Adaptive Sampling of Ocean Processes
Using an AUV with a Gaussian Proxy Model

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Abstract: This paper presents methods for building and exploiting compact spatial models on board an autonomous underwater vehicle (AUV) towards tracking suspended material plumes. Aiming to improve real-time monitoring of dispersal dynamics connected to marine industries such as oil and mine tailing. By exploiting in-situ information from sensors, the AUV is able to assimilate and adapt the mission capitalizing on all the information available. The spatial model is built using Gaussian process approximations and an objective function for path planning is suggested to maximize the value of the collected information.

Keywords: Gaussian processes, Adaptive sampling, AUV, Oceanography

1. INTRODUCTION

Creating models describing the ocean is challenging because of its large scale nonlinear processes and high spatio-temporal variability. Existing models continuously refine numerical methods towards improving accuracy, (Griffies et al., 2000). Still, model verification and data assimilation continues to be a challenge that prompts the need for data sampled from the ocean. Such data is commonly obtained using either: remote sensing, ships, and buoys. This data is usually an expensive enterprise to collect. Hence, the ocean tends to be undersampled and strategic planning of missions are essential to retrieve as much information as possible. Planning of missions are usually based on historical data or simulation data from numerical models, but often the real world differs much from these data. Hence, being able to adapt the mission in real-time, adjusting the plan based on current observations, will likely improve the modeling efficiency.

In this paper we focus on a method using an AUV for sampling in-situ oceanographic data with a goal of tracking suspended material plumes, and being able to adjust the mission in real-time. To obtain real-time adaption, a faster-than-real-time particle model onboard the AUV is required. The numerical models have a high computational load, making them unfit for running on embedded robotic systems with both energy, time, and hardware constraints. Hence, a simpler, more compact model approximating the processes is built based on Gaussian processes (GP). This simplified model represents the current state of the ocean at the time, and can be updated when new information are added.

In addition to the GP proxy model, this paper presents an objective function for path planning aiming to maximize the value of information from the samples. The objective function explores the area by choosing locations assumed to be information rich, but still considers the limitations of the AUV.

As a case study, an area in Frænfjorden (Norway) containing a seafill for submarine mine tailings is investigated. The goal is to track the particle dispersal near this seafill, aiming to improve real-time monitoring of dispersal dynamics in the marine industries. Two existing numerical ocean models, SINMOD and DREAM, are used to train the GP proxy model creating a prior proxy model of the area. Having the prior model ready, the AUV can be deployed, and sensor readings can be used to update the proxy model onboard the AUV in real-time. In this paper a simulation study is done using data from the numerical models as sensor readings for the AUV. Figure 1 gives an overview
Fig. 1. Block diagram showing the simulation routine. A prior GP proxy model is built using training data from SINMOD and DREAM. Then sensor readings are used to update the proxy model real-time onboard the AUV, and the updated model is used to find the next sampling locations. In the simulation study, the sensor readings are provided by a test data set from SINMOD and DREAM.

of the method proposed in this paper, showing a block diagram of the simulation routine.

1.1 Related work and contribution

GPs (Cressie and Wikle, 2011; Eidsvik et al., 2015) are a powerful tool for creating non-parametric, simple and time-effective models, and are widely used when creating a simplified spatial model. Using GPs for environmental sensing is among others explored in (Krause et al., 2008; Zhang et al., 2012; Binney et al., 2010; Das et al., 2015).

In (Krause et al., 2008), a method for static sensor placements is suggested using GPs and maximization of mutual information. Others use moving sensors attached to robotic vehicles, as in (Zhang et al., 2012) where an AUV is used to track an upwelling front or in (Das et al., 2015) which use an AUV to collect samples for ex-situ analysis, selecting the sampling locations based on previous missions and maximizing a utility function.

When introducing robotic vehicles for sampling, path planning is required to obtain the optimal sampling path. This is among others discussed in (Binney et al., 2010) which use the measure of mutual information to optimizing information gain along a 2D path for a marine glider. This is further elaborated and tested with a surface vehicle in (Binney et al., 2013), where also a comparison of greedy vs. recursive greedy approaches is explored for a similar problem.

(Zhang and Sukhatme, 2007) create an adaptive sampling algorithm based on local linear regression and minimizing of estimation error for a sensor network including static sensors and an AUV. (Yilmaz et al., 2008; Jadaliha and Choi, 2013) discuss environmental sensing and adaptive sampling using more than one robotic vehicle.

A common approach when building a GP model is to assume stationary variance, but when modeling particle transportation there is reason to believe that some sites vary more than others. In this paper an approach using non-stationary variance is suggested, using empirical variance from numerical models as training data for the model variance.

Section 2 presents preliminaries explaining the spatial model and data assimilation procedures. The method used is presented in section 3, before section 4 presents simulation results.

2. MODELLING

Having a complex numerical model describing the ocean onboard the AUV is not practical due to computational limitations. Keeping an onboard representation of the environment is resolved using a simpler proxy model, based on Gaussian processes (GP). This section gives a short introduction to the spatial modelling and the data assimilation methods used in this paper.

2.1 Numerical oceanographic models

Numerical oceanographic models are in this paper used both to train the proxy model and for simulation purposes. SINMOD and DREAM are two existing models that describe ocean dynamics, and the release and transport of drill cuttings, respectively. SINMOD is a fully coupled hydrodynamic, sea ice and ecological ocean model (Slagstad and McClimans, 2005; Lindstrom et al., 2009). It is based on fundamental NavierStokes equations and uses a nesting technique where high resolution models obtain their boundary conditions from larger model domains with lower resolution. This can be repeated in several steps to achieve high resolution for selected areas. SINMOD is established in configurations with horizontal resolutions ranging from 20 km to 32 m. DREAM is a Lagrangian particle transport model which can be used to simulate behaviour and fate of marine pollutants, including particulate discharges from drilling operations (Rye et al., 1998, 2008). It provides time series of both concentrations of released materials in the water column, as well as deposition of these materials onto the sea floor. Input to the DREAM model includes hydrodynamic data, which will be delivered by SINMOD, as well as information about the release (amount, rate, densities, grain size distribution).

For generating the forecast data as input for the AUVs onboard model, SINMOD has been set up in a 32 m resolution setup. Bathymetry data is based on DBM Sor-Norge, supplemented by OLEX data recorded by SINTEF Materials and Chemistry inside Frænfjorden. The atmospheric input data is produced using the Weather Research and Forecasting (WRF) (http://www.wrf-model.org/index.php) model simulated with boundary values from the ERA-Interim reanalysis, and climatologic data for freshwater run-off is used. This data is then forwarded and used as input for the DREAM model. The model area is Frænfjorden (Norway) and the data is from two consecutive days April 1st and April 2nd 2013. Data from 1st April is used...
as training data for the proxy model, and data from 2nd April is used as test data in the simulation study.

2.2 Spatial Model

A Gaussian process is chosen to model the underlying spatial dependencies of the particle concentration. The domain is divided into a regular grid with $N$ grid points $[s_1, \ldots, s_N]$, and the particle concentration in location $s_i$ are assumed to be Gaussian with mean $\mu_i$ and variance $\sigma_i^2$. The random variable defining the state of location $s_i$ is denoted $x(s_i)$. Hence, the joint distribution of the state at all the locations $x = [x(s_1), \ldots, x(s_N)]$ is multivariate Gaussian

$$x \sim N(\mu, \Sigma)$$ (1)

with mean vector $\mu = [\mu_1, \ldots, \mu_N]^T$ and a positive definite covariance matrix $\Sigma$. The diagonal of the covariance matrix contains the variances $\sigma_i^2$, and the off-diagonal elements describe the correlation between the locations.

The fundamental concept of modelling spatial correlation needs to fulfill two main properties: i) that correlation decays with distance and ii) that the covariance matrix is positive definite. To achieve this, it is common to use known correlation functions or kernels. By comparing covariance functions with the empirical covariance of the training data, Matern (3/2) kernel (Matérn, 2013) is estimated using training data by choosing the best fit with high variance leads to a reduction in total variance, and the increase in variance due to the dynamics of the particle transportation is modeled. But this temporal process alone does not model the dynamic process, and hence, we rely on the observations from the AUV to catch the changes.

The observation model is given by

$$y_i = G(x_i) + \epsilon_i.$$ (7)

Here, $G$ is the sampling design, a matrix that contains 1 entries only at the sampled indices, otherwise it is 0. $\epsilon_i \sim N_N(0, \Omega)$ is a normally distributed error term with zero-mean and covariance $\Omega$, assumed to be Gaussian, describing the measurement noise.

Exploiting the properties of the Gaussian distribution the conditional updated mean and covariance matrix at time step $t$: $\mu_t = E(x_i | y_1, \ldots, y_t)$ and $\Sigma_t = \text{Cov}(x_i | y_1, \ldots, y_t)$ can be found by (Rasmussen and Williams, 2005)

$$K_t = \Sigma_{t-1} G_t^T (G_t \Sigma_{t-1} G_t^T + \Omega)^{-1}$$

$$\mu_t = \mu_{t-1} + K_t(y_t - G_t \mu_{t-1})$$

$$\Sigma_t = \Sigma_{t-1} - K_t G_t \Sigma_{t-1} + V \Sigma_0.$$

3. METHOD

Having set the foundation by suggesting a proxy spatial model in section 2, we now proceed to explain the adaptive sampling method, including the path planning method using an objective function and the overall sampling algorithm.

3.1 Objective function

To obtain an information rich path for the AUV, an objective function is suggested. The function is created based on three criteria.

1. Locations with high variance are preferred
2. Locations close to the previous sampling location are preferred
3. Locations with high predicted concentration are preferred

The first criterion is chosen because observing in areas with high variance leads to a reduction in total variance, hence creating a more accurate model. This criterion also ensures that the AUV travels to areas that are unexplored. The second criterion comes from the speed limitation of
The method is a greedy method that sequentially chooses the best sampling location. First, the spatial GP model is created using training data from simulations. Then the sampling starts by evaluating the objective function and choosing the location which maximizes it. After reaching the desired location and doing observations, the GP model is updated and the variance is increased in the unobserved locations.

4. SIMULATION RESULTS

Data for April 1st 2013 describing the particle concentration in the fjord obtained from DREAM was used to train the GP, and to create the prior mean $\mu_0$ and covariance $\Sigma_0$. For simplicity, only a small area around the seafall was considered and the area was divided into a regular grid with grid cells of size $32 \times 32$ meters (the same grid as for the simulation data). Also, in this initial simulation only one depth layer was considered at $\approx 15$ m depth, but this could be expanded to 3 dimension considering multiple snapshots in different depth layers. Figure 2 shows the bathymetry of the fjord and the selected area as a red rectangle. From the training data it was observed that the distribution of particles in the location of the seafall was rapidly changing and had very little correlation with the neighboring sites. Thus, this location was disregarded in our model. When plotting the results, this was handled by setting the variance to 0 in the location, and using the true value from the test data as the mean.

The spatial model and the sampling method was implemented using the language R (R Core Team, 2017), and test data from DREAM (April 2nd) was used as sensor readings for the AUV. Hence, for this simulation we consider the test data from DREAM to be the true distribution at all time. The time steps was discretized into intervals of 5 minutes. A total of 54 updates were simulated, which corresponds to monitoring the outlets for 4.5 hours (270 minutes).

The results of the simulation study is shown in Figure 3, showing results at four different time steps. The particle concentration is measured in $\mu g/L$, and the color bar shows the intensity at each location. The x-and y-axis shows the distance in metres from the seafall. The first column of plots shows to the true values from DREAM. Hence, for this simulation we consider the test data from DREAM to be the true distribution at all time. The time steps was discretized into intervals of 5 minutes. A total of 54 updates were simulated, which corresponds to monitoring the outlets for 4.5 hours (270 minutes).

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Fig. 3. Results of the simulation study at four different time steps $t = 0, 18, 36, 54$ corresponding to [0, 90, 180, 270] minutes. The particle concentration is measured in $\mu g/L$, and the color bar shows the intensity at each location. The x-and y-axis shows the distance in metres from the seafill. The first column of plots corresponds to the true values (a), (d), (g) and (j). The predicted mean particle concentration is shown in the second column (b), (e), (h) and (k), and the third column corresponds to the prediction variance (c), (f), (i) and (l). The path of the AUV is plotted together with the prediction variance as a red line, the small white dots shows the 10 most recent sampling locations and the large dot indicates the current position of the AUV.

The objective function controls the AUV path quite well, leading it to unexplored areas on the one hand, and in most cases assuring a reasonable travel length for the AUV. The travel distance of the AUV lies between 100-300 metres for most time steps, which is a suitable distance given the time step length and the AUV speed. Still, the method sometimes results in the AUV taking too large steps, a clear example can be seen in (f). A possible improvement could be obtained by better tuning of the parameters $\theta$ and $V$, but this would only help to a certain degree. Perhaps a better idea for future work would be to add constraints to the travel length of the AUV when doing path planning.

Another issue with the model, is that it does not seem to keep up with the rapid changing of the ocean process. Since the model relies on the observations from the AUV to catch the change in the particle concentration, the prediction results far from recently sampled locations will be inaccurate. When the dynamics of the particle transportation are fast, we will get a delay in the updating of the model. As an example, the prediction results in the upper left area can be considered. At $t=18$, the prediction in this area shows a smaller concentration than the true value. Then at $t=36$, the predicted concentration has increased in this area, but in the true model the particles have moved resulting in a low density. Finally, at $t=54$ the predicted and the true value is quite similar. This example shows the delay in the predicted values.
5. CONCLUSION AND FUTURE WORK

A method for adaptive sampling of ocean processes using an AUV is suggested, and tested using simulation data from numerical models of particle transportation near a seafloor. The spatial model reconstructs the true field quite well, showing the same tendencies as the true field. Still, the temporal variability of the particle transporting is faster than the AUV can keep up with, indicating that more samples from for example multiple vehicles or buoys and/or a better temporal model is required.

Future work includes expanding the model such that it considers the temporal variability of particle transportation, such that the the non-stationarity of the model is not driven by the collected data alone. Path planning can be improved both by considering optimizing for a sequence of points instead of only choosing one sampling location at a time, and by adding constraints to the travel length of the AUV. Fieldwork is also planned, enabling testing of the method in real ocean conditions. This will give insight in how the method works in the real world, and how this differs from simulation.

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REFERENCES


