Informative Path Planning for Single Agent Aerial Systems in Industrial Complexes

1st Robert (Will) Byers
Golden, USA
robert_byers@mines.edu

***Abstract*—My project is an information theoretic objective based orienteering problem with a single aerial robot (drone). Using Shannon entropy, I model a series of points of interest (POIs) in a geographically dispersed industrial facility, wherein each POI represents a critical piece of equipment. Each POI has an associated probability which represents a prior belief about the status of that piece of equipment. Using this setup, I implement 4 different path planning strategies for the battery constrained drone and show that the distance informed algorithms outperform their naive counterparts.**

I. Introduction

The term "industrial facilities" can be used to describe large scale, complex logistical and manufacturing hubs which produce and help distribute goods. Examples of industrial facilities can be oil refineries, chemical production sites and nuclear power plants. Industrial hubs can lose an average of 172 operation hours per year [1] which can amount to large scale supply chain disruptions and lost profit. From 2009-2011, there were an estimated 1700 oil refinery shutdowns due to mechanical, electrical or power failures [2]. When a production shutdown occurs, it can be logistically challenging to quickly find and repair broken infrastructure or equipment due to the large scale of these areas. For example, US oil refineries require an average of 1111 acres of land [3].

Additionally, the employment of large scale static sensor networks requires large capital investments to successfully purchase and install. Industrial facilities such as oil refineries are known to utilize large scale deployments of sensing equipment for monitoring processes and key equipment. However, high-quality monitoring instrumentation can be expensive. For example, an industrially rated MX2A temperature probe can be $740 [4]. Purchasing large volumes of this sensing equipment to monitor all critical infrastructure can be a major expense, and each sensor can only monitor a single specific area. As new equipment may be added or facility processes changed, additional sensors would need to be purchased and integrated into the existing monitoring system. With these considerations in mind, more cost effective and dynamic solutions could provide increased monitoring flexibility at a reduced cost compared to more traditional sensor based networks.

Due to the aforementioned challenges in industrial complex operation, I propose the use of aerial robotic technologies (henceforth referred to as drones) to assist in the detection of faulty or broken critical equipment in a geographically dispersed area such as an oil refinery. Using drone technology to quickly check a series of POIs can save critical time at the onset of a equipment related shutdown by decreasing the time required to find malfunctions. Additionally, the cost of purchasing and maintaining a single drone is far a more cost effective and multipurpose solution to check on a series of POIs during a shutdown. As expansions or changes to the plants processes occur, the drone can be updated to reflect new POIs with 0 cost to the plant operators.

Using a single drone, I propose, implement and compare 4 different path planning strategies for the drone to attempt to maximize the amount of information gain over the entire industrial complex system. The results gathered from my simulations show a clear benefit to the inclusion of distance metrics when designing information theoretic objectives for autonomous systems.

I have chosen this problem formulation to serve as an introductory project for me to combine and practice topics from our Active Sensing and Perception class. The research I have been beginning to participate in this semester has a lot of its foundations in orienteering work, so this project felt like a good introductory work to assist in my continuing research.

II. Related Work

Exploration of an unknown environment using frontier based approaches is a well studied problem which encompasses a large volume of existing work beginning with the classic work by Yamauchi in [9]. More recently, information theory and entropy have been increasingly used to inform robotic path planning and orienteering algorithms. Many recent works that utilize information entropy to model and inform orienteering problems have considered unknown environments such as the work in [6]. My work relies on global knowledge given to the drone before its traversal task from a relatively static environment (industrial facilities change infrequently).

However, there have been published works such as [5] and [7] which define similar orienteering problem sets to the formulation presented in this work. [5] presents a multi-agent robotic system which uses Gaussian Processes to model natural phenomenon and information theory to inform robotic path planning in a large lake. This work uses onboard battery supplies as the main system constraint and defines a similar problem statement to the industrial complex entropy reduction problem stated in my work, but allows for multi agent systems. The authors provide experimental data for the single robot case as well. The authors exploit spatial decomposition and branch and bound techniques in the development of their single robot algorithm *eMIP* which is then extended to the multi-robot case.

Work [7] was published 2 years prior to [5] which focuses on optimizing the path of a single robot to maximize a submodular function. The authors of this work provide a "quasi-polynomial time algorithm" for a traditional single agent orienteering problem. The foundations of the *eMIP* algorithm begin with the quasi-polynomial time algorithm presented in [7].

More recent work presented in [8] focuses on the multi-agent orienteering problem, where failures and adversarial environmental conditions can impact agents during operation. [10] again utilizes multi-agent systems and information theory to explore a orthogonal polygon shape.

The considerations that works [5], [7], [8] and [10] focus on would make excellent foundations for future work on this project. The multi-agent approach is a natural extension of the work examined in this project, but a highly more complex scenario to simulate. These works all incorporate similar ideas such as the employment of information theory to inform robotic orienteering.

The set orienteering problem (SOP) attempts to simplify the traditional orienteering problem by partitioning all vertices into disjoint sets. These disjoint sets are then weighted according to their cumulative reward outputs. Both the SOP and traditional orienteering problem have been proven to be NP-hard [12]. By introducing kmeans clustering into 2 of my orienteering algorithms (naive kmeans and distance informed kmeans), I have extended this work to almost cover the SOP. However, the SOP awards an agent all of the profit given by all of the points in a cluster by only requiring that a single point within that cluster to be visited. My work requires that each point still be visited in order to be rewarded that points information gain. However, there has been extensive work done using the SOP such as in [11] which presents an adaptive memory matheuristic which demonstrates great results.

Overall, it does seem that subsets of elements of my project have been used in other projects. The previously mentioned works incorporate information theoretic objectives for multi-agent systems in usually unknown or dynamic environments. My work is a simpler, single agent formulation of these more complex problem definitions. [12] presents a slightly dated survey of orienteering problem variations and the work that has been done in these areas. If I were to take my work further after this project, the field of robotic orienteering algorithms/heuristics is rich with previously established research and filled with various formulations.

III. Approach

In our simulated industrial facility environment, we define a central complex which includes operations and maintenance staff. This control location can be assumed to be centrally located within the entire plant as to monitor the various stages and processes contained within the complex. Our mock industrial simulation has a series of red points called points of interest (POIs). Each POI will represent the 2D location of a particular piece of critical industrial equipment or infrastructure that could be malfunctioning at the time of a plant shutdown. These POIs will each have an associated probability value between 0.0 and 1.0 which represent the prior belief of experienced plant operators as to the probability that a piece of equipment is functioning.

Each POI probability will be used to calculate Shannon entropy in units of bits using the following equation:

$$H(X) = -\sum_{x \varepsilon X} P(X=x) log_2(X=x) \tag{1}$$

For example, POIs close to the control location will have a higher probability, representing the relatively strong belief of the plant operators that those closer POIs are not malfunctioning. POIs further away from the central location are more likely to have lower probability values, representing a strong belief that those pieces of equipment are currently malfunctioning. Equipment at a further distance from the central operation complex may be harder to maintain consistently and therefore, may be assigned lower probabilities to reflect the maintenance staff's belief that this equipment has a higher likelihood of malfunction. Intermediately distanced points are more likely to have probabilities close to 0.5, therefore maximizing information gain. Information gain for these POIs will be among the highest in the entire model as discovering their true operational status will reduce the overall entropy in the system model the greatest. Intuitively, if a plant operator is 50% sure that a piece of equipment is malfunctioning, this represents the highest amount of uncertainty possible for a POI (functional vs multifunctional status equally likely). These POIs and their associated probabilities will be given as global knowledge to the drone before operation.

In the context of this specific problem, I argue that utilizing information theory is an effective and preferable strategy. In the specific scenario I propose, plant operators are only aware that a shutdown has occurred, and are unsure of how many POIs may be malfunctioning. Using information theory to model the prior belief (in the form of the probability that a POI is functioning) and to inform the path planning algorithm for the drone is an intuitive and preferable solution. Maximizing information gain and minimizing the plants entropy reduces the uncertainty in the overall operating environment. Using the drone to quickly assess which POIs are functioning (even if a malfunction is not found by the drone) would be of great value to plant operators as they are able to then focus and direct more expensive resources to investigate POIs the drone was unable to reach with a higher certainty of finding the equipment

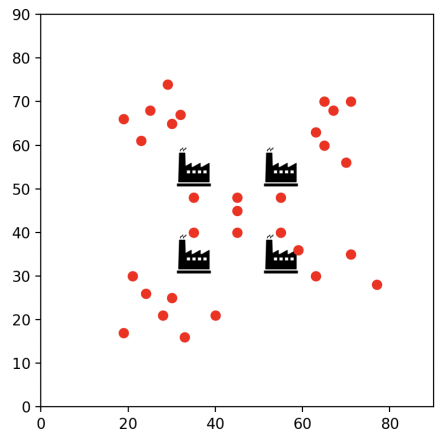

Fig. 1. Example of simulated industrial environment used for experiments

failure. Modeling POIs using probabilities provided by the maintenance staff ensures that the drone is selecting POI routes that will maximally reduce the uncertainty in the overall POI space given its battery constraint, allowing decision makers to better and more quickly direct critical resources.

For each POI, there are 2 possible states: functional or malfunctioning. With a set of binary outcomes, we can use the form of Shannon entropy for a Bernoulli distribution in the form of (p is the probability of a POI functioning):

$$H(X) = -(plog_2p + (1-p)log_2(1-p)) \tag{2}$$

Figure 1. shows a simulated industrial complex experiment graph. Each black factory icon represents a control center while each red dot denotes a POI.

To assist in the identification of broken equipment or infrastructure, a drone will need to intelligently travel between POIs to maximize information gain (Shannon entropy bits) while keeping the drone's battery above 0. In this simulation, the drone will start with some maximal battery energy defined as e and decrement this battery value by the magnitude of the euclidean distance between 2 points. The drone's onboard battery supply is the main constraint for our model.

To inform the drones next travel decision, I propose 4 different algorithms that attempt to maximize information gain given a finite onboard energy supply:

The *Naive Greedy* algorithm chooses the next POI to travel to by selecting the POI with the largest information gain from the remaining unvisited POIs. This algorithm attempts to maximize information gain by always choosing the maximally beneficial POI at each iteration.

The *Distance Informed Greedy* algorithm calculates an information gain to distance ratio for all remaining POIs and then chooses the maximal remaining POI using this ratio. The *Distance Informed Greedy* algorithm attempts to encourage the drone to choose nearby POIs to its currrent position, thereby reducing the energy expenditure required to traverse to the next POI.

The *Naive Kmeans* algorithm attempts to cluster POIs together and to assign these clusters with their entire expected information gain. The drone will travel to clusters based by choosing the most informative remaining cluster. Once at a cluster, the drone will traverse as many of the POIs as possible until it depletes its onboard energy or successfully finishes visiting all cluster POIs, wherein the drone will begin the next iteration of the algorithm.

Finally, the *Distance Informed Kmeans* algorithm makes a similar change to the *Distance Informed Greedy* algorithm by making cluster travel decisions based on a distance to information gain ratio. As with the *Distance Informed Greedy* algorithm, this algorithm attempts to prevent long distance travel by encouraging local exploration of nearby POIs.

IV. Results

To evaluate and compare these algorithms, we will record the information gain achieved by each algorithm as compared to the total entropy of the system. Our primary simulation has 30 POIs spread around 4 separate control centers and the drone has 300 energy units available as onboard power. Figures 2-5 show the paths that each algorithm produces for the drone (drone begins at coordinate 0,0) for the same experiment (same POIs and drone). Table 1 provides the reduction in entropy for each algorithm.

Algorithm	Information Gained (bits)	Total Entropy (bits)	Reduction in Entropy %
Naive_Greedy	6.57	19.30	34.08%
Distance_Greedy	17.84	19.30	92.42%
Naive_Kmeans	14.62	19.30	75.77%
Distance_Kmeans	15.94	19.30	82.60%

TABLE I
ALGORITHM RESULTS FOR 30 POI EXPERIMENT

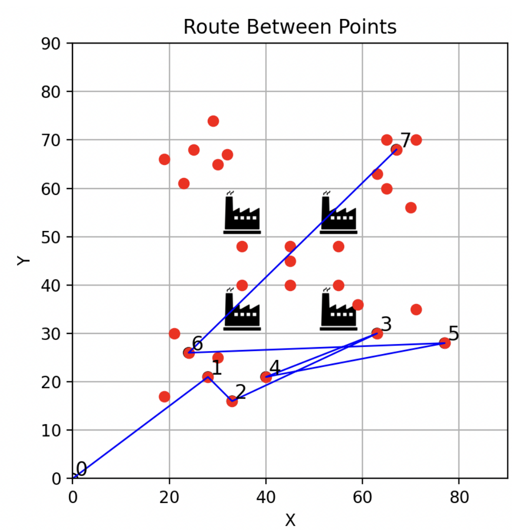

Fig. 2. Naive Greedy Algorithm Results

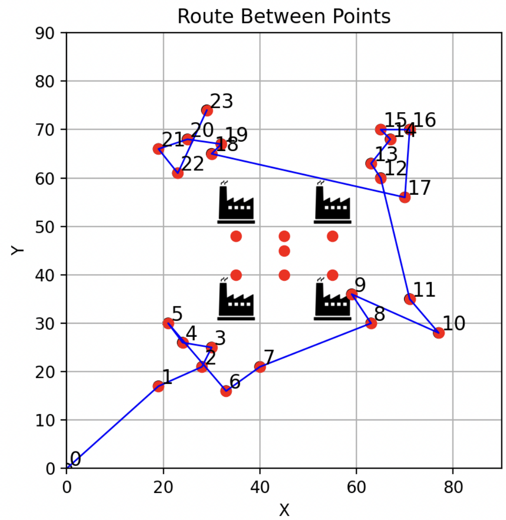

Fig. 3. Distance Informed Greedy Algorithm Results

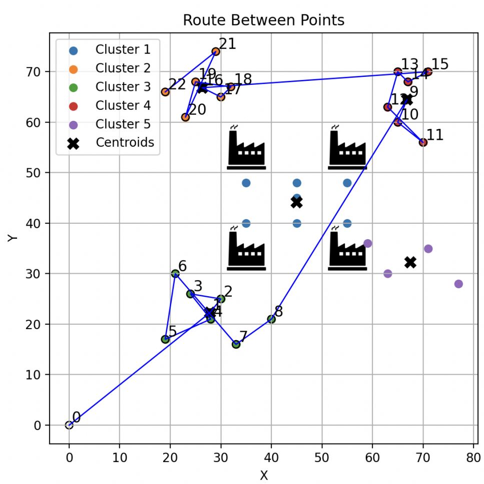

Fig. 4. Naive Kmeans Algorithm Results

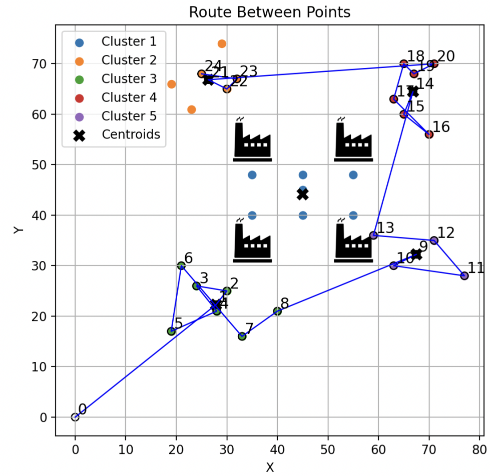

Fig. 5. Distance Informed KMeans Algorithm Results

We can see that the *Distance Informed Greedy* algorithm noticeably out performs the other algorithms with a reduction in system entropy of 92%. This is far superior to the *Naive Greedy* algorithm which expends much of its battery energy to travel great distances to reach the next maximal POI. Conversely, the *Distance Informed Greedy* algorithm uses much less energy to explore nearby, less informative points. Between both algorithms, the *Distance Informed Greedy* algorithm successfully visits 23 of the POIs while the *Naive Greedy* algorithm visits only 7. Using distance to encourage nearby points to be explored (even though they yield lower information gain) is clearly a more effective strategy for exploring a large set of geographically distributed POIs.

Both clustering algorithms are additionally shown to be far superior to the *Naive Greedy* algorithm. The clustering algorithm forces the drone to explore local POIs within a cluster before traversing to the next cluster. This behavior of exploring nearby neighbors before moving to more distant (and potentially more informative) POIs or POI clusters is far more effective than the *Naive Greedy* algorithm.

Between the clustering algorithms, the *Distance Informed Kmeans* algorithm achieves almost 7% more of a reduction in total system entropy as compared to the naive approach. In figures 4 and 5, we can see the the *Distance Informed Kmeans* algorithm selects cluster 5 after traversing cluster 3. This reduces the number of POIs visited in cluster 2 at the end of the tour, however the information gain of the cluster 5 POIs is obviously more than enough to compensate for the missed POIs in cluster 2 as compared to the naive approach. As with the non-clustering algorithms, we can see that it is preferable to use less energy to explore closer, less informative clusters. Using this idea, the drone will end up visiting more nodes overall and end with a higher information gain.

The results demonstrated by these algorithms show a clear and significant advantage to designing distance aware reward functions for orienteering algorithms.

V. Conclusion

Given a large scale, dispersed industrial facility where equipment malfunctions frequently cause costly shutdowns, I show that a single drone system could be employed to effectively and quickly survey predefined points of interest. Utilizing single drone systems as implement in this project could prove to be highly cost effective as compared to other more traditional static sensor approached. More specifically, my results show that integrating distance into reward functions encourages autonomous systems to make more energy aware decisions, thereby increasing accumulated reward through implicit battery conservation as compared to more traditional maximization techniques.

Future work on this project could include creating multi-agent distributed systems of both heterogeneous and homogeneous drone team compositions complete with central planning and coordination machines. Additionally, introducing a more realistic energy consumption model for the drones would provide more accurate experimental results. Finally, creating hybrid strategies wherein different strategies are dynamically chosen during operation to best cater to field conditions could be a source of even greater information gain.

Personally, I have learned a great deal on this project. I have realized through researching the field of orienteering, that there is a diverse set of high-quality research that explores many different versions of the orienteering problem. This project has provided me with the foundations to go and study the more complex formulations and work that has been done for multi-agent systems and for more dynamic environments.

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