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Odor Source Localization using Gaussian Process Regression

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Abstract: Effectively finding the odor source in a diffusive environment has numerous potential applications in environmental monitoring and robotics. In this work, we explore adaptive sampling with Gaussian process regression to achieve odor field mapping in a simulated environment. The simulation results show that compared to non-adaptive searches, adaptive sampling performs better in modeling the odor field and the odor source location.

Keywords: Adaptive Sampling, Environmental Modeling, Chemical Plume Tracing

1. INTRODUCTION

The implementation of source seeking algorithms on artificial systems have gained significant attention among researchers due to its potential application ranging from search and rescue missions, detection of hazardous materials in public areas, and environmental monitoring such as in the case of a forest fire. The main goal of the source seeking algorithm is to locate positions of a local measurement maxima under a specific concentration field. While several environmental conditions could be considered for this task, the focus of this paper is to rapidly locate the position of an odor emitting source, using an autonomous system.

The major challenge in the odor source localization task, lies in the inherent spatial and temporal dynamics of the odor substances under turbulent conditions. In general, turbulent flow is the dominant flow under most environments targeted for odor search tasks. The major difficulty in navigating through such environment, lies in the complex plume structure, where the odor concentration rapidly fluctuates in an unpredictable manner. This results in situations where instantaneous odor concentration measurement, when the global property of the plume structure is taken into account, may not correctly reflect the concentration property of the specific location. To overcome these issues, several approaches have been proposed in the past[1], such as gradient based algorithm and bio-inspired algorithm.

In this work, we focus on the on the use of the Gaussian process regression to accomplish the localization task. Gaussian process have have been used to model various spatio-temporal processes. Their non-parametric nature, allows the agent to search the environment without extensive *a priori* information about the environmental characteristics. While Gaussian process regression has been applied to gas distribution modeling in the past[2], there are mainly two issues with the conventional approaches. Firstly, it uses a predefined sampling trajectory similar to a lawnmower pattern, which reduces the efficiency of the overall search. Secondly, most research have focused on creating maps of the environment based on the average odor concentration at each sampling location. However, research into the olfactory processing of biological organisms have suggested that the nonlinear relationship between the odor concentration and the encoded information plays an important role in capturing relevant information about the location of the emission source[3]. To overcome these issues, in this work we first implement an adaptive sampling strategy, then apply a nonlinear filter based on receptor binding. In this work we focus on the former part.

2. METHODS

2.1. Gaussian Process Regression

Gaussian Process Regression can be used to create a Gaussian probability distribution of the phenomenon of interest using the collected training data X_n. The probability distribution $f(X_n)$ is characterized using a mean function $m(X_n)$ and a covariance function $K(X_n, X_n)$.

$$f(X_n) \sim N[m(X_n), K(X_n, X_n)] \tag{1}$$

Given an input position position $X_n = (x_1, x_2 ... x_n)$, and Gaussian noise $\epsilon \sim N[0, \sigma_n^2 I_n]$, the observed value y can be expressed as follows.

$$y = f(X_n) + \epsilon \tag{2}$$

If we assume that the mean function of the prior distribution is set to a constant zero $m_0(x) = 0$, and the observed value is $\mathbf{y} = [\mathrm{y}_1, \mathrm{y}_2, ..., \mathrm{y}_\mathrm{n}]$, the conditional posterior mean function $\hat{m}(x)$ and covariance function $\hat{v}(x, x')$ for a testing location x can be expressed as follows.

$$\begin{aligned} \hat{m}(x) &= \mathbf{k}_\mathrm{n}(\mathrm{x})^\mathrm{T}(\mathrm{K}_\mathrm{n,n} + \sigma^2\mathrm{I}_\mathrm{n})^{-1}\mathbf{y} && (3) \\ \hat{v}(x, x') &= k(x, x') \\ &\quad -\mathbf{k}_\mathrm{n}(\mathrm{x})^\mathrm{T}(\mathrm{K}_\mathrm{n,n} + \sigma^2\mathrm{I}_\mathrm{n})^{-1}\mathbf{k}_\mathrm{n}(\mathrm{x}') && (4) \end{aligned}$$

In the above equation, $k(x, x')$ is the kernel function, and $\mathbf{k}_\mathrm{n}(\mathrm{x})$ follows Eq. (5).

$$\mathbf{k}_\mathrm{n}(\mathrm{x}) = (\mathrm{k}(\mathrm{x}_1, \mathrm{x}), ..., \mathrm{k}(\mathrm{x}_\mathrm{n}, \mathrm{x}))^\mathrm{T} \tag{5}$$

2.2. Gaussian Process Upper Confidence Bound

The acquisition function plays an important role in selecting the most effective points to sample from the target environment. In this work, we have selected the Gaussian Process Upper Confidence Bound(GP-UCB) as the

† Ryota Yanagisawa is the presenter of this paper.

Table 1 The RMSE and the Euclidean distance for three different sampling methods

	RMSE	Euclidean distance (px)
Lawnmower	4.66×10^{-2}	31
Constant beta	3.69×10^{-2}	10
Variable beta	2.94×10^{-2}	2

acquisition function. GP-UCB is capable of balancing out the ratio between exploitation and exploration by utilizing an information-theoretic criterion as shown in Eq. (6) where X represents the possible search location.

$$x_{next} = \arg\max_{x \in X}[\mu + \beta\sigma^2] \tag{6}$$

The ratio between exploitation and exploration can be tuned using the parameter β. For this work, we have selected two types of ways to calculate β. The first type keeps β at a constant value regardless of iteration number, which means that the ratio between exploitation and exploration is kept constant throughout the search. The second type sets β as $\beta = k/n$, where k is a constant value parameter, and n is the number of iteration at the point of calculation. This effectively increases the level of exploitation as the number of sampling iteration grows.

To implement GP-UCB into odor source localization task, the sampling location is selected within a certain radius from the current agent position.

2.3. Plume Model

To test the Gaussian Process Regression method in an *in-silico* model, a odor plume model in [4] was utilized. In the model, the mean stationary concentration field for an odor source located at position r_0 was characterized by emission rate R, particle lifetime τ, isotropic effective diffusivity D, and advection current V. In the two-dimensional field, an analytical solution for the advection-diffusion equation can be obtained using the following equations.

$$c(r|r_0) = \frac{R}{2\pi D} e^{\frac{-(y-y_0)V}{2D}} K_0\left(\frac{|r-r_0|}{\lambda}\right) \tag{7}$$

$$\lambda = \sqrt{\frac{D\tau}{1+\frac{V^2\tau}{4D}}} \tag{8}$$

3. RESULTS

To test whether the GP-UCB algorithm could be applied to an odor source localization task, we applied three different algorithms to a simulated plume model from 2.3. The three algorithms were lawnmower, constant beta, and variable beta. Lawnmower selects evenly spaced points from the map and moves in a predefined trajectory. Constant beta and variable beta uses GP-UCB from 2.2, and moves the mobile sensor according to the acquisition function. In all cases, the parameters for the simulated plumes were set as follows, $R = 1, \tau = 1000, D = 0.002, V = 0.5$. The starting position was (35,2) and the source position was (8,12).

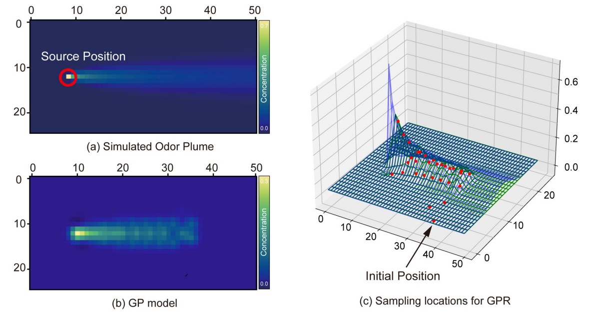

Fig. 1 Results for the simulated odor plume(a), and the reconstructed concentration map using the GP model(b). The sampling locations chosen by the variable beta method is shown in (c).

The result using the variable beta method are shown in Fig. 1. The odor concentration map from the simulated plume model is shown in Fig. 1(a). The mean concentration map generated from the learned GP model after 30 iterations is shown in Fig. 1(b), and the points that were sampled during the search are shown in Fig. 1(c). In Table 1, the RMSE between the simulated plume and the GP model, as well as the euclidean distance between each points of maxima are shown.

4. CONCLUSION

In this work, we have applied GP-UCB to the odor source localization task. The simulation results show the advantages of using adaptive sampling with GP-UCB compared to predefined trajectory. While the result is limited due to the differences between the ideal simulation and the real environment, further testes will be conducted under realistic environments in the future.

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