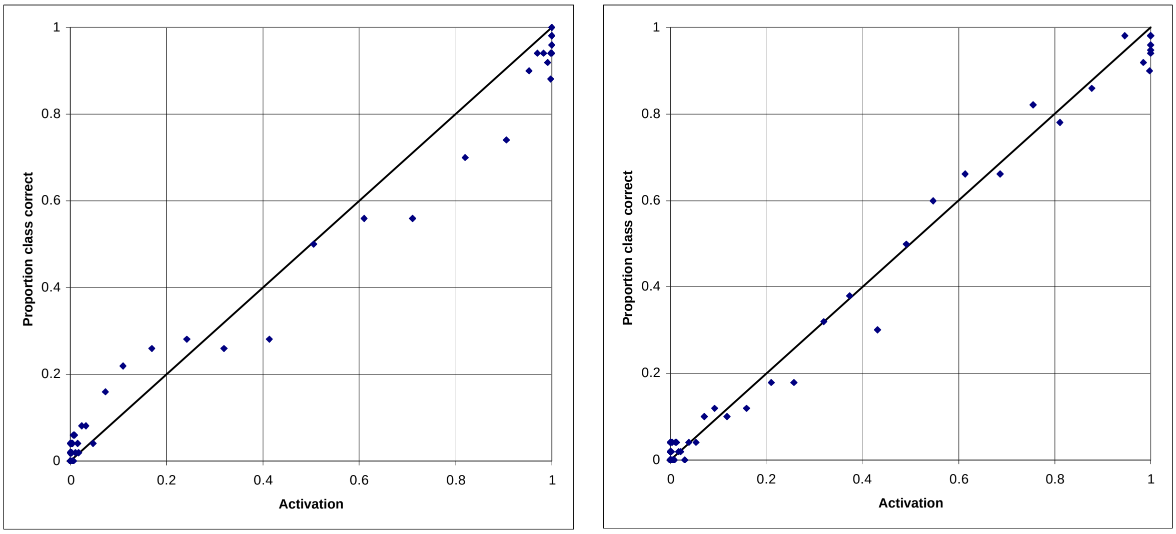
Thematic Uncertainty

Methods of deriving per-pixel measures of thematic uncertainty were tested using MLP and PNN classifiers. The classifications of the Ainsdale sand dune habitat had similar overall accuracy for the MLP (Tau = 0.815) and PNN (Tau = 0.818).

The output activation levels were tested for suitability as uncertainty measures, using the assumption of a linear relationship between activation and uncertainty. A strong and statistically significant relationship was found between the uncertainty measures derived and the proportion of correctly classified pixels for the MLP (r^2 = 0.989; F-value = 11416; degrees freedom = 124; p<0.001) and the PNN ((r^2 = 0.993; F-value = 18859; degrees freedom = 124; p<0.001) (Figure 1)

Figure 1 Proportion of correct pixels as a function of activation level

A MLP B PNN



Geometric and Misregistration Errors

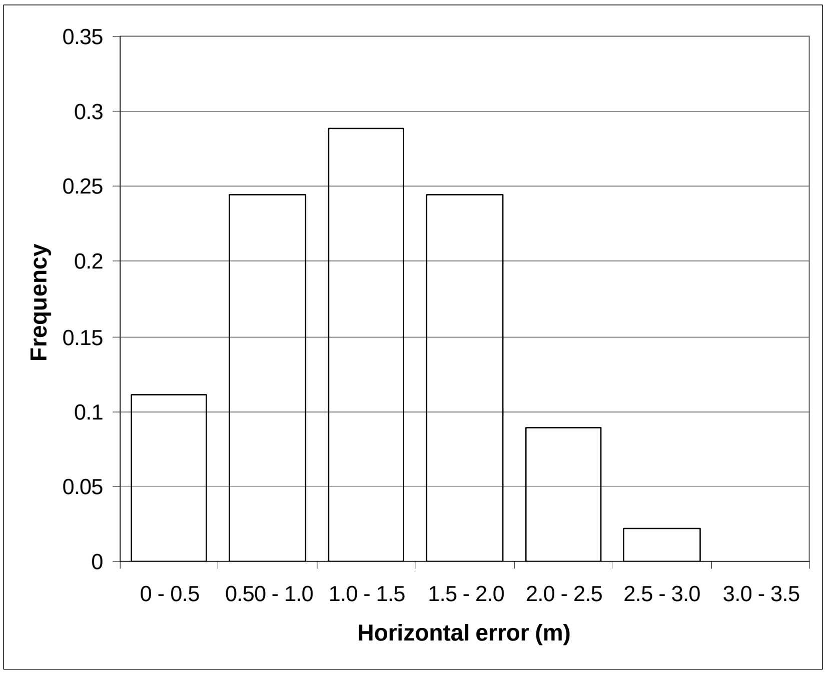
Errors within the geometric correction process may be due to either:

- System error. The GPS, IMU or calibration errors

- Orthometric errors. Horizontal positional error due to difference between the DSM used in geocorrection and the actual height.

In order to assess geometric uncertainties of the CASI automated geocorrection system, data were flown over a test site at Coventry Airport, UK. Easily recognisable points on the site were surveyed using dGPS.

Figure 2 Frequency of CASI horizontal errors



The CASI data were geocorrected, as described above. The DSM used was derived by using a nearest neighbour resampling of dGPS surveyed points used to test the horizontal accuracy of the CASI data. This provided high precision elevation data at the points used to test horizontal accuracy, minimising orthometric errors in the geocorrection process. As the orthometric error was minimised, the major error component is therefore due to the system.

The GPS and CASI positions of the surveyed points were compared to derive error measures. The relationships between positional uncertainty and viewing angle and rate of attitude change were tested and found to be not statistically significant. Uncertainty functions were derived that described the relationship between a given horizontal error and its probability of occurrence (Figure 2).

The results obtained were combined with a simple model of orthometric errors to provide an overall measure of geometric uncertainty. The geometric uncertainty model was used to provide a model of the misregistration between CASI images. This model was tested using an urban area next to the Ainsdale test site. The positions of easily identifiable points on the 2001 and 2002 data sets were estimated and the misregistration error was compared to that estimated by the model.

Conclusions

Thematic and misregistration uncertainty measures for airborne remote sensing data can be generated from neural network classifiers and instrumentation uncertainty. These measures have the potential to be used as inputs for change detection allowing the spatial context of change to be modelled on a per-pixel basis in a probabilistic framework.

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