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Entrotaxis as a strategy for autonomous search and source reconstruction in turbulent conditions

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ABSTRACT

This paper proposes a strategy for performing an efficient autonomous search to find an emitting source of sporadic cues of noisy information. We focus on the search for a source of unknown strength, releasing particles into the atmosphere where turbulence can cause irregular gradients and intermittent patches of sensory cues. Bayesian inference, implemented via the sequential Monte Carlo method, is used to update posterior probability distributions of the source location and strength in response to sensor measurements. Posterior sampling is then used to approximate a reward function, leading to the manoeuvre to where the entropy of the predictive distribution is the greatest. As it is developed based on the maximum entropy sampling principle, the proposed framework is termed as Entrotaxis. We compare the performance and search behaviour of Entrotaxis with the popular Infotaxis algorithm, for searching in sparse and turbulent conditions where typical gradient-based approaches become inefficient or fail. The algorithms are assessed via Monte Carlo simulations with simulated data and an experimental dataset. Whilst outperforming the Infotaxis algorithm in most of our simulated scenarios, by achieving a faster mean search time, the proposed strategy is also more computationally efficient during the decision making process.

1. Introduction

The search for an emitting source of weak, intermittent or noisy signals is an important task for mankind and the natural world. Within the animal kingdom, maximising searching efficiency is of great importance where food sources can be sparse and the mating race is competitive. Autonomous searching strategies have several applications that can benefit civilisation, where a recent example is the search for the missing passenger aircraft, Malaysia Airlines flight MH370 [1].

Optimising the efficiency of search paths is vital when rapid search times have the potential to save lives, for instance: searching for a hazardous toxic gas, localising explosive mines [2], search and rescue missions [3], and even diagnosing medical conditions [4]. Other applications include: locating a lost piece of equipment [5], resource exploration [6] and space exploration [7]. In this paper, we focus on the search and source term estimation of a hazardous source of unknown strength, dispersing in a turbulent medium. Source term estimation is an ill-posed, highly non-linear inverse problem where the strength and location of a source are estimated by fusion of prior information, sensory data, and mathematical models. Reconstruction of the source term enables prediction of the future extent of hazardous contamination, with applications in emergency response following an accidental or deliberate release of harmful chemical, biological, radiological or nuclear (CBRN) material [8].

Searching strategies are adapted to capitalise upon the availability of sensing cues or prior information. In the absence of information or cues, it is common to execute a systematic or random search. Systematic search paths, such as parallel sweep and Archimedean spiral [9], are effective methods provided that the target of interest is stationary, there is no available information, and if efficiency is not the priority. In early works of search theory, systematic searches were studied by the US navy, to optimise aircraft flight paths whilst hunting submarines [9]. In the animal kingdom systematic trajectories are rarely observed, nonetheless there is evidence to suggest that desert ants follow an Archimedean spiral path whilst foraging [10]. Random searches can be argued to be the most prevalent in nature. For instance, Albatrosses, among many other species, have been observed to display lévy flight patterns [11] whilst hunting. A large dataset of the movement of open-ocean predatory fish provides supporting evidence that hunters follow lévy patterns where prey is sparse, although it is suggested Brownian motion is observed when prey is abundant [12]. Regardless, the lévy hypothesis is a source of dispute within the literature

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and alternative hypotheses may be more probable [13].

When prior knowledge or sensing cues are available, the search strategy is adapted to exploit the extra information. Chemotaxic strategies use concentration gradients to direct motion towards an emitting source. Bacteria, such as Escherichia coli, use Chemotaxis to move towards the greatest supply of energy by slowly climbing positive concentration gradients [14]. However, in sparse sensing conditions, which can be caused by a weak source, large distances or turbulent mixing, Chemotaxic strategies are abandoned as irregular gradients and intermittent sensing cause them to lose performance or fail. Anemotaxis concerns the use of wind information to help guide the searcher, a strategy which has been observed in honeybees [15] and the male silkworm moth [16], among others.

Most aforementioned biologically-inspired search strategies can be regarded as reactive, where observations trigger predefined movement sequences to localise a source [17,18]. Alternatively, approaches have been developed based on information-theoretic principles, otherwise known as cognitive strategies. Information theory was first applied to the search problem to optimise effort during aerial reconnaissance [19]. The Shannon entropy, from the theory of information and communication, was used to compare the effectiveness of different pre-planned strategies. Recent cognitive search strategies make decisions on-line, formulated as a partially-observable Markov decision process (POMDP) [20]. The POMDP framework utilises state, action and reward. For our problem, the state refers to the current knowledge about the source, the actions are movements towards potential future measurement locations and the reward is a quantity to describe the gain in information supplied by the corresponding action. Infotaxis is a cognitive search strategy proven to be effective in the sparse sensing conditions where gradient based approaches would be unsuitable [21]. By assuming environmental parameters and the source strength were known, Bayes rule was applied to update a probabilistic map of source location throughout the search, in response to sparse sensory cues in the form of particle encounters with a sensor [22]. Considering one-step ahead manoeuvres on a square lattice, the most informative actions were selected based on minimising the expected entropy of the posterior distribution, with an adaptive term to bias the searcher's movements towards the source as levels of uncertainty were reduced. The strategy showed robustness to significantly sparse conditions and has thus inspired several studies proposing modifications and extensions [23,24]. A critical extension of the algorithm was its implementation in the sequential Monte Carlo framework, using a particle filter, alleviating its grid based implementation and allowing the source strength to be included as a parameter to be estimated [25]. Several reward functions were compared including an Infotaxic II reward, which removed the Infotaxis' bias towards the source, and a reward based on the Bhattacharyya distance. Although the differences among strategies were marginal, the Infotaxis II reward slightly outperformed the others in numerical simulations.

Perhaps the strongest argument that favours a reactive search strategy over the cognitive approach is the higher computational cost of the cognitive search. Aside from the possible complexity of the underlying dispersion and sensor models, the cognitive strategies require a new posterior distribution to be calculated, for each possible future measurement, at each considered location. This could pose a serious problem in conditions where the number of possible measurements or actions increases, or in the development of multiple-step ahead or collaborative multi-agent search strategies. Despite the computational burden, cognitive strategies are preferred due to their probabilistic nature. They have been shown to be more robust in sparse conditions [18], and additional parameters (such as the source strength and potentially the time of release) can be estimated. The latter falls into the domain of source term estimation, reviewed in [8]. Typically, source term estimation or reconstruction is performed using a network of static concentration sensors. Observations are fused with meteorological data and a dispersion model in order to gain a point estimate or posterior probability density function of source parameters through optimisation [26,27] or Bayesian inference [28] algorithms. The cognitive search formulation has enabled information-driven control for source estimation using a mobile sensor [29].

This paper proposes an alternative cognitive search and source term estimation strategy, termed as Entrotaxis. Similar to previous work [25], the sequential Monte Carlo framework is used to update probability distributions of source parameters. Maximum entropy sampling principles are newly used to guide the searcher [30], hence we coined the name 'Entrotaxis' by following the name convention in the literature [21,25]. The approach follows a similar procedure to Infotaxis II [25] in a way that the probabilistic representation of the source is used; however, the reward function considers the entropy of the predictive measurement distribution as opposed to the entropy of the expected posterior. Essentially, Entrotaxis will guide the searcher to where there is the most uncertainty in the next measurement, while Infotaxis will move the searcher to where the next measurement is expected to minimise the uncertainty in the posterior distribution. The maximum entropy sampling principles upon which the algorithm is built are rather intuitive, where it is considered the most is learnt by sampling from where the least is known. This approach has proven to be effective in the literature on optimal Bayesian experimental design [30]. Whilst outperforming the Infotaxis algorithm in several conditions by more rapidly localising the source, the proposed Entrotaxis strategy is also slightly more computationally efficient as hypothesised posterior distributions do not have to be computed in the decision making.

The remainder of this paper is organised as follows. In Section 2, we formulate the problem, including mathematical equations that model the spread of emitted particles and the number of particle encounters with the sensor. In Section 3, the conceptual solution of the Entrotaxis algorithm is described, covering parameter estimation and mobile sensor control. In Section 4, we describe the sequential Monte Carlo implementation of the Entrotaxis algorithm. In Section 5, an illustrative run is presented, the Infotaxis II algorithm is briefly described, and numerical simulations compare the difference in performance and search characteristics between the two strategies. The results using an experimental dataset are given in Section 6, and finally, Section 7 presents conclusions and future work.

2. Problem description

The autonomous search algorithm is to guide a searcher to localise and reconstruct the source of a constant emission of particles characterised by the unknown source term vector $\theta_s = [\mathbf{r}_s\ Q_s]^\top$, where $Q_s \in \mathbb{R}^+$ is the emission rate of the source located at $\mathbf{r}_s = [X_s\ Y_s]^\top \in \Omega$, where $\Omega \subset \mathbb{R}^2$ denotes the search area. The autonomous searching agent located at $\mathbf{p}_k = [x_k\ y_k]^\top \in \Omega$ and equipped with a particle detector of area a, is to navigate the environment, choosing from the admissible set of actions $U_k = \{\uparrow, \downarrow, \leftarrow, \rightarrow\}$, the move $\mathbf{u}_k^* \in U_k$ that is expected to yield the most information.

The searcher shall collect measurements in the form of the number of particle encounters $d \in \mathbb{Z}^+$ with the sensor. The particles emitted from the source disperse through the domain under turbulent transport conditions. We adopt the three dimensional model $R(\mathbf{p}_k|\theta_s)$ presented in [21], to denote the rate of particles encountered by a spherical sensor of radius a at position $\mathbf{p}_k$ from the source defined by the source term vector θ_s. Particles emitted from the source have a finite lifetime τ, propagate with isotropic effective diffusivity σ (which approximates the combined effect of turbulent and molecular diffusion) and are advected by a mean current or wind v [21]. Adopting a sign convention that sets the wind in the direction of the negative y axis yields the analytical solution:

$$R(\mathbf{p}_k|\theta_s) = \frac{aQ_s}{\|\mathbf{p}_k - \mathbf{r}_s\|} \exp\left[\frac{-\|\mathbf{p}_k - \mathbf{r}_s\|}{\lambda}\right] \exp\left[\frac{-(y_k - Y_s)v}{2\sigma}\right], \tag{1}$$