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Value of information and mobility constraints for sampling with mobile sensors

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ABSTRACT

Wireless sensor networks (WSNs) play a vital role in environmental monitoring. Advances in mobile sensors offer new opportunities to improve phenomenon predictions by adapting spatial sampling to local variability. Two issues are relevant: which location should be sampled and which mobile sensor should move to do it? This paper proposes a form of adaptive sampling by mobile sensors according to the expected value of information (EVoI) and mobility constraints. EVoI allows decisions to be made about the location to observe. It minimises the expected costs of wrong predictions about a phenomenon using a spatially aggregated EVoI criterion. Mobility constraints allow decisions to be made about which sensor to move. A cost-distance criterion is used to minimise unwanted effects of sensor mobility on the WSN itself, such as energy depletion. We implemented our approach using a synthetic data set, representing a typical monitoring scenario with heterogeneous mobile sensors. To assess the method, it was compared with a random selection of sample locations. The results demonstrate that EVoI enables selecting the most informative locations, while mobility constraints provide the needed context for sensor selection. This paper therefore provides insights about how sensor mobility can be efficiently managed to improve knowledge about a monitored phenomenon.

1. Introduction

The importance of environmental monitoring has been widely recognised for applications such as mapping of contaminants (Horsburgh et al., 2010; Milton and Steed, 2007), levels of exposure to hazardous substances (Dubois et al., 2011; Melles et al., 2011) and species distribution (Zerger et al., 2010). Rational decisions about natural resource management and emergency responses rely on information gathered by sensors. How these sensors are distributed affects sampling design (de Gruijter et al., 2006) and, as a consequence, decision making. For instance, Heuvelink et al. (2010) illustrated the effect of sensor placement on dose predictions and decision making in a nuclear emergency situation. Erroneous predictions of an absence of radioactivity (false negatives) will lead to warnings not being triggered, whereas wrong predictions of the presence of radioactivity (false positives) will trigger unnecessary actions, such as the evacuation of residents and the deployment of rescue teams. The costs of prediction errors can be minimised by adapting spatial sampling to local variability.

Wireless sensor networks (WSNs) are increasingly used in environmental monitoring. They enable real-time monitoring with spatial and temporal resolutions never captured before (Nittel, 2009; Porter et al., 2009; Rundel et al., 2009; Zerger et al., 2010). WSNs are composed of autonomous and wirelessly networked sensors spatially distributed in a study area (Akyildiz et al., 2002). When using stationary WSNs, spatial sampling can be adapted to local variability by using sleeping and waking up mechanisms (Hefeeda and Bagheri, 2008; Willett et al., 2004). This requires a high sensor density. However, mobile WSNs offer new opportunities to adapt spatial sampling using a reduced number of mobile sensors (Liu et al., 2005; Rundel et al., 2009; Singh et al., 2006). Mobility is achieved by attaching sensors to mobile objects, such as robots (Dantu et al., 2005), people (Campbell et al., 2008), bicycles (Eisenman et al., 2007), vehicles (Zoysa et al., 2007) and animals (Juang et al., 2002; Sahin, 2007). If mobility is controlled, the locations of sensors can be changed to achieve specific goals (Jun et al., 2009), such as adapting sampling to local variability. In the paper, we consider the situation where the monitored phenomenon has a slower temporal rate as compared to the speed at which the sampling is done. More particularly, we assume that reality does not change during sampling. While this may seem a serious restriction, it is quite a common situation for example when assessing soil contamination (Rodriguez-Lado et al., 2008; Romic et al., 2007), natural radioactivity (Heuvelink and Griffith, 2010), and biodiversity (Zerger et al., 2010).

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When sampling with mobile sensors, two decisions have to be made: where the observation should be made, and which sensor should be moved to the location to make the observation. The first decision is to identify a sampling location to optimise a certain objective. The second decision is to choose a sensor to move to the identified location such that sensor mobility is efficiently managed.

Different approaches for deciding where to make the observation have been studied. Coverage-oriented approaches select locations according to geometric criteria, such as Voronoi diagrams and virtual forces (Wang et al., 2009). Information-theoretic approaches (e.g. entropy and mutual information) seek to reduce uncertainty resulting from sensor mobility (Krause et al., 2008). These approaches, however, have limitations. For example, they do not consider the phenomenon under investigation (Krause et al., 2008; Walkowski, 2008), they do not identify misclassification types (false positives and false negatives) and they do not assess locations for their potential to minimise misclassifications (Donaldson-Matasci et al., 2010).

An alternative approach is to use the expected value of information (EVoI). This method evaluates the expected relevance of observations made at certain locations, prior to making the observation (Bhattacharjya et al., 2010; de Bruin et al., 2001; Kangas, 2010). It compares the expected cost of making predictions using the available observations with the cost when an additional observation has been made in a new location. The EVoI is the reduction in the expected cost of prediction errors achieved by making the additional observation. The location of this additional observation can be selected by choosing the location that gives the highest EVoI. EVoI considers the phenomenon state and it allows decisions to be made based on the relevance of locations and different misclassification types. We therefore propose an EVoI maximisation criterion.

When deciding on which sensor to move to the new sample location, intuitively the best sensor would appear to be the closest one. However, constraints on the mobility of a sensor may make moving it costly or even impossible (Ballari et al., 2012; Walkowski, 2008; Younis and Akkaya, 2008). These constraints may be hard or soft constraints. Hard mobility constraints make it impossible for the sensor to be moved: it may itself be immobile or movement may be obstructed by barriers between the current sensor location and that to be sampled. Soft mobility constraints include energy, terrain slope, speed, and sensor connectivity for data transmission. For example, moving up a slope is more costly than travelling downhill. In a previous study, sensors were selected using a weighted-distance approach (Verma et al., 2006). Walkowski (2008) proposed the concepts of time geography to analyse constraints and select sensors within potential activity areas. Zou and Chakrabarty (2007) employed cost evaluation techniques to trade off target tracking improvements against mobility constraints.

Although these studies have integrated and prioritised mobility constraints, none of them have addressed their potential dependent influences. The influences of mobility constraints should not be considered independently of each other and may be dependent on the presence of other constraints. For instance, if sensors are carried by robots, battery status may affect both mobility and sensing capabilities, but if sensors are carried by people, battery status does not constrain mobility. The influence of sensor energy therefore depends on the type of mobile object. These dependencies should be taken into account because they can make influences of mobility constraints stronger, weaker or even inapplicable.

For deciding which sensor to move, we propose a cost-distance minimisation criterion that integrates mobility constraints with dependent influences. The cost-distance to move a sensor under mobility constraints is estimated using influence diagrams (IDs), a useful way to represent and make decisions (Howard and Matheson, 2005; Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2007). Like decision trees, IDs link together the variables of a decision (i.e. factors, costs and decisions). The advantage of IDs over decision trees is that they provide a more compact representation of dependencies and more efficient computation when a high number of constraints are integrated (Varis, 1997).

This paper and the accompanying R script (R Development Core Team, 2010) illustrate a spatial sampling approach for use with mobile sensors that aims to maximise EVoI from new observations and minimise the cost-distance of sensor movement under mobility constraints. In the present study these two objectives are considered in separate steps.

First, we introduce EVoI, the calculation of misclassification costs, and the use of an aggregated EVoI. Then we describe the calculation of the cost-distance for moving a sensor under mobility constraints. A synthetic study case is described in Section 4. Section 5 contains the results and discussions. Finally, conclusions are presented.

2. Related work

There is a substantial body of literature on mobile sensors and location selection. Surveys can be found in Wang et al. (2009, 2012) and Younis and Akkaya (2008). Several studies aim to select sensor locations to optimise network configuration, in terms of data transmission and connectivity (Ekici et al., 2006) or energy conservation (Basagni et al., 2008; Jain et al., 2006; Wang et al., 2010).

On the other hand, coverage-oriented approaches aim to select sensor locations in order to optimise spatial coverage of the study area. The coverage optimisation may be achieved by locating sensors at the centroids of k-means clusters (Walvoort et al., 2010) or by using virtual forces which repel sensors from each other and from obstacles (Howard et al., 2002) or Voronoi diagrams and Delaunay triangulation (Argany et al., 2011). Similarly, in geostatistics the aim of sampling often is to minimise the (mean) kriging error variance (Brus and Heuvelink, 2007; Walkowski, 2008). The drawback of the above methods is that spatial sampling is adapted according to geometric criteria while it is not affected by characteristics of the monitored phenomenon.

Other approaches rely on ancillary data or covariates, such as digital elevation models, aerial or satellite imagery, and climate information, which are assumed to be correlated with the phenomenon of interest. For example, Minasny et al. (2007) used a quadtree method with secondary data to sparsely sampling in relatively uniform areas and more intensively where covariate variation is large. Minasny and McBratney (2006) used a Latin hypercube method to select locations that provide a full coverage of the range of each secondary variable. Brus and Heuvelink (2007) minimised the spatial average of the universal kriging variance to obtain the right balance between sparsing sensors in geographic and feature spaces.The applicability of these approaches, however, is restricted to the availability of ancillary data. For instance, they might not be available for the whole study area or with the required resolution, or they might be expensive to acquire.

Information-theoretic approaches employ entropy and mutual information to improve information quality by reducing uncertainty about the true state of the phenomenon (Krause et al., 2008). These measures, however, do not depend on how data about the state of the phenomenon is used in decision making (Donaldson-Matasci et al., 2010). They are measures of information quality, but they do not reflect the quality of the decision that will be made with sensor observations. In contrast, based on decision theory, our method considers both the network configuration and the information obtained from sensor observations.