

A Deployment Strategy for UAV base Stations for Mobile CrowdSensing Applications

Michele Girolami^a, Stefano Chessa^{a,b}, Luca Fenucci^c

^aISTI-CNR, Institute of Information Science and Technologies, Pisa, Italy

^bUniversity of Pisa, Italy

^cUniversity of Bologna, Italy

Abstract

TODO

Keywords: CrowdSensing, Mobility Analysis, Detour

1. Introduction

2. Related Works

3. The Coverage Model

3.1. The Reference Scenario

Our reference scenario consists of a typical CrowdSensing architecture designed to collect sensing information from specific locations of interest. The architecture we refer to is composed by a back-end server and a set of end-devices. The back-end assigns *sensing tasks* to the end-devices and it stores the data collected. A task is a specific action to be completed from one or more end-devices. Such action might or might not require the explicit user intervention. Examples of sensing tasks are: collecting environmental data, taking a picture of a place or recording a short movie. The end-devices are generally user's pocket devices such as smartphones; such devices offer sensing capabilities through virtual and environmental sensors commonly available on commercial products.

End-devices are not static, rather they move according to patterns of human mobility in urban areas. Hence, the amount of retrievable data as well as the locations covered strictly depend on the way people roam indoor and outdoor. However, we also observe that those locations not yet covered by

any device, might be covered as well if at least one user accepts a *reasonable* detour towards such location. Detouring to a location implies that a user deviates from its original path in order to pass through a specific location. This is the case of a pedestrian that accepts to walk through a square close to its final destination. The probability of detour is strictly influenced by several factors: the detour time overhead, the existence of a reward and the user’s transport. More specifically, pedestrians are intuitively more likely to accept the detour, since they are free to walk with few limitations. Differently, users on a bus more rarely will accept to change their original plan.

Our goal is measuring how much locations of interest for a CrowdSensing measurement campaign can be covered by users passing through a location or willing to accept a detour. As a representative example, we report in Figure 1 a 3D coverage map. The z-axis reports the coverage probability obtained by also considering the probability a user accepts to detour. The higher the value on the z-axis, the higher the probability that the corresponding location is covered with data provided by the end-users. Such map allows to easily spot depopulated locations, namely locations from which it is unlikely to retrieve data from the end-devices. A CrowdSensing initiative can consider such quantitative assessment to optimize the data collection campaign by e.g. increasing the amount of involved users, further inactivating users in covering specific locations, adopt complementary devices able to sense the environment, such as drones or sensing units mounted on busses. We refer to subsection 3.2 for a description of our coverage probabilistic model.

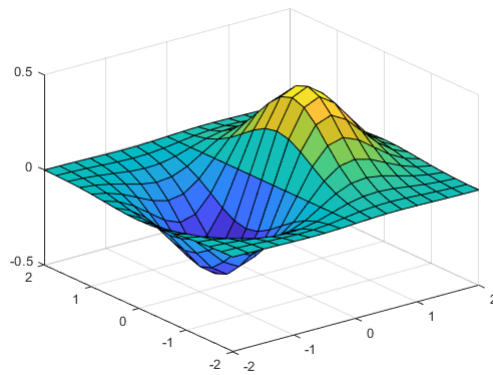


Figure 1: Coverage map with a detour probability model.

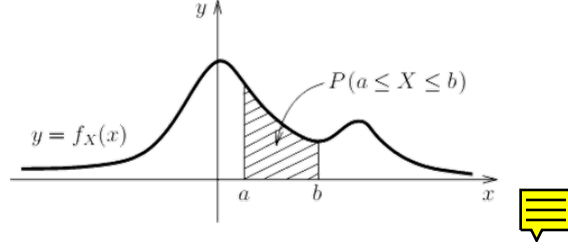


Figure 2: Esempio di intervallo di integrazione nel nostro caso usiamo $x - \Delta, x + \Delta$

3.2. The Coverage Probabilistic Model

We define L as the set of locations of interests, with $|L| = H$. We assume the existence of a set of users joining the CrowdSensing data collection campaign, they are represented as $U = \{u_1 \cdots u_k\}$, with $|U| = K$. Every user $u_i \in U$ moves along a set of trajectories, namely on ordered sequence of way-points $(x, y)_{t_0} \cdots (x, y)_{t_N}$. Given a location of interest and a way-point, it is possible to measure the physical distance with function δ , e.g the geodetic distance.

We now define the *coverage* of a location, e.g. $l_h \in L$ as the probability that any of the users in U move close to l_h , so that to gather data from such location. More specifically, we compute for every user's trajectory, the probability that the user accepts detouring towards l_h . Following an intuitive idea, the closer a user is to a location, the higher the probability he/she accepts the detour. Our models consists in the definition of three random variables.

We define the random variable $X_{ij}^h : \Omega \rightarrow \mathbb{R}^+$, with Ω the set of events in the form: location l_h is covered by user u_i at distance j . The variable X_{ij}^h associates to every event in Ω a numeric value which is the physical distance between the user's position location l_h . Such values are continuous in \mathbb{R}^+ , therefore the probability $P(X_{ij} \in [x - \Delta, x + \Delta])$ for any given increment Δ is given by:

$$\int_{x-\Delta}^{x+\Delta} f_{X_{ij}^h}(x) dx \quad (1)$$

with f the probability density function. We generalize equation 1 with the probability the location l_h is covered by user u_i at any distance from l_h . More specifically, we compute the probability that the user u_i detours to l_h from any way-point along its trajectories. We define the r.v. $X_i^h : \Gamma \rightarrow \mathbb{R}^+$, with Γ the set of events in the form: location l_h is covered by user u_i at any

distance x from l_h . We assume that the r.v. X_{ij}^h are all independent, since the probability the user u_i detours towards l_h is independent from the trajectory followed. The probability of events in Γ is given by:

$$X_i^h \in [x - \Delta, x + \Delta] = 1 - \prod_{\forall x \in [x - \Delta, x + \Delta]} 1 - P(X_{ij} \in [x, x + \Delta]) \Delta \quad (2)$$

$$X_i^h \in [x - \Delta, x + \Delta] = \prod_{\forall x \in D_i^h} P(X_{ij} \in [x - \Delta, x + \Delta]), \forall \Delta \quad (3)$$

where D_i^h are the distance measures between way-points of u_i 's trajectories and the location l_h . From equation 3 we model the probability the location l_h is covered by a generic user in U following any of its trajectories. We define the r.v. $X^h : \Theta \rightarrow \mathbb{R}^+$, with Θ the set of events in the form: location l_h is covered by any user at any distance x from l_h . The probability of events in θ is given by:

$$P(X^h \in [x, \Delta x]) = 1 - \prod_{\forall u_i \in U} P(X_i^h \in [x, \Delta x]) = 1 - \prod_{\forall u_i \in U} (1 - \prod_{\forall x \in D_i^h} (1 - P(X_{ij} \in [x, x + \Delta x]))), \forall \Delta \quad (4)$$

$$P(X^h \in [x - \Delta, x + \Delta]) = \prod_{\forall u_i \in U} P(X_i^h \in [x - \Delta, x + \Delta]) = \prod_{\forall u_i \in U} (\prod_{\forall x \in D_i^h} (P(X_{ij} \in [x - \Delta, x + \Delta]))), \forall \Delta \quad (5)$$

We model the probability the location l_h is covered by considering all the users in U and all the trajectory's followed by the users. We finally consider that users too far from a given location will more likely avoid a detour, we introduce the detour radius τ modelling the maximum admissible distance for a user to accept or not a detour towards location l_h .

3.3. A Data-Driven UAV Deployment Strategy

- Formalizzazione del problema di posizionamento, ad esempio secondo la tesi di E.C

72 • algoritmo stations positioning e localCover

73 • descrizione delle zone non ammesse e dell'ottimizzazione

74 • pseudo-codice

75 **4. The Experimental Data Set: the GeoLife Case-Study**

76 • Descrizione di GeoLife grafici con: aggregato fire, numero gps nel

77 tempo, heatmap giorno mese

78 • Introdurre la carenza di tracce e la necessità di incrementare le gps

79 • Processo per arricchire il dataset (stop place, 3 tipi di trasporti

80 • Grafici di confronto sul periodo selezionato: numero di GPS nel tempo,

81 heatmap

82 **5. Experimental Settings and Results**

83 *5.1. Measuring the Coverage*

84 • Scenario 1 - Environmental Monitoring: locations places along a regular

85 grid, 5Km in-between distance

86 • Scenario 2 - POI Monitoring: locations selected as squares, museums,

87 commercial centers, train+bus stations

88 • Scenario 3 - Pedestrian Mobility Flows: locations selected with sub-

89 ways' stations

90 *5.2. UAV Deployment based on the Coverage Maps*

91 per ogni scenario mostriamo il posizionamento della stazione, punti cop-

92 erti e bechmark random

93 **6. Conclusions**

94 **References**