A COMPREHENSIVE MODELING FRAMEWORK FOR AIRBORNE MOBILITY

Junfei Xie

Thesis Prepared for the Degree of

MASTER OF SCIENCE

UNIVERSITY OF NORTH TEXAS

December 2013

APPROVED:

Yan Wan, Major Professor

Jae H. Kim, Committee Member

Kamesh Namuduri, Committee Member

Shengli Fu, Committee Member and Chair of
the Department of Electrical
Engineering

Costas Tsatsoulis, Dean of the College of
Engineering

Mark Wardell, Dean of the Toulouse Graduate
School

Xie, Junfei. A Comprehensive Modeling Framework for Airborne Mobility. Master of Science (Electrical Engineering), December 2013, 56 pp., 2 tables, 14 illustrations, references, 65 titles.

Mobility models serve as the foundation for evaluating and designing airborne networks. Due to the significant impact of mobility models on the network performance, mobility models for airborne networks (ANs) must realistically capture the attributes of ANs. In this paper, I develop a comprehensive modeling framework for ANs. The work I have done is concluded as the following three parts. First, I perform a comprehensive and comparative analysis of AN mobility models and evaluate the models based on several metrics: 1) networking performance, 2) ability to capture the mobility attributes of ANs, 3) randomness levels and 4) associated applications. Second, I develop two 3D mobility models and realistic boundary models. The mobility models follow physical laws behind aircraft maneuvering and therefore capture the characteristics of aircraft trajectories. Third, I suggest an estimation procedure to extract parameters in one of the models that I developed from real flight test data. The good match between the estimated trajectories and real flight trajectories also validate the suitability of the model. The mobility models and the estimation procedure lead to the creation of “realistic” simulation and evaluation environment for airborne networks.

Copyright 2013

by

Junfei Xie

ACKNOWLEDGEMENTS

First, I would like to offer my sincerest gratitude to my major advisor Prof. Yan Wan, who has supported me throughout my M.S. study with her great patience, encouragement and mentoring. I could not have imagined having a better advisor and mentor. My sincere thanks also go to the rest of my thesis committee: Dr. Jae H. Kim from Boeing Research & Technology, Prof. Shengli Fu and Prof. Kamesh Namuduri for their insightful comments and encouragement. I would also like to thank all of my friends and lab mates for their company, support, and discussion. Finally, I thank my parents who always support and encourage me with their best wishes. Without them, I could not have the chance to pursue the Master's Degree.

TABLE OF CONTENTS

	Page
ACKNOWLEDGEMENTS	iii
Chapters	
1. INTRODUCTION	1
1.1 Motivation	1
1.2 Overview of the Thesis	2
2. ANALYSIS OF MOBILITY MODELS FOR AIRBORNE NETWORKS.....	4
2.1 Introduction	4
2.2 Description and Evaluation of Existing AN-specific Mobility Models	5
2.3 Further Comparison of the Mobility Models.....	15
2.4 Conclusion.....	18
3. A COMPREHENSIVE MODELING FRAMEWORK FOR AIRBORNE MOBILITY...19	
3.1 Introduction	19
3.2 3-D Smooth-Turn Mobility Models.....	21
3.3 Realistic Boundary Models.....	27
3.4 Conclusion.....	32
4. ESTIMATION AND VALIDATION OF THE 3-D SMOOTH-TURN MOBILITY MODEL FOR AIRBORNE NETWORKS.....	33
4.1 Introduction.....	33
4.2 Estimation Based upon Actual Aircraft Trajectories.....	34
4.3 Conclusion.....	47
5. CONCLUSION AND FUTURE WORK.....	48
5.1 Conclusion.....	48

5.2 Future Work.....	48
REFERENCES	49

CHAPTER 1

INTRODUCTION

1.1 Motivation

With more manned and unmanned vehicles in the airspace, communication among these aerial vehicles is envisioned to be critical for safe maneuvering, real-time information sharing, and coordination for mission success. Airborne networking is significantly more challenging as compared to the networking of ground sensor networks with fixed topology or slow mobility. The major difficulties reside in the unique attributes of airborne networks (ANs), including high node mobility, frequent network topology changes, mechanical and aerodynamic constraints, strict safety requirements, and harsh communication environment [1], [2]. Because of these properties, networking protocols that are built for traditional ground-based networks will not work well for ANs. Most of the current research efforts including the newly developed ones that used field tests [3], [4] and simulation environments (e.g., EMANE/CORE [5], [6], NS-3 [7] and OPNET [8], [9]), are focused on evaluating the performance of networking protocols.

While previous investigations provided invaluable insights into airborne networking, they also point out one critical need in the current AN research: realistic mobility models. By realistic, it means that the models are able to capture the unique mobility attributes of ANs, such as high mobility, mechanical and aerodynamic constraints, and safety requirements (e.g., maintaining a safe separation distance). The need to use mobility models to evaluate networking performance is driven by the fact that field tests are very costly and restricted to specifically designed settings which make it hard to generalize performance evaluation results. As such, running simulations over random mobility models that cover a large number of scenarios is considered to be a less expensive and more systematic and robust alternative

[10]. However, the mobility models---random walk (RW), random direction (RD), random waypoint (RWP), and Gauss Markov---that serve as the kernel of most simulation environments are designed for traditional mobile ad hoc networks (MANETs) [10]-[12]. As the mobility of ground vehicles is very different from that of aerial vehicles due to aerodynamic constraints, MANET models may not truthfully emulate ANs. Because of the significant impact of mobility models on the performance of networking protocols [9], [10], [13], using MANET models for performance evaluation may lead to misleading results. This limitation suggests an urgent need to develop realistic AN mobility models to facilitate the accurate evaluation and design of airborne networking.

This thesis aims to develop a comprehensive modeling framework for airborne networks research. In particular, the contribution of this thesis is threefold. The first is a comparative analysis and comparison of existing AN mobility models based upon the metrics such as networking performance and ability to capture mobility attributes of ANs. The second contribution is the construction of a comprehensive modeling framework for airborne networks including 3-D mobility models and realistic boundary models. These random mobility models obey physical laws governing aerial maneuvers, and thus capture the smoothness of aerial trajectories. They are also simple enough to facilitate tractable evaluation and design. The third contribution is validation and a systematic procedure to configure the 3-D AN mobility model through extracting model parameters from real flight test data. Per the author's knowledge, the AN mobility modeling framework and the model parameter estimation procedure are the first effort in the literature to create "realistic" simulation and evaluation environment for airborne networks.

1.3 Overview of the Thesis

The remainder of this thesis is organized as follows. Chapter 2 describes five mobility models developed for ANs, including semi-random circular movement mobility model, three-way random and pheromone repel mobility models, smooth-turn mobility model, flight-plan mobility model, and multi-tier mobility models (see also the conference publication [63]). These models to facilitate model selection is further evaluated, based upon 1) networking performance, 2) ability to capture mobility attributes of ANs, 3) the degree of randomness, and 4) the associated applications.

Chapter 3 introduces two 3-D smooth turn (ST) mobility models extended from the basic 2-D ST mobility model (see also the conference publication [64]). The first one is the 3D z -dependent ST mobility model, and the second one is the 3-D z -independent ST mobility model. In the end, boundary models for the 3-D ST models are discussed, such that aerial nodes maintain smooth trajectories at boundaries.

Chapter 4 describes the procedure to estimate the 3D z -independent ST mobility model parameters from real flight trajectories (see also the conference publication [65]). The estimated parameters are optimized based upon a tradeoff between estimation error and correlation factor between neighboring randomly selected intervals. The good match between the estimated trajectories and real flight trajectories validates the suitability of this model for ANs.

Finally, Chapter 5 includes a conclusion and brief discussion of future works.

CHAPTER 2

ANALYSIS OF MOBILITY MODELS FOR AIRBORNE NETWORKS

2.1 Introduction

Mobility models provide the theoretical foundation necessary for evaluating the performance of network protocols. Since the fidelity of evaluation results depends on the accuracy of mobility models, it is critical to choose an accurate mobility model that reflects realistic movement patterns of nodes in the network. However, as most existing mobility models are designed for traditional mobile ad hoc networks (MANETs), they cannot capture the unique movement patterns of aerial vehicles. For example, in the widely used mobility models such as random waypoint (RWP)[10], [14] and random direction (RD)[10], [15], [16], mobile nodes are assumed to be capable of making sharp turns and quickly changing directions that are not suitable for airborne nodes, therefore using MANETs models for performance evaluation may lead to misleading results. This limitation suggests an urgent need to comprehensively investigate AN mobility models, so as to permit the development of simulation environment and subsequent evaluation and design of AN networking strategies.

Very recently, there were some studies on understanding the unique features of aerial mobility and capturing them in realistic mobility models. Contributions of this chapter include a comparative analysis of existing AN mobility models and evaluation based upon the metrics such as the networking performance and ability to capture mobility attributes of ANs. In addition, this chapter compares these models based upon the degree of randomness and the associated applications.

It is worthy to note that AN mobility modeling is related to several other fields, including but not limited to aerial target tracking [17]-[20], and the control and coordination of UAVs [21]-[24]. These fields are also partially concerned with the modeling of aerial

vehicle trajectories. As these studies investigate the physical behavior of aerial vehicles in detail, they provide the theoretical foundations and insights to develop AN mobility models.

The remainder of this chapter is organized as follows. Chapter 2.2 describes and evaluates five mobility models recently developed for ANs. Chapter 2.3 contains a further comparative study of existing AN mobility models to facilitate model selection. Chapter 2.4 provides a brief conclusion.

2.2 Description and Evaluation of Existing AN-Specific Mobility Models

This section presents several mobility models recently developed specifically for ANs. These models distinguish from the MANET models in that they capture smooth aerial turns determined by mechanical and aerodynamic constraints. Here, this section thoroughly describes their fundamentals, and evaluate them based upon 1) mobility patterns, 2) AN networking performance if there is any, and 3) ability to capture high mobility, mechanical and aerodynamic constraints, and safety requirements.

2.2.1 Semi-Random Circular Movement Mobility Model

The semi-random circular movement (SRCM) mobility model restricts UAVs to circle around a fixed center with variable radii [25]. This model is developed for scenarios where a potential target location is known, and UAVs are dispatched to collect information in nearby area. A typical application is search and rescue, in which the last known location of the lost victim can naturally serve as the circling center.

1) Model description: In the SRCM model, each aerial node is assumed to be moving independently on a 2-D disk with a fixed center and radius R (see Figure 2.1a). Initially, a node starts from a point on the disk with polar location (r, θ) , where $0 \leq \theta < 2\pi$, and $r \in \{\frac{i}{n} R\}, i \in \{1, 2, \dots, n\}$. Along the circle defined by r , the node then selects a speed v

uniformly distributed in $[v_{min}, v_{max}]$ and a destination with travelling angle φ uniformly distributed in the interval $[\varphi_{min}, \varphi_{max}]$. Once the node reaches the destination, it randomly selects another speed v and destination with travelling angle φ along the same circle, and moves toward it. This process continues until the node completes a round. Upon the completion, it randomly chooses another radius $r \in \{\frac{i}{n} R\}$, transmits to this new circle, and repeats the above process.

2) *AN networking performance*: Fixing the circling center simplifies the performance analysis, and also brings in tractable properties in terms of node distribution, coverage, and network connectivity. In particular, it was shown in [25] that the node distribution is approximately uniform, through both mathematical analysis and numerical simulation. Besides this, compared to the RWP model, the SRCM model has faster coverage speed and larger steady-state coverage percentage. Furthermore, the SRCM model demonstrates less fluctuation in connectivity probability, indicating a more stable communication network.

3) *Ability to capture mobility attributes of ANs*: The SRCM model guarantees smooth turning trajectories constrained by mechanical and aerodynamic laws, except during the transitioning from one circle to another. The model assumes that the transition time is much less than the circling time and as such the non-smooth movement during transitioning is neglected. However, fixed circling center places constraints on mobility variability. High speed is easily ensured, similar to all other mobility models. Safety constraint can potentially be addressed, if a mechanism is added to restrict multiple vehicles from selecting the same circle.

a)

b)

Fig. 2.1 Sample trajectories of a) SRCM, b) three-way random mobility model.

2.2.2 Three-way Random and Pheromone Repel Mobility Models

Two models were developed in [13], [26], [27] for group reconnaissance applications:

1) a Markov chain based three-way random mobility model, and 2) a graphically constrained

mobility model, named the pheromone repel model. The pheromone repel model is developed based upon the three-way random mobility model; in addition, it permits each aerial node to adjust its direction to enhance scan coverage, through avoiding areas which have recently been visited.

1) Model description: Let us first describe the basic three-way random mobility model, and then the modifications that lead to the repel model. In the three-way random mobility model, the heading speed and turn radius are assumed to be constants. The mobility pattern is defined as a Markov chain, the states of which represent three mobility modes: going straight (denoted as s_1), turning left (s_2), and turning right (s_3). The selection of mobility mode at the next time step $k + 1$ is dependent upon the current mode at time step k , with the conditional probability defined in the probability transition matrix $P(s[k + 1]|s[k]) \in R^{3 \times 3}$, where

$$s[k] = \begin{bmatrix} s_1[k] \\ s_2[k] \\ s_3[k] \end{bmatrix}, \text{ and the } (i, j)\text{-th entry represents the probability to jump from state } s_i \text{ to state } s_j.$$

Based upon data, the numerical transition matrix used in [26] is $P(s[k + 1]|s[k]) =$

$$\begin{bmatrix} 0.8 & 0.1 & 0.1 \\ 0.3 & 0.7 & 0 \\ 0.3 & 0 & 0.7 \end{bmatrix}. \text{ Diagonal entries being larger indicate that the vehicle is more likely to}$$

maintain its current mode; keeping straight movement or making a typical smooth turn.

Movement at boundaries is similar to that of the Gauss-Markov model; if a vehicle is within certain distance to the boundary, it chooses a turning direction away from the boundary, until the heading direction is pointing toward the inner side of the region, e.g., the angle between the heading direction and the normal line to the boundary reaches a value randomly selected between $\pm \frac{\pi}{4}$ [28]. In the distributed pheromone repel model, the probability to select mobility mode is guided by pheromone maps. In particular, the field is partitioned into small grids. Each aerial node tracks a pheromone map of the field, marking the time instances k_i that the node visits each grid i within a time span $\bar{k}$. Neighboring

vehicles within the transmission range can merge their pheromone maps through regular broadcasting. The local merged pheromone map produces a measure called pheromone smell, capturing the local view of how recently each grid is visited. Mathematically, the pheromone smell for grid i at time k is expressed as $ps_i[k] = I(k_i - (k - \bar{k}))$, giving more weight to a more recent visit. Here the function $I(x)$ equals x when $x > 0$ and 0 when $x \leq 0$. Each vehicle then determines its mobility mode according to the aggregated pheromone smell. In particular, the probability to choose the mobility mode s_j at time k is defined as $\frac{\sum_{i \in \text{circles } 1,2,\&3} ps_i[k] - \sum_{i \in \text{circle } j} ps_i[k]}{2 \sum_{i \in \text{circles } 1,2,\&3} ps_i[k]}$, where circle j includes all grids in a defined circle ahead of the scan area at time k : with $j = 1$ denoting the circle straight ahead, $j = 2$ denoting the circle to the left, and $j = 3$ denoting the circle to the right. In the case that the aggregated pheromone smells in all three circles are 0, the basic three-way random mobility model is used to determine the probability of mode selection.

2) *Networking performance*: The pheromone repel model has improved coverage properties compared to the three-way random model. The simulations suggest that it has a faster coverage speed and larger scan coverage percentage at the steady state; in addition, the intervals between consecutive scans are more uniformly distributed, avoiding rescanning an area very recently visited. The price paid is network connectivity: the pheromone-repel model tends to have larger number of disconnected clusters compared to the three-way random mobility models in transient time. Because of the lack of connectivity, traditional MANETs routing protocols may not work the well. The same group proposed the geographic routing protocol (named location aware routing opportunistic delay-tolerant networks (LAROD)) and a location service (named the location dissemination service (LoDiS)) for such type of intermittently-connected mobile ad hoc networks (IC-MANETs) [13], [28]. Simulations suggest that LAROD-LoDiS has better networking performance than the spray and wait protocol, in terms of delivery ratio and overhead. In addition, comparison between the

pheromone repel and RWP models using the LAROD-LoDiS protocol supports the statement that mobility models play significant roles in the performance of routing strategies, and thus the mobility research for ANs is of significant value.

3) *Ability to capture mobility attributes of ANs:* Both the three-way random and pheromone repel models allow aircraft to perform typical turns with constant turn rate, reflected of mechanical and aerodynamic constraints. Unlike the SRCM model, these two models do not require the turn center to be fixed; however, the turn radius is fixed, constraining the mobility variability. Safety constraint is not addressed.

2.2.3 2-D Smooth-Turn Mobility Model

The 2-D smooth-turn (ST) mobility model was developed to capture the tendency of freely-moving airborne vehicles toward making smooth trajectories (e.g., straight trajectories or typical turns with large radius) [29]-[30]. This is made possible by directly modeling the centripetal and tangential accelerations, following the physical laws of aerial turning objects. Such mobility patterns are typical in applications such as patrolling. This section first introduces the smooth-turn concept using the basic 2-D formulation, and then evaluates the model based upon networking performance and ability to capture AN mobility attributes, and also discusses its connection with the three-way random mobility model discussed in Chapter 2.2.2.

1) *Basic model description and statistical properties:* In the basic 2-D ST mobility model, an aerial vehicle selects a point on the 2-D plane along the line perpendicular to its heading direction and circles around it for an exponentially elapsed duration with mean $1/\lambda$, where $\lambda \neq 0$ is a finite number. The perpendicularity ensures smooth turning trajectories. The circling dynamics are mathematically captured by

$$\dot{\Phi}(t) = -\omega(t) = -v/R \quad (2-1)$$

$$\dot{l}_x(t) = v_x(t) = v \cdot \cos(\Phi(t))$$

$$\dot{l}_y(t) = v_y(t) = v \cdot \sin(\Phi(t))$$

where $l_x(t)$, $l_y(t)$, $v_x(t)$, $v_y(t)$, $w(t)$ and $\Phi(t)$ represent x coordinate, y coordinate, velocity in x direction, velocity in y direction, angular velocity, and heading angle of an aerial node at time t . The forward speed v is assumed to be a constant in the basic model. The inverse of R is normally distributed with zero mean and variance σ^2 , so as to capture the preference toward straight trajectories and slight turns. Once the exponentially elapsed duration is completed, the vehicle chooses another R , determines the new turn center, and repeats the above process.

The three parameters v , λ , and σ^2 in the model can be selected to capture a wide range of aerial moving patterns. In particular, a smaller λ indicates that the vehicle tends to continue its current turn center instead of choosing a new one. Moreover, a larger σ^2 indicates more chances for turns with small radii.

The behavior of vehicles at boundaries can be modeled as reflecting back to the region, or wrapping around and appearing at the other side of the region.

Using the reflection boundary model, the simulation model for the ST model can be represented in the following. Here assume that Δt is the simulation sampling time. The turning angle at each time step $k\Delta t$ is then represented by $\theta = \frac{v}{r(T_i)}\Delta t$, where $T_i \leq k\Delta t \leq T_{i+1}$, and T_i and T_{i+1} are the two consecutive time instances to change turn radius

$$c_x(T_i) = l_x(T_i) + r(T_i) \sin(\Phi(T_i)) \quad (2-2)$$

$$c_y(T_i) = l_y(T_i) - r(T_i) \cos(\Phi(T_i))$$

$$\Phi[k+1] = \Phi[k] - \theta - 2\pi \left\lfloor \frac{\Phi[k] - \theta}{2\pi} \right\rfloor$$

$$l_x[k+1] = c_x(T_i) - r(T_i) \sin(\Phi[k+1])$$

$$-2W \left\lfloor \frac{c_x(T_i) - r(T_i) \sin(\Phi[k+1])}{2W} + 0.5 \right\rfloor$$

$$l_y[k + 1] = c_y(T_i) + r(T_i) \cos(\Phi[k + 1])$$

$$-2W \left\lfloor \frac{c_y(T_i) - r(T_i) \cos(\Phi[k + 1])}{2L} + 0.5 \right\rfloor$$

where $c_x(T_i)$ and $c_y(T_i)$ represent the location of the turn center at T_i , and W and L represent the width and length of the simulation region. The floor functions realize the reflection boundary model (see [29] for the details). A sample trajectory using this simulation model is shown in Figure 2.2.

The tractability permitted by the simple dynamics makes possible further statistical analysis such as the node distribution and the number of neighbors. It was proved in [29] that the model has uniform distribution, which adds to the value of this model, as rich statistical results can be achieved from the uniformity.

Fig. 2.2 Sample trajectory of the 2-D ST model [26].

2) *Networking performance*: The tractability permitted by the simple dynamics makes possible further statistical analysis such as the node distribution and the number of neighbors. It was proved in [29] that the basic 2-D model has uniform distribution, which adds to the value of this model, as rich statistical results can be achieved from the uniformity.

3) *Ability to capture mobility attributes of ANs*: The model captures smooth turns with flexible radii. As it is constructed using aerial kinetics, the model naturally captures the spatiotemporal correlation of accelerations. Second, the model has very simple dynamics. It also captures high mobility and frequent network topology changes. Aerial nodes in this model are free to travel inside the simulation area with variable turn center and turn radius. Besides the smooth trajectory constraints and possible safe requirements, no other constraints limit the movement of aerial nodes.

Here, the ST model is connected with the RD model and the basic three-way random model. Similar to the basic RD model, an aerial node randomly chooses a direction for an exponentially elapsed duration. The only difference is that the RD model chooses a random straight direction, whereas the ST model chooses a random turn radius. The three-way random model can be considered as a variant of the ST model. As opposed to the fixed duration between the changes of directions in the three-way random model, the duration in the basic ST mobility model is random. Moreover, the turn radius in the ST mobility model can take continuous values in a large range, but in the three-way model, three values are considered: $+r$, $-r$, and ∞ , representing right turn with radius r , left turn with radius r , and the straight trajectory. Furthermore, the probability of direction selection in the three-way random model is state-dependent; but in the basic ST model is based upon the exponentially elapsed duration distribution and the radius distribution.

2.2.4 Flight-Plan-Based Mobility Model

Pre-defined trajectory plans may be directly used as mobility models [31]. Such pre-defined plans may not exist for completely autonomous ANs; however, they are typically available for ANs that involve commercial flights, cargo planes, and pre-defined AN backbones [31], [32].

1) Model description and the use in mobility-aware routing: In [31], pre-defined flight plans together with the mobility-aware routing and mobility dissemination protocol (MARP/MDP) are used to effectively maintain the networking of AN backbone nodes. In particular, initial flight plans are recorded in a global mobility file, which contains the location and gesture information of each aircraft, tagged with time. The global mobility file is then used to generate a time-dependent network topology (TDNT) map and then the routing table for each time. Uncertainties in the environment (such as weather) might cause deviations from the flight plan. A hello-and-acknowledge mechanism is used to check if the TDNT is up-to-date. If not, the TDNT map is updated and then a new routing table is generated.

2) Networking performance: To understand the performance of the model and the associated routing protocols, a small-scale network with four nodes in circular movement and a medium-scale network with 18 nodes in circular and race-track movement is constructed. The MARP/MDP protocol is shown to outperform the AODV and OLSR protocols in terms of throughput, latency, and package delivery ratio. The overhead of this routing protocol is slightly worse than that of AODV and OLSR. This study also suggests the importance of mobility models, and its use in developing high-performance routing protocols for ANs.

3) Ability to capture mobility attributes of ANs: Because of the current safety concerns in flying autonomous aerial vehicles, flight plans are typically available. The model captures

high mobility, safe constraints, and aerodynamics, as they are both reflected by the flight plans.

2.2.5 Multi-Tier Mobility Models

The airspace is highly heterogeneous with aerial vehicles of different types and operating for different missions [33]. As it is impossible to use a common mobility model for all these vehicles, networking in such heterogeneous networks requires mobility models that permit multiple mobility patterns. To meet this need, multi-tier mobility models (belonging to the category of hybrid models) are introduced (see [1], [31], [32], [34]). In particular, the multi-tier mobility model in [1] contains aircrafts of different types flying at different altitudes. Aerial networks may also be connected to fixed control stations or ground vehicle teams to form multi-domain communication networks [1], [31], [33].

ANs with backbone structures can be modeled using multi-tier mobility models [31], [32], [34], [35]. As robust networking is very difficult to establish for highly random autonomous ANs, imposing designable deterministic backbone structures can significantly enhance the reliability and scalability of ANs. In particular, the backbone nodes have planned trajectories [31],[36] that serve as the base stations (or fusion centers) [36], [37] for information exchange among themselves, and with other vehicles. In [36], the UAV backbone nodes are moving deterministically in circles, but with designable velocities, locations, radii and transmission ranges. Algorithms were developed to design these parameters for two goals: 1) maintaining connection among the backbone nodes, and 2) achieving wide coverage.

2.3 Further Comparison of the Mobility Models

As mobility models have determining effect on routing performance, choosing the suitable mobility model is critical for the evaluation of networking performance. In Chapter

2.2, these models are evaluated and compared according to 1) mobility patterns, 2) basic AN networking performance studies, and 3) suitability for ANs in terms of high mobility, mechanical and aerodynamic constraints, and safety requirements. In this section, the above AN mobility models are further compared from two additional aspects: 1) randomness level, and 2) associated application. The discussion here represents a first step toward a systematic procedure to select and configure mobility models for different scenarios of interest. Note that a comprehensive comparison of networking performance using these models and real flight tests will also help with deciding model selection criteria. This study is left to the future work.

1) *Randomness*: The degree of randomness is a natural metric to characterize and differentiate mobility models [29], [30]. Because of the difficulties facing a robust networking of autonomous ANs, deterministic pre-defined flight plans are typically adopted nowadays in small-scale field tests. However, with the rapid growth of this field, it is envisioned that less controllable flight trajectories and more random AN topologies will appear in the future.

In [29], an entropy rate-based measure was introduced to quantify the degree of randomness for mobility models. The entropy rate is defined upon a Markov chain representation of the mobility. In the Markov chain, each state captures the mobility status of an aerial node, such as location, heading direction, speed, and so on, depending upon the specific scenario. The entropy-rate-based randomness measure is then defined as: $H = -\int_i \int_j p_i Q_{ij} \ln Q_{ij}$, where P_i represents the probability to stay at status i , Q_{ij} represents the probability to jump from status i to status j in a unit time Δt .

In [29], the randomness of four mobility models including RD, ST, SRCM, and FP are quantified using this randomness measure. Through configuring the models with a similar set of parameters such as forwarding speed ($v = 40m/s$), waiting time interval distribution

(exponential with $\lambda = 2/s$), it is found that the randomness of RD, ST, SRCM, and FP are in a decreasing order: RD around 0.018, ST typically below this, SRCM at the order of 10^{-6} , and FP almost negative.

Similarly, the randomness of the three-way random mobility model can be found. Using the transition matrix presented in Chapter 2.2.2 as the example, first note that the probability to move forward, left, or right at steady state is $p_1 = 0.6$, $p_2 = 0.2$ and $p_3 = 0.2$, respectively. Assume $\Delta t = 0.001s$ to be consistent with that in [29]. As the vehicle only changes the mode at the end of every $2s$ [13], it is found that the entropy rate as

$$\begin{aligned} H &= -\int_i \int_j p_i Q_{ij} \ln Q_{ij} = -\sum_i p_i \sum_j Q_{ij} \ln Q_{ij} \\ &= -\frac{0.6\Delta t}{2} (0.8 \ln(0.8) + 0.2 \ln(0.1)) \\ &\quad - \frac{0.4\Delta t}{2} (0.7 \ln(0.7) + 0.3 \ln(0.3)) = 3.3 \times 10^{-4} \end{aligned} \quad (2-3)$$

Comparing to the other mobility models (see results in [29]), its randomness level is higher compared to the SRCM model, but lower than all the other models. To permit a fair comparison with the ST model, also assume that the waiting time interval to change mobility mode has the same exponential distribution with $\lambda = 2/s$. As within Δt , the vehicle has a probability of $\lambda\Delta t$ to change mode and $1 - \lambda\Delta t$ to keep its current mode, its randomness is found as

$$\begin{aligned} H &= -\sum_i p_i \sum_j Q_{ij} \ln Q_{ij} \\ &= -0.6((1 - \lambda\Delta t) \ln(1 - \lambda\Delta t) + 0.8\lambda\Delta t \ln(0.8\lambda\Delta t) + 0.2\lambda\Delta t \ln(0.1\lambda\Delta t)) \\ &\quad - 0.4((1 - \lambda\Delta t) \ln(1 - \lambda\Delta t) \\ &\quad + 0.7\lambda\Delta t \ln(0.7\lambda\Delta t) + 0.3\lambda\Delta t \ln(0.3\lambda\Delta t)) = 0.0157 \end{aligned} \quad (2-4)$$

which is comparable to that of the ST mobility model.

2) *Application-type*: Another more straightforward criterion to compare and select mobility model is the application-type. In different applications, the ANs are typically associated with different mobility patterns. As suggested by [29], the ST mobility model is most suitable for patrolling; the SRCM model has some predefined information and is suitable for search and rescue applications; and the flight plan model is good for cargo and transportation scenarios. Furthermore, it is also noted that the pheromone repel mobility model is suitable for group reconnaissance application that requires fast coverage.

2.4 Concluding Remarks

This chapter represents the first attempt to comprehensively study the mobility models of airborne networks noting that there is very limited existing research in this field. In particular, this chapter analyzes and compares the existing mobility models for airborne networks. Besides investigating the specifics of each mobility model, this chapter evaluates these models based upon the following metrics: i) AN networking performance, and ii) whether the particular mobility patterns are realistic to capture AN mobility attributes. These models are further compared in terms of i) the degree of randomness and 2) the associated AN applications, to facilitate model selection.

CHAPTER 3

A COMPREHENSIVE MODELING FRAMEWORK FOR AIRBORNE MOBILITY

3.1 Introduction

Realistic random mobility models for airborne networks (ANs) are highly desirable to evaluate and design airborne networking. As introduced in the above chapter, several preliminary mobility models have been developed specifically for ANs. The semi-random circular movement (SRCM) mobility model [25] restricts unmanned aerial vehicles (UAVs) to circle around a fixed turn center with variable radii; it is envisioned that this model may be suitable for search applications where the potential target location may be known beforehand and is used as the fixed turn center. The Markov chain based three-way random mobility model and the enhanced pheromone repel model [26-28] permit variable turn centers, but restrict turn radius to be one of three values, $+r$, $-r$, and ∞ ; these models are designed for reconnaissance applications. As these models place unnecessary constraints on turn center and turn radius which are not typically observed in aerial maneuvers, a general 2-D smooth-turn (ST) mobility model [29-30] is developed, which allows aircraft to perform either straight trajectories or smooth trajectories with variable slight turns. This model is based on two common aircraft maneuvers. One is called cruise [38], which says that an aircraft has balanced forces and as such is moving in a straight line at a constant speed. The “speed” mentioned in this thesis is airspeed (i.e., speed relative to the air [39]), which can be read from the airspeed indicator. Since wind speed is assumed to be zero, horizontal component of airspeed is equal to groundspeed [39] at the same altitude. The other is called level coordinate turn, which indicates that an aircraft has balanced forces but a non-zero constant bank angle [40], and hence is performing steady and level turn with constant turn rate and heading speed.

However, aircraft maneuvers are not restricted to these two categories. Other typical maneuvers include climb [41], descend, steep turns, skidded turns, slipping turns, spirals, etc. [42]. These diverse maneuver types suggest that 2-D AN mobility models are not sufficient. A more comprehensive investigation of 3-D aerial movement patterns and the development of realistic 3-D AN mobility models are necessary to facilitate the accurate evaluation and design of airborne networking.

In this chapter, a comprehensive modeling framework for airborne networks is developed. Extended from the author's previous results on the development of 2-D ST mobility model [29-30], this modeling framework includes: 1) mobility models that capture smooth 3-D trajectories, and 2) realistic boundary models. The features of this modeling framework include the following:

1) Realistic capturing of 3-D aerial mobility. Two 3-D smooth-turn mobility models are introduced to permit changing flight altitudes. This facilitates modeling of military aircraft performing “high-g” turns. One model captures the correlation of movement among all three dimensions. In the second model, z -dimensional movement is assumed to be independent from the other two dimensions. Distinct from the Gauss-Markov-type models [10], [43], [44], these models capture the correlation of acceleration across temporal and spatial coordinates during turns according to physical laws.

2) Flexible user configuration. The modeling framework is kept very general to incorporate a variety of movement patterns corresponding to different applications. The modeling framework can be configured easily by selecting model parameters. For instance, the model may be reduced to the three-way random mobility model described in Ref. [25-28] by fixing turn radius and enforcing additional small modifications. Furthermore, the procedures to estimate model parameters from flight field test data are summarized. This procedure maximizes the value of field tests, by producing random mobility models that

capture the statistical features of field tests. The configured mobility models can in turn produce a large number of trajectories following the same statistics of the original field tests.

The rest of this chapter is organized as follows. Chapter 3.2 introduces two 3-D ST mobility models extended from the basic 2-D ST mobility model. Chapter 3.3 discusses realistic boundary models. Chapter 3.4 provides a brief conclusion.

3.2 3-D Smooth-Turn Mobility Models

The basic 2-D ST mobility model as introduced in Chapter 2.2.3 is very simple but it does not consider the movement of aircraft along the vertical dimension. Furthermore, the turn radius and waiting time interval follow canonical random distributions which may not be general enough. In addition, realistic behavior when aerial vehicles are close to boundaries is not properly modeled. To equip the model with the above missing capabilities, two 3-D ST mobility models are developed, which are extended versions of the basic 2-D ST mobility model. The set of new models are more comprehensive and flexible for user configuration, and hence better serve for the evaluation and design of reliable routing protocols.

This section introduces two new 3-D ST mobility models: z -dependent ST mobility model and z -independent ST mobility model. Both models follow the basic concept of the 2-D ST mobility model: an aerial vehicle circles around a randomly selected turn center before it chooses another center. The major difference between these two 3-D mobility models is whether aircraft mobility along the z direction is dependent upon the mobility on the x, y plane. It is envisioned that these two 3-D ST mobility models may be suitable for different AN applications. For instance, z -independent ST mobility model may well capture normal maneuvers in civilian applications; and the z -dependent ST mobility model may be able to describe maneuvers in air shows and military applications.

3.2.1 z -Dependent ST Mobility Model

This model describes the correlation of an aircraft's motion on the x , y plane and z -dimension through the introduction of maneuver plane (determined by an aircraft's tangential and normal acceleration vectors). The idea is that an aerial vehicle circles around a fixed turn center on the *maneuver plane* [45] with a constant forward speed for a randomly selected duration before it chooses a new turn center and a new speed. The new turn center is on the plane perpendicular to the current heading direction. This perpendicularity guarantees the smoothness of trajectories.

This model has the following assumptions. Within each randomly selected waiting time interval,

- 1) the lift acceleration L normal to the aircraft wing plane is constant;
- 2) the bank of angle [40] β around the roll axis is constant;
- 3) both the sideslip angle and angle of attack (AOA) [46] are zero;
- 4) environmental effects, such as wind and rain, etc., are ignored;
- 5) the effects of gravity on tangential and normal accelerations are ignored;
- 6) the thrust-drag acceleration D along the aircraft velocity direction is zero.

Assumptions 1-4 permit treating an aircraft as a point mass following planar trajectories [45], [47-49] in a maneuver plane. The aircraft's tangential and normal accelerations can be described by the following equations:

$$a_t(t) = D + g_t(t) \quad (3-1)$$

$$a_n(t) = L \cos \beta + g_n(t) \quad (3-2)$$

where $g_t(t)$ and $g_n(t)$ are the components of gravity along the heading and normal directions at time t . Assumptions 5 and 6 lead to zero a_t and constant a_n , and hence ensure that an aircraft will have a constant turn rate and a constant speed within the duration.

Also note that at the beginning of each randomly selected duration, the change of turn

centers results in the switching of maneuver planes. The velocity vector at that moment is on the line intersecting the old and new maneuver planes. Two additional assumptions are enforced for this model. First, assume that the change of heading speed (i.e., the amplitude of the velocity vector) can be immediate, neglecting the gradual speed change process realized through controlling the thrust-drag force. Second, assume that the change of maneuver plane is also immediate, neglecting the gradual process realized through altering the bank angle and lift force.

Now the mathematics of the model is described. During each randomly selected duration, the aircraft position vector $p(t)$, velocity vector $v(t)$ and acceleration vector $a(t)$ at time t in the universal coordinate frame are described by the following relationship [18]:

$$\dot{p}(t) = v(t) \quad (3-3)$$

$$\dot{v}(t) = a(t) \quad (3-4)$$

As the aircraft circles around a fixed turn center p_c with a constant turn rate Ω , the following equations hold:

$$v(t) = \Omega \times (p(t) - p_c) \quad (3-5)$$

$$a(t) = \dot{\Omega} \times (p(t) - p_c) + \Omega \times (\dot{p}(t) - \dot{p}_c) = \Omega \times v(t) \quad (3-6)$$

where symbol $\times$ denotes the vector cross product operation. As turn rate is a constant, $\dot{\Omega} = 0$. Equation (3-6) further leads to the expression of Ω

$$\Omega = \frac{v(t) \times a(t)}{\|v(t)\|^2}. \quad (3-7)$$

Furthermore, differentiation of Equation (3-6) leads to

$$\dot{a}(t) = \dot{\Omega} \times v(t) + \Omega \times \dot{v}(t) = -w^2 v(t) \quad (3-8)$$

where w is the magnitude of Ω with the expression

$$w = \|\Omega\| = \frac{a_n}{v} = \frac{v}{R}, \quad (3-9)$$

where $v = \|v(t)\|$ is the constant heading speed. Then the state-space dynamics of this

model is described as

$$\dot{x}(t) = \begin{bmatrix} 0_{3 \times 3} & I & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & I \\ 0_{3 \times 3} & -w^2 I & 0_{3 \times 3} \end{bmatrix} x(t) \quad (3-10)$$

where the state $x(t) = [p(t), v(t), a(t)]'$, and I is the identity matrix. By sampling the state $x(t)$ every Δt seconds, convert this continuous-time model to the discrete-time model where

$$x[k+1] = \Phi(\Delta t, w)x[k] \quad (3-11)$$

The state transition matrix $\Phi(\Delta t, w)$ is represented as

$$\Phi(\Delta t, w) = \begin{bmatrix} 1 & \frac{\sin(w\Delta t)}{w} & \frac{1-\cos(w\Delta t)}{w^2} \\ 0 & \cos(w\Delta t) & \frac{\sin(w\Delta t)}{w} \\ 0 & -w\sin(w\Delta t) & \cos(w\Delta t) \end{bmatrix} \otimes I = B \otimes I, \quad (3-12)$$

where $\otimes$ is the kronecker product. With the knowledge of speed v and turn radius R , Equations (3-9) and (3-12) can be used to generate flight trajectories. In particular, the position, velocity and acceleration of the aircraft in x , y , and z directions $p_x, p_y, p_z, v_x, v_y, v_z, a_x, a_y, a_z$ at the $(k+1)$ -th sample time can be computed as

$$\begin{bmatrix} p_x[k+1] \\ v_x[k+1] \\ a_x[k+1] \\ p_y[k+1] \\ v_y[k+1] \\ a_y[k+1] \\ p_z[k+1] \\ v_z[k+1] \\ a_z[k+1] \end{bmatrix} = \begin{bmatrix} B & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & B & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & B \end{bmatrix} \cdot \begin{bmatrix} p_x[k] \\ v_x[k] \\ a_x[k] \\ p_y[k] \\ v_y[k] \\ a_y[k] \\ p_z[k] \\ v_z[k] \\ a_z[k] \end{bmatrix} \quad (3-13)$$

At the end of randomly selected duration, the aircraft randomly selects a new velocity v (with only magnitude changes but not direction), and a new turn center p_c (p_{cx}, p_{cy}, p_{cz}) on the plane perpendicular to its velocity direction. The new turn center is uniquely determined by a randomly selected new turn radius R and altitude of the new turn center p_{cz} . Mathematically, the position of the new turn center p_c can be determined by solving the

following two equations:

$$\begin{cases} v_o \cdot \overrightarrow{p_o p_c} = 0 \\ \|\overrightarrow{p_o p_c}\| = R \end{cases} \quad (3-14)$$

where $p_o(p_{ox}, p_{oy}, p_{oz})$ and $v_o(v_{ox}, v_{oy}, v_{oz})$ are the position and velocity vector of the aircraft at the time of change, and $\overrightarrow{p_o p_c}$ presents the vector pointing from the aircraft to the new turn center. Furthermore, p_{cz} should be in the range of

$$p_{oz} - K \leq p_{cz} \leq p_{oz} + K \quad (3-15)$$

with $K = R \cdot \cos(\sin(\frac{|v_{oz}|}{\|v_o\|})^{-1})$, otherwise Equation (3-14) is unsolvable. Two solutions can be found from Equation (3-14), with one selected randomly. The radius R and duration τ can follow the Gaussian and exponential distributions as in the 2-D model, and the altitude of turn center can follow the Gaussian distribution, or more complicated distributions estimated from field test data.

Fig. 3.1 Sample trajectory of the z -dependent ST mobility model.

3.2.2 z -Independent ST Mobility Model

The z -independent ST mobility model assumes that aircraft movement along the z

dimension is independent from that on the x, y plane. This assumption usually holds for civilian applications, in which vertical movement is typically limited [18]. Under such assumption, mobility along the x, y plane and the z dimension can be analyzed separately.

In the x, y plane, an aerial vehicle follows the same dynamics as that in the basic 2-D ST mobility model [29-30]. The vehicle circles around a turn center, with radius R and speed v_{xy} , before it chooses another center. Along the z dimension, the aerial vehicle is assumed to maintain a constant acceleration a_z during each randomly selected duration, therefore allowing the speed along z dimension and also the altitude to vary.

The continuous-time dynamics of this model within a randomly selected duration is given by

$$a_{t_{xy}}(t) = 0 \quad (3-16)$$

$$a_{n_{xy}}(t) = v_{xy}^2/R$$

$$\dot{\Phi}_{xy}(t) = -w_{xy}(t) = -v_{xy}/R$$

$$\dot{p}_x(t) = v_x(t) = v_{xy}\cos(\Phi_{xy}(t))$$

$$\dot{p}_y(t) = v_y(t) = v_{xy}\sin(\Phi_{xy}(t))$$

$$\ddot{p}_z(t) = \dot{v}_z(t) = a_z$$

where $a_{t_{xy}}(t)$, $a_{n_{xy}}(t)$, $\Phi_{xy}(t)$, and $w_{xy}(t)$ represent tangential and normal accelerations, heading angle and angular velocity on the x, y plane at time t . The discrete-time dynamics can be derived using a similar procedure discussed in Chapter 2.2.3. A sample trajectory is shown in Figure 3.2.

Fig. 3.2 Sample trajectory of the z -independent ST mobility model.

3.3 Realistic Boundary Models

In this section, the boundary models implemented for the 3-D smooth-turn (ST) mobility models are described. They are developed based upon the “*buffer*” model used in the Gauss-Markov mobility model [1], [10] and the model implemented in the Reconnaissance mobility models [26-28].

Various boundary models have been used in the literature. Typical boundary models include the “wrap-around” model [16], “reflection” model [1], and the “buffer” model [1], [10]. In the “wrap-around” model, when an aircraft hits the boundary, it wraps around and appears at the opposite side of the region. In the “reflection” model, the aircraft is reflected into the simulation area when it hits the boundary. These two models show sharp directional changes, which are not expected in real aerial trajectories.

Compared with “wrap-around” and “reflection” boundary models, the “buffer” model and the boundary model used in Reconnaissance mobility models are more reasonable to capture aerial mobility at boundaries. In the “buffer” model, an aircraft is forced away from

the boundary with the help of a buffer zone defined as the region between the boundary and the inner zone. In the reconnaissance mobility models, if the aircraft moves closer than the turn radius to an edge, it turns towards the center of the simulation area until the angle between its direction and the normal of the edge reaches a randomly selected value between -45° and 45° . Based upon similar ideas, boundary models for the 3-D ST mobility models are developed.

In this new boundary model, a buffer zone with depth d_x, d_y, d_z (distance from the edge of the inner zone to the simulation boundary) for safe operation at boundaries is adopted. In Figure 3.3, the area between the blue cube and the grey cube is the buffer zone. If the aircraft enters the buffer zone, it stops current motion immediately and reselects a new motion pattern to move out of the buffer zone. Due to the difference between z -dependent and z -independent mobility models along the vertical direction, their boundary models are also slightly different as discussed below.

Fig. 3.3 The area between the blue cube and the grey cube is the buffer zone.

3.3.1 Boundary Model for the z -Dependent ST Mobility Model

In the boundary model for the z -dependent ST mobility model, the depth of the buffer zone $d_x = d_y = d_z = 2R_s$, where R_s is the minimum safe turn radius. As shown in Figure 3.3, when an aircraft reaches the buffer zone, it reselects a turn center with turn radius equal to R_s on current maneuver plane, and circles around it either clock-wise or anti-clockwise. The aircraft maintains this mobility pattern until it leaves the buffer zone. As shown in Figure 3.4a, $2R_s$ is necessary to ensure that the aircraft stays within the simulation area. Furthermore, it is noted that R_s can be either speed-dependent or speed-independent. If R_s is set as the minimum safe turn radius associated with the current speed, the aircraft can maintain the current speed when it reaches the buffer zone. The drawback is that the buffer length is speed-dependent, and the aircraft needs to continuously check the current speed to determine the depth of buffer area. If R_s is set as the minimum safe turn radius of this aircraft type, the aircraft does not need to check its own speed to determine the depth of buffer area, but it needs to reselect its speed to be the one associated with the minimum safe turn radius when it reaches the buffer zone.

3.3.2 Boundary Model for the z -Independent ST mobility model

In the boundary model for the z -independent ST mobility model, the strategy on the x, y plane can be precisely same as that used for the z -dependent ST mobility model. In particular, if an aircraft enters the buffer zone with $d_x = d_y = 2R_s$, it reselects the turn center with turn radius R_s . An alternative approach is shown in Figure 3.5a. An aircraft can check its heading with respect to the boundary when it reaches the buffer zone. If the heading is to the right of the vector normal to the boundary, the vehicle turns right with radius R_s ; otherwise it turns left. This strategy can reduce the buffer depth from $2R_s$ to $(1 + \frac{1}{\sqrt{2}})R_s$ (see Figure 3.5b as a proof).

Fig. 3.4. a) Boundary model for z -dependent mobility model. When the aircraft reaches the buffer zone, it reselects a turn center with turn radius equal to R_s on current maneuver plane and circles around it either clockwise or anticlockwise. b) The critical situation suggests that $d_x = d_y = d_z = 2R_s$ is necessary to ensure the aircraft to stay within the simulation area.

Now let us discuss the strategy along the z dimension. The buffer depth d_z to the upper ceiling is defined as $\frac{v_{ascend}^2}{2|a_{descend}|}$, where v_{ascend} is the maximum ascending speed, and $a_{descend}$ is the maximum descending acceleration. If an aircraft reaches the buffer zone near the ceiling, it chooses a descending acceleration less than or equal to $\frac{2d_z}{v_z^2}$, where v_z is the current speed along the z dimension. Similarly, depth d_z to the bottom is defined as $\frac{V_{descend}^2}{2|a_{ascend}|}$, where $V_{descend}$ is the maximum descending speed, and a_{ascend} is the maximum ascending acceleration. Once an aircraft reaches the buffer zone near the bottom, it chooses the ascending acceleration less than or equal to $\frac{2d_z}{v_z^2}$, where v_z is the current speed along the z dimension. The above strategy will ensure that when the aircraft reaches the upper or bottom boundary of the simulation area, its speed toward the boundary is less than or equal to zero,

and thus never cross the boundary.

Fig. 3.5. a) An alternative strategy when the aircraft is close to the boundary for the z -independent mobility model: if the heading is at the right side of the normal vector to the boundary, the aircraft turns right. b) The critical situation suggests that $d_x = d_y = (1 + \frac{1}{\sqrt{2}})R_s$ is necessary for the aircraft to stay within the simulation area.

3.4 Conclusion

In this chapter, two 3-D airborne networks (ANs) mobility models are developed to serve as the modeling framework for ANs. Both models are extended versions of the basic 2-D smooth-turn (ST) mobility model, as they follow the same idea: a vehicle randomly chooses a turn center, and circles around it, before choosing another turn center. The z -dependent ST mobility model captures the correlation of aerial mobility along three dimensions, by restricting the movement of aerial vehicles on maneuver planes, which may or may not be horizontal. The z -independent ST mobility model assumes that the movement along the z dimension is completely independent from that on the x, y plane. Both mobility models capture realistic flight trajectories featured by straight lines and large-radius curves. It is envisioned that the two 3-D mobility models may be suitable for different AN applications.

The z -independent mobility model typically has less variation along the z -dimension, and thus is suitable for civilian and commercial AN applications. The z -dependent mobility model may involve large variation along the z -dimension correlated with movement on the x, y plane, and is thus more suitable to describe aerial mobility in some military applications and air shows. In the end of the chapter, realistic boundary models for the 3-D ST mobility models are also suggested. It is noted that the 3-D mobility models in this chapter are very simple under a set of assumptions. In the future work, the author will consider more general and flexible models with fewer assumptions and capture more complicated group behaviors such as collision avoidance. The author will also provide a comprehensive guideline for selecting appropriate mobility models for different AN applications and user interests. The author envisions that these efforts will significantly help researchers in their studies on ANs.

CHAPTER 4

ESTIMATION AND VALIDATION OF THE 3-D SMOOTH-TURN MOBILITY MODEL FOR AIRBORNE NETWORKS

4.1 Introduction

Mobility models serve as the foundation for simulating and evaluating networking protocols [10], [12], [50]. Airborne networking is a relatively new area of research in which traditional mobile ad hoc network (MANET) mobility models such as random waypoint (RWP) and random walk (RW) are typically used for evaluating protocol performance [51-52]. Since mobility models significantly impact the performance of networking protocols [10], [12], and traditional mobility models do not capture aerial mobility appropriately, their use in simulation and evaluation of airborne networks (ANs) may lead to misleading results.

In order to fill the need, AN mobility models that are realistic in capturing smooth trajectory of an aerial vehicle are developed, and are simple enough for parameter estimation and tractable analysis as introduced in Chapter 2 and 3. In particular, 2D and 3D smooth-turn (ST) mobility models that follow the physical laws that govern the spatiotemporal correlation of aerial turns are developed. It was proved in [29-30] that the basic 2D ST mobility model (unlike the RWP model) has uniform node distribution which leads to tractable connectivity analysis. For example, the connectivity analysis provides information such as the statistics of number of neighbors, and the k -connectivity of the network among others.

This chapter presents a process that uses real flight test data to validate the 3D z -independent ST mobility model. The general procedures to tune model parameters from real data are presented. Constructing a mobility model from real flight data has the following advantages. First, the mobility model can produce a large number of trajectory ensembles following the statistics of the original flight test data. Utilizing such rich trajectory ensembles

for performance evaluation optimizes the returns on expensive flight tests. Second, the resulting model leads to statistical analysis of varying network connectivity, and thus facilitates the analysis and design of networking protocols. Third, the resulting mobility model can also be used as a prediction model for the design of mobility-driven networking protocols.

In order to obtain realistic evaluation environment for mobile networks [10], [12], it is very critical to validate and configure mobility models according to realistic settings. However, it is noted that there are very limited research studies along these lines in the literature [43-44], [49], [53-54]. Examples include studies such as the parameter estimation in Gauss-Markov models for location prediction purposes [43-44], [53-54]. The work represents the first of a kind study on model validation and parameter estimation for airborne mobility models.

The chapter is organized as follows. Chapter 4.2 describes the procedure to estimate model parameters from real flight trajectories and estimation results. Chapter 4.3 contains a brief conclusion and discussion of future work.

4.2 Estimation Based upon Actual Aircraft Trajectories

This section describes the procedure to estimate parameters in the 3D z -independent ST mobility model from real flight test data. This process also validates the capability of the z -independent ST mobility model in capturing the attributes of aerial movement. The resulting model can be used as a prediction model or a model for random trajectory generation.

The field test data include five trajectories of the DC-3 aircraft, denoted as A, B, C, D and E, each lasting around 8 minutes, with aircraft heading speed in the range of 3.5945~86.4812m/s, and aircraft travelling within the altitude of 199.7810~1361.5m. Each of

the five datasets consists of 3D nodal position data in the WGS-86 standard (a world geodetic system represented by latitude γ , longitude λ and height h), and velocity data in the east-north-up (ENU) coordinates. All recordings are sampled at $\Delta T = 0.1s$. The estimation procedure includes four major steps: data preparation, estimation of trajectory-specific random variable values, estimation of a key threshold, and estimation of parameters in model random variables. Chapter 4.2.5, also shows results on using the estimated parameters to generate random trajectory ensembles.

4.2.1 Data Preparation

1) Coordinate transformation: Before parameter estimation, the position data needs to be converted from the WGS-86 standard to the ENU coordinates first, since such local ENU Cartesian coordinate system is more intuitive and practical than geodetic coordinates for navigation analysis [55]. Transformation from the geodetic system to ENU coordinates is a two-stage process. First, convert position data from the geodetic system to the earth-centered earth-fixed (ECEF) coordinates (represented as $[X, Y, Z]$) using the following formula [56-57]:

$$\begin{aligned} X &= (N(\gamma) + h)\cos(\gamma)\cos(\lambda) \\ Y &= (N(\gamma) + h)\cos(\gamma)\sin(\lambda) \\ Z &= (N(\gamma)(1 - e^2) + h)\sin(\gamma) \\ N(\gamma) &= a/\sqrt{1 - e^2\sin^2(\gamma)} \end{aligned} \tag{4-1}$$

where the constants a and e are the semi-major axis and the first numerical eccentricity of the ellipsoid respectively. $N(\gamma)$ is the distance from the surface to the z -axis along the ellipsoid normal.

Then $[X, Y, Z]$ is converted to the ENU coordinates, denoted as $[X_e, Y_n, Z_u]$, using the following formula [55-56]:

$$\begin{bmatrix} X_e \\ Y_n \\ Z_u \end{bmatrix} = \begin{bmatrix} -\sin(\lambda) & \cos(\lambda) & 0 \\ -\sin(\gamma)\cos\lambda & -\sin(\gamma)\sin(\lambda) & \cos(\gamma) \\ \cos(\gamma)\cos\lambda & \cos(\gamma)\sin(\lambda) & \sin(\gamma) \end{bmatrix} \begin{bmatrix} X - X_r \\ Y - Y_r \\ Z - Z_r \end{bmatrix} \quad (4-2)$$

where $[X_r, Y_r, Z_r]$ represents the position of radar, or the reference point. Here, the first point of each data set is supposed to be the reference point.

2) *Data preprocessing*: The velocity along the z direction has noticeable fluctuations (see also Figure 4.2c), which can be considered as noise caused by environmental and measurement factors. To eliminate the effect of noise to the estimation performance, the altitude data Z_u is smoothed using the “moving average” algorithm [58]. The resulting position data well capture the trend of altitude change. The processed altitude data are then used to calculate vertical speed v_z through differentiation. In the rest of this chapter, $x_i, y_i, z_i, v_{x_i}, v_{y_i}$, and v_{z_i} are used to represent the position and velocity data along x, y , and z directions at i -th sample time T_i after coordinate conversion and de-noising. The five resulting trajectories are shown in blue in Figure 4.1. Clearly, they demonstrate a combination of roughly straight trajectories and circular turns, concurring with the concept of ST models.

Fig. 4.1 Five segments of trajectories equally scaled in three directions. Blue curves represent the flight field test data after conversion and smoothing. Red curves are estimated trajectories based upon the ST model.

4.2.2 Estimation of Trajectory-Specific Random Variable Values

This section shows the estimation of values that the random variables in the z -independent ST mobility model take. First the extraction of turn radius R , speed v_{xy} , turn rate w and acceleration along the z direction a_z at each time instance, denoted as R_i , v_{xy_i} , w_i and a_{z_i} at the sample time T_i , from the position and velocity data described in Chapter 4.2.1 is shown. The data are then be used to estimate the values of all variables (including turn radius R , waiting time interval τ , speed v_{xy} , turn rate w and acceleration along the z direction a_z) during each waiting time interval, which are respectively denoted as $\hat{R}_j$, $\hat{\tau}_j$, $\hat{v}_{xy_j}$, $\hat{w}_j$ and $\hat{a}_{z_j}$ for the j -th waiting time interval, in Chapter 4.2.2.

1) *Extraction of $\mathbf{R}_i$, $\mathbf{v}_{xy_i}$, $\mathbf{w}_i$ and $\mathbf{a}_{z_i}$ at each time instance $\mathbf{T}_i$* : As the movement along the z direction is independent from that along the x, y directions, only the position and velocity data along the x, y coordinates are used to calculate the turn radius $\mathbf{R}_i$ and turn rate $\mathbf{w}_i$. Note that any two adjacent location points (sampled every 0.1s) with known heading directions (as indicated by the speed along the x, y directions) can determine a circular arc and a turn radius $\mathbf{R}_i$. A positive $\mathbf{R}_i$ represents turning right and a negative $\mathbf{R}_i$ represents turning left. At an extreme, a strictly straight trajectory has an infinite radius. Assuming that an aircraft has a constant speed during the movement from $\mathbf{T}_i$ to $\mathbf{T}_{i+1}$, the speed $\mathbf{v}_{xy_i}$ and the turn rate $\mathbf{w}_i$ at $\mathbf{T}_i$ can be computed as:

$$v_{xy_i} = \sqrt{v_{x_i}^2 + v_{y_i}^2} \quad (4-3)$$

$$w_i = v_{xy_i} / R_i$$

A large R_i ($R_i \gg v_{xy_i}$) leads to a small w_i , indicating a more straight movement.

Assume that acceleration $\mathbf{a}_{z_i}$ maintains constant within each sampling time step, then:

$$a_{z_i} = (v_{z_{i+1}} - v_{z_i}) / \Delta t. \quad (4-4)$$

2) *Estimation of $\hat{R}_j$, $\hat{t}_j$, $\hat{v}_{xy_j}$, $\hat{w}_j$ and $\hat{a}_{z_j}$ during each waiting time interval*: With the assumption that during each waiting time interval the speed and turn rate are constants, the length of each waiting time interval based on the turn rate w_i can be determined. Specifically, w_i at each time point from the initial time T_1 is scanned. If the change of w_i does not exceed a threshold w_{thrd} until the time point T_i , $[T_1, T_i]$ is considered as the first waiting time interval. For the clarity of presentation, $[T_1, T_i]$ is rewritten as $[T_{11}, T_{i1}]$ where the first subscript represents the index of time instance, and the second subscript represents the index of waiting time interval. This procedure continues until finishing scanning w_i . The estimated

value of each variable within the j -th waiting time interval $[T_{mj}, T_{nj}]$ can then be calculated using the least square estimation as:

$$\begin{aligned}\hat{w}_j &= \frac{1}{n-m} \sum_{i=m}^n w_i \\ \hat{v}_{xyj} &= \frac{1}{n-m} \sum_{i=m}^n v_{xyi} \\ \hat{R}_j &= \hat{v}_{xyj} / \hat{w}_j \\ \hat{t}_j &= (n-m)\Delta t\end{aligned}\tag{4-5}$$

where mj represents that the start sample index of the j -th interval is m , and nj represents that the end sample index of the j -th interval is n . The acceleration along the z direction within the j -th waiting time interval can be computed by

$$\hat{a}_{zj} = (v_{znj} - v_{zmj}) / (T_{nj} - T_{mj})\tag{4-6}$$

where v_{zmj} and v_{znj} are the velocities along the z direction at the time instances T_{mj} and T_{nj} .

Note that $\hat{R}_j$, $\hat{t}_j$, $\hat{v}_{xyj}$, $\hat{w}_j$ and $\hat{a}_{zj}$ can further be used to estimate x , y and z coordinates and vertical speed of aircraft at each sample time $T_i \in [T_{mj}, T_{nj}]$, denoted as $\hat{x}_i$, $\hat{y}_i$, $\hat{z}_i$, and $\hat{v}_{zi}$. The red curves in Figure 4.1 show the estimated trajectories. Figure 4.2 shows the estimated turn rate $\hat{w}_j$, speed in the x, y plane $\hat{v}_{xyj}$, speed along the z direction $\hat{v}_{zi}$, and altitude $\hat{z}_i$ for the data set A. The threshold w_{thrd} is 0.026 (rad/s).

Fig. 4.2 Comparison of the estimated and actual a) turn rate, b) velocity in the x, y plane, c) velocity along the z direction, and d) altitude, for the field test dataset A.

4.2.3 Determination of Threshold w_{thrd}

The selection of threshold w_{thrd} significantly affects the performance of the estimated trajectory. In particular, a smaller threshold leads to larger number of waiting time intervals with smaller length for each interval. This leads to better estimation accuracy, at a cost of poorer model predictability. A systematic approach to choose the best threshold is developed, through balancing between estimation error and the correlation of turn rates across adjacent waiting time intervals. This approach is based upon the understanding that a small threshold leads to high correlation of turn rates across different waiting time intervals, violating the

assumption of the independence of turn rates. Here let us first illustrate the calculation of the two metrics: estimation error and correlation. Then the algorithm to choose the best threshold w_{thrd} , and the resulting model parameters is shown.

1) *Evaluation of estimation error*: Estimation performance is typically evaluated based upon measures such as root mean squared error (RMSE) [49], [54] r-square [59], sum of squares due to error (SSE) [60]. In order to penalize large errors at small portions of the trajectories (especially at the end of some waiting time intervals), use the following equation to evaluate error:

$$Error = \sqrt[4]{\frac{1}{N} \sum_{i=1}^N ((x_i - \hat{x}_i)^4 + (y_i - \hat{y}_i)^4 + (z_i - \hat{z}_i)^4)} \quad (4-7)$$

where N is the total number of samples.

Fig. 4.3 Evaluation of a) error, b) correlation coefficient.

Figures 4.3a shows the estimation performance of the five trajectories with different w_{thrd} . When the threshold is small, the error is close to 0, indicating a good estimation performance. Moreover, the change of error is very slow at low threshold values; however the change becomes significant for a majority of data sets when the threshold is beyond about 0.035(rad/s).

2) *Evaluation of correlation*: Use Pearson's correlation coefficient [62] as an indicator of the correlation of turn rates between adjacent waiting time intervals:

$$\rho = \frac{\sum_{j=1}^{M-1}(\Psi_j - \bar{\Psi})(\Theta_j - \bar{\Theta})}{\sqrt{\sum_{j=1}^{M-1}(\Psi_j - \bar{\Psi})^2} \sqrt{\sum_{j=1}^{M-1}(\Theta_j - \bar{\Theta})^2}} \quad (4-8)$$

where $\Psi = \{\hat{w}_1, \hat{w}_2, \dots, \hat{w}_{M-1}\}$, $\Theta = \{\hat{w}_2, \hat{w}_3, \dots, \hat{w}_M\}$, and $\bar{\Psi}$ and $\bar{\Theta}$ are the mean values of Ψ and Θ . M is the total number of waiting time intervals. As shown in Figure 4.3b, the correlation coefficient ρ typically decreases with the increase of w_{thrd} , suggesting that a larger threshold leads to less correlation among the turn rates across adjacent waiting time intervals. When w_{thrd} keeps decreasing, the correlation becomes negatively correlated for a majority of trajectories. The strong negative correlation when w_{thrd} is large does not convey much information, as the number of waiting time intervals is very small at this stage. An exception is the strong correlation for all thresholds observed in trajectory B, due to its special circular trajectory.

3) *Algorithm to choose w_{thrd}* : The algorithm to choose w_{thrd} is based upon the tradeoff between the estimation error and correlation across adjacent waiting time intervals. Specifically, the algorithm is composed of two steps. The first step filters out the thresholds that do not meet certain error requirement. The second step chooses the threshold with the weakest correlation among remaining possible thresholds.

Step 1: Find the threshold w_{thrd1} such that for all thresholds less than w_{thrd1} , their error values are less than a constant chosen by users. In this study, the value is set to 270m.

Step 2: For all thresholds less than w_{thrd1} , find the one with the minimum absolute value of correlation coefficient, which is denoted as $\hat{w}_{thrd}$.

The thresholds selected using the above algorithm for trajectory A, B, C, D and E are respectively 0.026, 0.027, 0.035, 0.035 and 0.048 (rad/s).

4.2.4 Estimation of Parameters in Model Random Variables

In order to generate trajectories, the probability distribution of each random variable in the model is estimated. There are four random variables in the z -independent model, including the turn radius R , waiting time interval τ , speed v_{xy} and acceleration along the z direction a_z . The estimated random variables are denoted as $\tilde{R}$, $\tilde{\tau}$, $\tilde{v}_{xy}$, and $\tilde{a}_z$, respectively. Then estimate the probability density functions and corresponding parameters of these random variables based upon all five real flight trajectories.

1) *Turn radius $\tilde{R}$* : The probability density function based upon $\mathbf{R}_i$ at each time instance $\mathbf{T}_i$, is obtained in Chapter 4.2.2. As shown in Figure 4.4, the probability density function of $1/|\tilde{R}|$ approximately follows exponential distribution with mean $\frac{1}{\tilde{\lambda}_r} = \frac{1}{N} \sum_{i=1}^N \frac{1}{|R_i|}$:

$$f\left(\frac{1}{|\tilde{R}|}\right) = \tilde{\lambda}_r e^{-\tilde{\lambda}_r \frac{1}{|\tilde{R}|}} \quad (4-9)$$

Left turns and right turns are typically assumed with the same probability.

Fig. 4.4 Probability distribution of the inverse of turn radius.

2) *Waiting time interval $\tilde{\tau}$* : The probability density function of $\tilde{\tau}$ is plotted in Figure 4.5 using the estimated waiting time interval $\hat{\tau}_j$ obtained in Chapter 4.2.2. It approximately follows exponential distribution with mean $\frac{1}{\hat{\lambda}_t} = \frac{1}{M} \sum_{i=1}^M \frac{1}{|\hat{\tau}_j|}$. The small bias is ignored considering the lack of data and the wide use of exponential distributions in modeling the waiting time intervals between the occurrences of random events.

Fig. 4.5 Probability distribution of waiting time interval.

3) *Speed $\tilde{v}_{xy}$* : The simplest way to choose a speed $\mathbf{v}_{xy}$ in each waiting time interval is to assume that $\mathbf{v}_{xy}$ at each interval follows identical independent distributions. Instead, a Gauss-Markov model is used here to capture the correlation of speeds. In particular, the speed at the k -th waiting time interval, $\tilde{v}_{xy_k}$ is modeled by the following equation [43-44], [61]:

$$\tilde{v}_{xy_k} = \alpha \tilde{v}_{xy_{k-1}} + (1 - \alpha)\mu + \sqrt{(1 - \alpha^2)}D_{k-1} \quad (4-10)$$

where α ($0 < \alpha < 1$) is a correlation factor, μ is the mean speed as $t \rightarrow \infty$, D_{k-1} is a random variable following a normal distribution denoted by $N(0, \sigma^2)$, and σ is the standard deviation of speed as $t \rightarrow \infty$.

Given M samples of the estimated speeds $\hat{v}_{xy_1}, \hat{v}_{xy_2}, \dots, \hat{v}_{xy_M}$ from Chapter 4.2.2, the estimated values of μ , σ and α , denoted by $\hat{\mu}, \hat{\sigma}$ and $\hat{\alpha}$ are computed according to the following equations [44] [54]:

$$\begin{aligned}\hat{\mu} &= \frac{1}{M} \sum_{j=1}^M \hat{v}_{xy_j} \\ \hat{\sigma}^2 &= \frac{1}{M-1} \sum_{j=1}^M (\hat{v}_{xy_j} - \hat{\mu})^2 \\ \hat{\alpha} &= \begin{cases} 1, & \text{if } \hat{\sigma} \approx 0 \\ \max\left(0, \frac{\hat{\sigma}'^2}{\hat{\sigma}^2}\right), & \text{otherwise} \end{cases}\end{aligned}\tag{4-11}$$

where $\hat{\sigma}'^2 = \frac{1}{M-1} \sum_{j=1}^{M-1} (\hat{v}_{xy_j} - \hat{\mu})(\hat{v}_{xy_{j+1}} - \hat{\mu})$. Estimated parameters for each trajectory are shown in Table 4.1. The average of these parameters from five trajectories, denoted as $\tilde{\mu}, \tilde{\sigma}$, and $\tilde{\alpha}$, are used to generate trajectories in Chapter 4.2.5.

TABLE 4.1 Parameter estimation of speed in x, y plane

Label of Trajectory	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\alpha}$
A	69.9126	4.9418	0.7977
B	25.0729	25.0315	0.9714
C	55.0158	5.1042	0.6598
D	58.3248	4.0780	0.6637
E	62.8509	8.7500	0.9342

4) *Acceleration along the z direction $\tilde{\alpha}_z$* : Using all acceleration data of the five trajectories obtained in Chapter 4.2.1, the probability distribution of $\tilde{\alpha}_z$ is shown in Figure 4.6. The probability density function is approximately expressed as

$$f(\tilde{\alpha}_z) = \lambda_a e^{-\tilde{\lambda}_a |\tilde{\alpha}_z|} / 2 \tag{4-12}$$

where $\frac{1}{\tilde{\lambda}_a} = \frac{1}{N} \sum_{i=1}^N \mathbf{a}_{zi}$. The bias may be caused by the lack of data and effect of smoothing.

Fig. 4.6 Probability distribution of acceleration along the z direction.

The vertical acceleration at each waiting time interval $\tilde{a}_{zk}$ is selected based upon the above distribution. To avoid the speed along the z direction exceeding the range $[v_{min}, v_{max}]$, also check if the selected acceleration is within the range

$$\frac{v_{min} - \tilde{v}_{zk1}}{\tilde{\tau}_k} \leq \tilde{a}_{zk} \leq \frac{v_{max} - \tilde{v}_{zk1}}{\tilde{\tau}_k} \quad (4-13)$$

where $\tilde{v}_{zk1}$ is the speed at the beginning of the k -th waiting time interval, and $\tilde{\tau}_k$ is the length of the interval.

The six estimated parameters for random variables in the stochastic model are listed in the following table:

TABLE 4.2 Estimated parameters

Parameters	Estimated value
$\tilde{\lambda}_r$	2.1454×10^3 (m)
$\tilde{\lambda}_t$	0.1116 (s^{-1})
$\tilde{\lambda}_a$	1.2160 (s^2/m)
$\tilde{\mu}$	54.2354 (m/s)
$\tilde{\sigma}$	9.5811
$\tilde{\alpha}$	0.8054

4.2.5 Random Trajectory Generation

Extracting parameters for the mobility model from the field test trajectories allows us to generate rich trajectory ensembles with same statistics of the original flight test data. Figure 4.7 shows some trajectory ensembles generated using the parameters in Table 4.2.

Fig. 4.7 Random trajectories generated by the 3D z -independent ST mobility model.

4.3 Concluding Remarks

The smooth-turn mobility model is a simple model that captures the random smooth maneuvering of aerial vehicles following the physical laws of turning aerial objects. A procedure to use real field test trajectory data to estimate and validate the 3D z -independent smooth-turn mobility model is introduced. The estimated trajectories match well with the original trajectories, suggesting the feasibility of the model in modeling smooth aerial turns. The 3D z -independent smooth-turn mobility model assumes that the movement along z direction is independent from that in the x, y plane, which may not be true for all situations. In the future work, the author will further analyze this assumption and use flight test data to evaluate the z -dependent mobility model.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

In this thesis, the existing AN-specific mobility models are analyzed and compared based upon their AN networking performance, ability to capture AN mobility attributes, degree of randomness and associated AN applications. Then two 3-D AN mobility models are introduced, both of which capture realistic flight trajectories featured by straight lines and large-radius curves. The z -dependent ST mobility model captures the correlation of aerial mobility along three dimensions; and the z -independent ST mobility model assumes that the movement along the z dimension is completely independent from that on the x, y plane. Realistic boundary models which ensure the smoothness of trajectories at boundaries are also introduced. Finally, the procedure to estimate parameters for the z -independent ST mobility model using real flight test data is illustrated. The good match between estimated trajectories and original trajectories also suggests the feasibility of the model in modeling smooth aerial turns.

5.2 Future Work

In the future, the author will enhance the two 3-D ST mobility models with a variety of new features, such as variable speed and turn rate, safety constraint and group behavior. Additionally, the author will also use real flight test data to estimate parameters for the z -dependent ST mobility model. Last but not least, the author will implement the two 3-D ST mobility models into simulators to evaluate their networking performance, which provides further insights to select and configure AN mobility models,

REFERENCES

- [1] D. Broyles, A. Jabbar, and J. P. G. Sterbenz, "Design and Analysis of a 3-D Gauss-Markov Mobility Model for Highly Dynamic Airborne Networks," in *Proceedings of International Telemetry conference*, San Diego, CA, Oct. 2010.
- [2] Y. Wang and Y. J. Zhao, "Fundamental Issues in Systematic Design of Airborne Networks for Aviation," in *Proceedings of the IEEE Aerospace Conference*, pp. 8-pp, Mar. 2006.
- [3] B. N. Cheng, R. Charland, P. Christensen, A. Coyle, and E. Kuczynski, "Characterizing Routing with Radio-to-Router Information in an Airborne Network," in *Proceedings of the 2011 Military Communication Conference*, Baltimore, MD, pp. 1985-1990, IEEE, Nov. 2011.
- [4] B. N. Cheng, R. Charland, P. Christensen, L. Veytser, and J. Wheeler, "Evaluation of a Multi-hop Airborne IP Backbone with Heterogeneous Radio Technologies," in *Proceedings of the first ACM MobiHoc workshop on Airborne Networks and Communications*, Hilton Head, SC, pp. 37-42, Jun. 2012.
- [5] J. Ahrenholz, "Comparison of Core Network Emulation Platforms," in *Proceedings of IEEE MILCOM Conference*, San Jose, CA, pp. 864-869, Oct. 2010.
- [6] J. Ahrenholz, C. Danilov, T. R. Henderson, and J. H. Kim, "Core: A Real Time Network Emulator," in *Proceedings of IEEE MILCOM Conference*, San Diego, CA, pp. 864-869, Nov. 2008.
- [7] "The ns-3 network simulation," <http://www.nsnam.org>.
- [8] "Opnet," <http://www.opnet.com/>.
- [9] J. P. Rohrer, E. K. Cetinkaya, H. Narra, D. Broyles, K. Peters, and J. P. G. Sterbenz, "AeroRP Performance in Highly-Dynamic Airborne Networks Using 3D Gauss-

- Markov Mobility Model,” in *Proceedings of Military Communications Conference*, Baltimore, MD, pp. 834-841, Nov. 2011.
- [10] T. Camp, J. Boleng, and V. Davies, “A Survey of Mobility Models for Ad Hoc Network Research,” *Wireless Communication and Mobile Computing*, vol. 2, no. 5, pp. 483-502, Oct. 2002.
- [11] *Instrument Flying Handbook*. Oklahoma City, OK: United States Department of Transportation, Federal Aviation, Airman Testing Standards Branch, AFS-630, 2008.
- [12] F. Bai and A. Helmy, “A Survey of Mobility Modeling and Analysis in Wireless Ad Hoc Networks,” *Wireless Ad Hoc and Sensor Networks*, New York: Springer, Oct. 2006.
- [13] E. Kuiper and S. Nadjm-Tehrani, “Geographical Routing with Location Service in Intermittently Connected MANETs,” *IEEE Transactions on Vehicular Technology*, vol. 60, no. 2, pp. 592-604, 2011.
- [14] C. Bettstetter, and H. Hartenstein, and X. Pérez-Costa, “Stochastic properties of the random waypoint mobility model,” *Wireless Networks*, Vol. 10, No. 5, 2004, pp. 555-567.
- [15] B. Gloss, and M. Scharf, and D. Neubauer, “A more realistic random direction mobility model,” in *Proceedings of the Fourth Management Committee Meeting*, Wurzburg, Germany, Vol. 52, 2005, pp. 1-12.
- [16] P. Nain, and D. Towsley, and B. Liu, and Z. Liu, “Properties of random direction models,” in *Proceedings of the 24th Annual Joint Conference of the IEEE Computer and Communications Societies, INFOCOM*, Vol. 3, 2005, pp. 1897-1907.
- [17] J. P. Helferty, “Improved Tracking of Maneuvering Targets: the Use of Turn-Rate Distributions for Acceleration Modeling,” in *Proceedings of the 1994 IEEE*

International Conference on Multi-sensor Fusion and Integration for Intelligent Systems, La Vegas, NV, pp. 515-520, Oct. 1994.

- [18] X. R. Li and V. P. Jilkov, "A Survey of Maneuvering Target Tracking: Dynamic Models," in *Proceedings of SPIE Conference on Signal and Data Processing of Small Targets*, vol. AES-6, no. 4048, pp. 212-235, Apr. 2000.
- [19] N. Nabaa and R. H. Bishop, "Validation and Comparison of Coordinated Turn Aircraft Maneuver Models," *IEEE Transactions on aerospace and electronic systems*, vol. 36, no. 1, pp. 250-255, Jan. 2000.
- [20] R. A. Singer, "Estimating Optimal Tracking Filter Performance for Manned Maneuvering Targets," *IEEE Transactions on Aerospace and Electronic Systems*, vol. AES-6, no. 4, pp. 473-383, Jul. 1970.
- [21] E. Boivin, A. Desbiens, and E. Gagnon, "UAV Collision Avoidance Using Cooperative Predictive Control," in *Proceedings of the 16th Mediterranean Conference on Control and Automation*, Adaccio, France, pp. 682-688, Jun. 2008.
- [22] F. Borrelli, T. Keviczky, and G. J. Balas, "Collision-Free UAV Formation Flight Using Decentralized Optimization and Invariant Sets," in *Proceedings of 43rd IEEE Conference on Decision and Control*, Atlantis, Bahamas, vol. 1, pp. 1099-1104, Dec. 2004.
- [23] D. M. Stipanovic, G. Inalhan, R. Teo, and C. Tomlin, "Decentralized Overlapping Control of a Formation of Unmanned Aerial Vehicles," *Automatica*, vol. 40, no. 8, pp. 1285-1296, 2004.
- [24] C. Zhou, M. Kei, S. Zhou, and W. Zhang, "Collision-Free UAV Formation Flight Control Based on Nonlinear MPC," in *Proceedings of International Conference on Electronics, Communications and Control (ICECC)*, Ningbo, China, pp. 1951-1956, Sept. 2011.

- [25] W. Wang, X. Guan, B. Wang, and Y. Wang, "A Novel Mobility Model Based on Semi-Random Circular Movement in Mobile Ad Hoc Networks," *Information Science*, vol. 180, no. 3, pp. 399-413, Feb. 2010.
- [26] E. Kuiper and S. Najim-Tehrani, "Mobility Models for UAV Group Reconnaissance Applications," in *Proceedings of the International conference on Wireless and Mobile Communications*, Bucharest, Romania, pp. 33-48, Jul. 2006.
- [27] E. Kuiper, "Mobility and Routing in a Delay-Tolerant Network of Unmanned Aerial Vehicles," *Master Thesis*, Linköping, 2008.
- [28] E. Kuiper, "Geographic Routing in Intermittently-Connected Mobile Ad Hoc Networks: Algorithms and Performance Models," *Ph.D. dissertation*, Linköping, 2012.
- [29] Y. Wan, K. Namuduri, Y. Zhou, and S. Fu, "A Smooth-Turn Mobility Model for Airborne Networks," *IEEE Transactions on Vehicular Technology*, vol. 62, issue. 6, 2013.
- [30] Y. Wan, K. Namuduri, Y. Zhou, D. He, and S. Fu, "A Smooth-Turn Mobility Model for Airborne Networks," in *Proceedings of the first ACM MobiHoc workshop on Airborne Networks and Communications*, Hilton Head, SC, pp. 25-30, Jun. 2012.
- [31] A. Tiwari, A. Ganguli, A. Sampath, D. Anderson, B. h. Shen, N. Krishnamurthi, J. Yadegar, M. Gerla, and D. Krzysiak, "Mobility Aware Routing for the Airborne Network Backbone," in *Proceedings of Military Communications Conference*, San Diego, CA, pp. 1-7, Nov. 2008.
- [32] A. Sen, P. Ghosh, T. Silva, N. Das, and A. Kundu, "Architecture and Algorithms for an Airborne Network," <http://netsci.asu.edu/drupal/node/5#tech>.

- [33] K. Sampigethaya, R. Poovendran, S. Shetty, T. Davis, and C. Royalty, "Future E-Enabled Aircraft Communications and Security: The Next 20 Years and Beyond," in *Proceedings of the IEEE*, vol. 99, no. 11, pp. 2040 -2055, Nov. 2011.
- [34] S. Shirazipourazad, P. Ghosh, and A. Sen, "On Connectivity of Airborne Networks in Presence of Region-Based Faults," in *Proceedings of Military Communications Conference, 2011-MILCOM*, Baltimore, MD, pp.1997-2002, Nov. 2011.
- [35] S. Milner, S. Thakkar, K. Chandrashekar, and W. L. Chen, "Performance and Scalability of Mobile Wireless Base-Station- Oriented Networks," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 7, no. 5, pp. 69-79, 2003.
- [36] S. Shirazipourazad, P. Ghosh, and A. Sen, "On Connectivity of Airborne Networks with Unpredictable Flight Path of Aircrafts," in *Proceedings of the first ACM MobiHoc workshop on Airborne Networks and Communications*, Hilton Head, SC, pp. 1-6, Jun. 2012.
- [37] Y. Wan, K. Namuduri, S. Akula, and M. Varanasi, "The Impact of Multi-Group Multi-Layer Network Structure on the Performance of Distributed Consensus Building Strategies," *International Journal of Robust and Nonlinear Control*, Published online before print, Jan. 2012.
- [38] Performance Phase, "Cruise performance theory," Sep. 1993, URL: <http://www.dtic.mil/cgi-bin/GetTRDoc?Location=U2&doc=GetTRDoc.pdf&AD=ADA320213>
- [39] H. W. Glauert, *The elements of aerofoil and airscrew theory*, chapter 2, Cambridge University Press, 1947
- [40] "Bank angle and the physics of standard rate turns", URL: http://www.luizmonteiro.com/Article_Bank_Angle_for_Std_Rate_01.aspx

- [41] “Forces in a climb,” NASA, URL: <http://www.grc.nasa.gov/WWW/k-12/airplane/climb.html>
- [42] “All types of turns,” URL: <http://flighttraining.aopa.org/students/presolo/skills/turns.html>
- [43] B. Liang, and Z. J. Haas, “Predictive distance-based mobility management for PCS networks,” in *Proceedings of Eighteenth Annual Joint Conference of the IEEE Computer and Communications Societies*, IEEE, Vol. 3, 1999, pp. 1377-1384.
- [44] B. Liang, and Z. J. Haas, “Predictive distance-based mobility management for multidimensional PCS networks,” *IEEE/ACM Transactions on Networking*, Vol. 11, No. 5, 2003, pp. 718-732.
- [45] R. F. Berg, “Estimation and Prediction for Maneuvering Target Trajectories,” *IEEE Transactions on Automatic Control*, Vol. AC-28, No. 3, Mar. 1983, pp. 294-304.
- [46] R. F. Stengel, “Flight dynamics,” *Aircraft Engineering and Aerospace Technology*, Vol. 77, No. 3, 2005.
- [47] R. H. Bishop, and A. C. Antoulas, “Nonlinear Approach to Aircraft Tracking Problem,” in *Proceedings of the 1991 AIAA Guidance, Navigation and Control Conference*, Vol. 1, Aug. 1991, pp. 692-703.
- [48] R. H. Bishop, and A. C. Antoulas, “Nonlinear Approach to Aircraft Tracking Problem,” *Journal of Guidance Control and Dynamics*, Vol. 17, No. 5, 1994, pp. 1124-1130.
- [49] N. Nabaa, and R. H. Bishop, “Validation and comparison of coordinated turn aircraft maneuver models,” *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 36, No. 1, 2000, pp. 250-259.

- [50] R. R. Roy, *Handbook of Mobile Ad Hoc Networks for Mobility Models*. New York: Springer, 2011.
- [51] K. Namuduri, Y. Wan, M. Gomathisankaran, and R. Pendse, "Airborne Network: a Cyber-Physical System Perspective," in *Proceedings of the First ACM MobihHoc Workshop on airborne Networks and Communications*, Hilton Head, SC, pp. 55-60, Jun. 2012.
- [52] T. Saadawi, "Optimizing Airborne Networking Performance with Cross-Layer Design Approach," *Res. Foundation*, City Univ. New York, New York, Tech. Rep. AFRL-RI-RS-TR-2009-167, Jun. 2009.
- [53] K. T. Feng, C. H. Hsu, and T. E. Lu, "Velocity-assisted predictive mobility and location-aware routing protocols for mobile Ad Hoc Networks," *IEEE Transactions on Vehicular Technology*, vol. 57, no. 1, pp. 448-464, Nov. 2008.
- [54] B. Liu, M. Chen, and M. Tsai, "Message-efficient location prediction for mobile objects in wireless sensor networks using a maximum likelihood technique," *IEEE Transactions on Computers*, vol. 60, no. 6, pp. 867-878, 2011.
- [55] Geodetic datum, http://en.wikipedia.org/wiki/Geodetic_datum.
- [56] S. P. Drake, *Converting GPS coordinates $[\phi, \lambda, h]$ to navigation coordinates (ENU)*. DSTO Electronics and Surveillance Research Laboratory, 2002.
- [57] C. Y. King, "Virtual instrumentation-based system in a real-time applications of GPS/GIS," in *Proceedings of Recent Advances in Space Technologies*, RAST'03, IEEE, 2003.
- [58] T. O'Haver, Smoothing, Jan. 2001, Retrived from <http://terpconnect.umd.edu/~toh/spectrum/Smoothing.html>

- [59] A. Colin Cameron, Frank A. G. Windmeijer, “An R-squared measure of goodness of fit for some common nonlinear regression models,” *Journal of Econometrics*, vol. 77, no. 2, pp. 329-342, Apr. 1997.
- [60] L. L. Kupper, K. E. Muller, and A. Nizam, *Applied regression analysis and multivariable methods*, Ed. David G. Kleinbaum. 3rd ed. Pacific Grove: Duxbury Press, 1998.
- [61] J. P. Rohrer, E. K. Cetinkaya, H. Narra, D. Broyles, K. Peters, and J. P. Sterbenz, “AeroRP performance in highly-dynamic airborne networks using 3D Gauss-Markov mobility model,” in *Proceedings of Military communications conference, MILCOM*, IEEE, pp. 834-841, Nov. 2011.
- [62] L. Rodgers, Joseph, and W. Alan Nicewander, “Thirteen ways to look at the correlation coefficient,” *The American Statistician*, Vol. 42, No. 1, pp. 59-66, 1988.
- [63] J. Xie, Y. Wan, J. Kim, S. Fu, K. Namuduri, “Analysis of mobility models for airborne networks”, in *Proceedings of MILCOM*, San Diego, Nov. 2013.
- [64] J. Xie, Y. Wan, K. Namuduri, S. Fu, J. Kim, “A comprehensive modeling framework for airborne network”, in *Proceedings of AIAA Infotech@Aerospace Conference*, Boston, Aug. 2013.
- [65] J. Xie, Y. Wan, K. Namuduri, S. Fu, G. Peterson, J. Raquet, “Estimation and validation of the 3D smooth-turn mobility model for airborne networks”, in *Proceedings of MILCOM*, San Diego, Nov. 2013.