Proceedings of the SICE Annual Conference 2017
September 19-22, 2017, Kanazawa University, Kanazawa, Japan

Map-Reduce Gaussian Process (MR-GP) for Multi-UAV based Environment Monitoring with Limited Battery

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Abstract: Environment monitoring is a challenging task owing to its ever changing dynamics. Furthermore, deploying a team of resource constrained robots to persistently monitor the environment encompasses intelligently selecting the training samples which are spread across a significantly large area to conservatively spend the resources allocated. In order to accomplish this using a team of fully autonomous self-reliant robots, we pose this problem as a map-reduce architecture: *Map* phase involves each individual member gathering its training samples and generating the best possible model of the environment followed by the *Reduce* phase where we merge all these models into a single globally consistent model to infer the environment dynamics. Our preliminary contributions to both these phases have shown significant ease to parallelize the process of gathering training samples whilst reducing the over-all model uncertainty. We demonstrated these results in a communication devoid simulated environment using publicly available datasets.

Keywords: Autonomous Decentralized Systems , Intelligent Systems , Computational Intelligence

1. INTRODUCTION

In recent times, the domain of *robotics* and *machine learning* have evolved significantly, thereby allowing us to develop intelligent and autonomous robots. Robots have shown to be useful in battlefields [1], assembly lines [2], environment monitoring [3] and a plethora of such application. Amidst these, our main focus will be environment monitoring since the growing environmental pollution is an alarming concern and must be paid heed to.

Environment monitoring in itself is a conglomeration of several robotics (wide-area coverage, path planning) and machine learning (big data processing, inference, modeling) problems and still has a lot of scope for improvements. An example situation could be to monitor the aquatic pollution levels of a reservoir, the water from which is then used for agricultural purposes by farmers in surrounding areas. High levels of pollution could infect the crops which in turns populates up the food-chain. Measurement samples could be in terms of measuring harmful chemicals like Mercury, pesticides, etc. Other related application could be in monitoring the pollution caused by motor vehicles on the road or atmospheric pollutants that remain suspended in the air like ozone amongst many others. The aim of this paper is to present a technique generic enough which not only fits any heterogenous team of mobile robots but also is not limited to any specific application. Since most of the environmental phenomenon demonstrate temporally evolving spatial variations thus, developing a precise spatiotemporal model is preliminary challenge which is complicated by the fact that we have to rely on mobile robots which have limited resources (fight time, travel time, travel distance, payload capacity etc.). Thus, our task is two fold: *resource constrained path planning* and *accurate modeling*.

Previously the problem of gathering measurement samples was solved using static sensors [4] but while monitoring spatiotemporal environmental phenomenon the area to be monitored is significantly large and not all locations can be observed at the same time. Since, the dynamics of the field are evolving temporally, we cannot rely on static sensors for long term persistent monitoring. If we had to do this, we would need a significantly large amount of sensors to envelop the entire area [5]. This problem can easily be tackled by robots equipped with appropriate sensors which can autonomously deduce the best locations to observe. Thus, the robot can help gather the training samples but the choice of machine learning model which they are fed too plays a key role in understanding the environment. This is solved using a non-parametric class of Bayesian models called *Gaussian Process* (GP) [6] which elegantly infers the underlying environmental dynamics whilst simultaneously taking into account the prediction uncertainty in inference. Although, these models have proven to be significantly successful in the machine learning literature, when applying them to robotics domain we are faced with a dilemma: these models are highly data driven models and their prediction performance is closely coupled to the size of the training set. However, owing to limited resources allocated, a robot can only gather a handful samples from the field, thus, the model performance can be compromised if the training samples are not chosen wisely.

The main contribution of this paper is to extend the distributed GP [7] framework, such that multiple robots can individually generate models of the environment without having to communicate either with the base station or amongst the team. In doing so, we enforce resource utilization constraints from [8] to ensure conservative resource utilization and then fuse all the indepen-

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dent models into a globally consistent model by pointwise weighted fusion of individual predictions based on the responsibility of each of the experts. We pose this is a fully decentralized exploration with centralized data fusion problem for communication devoid environments. Although, communication between robots can lead to better models but in doing so, the robots would need to take care of network connectivity and message filtering. These have already been considered by researchers in [9, 10] and hence we do not intend on considering such parameters and design our approach for extremely harsh environment settings.

2. RELATED WORK

Existing research in environment monitoring focuses on mainly two areas: *Efficient modeling* of spatiotemporal phenomena and *Informative sensing* for gathering informative samples.

2.1. Spatiotemporal Modeling

Inference and prediction of values in spatiotemporal domain has been studied previously in the machine learning literature and GP regression [6] have been shown to perform significantly well. Their strength is not only the non-parametric nature but also the ability to quantize the uncertainty of model. Some people have studied enhancements of GPs like a linear opinion pool of experts called Mixture of Experts [11] or Kernel DM+V/W algorithms for inferring environment dynamics whilst taking wind disturbances into account which in turn affect the gas distribution [12]. Other researchers tend to focus more on enhancing the kernels. For e.g., in [13], the researchers develop a non-stationary non-separable spacetime covariance kernel since the dynamics in spatial domain and temporal domain may not show similar variations and in [14], the researchers propose area kernels to deal with continuous measurements instead of point measurements.

2.2. Information-theoretic Path Planning

Information-theoretic path planning refers to planning paths such that maximal information about the environment can be acquired during exploration. Thus, people tend to use a chosen measure of information like entropy [4], mutual information gain [15] etc. to drive their path planning strategy. In recent times, researchers have also started to investigate the *Orienteering Problem* [16, 17] in terms of spatially correlated network of nodes like [18] where they use Mixed Integer Quadratic Programming. In [19], the researchers proposed a fully Bayesian framework for allowing the robots to autonomously infer the most important regions to monitor by defining the appropriate acquisition function. In doing so, the researchers can deduce that it is more beneficial to monitor areas of high measurements than areas of more information in most environment monitoring settings.

3. PROBLEM FORMULATION

In this section, we formally define the scenario in which we plan on deploying our robot team and our *Map-Reduce* System.

3.1. Sensing Scenario

Our sensing scenario is shown in Fig. 1: We want to monitor a large scale spatiotemporal environmental phenomenon using a budget constrained team of mobile robots like UAV's which have limited battery life restricting their flight time. The problem then becomes to observe as many informative samples as possible in order to generate the best possible model by the end of the mission time.

3.2. Formal Definition

We wish to model a spatio-temporal environment $\mathbf{z}{=}\mathbf{f}(\mathbf{x}){+}\boldsymbol{\epsilon}$, where $\mathbf{x}{\in}D{\subset}\mathbb{R}^d$ are inputs and $\boldsymbol{\epsilon} \sim \mathcal{N}(0, \boldsymbol{\sigma}_n^2)$ is i.i.d. Gaussian measurement noise. We place a Gaussian process (GP) prior on the spatiotemporal phenomenon f and write $f \sim GP$. We also define $\mathbf{z_x}$; $\forall \mathbf{x}{\in}O$ as the observed measurements and $\mathbf{z_{x^*}}$; $\forall \mathbf{x}^*{\in}U$ as the corresponding predictions at the unobserved locations. Then, $\mathbf{z_{x^*}}$ is a GP, and any of its finite subsets is a multivariate Gaussian distribution [6]. We also define $O \subset D$ as the set of observed inputs and $U \subset D$ as the set of unobserved inputs such that $U \cap O = \emptyset$ and $U \cup O = D$. For $k \in \{1, \dots, K\}$ representing the robot-index, we represent the total number of observations by $O_{global} \triangleq (\bigcup_{k=1}^{K} O_k)$. We associate a sensing cost $C_S(\mathbf{x}^*)$ and a travel cost $C_T(\mathbf{x}, \mathbf{x}^*)$ for observing measurements at new location $\mathbf{x}^*$. We define a maximum sampling budget as B and the remaining available budget as B_{res}.

3.3. System Architecture

Our architecture is shown in Fig. 2: During the *Map phase* each robot utilizes our resource constrained active sensing framework from [8] in order to plan the most informative trajectories with homing guarantees. Every time a new measurement is gathered we update our prediction model and repeat this cycle until the budget is critically low. When all robots reach this termination condition, they pass on their learnt models to the base station, which then is tasked with the integration of all models into a globally consistent model which we refer to as the *Reduce phase*. This phase performs weighted fusion of individual predictions from each expert for each test point by evaluating the corresponding responsibilities which are then normalized to serve as weights for pointwise fusion. We refer to this as *Fusion of Distributed Gaussian Process Experts (FuDGE)*.

4. CONCLUSION AND FUTURE WORKS

In this paper, we posed the environment monitoring problem as a *Map-Reduce* architecture, where during the *Map* phase each robot individually generates the model of the spatiotemporal environment which are fused together

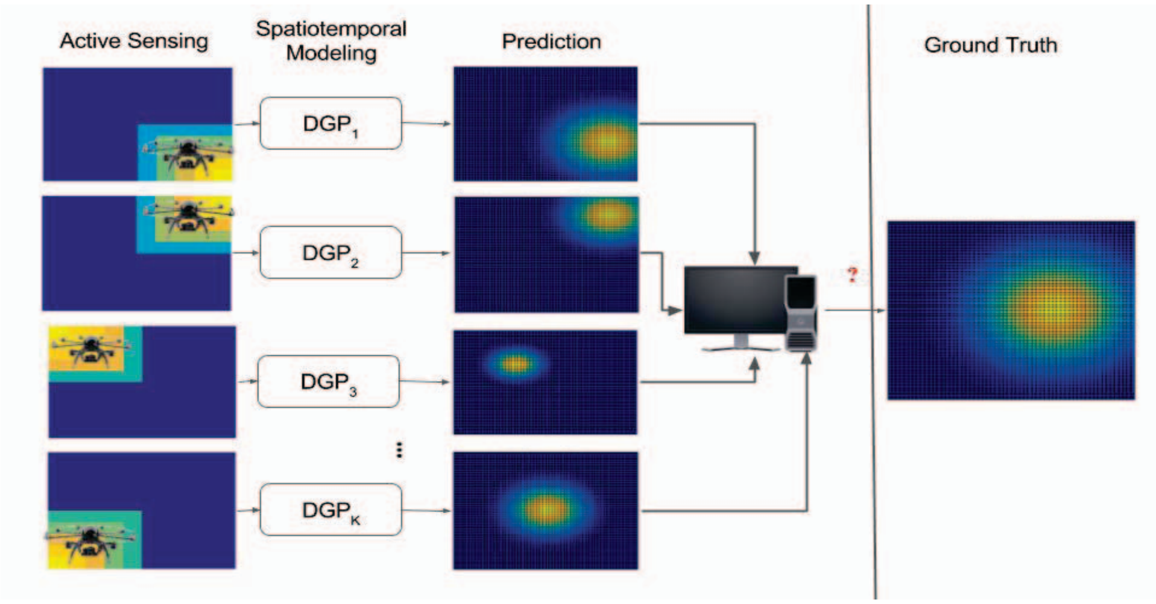

Fig. 1: (**Sensing Scenario**) Each robot is gathering its own observations which are then fed to a GP model to predict the dynamics of the environment. Multiple robots generate slightly conflicting models and off-load them to the base station at the end of the respective mission times. Then it is a challenge for the base station to integrate all models into a globally consistent model in order to be able to compare the performance to the ground truth.

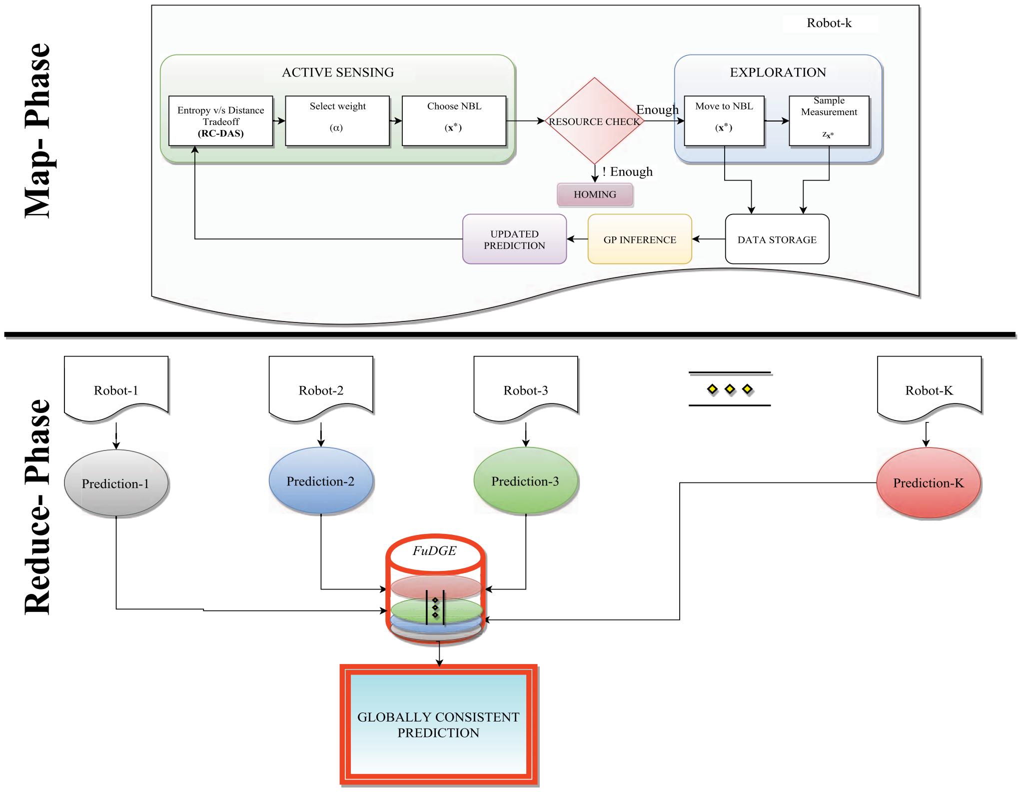

Fig. 2: (**System Architecture**) Here, we demonstrate the overall flow of our *MR-GP* architecture. During the *Map phase* each robot individually gathers training samples to generate predictions which during the *Reduce Phase* are integrated together to obtain a globally consistent model.

during the *Reduce* phase. In doing so, we not only solve the wide area monitoring problem by using a fully decentralized team of robots but simultaneously, split the computational load over the entire team such that considerably large areas of the environment can be observed.

We have only just begun to solve this problem and the solution is far from complete. We have proposed a surrogate function to solve the multi-objective optimization problem of trading off model performance to resource utilization. However, there may be better cost functions which further enhance the model performance by also considering the robot dynamics and external disturbances which may prevent the robot from actually approaching the chosen *next-best-location*. As far as the choice of weights is concerned, we have adopted a rather deterministic approach but in reality uncertainty in resource utilization should be considered for which probabilistic battery consumption model must be developed. We have considered a situation similar to the work of [18] where the locations are pre-defined and discrete collection of nodes however, in real life, the measurements are continuous and the robot has the capability of flying from its current location to any other location within the sensing boundary. Thus, we should replace our current kernel with area kernels [20] for making the situation more realistic. Currently, we assume lack of all sorts of communications to develop our approach for extremely harsh environment. However, in doing so, we are still incurring some resource wastage since more than one robot may want to gather overlapping training samples owing to uncoordinated exploration. Thus, we need to further investigate and reduce such losses.

ACKNOWLEDGEMENTS

This work was supported by the Industrial Convergence Core Technology Development Program (No. 10063172) funded by MOTIE, Korea.

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