Mobile In-Situ Sensor Platforms in Environmental Research and Monitoring

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Abstract. The use of Unmanned Aerial Vehicles and Autonomous Underwater Vehicles as mobile sensor platforms in environmental science is growing. While the vehicles and sensor technology have reached maturity for practical operation, we observe that the potential of artificial intelligence allowing these devices to perform their tasks autonomously is not utilized. We give an overview of current applications of such mobile sensor platforms in the domains oceanography, meteorology and atmospheric dispersion and discuss the approaches for intelligent adaptive sensor movement proposed in research and applied in practice.

Keywords. mobile sensors, sensor movement planning, Unmanned Aerial Vehicles (UAV), Autonomous Underwater Vehicles (AUV)

Introduction

Technological advances of Unmanned Aerial Vehicles (UAV) and Autonomous Underwater Vehicles (AUV) generate new opportunities in environmental research and applications. UAVs and AUVs are increasingly being deployed as sensor platforms in environmental exploration and monitoring, or emergency response. There are growing efforts and investment in unmanned aircraft technology for earth science by European and US national research institutions [13,12]. Unmanned vehicles have the ability to operate in remote areas with limited accessibility by humans, or in hostile and hazardous environments, avoiding direct human intervention and risk to humans. An obvious example is the assessment of pollution from chemicals that are poisonous, odourless and opaque gases, where vision sensors (i.e. remote sensing) are not applicable. This paper will provide an overview of the current use and concepts for use of mobile in-situ sensor platforms in environmental exploration and monitoring. We will discuss examples from the domains oceanography, meteorology and atmospheric dispersion. Our special interest is in concepts and algorithms for intelligent movement strategies for in-situ sensor platforms. This brings us to the fundamental problems of integrating mobile in-situ sensor data into environmental models and using environmental models for efficient use of mobile in-situ sensors, which both constitute research challenges of multi-disciplinary interest to Geographic Information Science .

1. Environmental applications of mobile in-situ sensor platforms

Mobile in-situ sensors are employed in environmental research and monitoring for various tasks. This section will review their current use in the three major application areas oceanography, meteorology and atmospheric dispersion.

1.1. Oceanography

Scientific mapping and survey missions of the deep sea have traditionally been performed by inhabited submersibles, towed vehicles, and tethered remotely operated vehicles (ROVs). These are now being replaced by AUVs due to superior mapping capabilities and improved logistics [30]. These AUVs carry sensors like cameras, sonars, but also in-situ sensors for conductivity, temperature, or chemicals, mass spectrometers or magnetometers. Yoerger et al. deployed an AUV for the exploration of hydrothermal plumes and the discovery of hydrothermal vents [29]. Other applications are estimating the heat flux from vent fields, the exploration of cold seeps or bathymetric and magnetic mapping [30]. AUVs are used in research expeditions under the Arctic ice, where the operation of inhabited submersibles is considered too risky and the ice permits the use of towed or remotely operated vehicles. NASA's Astrobiology Science and Technology for the Exploration of Planets program funded an expedition for the exploration of hydrothermal vent fields in the Arctic in 2007 with the explicit goal of investigating robotic technology to explore Europe's ice-covered ocean [16]. Ramos and Abreu describe AUV surveys of wastewater plumes from coastal sewage discharges [20]. These surveys aim at a better understanding of the dilution processes and predicting environmental impacts. AUVs equipped with mass spectrometers have been used for analysing naturally occurring oil seeps and also for tracking subsurface oil leaks from damaged blow-out preventers. When the blow-out of the Deepwater Horizon offshore oil drilling rig in April 2010 caused the largest oil spill in history, researchers deployed AUVs equipped with mass spectrometers and found a continuous subsurface oil plume of more than 35 kilometers in length [3].

1.2. Meteorology

Unmanned aircraft technology is increasingly employed in meteorological research to complement observations of meteorological towers and radiosondes. The robotic aircraft Aerosonde was first used for meteorological observations in the Arctic in Alaska in 1999 [4]. The Aerosonde is equipped with sensors for relative humidity and air temperature and is continuously improved for operation in Arctic weather conditions. One future goal is to use the Aerosonde in targeted or adaptive observational strategies to provide input to operational numerical weather prediction models. Van den Kroonenberg et al. describe an unmanned aircraft called M^2AV, which is collecting horizontal wind vector data for boundary layer research [25]. The M^2AV is equipped with a five-hole probe for wind measurements and a combined temperature and relative humidity sensor and performed flights in the Weddell Sea of the Antarctic in 2007. Reuder et al. used an unmanned aircraft system equipped with sensors for temperature, humidity and pressure to obtain profiles for atmospheric boundary layer research in 2007 and 2008 in Iceland and Spitsbergen [21]. They also describe a study using a UAV to monitor the horizontal variability of

Figure 1. The Ifgicopter equipped with humidity and temperature sensors.

temperature and humidity fields above different types of agricultural land use. Frew and Argrow propose an unmanned aircraft system to study the process of tornado formation in severe convective storms, which requires in-situ measurements of the thermodynamic and microphysical properties in the rear-flank region of supercell storms [9]. The Ifgicopter project at the Institute for Geoinformatics in Münster uses microcopters for identifying boundary layers near the ground [27]. Figure 1 shows the Ifgicopter equipped with humidity and temperature sensors. The microcopter is also used for research on vertical distributions of methane gases and for locating emitters of methane.

1.3. Atmospheric Dispersion

The deployment of UAVs for surveillance tasks of atmospheric dispersion of gas or particles, i.e. toxic emissions, is well-motivated but compared to applications in meteorology and oceanography it did not mature beyond an experimental stage to this day. UAVs and swarms of UAVs equipped with in-situ sensors are proposed in a number of application scenarios including environmental monitoring and emergency response [2]. Daniel et al. propose a system architecture for a swarm of micro unmanned aerial vehicles for the assessment of contaminants in the air in emergency response called AirShield [5]. The AirShield project is funded by the German Federal Ministry of Education and Research as part of a program for protection systems for security and emergency services. One practical example for a kind of UAV deployed in atmospheric dispersion monitoring is the work of Harrison et al., who equipped a balloon (radiosonde) with charge and aerosol particle sensors to investigate the volcanic ash plume generated by the Eyjafjallajökull in Iceland in April 2010, which prohibited aviation for several days over large parts of Europe [10]. Volcanic ash constitutes a serious threat to aviation and thus is continuously monitored by the nine Volcanic Ash Advisory Centers[1], which have to run their models on the basis of satellite imagery with limited availability due to temporal delay and cloud

[1] http://www.meteo.fr/vaac/eindex.html

coverage. This is one example for an application where quick availability of in-situ data collected by unmanned aircraft systems would be beneficial.

2. Approaches for intelligent sensor movement

An intelligent movement strategy for a mobile sensor is crucial to effectively perform time-critical observation tasks or to account for the dynamics of a phenomenon to be observed, e.g. to track a pollutant plume. Research in statistics and artificial intelligence has brought about various concepts for movement strategies for mobile in-situ sensors. These address different observation goals such as mapping a phenomenon, locating the source of an emission, or delineating an area where measurements exceed some threshold. We will give an overview of approaches for intelligent sensor movement proposed in research, which we divide into biomimetic and model-based approaches, and approaches being applied in practice.

2.1. Biomimetic approaches proposed in research

Different sensor movement strategies for locating sources of gas or odours, which have been developed in robotics, are inspired by nature, e.g. insect orientation. For example Ishida et al. and Li et al. suggest to mimic insect orientation strategies to pheromone with robot platforms [14,17]. Marques et al. discuss odour source localization strategies inspired by male silkworm tracking of female moth pheromone [18]. The main shortcomings of these methods are that they can only deal with odour sources that are not moving and that they require wind information.

2.2. Model-based approaches proposed in research

Several methods utilize a model of the observed phenomenon. This model can be for example a numerical model based on partial differential equations describing a dispersion process. Patan et al. and Song et al. propose methods of optimal sensor motion planning for parameter estimation of distributed systems [19,23]. Walkowski describes a geostatistical approach for sensor network optimization that uses the kriging variance as a measure of the information deficit at a location, i.e. the need for additional measurements [26]. A similar idea can be found in Elston et al., who use the geostatistical concept of the variogram to identify regions of high variability, which they associate with high scientific interest [7]. Heuvelink et al. propose a geostatistical methodology for optimizing the allocation of mobile measurement devices complementing a static radioactivity monitoring network [11]. Spatial simulated annealing is used to optimize the sampling design according to the criterion of minimizing the costs of false classifications into above or below intervention level concentrations. The reference concentration map is based on the outcome of a physical atmospheric dispersion model. These geostatistical approaches address the problem of positioning a mobile sensor within an existing network of mobile sensors and thus are not easily applicable to a scenario with one or only few mobile sensors. Moreover, these methods identify some sensor location within the study area rather than one step of a continuous sensor movement.

Other approaches use qualitative models of the observed phenomenon. Subchan et al. present a method for cooperative path planning of two UAVs to detect and model the shape of a contaminant cloud, which is modelled as a discrete Gaussian shaped plume [24]. The boundary is approximated by connecting the entry and exit points detected by the UAVs with line segments of constant curvature to form splinegons. This method however uses a static model and does not address the temporal dynamics of the contaminant cloud. Brink proposes a concept for spatio-temporal reasoning about a gas plume based on a Gaussian model as a basis for adaptive sensor movement [1]. This approach infers qualitative information about the plume movement and size from the sensor data that is relevant for tracking a moving plume. The main drawback of these qualitative methods is that they yield only imprecise results. However, compared to the methods that use quantitative models, they also require less or less precise information as input.

2.3. Approaches applied in practice

Very few UAV or AUV explorations in environmental science are automated in terms of an intelligent adaptive movement strategy. Yoerger et al. employ a movement strategy for hydrothermal vent discovery and exploration with an AUV that begins with a conventional grid survey and then revisits the locations of clusters of anomalous sensor readings, which are ranked according to their relative value of being revisited [29]. For assessing the extent of the hydrocarbon plume resulting from the Deepwater Horizon oil spill Camilli et al. navigated the AUV in a zig-zag pattern starting from the leak [3].

3. Conclusion

Developing intelligent autonomous mobile sensor platforms poses a couple of open interdisciplinary research questions, among which we identify two important aspects. The first aspect is the integration of geospatial information relevant for the exploration or monitoring task. In the context of monitoring contaminant dispersion using UAVs Daniel et al. point to the need for integration of dynamic and static data, such as safety relevant geodata, e.g. locations of kindergartens, schools, hospitals and retirement homes, and terrain and weather data [5]. This information can be used to increase efficiency of the observation by concentrating the measurements where the data is most urgently needed.

The second aspect is the development of intelligent sensor movement strategies that are able to efficiently collect the data relevant for a specific observation task [8]. This requires the integration of environmental models describing the behaviour of the observed phenomenon, e.g. atmospheric dispersion models, or models describing underlying and related phenomena such as weather nowcasts and forecasts. Daniel et al. suggest real-time dispersion modelling of aerosols and gases as a basis for flight routes of UAVs and using the collected sensor data to enhance the model [5]. This type of high-fidelity models can be too computationally intensive to be included in a real-time path planning loop or there can be too little data to characterize the phenomenon with sufficient accuracy [7]. Frew and Argrow propose the combination of real-time science driven control of unmanned aircraft systems with online modeling and data assimilation using domain-specific reduced order phenomenological models [9]. They envision vehicles that have simple models of atmospheric phenomena onboard that only retain features of the environment necessary for their guidance. Research in Geosensor Networks elaborates on object-based models of dynamic environmental phenomena [6,28,15,22]. Object-based modelling of the observed phenomenon (as for example in [24,1] mentioned in Section 2.2) might be a reasonable approach to meet the requirements of 1) sensor movement planning in real-time and 2) applicability in situation where there is little phenomenological information.

This paper illustrates the state of the art in autonomous mobile in-situ sensor platforms for environmental exploration and monitoring. The presented examples from practice reveal a gap between the advances in vehicle and sensor technology, which is mature to operate in practice, and the development of artificial intelligence, and sensor data integration and modelling, which seems to lag behind. This review suggests, that there is currently no generic method for navigating mobile sensors, which would make use of all potentially available phenomenological and other relevant data and allow to automate an exploration or monitoring task. We think that future research in this area would be of high benefit to various geo-disciplines and is essential to fully exploit the large potential of UAV and AUV technology for environmental sciences.

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