Modeling and Decision Making in Spatio-Temporal Processes for Environmental Surveillance

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I. Motivation and Methodology

A broad class of environmental monitoring applications, including meteorology and climatology, epidemiology, ecology, demography, forestry, fishery and others, require distributed sensing capabilities [1] due to the dynamics exhibited in both space and time. Understanding and modeling such complex space time dynamics with only static sensors would require an impractically large number of sensors to be distributed across the complete spatial extent of the observed environment. Mobile robots equipped with sensors offer an alternative to a network of static sensing elements for high spatial coverage but at the cost of increased delay (sampling latency). Several path planning approaches have been proposed in the literature to adaptively sample the environment to reduce the latency while still providing high fidelity sampling [2]–[5].

At the core of each path planning approach is a model representing the space-time dependencies. Learning such complex and non-deterministic spatio-temporal dynamics, for accurate predictions, is challenging. A typical modeling procedure adopted in the field of environmental science is to manually specify partial differential equations governing the behavior of the observed phenomena [6]. This, however, relies on experts and usually requires time consuming validation experiments [7].

In this work we consider a machine learning approach to the problem where a spatio-temporal Gaussian process model is learned through an optimization procedure. The model is then used for path planning. We propose a path planning method in continuous domain that can exploit the Gaussian Process based modeling to guide informative sensing. Our proposed greedy path planning algorithm uses *information gain* as the objective function. We assume that $X_t = (\mathbf{s}_1; t_1), \ldots, (\mathbf{s}_N; t_N)$ be the training set of N observation locations, available to learn the hyper-parameters of the covariance function. With the learned hyper-parameters, the trained model is used for testing on the spatio-temporal dataset. We define a timestep to be an instance of the environment during which the observed phenomena is assumed to be static.

A major difficulty for modeling spatio-temporal stochastic processes with GPs is the definition of a valid covariance function that can accurately account for space-time dependencies. We study a generic approach for creating several classes of valid non-stationary, spatio-temporal GP models. After learning the parameters associated with the corresponding covariance model, path planning is performed in continuous domain, incrementally adding new data points to the model. We present extensive empirical evaluation comparing several classes of GP models using different real world sensing datasets. We validate the proposed methodology of model learning and path planning using a Networked Info Mechanical System (NIMS, a tethered robotic system). A detailed presentation of this study was published in the proceedings of ICRA 2010.

II. Experiments

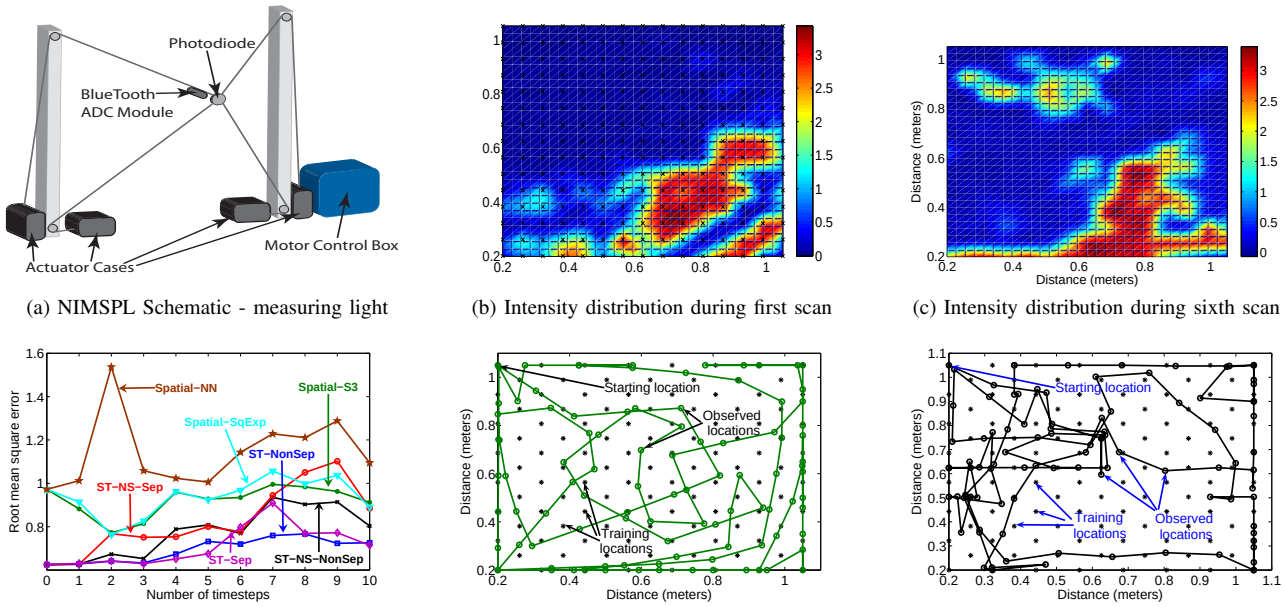
Prediction using Gaussian Process depends on effective modeling of the covariance structure for the phenomena of interest. In this work, we compare the following covariance functions:

1) Stationary spatial covariance functions, (*Spatial-SqExp*) and (*Spatial-S3*).
2) Non-stationary spatial covariance function (*Spatial-NN*).
3) Stationary, non-separable, spatio-temporal covariance function (*ST-NonSep*).
4) Stationary, separable, spatio-temporal covariance function (*ST-Sep*).
5) Non-stationary, non-separable, spatio-temporal covariance function (*ST-NS-NonSep*).
6) Non-stationary, separable, spatio-temporal covariance function (*ST-NS-Sep*).

Experiments were conducted on an actual robotic system for a critical application of monitoring light intensity in the forest understory. Networked InfoMechanical System for Planar actuation (NIMS-PL), a four cable based robotic system, was used for performing the system experiments [11]. NIMS-PL consists of four tension controlled cables capable of actuating a generic sensor to provide planar spatial coverage. A schematic of NIMS-PL system actuating a light sensor in a vertical plane is shown in Fig. (1a).

A key challenge in understanding the CO_2 sink (or the photosynthetic rate) of plants in the understory is to characterize the dynamic light intensity patterns that exist in that environment. We used our study of spatio-temporal covariance functions to analyze the effectiveness of modeling light intensity as Gaussian Processes with spatio-temporal covariance functions.

A series of 10 images were collected to capture the light distribution under a tree canopy in San Jacinto mountains reserve (Southern California) [13] using a downlooking camera. These images were captured approximately every 10 minutes from circa 8:40 am to 10:10 am. Then, we projected these images onto a screen to be sampled using a light sensor



(a) NIMSPL Schematic - measuring light

(b) Intensity distribution during first scan

(c) Intensity distribution during sixth scan

(d) Performance comparison

(e) Selected path for *Spatial-S3*

(f) Selected path for *ST-NS-NonSep*

Fig. 1: Results from system experiments - measuring light intensity using NIMSPL.

attached to NIMS-PL. There is an ongoing work in correlating light intensity data collected using such approaches with photosynthetically active radiation that is important for understanding the photosynthetic rate. We collected light intensity data at a uniform grid of 15x15 for each projected image. The data is transmitted over bluetooth to the motor controller, to synchronize the sensor location and sensor data.

Fig. (1b) and Fig. (1c) illustrate the interpolated intensity data, at each of the 225 locations, collected using NIMSPL during first and sixth scan respectively. All the observed locations are also marked in Fig. (1b). As illustrated by the two intensity distribution plots (corresponding to light intensity distribution as captured after a separation of 50 minutes), the phenomena displays considerable dynamics and hence it is of potential interest to quantify the effectiveness of spatio-temporal covariance functions in Gaussian Process regression.

We used a subset of 112 of these 225 locations to learn the hyper-parameters of the covariance functions. These 112 locations are marked in Fig. (1e). In this case, observations were allowed to be obtained anywhere in the continuous domain and were not constrained to grid locations. Since the path planning algorithm is optimizing a non-convex optimization problem, if it is not able to find an appropriate next location to observe, we move it to the nearest unobserved location from the 225 grid locations. The path planning algorithm was allowed to observe a maximum of 10 locations for each timestep (making a total of 100 observations for 10 timesteps).

Fig. (1d) compares the root mean square error (Y-axis) for each covariance function for the corresponding timestep (X-axis). The spatio-temporal covariance functions - *ST-Sep, ST-NonSep, ST-NS-Sep, ST-NS-NonSep* provide better prediction accuracy compared to spatial covariance functions - *Spatial-S3, Spatial-SqExp, Spatial-NN*. Within the spatio-temporal covariance functions, the stationary non-separable covariance function (*ST-NonSep*) provides the best performance.

Fig. (1e) and Fig. (1f) display the path selected for *Spatial-S3* and *ST-NS-NonSep* covariance functions respectively. With *ST-NonSep* covariance function learning the time correlations, more number of observations are made in the region with high variance (light spots arriving for a short duration during the complete time duration represented by the upper left corner as illustrated in Fig. (1c)). The simple spatial covariance function, *Spatial-S3*, makes uniform observations across the complete area. Further, both the paths tend to take a significant number of observations along the edge. Since we used the actual light sensor to measure the intensity of the projected image, the locations along the edge had significant noise from the ambient light. Large noise, increase the entropy of such locations along the edge and hence the increase in the corresponding reward achieved by visiting such locations (by minimizing the overall entropy.

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