Optimal Trajectory Planning of Drones for 3D Mobile Sensing

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***Abstract*—Projecting the population distribution in geographical regions is important for many applications such as launching marketing campaigns or enhancing the public safety in certain densely-populated areas. Conventional studies require the collection of people's trajectory data through offline means, which is limited in terms of cost and data availability. The wide use of online social network (OSN) apps over smartphones has provided the opportunities of devising a lightweight approach of conducting the study using the online data of smartphone apps. In this paper, we propose the concept of geo-homophily in OSNs to determine how much the data of an OSN can help project the population distribution in a given division of geographical regions. Specifically, we establish a three-layer theoretic framework that first maps the online message diffusion among friends in the OSN to the offline population distribution over a given division of regions via a Dirichlet process, and then projects the floating population across the regions. By experiments over large-scale OSN datasets, we show that the proposed prediction models have a high prediction accuracy in characterizing the process of how the population distribution forms and how the floating population changes over time.**

I. Introduction

Unmanned aerial vehicle (UAV), commonly known as drone, is an aircraft without a human pilot aboard, which is commonly used in measurement and sampling. Compared to manned aircraft, drones are more suitable for data collections and mobile sensing applications that capture different dimensions of signals in the environment that are beyond our sensing capability, such as aerial photography, 3D wireless signal survey, air quality index (AQI) measurement.

However, civilian drones are still not popular these days. Furthermore, a lot of drone companies were broken down. It could be a quite confusing problem if you have never come into attach with a drone. If you've actually tried using them, you could find that civilian drones do not really apply to daily life due to:

- Low battery available time.
- Great noise during flight.
- Wing rock and more battery drain caused by poor carrying capacity.

Therefore, in order to make more use of existing drones, we must consider the following problem: **How to complete measurement (or flight) in the shortest possible time? Furthermore, in the three-dimensional space?**

Similar to traditional sensor networks and mobile base station, we consider data collection in mobile environment. So total time consumption consists of two parts: **flight time** and **measure time**. While we also have the following difference:

- We consider optimal algorithm in two-dimensional space.
- We use the routing algorithm based on graph theory apart from traditional greedy algorithms.

In this paper, we consider mobile sensing in three-dimensional space. We divide three-dimensional space into a network of observation locations (OLs) and select critical observation locations (COLs) from OLs to cover measurement space, which could be formulated as a constraint set coverage problem in graph theory. Specifically, we consider the following two special cases:

1) *Consider measurement time only*: Under this condition, we assume flight time negligible and consider measurement time only. In order to minimize measurement time, we should select least OLs to cover OL-network. Therefore, we could formulate this problem as a minimum dominating set (A dominating set in a graph G is a subset of vertices S such that every vertex in $V(G)\S$ is a neighbor of some vertex of S.) problem in lattice, which has been studied for a long time.
2) *Consider flight time only*: Under this condition, we assume measurement time negligible and consider flight time only. In order to minimize flight time, we should choose the shortest OL-path in OL-network. Therefore, we could formulate problem as a minimum dominating path (A dominating path is a dominating set as well as a trail where all vertices (except possibly the first and last) are distinct. Briefly, it is a dominating set as well as a path.) problem in lattice, which has not been solved before. In this paper, we solved this problem in grid and give an expand in three-dimensional space.

Because of algorithms we use is based on graph theory, We could solve two problems above optimally in O(1)time. We use drones to verify our simulation in multiple scenarios. We find out that the flight time we use is less than ordinary approach.

II. Related Work

A. 3D mobile sensing

B. Route planning in conventional wireless sensor networks

III. System Model

In this section, we establish a three-dimensional (3D) network model that characterizes the ordinary mobile sensing scene for drone. Then, we analyse correlation between OLs and relationship between 3D and 2D network model.

Afterwards, we formulate the COL selection problem as a constraint set coverage problem. To simplify problem, we consider two special scenes respectively. In the first scene, we only consider measurement time which transform problem into the minimum dominating set problem. In the second scene, we only consider flight time which transform problem into the minimum dominating path problem. We will make further discussion in next subsection. Finally, we define variables that would be used to mathematical proof next section.

A. Network establishment

Dividing a 3D space into cuboids: We assume sensing object is largely same in fixed area for every position in 3D space. So we divide a 3D space into cuboids with a meters long, b meters wide and h meters high. We define the center point of cuboid i as its observation location (OL) (as shown in Figure 4), which is denoted by the 3-tuple (longitude, latitude, and altitude), i.e.,

$$OL_i = (x_i, y_i, z_i),$$

where x_i, y_i, z_i are 3D coordinates of OL_i.

3D network of OLs: The divided cuboids of a 3D space and the corresponding OLs can form a 3D network graph $G = (V; E)$, where V denotes the set of vertices and E represents the edges connecting neighboring vertices. Specifically, the OL inside each cuboid i is considered as a vertex in G, and an edge (i, j) exists if cuboid i is the same as cuboid j in two coordinates and adjacent to cuboid j on the third dimension. Therefore, the 3D network of OLs forms a three-dimensional lattice which has fine topology structure.

Levels of OLs: Obviously, cuboids in lattice could be classified by height level. We call the ground level as level 1 at height of $\frac{h}{2}$ m, one level above as level 2 at height of $\frac{3l}{2}$ m.

B. Time consuming

For general mobile sensing, total time consuming consists of flight time and measurement time. And time consuming depends on COLs selected from OLs. **Measurement time**: Measurement time is total time spend on mobile sensing. Since we formulate 3D space into lattice, measurement time is proportion to the number of COLs we select. The function is written as:

Flight time: Flight time is total time spend on UAV's flight. Since we formulate 3D space into lattice, we use Hamiltonian distance to characterize distance between OLs. So the flight time is proportion to the length of trajectory. The function is written as:

Therefore total time consuming function can be written as:

C. Correlation between OLs

To characterize the general mobile sensing process, we assume adjacent OLs have correlation. To characterize different adjacency, we consider following two typical scenarios in mobile sensing.

Star adjacency: In this scenery, we assume OL's neighbors are star adjacent so the sum of three coordinates difference is at most 1 and the coverage set of an OL is the union of its vertex adjacent neighbors and itself. Specifically, an OL has two neighbors in every dimension and the total size of coverage set is 7.

Cubic adjacency: In this scenery, we assume OL's neighbors are cubic adjacent so the max of three coordinates difference is at most 1 and the coverage set of an OL is OLs in a cube whose center is the target. Specifically, an OL has eight neighbors in each plane and the total size of coverage set is 27.

D. Problem formulation

Given a 3D space, we first establish a 3D OL network $G = (V; E)$ which forms a 3D lattice. Each OL in lattice has a coverage set (that contains correlated OLs with predictable sensing object). Due to drones' limited battery life, we should complete flight and measurement in the shortest time. Hence, we select some OLs as COL to minimize time consuming while cover whole OL network and formulate the problem as a set coverage problem in 3D lattice.

Simplification from adjacency: We have discussed about different adjacencies in the last subsection and in this subsection we can simplify the problem in these scenarios.

1) *Star adjacency*: In actual mobile sensing scenery using UAV, we often consider two dimensions only in this scenery because usually two distant OLs in a line is not predictable, i.e., OLs in different levels. Then, we could divide 3D lattice graph into multiple 2D grids and consider set cover problem in each grid.
2) *Cubic adjacency*: In this scenery, if an UAV flight over a plane, then whole coverage set include the plane and its adjacent planes. Then, we could also simplify 3D lattice graph into multiple 2D grids and take advantage of its periodic structure.

Therefore, instead of 3D lattice, we formulate the problem into constraint set coverage problem in grid.

Two special cases of time consuming: In section , we have discuss the components of total time consuming. But in actual scene, we usually consider only one part of it. Therefore, in this paper we will consider following two scenarios.

1) *Consider measurement time only*: In this scenery, we assume flight time negligible and consider measurement time only. As we show in , measurement time is proportion to the number of COLs. So we should select least OLs as COLs to cover OL-network. We could formulate this problem as a minimum dominating set problem in grid.
2) *Consider flight time only*: In this scenery, we assume measurement time negligible and consider flight time only. As we show in, flight time is proportion to the length of UAV's trajectory. So we should find the shortest OL-path in grid and select OLs in path as COLs to cover OL-network. We could formulate this problem as a minimum dominating path problem in grid.

Therefore, we will discuss these two problems above in the next section and give corresponding certifications.

E. Variable definitions

For the convenience of proof in next section, we define some variables following.

$G = (V, E)$ denotes 3D OL network graph. $L_{m,n}$ denotes grid graph with m rows and n columns. For graph G, $V(G)$ denotes set of vertexes in G. For any vertex $v, y \in V$, $N[y] = \{v \in V : yv \in E\} \cup \{y\}$ is the closed neighborhood of y (i.e., the set of neighbors of y and y itself). And for $S \subset V$, $N[S] = \bigcup_{v \in S} N[v]$. G_3 denotes rightmost three columns in $L_{m,n}$ and G_n denotes leftmost n columns in $L_{m,n+3}$. $\gamma(G)$ denotes the domination number of G which is the minimum size of a dominating set of G. $\gamma_l(G)$ denotes the minimum size of a dominating path of G. For convenience, we assure dominating path L as a special case of connected dominating set which could be represented as a vertex set.

IV. Proof

A. Minimum dominating set

B. Minimum dominating path

Lemma 1. *Let $n > 3$, $m > 0$ be integers, and L is a dominating path in $G = L_{m,n}$. Then $|L \bigcap V(G_3)| \geq m$. Further, if $3 \nmid m$, then $|L \bigcap V(G_3)| \geq m + 1$.*

Proof: We follow proof. Since is for connected dominating set and dominating path is a special dominating set, the conclusion as well as the analyzing method of this paper is also applicable to dominating set. ■

In lemma , we know that every dominating path L in $L_{m,n}$ has at least m vertexes in the three rightmost columns. Therefore, we will consider the three periodicity of dominating path. Specifically, we could construct dominating path in three columns or three rows.

Connecting vertex and dominating vertex: Since dominating path L has both connectivity and dominance, there is thus some vertex v which $N[v] \cap N[L - v] = N[v]$. In other word, the dominating set of v is contained in the dominating set of other vertexes and v is used to connect other vertexes. It is necessary part which connects a dominating set to a dominating path. We defines this kind of vertex as **connecting vertex** whose main effect is connecting vertexes and the other as **dominating vertex** whose main effect is dominating vertexes. Similar with G_n and G_3, We denote D_n and D_3 as dominating vertexes in G_n and G_3 columns respectively. And we also denote C_n and C_3 as connecting vertexes in G_n and G_3 respectively and denote $C_{n,3}$ as connecting vertexes between G_n and G_3.

Therefore, we could split L into several parts: $L = D_n \cup D_3 \cup C_n \cup C_3 \cup C_{n,3}$.

Lemma 2. *Let $n \geq 3$ and L is dominating path of $G = L_{m,n+3}$. There must exists one condition that D_n is no less than dominating vertexes in ($L_{m,n}$ and there exists some vertex in G_n whose private neighbor is in G_3.*

Proof: We follow proof. Since is for connected dominating set and dominating path is a special dominating set, the conclusion as well as the analyzing method of this paper is also applicable to dominating set. ■

V. Optimal Trajectory Planning Algorithms

A. Distribution of Message Diffusions

B. Export Message Pattern (EMP)

C. Self Message Pattern (SMP)

D. Floating Population Inference Model

VI. Evaluation

A. Datasets

B. Geo-homophily of OSNs

1) Geo-homophily of WeChat:

2) Geo-homophily of Gowalla:

C. Stability of Divided Regions

D. Performance of UDM

E. Performance of FPIM

VII. Conclusions

In this paper, we propose a systematic study on the population distribution projection over offline geographical regions by analyzing the geographical attributes of online social networks (OSNs). We propose the concept of geo-homophily in OSNs to establish the correlation between online message diffusion and the stability of geographical regions where a population distribution can be drawn. We formulate the population distribution problem from the perspective of Dirichlet process, and present prediction models to show the process that OSN users are distributed into regions, and infer the floating population across regions. By experiments over the large scale datasets, it is shown that the online message diffusions can help evaluate the stability of geographical regions, which further facilitates the determination of population distribution over fixed regions; the proposed prediction models have a high prediction accuracy in inferring the change of floating population across regions.

References