THE ISOSCELES-TRIANGLE UNCERTAINTY MODEL: A SPATIOTEMPORAL DATA MODEL FOR CONTINUOUSLY CHANGING DATA

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ABSTRACT:

In recent years, many emerging applications deal with *continuously changing data objects* (*CCDO*), such as stock values, manned or unmanned vehicles, pedestrians, and sensed stimuli values. To support large-scale CCDO applications, one requires an efficient data management system that can store, update, and retrieve large sets of CCDOs. Although actual CCDOs can continuously change, computer systems cannot deal with continuously occurring infinitesimal changes. Thus, in the data management system, each object's spatiotemporal values are always associated with a certain degree of uncertainty at every point in time, and the queries are mostly processed over estimates characterizing the uncertainty. Unfortunately, the related techniques for storing, updating, and retrieving CCDOs have been developed on an ad hoc basis, and there is a marked lack of formal explication of the ontological concepts of the uncertainty of CCDOs. In addition, most related techniques are designed to support only low-dimensional CCDOs, such as vehicles and persons moving in 2- or 3-dimensional space. This paper presents our ontological framework and logical and mathematical bases for capturing and managing CCDOs of widely varying dimensionality.

1. INTRODUCTION

An increasing number of emerging applications deal with a large number of continuously changing (or moving) data objects (CCDOs), such as vehicles, humans, animals, sensors, nano-robots, orbital objects, economic indicators, temporal geographic objects, and bank portfolios (or assets). For example, in earth science applications, temperature, wind speed and direction, radio or microwave image, and various other measures (e.g., CO2) associated with a certain geographic region can change continuously. Several models of watches and handheld devices equipped with a GPS are already available to consumers. Accordingly, new services and applications dealing with large sets of CCDOs are appearing.

Many types of emerging CCDOs, ranging from combined sensor data streams associated with networked sensor systems through multispectral imagery representing multiple time slices of a given geographic region, exist in a high-dimensional space. Typical earth science applications that consider temperature, wind speed and direction and various other measures (e.g., CO2) associated with a given sensor station are subject to continuous change. In the future, more complex and larger applications that deal with higher dimensional CCDOs (e.g., a moving sensor platform capturing multiple stimuli) will become commonplace – increasingly complex sensor devices will continue proliferate alongside potential applications associated therewith. Efficient support for these CCDO applications will offer significant benefit in many broader challenging areas including satellite image analysis, sensor networks, homeland security, internet security, environmental control, and disease surveillance.

To support large-scale CCDO applications, one requires a data management system that can store, update, and retrieve large sets of CCDOs. Each CCDO has both multidimensional-temporal (i.e.., 2 or 3D geographic space or other information dimensions that vary with time) properties representing its continuous trajectory in an information space-time continuum as well as non-temporal properties such as identification, phone number, and address (step functions of time). Conventional database and GIS technology can efficiently manage the non-temporal properties of CCDOs. Though such systems are capable of managing temporal data, the approach requires that the temporal dimension be highly discretized. Therefore, important and interesting research issues arise related to the development of a generic CCDO model, the data management systems for storing and updating CCDO trajectories, and the mechanisms to process queries referring to these trajectories.

Importantly, although CCDOs can continuously move or change, computer systems cannot deal with continuously occurring infinitesimal changes – this would effectively require infinite computational speed and sensor resolution. Thus, each object's combined attribute values (states) spanning multiple dimensions – location as the lowest order derivative in the spatiotemporal context, and velocity and acceleration as higher order derivatives – can only be discretely updated. Hence, the location of an object in space-time is always associated with a degree of uncertainty at every point in time. The current and future locations of each object is estimated (via extrapolation), and the past locations of an object are represented by a sequence of connected segments, each of which joins two consecutive reported locations (states) using an interpolative estimation method. In turn, each segment is associated with a corresponding degree of uncertainty that encloses all possible unknown locations of the object for that segment.

Unfortunately, the related techniques for storing, updating, and retrieving CCDOs have been developed on an ad hoc basis, and

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there is a marked lack of formal explication of the ontological concepts of the uncertainty of (low to high) multidimensional CCDOs. Hence, developing a CCDO application system by simply adopting the known techniques may result in various anomalies, data redundancy, data inconsistency, and inefficient query systems. This paper presents our framework for capturing and managing the uncertainty of low- to high-dimensional CCDOs using geographic spatiotemporal objects as the exemplar. Section 2 summarizes related techniques and models. Section 3 presents our ontological basis characterizing CCDOs, and Section 4 presents a novel new uncertainty model called the Isosceles-Triangle Uncertainty Model (ITUM) capable of supporting CCDOs of varying dimension.

2. RELATED WORK

Several application-specific models of uncertainty have been proposed. One popular uncertainty model is that, at any point in time, the location of the object is within a certain distance *d*, of its last reported location. If the object moves further than *d*, it reports its new location and possibly changes the distance threshold *d* for future updates (Wolfson et al., 1999). Given a point in time, the uncertainty is a circle with radius *d*, bounding all possible locations of the object.

Another model assumes that the object always moves along straight lines (linear routes). The location of the object at any point in time is within a certain interval, centered at its last reported location, along the line of movement (Wolfson et al., 1999). Different CCDO trajectory models that have no uncertainty consideration are found in the literature (Pfoser and Jensen, 2001). These models make sure that the exact velocity is always known by requiring updates at the data management system whenever the object's speed or direction changes. Other models assume that the object travels with known velocity along a straight line, but can deviate from this path by a certain distance (Sistla et al., 1998; Trajcevski et al., 2002).

An important study on the issues of uncertainty in the recorded past trajectories (history) of CCDOs is found in (Pfoser and Jensen, 1999). Assuming the maximum velocity of an object is known, they prove that all possible locations of the object during the time interval between two consecutive observations (states) lie on an error ellipse. A complete trajectory of any object is obtained by using linear interpolation between two adjacent samples. That is, a trajectory is approximated by a sequence of connected straight lines each of which connects two consecutively reported CCDO observations. By using the error ellipse, the authors demonstrate how to process uncertainty range queries for trajectories. Unfortunately, the error ellipse defined and proved in (Pfoser and Jensen, 1999) is, in fact, the projection of the three-dimensional uncertainty region onto the two-dimensional data space and is thus unsuitable for higher dimensional data. While it is conceivable that hyper-ellipsoids may be suitable for higher dimensional data, the limitation of the linear interpolation between foci of the ellipse remains.

Our approach, a mechanism that explicitly leverages an understanding and characterization of uncertainty for a generalized case of the CCDO, offers an alterative construct suitable for higher dimensional data. We call this uncertainty model the *isosceles-triangle uncertainty model* (*ITUM*).

3. THE CCDO CONCEPT

Before presenting our uncertainty model (i.e., the isosceles-triangle model for CCDOs), we explicate "CCDO" through a series of ontological abstractions. This represents a conceptual CCDO model. To be practical, this model is also presented as a generic ER (Entity-Relationship) diagram that can be readily implemented and created in a relational or object-relational database management system.

The formalization of the CCDO concept begins with the development of the ontology of a generic CCDO. The ontological construct characterizing the CCDO offers certain advantages compared to the existing and ongoing ad hoc approaches: (1) the ontology enables us to better understand the very nature of various CCDOs and defines the possible application domain of the developed framework; (2) enables us to easily expand or select a subset of the framework to systematically support the concepts required by a given CCDO application (e.g., for geographic spatiotemporal objects) without anomalies.

For purposes of this effort, we consider "ontology" from the perspective as described in (Guarino, 1998) as, "a specific vocabulary used to describe a certain reality, plus a set of explicit assumptions regarding intended meaning of the vocabulary words." In the context of the development of the ontology of CCDOs, the "certain reality" is that an object moving through a multidimensional information space-time continuum can be abstracted as a point. The "explicit assumptions" relate to the manner in which the various factors, such as a discrete update policy used, the characteristics of the reported properties, and the maximum velocity at which information is subject to change in any given dimension, are used to modify or adjust the corresponding uncertainty associated with the object.

Reconsidering the geographic spatiotemporal object as the exemplar, a CCDO trajectory is a sequence of connected segments in space-time, and each segment has two endpoints that are consecutively reported (factual) states of the CCDO. Figure 1 shows a generic CCDO schema that can support the ontological concepts explicated in Table 1. The schema in Figure 1 is an ER (Entity-Relationship) diagram that represents an instanced object in a generic CCDO database.

***Continuously Changing Data Object* (*CCDO*):**
A CCDO consists of one or more *trajectories* and zero, one, or more non-temporal properties.
***Trajectory*:**
A trajectory consists of *dynamics* and *f*:*time* → *snapshot*, where *time* is a past, current, or future point in time.
***Snapshot*:**
A snapshot is a probability distribution that represents the probability of every possible *state* at a specific point in time. Depending on the *dynamics* and update policies, the probability distribution may or may not be bounded.
***State*:**
A state is a point in a multidimensional information space of which time is one dimension. Optional properties of a state are velocity (i.e., direction and speed of changes in values, the 1st derivative), acceleration (i.e., changes in the rate of change, the 2nd derivative), and higher derivatives.
***Dynamics*:**
The dynamics of a trajectory is the lower and upper bounds of the properties (i.e., multidimensional location within an

information space, velocity, acceleration, and higher derivatives) of all states of the trajectory.

Table 1. A basic ontological abstraction of a CCDO.

Examination of the basic ontology and the commensurate ER diagram, one may observe the following: (1) snapshots are not represented in the schema; (2) only a subset of states, called reported states, are included in the schema. These differences exist due to the fact that a database cannot be continuously updated. The reported states are the factual known states of the CCDOs, and these known factual states can be committed to the database. All in-between states and future states of the CCDOs are then interpolated and extrapolated on the fly (Yu et al., 2004). Because these "estimated" states are not exact, each of them is associated with a degree of uncertainty (a snapshot). Note that, between two known factual states, a theoretically infinite number of possible states may exist.

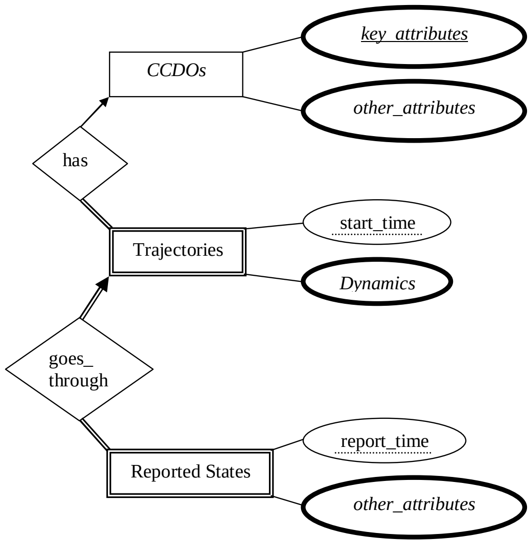

Figure 1. An ER diagram representing a generic CCDO set – a bolded ellipse represents a set of attributes).

Given the theoretic possibility of an infinite number of states between two factual states, a mathematical model and computational approach is required to efficiently manage the "in-between" and future states snapshots. Our approach to this process discussed in Section 4.

4. THE ITUM

Consider an object moving through one dimension of space (e.g., X or Y) and time. This object has a starting position and a finishing position that are known spatiotemporal values. Figure 2 shows our view of a trajectory segment connecting two known (reported) states of a CCDO. Let M be the maximum rate of change in one dimension (i.e., the norm of the maximum possible velocity) of a CCDO, A be the known state (value) of this CCDO at t_i, and B be the state at time t_j. Then all possible states of the CCDO between t_i and t_j are bounded by the lines where $|\cot\theta| = M$. The shaded region covers all possible locations (i.e., more generically, states) of the CCDO between t_i and t_j. We call this region the "*uncertainty region*" of the trajectory segment. The *snapshot* of the CCDO at t_k that is between t_i and t_j is the cross section of the uncertainty region produced by the cutting line $time = t_k$. Note that the uncertainty region in Figure 2 is the overlapping region of two isosceles triangles – the equal sides meet at vertex A (resp., B) and the other side, which is perpendicular to the time axis, has a length of $2 \times M \times (t_j - t_i)$ at t_j (resp., t_i).

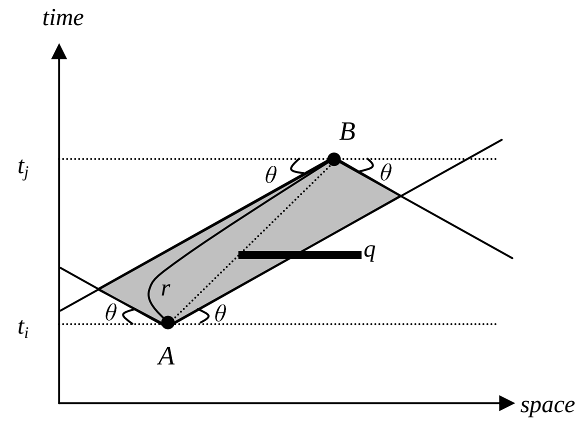

Figure 2. An interpolated trajectory r of a CCDO that can possibly satisfy contained_by(r, q), where q is a logical query region overlapping the set of possible CCDO states.

Similarly, when a CCDO continuously changes in a two-dimensional information space (e.g., geographic space or X, Y), the uncertainty region of each trajectory segment connecting three-dimensional spatiotemporal points A and B is represented by the overlapping region of the two cones whose vertices are A and B, respectively (see Figure 3). Analogous to the isosceles triangle in a single dimension information space, each cone is a right circular cone with height = t_j-t_i, and the radius of the base of each corn is $M \times (t_j - t_i)$. The slant of each cone is represented by a parametric function (Yu et al., 2004). Note that, when M is not known, the uncertainty region is bounded only by the boundaries of the information space*.

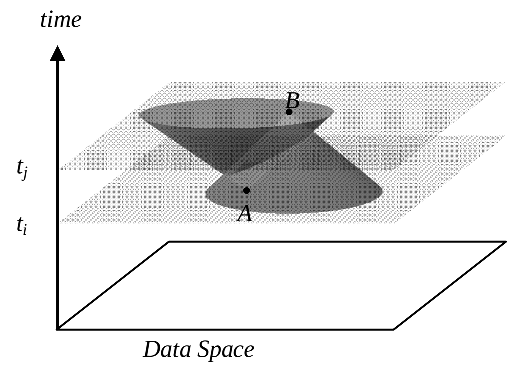

Figure 3. The trajectory segment created by the intersecting data spaces.

In keeping with the intended generic nature of the CCDO, the following theorem and proof offer a logical basis for extending the ITUM approach to higher dimensional data.

Theorem 1. Given the norm of the maximum possible velocity M and two d-dimensional temporally varying points (reported state) P_1 and P_2, where P_1.time < P_2.time, the uncertainty region between P_1.time and P_2.time is the overlapping region of $Cone_1$

* In most database applications, indexed data values are normalized to a range of floating-point numbers between 0 and 1 by an order-preserving domain transformation.

and $Cone_2$, where $Cone_1$ (resp., $Cone_2$) is a hyper-cone defined as follows: (1) the top is P_1 (resp., P_2); (2) the base is a (d-1)-dimensional hyper-circle that is perpendicular to the time dimension at P_2.time (resp., P_1.time); (3) the projection of the top onto the base hyper-circle is the center of the circle; (4) any surface point along the linear line connecting the top and a boundary point of the base circle can be interpolated by a linear parametric function $P(t)=a_0+a_1t$. One can derive the coefficients of this polynomial by solving the following constraints for a_0 and a_1: $P(t=0)$ = the top; $P(t=P_2.time-P_1.time)$ = the boundary point.

Proof.
=> Suppose that there is a possible state P that is in the exterior of $Cone_1$. Then to travel from P_1 to P, the required velocity must exceed M. However M is given as the norm of the maximum possible velocity. By contradiction, P cannot be exterior to $Cone_1$.
<= Suppose that there is a possible state P that is in the exterior of $Cone_2$. Then to travel from P to P_2, the required velocity must exceed M. However M is given as the norm of the maximum possible velocity. By contradiction, P cannot be exterior to $Cone_2$ □

A snapshot contains an infinite number of possible states when the data space is a continuum. The next problem that we should solve is "what is *the most likely state at a given time t*?" This question is especially important when the uncertainty regions are bounded only by the boundaries of the data space (i.e., $M = \infty$). In this case, given any query point, or region, at a certain point t in time, every CCDO has a non-zero probability that it intersects the query point or region at t, except for the CCDOs that have an exact state at t. Therefore, most query results will include all CCDOs. Retrieving all CCDOs for each query is not feasible considering large CCDO sets.

The simplest approach is the conventional linear model that connects two consecutively reported states using a straight line. In this model, the most likely in-between states between two reported states are represented by the straight line connecting the reported states. However, (Yu et al., 2004) provides a series of better methods that can significantly reduce the errors associated with the most likely states. In (Yu et al., 2004), the most likely trajectory of a CCDO is a spline (Catmull and Rom, 1974) composed of a sequence of first or higher degree curves (e.g., parametric cubic function)[*]. The conventional linear model is a special case of this. When the 3rd degree method in (Yu et al., 2004) is used, each state contains not only a spatiotemporal location but also a velocity (i.e., direction and speed), which can be used to derive the slope of the tangent at the location. Since each reported state is used as the joint of two adjacent trajectory segments, each pair of adjacent curve segments have the same slope (and speed) of the tangent at the joint (no visible angle). (Yu et al., 2004) reported that this 3rd degree trajectory representation produced smaller errors (up to 3 times smaller) and standard error deviations (up to 5 times smaller) compared to the linear interpolation scheme for ground vehicle trajectories. That is, given a fixed maximum deviation, this 3rd degree trajectory representation can significantly reduce the number of required joint (reported) states. (Yu et al., 2004) also showed that the added computation overhead is insignificant considering the added benefits of this model. The uncertainty region and snapshots of the future trajectory of a CCDO can be computed in a similar manner (e.g., by extending the uncertainty boundaries of B in Figure 2 in the opposite direction along the time dimension). However, estimating the most likely future trajectory is more challenging and requires additional considerations (Yu et al., 2004).

If not only velocity P' but also acceleration P'' (the second derivative of the real trajectory at the joint) are sensed, we can use a 5th degree polynomial $P(t) = a_0+a_1t+a_2t^2+a_3t^3+a_4t^4+a_5t^5$. Given two joint points $<P_i, P_i', P_i''>$ and $<P_j, P_j', P_j''>$, one can derive the coefficients of the polynomial by solving the following constraints for a_0, a_1, a_2, a_3, a_4, and a_5: $P(t=0) = P_i$; $P(t=P_j.T-P_i.T) = P_j$; $P'(t=0) = P_i'$; $P'(t=P_j.T-P_i.T) = P_j'$; $P''(t=0) = P_i''$; $P''(t=P_j.T-P_i.T)=P_j''$. By generalizing this, we can connect two joint points using the following generalized parametric function:

$$P(t) = \sum_{k=0}^{2n+1} a_k t^k \,, \qquad (1)$$

where n is the number of derivatives written in each joint record.

Observe that the 3rd degree trajectory curve (i.e., n=1) generates visually smooth curve segments (i.e., the location changes smoothly) but, in each segment, the acceleration changes linearly. The 5th degree polynomial (i.e., n=2) generates a curve segment in which location, velocity, and acceleration change smoothly. This generalized trajectory model, that we propose in this paper, enables us to actually investigate optimization solutions that, given a proper description of a CCDO set, can choose the most efficient equation (i.e., n). For example, unlike fast changing objects, some slowly changing objects (e.g., animals and humans) can change velocity more abruptly.

Processing a query with uncertainty means that each result data item is associated with the probability (or likelihood) that the item really satisfies the query predicate. In Figure 2, the trajectory can possibly intersect the query region q because the snapshot (cross section of the uncertainty region) that represents all possible states at the time of q overlaps the range of q.

In Figure 2, the dotted straight line connecting A and B represents the most likely trajectory calculated by the conventional linear model; the curve represents the most likely trajectory produced by a higher order trajectory model. As shown in Figure 4a, when the linear model is used, the peak of the probability of possible states is close to the centre of the snapshot, resembling a bounded normal distribution. Because q reaches the peak point, the probability that there is a state that is covered by the range q is near 50%. In contrast, a more precise higher order computation model (the curve in Figure 2) shows a more skewed distribution of possible states (Figure 4b), since the most likely trajectory curve passes through the left-hand side of the snapshot centre. Thus, in Figure 4b, the probability that this trajectory satisfies the query condition is much lower than 50%.

Following Azzalini (Azzalini and Valle, 1996) and the associated R project skew-normal package (R Development Core Team, 2004), two parameters, Ω (multivariate correlation matrix) and α (multivariate shape parameter vector) - more fully explicated in (Azzalini and Capitanio, 1999) - can be used to

[*] A single high-degree curve is not desirable because of the following reasons: (1) the polynomial may take very large values between the points, and the size of these excursions can grow exponentially with the degree N of the polynomial; (2) the polynomial can be very sensitive to small changes in the points.

control the shape and association of a skewed-normal random distribution. The shape and association parameters allow for parametric control of representative positional probability associated with higher derivatives such as velocity and acceleration. In turn, the threshold determining whether any given portion of an uncertainty region satisfies a query can be parametrically managed.

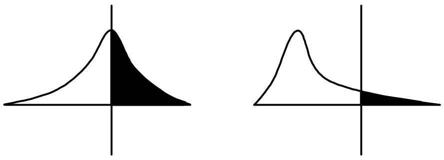

Figure 4. Probability distributions associated with queries uncertainty regions.

One can observe that, as discussed earlier in this section, when *M* is not known, the snapshot covers from the low-endpoint to the high-endpoint of the data space, and the probability becomes different.

In order to support the CCDO queries limiting the minimum probability that the result object satisfies the query predicate or the maximum number of result objects, the most recently proposed related query processing algorithm (Cheng et al., 2004) can be used.

5. CONCLUSION

More and more database applications deal with large sets of multidimensional objects that can continuously change (or move) over time. Most related techniques are designed for managing low-dimensional, physically moving objects. However, in recent years, an increasing number of applications require an efficient data management system that can cope well with high-dimensional CCDOs (continuously changing data objects).

In this paper, we proposed a practical framework for managing (low to high) multidimensional CCDOs. The proposed CCDO concept is practical in that the generic schema can be easily specialized and readily created in a transactional database environment. In addition, the novel ITUM (Isosceles-Triangle Uncertainty Model) and the trajectory computation methods can support not only conventional CCDOs that move in 2- or 3-dimensional geographic space but also emerging high-dimensional CCDOs, such as combined sensor streams and satellite data. Importantly, we demonstrate the derivatives such as acceleration and velocity that are typically associated with objects moving through geographic space are equally relevant when examining the general case of a more generic multidimensional continuously changing data object.

In many applications, the environment through which an object is moving is likely to affect the set of probable locations associated therewith. In our future work, we will investigate an efficient approach to modelling (low to high) multidimensional uncertainty wherein environmental objects are incorporated.

REFERENCES

Azzalini and Capitanio, A., 1999. Statistical applications of the multivariate skew-normal distribution. *Journal of the Royal Statistical Society*, Series B(61), pp. 579-602.

Azzalini and Valle, A.D., 1996. The multivariate skew-normal distribution. *Biometrika*, 83, pp. 715-726.

Catmull, E. and Rom, R., 1974. A Class of Local Interpolation Splines. *R.E. Barnhill and R.F. Riesenfled, editors, Computer Aided Geometric Design*, Academic Press, New York.

Cheng, R., Kalashnikov, D., and Prabhakar, S., 2004. Evaluating Probabilistic Queries over Imprecise Data. *IEEE Transactions on Knowledge and Data Engineering*, 16(9), pp. 1112-1127.

Guarino, N., 1998. Formal ontology and information systems. *N. Guarino, ed., FOIS'98*, IOS Press, Trento, Italy, pp. 3-17.

Pfoser, D. and Jensen, C.S., 1999. Capturing the Uncertainty of Moving-Objects Representations. *Proc. SSDBM Int. Conf. on Scientific and Statistical Database Management*, pp. 123-132.

Pfoser, D. and Jensen, C.S., 2001. Querying the Trajectories of On-Line Mobile Objects. *Proc. ACM MobiDE International Workshop on Data Engineering for Wireless and Mobile Access*, pp. 66-73.

Sistla, P.A., Wolfson, O., Chamberlain, S., and Dao S., 1998. Querying the Uncertain Position of Moving Objects. *Temporal Databases: Research and Practice*, 1399.

R Development Core Team, R: A language and environment for statistical computing, *R Foundation for Statistical Computing*, Vienna, Austria, 2004.

Trajcevski, G., Wolfson, O., Zhang, F., and Chamberlain, S, 2002. The Geometry of Uncertainty in Moving Object Databases. *Proc. Int'l Conf. on Extending Database Technology*, May.

Wolfson, O., Sistla, P.A., Chamberlain, S., and Yesha, Y, 1999. Updating and Querying Databases that Track Mobile Units. *Distributed and Parallel Databases*, 7(3), pp. 257-387.

Yu, B., Kim, S.H., Bailey, T., and Gamboa, R., 2004. Curve-Based Representation of Moving Object Trajectories. *IEEE IDEAS International Database Engineering and Applications Symposium*, pp. 419-425.