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 measurement, as well as inaccuracy in location.

Problem Definition

Data collected from a surveying sensor along a trajectory $t \in [1, T]$ are denoted as $\boldsymbol{d}_t = \{(x_1^t, y_1^t), \ldots, (x_{n^t}^t, y_{n^t}^t)\}$, where parameters $\boldsymbol{x}$ is location, $\boldsymbol{y}$ is measurement of an environmental parameter and $\boldsymbol{n^t}$ is the number of data points. With sensor data along all $\boldsymbol{T}$ trajectories, we obtain the training data set $\boldsymbol{D} = \{\boldsymbol{d}_1, \ldots, \boldsymbol{d}_t\}$.
Our algorithm is designed to predict the values of the environmental parameter $\boldsymbol{Y^*}$ at new locations $\boldsymbol{X^*}$.

Location Errors in Sensor Data

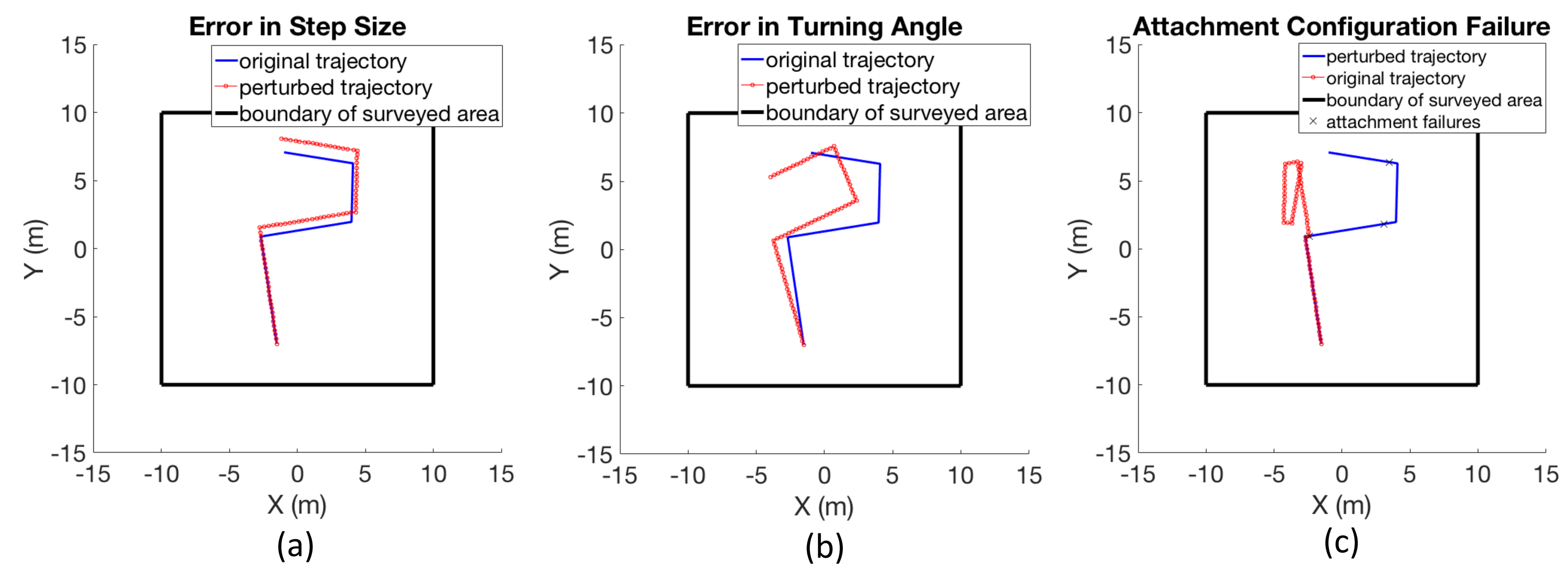


Figure 1: Location errors considered

Three types of location errors are considered, as shown in the above figure. (a) Failure in estimating a mobile sensor's step size leads to drift over time. (b) Inaccuracy in executing a turn precisely results in rotational deformation. (c) Change of a sensor attachment often introduces a sudden heading change.

Proposed Algorithm

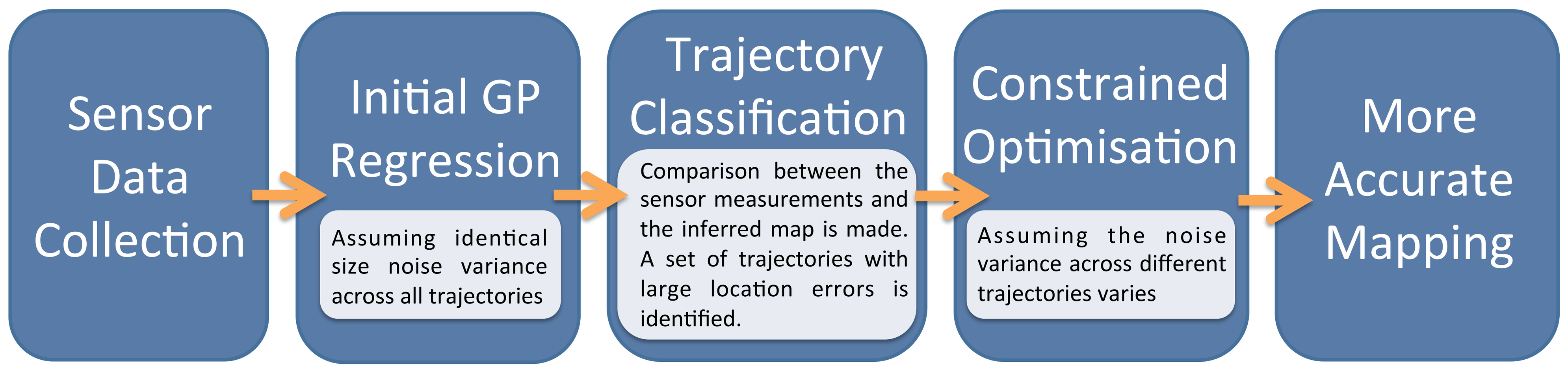
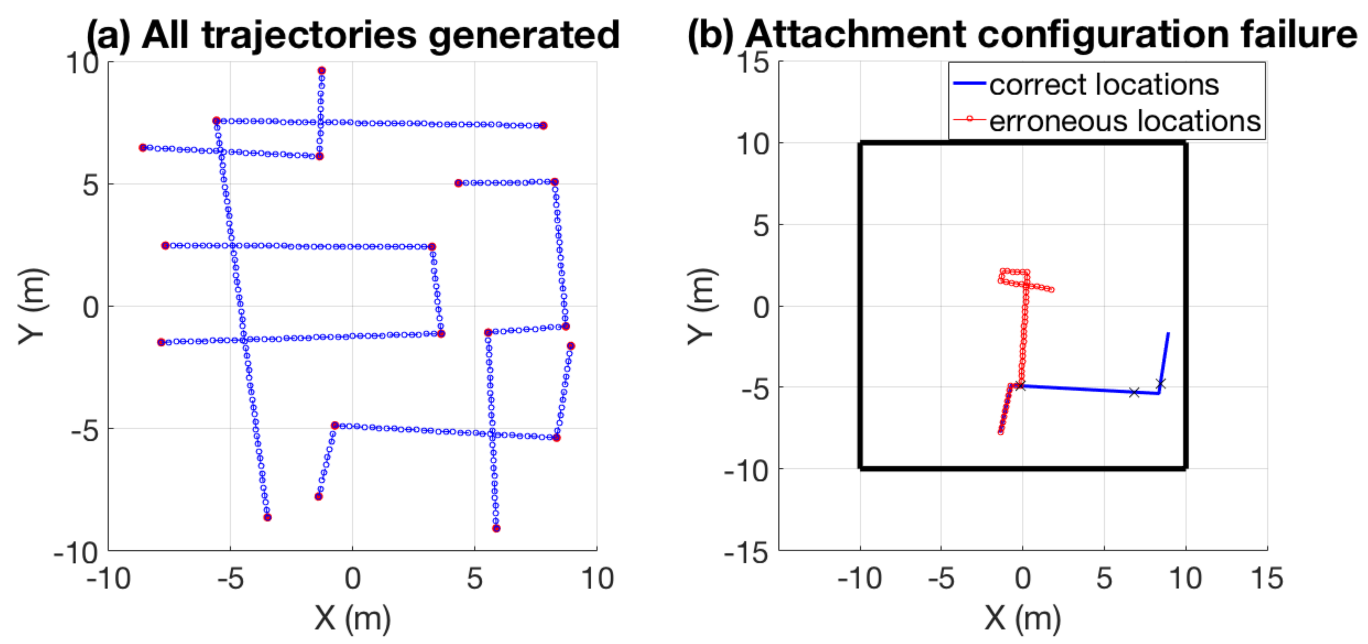


Figure 2: Our algorithm applies GP regression and constrained optimisation to achieve an accurate mapping of the environment parameters of interest.

Illustrative Example



Data Generation

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

Initial GP Regression

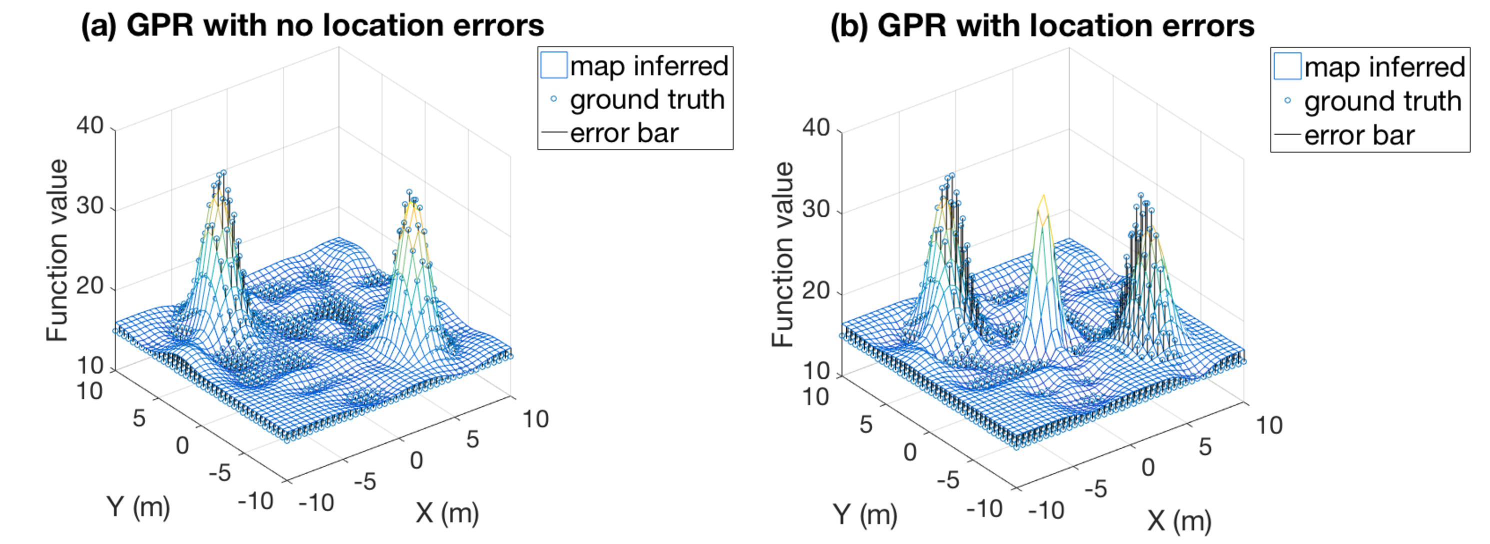


Figure 4: (a) shows the map generated by GP regression if all trajectories are accurate. This can be considered as the best mapping result we can achieve. (b) illustrates a fake peak (middle) is generated by applying standard GP regression directly to the sensor data with inaccurate location information.

Trajectory Classification

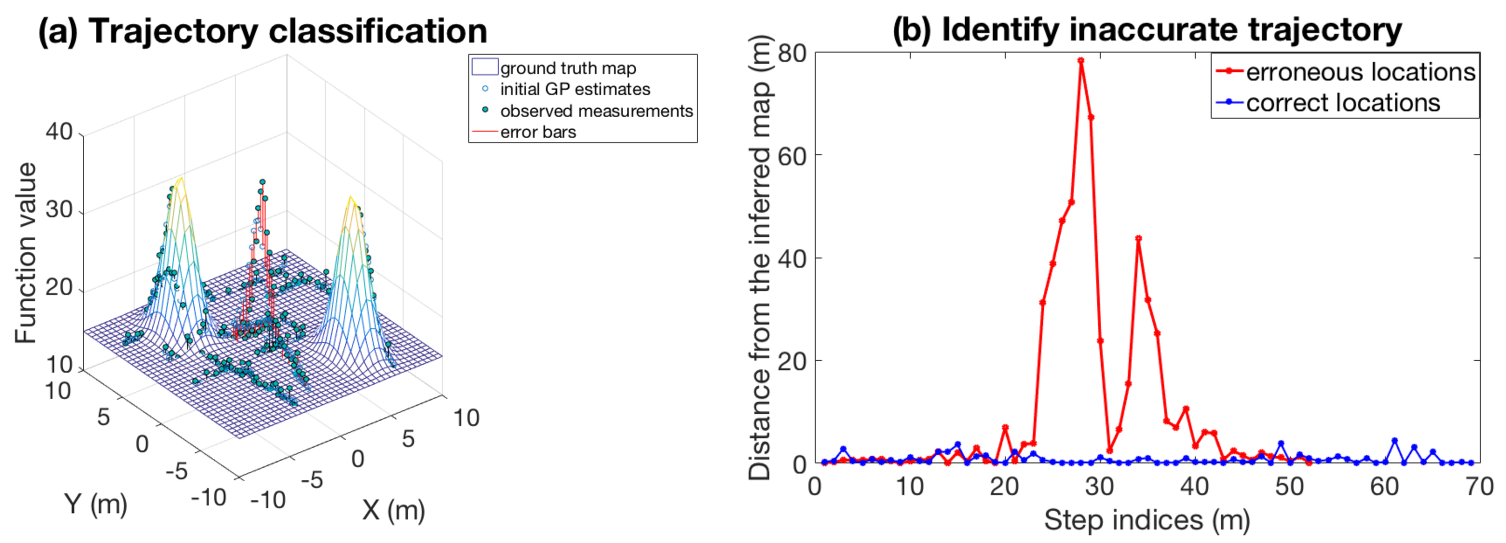


Figure 5: (a) Differences between the observed function values and the inferred map from the initial GP regression is computed. (b) Trajectories with high values of difference are classified as inaccurate.

Constrained Optimisation

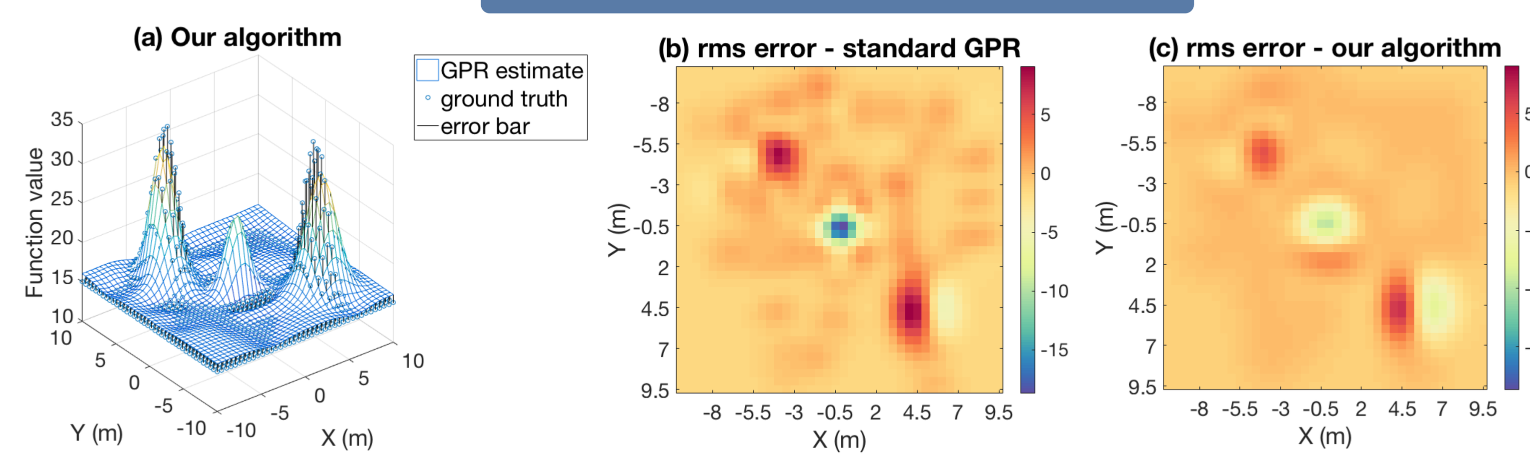


Figure 6: (a) Our algorithm successfully identifies the fake peak and manages to shrink its size. (b) Standard GP regression infers noisy estimates in the middle of the map. (c) In the proposed robust GP regression, the overall root mean squared (rms) errors are reduced.

Contact Information

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