ID42 - A SURVEY ON AUTOMATIC HABITAT MAPPING

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Abstract

Habitat mapping can help assess the health of an ecosystem but the task is not always straightforward as, depending on the environment to be mapped, data types can be very different, such as marine and land habitats where in one case you can use sonar images and in the other satellite pictures. In this survey we explore works that used machine learning models when performing habitat mapping.

Keywords – Machine Learning, Habitat Mapping, European Nature Information System.

I. INTRODUCTION

Habitats and biological communities all over the world are being exposed to high risks of extinction because of climate changes, contamination, intrusive species or over-abuse [1]. Habitat mapping can, this way, give a superior comprehension of the outcomes of human activities and decisions to help overseeing biological communities with the end goal of safeguarding them [2].

Mapping habitats in big areas can be a time-consuming task as areas can span very wide throughout land or marine areas. The mapping should be done in accordance with a biological or geographical criterion, such as the European Nature Information System (EUNIS), to provide habitat information of the local area.

Marine habitats struggle with the fact that light does not travel through deep seabed floors. In that case, sonar images have better quality than optic images although they are difficult to analyse by humans. Location accuracy is also a concern when retrieving data from underwater environments.

In the following sections we describe habitat mapping applications using ML models.

II. MACHINE LEARNING MODELS FOR HABITAT MAPPING

Machine Learning (ML) is currently used for decisions simulation, image surveillance, forecast and diagnosis predictions, marketing and sales, manufacturing processes and so on [3]. All these applications have tremendous amount of data to analyse allowing for ML models to be a good option to automatize problem solving.

ML models such as Decision Trees (DTs), Support Vector Machines (SVMs), Random Forest (RF), Maximum Likelihood Classifiers (MLCs), Artificial Neural Networks (ANNs) or Convolutional Neural Networks (CNNs) have been used throughout the years to solve decision making problems.

Numerous works (see Table 1) pursued this objective by trying different ML models to perform habitat mapping, such as Kobler et al. [4] who used a DT model to classify forest habitats with EUNIS by using IKONOS satellite images. Ierodiaconou et al. [5] and Hasan et al. [6] used multibeam data to perform marine habitat using DT, SVM, RF and MLC. Petropoulos et al. [7] used Hyperion hyperspectral data to perform land habitat mapping and comparing the classifications of an SVM and an ANN. Mascaro et al. [8] and Diesing et al. [9] both use a RF model although for different habitat and data types whereas the first perform forest mapping with aerial images and the latter used multibeam data to perform marine habitat mapping. For last, the works of Berthold et al. [10], Gómez-Ríos et al. [11] and Diegues et al. [12] use a CNN model to perform marine habitat mapping. Berthold et al. [10] classified seabed sediment by retrieving sidescan sonar imagery. Gómez-Ríos et al. [11] performs coral classification. Diegues et al. [12] predicted EUNIS habitat types by using a pre-trained CNN and fine-tuning the model using data augmentation.

III. CONCLUSIONS

In this survey we tackled the problem that habitat mapping solves and described some challenges that the task may present. We also presented works that mapped either land, forest and marine habitats by using different data types, such as sonar, satellite or camera images and used different ML models.

Mapping big areas can be challenging but using an automatic approach with a ML model can help with the task. The approaches presented benefit from ML models since the 2000s where DTs were used. SVMs, RF or the most recent Deep Learning (DL) approaches (ANNs and CNNs) are still being used to solve this application with CNN models starting to become a tendency as it is a trending topic in image classification.

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Author	Year	Habitat Type	Data Type	ML Model
Kobler et al. [4]	2006	Forest	Satellite	DT
Ierodiaconou et al. [5]	2007	Marine	Multibeam	DT
Hasan et al. [6]	2012	Marine	Multibeam	DT, SVM, RF and MLC
Petropoulos et al. [7]	2012	Land	Hyperion Hyperspectral	SVM and ANN
Mascaro et al. [8]	2014	Forest	Aerial	RF
Diesing et al. [9]	2014	Marine	Multibeam	RF
Berthold et al. [10]	2017	Marine	Sidescan Sonar	CNN
Gómez-Ríos et al. [11]	2018	Marine	Camera footage	CNN
Diegues et al. [12]	2018	Marine	Camera footage	CNN

Table 1. Examples of related work of habitat mapping using machine learning.

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ID43 - TOOLS FOR DEEP-SEA NAVIGATION

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Abstract

The SIDENAV and DEEPFLOAT innitiatives aims to develop a demonstrator that validates and apply technology that enables golds between the exploitation of mineral resources in deep-sea waters under Portuguese jurisdiction (for example the Mid-Atlantic Ridge).

The Portuguese Sea is characterized by a high depth, and many natural resources are at depths greater. This makes it difficult or even hinders its exploitation through either autonomous or even through tele-operated systems use. Sustainable industrial exploitation of these marine resources require the ability to have deep sea to surface transport systems with high accuracy navigation capabilities at sustainable costs.

Underwater operations are carried out by dedicated systems and for the most part with the use of ROVs (remotely operated vehicles) and AUV's (autonomous underwater vehicles) operated from a ship or a land base station. These systems are used in a wide variety of tasks, such as, installation of equipment and maintenance in the offshore industry O&G (Oil and Gas), in the inspection of pipelines, underwater data lines, underwater observatories, power generation systems, underwater mining, as well as, the collection of information for a wide range of activities with great economic value.

The movement in the water column, descent and ascent, are typically performed by buoyancy control or by conventional underwater thrusters (electric motors with propellers) using the localized movements/behaviours (such as hovering and faster manoeuvres) when necessary. The payload capacity requirements and task performance without the need for outside intervention, low power consumption and the high depth are very demanding. Based on the problem presented in the preceding paragraphs, the primary goal of the project is to develop hybrid variable ballast systems. In order to extend the range of possible operations to be held in high external pressure environments, reducing energy consumption by maximizing payload capacity and fine control in confined environments such as mining in mines with high groundwater levels (typically submerged operation). This type of system can be used in various types of underwater vehicles (AUV's, Landers or ROV's) or for the transport of materials or tools in the open sea or other freshwater environments. The proposed concept in this project consists of a flexible variable ballast system for deep underwater applications with advanced control capabilities. This system consists of a component that allows varying the buoyancy of a wide range of vehicles and systems for operation in the ocean environment, at different depths up to 1000m. Allows variation of buoyancy, for vehicles buoyancy trimming systems, or to change of direction of the vehicle with changes in buoyancy, and, more significantly to perform the ascend/descent motion control in the water column in an efficiently manner.

Figure 1 – TURTLE Hybrid Lander