

ADVANCES IN OBJECT-BASED IMAGE CLASSIFICATION

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ABSTRACT:

This paper presents a review of object-based image classification, outlining recent developments, assessing current capabilities and signposting future implications. Object-based classification methods are described, outlining advantages over other forms of classification, and limitations in the object-based approach. Examples are provided from the UK, drawing in particular on the national Land Cover Map products, the most recent two issues of which involve object-based classification. Continuing development in, and demand for, object-based classification is described in the context of contemporary technology and ubiquitous geospatial information.

1. INTRODUCTION

Early attempts at land cover classification using remotely sensed imagery were dominated by pixel-based methods, where land cover classes are assigned to individual pixels. For instance, the Land Cover Map of Great Britain 1990 used multi-temporal Landsat 5 Thematic Mapper data to produce a 25 m spatial resolution pixel-based product (Figure 1) recording 25 land cover types (Fuller *et al.* 1994).

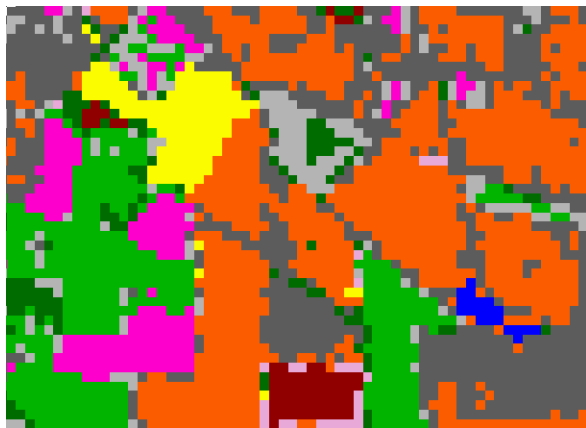


Figure 1. Pixel-based classification used in the Land Cover Map of Great Britain 1990. This sample represents an area of approximately 1.5 km by 1.0 km in the agricultural region of East Anglia. The pixels are 25 m on a side and the colours represent arable crops except for water (blue).

Although pixel-based approaches have certain strong merits and remain in widespread use, operating at the spatial scale of the pixel can have major drawbacks. Chief among these is that a pixel's spatial extent may not match the extent of the land cover feature of interest. For instance, the problem of mixed pixels is well known, whereby a pixel represents more than a single type of land cover (Fisher 1997), often leading to misclassification. This can be compounded by the effect of the sensor point spread function on the area sampled per pixel. Another common problem, though, and one that is less often considered, is where

the object of interest is considerably larger than the pixel size (Carleer *et al.* 2005). Consider, for example, an agricultural agency that wishes to calculate an inventory of arable crops. Where the objective is simply to identify the crop type in each relatively large field (e.g., > 1 ha), relatively small pixels (e.g., spatial resolution = 4 m) may be inappropriately classified as a result of within-field variation. That is, in a field of, say, winter wheat, an individual pixel may be incorrectly classified as bare soil, forest or some other crop class, due to, respectively, crop stress, the presence of a tree or a patch of relict vegetation from earlier crop rotation.

A solution to the difficulties associated with pixel-based classification may be to operate at the spatial scale of the objects of interest themselves, rather than relying on the extent of image pixels (Flanders *et al.* 2003, Hay and Castilla 2006, Platt and Rapoza 2008). For instance, an object-based approach was developed as part of the Classification of Environment with Vektor and Raster- Mapping (CLEVER-Mapping) project (Dean and Smith, 2003) and used for the production of the 1997 Land Cover Map of Jersey (Smith and Fuller, 2001) and the Land Cover Map 2000 (LCM2000) of the UK (Figure 2) (Fuller *et al.* 2002).



Figure 2. Object-based classification used in the Land Cover Map 2000. This sample shows the same area and land cover classes as Figure 1.

By removing the possibility of misclassifying individual pixels, object-based classification can be markedly more accurate than pixel-based classification (Aplin *et al.* 1999, Platt and Rapoza 2008). Other benefits exist too. By focussing on real-world objects, maps produced in this way may be more recognisable and directly usable by analysts (Benz *et al.* 2004, Wu *et al.* 2007). In the agricultural example used above, reports and statistics could be produced on a per-field basis, likely matching field records commonly used and required by agricultural bodies. Importantly, this object-based information can be integrated with other spatial data in vector-based geographical information system (GIS) environments (Geneletti and Gorte 2003, Benz *et al.* 2004, Walter 2004), and used widely in spatial analysis.

2. OBJECT-BASED SPATIAL FRAMEWORKS

Various approaches to object-based image classification exist. A key issue is how to characterise spatially the objects to be used in the classification process. Where only remotely sensed imagery is available, objects can be identified on the basis of (spatial) patches of spectrally similar pixels, as used in the LCM2000 (Figure 3). This is often referred to as segmentation (Haralick and Shapiro 1985, Fuller *et al.* 2002, Carleer *et al.* 2005, Im *et al.* 2008). Again with reference to the crop example described earlier, this may simply involve grouping individual wheat pixels to form a wheat field.

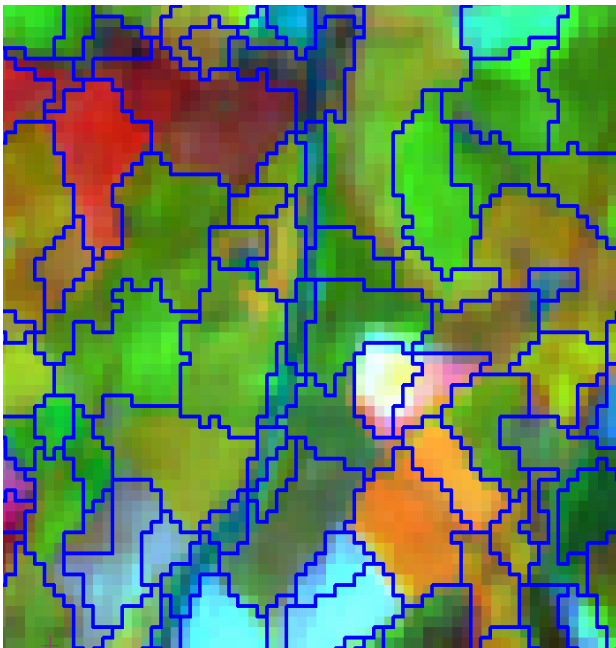


Figure 3. Segmentation used to identify objects in the Land Cover Map 2000. This sample represents an area of agricultural land cover in the West Country of the UK, approximately 1.5 km by 1.5 km.

Image-based object identification is generally approached in one of two ways. First, region growing techniques can be employed to group adjacent pixels with similar spectral values into individual objects (Gao *et al.* 2006). This is a fairly direct approach. Second, edge detection techniques can be used to identify discontinuities (i.e. object boundaries or edges) throughout an image. These boundaries can be extracted and

used to build polygons for object-based classification (Carleer *et al.* 2005). Clearly both of these approaches have the benefit that no additional spatial data are used for classification. However, drawbacks also exist. Notably, objects derived from imagery may not wholly accurately represent the desired object structure. Where, for instance, multiple wheat fields exist adjacently, these may be merged to form a single object when using an image-derived method.

An alternative to deriving objects directly from remotely-sensed imagery is to supplement imagery with other spatial data, often digital vector map data (Figure 4). In this case, objects, characterised by the vector polygons, are assigned land cover values derived from the imagery (Walter 2004, Smith *et al.* 2007, Wu *et al.* 2007). One simple technique, for instance, is to calculate the modal land cover class (as determined by the number of pixels) for each object (Aplin *et al.* 1999).

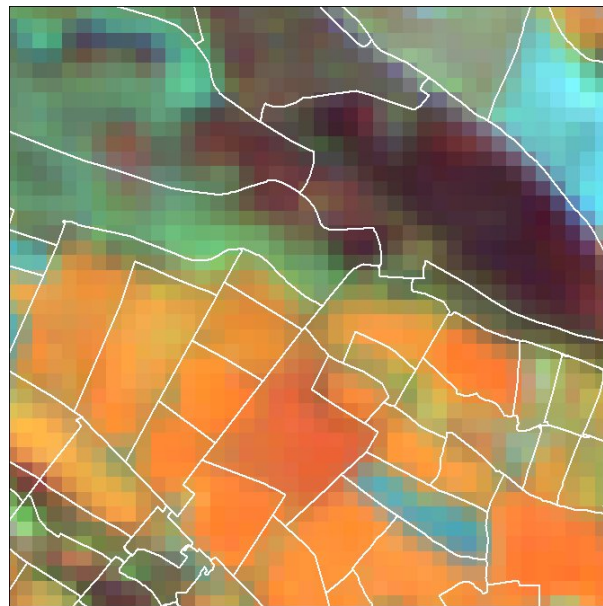


Figure 4. Vector map data used to characterise objects. This sample represents generalised digital cartography overlain on a Landsat Thematic Mapper image, covering an area of 1 km by 1 km.

The incorporation of digital cartography or other vector data in the object-based classification process is not necessarily a straightforward process. Where digital cartography is available, the scale of the mapping and its original purpose may not match well with the new land cover mapping task, and some mechanism for generalisation is often required. For instance, Aplin and Atkinson (2004) used object-based texture measures to identify missing vector boundaries, which were then inserted manually prior to object-based classification. Manual generalisation methods tend to be time-consuming and expensive, while automated generalisation methods can be application-specific and often require specialist hardware and software (Smith *et al.* 2007).

3. ADVANCES IN CLASSIFICATION TECHNIQUES

The concept of object-based classification is fairly well established, with examples of such work dating back to the 1980s (e.g., Mason *et al.* 1988). These early attempts at object-based classification, though, were hindered by technological limitations, leading to their being rather simplistic. Since then,

object-based classification techniques have developed considerably, with two main factors instrumental to their growing availability and use. First, the increasing sophistication of GIS technology – in particular, raster/vector integration capabilities (Cowen et al. 1995) – meant that (raster) image pixels could be combined readily with (vector) objects, providing a relatively straightforward (and widely available, due to the rapidly growing use of GISs) approach to object-based classification (Janssen and Molenaar 1995). Second, the commercial release of a dedicated object-based image analysis system – first known as eCognition in the early 2000s (Flanders et al. 2003, Platt and Rapoza 2008), with a later version named Definiens Enterprise Image Intelligence Suite – has effectively brought object-based image classification to a mainstream (non-GIS specialist) audience. The object-based UK Land Cover Maps have been based on the 1Spatial Gothic object-oriented database technology which is well suited to the land parcel paradigm and raster/vector integration (1Spatial 2008). Other packages which implement object-based image analysis are now available commercially, including ENVI's Feature Extraction module (ITT 2008).

Many examples of object-based image classification have attempted to replicate traditional pixel-based classification techniques, but using the spatial scale of the object instead of the pixel. For instance, the maximum likelihood classification algorithm has been used for object-based classification, either (i) by classifying objects directly (e.g., by comparing each object's group of pixels as a whole against the training classes – this approach was used in the LCM2000) (Kiema 2002, Dean and Smith 2003, Walter 2005) or (ii) by first classifying pixels individually and then grouping these to populate each object (e.g., by calculating the modal class per object) (Aplin et al. 1999, Geneletti and Gorte 2003). Recently, fuzzy classification has been used as an approach for object-based analysis (Benz et al. 2004). For instance, Aplin and Atkinson (2001) located fuzzy (sub-pixel) land cover class proportions spatially by segmenting pixels according to polygon boundaries, while Shackelford and Davis (2003) used sub-pixel class proportions to derive new land cover classes at the object-based scale.

Much current work focuses on the application of object-based analysis to temporal studies (Walter 2004, Zhou et al. 2008). For instance, Im et al. (2008) compare various pixel- and object-based change detection techniques, concluding that advanced object-based approaches are superior. Object-based change detection has been applied to various environmental concerns, including urban growth (Zhou et al. 2008) and shrubland encroachment (Laliberte et al. 2004, Stow et al. 2008).

Since the emergence of fine spatial resolution satellite sensor imagery (IKONOS, QuickBird, OrbView-3, etc.), object-based classification has been applied extensively to this type of data (Wang et al. 2004, Carleer et al. 2005, Mallinis et al. 2008). This is perhaps not surprising given that a chief driver for using object-based classification is to overcome the within-object variation that can lead to pixel-based misclassification. Clearly, for a given classification scheme, the finer the spatial resolution, the greater the chances of within-object variation (Aplin et al. 1999, Carleer et al. 2005). Object-based classification of fine spatial resolution imagery has been used in particular where target features are relatively small. For instance, various studies have tested this approach to map trees or areas of woodland. Guo et al. (2007) and Mallinis et al. (2008) employed QuickBird imagery to map, respectively, oak tree mortality and

natural forest parcels. Fine spatial resolution imagery is also useful for coral reef mapping, due to the remoteness of reefs and their small spatial characteristics, and object-based classification has been tested for this purpose too (Benfield et al. 2007).

4. LAND COVER MAP 2007

Preparations are now underway for a further update of the UK national land cover product with a target summer of 2007 (LCM2007). This product will again be object-based, but this time digital cartography will be adapted to give an object structure that more accurately reflects the true structure of the landscape. Since the release of LCM2000, the Ordnance Survey (OS) of Great Britain have produced a product called MasterMap (MM) by topologically structuring existing digital line work. The structuring of the data produces land parcels/real world objects rather than disconnected line work. This dataset is far too detailed for effective integration with Earth Observation (EO) data with a 20 to 30 m spatial resolution, but is suited to automated generalization. The spatial structure of the next UK land cover product will be mainly generalized OS MM supplemented by agricultural land parcel data and sub-segmentation of large heterogeneous land parcels. The LCM2007 land parcels will have a minimum mapping unit of 0.5 ha and a MFW of 20 m. The classification of the land parcels will be based on multi-temporal EO data using a similar process to LCM2000.

5. SUMMARY

From this paper it can be seen that the field of object-based image classification is rapidly evolving and aligning itself to some of the key challenges facing the field of remote sensing. As the technology of computer science and geographic information advance, so the methods and techniques that can be applied are also advancing. This area of work relies on sourcing a wide range of different data and collating it within advanced database structures. The analyses that are being applied are now less related to simple mathematical relationships and more to do with our understanding of landscapes and the processes and patterns within them. Object-based approaches are offering a means of exploiting the relatively new and now widely used very fine spatial resolution datasets in an automated fashion, rather than relying on manual airphoto interpretation approaches. Finally, the remote sensing analyst can now work with data and present results in a format that is more closely aligned to end user requirements and perceptions, allowing the client community to improve usability and uptake.

The field of geographic object-based image analysis (GEOBIA) is now developing an identity of its own within the remote sensing discipline with annual conferences that bring together the academic, application and commercial communities. This type of activity will therefore continue to develop and become even more established in mainstream remote sensing.

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