Gaussian Process Based Spatial Inference of Environmental Properties with Noisy Location Data

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Introduction

Building a map of some environment property, such as humidity and temperature, has many real-life applications. For example, operators of underground mining sites would like to monitor the concentration of toxic gases to guarantee their workers are not exposed to hazards; house owners want to estimate the temperature distribution over their properties to manage energy consumption efficiently. The challenge of such mapping tasks lies in the inaccurate location information of the sensor data collected.

In our work, we introduce Gaussian Process (GP) based approach to tackling problems caused by inaccurate location information. Our contributions are:

- A novel algorithm is proposed to build a map based on sensor data with inaccurate location information.
- Location accuracy in the sensor data is inferred per trajectory. Thus, trajectories with large drift and distortion can be identified.
- Uncertainty of the mapping is obtained by considering noise in the sensor measurements, as well as inaccuracy in location.

Problem Definition

Data collected from a surveying sensor along a trajectory \( t \in [1, T] \) are denoted as \( d_t = (x_t^1, y_t^1), ..., (x_t^n, y_t^n) \), where parameters \( x \) is location, \( y \) is measurement of an environmental parameter and \( n \) is the number of data points. With sensor data along all \( T \) trajectories, we obtain the training data set \( D = \{d_1, ..., d_T\} \). Our algorithm is designed to predict the values of the environmental parameter \( y^* \) at new locations \( X^* \).

Proposed Algorithm

Sensor Data Collection

Initial GP Regression

Trajectory Classification

Constrained Optimisation

More Accurate Mapping

Figure 2: Our algorithm applies GP regression and constrained optimisation to achieve an accurate mapping of the environment parameters of interest.

Illustrative Example

(a) All trajectories generated

(b) Attachment configuration failure

Figure 3: (a) 5 trajectories are generated by a user. (b) The attachment configuration failure is introduced to one of the trajectories.

Data Generation

Figure 4: (a) QPR with no location errors

(b) QPR with location errors

Figure 5: (a) Differences between the observed function values and the inferred map from the initial GP regression is computed. (b) Trajectories with high values of difference are classified as inaccurate.

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