A Terrain-Aware Markovian-Mobility Model for VANets

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***Abstract*—Modeling the mobility of manual and under-powered vehicles (e-bikes, e-scooters, bikes, etc) is highly dependent on the terrains they cover. Variations in terrain significantly impact their acceleration and thus displacement across their trajectories. Estimating their location is critical to ensuring the underlying communication infrastructure can "cover" them. With the increase in their adoption, staying connected has become essential, as it allows them to communicate during emergencies and sustain critical tracking services. To achieve reliable connectivity, it is crucial to develop an accurate model of bike trajectory that considers the terrain, since variations in elevation can significantly impact bike movement. This paper presents a terrain-aware mobility model, named Terrain-Aware Mobility (TaM), designed to enhance the accuracy of trajectory predictions building on a Gauss-Markov model. The goal of TaM is to accurately model mobility under variations of terrain slopes, and thus to optimize the placement of wireless access points (WAPs) throughout deployment areas, ensuring that all vehicles remain consistently connected, which is crucial for their safety.**

***Index Terms*—gradient, mobility model**

I. Introduction

This research aims to optimize wireless connectivity for cyclists by enhancing bike trajectory predictions. A significant barrier to the broader adoption of biking is the inadequate connectivity in biking areas, particularly during emergencies and in crowded situations, where existing wireless infrastructures struggle to support the volume of users and their mobility. This underscores the need for accurate mobility prediction models to facilitate effective wireless access point placement. To improve these trajectory predictions, the research will factor in the terrain, including variations such as uphill and downhill gradients. With cycling rates increasing between 11% and 48% on average, maintaining these habits could generate health benefits valued between \$1 and \$7 billion per year [1] [8].

Accurately predicting bike trajectories in urban settings is challenging due to the influence of terrain on speed, which subsequently affects movement patterns and trajectories. While existing mobility models such as the Paparazzi Model, the Distributed Pheromone Repel (DPR) Mobility Model, and the Gauss-Markov Model assist in simulating bike movements, they often do so with varying degrees of success. Unfortunately, these current solutions frequently neglect to adequately incorporate terrain effects, resulting in suboptimal placement of wireless access points (WAPs) and connectivity gaps that hinder effective cycling experiences.

A major hurdle to the wider adoption of biking is the lack of connectivity in areas of interest, such as biking trails, where emergency services and reliable communication are significantly lacking. This issue is further exacerbated in high-density situations, where groups of cyclists strain neighboring cellular and wireless infrastructures, making it difficult to handle the influx of users and their mobility needs during hand-offs between stations. While pre-planning the placement of wireless access points (WAPs) can help alleviate connectivity issues, it heavily relies on the accuracy of mobility prediction models. Unfortunately, most existing models often fail to account for the impact of terrain variation on bike speed and acceleration, leading to inaccurate location estimates that compound mobility and calculation errors. Ensuring reliable wireless connectivity is essential for enhancing cyclist safety and navigation, particularly in urban environments with complex terrains, as inadequate connectivity can increase the risk of accidents. Cyclists may struggle to receive timely updates about hazards or changing road conditions, which can contribute to collisions in high-traffic areas. Therefore, effective connectivity is crucial for promoting safer cycling experiences and preventing potential incidents. This paper proposes a terrain-aware mobility model that incorporates gradient effects on bike trajectories, allowing for more accurate predictions and better optimization of WAP placement.

The proposed model integrates terrain gradients into the Gauss-Markov (GM) mobility model, enhancing its adaptability and realism for urban cycling scenarios. Unlike traditional models, this approach accounts for the dynamic nature of terrain, resulting in improved accuracy in trajectory prediction and wireless access point (WAP) placement. Validation of the model was conducted through simulations across various terrain types, and the results were compared against traditional models, demonstrating a significant improvement in prediction accuracy and connectivity coverage.

The remainder of this paper is organized as follows. Section II elaborates on current mobility models that adapt to VANet movement, and pertinent background in terrain calculations and registration. Section III introduces our terrain-aware mobility model, and the terrain calculation parameters. Section

IV details our performance evaluation and simulations that span different scenarios of terrain and mobility variations. We conclude in Section V and introduce critical next steps in this domain.

II. Mobility Models for VANets

To effectively predict bike trajectories, it is essential to explore various mobility models that can capture the nuances of movement. Three distinct mobility models—Paparazzi, Distributed Pheromone Repel (DPR), and Gauss-Markov (GM)—each offering unique approaches to movement simulation. The Paparazzi Model is examined for its structured, deterministic movement patterns, which could be valuable for scenarios requiring precise trajectory predictions. The DPR Model, known for its pheromone-based exploration strategies, provides insights into coverage and area exploration. Finally, the GM Model, with its adaptability and incorporation of terrain effects, offers a realistic approach to simulating bike movements in varied urban terrains.

A. Paparazzi Model

In Paparazzi Mobility (PPRZM) Model the nodes in the simulation can follow one of five predefined movement patterns: Way-Point (travel between specific points), Stay-At (hover at a location), Eight (move in a figure-eight pattern), Oval (move in an oval path), and Scan (sweep a defined area).At the start of the simulation, each node chooses one of these movement patterns [2]. It also selects its starting location and speed. Then each node's altitude is randomly set initially and remains constant throughout the simulation period. Finally, the node moves according to the chosen pattern, updating its position based on the selected speed and direction. The patterns have specific rules for how the node should move.

B. Distributed Pheromone Repel (DPR) Mobility Model

The Distributed Pheromone Repel (DPR) Mobility Model uses Pheromone Map Creation. A grid map is used to track where nodes have already flown, with each grid segment showing when it was last covered. So first each node uses the pheromone map to decide where to move. It considers the movement of other nodes and the pheromone information from their paths. Next, based on the pheromone map, a node decides whether to go straight or turn left/right [3]. The goal is to cover new areas rather than revisiting areas with strong pheromone traces. nodes prefer to move to areas with fewer pheromones, which helps in covering new ground and avoiding overlapping with other nodes. While this method improves coverage of the area, it can lead to poor connectivity because nodes tend to move away from each other due to the pheromone repel effect [10].

C. Gauss-Markov Model

The Gauss-Markov (GM) Mobility Model describes a method for simulating the movement of nodes (like vehicles). At the start of the simulation, each node is assigned an initial speed and direction. Then at regular time intervals, the node's speed and direction are updated based on its previous speed and direction [4]. This means that the node's new movement is influenced by its past movements. The extent of randomness in the node's movement is controlled by a single parameter, allowing the model to adapt the degree of unpredictability in the movement. Finally using the updated speed and direction, the new position of the node is calculated at each interval [4]. The node continues to move according to these updated values throughout the simulation, with its trajectory influenced by the controlled randomness and memory of past movements [9].

The basic Gauss-Markov 2-dimensional model can be extended to three dimensions [6]. In the extension, it starts with the speed and direction variables found in the 2-dimensional GM, and a third variable is added to track the vertical pitch of the mobile node with respect to the horizon. This would be helpful when modeling nodes such as an airplane.

D. Impact of urban routes on mobility

For predicting bike trajectories in urban environments, considering terrain effects, the Gauss-Markov (GM) model with gradient-based acceleration adjustments emerges as the most suitable choice. This model effectively adapts to elevation changes, allowing for realistic simulations of bike speed variations on uphill and downhill segments, which is crucial for accurately modeling bike movement in varied urban terrains.

The Paparazzi (PPRZM) model is more effective when specific movement patterns are needed. It excels in scenarios such as a biking group following a tour leader or participants in a race, where all members are generally moving in the same direction. This model is well-suited for route-based simulations but may not capture the nuanced, continuous adjustments in bike trajectories needed for urban settings.

The Distributed Pheromone Repel (DPR) model is best for exploration and coverage scenarios. However, its focus on avoiding previously covered areas makes it less ideal for modeling realistic bike movements in urban environments. DPR's approach to movement could lead to less realistic trajectories for bikes, as it does not account for terrain effects.

In summary, the GM model provides the most realistic and adaptable simulation for urban bike trajectories, particularly when terrain effects are considered. PPRZM is useful for scenarios requiring specific movement patterns, while DPR is more suited for exploration but less effective for realistic urban bike movement modeling.

III. Terrain-aware Markovian Mobility Model

- By incorporating terrain data into the Gauss-Markov (GM) Mobility Model, we enhance the model's ability to simulate bike movements accurately.

- This update allows the model to account for terrain variations that cyclists encounter.

- In cycling, "gradient" refers to the steepness of a road segment, which significantly influences bike movement.

- A flat road has a gradient of 0%, while steeper inclines, such as a 10% gradient, create more resistance than gentler gradients of 5% [5].

- Integrating terrain gradients leads to more realistic predictions of bike trajectories.

- Improved accuracy in trajectory predictions facilitates optimal placement of wireless access points (WAPs), ultimately enhancing connectivity for cyclists in urban environments.

A. Gauss-Markov Mobility Model Algorithm

The traditional Gauss-Markov mobility model simulates the movement of nodes in a 2D space by balancing movement-memory and randomness with a tuning parameter alpha α.

Initially each node starts with an initial speed and direction, as well as predefined average speed ($\overline{s}$) and direction ($\overline{d}$). After a predetermined time interval (Δt), the node's new speed (s_n) and direction (d_n) are calculated as follows [6] :

$$s_n = \alpha \cdot s_{n-1} + (1-\alpha)\overline{s} + \sqrt{(1-\alpha^2)} \cdot s_{x_{n-1}} \tag{1}$$

$$d_n = \alpha \cdot d_{n-1} + (1-\alpha)\overline{d} + \sqrt{(1-\alpha^2)} \cdot d_{x_{n-1}} \tag{2}$$

These new speed and direction are dependent on: the previous speed s_{n-1} and direction d_{n-1}; the pre-determined average speed $\overline{s}$ and direction $\overline{d}$ and the noise from the Gaussian distribution that gives randomness to the new speed $s_{x_{n-1}}$ and direction parameter $d_{x_{n-1}}$ [6] .

The Gauss-Markov (GM) model operates with a single parameter α which adjusts how the model behaves. The role of α is to balance memory and randomness in node movement. When $\alpha = 0$ the movement is entirely random, relying solely on average values and Gaussian noise, with no influence from previous states. Conversely, when $\alpha = 1$ the movement is perfectly predictable, losing all randomness and maintaining the same speed and direction as the previous time step, indicating full memory of past states [6]. For values of α between 0 and 1, the model provides a blend of memory and randomness, where the node's movement is influenced by both its previous state and random factors.

B. Incorporating terrain variations in the TaM

- To model the trajectory of biking using the Gauss-Markov mobility model, incorporating the gradient of the terrain into the speed calculation can significantly improve accuracy.

- The gradient is typically expressed as a percentage, which indicates the rise over run

- The nature of these gradients inherently affects acceleration, necessitating a nuanced approach to modeling bike trajectory.

-The acceleration of a node, n, influenced by the terrain gradient at time n, denoted as A_n^t, is formulated as follows:

$$A_n^t = \frac{G_n^t}{\mu} \cdot \lambda \tag{3}$$

- Here, the gradient is normalized by the maximum gradient, μ, and subsequently scaled by the factor λ to account for its impact on speed.

- In the terrain-aware model, the next location is calculated at each time interval based on the current location, speed, direction, and the gradient experienced.

- Specifically, at time interval n, a node's position is calculated as follows :

$$\hat{s}_n = \frac{G_n^t}{\mu} \cdot \lambda + (\alpha \cdot s_{n-1} + (1-\alpha)\overline{s} + \sqrt{(1-\alpha^2)} \cdot s_{x_{n-1}}) \tag{4}$$

$$\hat{d}_n = \alpha \cdot d_{n-1} + (1-\alpha)\overline{d} + \sqrt{(1-\alpha^2)} \cdot d_{x_{n-1}} \tag{5}$$

$$x_n = x_{n-1} + s_{n-1} \cdot cos \cdot d_{n-1} \tag{6}$$

$$y_n = y_{n-1} + s_{n-1} \cdot sin \cdot d_{n-1} \tag{7}$$

where x_n, y_n and x_{n-1}, y_{n-1} are the x and y coordinates of the bike's position at the nth position respectively.

IV. Performance evaluation of TA-GM and WAP placement

- A topographical map effectively illustrates elevation changes in terrain by using contour lines, which connect points of equal height, allowing for a clear visualization of the landscape's relief and variations in altitude, as shown in Fig 1. This figure depicts the translation from elevation values to gradient calculations, which are pivotal to displacement calculations in TaM.

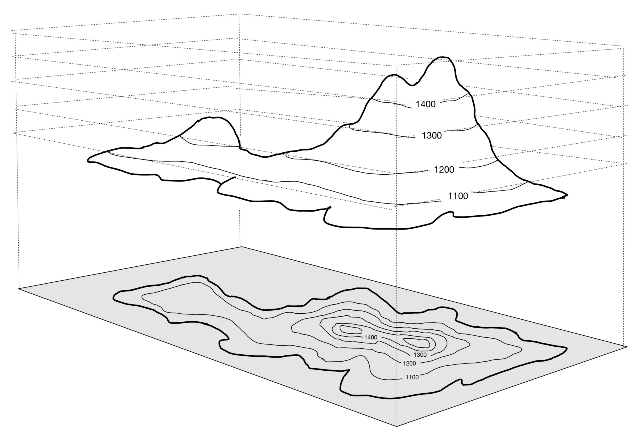

Fig. 1. A topographical map demonstrating the mapping of elevations to gradient values.

- Fig. 2 illustrates the travel pattern of a node using the Gauss-Markov Mobility Model. The node begins its movement at the position (3, 3) and continues for 250 seconds. In Fig. 2, n represents 1 second, α is set to 0.75, $s_{x_{n-1}}$ and $d_{x_{n-1}}$ are drawn from a random Gaussian distribution, with a fixed speed s of 5 m/s and a directional angle d of 45 degrees.

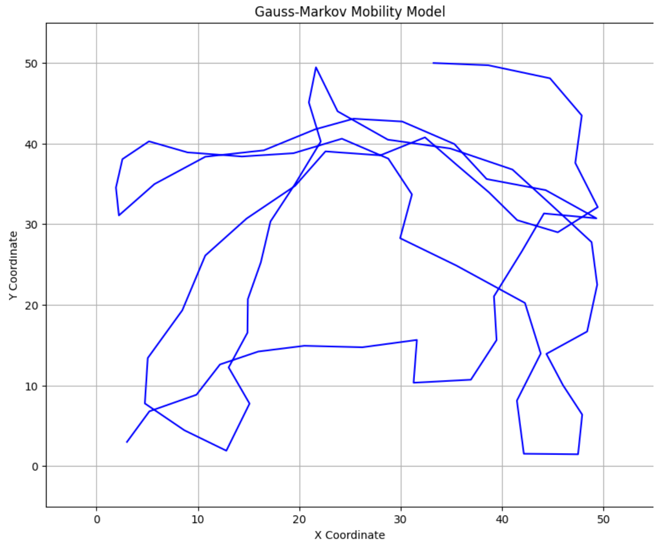

Fig. 2. Traveling pattern of an node using the Gauss-Markov Mobility Model

- Road Cycling: Gradients of up to 5%-8% are common for sustained climbs.

- Mountain Biking: Steeper gradients can reach 10%-15% for short sections, with very experienced riders able to handle even steeper slopes, especially on technical trails.

- In practical modeling, understanding the gradient's impact on cycling performance is essential. A maximum gradient of 15 is often used, as it reflects challenging but manageable conditions for most cyclists [5]. Adjustments can still be made based on specific routes or athlete capabilities.

- The factor of 2.5 scales the impact of the gradient on speed [7].

- The terrain aware model extracted data the gradient values along a trail going through the city of Carbondale that is located south of Chicago, USA.

A. Performance Metrics and experiment setup

- First, the traditional Gauss-Markov (GM) model simulation is executed, as illustrated in Fig. 3, providing a foundational understanding of the node's movement dynamics.

- Next, the gradient values corresponding to the distance along the trail dataset are extracted. These gradient changes are visually represented in Fig. 4 using contour lines, showcasing a specific section of the trail.

- Finally, the terrain-aware mobility model analyzes the node's location in relation to the gradient values and their impact on speed, as depicted in Fig. 5.

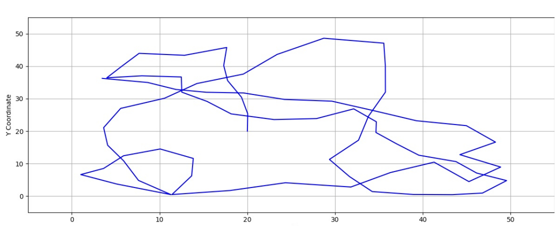

Fig. 3. GM model

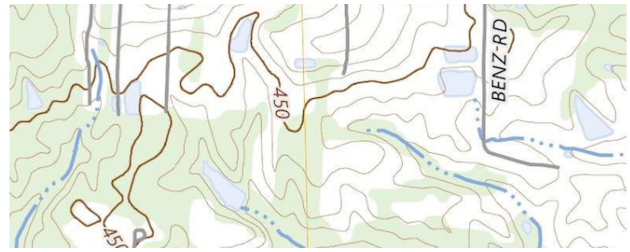

Fig. 4. Topography of a section of the biking trail

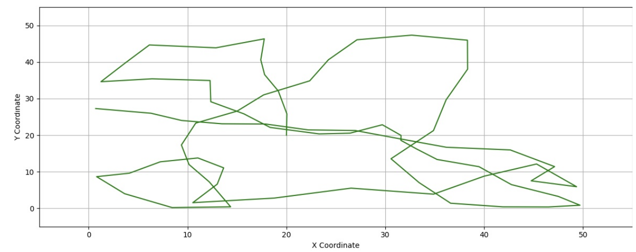

Fig. 5. Terrain Aware Model, representing the cycling trail

- To effectively compare the two models, Fig. 6 illustrates the first 30 steps of each, highlighting their differences in trajectory.

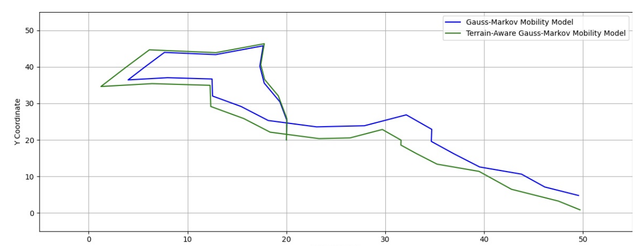

Fig. 6. Representation of the first 30 steps contrasting accuracy of trajectory prediction between TaM and the base GM models

- Metrics for evaluation the effectiveness of the proposed model: connectivity reliability for bike riders, reduction in dead spots compared to traditional deployment methods.

- Deploying wireless access points (WAPs) based on the GM model can lead to location mismatches, resulting in connectivity loss. While WAPs may overlap in relatively flat areas, such as the start of the trail, many cyclists prefer off-road and hilly terrains. In these regions, the risk of accidents increases, making reliable connectivity essential for safety.

- In contrast, the terrain-aware model optimizes WAP deployment by more accurately predicting a cyclist's location due to its consideration of gradient changes, as illustrated in Fig. 6.

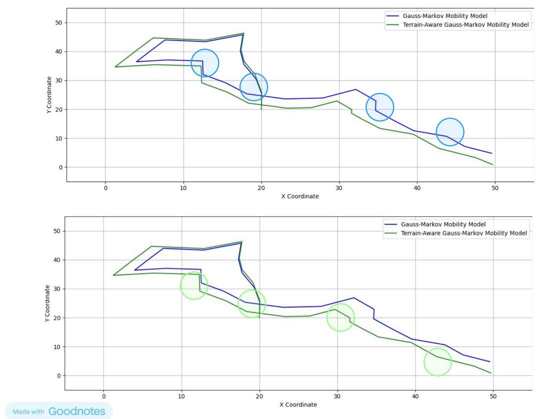

Fig. 7. WAP deployment based on mobility model

- Errors in location estimation cause significant connectivity challenges, especially when compounded over multiple time rounds. That is, if there is a 5 percent error in displacement over each round, then over ten rounds the error will significantly compound to over 5 to the power 10.

- To demonstrate the impact of factoring in gradient, we show the error in location calculations over 5, 10 and 20 GM movements, comparing the location of a GM model to that of our Gradient GM model. The error is calculated as a ratio of error displacement over region span: the distance between the farthest points on the covered map.

V. Conclusions

The terrain-aware model outperforms the traditional Gauss-Markov (GM) model in optimizing wireless access point (WAP) placement, providing more accurate predictions of cyclist locations across diverse terrains. The analysis of gradient values and topographical maps enhances the understanding of connectivity challenges, particularly in hilly or off-road environments. Future research should investigate the impact of additional environmental factors, such as weather conditions, traffic patterns, and cyclist fatigue, on mobility and connectivity, aiming to develop more comprehensive models.

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