APPLICATION OF GEOBIA TO MAP THE SEAFLOOR

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ABSTRACT:

Geographic Object-Based Image Analysis (GEOBIA) has been successfully employed to map terrestrial environments. However, 71% of Earth's surface is covered by seawater and standard optical methods suitable for mapping the land surface have limited application in such environments. Application of GEOBIA to marine environments has nevertheless been attempted and can generally be subdivided into three domains: 1. The intertidal zone and shallow subtidal zone have been mapped with optical data and application of GEOBIA in such environments can be seen as a seaward extension of terrestrial approaches. 2. Photographs of the seafloor give very detailed but spatially limited information. GEOBIA methods have been applied to classify benthic species and habitats and estimate seafloor complexity among others. 3. Due to the rapid attenuation of light in water, the method of choice to map the seafloor employs sound. Modern multi-beam echosounders map the seafloor in high detail. Such sensors measure the topography (water depth) and the strength of the returning signal (backscatter), which can be used to characterise the seafloor substrates and habitats. This contribution will focus on the application of GEOBIA to marine acoustic datasets. A generic workflow for object-based acoustic seafloor mapping will be showcased and the current state of the application of GEOBIA to marine acoustic data will be discussed.

1. INTRODUCTION

It has been said that the Earth's ocean is the final frontier and that we know more about the surface of Mars than the floor of our oceans. Only 5 – 10% of the seafloor is mapped with a resolution comparable to that on land (Wright and Heyman, 2008) due to the fact that optical methods are incapable of penetrating the water column apart from the shallowest marginal parts of the world ocean. Unsurprisingly, there have been limited attempts so far to apply GEOBIA to marine data sets with the aim to map the seafloor.

Marine Object-Based Image Analysis (MOBIA), here defined as the application of GEOBIA to marine data sets with the aim to map the seafloor geomorphology, geology and habitats, is a nascent science discipline, but most advanced where optical remote sensing imagery collected from satellites and remotely operated aircraft systems ('drones') has been utilised to map intertidal and shallow subtidal habitats. Among the most frequently mapped habitats are mangroves (Conchedda et al., 2008; Heumann, 2011; Wang et al., 2004), saltmarsh (Moffett and Gorelick, 2013; Ouyang et al., 2011), seagrass (Lathrop et al., 2006; Lyons et al., 2012; Roelfsema et al., 2014) and coral reefs (Benfield et al., 2007; Knudby et al., 2011; Phinn et al., 2012).

Seafloor photographic images, collected from various platforms, such as drop-frames, benthic sledges, remotely operated vehicles and autonomous underwater vehicles, might be interpreted separately or stitched together to derive geo-referenced photo-mosaics. Such image data sets could be analysed with GEOBIA methods to map habitats and derive (semi-)quantitative information (e.g. seafloor complexity); however a significant drawback is the very limited footprint on the order of 1 m^2 to several 100 m^2 and few examples exist in the peer-review literature (Lacharité et al., 2015).

The preferred method to map the seafloor in sufficient detail utilises sound rather than light, as sound is much less attenuated and travels over significant distances in the water column. Modern multibeam echosounders (MBES) survey the seafloor in high detail and typically measure two parameters: the travel time of the sound from the transducer to the seafloor and back to the receiver, which can be converted to water depths and the intensity of the returned signal, commonly known as backscatter strength. From the depth data, it is possible to construct detailed digital elevation models and derive secondary variables, such as seafloor slope and rugosity. The backscatter strength is influenced by various factors, such as the geometry of the sonar-target system, the physical characteristics and the intrinsic nature of the seafloor (Blondel, 2009), but yields an interpretable acoustic image of the makeup of the seafloor surface. It is mainly this kind of imagery that has proved most useful for mapping seafloor sediments and habitats (Brown et al., 2011). Due to the fact that MBES typically survey with one acoustic frequency those backscatter images are essentially limited to one band.

The resolution of acoustic seafloor imagery is dependent on the beam width and the water depth. Typical shallow water MBES collect data with a spatial resolution of c. 1 m to 5 m. Features of interest are typically larger than that (H-resolution case) and object-based approaches are appropriate under these circumstances (Blaschke et al., 2014). Since Lucieer's (2008) paper on object-based mapping of benthic marine habitats, uptake of GEOBIA methods has been slow but is currently accelerating with studies published in the peer-review literature (e.g. Diesing et al., 2014; Lucieer and Lamarche, 2011; Montereale Gavazzi et al., 2016) and presented at conferences. This contribution will showcase a generic workflow for categorical seafloor mapping based on acoustic data sets and ground-truth observations.

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2. GENERIC WORKFLOW

Because the interpretation of seafloor acoustic imagery is significantly less unequivocal than optical images of the land surface, ground-truth observations are usually required. These might be seafloor still images interpreted with respect to substrate or habitat type or physical samples of the seafloor taken with grab samplers. Collected sediment samples might be analysed for their grain-size distribution and content of benthic species and classified accordingly. The need for samples does mean that the classification process is typically sample-based rather than rule-based. A generic workflow is shown in Figure 1.

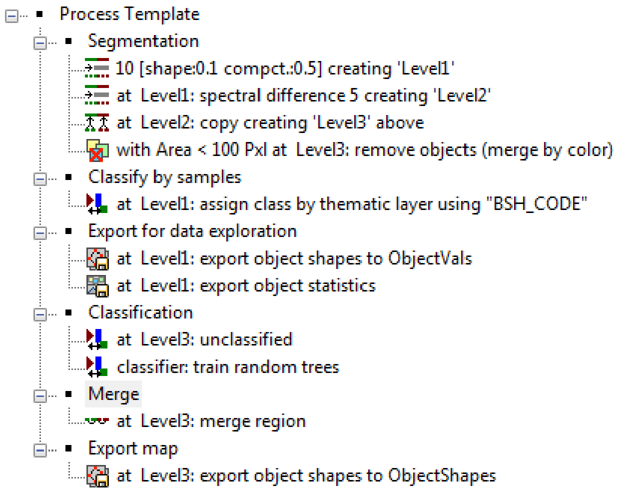

Figure 1. Generic workflow for acoustic seafloor mapping.

2.1 Segmentation

Segmentation is typically carried out with the multiresolution segmentation algorithm utilising suitable image layers. The scale parameter might be estimated via the Estimation of Scale Parameter tool (Drăguţ et al., 2010) or via visual assessment of the segmentation results. Further segmentation steps might include merging of objects with the spectral difference algorithm and removal of small objects of a size below a defined minimum mapping unit.

2.2 Classification by samples

Ground-truth information brought into the project as a thematic layer (shape file) is utilised to classify image objects that coincide with these samples. Image object features that are deemed potentially useful for further classification are then selected and feature values extracted for every classified object.

2.3 Feature selection

We have developed a browser-based tool utilising Shiny, a web application framework for R, to select important and remove correlated features. Feature selection is carried out with the Boruta algorithm (Kursa and Rudnicki, 2010) and correlated features can be identified with a correlation matrix.

2.4 Data exploration/model building

Additionally, the tool allows the user to display the data as box plots and density curves for the selection of suitable thresholds for classification. Alternatively, Conditional Inference (CI) analysis (Hothorn et al., 2006) might be carried out. The resulting decision tree (Figure 2) is easily translatable into an eCognition rule-set.

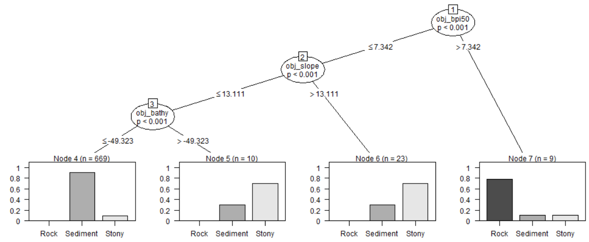

Figure 2. Example of CI decision tree that can be translated into a rule-set.

2.5 Classification

Classification in eCognition might be carried out in three different ways, a) by applying simple rules and thresholds as derived by data exploration, b) by translating the CI decision tree into a rule-set or c) by utilising the implemented machine learning algorithms (e.g. Random Forest, Breiman, 2001). Once acceptable results are achieved, image objects are merged by class and the final results exported as a shape file.

3. DISCUSSION

Automated and repeatable acoustic seafloor classification is still in its infancy, but progress could be accelerated by learning from terrestrial remote sensing (Diesing et al., 2016). The same is true for the application of GEOBIA to acoustic data. It is encouraging to see the increasing amount of studies presented at conferences such as GeoHab (geohab.org). However, more research is needed to fully assess and exploit the true potential of GEOBIA in relation to acoustic seafloor mapping. Only a limited amount of features available for classification is typically utilised. These are most frequently object statistics and to a lesser extent texture and shape features. There has been little usage of object relationships and the concept of hierarchy in landscapes (Burnett and Blaschke, 2003), represented as segmentations at different levels, has hardly been investigated so far.

A limiting factor in acoustic seafloor mapping is the missing spectral resolution of backscatter data, which typically consists of one band. Hence, it is not possible to derive band ratios or exploit spectral signatures. The potential for improved seafloor classification with 3-band acoustic backscatter data has recently been demonstrated (Hughes-Clarke, 2015; Tamsett et al., 2016) and it is hoped that multi-spectral MBES will become the standard in seafloor mapping.

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