3D Modeling Moving Objects under Uncertainty Conditions

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Abstract

Geospatial information systems (GIS) have been applied in modeling environmental and ecological systems. 3D Moving objects are spatio-temporal objects whose location and/or extent change over time, and they are among those recent evolutions that emerged to fulfill some of the new requirements for GI community. Many of the earlier works were based on the assumption that exact trajectory information was available (or could be obtained) at every time instant. Unfortunately, this assumption cannot be guaranteed in real applications where trajectory information is associated inherently with uncertainty and lack of complete and precise knowledge. In this paper, we explore how a trajectory is influenced by uncertainty. Then we study the nature of 3D moving object trajectories in the presence of uncertainty and we introduce two data models for uncertain trajectories that are used to represent moving objects. By using this model in a case study, we obtain the most probable answer where we consider a 3D moving object path under uncertain conditions and lack of knowledge.

1. Introduction

For some spatiotemporal applications, it can be assumed that the modeled world is precise and bounded. While these simplifying assumptions are sufficient in some applications, they are unnecessarily for many other applications, such as navigational applications that manage data with spatial and/or temporal extents.

Moving object databases appear in numerous applications such as emergency services, navigational and military services, flight management and tracking, m-commerce, and various location based services as fleet management, vehicle tracking, and mobile advertisements. These advancements demand new techniques for managing and querying changing location information. One of the key research issues with moving objects is the management of uncertainty. Many of the earlier works were based on the assumption that exact trajectory information was available (or could be obtained) at every time instant. Unfortunately, this assumption cannot be guaranteed in real applications where trajectory information is associated inherently with uncertainty and lack of complete and precise knowledge. Inspired by the importance of this subject we first explore how a trajectory is influenced by uncertainty, and then we study the nature of moving object trajectories in presence of uncertainty. We introduce two data models for uncertain trajectories that are used to represent moving objects in 3D space (2D positional and 1D temporal). By using these models, we can query uncertain databases with moving objects having measurement errors.

There are several works towards modeling and querying moving objects with uncertainty. Pfoser and Jensen discuss [7] spatiotemporal indeterminacy for moving objects data and present a formal quantitative approach to include uncertainty in modeling the moving object. The authors limit the uncertainty to the previous position of the moving objects and the error may become very large as time approaches [7]. It describes the methodology to compute and utilize error information of moving objects' trajectories. The approach, however, is limited to point objects; also, it does not take temporal errors into account. Pfoser and Tryfona [8] take a more pragmatic approach in that the world is modeled in terms of spatial data types, and fuzziness is expressed as related to the data types and the operations on them.

Trajcevski et al.[3] address the problem of querying moving objects' databases, which capture the inherent uncertainty, associated with the location of moving objects. They propose a model for trajectory as a 3D cylindrical body that incorporates uncertainty in a manner that enables efficient querying. Yu et al. [1] propose a practical framework and mathematical basis for managing and capturing multidimensional continuously changing data objects. Mokhtar and Su [4] introduce a data model for uncertain trajectories of moving objects in which the trajectory is a vector of uniform stochastic processes. Ding and Güting [2] discuss how the uncertainty of network constrained moving objects can be reduced by using reasonable modeling methods and location update policies and then present a framework to support variable accuracies in presenting the locations of moving objects.

The rest of the article is structured as follow. In section 2 we define uncertainty concepts for a trajectory. Section 3 presents two major sources of uncertainty in a trajectory. In section 4 we present our two proposed models for querying a database of trajectories with uncertainty using weighted interpolation for 3D moving object's location. Finally, section 5 gives concluding remark and outlines the direction for future work.

2. Uncertainty in Moving Objects

Uncertainty is an inherent property of information location of moving objects. Unless uncertainty is captured in the model and query language used, the burden of factoring uncertainty into answers to queries is left to the user. For example, consider a ship equipped with GPS that can transmit its positions to a central computer. At the central site the data is processed and utilized. Example queries occurring in such an application are as follows:

- Which ship is nearest to a destroyed ship?
- A what time will "ship A" reach "island B"?
- Compute the best direction of motion for the ship in order not to bump into a seen rock.

If we consider uncertainty in information and trajectory, the questions have no clear answers. Taking uncertainty into account, we can restate the questions as follow:

- Which ship will be, with a 50% probability, within 100 meters of ship A in 20 minutes?
- How likely is it that "ship A" reaches "island B" without being hit by a storm that will happen between 9:00 and 12:00 ?
- Compute the minimum temporal range so that ship A could be in region B.

To answer these questions we need an abstract model with quantifiable uncertainty and by using that model, we can obtain the most probable answer.

3. Types of Uncertainty in Trajectory

A first step in incorporating uncertainty into a representation of trajectories is to quantify it. Thus, in section 3 we want to define errors introduced by the trajectory acquisition process.

3.1 Measurement error

Generally, an error can be introduced by inaccurate measurements [5]. The accuracy and thus the quality of the measurement depend largely on the technique used. This paper assumes that GPS is used for the sampling of positions. Two assumptions are generally made when talking about the accuracy of the GPS. First, the error distribution is assumed to be Gaussian. Second, we assume that the horizontal error distribution is circular [9]. Figure 1 visualizes the error distribution. In addition to the mean, the standard deviation, σ, is a characteristic parameter of a normal distribution. Within the range of $\pm\sigma$ of the mean 39.35% of the probability is concentrated in a bivariate normal distribution (2-dimensional).

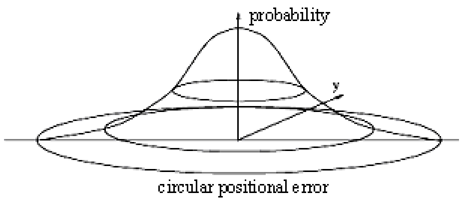

Fig. 1. Positional error in the GPS [7]

3.2 Uncertainty in sampling

We capture the movement of an object by sampling its position using a GPS receiver at regular time intervals. This introduces uncertainty about the position of the object that is affected by the frequency with which position samples are taken, i.e., the sampling rate. This, in turn, may be set by considering the speed of the object and the desired maximum distance between consecutive samples [7].

By looking Figure 2(a), one would assume that the straight-line best resembles the actual trajectory of the object. In Figure 2(b) we can obtain the better trajectory that is more similar to the actual one by increasing the sampling rate or decreasing the moving object speed. The difference between the two trajectories shows the "uncertainty”.

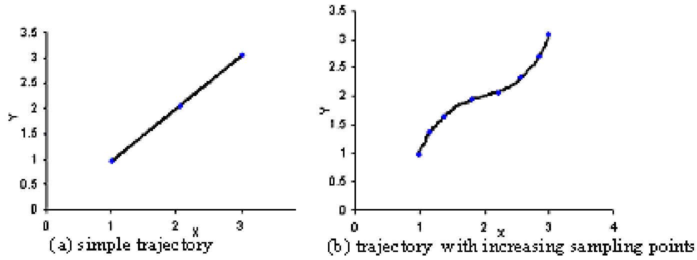

Fig. 2. Uncertainty in a trajectory

For better understanding, consider the trajectory in a time interval $[t_1; t_2]$, delimited by consecutive samples. We know two positions, P_1 and P_2, as well as the object's maximum speed, v_m (see Figure 3). If the object moves at maximum speed v_m from P_1 and its trajectory is a straight line, its position at time t_x will be on a circle of radius $r_1 = v_m(t_1 + t_x)$ around P_1 (the smaller dotted circle in Figure 3). Thus, the points on the circle represent the furthest position away from P_1 the object can get at time t_x. If the object's speed is lower than v_m, or its trajectory is not a straight line, the object's position at time t_x will be somewhere within the area bounded by the circle of radius r_1. Next, we know that the object will be at position P_2 at time t_2.

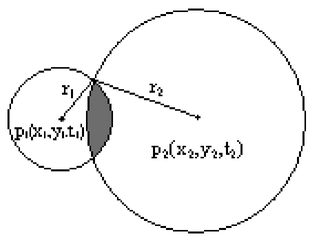

Fig. 3. Uncertainty between samples [8]

Thus, applying the same assumptions again, the object's position at time t_x is on the circle with radius $r_2 = v_m(t_2 - t_x)$ around P_2. If the object moves slower or its trajectory is not a straight line, it is somewhere within the area bounded by the dotted circle. The above constraints on the position of the object mean that the object can be anywhere in the intersection of the two circular areas at time t_x. This intersection is shown by the shaded area in Figure 3. In the following, we present two models to handle this uncertainty in order to calculate the most probable answer in the shadow area.

4. Two Models for Trajectories with Uncertainty

As mentioned with GPS technology, a 3D moving object's position can be determined instantaneously with some errors and the moving object's speed would be affected. These matters lead us to introduce a new approach to sample 3D position (x, y, t) between sampling point or future position for a moving object in order to gain the most probable answer to uncertainty.

We will not consider any error connected to the times of measurements. We assume that we know precisely the time when a position sample was observed. This assumption seems to be justified when using GPS and its precise clocks as a measuring device. In this section, we introduce two models for our uncertain trajectory.

4.1 The first model

First, we want to find a moving object's 3D position in future. As shown in Figure 4, we have a moving object that its positions at time intervals are recorded and we want to find its position at a precise time t_x in future. In this model, it is assumed that the direction of the object's speed is known and definite.

Considering variable speed for moving object, we assume maximum and minimum speeds, called V_{max} and V_{min}, between each two points. They are calculated as follow:

$$V_{i\min} = \frac{d_i - \delta d_i}{t_{i+1} - t_i} \ \& \ V_{i\max} = \frac{d_i + \delta d_i}{t_{i+1} - t_i} \tag{1}$$

$$d_i = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \tag{2}$$

where δd is measurement error and d_i is the distance between each consecutive point and i is a counter for sampling points and n is the number of points as shown in Figure 4.

As represented in Equations (3) and (4), we can calculate d_{nmin}, d_{nmax} (minimum and maximum distances between the last sampling point and moving object's 3D position in future at a precise time t_x), and estimate the uncertainty range, R_u, for new position at time t_n in future.

$$d_{n\max} = \max(V_{i\max}) * (t_n - t_{n-1}) \tag{3}$$

$$d_{n\min} = \min(V_{i\min}) * (t_n - t_{n-1}) \tag{4}$$

$$R_u = d_{n\max} - d_{n\min} \tag{5}$$

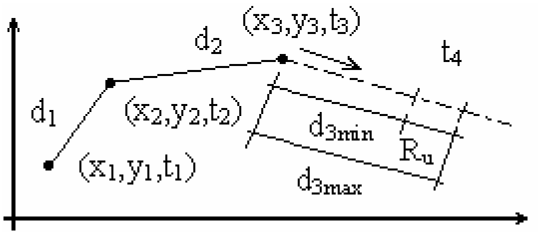

Fig. 4. Trajectory of a moving object with uncertainty

With this method, we can calculate a span in which the moving object actually will be a database of at time t_n (Equation (5)).

4.2 The second model

In the second model, we want to find the position M of an unknown moving object. The accuracy of each point depending on its measuring technique is different, thus points in this model have different errors. In comparison with the model shown in Figure 4, in this model, we consider more sampling points and calculate the probability positions M by 3D linear interpolation between each point i and point n. Then, in order to calculate the most probable answer among probable positions, we use weighted interpolation among these positions in which weights for all the points are represented in Equations (6) and (7) [6]:

$$w_{1i} = \frac{\frac{1}{\sigma_i}}{\sum_{1}^{n} \frac{1}{\sigma_i}} \quad , \quad w_{2i} = \frac{\frac{1}{d_i}}{\sum_{1}^{n} \frac{1}{d_i}} \tag{6}$$

$$W_i = \frac{(\sigma_i * w_{2i} + d'_i * w_{1i})}{\sigma_i + d'_i} \tag{7}$$

where σ_i is measurement error for sampling points and d_i is spatiotemporal distance between each point and unknown position *M*. w_{1i} is the weight corresponding to measurement error and w_{2i} is the weight introduced for spatiotemporal distance as shown in Equation (6). d'_i is the projection of d_i in 2-dimensional space (*x* and *y* coordinates Equation (8)) and n is the number of sampling points and i is a counter for sampling points. In Equation (9), (x_i, y_i, t_i) are the 3D coordinates of probable positions *M* and (*x, y, t*) are the 3D coordinates of unknown point *M*.

$$d'_i = \sqrt{(x_i - x)^2 + (y_i - y)^2} \tag{8}$$

$$d_i = \sqrt{(x_i - x)^2 + (y_i - y)^2 + (t_i - t)^2} \tag{9}$$

In order to calculate d_i we should consider an approximate 3D position for *M* called $M_i(x_i,y_i,t)$ at time t_x that could be calculated with a 3D linear interpolation between two desired points. Finally, we can combine the two introduced weights and calculate *M (x,y,t)* as presented in Equation (10) [6].We have considered five sampling points for a trajectory of a moving object that three of them have more measurement errors than the others. Point 5 shown in Figure 5 is determined with precise coordinate, points 1 and 4 are determined with an accuracy of 1 meter and the others have 3 meters accuracy and we can find an unknown position at precise time t_x for moving object shown in Figure 5.

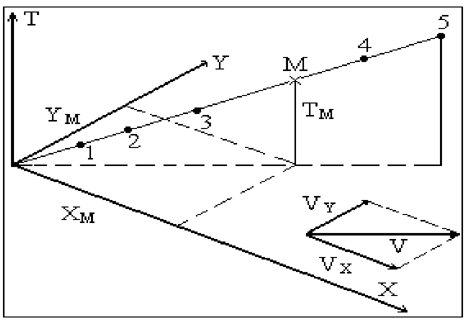

Fig. 5. Trajectory of a moving object in 3D space

$$x = \sum_{1}^{n} W_i x_i \quad \& \quad y = \sum_{1}^{n} W_i y_i \tag{10}$$

All database information is shown in Table 1 and final results of the modeling are shown in Table 2. In this example we sample unknown point at four times calculated with a 3D linear interpolation between each of the points and point 5.

Table 1. Database information for trajectory

Point	1	2	3	4	5
X(m)	112	255	419	580	651
Y(m)	183	254.5	336.5	417	452.5
E=Measuring Error (m)	1	3	3	1	0

Table 2. The results of 3D modeling

	T(s)	d	w_1	w_2	Xi_M(m)	Yi_M(m)	d'(m)	W
1	0	398.388	0.058	0.375	464.92	359.46	394.573	0.058
2	31	201.918	0.115	0.125	434.32	344.16	200.487	0.115
3	42	81.331	0.286	0.125	490.81	372.4	80.285	0.280
4	65	42.959	0.541	0.375	542.63	398.32	41.779	0.537
5	84	-	-	-	-	-	-	-
M	55	-	-	-	-	-	-	-

Finally, we calculate the most probable position of the unknown point by weighted interpolation as follow:

$$x = \sum_{1}^{n} w_i x_i = 506.32 \ \& \ y = \sum_{1}^{n} w_i y_i = 379.05$$

5. Conclusions and Future Research

The paper has proposed two models for acquiring and representing the movements of point objects assumptions under locational uncertainty. The 3D positions of objects were sampled at selected points in time and in the first model, the position of a 3D object has been predicted at exact time in future by increasing the uncertainty impact. In the second model, the positions (x, y, t) between these points at a given time are obtained using weighted interpolation. Results show that by implementing these models we can locate a moving object at specific time more similar to the exact location in comparison with conventional methods.

This work points to several directions for future research. Firstly, for the representation of the movement, we chose to linearly interpolate between measured positions. More advanced techniques may be used for this purpose. Secondly, two types of error measures were considered. Additionally, time error could be considered. In reality, the space considered will typically contain roads, railroad tracks, lakes, or other infrastructure that may be taken into account to reduce overall uncertainty and error in the database.

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