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

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(Received 24 April 2009; in final form 5 August 2009)

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 paper 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 with habitats demonstrates how possibility theory and its associated necessity function provide measures of certainty and uncertainty and support alternative realizations of the same remotely sensed data that are increasingly required to support different applications.

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]. Decision makers often require simpler representations of land cover. This paper is concerned with managing uncertainty in segmented image objects when spatially detailed fuzzy objects are aggregated to coarser objects.

Object-oriented classification of remotely sensed imagery allows the user to manipulate groups of pixels (or objects) that have been segmented from image data. A hierarchical rule-based approach with ancillary data classifies segmented objects. 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 other remote sensing approaches (Lucas et al. 2007).

Land cover classification from remotely sensed data is typically based on a classification scheme that is expected to address multiple purposes. Comber et al. (2008)
developed a context-sensitive approach to land cover mapping to allow different applications to be addressed. Such an approach supports alternative realizations of the same data and allows 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 objectives such as habitat reporting and agricultural payments. The resulting maps are called context sensitive because they have been produced to meet a particular need.

Bog habitats provide a useful example of the need for alternative 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). However, identifying the possible or uncertain spatial extent of bog provides information that supports important habitat restoration objectives. The mapping of bog is inherently uncertain as its vegetation components 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 but that 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: habitat objects and hierarchies

Vegetation habitats are defined at a range of spatial scales and granularity for national and international policy obligations. They are defined and delineated by the biological relationships between plant species and the biophysical niches that they occupy. They are frequently composed of aggregations of different individual patches of vegetation, making them difficult to identify directly in remote sensing analyses. In the UK the most detailed grain commonly used in the UK is the National Vegetation Classification (NVC; see Rodwell 1991 et seq.). Phase I habitats describe information at a coarser grain than the NVC and are used as a standard reporting method for most broad-scale habitat studies (JNCC 1990). Although, ideally, the Phase I habitats would be derived from image analysis directly (e.g. as vegetation communities, association types or ecotope units), other work has found this problematic (Lucas et al. 2007).

There is a wide literature describing hierarchical frameworks and relationships between different habitat object levels. Woodcock and Harward (1992) developed a nested hierarchical model to identify different granularities of forest features in the landscape. Their work was extended by Burnett and Blaschke (2003), who presented a hierarchical patch dynamics framework to model the aggregation from trees, identified in segmented remotely sensed data, to forest habitat patches. In this framework, low-level or ‘holon −1’ (their terminology) tree patches were identified by their attributes (‘holon −2’) and were combined to form focal (‘level 0’) forest patches suitable for woodpecker nesting and foraging. These in turn were aggregated to form a higher-level habitat matrix (‘level 1’) for woodpeckers. Laliberte et al. (2007) combined object-oriented classification with a classification tree analysis using a four-level hierarchical network of image objects. These levels were related horizontally (i.e. at the same segmentation level) and vertically to the level above to ‘super objects’ (their terminology) or below to ‘sub objects’. The hierarchical segmentation was used to distinguish different landscape features at different scales of analysis.
3. **Problem**

An initial segmentation has identified and classified fuzzy sub-objects. These are spectrally distinct classes characterized by contrasting dominant species (see Lucas et al. 2007). In some cases they resemble NVC-type classes and broadly relate to individual patches. For reporting purposes these sub-objects are to be amalgamated into larger units (super-objects) corresponding to Phase I habitats. A rule base was developed to identify the sub-objects habitat classes and a second rule base describing how the sub-objects nest into the super-object Phase I habitat classification (table 1). The problem is how to combine the fuzzy sub-object information into measures of confidence or support (belief, certainty, etc.) in the super-object class, while allowing for a plurality of super-object classes.

4. **Possibility theory**

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 (Parsons (1994) provides a good introduction), except that whereas Dempster–Shafer theory is additive, possibility theory is not. Instead, possibility theory uses a supremum function (or least upper bound) that relates to the maximum support for any given hypothesis. The possibility function states that \( \text{Poss}(X) \) is the supremum of \( \text{Poss} \{ w \} \), 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:

\[
\text{Nec}(X) = 1 - \text{Max}(\text{Poss}(\neg X))
\]

where \( \neg X \) describes ‘not \( X \)’. That is, the necessity function (Nec) 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 a set of rules, using sub-objects \( x \) as input, where \( X \) is made up of \( \{x_1, x_2, x_3, \ldots, x_N\} \) for the \( N \) sub-object specified in the rule for \( X \).

Fuzzy logic requires the use of a truth function (similar to an alpha cut in fuzzy classifications), the minimum level at which the fuzzy information is thought to be true, and it is therefore appropriate to specify this threshold of acceptability, \( T_{H_1} \), for membership of the habitat class \( H_1 \), where if \( f_{H_1}(X) \geq T_{H_1} \), then membership of class \( H_1 \) is true. Typically, the threshold is selected on the basis of an acceptable minimum support needed for the presence of that subclass. The objective is to calculate super-object membership values from sub-object attributes. We suggest three methods for generating super-object memberships that can be evaluated against \( T_{H_1} \):

1. A fuzzy MIN function to determine the possibility of super-object \( X \) belonging to class \( H \).
2. Count the number of sub-objects \( \{x_1, \ldots, x_N\} \) in the rule for \( X \) that 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. Object \( X \) also has potential membership to other classes \( (H_2, H_3, \text{etc.}) \). For example, three hypotheses have the
Table 1. The rule base used to allocate habitat classes to super-objects based on the proportions of their constituent sub-objects. All of the ‘Required’ conditions must be satisfied and at least one of the ‘One of’ conditions. Note rules specify minimum as well as maximum proportions.

| Sub-objects          | Dry acid heath | Wet heath | Blanket bog | Raised bog | Unimproved acid grassland | Acid flush | Bracken | Scattered bracken |
|----------------------|----------------|-----------|-------------|------------|---------------------------|------------|---------|------------------|
|                      | Required       | One of    | Required    | One of     | Required                  | One of     | Required | One of            |
| Blanket bog          |                |           |             |            |                           |            |         |                  |
| Bog moss             | ≤ 0.05         |           |             |            |                           |            |         |                  |
| Bogs                 |                |           |             |            |                           |            |         |                  |
| Bracken              |                |           |             |            |                           |            |         |                  |
| Calluna              |                |           |             |            |                           |            |         |                  |
| Cotton grass         |                |           |             |            |                           |            |         |                  |
| Festuca-Agrostis     |                |           |             |            |                           |            |         |                  |
| Heathy bog           |                |           |             |            |                           |            |         |                  |
| Juncus               |                |           |             |            |                           |            |         |                  |
| Molina               |                |           |             |            |                           |            |         |                  |
| Mossy fescue         |                |           |             |            |                           |            |         |                  |
| Nardus               |                |           |             |            |                           |            |         |                  |
| Vaccinium            |                |           |             |            |                           |            |         |                  |
| Veg, cluster         |                |           |             |            |                           |            |         |                  |
| Juncus               |                |           |             |            |                           |            |         |                  |
following support: \( f_{H_1}(X) = 0.9, f_{H_2}(X) = 0.8 \) and \( f_{H_3}(X) = 0.3 \), and 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.
\[
\text{Poss}(H_1) = 0.9 \\
\text{Nec}(H_1) = 1 - \max(\text{Poss}(H_2), \text{Poss}(H_3)) = 1 - 0.8 = 0.2 \\
\text{Poss}(H_2) = 0.8 \\
\text{Nec}(H_2) = 1 - \max(\text{Poss}(H_1), \text{Poss}(H_3)) = 1 - 0.9 = 0.1 \\
\text{Poss}\{H_1, H_2\} = 0.9 \\
\text{Nec}\{H_1, H_2\} = 1 - \text{Poss}(H_3) = 1 - 0.3 = 0.7
\]

5. Application to habitats

A data layer of empty super-object parcels was generated. 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 geographic information system (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 1. The parcel has an area of 6700 m\(^2\) and the sub-objects are 5 m pixels. Table 2 shows the three habitats whose rules were satisfied by the intersecting sub-object classes. The ‘Required’ 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 ‘One of’ 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 \( f_{H_1}(X), f_{H_2}(X) \) and \( f_{H_3}(X) \) are shown in table 2. The threshold applied to each hypothesis was 0.3.

For the proportional method of aggregation, only \( H_1 \) and \( H_3 \) (unimproved acid grassland and acid flush) have support above the threshold. This results in:
\[
\text{Nec}(H_1) = 0.15 \\
\text{Nec}(H_3) = 0.209 \\
\text{Poss}(H_1, H_3) = 0.85, \text{Nec}(H_1, H_3) = 0.801
\]

For the fuzzy MIN method of aggregation, again only \( H_1 \) and \( H_3 \) have support above the threshold. This results in:
\[
\text{Nec}(H_1) = 0.299 \\
\text{Nec}(H_3) = 0.628 \\
\text{Poss}(H_1, H_3) = 0.701, \text{Nec}(H_1, H_3) = 0.974
\]
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.

6. Conclusion

In the example, it can be concluded that both $H_1$ and $H_3$ are highly possible and that 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. 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 of 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.

According to our rule base, the super-object contains both habitats either as a mosaic or as 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
Table 2. (a) Rules and supporting values for the habitats whose conditions are satisfied in the example super-object. (b) The overall support for generated for each habitat.

(a)

| Sub-object     | Count | Mean  | Unimproved acid grassland | Scattered bracken | Acid flush |
|----------------|-------|-------|---------------------------|-------------------|------------|
|                |       |       | Required                  | One of Value      | Required   | One of Value | Required | One of Value |
| Bogs           | 0     | n/a   | < 0.1                     | 1                 | > 0.1      | 0.026       |          |              |
| Bracken        | 38    | 0.187 | > 0.25                    | 0.372             | > 0.1      | 0.372       |          |              |
| Cotton grass   | 0     | n/a   | < 0.1                     | 1                 |            |             |          |              |
| Festuca        | 269   | 0.372 | > 0.25                    | 0.372             | > 0.1      | 0.372       |          |              |
| Juneus         | 0     | n/a   | > 0.25                    | 0                 |            |             |          |              |
| Molinia        | 196   | 0.962 |                           |                   |            |             | > 0.3    | 0.701        |
| Mossy fescu    | 0     | n/a   | > 0.25                    | 0                 |            |             |          |              |
| Nardus         | 11    | 0.15  | > 0.25                    | 0                 |            |             |          |              |
| Veg/juncus     | 269   | 1     |                           |                   |            |             | > 0.1    | 1            |

(b)

|                      | Support | Unimproved acid grassland ($H_1$) | Scattered bracken ($H_2$) | Acid flush ($H_3$) |
|----------------------|---------|----------------------------------|---------------------------|---------------------|
| Proportion           | 0.791   | 0.199                            | 0.85                      |                     |
| Fuzzy MIN            | 0.372   | 0.026                            | 0.701                     |                     |
| Possibility          | 1       | 0.372                            | 1                         |                     |
to construct one for the underlying data values. The use of possibility with necessity (as a measure of certainty of the support relative to competing hypotheses) provides a useful measure of super-object heterogeneity.

Acknowledgements
The British National Space Centre co-funded a preparatory study under the GIFTSS programme, steered and generously supported by Dr Ian Thomas and Matt O’Donnell. The underlying classification work was conducted within the Countryside Council for Wales (CCW) contract, Mapping Habitats Across Wales Using Satellite Imagery (Contract No. FC 73-03-299). We thank Alex Turner, Stuart Mackintosh and Jane Stevens (Countryside Council for Wales) for their time and ecological discussions. Claire Horton (Welsh Assembly Government) is thanked for her support and for providing access to key data.

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