Engineering Applications of Artificial Intelligence 77 (2019) 46–58

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

# Orienteering-based informative path planning for environmental monitoring

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ARTICLE INFO

*Keywords:*
Informative path planning
Mobile sensors
Active learning
Gaussian process
Orienteering

ABSTRACT

The use of robotic mobile sensors for environmental monitoring applications has gained increasing attention in recent years. In this context, a common application is to determine the region of space where the analyzed phenomena is above or below a given threshold level — this problem is known as *level set estimation*. One example is the analysis of water in a lake, where the operators might want to determine where the dissolved oxygen level is above a critical threshold value. Recent research proposes to model the spatial phenomena of interest using Gaussian Processes, and then use an informative path planning procedure to determine where to gather data. In this paper, in contrast to previous works, we consider the case where a mobile platform with low computational power can continuously acquire measurements with a negligible energy cost. This scenario imposes a change in the perspective, since now efficiency is achieved by reducing the distance traveled by the mobile platform and the computation required by this path selection process. In this paper we propose two active learning algorithms aimed at facing this issue: specifically, (i) SBOLSE casts informative path planning into an orienteering problem and (ii) PULSE that exploits a less accurate but computationally faster path selection procedure. Evaluation of our algorithms, both on a real world and a synthetic dataset show that our approaches can compute informative paths that achieve a high quality classification, while significantly reducing the travel distance and the computation time.

## 1. Introduction

Environmental monitoring encompasses the analysis and actions required to characterize and monitor the quality of the environment. This includes the collection of information from the environment and the generation of a model that represents the specific phenomena of interest (La and Sheng, 2013; La et al., 2015; Garces and Sbarbaro, 2011). Computational methods are often used to facilitate environmental monitoring, for example Cheng et al. (2003) propose and expert system for the analysis of the water quality in a city. An other example is the monitoring of a body of water (e.g., lakes, rivers, coastal areas and so forth). In this case the analysis focuses on the generation of a model that describes how crucial parameters such as the presence of harmful algal blooms (Muttil and Chau, 2007) or the dissolved oxygen (DO) vary across the environment. Most environmental monitoring applications require the collection of large datasets, frequently in harsh conditions. In recent years the use of unmanned vehicles for monitoring spatial phenomena has gained increasing attention (Cao et al., 2013). The monitoring operation of a lake for example, could be performed through the use of autonomous surface vessels (ASVs), or by a heterogeneous system composed of marine, terrestrial and airborne platforms (Dunbabin and Marques, 2012).

When deploying unmanned vehicles for environmental monitoring, the data collection process must consider limited resources such as time, energy and computation power that constrain the operation range of the platforms. The goal is to use a mobile platform with low on-board computation power, such as the one showed in Fig. 1, to generate an accurate model of the environmental phenomena of interest. In this context (Hollinger and Sukhatme, 2014), it is important to select an informative path for the mobile agents to acquire as much information as possible while reducing the total traveled distance and hence the time and energy required to perform the analysis. As a further issue, autonomous mobile systems are usually equipped with low computational capacity. Therefore, if the path selection procedure is performed on-board during the monitoring operation, it is crucial to reduce as much as possible the computational complexity of the algorithms.

The literature offers different path selection strategies (Singh et al., 2009). Traditional nonadaptive (offline) methods generate the path before any observations are made. In contrast, adaptive (online) methods plan the path based on the previously collected data (Batalin et al., 2004; Rahimi et al., 2004; Singh et al., 2006). These adaptive techniques incrementally generate the model of the environmental phenomena of interest during the data collection phase and focus the information

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https://doi.org/10.1016/j.engappai.2018.09.015
Received 13 October 2017; Received in revised form 14 September 2018; Accepted 19 September 2018
Available online xxxx

**Fig. 1.** Mobile platform that we used: Platypus Lutra equipped with pH, Dissolved oxygen, temperature and electrical conductivity sensors. The computation is on board and performed by an Arduino Due and a smartphone.

collection process on specific regions of the environment where the phenomena exhibits critical values. For example, in a lake such a region could encompass the locations where the water's dissolved oxygen level is considered harmful for the environment. Another example could be the detection of contours of biological or chemical plumes (Pang and Farrell, 2006). From a general perspective, this can be seen as the problem of deciding if a quantity of interest is above or below a pre-specified threshold. This problem is typically referred to as the ''level set estimation problem'' in the literature (Hitz et al., 2014).

Previous work on the level set estimation problem such as the one proposed by Dantu and Sukhatme (2007) focused on a network composed by a combination of static and mobile sensors. In the manuscript of Gotovos et al. (2013) the proposed LSE algorithm uses Gaussian Processes (GPs) to identify sampling points that reduce uncertainty around a given threshold level of the modeled function. Even if the authors obtain a high quality classification with respect to threshold level (above or below) for the regions of the space using a low number of sampled locations, in their contribution the main algorithm does not explicitly take into account the path between the sampling locations. To partially consider this aspect, the authors propose a *batch* variant where a set of new sampling locations is selected in a batch such that it is possible to compute an efficient path between these points.

Hitz et al. (2014) describe a method designed for ASVs equipped with a probe that allows an aquatic sensor to be lowered into the water. Their LSE-DP algorithm, built on the LSE algorithm from Gotovos et al. (2013), uses a dynamic programming approach with a receding horizon to plan a feasible sampling path for the probe within a predefined vertical transect plane.

In a more recent work (Hitz et al., 2017) introduce an evolutionary strategy to optimize a path in continuous space. Specifically, authors parametrize a path as a cardinal B-spline with $n$ control points and propose a re-planning scheme to adapt the planned paths according to the measurements obtained from the environment.

This paper is inserted in the aforementioned scenario, and aims at facing the problem of level set estimation by using Active Learning (AL) techniques with sequential measurements. In a general discussion on active learning Liu et al. (2009) present the use of active learning techniques on spatial data where the cost is proportional to the distance traveled, ignoring the intermediate points along the path. In contrast, we have an additional objective, where we aim also at determining efficient paths for mobile sensors (instead of determining single sampling locations) so to optimize the data collection process. Specifically our techniques are motivated by the recent development of low-cost, small mobile platforms that can perform continuous-sampling in various body of waters (lakes, rivers and coastal areas). For example, consider the autonomous surface vessel shown in Fig. 1. This platform is small (about 1 meter long and 50 cm wide) and it is equipped with various probes that can measure parameters such as pH, dissolved oxygen, temperature, and electrical conductivity with sampling rate between 1 and 10 Hz. In this setting the cost in terms of energy to perform a single measurement is negligible, and the most crucial issue for the data collection process is the energy consumed to move the vessel. In fact, to meet the payload constraint of this platform, batteries must have a limited capacity that results in constraints on total path length. As a further constraint, we also want to take into account the low computational power of the hardware of this platform (composed of an Arduino Due board and an Android smartphone), which motivates the derivation of algorithms with reduced computational complexity.

We introduce a novel algorithm (SBOLSE) that makes use of an orienteering problem formulation for the level set estimation. SBOLSE aims to obtain a high quality classification of the analyzed regions while optimizing the total path length required by the mobile agent, rather than the number of samples extracted during the executions (which is an important criteria for previous works in the LSE domain). Moreover, to match the low computation power of mobile platforms, we introduce the use of several heuristics which significantly reduces the time required by the algorithm for the selection of an informative path. Finally, we also introduce a novel greedy path selection procedure (PULSE) which represents a baseline greedy strategy for comparisons.

Specifically, the main contributions[1] of this paper to the state of the art are:

- We propose a novel algorithm called SBOLSE, that uses an orienteering formulation to solve the level set estimation problem. The algorithm is specifically designed for continuous-sampling mobile sensors.
- We propose four different heuristics with the aim to reduce the computation time required to determine an efficient path with the SBOLSE algorithm.
- We propose a novel greedy algorithm called PULSE for selecting measurement paths that exploits a less accurate but computationally faster path selection procedure. PULSE only accounts for the presence of information, not the magnitude of information gain. It is used as a baseline strategy for comparisons in the continuous-sampling setting.
- We test our algorithms on a real world dataset of water pH level and on synthetic datasets extracted from $CO_2$ maps. We show that our approaches are better in terms of computation time required and path length, while achieving a high quality classification when compared to the state of the art techniques for level set estimation.

Notice that, the SBOLSE algorithm is based on several methodologies derived from different areas of computer science: LSE from information gathering, skeletonization from image processing, orienteering from graph theory and clustering. Our work shows that a clever combination of such methodologies results in an effective approach for addressing level set estimation with continuous measurement sensors.

Although our techniques has been introduced for environmental monitoring operations, they can be generalized to different applications where mobile sensors are used to model the information of the environment. Specifically, applications where a mobile sensors has to take measurements from the environment with a battery constraint and hence it is required to compute an efficient path. Examples can span across different context such as search and rescue operations (Scherer et al., 2015), precision agriculture (Tokekar et al., 2016; Popovic et al., 2016), sea-floor target localization (McMahon et al., 2017) and radio signal source localization (Shahidian and Soltanizadeh, 2016).

## 2. Problem statement and background

### 2.1. Problem statement

Following Gotovos et al. (2013), Bottarelli et al. (2016) and Bottarelli et al. (2017), we formalize the level set estimation as an active learning

[1] Aspects of this work have already been presented in the conference papers (Bottarelli et al., 2016) and (Bottarelli et al., 2017).