Managing uncertainty when aggregating from pixels to objects: context sensitive mapping and possibility theory

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Abstract

Object-oriented remote sensing software provides the user with flexibility in the way that remotely sensed data are classified through segmentation routines and user-specified fuzzy rules. This letter explores the classification and uncertainty issues associated with aggregating detailed ‘sub-objects’ to spatially coarser ‘super-objects’ in object-oriented classifications. We show Possibility Theory to be an appropriate formalism for managing the uncertainty commonly associated with moving from ‘pixels to parcels’ in remote sensing. A worked example demonstrates how Possibility theory and its associated Necessity function, provide measures of certainty and uncertainty and support alternative realisations of the same remotely sensed data that are increasingly required to support different policy objectives.

Key words: Possibility Theory, Uncertainty, Object-oriented classification

1. Introduction

Fuzzy representations of land cover are frequently produced in remote sensing analyses, providing the fuzzy membership of each pixel to each land cover class in the range [0, 1]. Policy makers often require simpler representations of land cover requiring fuzzy memberships to be crisped off, for instance by selecting the land cover with the highest membership, or to be aggregated into area-based reporting units (parcels or polygons). This letter is concerned with how the uncertainty associated with spatially detailed fuzzy ‘sub-objects’ is managed when aggregating to spatially coarser ‘super-objects’. This issue has come to the fore with the increased use of object-oriented classification in remote sensing.

Object-oriented classification of remotely sensed imagery allows the user to manipulate groups of pixels (or objects) that have been segmented from image data. Definiens Developer, previously eCognition, (Definiens, 2008) is a recent software development for the analysis of remote sensing data. It segments the imagery and uses a hierarchical rule-based approach with ancillary data to classify the segmented objects. Rules are encoded in a ‘knowledge base’, which specifies at what stage in the classification process they are applied. The objects produced by segmentation may reflect more intuitively the features of interest on the ground compared to traditional pixel based classifications. The knowledge base allows the sequence of rules to be manipulated and can reflect heuristic manual classification procedures and is able to

better represent ‘reality’ as perceived by ecologists, field surveyors and air-photo interpreters than others remote sensing approaches (Lucas et al., 2007).

Land cover classification from remotely sensed data typically produces a single classification scheme that is expected to address multiple purposes. However, for some of these purposes the information content may not be appropriate. For this reason, and primarily to allow different policy objectives to be addressed, a ‘context sensitive’ approach to land cover, vegetation and habitat mappings has been suggested and developed (Comber, 2006; Comber *et al*, 2008). This supports alternative realisations of the same remotely sensed data allowing different questions to be answered. For example, these may relate to conservation (what is there), habitat restoration (what could be there) and monitoring (what has happened there), and support different policy objectives such as habitat reporting, Common Agricultural Policy payments, monitoring of change, conservation and habitat restoration. The resulting maps are called context-sensitive because they have been produced to meet a particular need.

The habitat of ‘Bog’ provides an example of the requirements for and benefits of alternative context sensitive representations. Identifying the certain spatial extent of Bog is important for legal reasons (e.g., for prosecuting land owners for illegal burning on protected habitats) but identifying the possible or uncertain spatial extent of Bog provides more relevant information to support important habitat restoration objectives. The mapping of Bog is inherently subject to uncertainty as its constituent plant communities overlap with other habitats such as ‘Heaths’. There may, in this case, be patches of bog vegetation within the upper bound of the potential spatial extent of bog which are too small to be mapped independently of the surrounding heath vegetation. In these circumstances, the use of alternative representations can provide the necessary information to fulfil both objectives.

2. Background

2.1 Approaches to classification

Traditional, pixel-based techniques for classifying remotely sensed imagery typically match the characteristics of each pixel, either to a set of predefined classes (supervised classification) or to clusters of similar pixels (unsupervised classification) for a set number of predefined classes. Each pixel is evaluated for membership to each class and membership (fuzzy or crisp) is allocated based on a specified distance function. In these approaches each class and each object (or pixel) is treated in the same way.

A hierarchical object-oriented classification imposes a classification order where classes are allocated to objects only after classes higher up in the hierarchy have been allocated. This allows inheritance of attributes contributing to the definition of each class as the semantics of the classes are necessarily defined not only by the rules that exist in the knowledge-base at their ‘level’ in the hierarchy but also by the attributes they inherit. This approach to mapping is more logical and informed and provides better opportunities for developing local to national products.

2.2 Case study: habitats

Government agencies collect habitat information at a range of spatial scales and granularity for national and international policy obligations. The most detailed grain commonly used in the UK is the National Vegetation Classification (NVC). The NVC identifies 286 communities grouped into broad categories (e.g., 25 woodlands, 22 heaths, and 38 mires) and are described in Rodwell et al. (1991 etc). Phase I surveys capture information at a coarser grain than NVC and are used as a standard reporting method for most broad scale habitat studies. Guidance for the identification and recording of Phase I habitats in the field is given by the Joint Nature Conservancy Council (JNCC, 1990). The guidance on Phase I habitats was written for field surveyors rather than extracted from satellite imagery.

In this work, fuzzy sub-objects, which are spectrally distinct classes characterised by contrasting dominant species; see Lucas et al. (2007) have been identified at a fine spatial scale (in some cases this resembles NVC type classes) using an object-oriented classification.

There is then the need to amalgamate these classes into larger units (super objects) that correspond to Phase I habitats. A rule base was developed to identify the sub-objects habitat classes. The problem is then how to combine the fuzzy sub-object information into measures of confidence or support (belief, certainty, etc) in the super-object.

3. Problem

These sub-objects represent the most ecologically detailed information that it has been possible to extract from image data. They are the building blocks from which the habitat super-objects are constructed. Policy makers are interested in different final map products at the super-object level: classification of the *probable* habitats for national and international reporting, and classification of the *possible* habitats for restoration activities. In each case a measure of uncertainty is required to provide an indication of the reliability of the classification.

In order to allocate super-object segments to habitat classes, a set of rules encoded in a knowledge base has been created. The rules describe the habitat classes in terms of their constituent sub-objects, simplified examples of which are shown in Table 1. Of note is that different proportions of the same sub-object classes found in different habitats and the presence of different sub-object classes may be required (AND) or one of a number of options (OR), one of which must be present.

(Insert Table 1 about here – **Note** it is at the end of this document due to its orientation)

The problem is further complicated by the fuzzy memberships of each sub-object to each of sub-object classes. Figure 1 shows a small hypothetical area of 25 pixel sub-objects to illustrate this problem. The uncertainty attached to each imposes a further level of complexity and uncertainty to the process of aggregating them to super-objects in terms of assessing whether the area based rules are satisfied, combining the sub-object uncertainties and identifying the super-object habitat class.

Figure 1. An illustration of hypothetical overlapping spectral end members.

4. Methods

Possibility Theory (Dubois and Prade, 2001) handles incomplete information using a pair of dual set-functions ‘Possibility’ and ‘Necessity’. These are similar to the Belief and Plausibility functions in the Dempster-Shafer theory of evidence, except that whilst Dempster-Shafer is additive, Possibility is not. Instead it uses a supremum function, relating to the maximum support for any given hypothesis. The Possibility function states that $Poss(X)$ is the supremum of $Poss(\{w\})$, where w are the set of elements of X . The uncertainty associated with X is given by the corresponding Necessity function (Nec). Whereas the difference between the Belief-Plausibility pair in Dempster-Shafer functions provides a measure of the uncertainty of the inference, Necessity is defined as:

$$Nec(X) = 1 - Max(Poss(\neg X)) \quad (\text{Equation 1})$$

That is, it gives a simple measure of the certainty of the Possibility measure relative to competing hypotheses: the lower the Necessity value, the more competition there is.

We can consider Possibility and Necessity in relation to the habitat problem.

The class membership for the super-object, X , is determined by set of rules, using sub-objects x as input, where X is made up of $\{x1, x2, x3, \dots, xN\}$ for the N sub-object specified in the rule for X . Using a threshold is the appropriate Truth Function for fuzzy logic and it is therefore appropriate to specify an acceptability threshold, T_{H1} , for membership of the habitat class H_1 , where if $f_{H1}(X) \geq T_{H1}$ then membership of class H_1 is True. The problem is to convert the membership values and rules in the sub-objects to values super-objects. We suggest three methods for generating super-object memberships which can be evaluated against T_{H1} :

1. A fuzzy MIN function to determine the possibility of super-object X belonging to class H , as is used Definiens Developer.
2. Count the number of sub-objects $\{x1 \dots xN\}$ in the rule for X which are True. Support is the proportion of object X belonging to class H .
3. A fuzzy MAX function, where support for X is generated from the maximum support from the relevant rules in Table 1.

The Necessity can be evaluated for each method as follows. As object X also has potential membership to other classes (H_2 , H_3 , etc). For example, 3 hypotheses have the following support $f_{H1}(X) = 0.9$, $f_{H2}(X) = 0.8$ and $f_{H3}(X) = 0.3$, and that only

membership of H_1 and H_2 exceeds the acceptability thresholds. In the case of H_1 we have:

Both H_1 and H_2 are possible.

$$Poss(H_1) = 0.9$$

$$Nec(H_1) = 1 - \text{Max}(Poss(H_2), Poss(H_3)) = 1 - 0.8 = 0.2$$

$$Poss(H_2) = 0.8$$

$$Nec(H_2) = 1 - \text{Max}(Poss(H_1), Poss(H_3)) = 1 - 0.9 = 0.1$$

$$Poss(\{H_1, H_2\}) = 0.9$$

$$Nec(\{H_1, H_2\}) = 1 - Poss(H_3) = 1 - 0.3 = 0.7$$

5. Application to habitats

A data layer of empty super-object parcels was generated in Definiens Developer. Each super-object was populated with possible super-object habitats by assessing the intersecting sub-objects in the following way:

- A threshold of 0.1 was applied to the sub-object memberships as this was seen as the minimum support needed for the presence of that subclass;
- A zonal statistics GIS function was used to generate information about the number of sub-objects in each super-object above that threshold and their average value;
- The distribution of the sub-objects and their memberships values in the sub-object was compared with the rules for that habitat class, as in Table 1;
- Memberships were calculated from the Fuzzy Min, Possibility and the proportion of sub-objects satisfying rules for each super object;
- The Necessity functions for each aggregation were calculated using Equation 1.

The calculation of Necessity and identifying possible alternative habitats is illustrated with an example in central mid Wales in Figure 2. The parcel has an area of 6700m² and the sub-objects are 5m pixels. Table 2 shows the three habitats whose rules were satisfied by the intersecting sub-object classes. The AND conditions that relate to the absence of a particular sub-object class are binary: if satisfied they provide a support value of 1 and the maximum of the OR conditions is used in the calculation. The three hypotheses are Unimproved Acid Grassland (H_1), Scattered Bracken (H_2) and Acid Flush (H_3). The support from the proportion, fuzzy min and Possibility functions $f_{H1}(X)$, $f_{H2}(X)$ and $f_{H3}(X)$ with associated necessities are shown in Table 3. The threshold applied to each hypothesis was 0.3

Figure 2. The example super-object parcel in its landscape context.

			Unimproved Acid Grassland			Scattered Bracken			Acid Flush		
Sub-object	count	mean	AND	OR	value	AND	OR	value	AND	OR	value
Bogs	0	n/a	< 0.1		1						
Bracken	38	0.187				> 0.1		0.026			
Cottongrass	0	n/a	< 0.1		1						
Festuca	269	0.372		> 0.25	0.372	>0.1		0.372			
Juncus	0	n/a		> 0.25	0						
Molinia	196	0.962								> 0.3	0.701
Mossfesc	0	n/a		> 0.25	0						
Nardus	11	0.15		> 0.25	0						
Veg/juncus	269	1								> 0.1	1
			Support								
Proportion			0.791			0.199			0.85		
Fuzzy MIN			0.372			0.026			0.701		
Possibility			1			0.372			1		

Table2. Rules, supporting values and overall support for the habitats whose conditions are satisfied in the example super-object.

For the Proportional method of aggregation only H_1 and H_2 have support above the threshold. This results in:

$$Nec(H_1) = 0.15$$

$$Nec(H_3) = 0.209$$

$$Poss(H_1, H_3) = 0.85, Nec(H_1, H_3) = 0.801$$

For the Fuzzy MIN method of aggregation again only H_1 and H_2 have support above the threshold. This results in:

$$Nec(H_1) = 0.299$$

$$Nec(H_3) = 0.628$$

$$Poss(H_1, H_3) = 0.701, Nec(H_1, H_3) = 0.974$$

Using Possibility as the method of aggregation results in all three hypotheses having support above the threshold. This results in each having a necessity value of 0.

For this example we may prefer the greater discrimination between hypotheses offered by the Proportional and Fuzzy MIN aggregation of sub-objects to super-objects. In other cases, Possibility may be preferred. However the use the Necessity function as a measure of uncertainty in the support gives a simple yet intuitive measure of the certainty of the Possibility measure relative to competing hypotheses

In the example, it can be concluded that both H_1 and H_3 are highly possible and that when that ‘crisping up’ (e.g. for policy reporting) this is accepted as true: neither single habitat is necessary – because the other is possible – but the set of two is necessary. According to our rule base, the super-object contains both habitats either as a mosaic or an ecotone. We can know which by looking at the sub-object classes (for example, to examine how many of these are classed as each habitat). It might be that few or none are, in which case this is a mixture rather than a mosaic. An ecotone would be indicated by a gradient, perhaps towards adjacent objects with an unmixed class. We note that there is no error model arising out of the analysis, unless we want to construct one for the underlying data values.

6. Conclusion

The use of Possibility with Necessity (as measure of certainty of the support relative to competing hypotheses) provides a useful measure of super-object heterogeneity. The purpose of the letter was to introduce the problem and a possible solution and not to provide validation. However, the results and techniques reported are of relevance to a number of areas of work. First, the remote sensing community has embraced object-oriented image classification software. The use of object-oriented classifiers presents a new problem: how to move from the lower level objects to higher level ones whilst accommodating the uncertainty, whether ‘higher’ and ‘lower’ relate to spatial objects or the objects in the class hierarchy, or both. Second, the ability to be able to represent and explore the uncertainty associated with allocating a parcel to any one habitat class is important, especially in heterogeneous landscapes and those with high conservation value. Third, Possibility Theory has been shown to provide a useful tool for analyses to identify ecologically important habitats either for protection or restoration: it allows the question “what could be there” to be answered. Ongoing work will develop these ideas.

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