Providing Distribution Estimation for Animal Tracking with Unmanned Aerial Vehicles

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***Abstract*—This paper focuses on the application of wireless sensor networks (WSNs) with unmanned aerial vehicle (UAV) for animal tracking problem. The goal of this application is to monitor the target animals in large wild areas without any attachment devices. The WSN includes clusters of sensor nodes and a single UAV that acts as a mobile sink and visits the clusters. We propose a model predictive control (MPC) method that is used to guide the UAV in planning its path. We first build a prediction model to learn the animal appearance patterns from the sensed historical data. Then, based on the real-time predicted animal distributions, we introduce a path planning approach for the UAV that reduces message delay by maximizing the collected rewards. The experimental results show that our approach outperforms the greedy and traveling salesmen problem-based path planning heuristics in terms of collected *value of information*. We also discuss the results of other performance metrics involving message delay and percentage of events collected.**

***Index Terms*—unmanned aerial vehicle; UAV; animal monitoring; path planning; distribution prediction.**

I. Introduction

The ability to track the movement of animals in wild areas can offer many benefits to research and conservation efforts. By understanding the migration patterns of animals we can identify the areas that are most critical for conservation and we can track the effects of climate change and presence of humans or non-native species. By simultaneously tracking multiple species of animals we can investigate their relationship and inter-dependencies such as contention for resources.

Over the years, several studies proposed the use of wireless sensor networks (WSNs) for animal tracking. Most studies are based on mounting the sensors to the animals on special collars [1], [2] and require the sensors to transmit the collected data to a sink node. The advantage of this approach is collecting various information from the tracked animals such as location, body temperature, and heart rate. However, this approach is applicable to only certain species (e.g.,large and terrestrial animals). Moreover, mounting of the sensors is a difficult and expensive operation and the collars are intrusive and they might change the behavior of the animals. An alternative to this approach is to use sensors deployed in the terrain to detect and localize the animals [3], [4]. This can be accomplished through imaging sensors with built-in recognition facilities [5], [6], passive infrared sensors for night-time localization, or a combination of acoustic, seismic and ultrasonic sensors [7], [8].

This paper focuses on the animal monitoring problem in large wild areas. We consider large wildlife areas with sensors distributed to detect and recognize the wildlife appearance [9]. We consider the usage of sensors that detect animals in their vicinity and create *event* messages which contain information such as the detected type and location of the animal. The sensors are distributed and clustered based on virtual grids. Each cluster has a cluster head which is used to collect the events from sensors via hop-by-hop wireless communication and transmit to a UAV. The UAV acts as a mobile sink.

The goal of the UAV is to collect the event messages as soon as possible in order to maximize the value of information (VoI) [10]. If the UAV prioritizes well its visits, it can gather very valuable information. For instance, it can directly monitor animals and even take their picture [9]. Thus, the performance of the application highly relies on the UAV's path planning.

Our previous works [9], [11] define a mathematical metric for the VoI of the collected data as an exponential function that decays as time passes, and propose a Markov Decision Process (MDP)-based path planning for finding species such as zebras and leopards. In this paper we propose a model predictive control (MPC) method to help the UAV plan its path. First, we train a neural network that learns the animal appearance patterns from the collected historical data. Second, we apply the trained model to predict the future probability distribution of animal appearance. Finally, we propose a traveling salesman problem (TSP)-based path planning approach for the UAV using the real-time predicted animal distribution (TSP-D). Even though we focus on the animal monitoring application, the proposed MPC method is applicable to any time-sensitive data collection applications where historical data can be learned by our predictive model.

We evaluate the performance of the proposed predictive model and the path planning approach using a dataset [12] that includes traces of groups of white backed, lappet-faced vultures in Namibia. We compare the TSP-D path planning approach against greedy and Naive TSP heuristics and show that it outperforms other approaches in terms of VoI, message delay, and the percentage of events collected.

II. Related Work

Many tracking technologies have been proposed and implemented by engineers and wildlife researchers. One main technology of animal monitoring is the wearable GPS-based animal tracking devices. Juang et al. [1] present their ZebraNet project in which a low-power wireless system is built for position tracking of zebras. Their goal is to investigate system design ideas, wireless communication protocols, and how sensor specifications such as battery lifetime and weight limit the system performance. Similar wearable GPS devices are used to gather animal movement data in [2], [13].

Camera sensor networks emerge in recent years due to the advancements in hardware technology [11]. They greatly promote wild-life research by providing much more animal related information such as image, sound and video. He et al. [6] develop integrated camera-sensor networking systems for collaborative wildlife monitoring and tracking. They deploy an eMammal cyber infrastructure to analyze and manage wildlife monitoring data. Animal species recognition is accomplished by using some well-trained machine learning models. Similar studies based on camera sensor networks are conducted in [14], [15].

Mobile sinks such as UAVs provide great advantages in WSNs. They are flexible to move to specific areas of WSNs for different tasks. The common goal of path planning for mobile sinks is to maximize the information collected while minimizing the travel time. Li et al. [16] propose a path planning strategy for the UAV/UGV based on the genetic algorithm. Their goal is to build a ground map and plan an efficient path for disaster rescue. A local rolling optimization is applied to improve the path planing results. Cheng et al. [17] propose a TSP-based path planning approach for a mobile sink. The mobile sink visits a set of virtual points which are actually overlapping areas of communication ranges of sensors. Contribution values are assigned to virtual points for path planning of UAV. Sangare et al. [18] propose a MDP-based path planning approach for a Mobile Energy Station (MES) to recharge wireless-powered sensors. Sensor's energy is digitized into different levels such that different permutations of energy levels can be treated as network states in MDP. Our path planning is different from these models as it is based on the predicted animal distribution.

III. Animal Monitoring System

A. Network model

In this application, the objective is to monitor and track specific animals' appearance. The sensor nodes are deployed in the target wild area while a UAV operates as a mobile sink node for data collection.

We divide the whole area into virtual grids. In this scenario, the sensors that in a particular grid are considered as a cluster and one of them acts as the cluster head. Fig. 1 shows a snapshot of the divided virtual grids. The UAV visits cluster heads for data collection. After visiting a virtual grid, for instance Grid 6 in Fig. 1, the UAV can visit one of the neighboring grids or just hover over in the same grid.

1) Sensor nodes: As specified in [9], the sensors are responsible for animal monitoring and sending the sensed events to the cluster head. Sensor nodes are deployed by uniform random distribution in the large observation area. The sensors inside a virtual grid form a cluster and the cluster head is selected periodically. Sensors can communicate with the cluster head via direct or hop-by-hop wireless communication. A sensor creates a new *event message* when it detects an animal. Cluster head is responsible for receiving event messages from other sensors and then reporting all the event data to the UAV when the UAV comes into its transmission range.

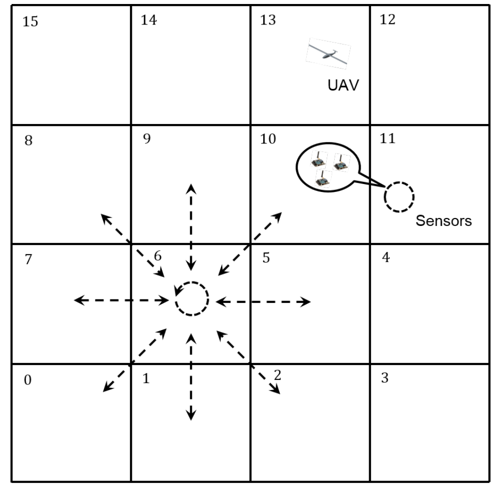

Fig. 1. The movement choices of the UAV when it flies over Grid 6.

2) Unmanned Aerial Vehicle: In this network model, the UAV is used as an autonomous mobile sink for gathering time-sensitive information. The usage of UAV brings advantages such as movement flexibility and high speed. Moreover, the UAV not only overcomes the geographical challenge but also has minimal effects on animals. Thus, our model is based on using a single UAV to collect data from the ground sensors, more specifically, the cluster heads of the virtual grids.

B. Animal distribution prediction

Directly detecting animals using UAV (e.g., using attached camera) in a large wild area is a hard problem. On the other hand, when we have sensed historical data from the target area, we can analyze the animals' movement patterns.

Fig. 2 shows examples of animal appearance pattern in two different virtual grids. As we can see, animals usually show up at specific hours in a day and a similar pattern is repeated every day. We start to build a model with the goal of learning the animal appearance in each virtual grid based on the observed regularities.

First, we divide a day into time-steps $\{t_0, t_1, ...t_M\}$ such that t_i means the i^{th} time-step of a day. Second, we count the number of detected animals at each time-step for every virtual grid. Fig. 3 shows the input and output that is used to train the predictive model. For time-step t_i, the input data x_i consists of two parts: d_i and e_i. d_i represents potential affecting factors such as time-step in the day, month. e_i represents number of animals detected in each virtual grid at time-step t_i. Given the input data x_i, we use a fully connected feed-forward neural network (Fig. 4) to predict the output data y_i' which is

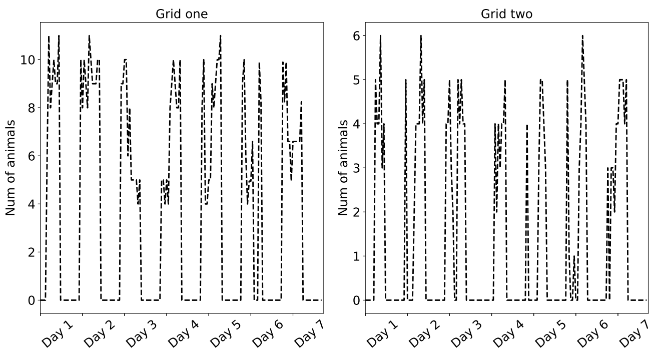

Fig. 2. Animal appearance patterns in two virtual grids.

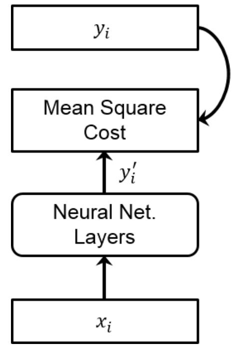

Fig. 4. Learning model structure.

the number of animals in each virtual grid in the next time-step. We define the cost as the mean squared error between predicted y_i' and the ground-truth y_i and minimize it using stochastic gradient descent.

With the trained model, we can predict the animal distributions by inputting the predicted distribution of the previous time-step. In addition, as the UAV visits some grids, the corresponding real number of animals in those virtual grids can be updated, i.e., a partially observed x_{i+1} can be obtained by updating some values of y_i'. Then, this x_{i+1} is used as input to predict the next time step distribution y_{i+1}'. It is important to point out that with this model, we can repeat the prediction for an arbitrary number of time steps without accessing to real observations. However, as the time goes, the prediction error compounds and the accuracy may drop.

C. Path planning with predicted animal distribution

In this application, we treat animal detection as an event and the corresponding event message should be collected as soon as possible. To enforce this desire, we define the metric *value of information* (VoI) to evaluate the importance of the collected information by the UAV. VoI is defined as the

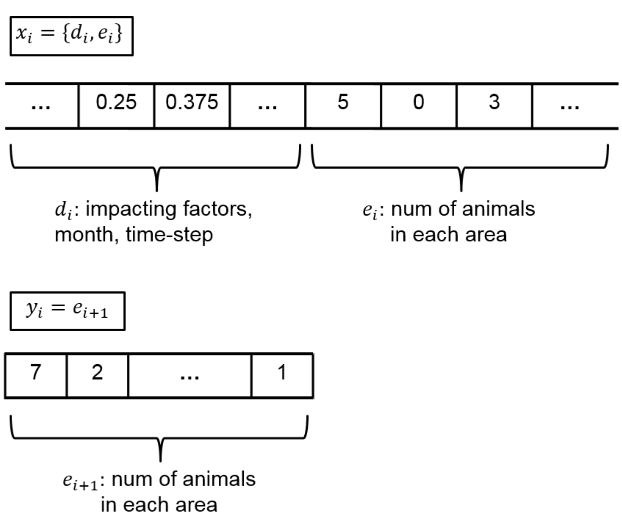

Fig. 3. Input and output data structure.

exponential decay function

$$F_{VoI}(t) = A \times exp\{-B * (t_{collect} - t_{initial})\}, \quad (1)$$

where A is the initial value of the event while B is the decay factor. Under this formulation, the objective of the path planning is to maximize the discounted values collected.

Given such a scenario, we propose a path planning approach based on the predicted animal distributions for each grid. Given a time period $[t, t+T]$ (where T is a hyper-parameter), finding the optimal path is similar to solving a traveling salesman problem (TSP) while the goal is to maximize the estimated rewards. We name our proposed path planning approach as *TSP-D* where "D" represents the continuously predicted animal distribution.

We implement a tree structure path exploration search to find the optimal path. As shown in Fig. 5, the numbers inside the tree nodes represent the indices of the virtual grids while the edges between them represent the travelling time for the UAV to a neighboring grid. This traveling time information depends on the area of sensor deployment.

Note that TSP is an NP-hard problem. But with the tree structure search, we can apply branch-and-cut strategy to reduce its complexity. In Fig. 5, grids are not connected to all other grids. Instead, they are only connected to a subset of them where the nodes are neighbors and it is possible for the UAV to fly to that neighbor (at most 9, including self). In addition, due to specific characteristics of animal movements, the distribution matrix is sparse. This allows us to further

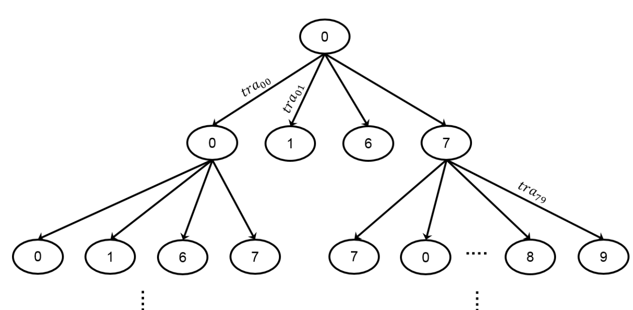

Fig. 5. Tree structure of path exploration.

prune the tree. More specifically, for each layer in the tree, candidate paths that end in the same virtual grid and contain the same event IDs collected, are merged into one path with the maximum values. Finally, the candidate path with the maximum value is chosen by the UAV. The pseudo code for the path planning approach is given in Algorithm 1.

Algorithm 1: Path planning of UAV

```
Travel time look up table:
t_table = d_table/speed_UAV
Pre-trained distribution prediction model Model
Current time-step t
Current animal distribution dist_cur
Path planning lookahead time T
Event creation period Δt
Function CutBranch(CandidatePaths, t):
    for PN in CandidatePaths do
        if t - PN.time > maxtime then
            /* max time to neighbors from t_table */
            remove(PN)
        end
        if Duplicate(PNs.id and PNs.events) then
            KeepMaxOne(PNs)
        end
    end
end
CandidatePaths = []
while t < t + T do
    if t%Δt == 0 then
        dist_cur = Model.predict(dist_cur, t)
        CreateEvents(dist_cur, t)
    end
    List = []
    for PN in CandidatePaths do
        /* PN: PathNode, last grid id of a path */
        Candidate =
          IsArrivalNeighbor(PN, t_table)
        List.add(Candidate)
    end
    UpdateDist(dist_cur) ← List
    UpdatePath(CandidatePaths) ← List
    CutBranch(CandidatePaths, t)
    t = t + 1
end
Path = MaxRewardPath(CandidatePaths)
return NextGrid(Path)
```

After visiting a grid, the UAV repeats the path planning algorithm to decide the next visiting grid. With the updated x (by the observation from current grid) and the $lookahead$ parameter T, algorithm 1 returns the next visiting grid.

IV. Experimental Study

A. Simulation environment

The proposed network model and the UAV path planning approach are evaluated in this section.

1) Dataset and UAV: We test our models with a real-world vultures dataset [12] which contains the movement traces of several groups of white backed & lappet-faced vultures in Namibia. The GPS traces are recorded with a sampling time interval of 10 minutes everyday from 6am to 6pm in years 2008 to 2010. A single UAV with a fixed speed of $50km/h$ is simulated for event data collection from cluster heads. In the case of battery exhaustion, we assume that the UAV can be recharged so that it can continue to work.

2) Performance metrics and baselines: To quantitatively evaluate the performance of a path planning strategy, we report the results according to three performance metrics in our simulation study.

- *Value of information (VoI)*. VoI is the main metric in this animal monitoring application and maximizing it is the primary goal in designing the path planning approaches.
- *Message delay*. Since event messages need to be kept in the sensor buffer until being sent to the UAV, message delay is an important metric. Long message delay may cause the loss of event messages.
- *Percentage of events collected*. Whenever an event is created by the sensor, we add a valid time period $isvalid$ for each event. In other words, this event expires and can not be collected anymore by the UAV after $isvalid$ amount of time.

TABLE I
Experimental parameters

Network size	$100km \times 100km$
Time unit	1 min
UAV speed	50 km/h
VoI parameters (A, B)	(10.0, 0.02)
Time step length	30 $mins$
Events generation period Δt	30 $mins$
Events expiration $isvalid$	300 $mins$

Table I includes the parameter values used in our experiments. For the performance evaluation of the proposed path planning approach TSP-D, we compare its outcome with the theoretical optimal approach, greedy approach with predicted distribution, and naive TSP-based approach.

B. Compared approaches

1) The optimal approach (TSP-D-Optimal): In this approach, we feed the UAV with the real animal distribution which we extract from the dataset. Note that this approach is only for comparison purposes and in practice cannot be realized since we cannot predict the future movements of animals with 100% accuracy.

2) Greedy with predicted distribution (Greedy-D): This approach also takes our predicted distribution into account, however, the UAV always purses the highest reward among the neighboring virtual grids instead of expanding different

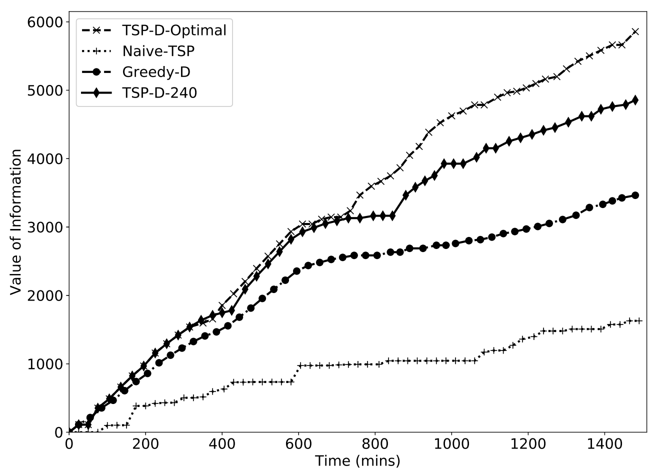

Fig. 6. Value of information performance.

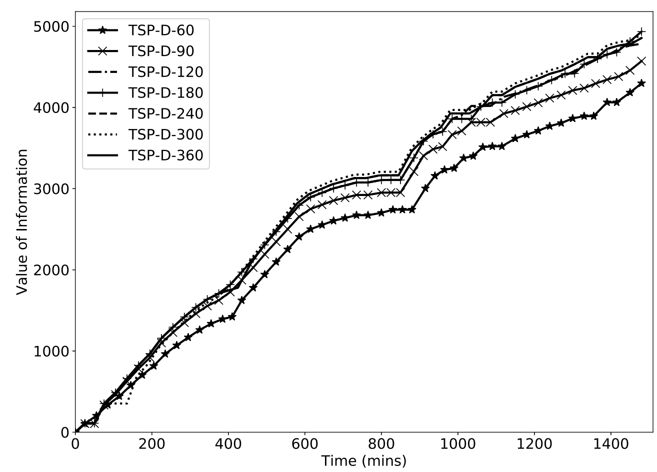

Fig. 7. The VoI performance with different look ahead time.

possible paths. If all neighboring grids have the same reward, a random selection will be considered.

3) Naive TSP without predicted distribution (Naive-TSP): In this approach, we do not provide any prediction information to the UAV. The UAV visits each cluster head in a fixed order.

C. Performance results

We report the performance of each path planning approach in terms of the three metrics: VoI, message delay and percentage of events collected. For our proposed TSP-D approach, we also show the results with different time-step look-aheads.

Fig. 6 shows the VoI performance collected by different path planning approaches. As we can see the Naive TSP is the worst approach here because it does not consider any animal distribution information. The Greedy-D approach is much better than the Naive TSP since it takes the predicted animal distribution as input into path planning. But it always pursues the highest neighboring reward which limits its overall performance. With the same predicted animal distribution as input, our proposed TSP-D outperforms the Greedy-D approach because our solution decides next visiting grid based on an estimated rewards in next $lookahead$ time (240 $mins$ in Fig. 6). However, compared with the optimal solution, TSP-D's performance is a bit worse. The reason is we are using our predicted animal distribution to do path planning. Note that although the optimal approach achieves better results, it is not practical as we explained before, therefore, the real winner is TSP-D approach.

Fig. 7 shows the VoI performance with different prediction durations. It can be seen that in TSP-D approaches, the performance with $lookahead$ time 60 $mins$ is lower than others. The reason would be the same with the Greedy-D approach that the local maximum reward limits the overall performance. As the $lookahead$ time increases, the performances of different approaches are very close to each other. It might be due to the effect of compounding error in predicting long-term future that misleads the UAV to explore areas where there expectation will not be met.

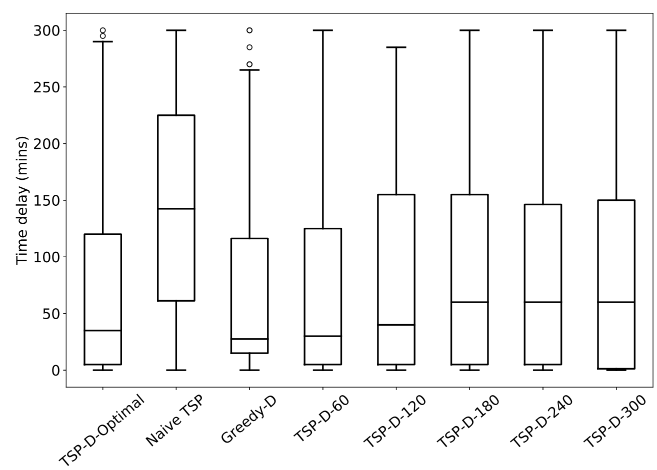

Fig. 8. Message delay performance.

Fig. 8 shows the box plot of message delay of each path planning approach. Naive TSP approach shows the worst performance due to not taking into account any animal information. It is interesting that the Greedy-D approach outperforms other approaches in this metric. The reason is that, in Greedy-D, the UAV always goes to the neighboring grid with highest probability of existing animals. It collects event data in a timely way but with the sacrifice of number of events collected, which can be seen in Fig. 9.

Fig. 9 shows the percentage of events collected by each path planning approach. Remember that an event validation time $isvalid$ is added to each event, so, if the event is not collected after $isvalid$ time, it expires. It can be seen that the Naive TSP achieves the best performance in this metric because the UAV goes in a fixed path which guarantees that most events can be collected finally. Greedy-D shows the worst performance. As we explained in Fig. 8, it collects events in a timely way with the sacrifice of total number of events collected.

Overall, it can be seen in the experimental results that TSP-D highly outperforms the other path planning approaches.

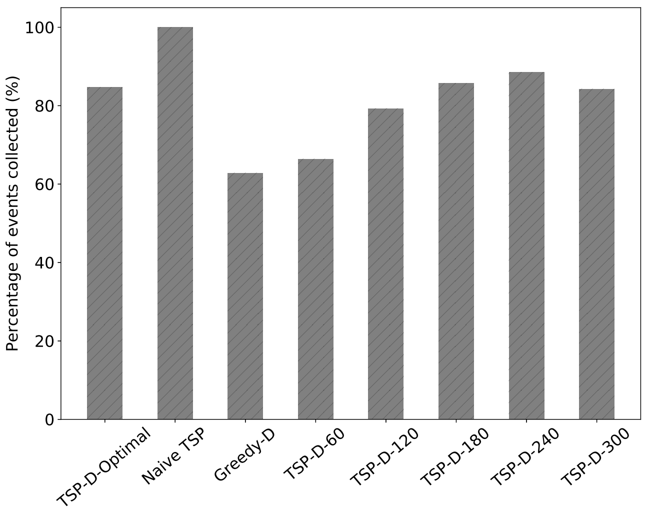

Fig. 9. Event message collection performance.

Compared to the greedy approach, TSP-D produces $(4855 - 3463)/3463 = 40\%$ increase in VoI and $(159 - 113)/113 = 41\%$ increase in number of events collected. Compared to the Naive TSP approach, TSP-D produces $(4855-1628)/1628 = 198\%$ increase in VoI and $(142 - 68)/142 = 52\%$ decrease in median message delay.

Although the greedy path planning approach also relies on the predicted distribution, it always goes to the neighboring grid with highest potential rewards. As we can see in Fig. 8 and Fig. 9, greedy mostly tries to minimize the message delay while Naive TSP tries to maximizes percentage of collected events. But both of them sacrifice a lot performance on other metrics. On the other hand, in TSP-D the UAV considers the overall rewards in the next $lookahead$ amount of time. Note that as the UAV collects data from grids, the predicted animal distribution can be partially updated with the observed values. In such a way, a higher performance path planning for the UAV can be obtained after every grid visit.

V. Conclusion

In this paper, we consider using UAV-aided WSNs for animal monitoring in wildlife areas. Motivated by the movement patterns of animals, first we build a model to learn the time-dependent animal distributions from historical data, and second, we use the real-time predictions of the trained model as the UAV plans its path to collect messages. We find the optimal path with a tree structure exploration strategy that performs multiple time-step look-aheads. The proposed path planning approach is evaluated using real-world mobility traces of vultures in Namibia. Simulation results show that the performance of the proposed approach results in an approximately 40% increase in both VoI and percentage of events collected compared to greedy approach, and a 198% increase in VoI and 52% decrease in median message delay compared to Naive TSP approach.

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