AUV Adaptive Sampling Methods

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Contributor: Jimin Hwang , Neil Bose , Shuangshuang Fan

Autonomous underwater vehicles (AUVs) are unmanned marine robots that have been used for a broad range of oceanographic missions. They are programmed to perform at various levels of autonomy, including autonomous behaviours and intelligent behaviours. Adaptive sampling is one class of intelligent behaviour that allows the vehicle to autonomously make decisions during a mission in response to environment changes and vehicle state changes. Having a closed-loop control architecture, an AUV can perceive the environment, interpret the data and take follow-up measures. Thus, the mission plan can be modified, sampling criteria can be adjusted, and target features can be traced.

autonomous underwater vehicle(s) maritime robotics adaptive sampling

underwater feature tracking in-situ sensors sensor fusion

1. Introduction

Autonomous underwater vehicles (AUVs) are unmanned marine robots. Owing to their mobility and increased ability to accommodate sensors, they have been used for a broad range of oceanographic missions, such as surveying underwater plumes and other phenomena, collecting bathymetric data and tracking oceanographic dynamic features. As the name suggests, autonomous behaviours [1] are one of their capabilities. Although defining autonomy in robotics can be ambiguous and the minimum level of autonomy depends on context, this paper is only concerned with decision autonomy [2] of unmanned robots. Seto [1] discriminated between autonomous behaviour and intelligent behaviour. The former is a collection of actions for known situations in which the robot is not allowed to adapt its tasks in situ. The latter, on the other hand, is the capability that the robot can adapt and complete its mission by reacting to unforeseen events. Intelligent behaviours of an AUV require a high level of autonomy. They include the ability to make decisions, interpret in-situ sensor data, diagnose the problems, make inference from data, suggest solutions and adapt the planned mission.

Demand for a high level of autonomy is increasing as the application of underwater robotics has expanded. Depending on the dynamics of a feature, different strategies and sampling methods may apply. Some ocean features evolve highly dynamically over time, some others relatively less so. If the spatial and temporal scales are known, the primary perspective of sampling will be how to adjust sampling distribution for measurements in accordance with the local variance. Scales also determine the number of survey agents that need to be involved. The mesoscale oceanographic features (in the order of 10 km) may require the coordinated effort of a fleet of platforms rather than a single vehicle, in order to obtain a more synoptic and cohesive data set [3].

2. Process of Adaptive Sampling

An AUV is normally fitted with sensors in order to undertake a mission. After sensor measurements are collected, they are analysed and interpreted into meaningful data. In an adaptive mission and based on the analysed data, an existing mission plan may be modified or renewed to optimise the AUV path for subsequent measurements.

One example of an adaptive sampling procedure may include: (1) investigate an initial set of sparse observations, which leads to the question of where to take the next measurements, and (2) revisit and conduct a finer scale survey. The underlying autonomous structure of the procedure requires three basic segments: sensing, diagnosis and adaptation. They resemble the cognition process of many biophysical entities. These steps are recursively executed in a closed loop process as shown in Figure 1. In the perceptive phase, the collected measurements are interpreted into meaningful data, while conforming to the current mission plan. Then, in the behavioural phase, details of the mission plan are updated to suit the mission goal/s. A description of each step is given below.

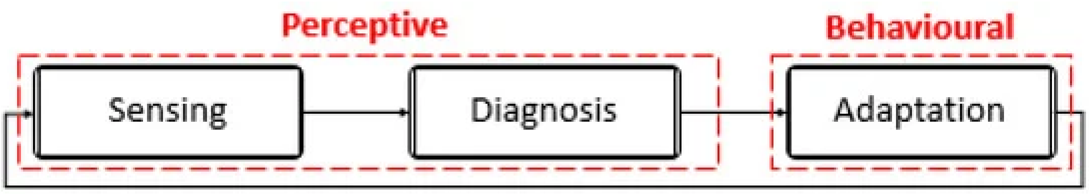

Figure 1. A closed-loop process of adaptive sampling consisting of three segments: perception, diagnosis and adaptation.

3. Target of Interest

Targeted marine phenomena or features can be categorised into physical, biological or chemical parameters depending on the measurable proxies and their inherent characteristics, respectively. Each target may take and evolve into a different form featuring different physical, biological and chemical properties in water. In accordance with their properties and dynamics, the sampling strategy may vary.

3.1. Physical Features

Three typical physical features in oceanographic research are introduced here: thermoclines, upwelling and internal waves. A thermocline is a thermally stratified body of water in which the vertical temperature changes significantly with depth [4]. Upwelling is an ocean process near coastal regions caused by a combination of wind and Ekman transport, which brings a cold deep-water mass upward while displacing the surface water in an offshore direction [5]. Internal waves at an internal interface (usually a density difference) are generated by a deep-sea earthquake or when a tidal wave meets a major obstacle, such as an ocean ridges or underwater mountains. As internal waves transport heat and nutrient-rich water upward into the surface layer, they are frequently observed in regions where a strong thermocline is present by Petillo [6]. An upwelling front can be sensed by encountering a region of vertical homogeneity of temperature, salinity and density in an otherwise stratified water column. Thus, temperature is a good indicator to sense the above physical phenomena in the ocean.

3.2. Biological Features

Phytoplankton biomass, as the foundation of the aquatic food pyramid, is a classic example of a biological feature that has been targeted in oceanographic research using an AUV. It plays an important role in marine ecology and the ocean carbon cycle. Driving rapid CO_2 sequestration, it generates harmful conditions for other organisms in the form of harmful algal bloom [7]. This biological feature is distinctive from other physical or chemical features (hydrothermal vents or oil plumes) in that it does not have a single source location to feed the bloom. Rather, it is driven by the essential ingredients for survival or growth, such as the amount of nutrients or light intensity. There is a zone where a good balance between light and nutrients provides a favourable habitat, such as in a thermocline region [8]. This can be the key proxy to search for a phytoplankton bloom. These blooms can be attributed to upwelling leading to nutrient flux [9], propagating internal waves by pressure and density gradients [10] and anthropogenic events [11][12].

3.3. Chemical Features

Chemical feature detection and tracking is another application of adaptive sampling using AUVs. Three distinctive chemical features have been the typical subjects: hydrothermal vents, chemical plumes and oil plumes. Hydrothermal vent plumes often form chimney-shaped structures at their point of exit from the seafloor. The temperature of the seawater as it exits the chimney structures can reach up to 450 °C. They are formed as freezing seawater percolates down through fissures in the ocean floor in the abyssal zone (deep ocean layer below 3000 m), gets heated, then conveys and dissolves minerals and metals from the rocks nearby [13] and is driven up out of the seafloor, forming the chimney-like structure made up of the dissolved minerals and metals. The term chemical plumes in this paper refers to any unnatural plume consisting chemical components derived from anthropogenic activities, such as the produced water plumes during the process of oil drilling and extraction and the wastewater from plant sites. Hydrocarbon (oil) plumes range from natural seeps to accidental oil spills at various scales.

Due to the unnatural or undesirable nature of chemical entities in the marine environment, the primary interest of AUV deployments generally tends to be looking for the feeding source or delineating the spatial extent of the chemical plume. It is useful to comprehend the characteristics and differences of each plume to effectively design an adaptive sampling strategy. Unlike biological features, chemical plumes are less likely to correlate with the physical properties of the surrounding water. Therefore, a particular chemical element itself is usually used as a proxy, resulting in the need for direct chemical sensors.

4. Mission Objectives of Sampling

Depending on the ultimate objective of each AUV mission, the principal approach in choosing a sampling method varies. For example, when the target is a dynamically dispersing plume, the primary objective is either searching for the source location [14][15] or sensing the highest concentrated peak [16][17] or mapping the two-dimensional boundary [18][19] or three-dimensional structure [6].

If there is a single source of a phenomenon, the survey strategies are often developed in a way to search for a maximum value: for example, the strongest concentration of chemicals or the highest flow velocity near the hydrothermal vent. The peak values indicate the origin of the phenomenon in many cases. One similar approach to this is a bio-inspired method, similar to that often observed in many insects' pheromone-modulated flight behaviour when looking for food or mating [14][20].

When the mission aims to define the spatial extent of a phenomenon such as a thermocline or upwelling, sampling methods often refer to the sudden rate of change or anomaly across the boundary [21][22][23]. In contrast to this, an isothermal line along the boundary could be sought using a desired threshold [6].

5. Multiple Platforms Networking

When planning any oceanographic mission, there is always a trade-off between the sensing coverage and resolution. They must be sufficiently adjusted and balanced so as to encompass the mission objective. Depending on the spatial and temporal scale, the number of vehicles involved and/or the sensor payloads need to be decided. Multiple vehicles are most likely to be involved, working as a mobile sensor network, when the mission is to monitor or track features with a high temporal variance or a widespread distribution. When a long-term endurance mission to explore a larger area is expected, a fleet of mobile platforms may be adopted to maximise the coverage without losing resolution. Zhang et al. [24] highlighted the importance of relevant spatiotemporal scales on detecting and classifying underwater features using multiple AUVs.

6. Conclusions

The dynamic nature of the global ocean environment, non-holonomic characteristics of current AUVs and limited underwater communications present considerable challenges and restrictions for AUV operations. However, with recent advances in adaptive systems, underwater operations are slowly becoming more autonomous.

The methodologies and approaches are subdivided based on different targets, mission objectives and the number of sampling agents. Development of in-field sensor technology and in-situ sample analysis has allowed the detection of a variety of targets and to perform tasks with numerous mission objectives in the global ocean. Adaptive sampling methodologies have enabled enhanced autonomy in AUV operations. The advances in acoustic communications have allowed more coordinated and cooperative control among multiple vehicles.

Researchers previously used multiple vehicles primarily to obtain simultaneous data at more than one point in an area of interest. Most multiple vehicle work to date has focused on a limited number of vehicles communicating with each other between a virtual body (leader) and follower agents. Their work has mainly focused on the multi-vehicle operation and trajectory design as opposed to the sampling behaviours. There is tremendous promise in operating multiple vehicles, especially once it becomes possible to operate swarms of vehicles obtaining many simultaneous data points. Limitations to date are primarily the limitations in underwater communication.

Most adaptive sampling to date has been based on gradient methods. Problems such as the tracking and delineation of patchy oil plumes and the intermittent release of thermal vents need to be addressed and surveyed by using a new class of methods. The most promising methods for these problems, in some cases proposed and used for chemical plumes that are not continuous, have focussed on bio-mimetic approaches that have modelled bacterium, insect or marine crustacean behaviour. This is expected to be the direction of future adaptive sampling work in this area.

To suit different mission characteristics, different types of search algorithm are valuable. AUV manufacturers producing vehicles for scientific missions are encouraged to provide adaptive mission capability on their vehicles, which might eventually include different search algorithms to tackle different problems of interest to the research community.

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