Simple Map-Matching Algorithm Applied to Intelligent Winter Maintenance Vehicle Data

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Intelligent winter maintenance vehicles are equipped with automatic vehicle location (AVL) technology, including differential Global Positioning System (DGPS) receivers and various additional sensors that collect equipment status and material use data. DGPS data points are associated with the nearest roadway centerline by calculating minimum perpendicular distances between each roadway centerline representation and the DGPS data points. Highly accurate roadway centerline maps and DGPS measurements are not always available. Thus, spatial mismatches may occur at converging and diverging roadways, divided highways, and intersections. Decision makers use winter maintenance performance measures to evaluate achievement of goals and objectives and to improve winter maintenance operations in public agencies. These performance measures are sensitive to spatial mismatches, which need to be resolved before calculations are done. This paper presents a simple map-matching algorithm that resolves spatial ambiguities by determining the correct roadway centerline on which the vehicle is traveling. The algorithm computes shortest paths between snapped DGPS data points using network topology and turn restrictions. A path is considered viable, and locations for the snapped DGPS data points correct, if similarity exists between values of calculated and recorded vehicle speeds. If a path is not feasible, DGPS points are snapped to alternative roadway centerlines contained within their buffers, shortest paths are recalculated, and speeds are again compared. Examples are presented to illustrate the implementation and effectiveness of the algorithm.

Automatic vehicle location (AVL) systems in conjunction with differential Global Positioning System (DGPS) technology are used to monitor, track, or locate vehicles in real time. These systems track vehicles in two or three dimensions, display their locations in two dimensions, and relate them to data referenced to a linear dimension (*1*). DGPS data points are associated with the nearest roadway by calculating the minimum perpendicular distances between each roadway representation and the DGPS data points. This process is called "snapping."

A map-matching problem occurs when a DGPS data point is snapped to a wrong roadway centerline as a result of a lack of accuracy in the digital cartography, the DGPS measurements, or both. Spatial mismatches result from inadequate DGPS data collection procedures, limits to the basic accuracy of the DGPS unit, limits to the accuracy of the geographic information system (GIS) data source, flawed GIS digital base map, or combinations of these factors. In Figure 1, the measured DGPS data point is incorrectly snapped to Road 2. Depicted by a triangle, the correct snapping location for this DGPS data point is Road 1. Normally, this type of problem occurs at converging and diverging roadways, such as ramps and divided highways, or when roads are in proximity to one another.

As a consequence of the map-matching problem, the calculated cumulative distance traveled by a vehicle along a roadway network is incorrect and, therefore, calculated values for winter maintenance performance measures that depend on cumulative distance are wrong. Examples of some affected performance measures are cycle time per storm and total quantities of salt and sand per storm. Accurate calculation of performance measures for winter operations is imperative because decision makers use them as indicators of how well their service and procedures meet guidelines and satisfy expectations. Thus, the need for correctly calculating winter maintenance performance measures is a major motivation for solving the map-matching problem.

Winter maintenance vehicles collect speed, environmental (e.g., pavement and air temperature), equipment status (e.g., plow up or plow down), and material use data (e.g., salt application rate) along with DGPS coordinate measurements. These data are transmitted to a central dispatch location in real time, as often as every 2 s, and are also stored on board the vehicle for later retrieval, processing, and analysis. The simple map-matching algorithm presented here takes advantage of speed and location information for the collected data points when determining the correct roadway centerline for travel of the vehicle.

LITERATURE REVIEW

The earliest map-matching algorithms, before GPS was developed in the 1970s, followed a semideterministic model (*2*). This model assumes that the vehicle has an initial location on a roadway and a given direction of travel. Conditional tests are applied to determine whether the vehicle is traveling on the known roadway by comparing turns from the vehicle location to a segment of the digital road map. A correction is applied whenever the heading of the vehicle changes (*3*). However, for this technique to work, generally the vehicle is assumed to follow a predetermined road. There is considerable

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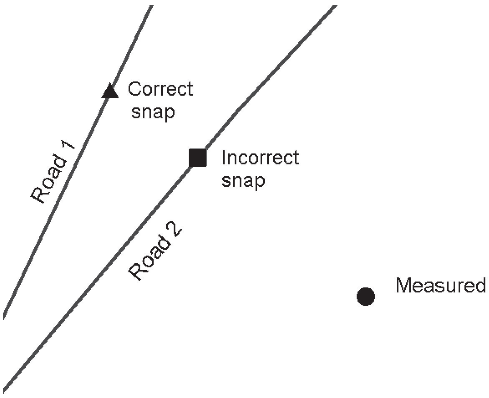

FIGURE 1 Incorrect snapping of measured DGPS data point due to spatial data error.

uncertainty when the vehicle travels off road because there is no longer any way to correct for errors (*4, 5*).

A probabilistic approach, described later, has the advantage of not assuming that the vehicle is always on a roadway. Vehicle heading error is calculated using an elliptical or rectangular confidence region and error models within which the true vehicle location can be determined. If the vehicle position in the region contains one intersection or road segment, a match is made and the coordinates on the road are used in the next position calculation. As a result, the algorithm yields the best-match segment along with the most probable matching point on the segment (*4, 5*).

White et al. discuss solutions to the map-matching problem for personal navigation assistants (*6*). Four different map-matching algorithms were implemented and tested: (*a*) use of minimum distance (point-to-curve), (*b*) comparison of heading information with arc and trajectory, (*c*) use of topology to select roads that are reachable from the current road, and (*d*) construction of piecewise linear curves from different paths, followed by comparison of them to centerline curves using points (curve-to-curve matching). It was concluded that these algorithms worked better when the distance between the GPS point and the closest road was small and that correct matches tend to occur at greater speeds on straight roadways.

Fuzzy logic is an effective way to deal with tasks that involve qualitative terms and concepts, vagueness, and human intervention. Expert knowledge and experiences used by a fuzzy-logic-based map-matching algorithm are represented as a set of rules to determine vehicle location (e.g., if the difference between the orientation of the roadway segment and the heading of the vehicle is small, then resemblance between the vehicle travel path and the candidate route is high) (*4, 7*). Kim and Kim propose an adaptive fuzzy-network-based C-measure algorithm that identifies the roadway on which a vehicle is traveling by comparing C-measures associated with each candidate roadway (*8*). These measures are membership functions that represent the certainty of the existence of a vehicle on a specific roadway. After the roadway is identified, the algorithm determines the vehicle position on the roadway by orthogonal projection. The algorithm requires the distance between the vehicle's GPS coordinates and its projected position on the roadway to be small. Furthermore, the shape of the roadway must be similar to the trajectory of the vehicle.

There has been abundant research on the application of Kalman filters in combination with DGPS and dead-reckoning signals to solve spatial mismatches. This integrated technology improves positioning accuracy by estimating white noise and error in the DGPS and then correcting the vehicle's position (*9–13*). Quddus et al. present a general map-matching algorithm that integrates GPS and dead-reckoning sensor data (position, velocity, and time) through an extended Kalman filter and uses them as input to improve performance of the algorithm (*14*). The physical location of the vehicle on a roadway link is determined empirically from the weighted averages of two state determinations of the vehicle position based on topological information and external sensors.

Particle filtering, based on a stochastic process, is another approach to the map-matching problem. Particle filters are recursive implementations of Monte Carlo–based statistical signal processing (*15, 16*). Gustafsson et al. evaluated in real time the technique of map-matching particle filters used to match a vehicle's horizontal driven path to a digital roadway map (*15*). They concluded that the particle filter converged relatively rapidly after a few iterations of the algorithm. The challenge of this map-matching technique is to find nonlinear relations and non-Gaussian sensor models that provide the most information about the vehicle's position. The authors assert that research is still needed to seek a reliable way to detect divergence and to restart the filter.

According to Lamb, a combination of Kalman filter and Markov model solves the problem of locating a vehicle traveling on a roadway network (*17*). A Kalman filter is used to provide a least-squares optimal estimate of the vehicle's position on a roadway segment, and a Markov model handles topological aspects of the location problem by providing a mechanism for expanding the hypothesized set of road segments, assigning them probabilities, and then removing the least probable segments.

Doherty et al. studied an algorithm that automatically matches GPS data points to roadway segments along a network (*18*). First, the algorithm joins GPS points to create a linear object forming the vehicle's track. Subsequently, it creates a buffer zone around the linear object and then identifies all the roadways that are totally included in the buffer to select the correct one.

Yet another approach uses a rotational variation metric for comparison between the historical vehicle trajectory and the possible candidate paths that lie in the vicinity of the vehicle at any instant in time (*19*). The candidate roadway path that best matches the DGPS vehicle path is the most likely roadway path for the vehicle. The metric quantifies the degree of similarity between two shapes in regard to variation in the angle between corresponding pairs of vectors tangent to the two shapes.

The multiple hypothesis technique described by Pyo et al. determines the correct roadway using a probabilistic approach (*20*). Roadway connectivity, direction, roadway facility information, and differences in vehicle position and heading are used in hypothesis tests against the roadways in a confidence region. Hypotheses having probability below a threshold are eliminated to reduce the number of candidates. A Kalman filter is used to estimate bias in position and heading, thus improving map-matching performance.

Taylor et al. describe an algorithm called road reduction filter (RRF) that uses differential corrections and height aids (*21*). RRF identifies all possible roadway candidates while systematically removing incorrect ones. RRF is improved by using shortest path network analysis and drive restriction information. A shortest path network routine calculates the distance through the roadway network from a vehicle's previous position to each potential present position offered by the algorithm. The drive restriction information routine selects roadways using direction and access information (*22*).

The map-matching procedure presented by Greenfeld consists of two algorithms (*23*). One algorithm assesses similarity between characteristics of the roadway network and the positioning pattern of the vehicle. The second algorithm performs topological analysis and applies a weighting scheme to match each GPS data point to the roadway network. The highest weighted score determines the most likely candidate for a correct match. The author indicates that further research is needed to determine the most accurate position of the vehicle along a roadway segment and to verify the accuracy performance of the algorithms.

The map-matching algorithms described in the literature review apply procedures with various levels of complexity used to resolve spatial ambiguities. As mentioned by Quddus et al., recent map-matching methods are more inclined to employ roadway network topology to identify correct roadways at complex intersections (*14*).

SIMPLE MAP-MATCHING ALGORITHM USING NEIGHBORING POINTS

The simple map-matching algorithm presented here determines the correct roadway centerline for vehicle travel by obtaining feasible shortest paths between snapped DGPS data points. The algorithm selects all roadways within a buffer around a DGPS data point and snaps the point to the closest roadway by determining the minimum perpendicular distance from the data point to each roadway. As shown in Figure 2, Points 1 and 2 are snapped to Ramp 2 because it is the closest roadway contained within the buffers around the points. Subsequently, the shortest path, displayed with a bold arrow, is obtained between the two snapped DGPS data points (S1 and S2) using network topology and turn restrictions. Only paths that follow traffic directions and allowable turns are used. The travel speed between

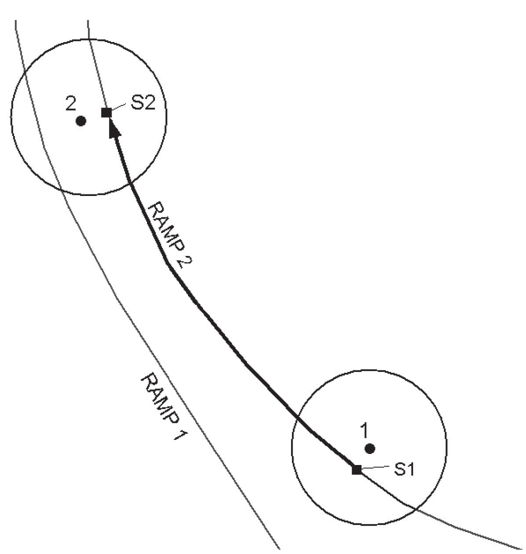

FIGURE 2 Example of snapping process to correct roadway for two DGPS data points using simple map-matching algorithm.

these two snapped DGPS points is determined by the length of the shortest path and the difference in time stamps for the points. The computed speed is compared with the average of the speeds at the data points collected by the vehicle while traveling. If the computed speed is within a range of 20 mph of the average recorded speed, then the obtained shortest path is viable and the snapped locations for Points 1 and 2 are accepted as correct.

The algorithm advances to the next DGPS data point, Point 3, snaps this point to the closest roadway centerline within its buffer, and calculates the shortest path between Point S2 and the newly snapped DGPS Data Point S3. If the path between S2 and S3 is not feasible because the speed comparison yields a large disparity, then the algorithm follows the flowchart illustrated in Figure 3. The algorithm determines whether feasible routes exist between the preceding and subsequent points bounding the DGPS data points of concern. For example, if there is no feasible path between the snapped points for Points 2 and 3, then the algorithm looks ahead by snapping Point 4 to the nearest roadway centerline in its buffer and determines whether the shortest path between snapped Points S3 and S4 is possible. If the tested path is not feasible, the algorithm snaps Point 3 to the next nearest roadway centerline in its buffer, obtaining Point Alt3. The algorithm illustrated in Figure 4 is initiated if an alternative roadway centerline exists in the buffer. This algorithm verifies whether a path is feasible between the alternative snapped location for Point 3 (where $k = 3$) and former and succeeding neighboring snapped Points 2 and 4 (where $k - 1 = 2$ and $k + 1 = 4$). If the shortest paths between these three points are not feasible because the speed comparison failed, the algorithm searches for other roadway centerlines in the buffer around Point 3 that have not been already been used in a feasibility path check. When a new candidate is found, Point 3 is then snapped to it, and the feasibility of shortest paths between snapped Points 2, 3, and 4 ($k - 1$, k, $k + 1$) is checked again. If these paths are feasible, then the spatial ambiguity is resolved, and the algorithm in Figure 4 terminates. If no alternative roadway centerline exists in the buffer for Point 3, the algorithm in Figure 4 stops without resolving the ambiguity using the alternative snapped location for Point 3 and exits back to the simple map-matching algorithm presented in Figure 3. The feasibility of the shortest path between snapped Points 2 and 4 is then tested. If this path is not feasible, the algorithm continues by snapping preceding Points 2, 1, and 0 one at a time to alternative roadways and determining whether feasible paths exist between these newly snapped points and snapped Point 3. If none of the five consecutive points (0 through 4) aid in solving the spatial mismatch between the snapped points for Points 2 and 3, then it is likely that no roadway centerlines in their buffers yield a feasible path, and larger buffers, more consecutive data points, or both need to be used by the algorithm. Once a feasible path is obtained, the intermediate points not used during the map-matching process are snapped to the roadway along that feasible path.

However, if a path is feasible between snapped Points 3 and 4, then, following the flow diagram in Figure 3, alternative roadway centerlines are sought within the buffer for Point 2. The algorithm in Figure 4 checks for feasibility of paths between the newly snapped Point 2 and the previous and subsequent snapped points. If there are no remaining alternative roadways in the buffer for Point 2 or if there is no feasible path between Point Alt2 and the neighboring points, then the simple map-matching algorithm in Figure 3 checks the feasibility of the path between snapped Points 1 and 3. If

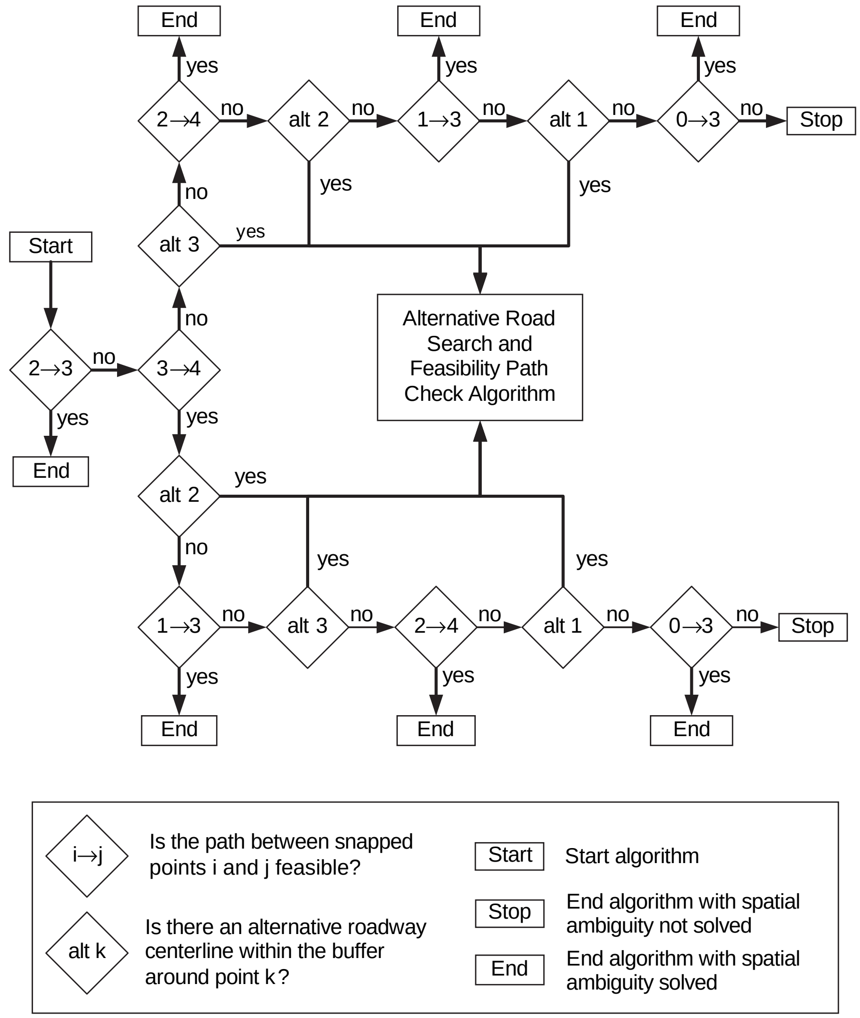

FIGURE 3 Simple map-matching algorithm flowchart.

this path is feasible, Point 2 is snapped to the roadway along that path and the spatial ambiguity is resolved. Otherwise, the algorithm begins repetitions by examining the next nearest roadway in the buffer for Point 3. The combination of both algorithms illustrated in Figures 3 and 4 calculates shortest paths between neighboring data points and alternative snapping locations for data points until a feasible path is obtained or until five consecutive points have been examined.

IMPLEMENTATION OF SIMPLE MAP-MATCHING ALGORITHM

The example illustrated in Figure 5 includes a set of DGPS data points collected every 5 s by a winter maintenance vehicle during the 2002–2003 winter season in Columbia County, Wisconsin. Columbia County's roadway centerline map has a nominal scale of 1:2,400. The spatial mismatch occurring at the diverging roadways in Figure 5 is resolved by implementing the simple map-matching algorithm. In this example, Points 0, 2, 3, and 4 are snapped to the nearest roadway in their buffers, resulting in Points S0, S2, S3, and S4, shown as rectangles. Points S0, S3, and S4 are on the Interstate 39 centerline, and Point S2 is on the ramp centerline. No roadways are contained in the buffer for Point 1, thus this point is not used in determining the feasible path. However, Point 1 is snapped to the correct roadway once the shortest path between the adjacent data points is determined to be feasible.

The shortest path between Points S0 and S2 is computed using network topology and allowable turns. Consequently, the speed comparison shown in Table 1 is performed to determine whether this path is feasible. In this case the obtained path is feasible because the difference between the average calculated and recorded speeds (26.8 and 31.5 mph, respectively) is within tolerance (20 mph). Therefore, the current snapped positions for Points 0 and 2 are initially assumed to be correct. The algorithm continues by finding the shortest path between the next pair of snapped points, S2 and S3. This path is not feasible because if the vehicle were at S2, it would have to exit down the ramp and travel approximately 5,125.9 ft in 5 s at an average speed of 699 mph to reach S3. Thus, either S2 or S3 or both were snapped to an incorrect roadway centerline. The algorithm now

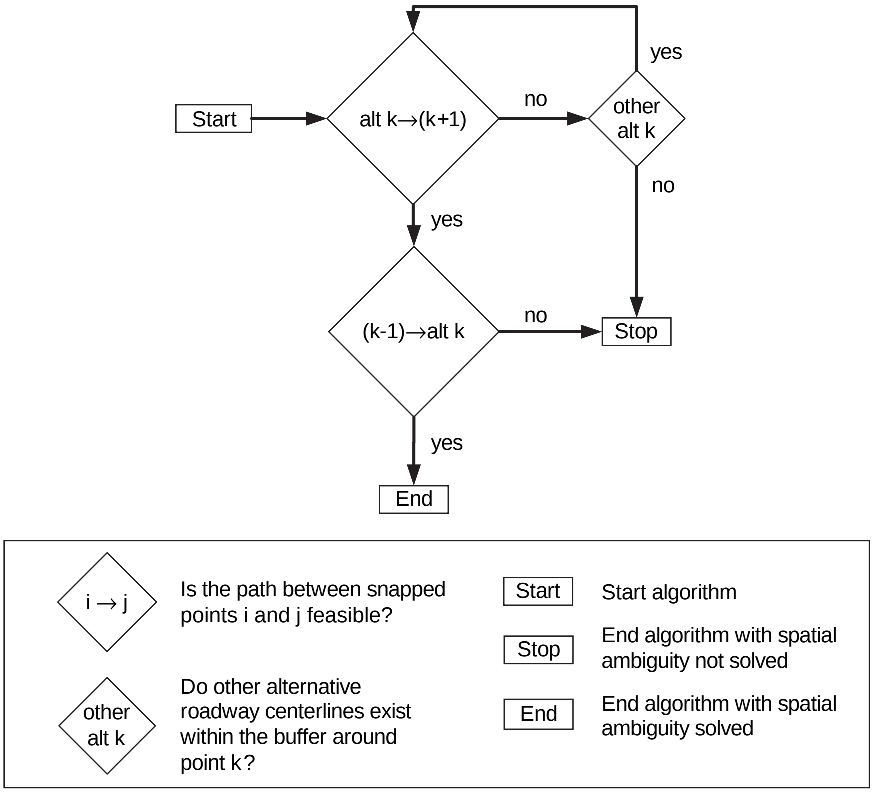

FIGURE 4 Algorithm for alternative roadway centerline search and feasibility path check.

looks ahead to S3 and S4 and determines that the difference between calculated (29 mph) and average recorded speeds (35 mph) is within tolerance. Therefore, an alternative roadway centerline is sought within the buffer around Point 2. Interstate 39 is found to be the next nearest roadway, resulting in Point Alt2, shown as a triangle in Figure 5. Feasibility is now checked for paths between the preceding

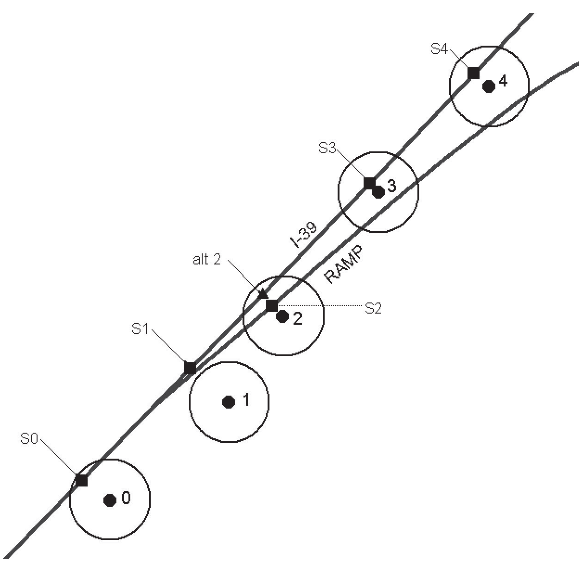

FIGURE 5 Example of simple map-matching algorithm at diverging roadways.

S0 and Alt2, and between Alt2 and its successor, S3. As indicated in Table 1, both computed shortest paths are feasible. The calculated speeds along these paths are within 20 mph of their respective average recorded speeds for the vehicle. Therefore, the spatial ambiguity at the diverging roadway is resolved, and the correct roadway for Point 2 is Interstate 39. Point S1 is then obtained by snapping Point 1 to the Interstate 39 centerline.

The algorithm resolves spatial ambiguities at converging roads, divided highways, and intersections in a similar manner. Figure 6 presents results of the algorithm for DGPS data points collected at an interchange in Columbia County, Wisconsin. Points, shown as circles, are the original measured DGPS data points. The incorrect snapping locations for these points are depicted as asterisks, and the correct snapping locations, determined after the algorithm has been executed, are illustrated by rectangles. The lines with bold arrows represent the shortest feasible paths between the correct snapped

TABLE 1 Speed Comparison for Determining Feasibility Shortest Paths

Data Points	Shortest Path Distance (ft)	Calculated Speed (mph)	Average Recorded Speed (mph)	Feasible Path?
S0 → S2	392.6	26.8	31.5	Yes
S2 → S3	5125.9	699	33	No
S3 → S4	213	29	35	Yes
S0 → alt2	392.8	26.8	31.5	Yes
alt2 → S3	215.7	29.4	33	Yes

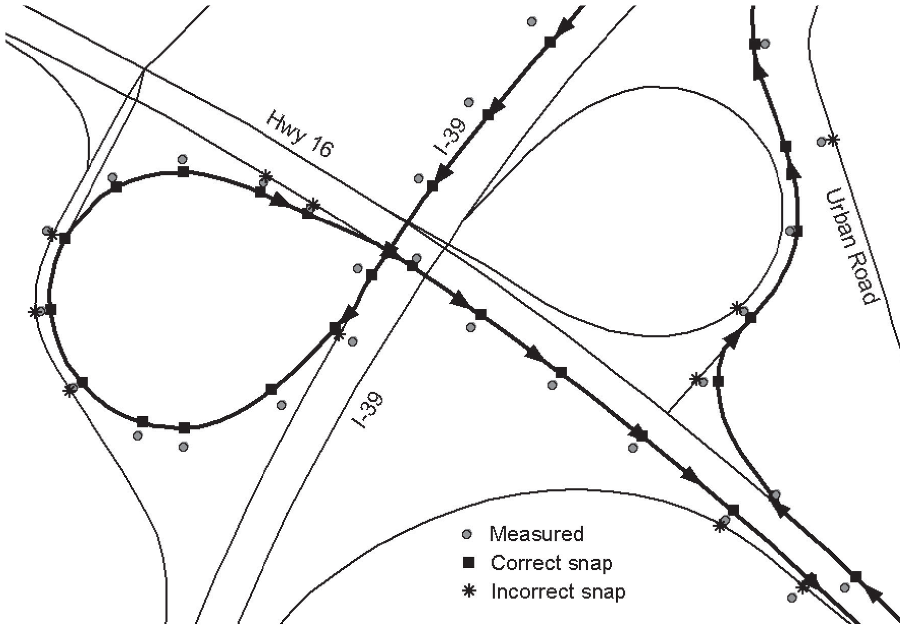

FIGURE 6 Results of simple map-matching algorithm at interchange in Columbia County, Wisconsin.

points. Eleven of 28 DGPS data points collected by the winter maintenance vehicle at the interchange shown in this figure are snapped to incorrect roadways. If the complete data set (i.e., 600 data points) collected in Columbia County is examined, 31 data points are incorrectly snapped. All of these spatial mismatches are resolved after implementing the simple map-matching algorithm. However, spatial ambiguities due to the vehicle traveling against allowable directions of travel or off the represented roadway are not resolved by the algorithm.

The appropriate buffer size employed by the simple map-matching algorithm depends on the quality and geometry of the spatial data (e.g., DGPS data points and digital roadway centerline map). The curve with diamonds, shown in Figure 7, illustrates the average percentage of DGPS data points contained in different buffer sizes

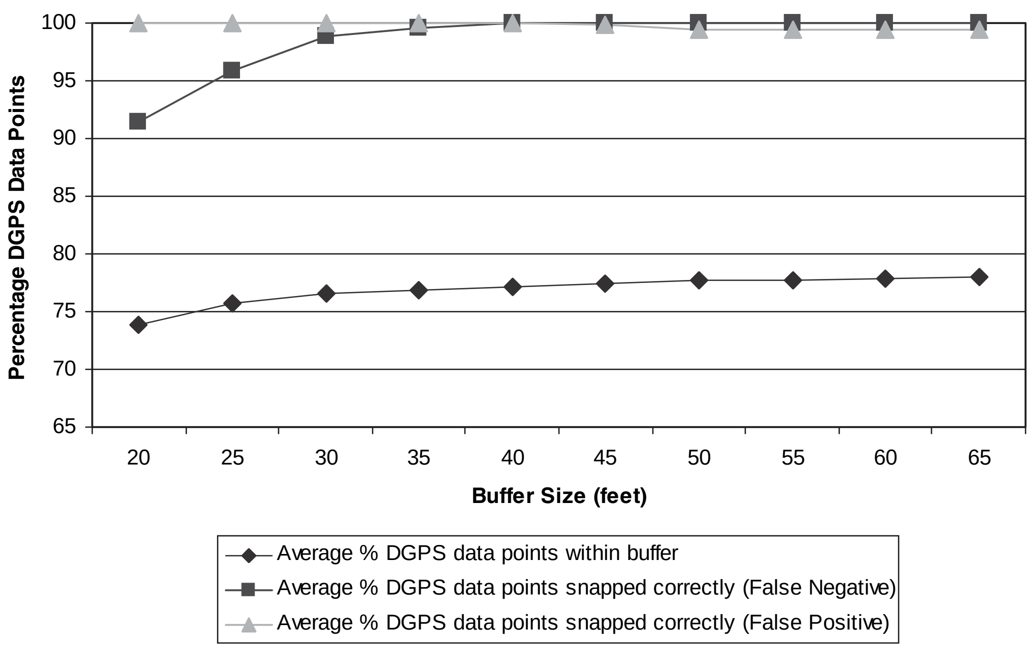

FIGURE 7 Average percentage of DGPS data points contained in different buffer sizes and average percentage of DGPS data points snapped correctly for different buffer sizes with data sets with 10 vehicle paths in Columbia County, Wisconsin.

computed using data sets with 10 vehicle paths. A buffer size of 35 ft around roadway centerlines contains, on average, more than 75% of the total Columbia County DGPS data points. This buffer size is sufficient to resolve 98% of the spatial ambiguities detected by the algorithm. The curve with rectangles indicates the percentage of DGPS data points snapped correctly when false negatives are included in the statistic. “False negatives” are points that failed to snap to any centerline when they should have snapped to one. These occur for buffer sizes less than 35 ft. The curve with triangles indicates the percentage of DGPS data points snapped correctly when false positives are included in the statistic. “False positives” are points that snapped to some centerline when they should not have snapped to any centerline. Small numbers of them occur when the buffer size is greater than 45 ft. These curves indicate that buffer sizes between 35 and 45 ft would correctly snap most of the DGPS data points.

The algorithm was also tested against data from Portage County, Wisconsin. The DGPS data collected in this county by winter maintenance vehicles during the 2001–2002 winter season have a temporal resolution of 10 s. The roadway centerline map for Portage County has a nominal scale of 1:24,000. Figure 8 illustrates that a buffer size of 45 ft around the roadway centerline map contains approximately 95% of the average total DGPS data points collected. This average was computed using data sets with 10 different vehicle paths. The percentage of DGPS data points contained in buffer sizes greater than 45 ft remains relatively constant. Figure 8 also shows the false negative and false positive curves. The false negative curve illustrates that as buffer size diminishes (<45 ft), more DGPS points are not snapped to any roadway centerline. The false positive curve, however, indicates that as buffer size increases (>50 ft), more DGPS points are snapped to a roadway centerline when none exists. The intersection of these curves shows that a buffer size between 45 and 50 ft would snap mostly all DGPS data points to the correct roadway centerline. However, the algorithm solved the spatial ambiguities for 97.7% of all the DGPS data points collected in this county independently from the buffer size.

Figure 9 presents an example in which the map-matching algorithm did not solve the map-matching problem correctly between Data Points 2 and 3. The roadway centerlines shown in this example are bidirectional; therefore, a feasible path, shown with a bold arrow, was obtained from Point 2 to Point 3 by traveling back north on Hwy 51 and then south on Hwy 16. The difference between the travel speed computed and the average speeds of the data points was within the 20 mph range. The snapped location for Points 0, 1, and 2 onto Hwy 51 are accepted as correct.

FUTURE RESEARCH

The simple map-matching algorithm solves spatial mismatches encountered in data from Columbia and Portage Counties, given their respective parameters (e.g., buffer size). Additional testing of the algorithm needs to be performed on other spatial data, with different temporal resolutions and accuracies, which may require different buffer sizes. In addition, a sensitivity analysis of other variables is essential to verify the performance of the simple map-matching algorithm. For example, the feasibility of a shortest path between snapped points is sensitive to the tolerance between computed and recorded speeds. Thus, further study is necessary to avoid incorrect snapping of DGPS data points to bidirectional roadway centerlines as presented in the example in Figure 9.

Future research is also required on the appropriate number of consecutive DGPS data points to be used by the algorithm. By increasing this number, the algorithm resolves spatial ambiguities that arise when alternative roadway centerlines are equally viable. It is expected that the appropriate number of consecutive DGPS data points will depend on the temporal resolution and positional accuracy of the data under consideration.

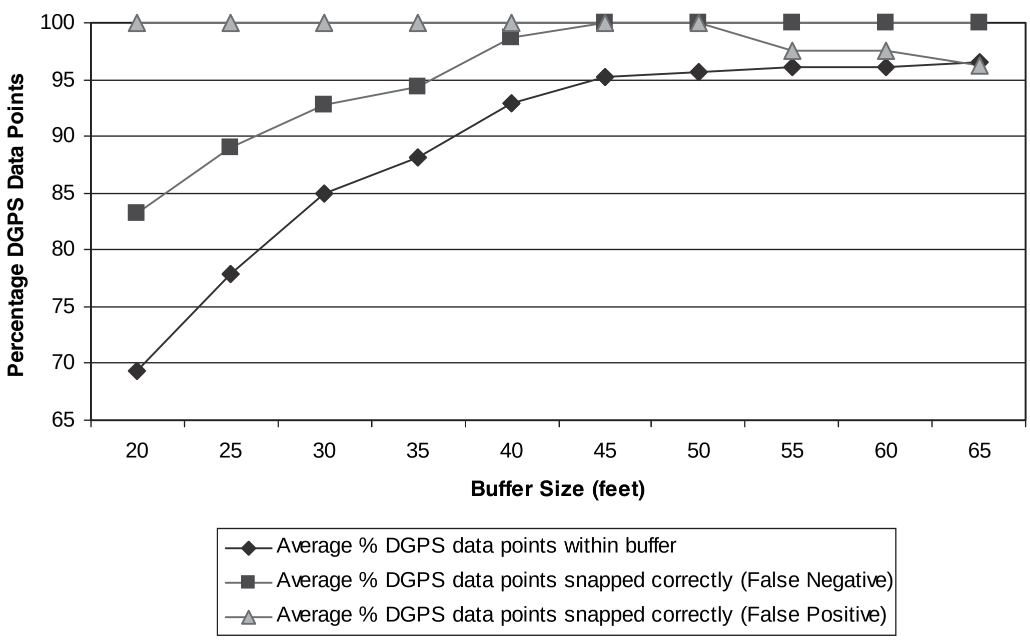

FIGURE 8 Average percentage of DGPS data points contained in different buffer sizes and average percentage of DGPS data points snapped correctly for different buffer sizes computed with data sets with 12 vehicle paths in Portage County, Wisconsin.

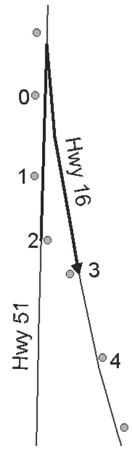

FIGURE 9 Example of incorrect snapping of DGPS data points after application of map-matching algorithm.

CONCLUSIONS

AVL technology (i.e., DGPS receivers) and various additional sensors are used by transportation agencies to collect positional, environmental, equipment status, and material use data for winter maintenance vehicles in real time. DGPS data points are associated with roadways by snapping to the nearest centerline in a GIS environment. Spatial ambiguities arise during this association because of errors in DGPS measurements and digital cartography. These can result in DGPS data points being snapped to incorrect roadway centerlines. Such mismatches affect calculation of cumulative distance traveled by the vehicles along a roadway network and, thus, propagate to the computation of winter maintenance performance measures. Decision makers use these performance measures to evaluate and improve winter maintenance operations.

The simple map-matching algorithm presented in this paper resolves many of these spatial ambiguities by examining the feasibility of paths between pairs of snapped data points. A viable path is the shortest-distance path between two snapped points that a vehicle can travel while following network topology and turn restrictions at a speed comparable to its average recorded speed. If a given shortest path is not feasible, then DGPS data points are related to other roadway centerlines in their buffers and new shortest paths are calculated; or adjacent DGPS data points are used to determine feasible paths.

An example showing step-by-step operation of the simple map-matching algorithm at diverging roadways in Columbia County, Wisconsin, was presented. The success of this algorithm in solving the map-matching problem depends on the size of the buffer used around DGPS data points to select the roadway centerlines. Because the quality and geometry of spatial data vary for each implementation, the algorithm employs different buffer sizes for each case. An analysis indicated that a buffer size ranging between 35 and 45 ft and between 45 and 50 ft for Columbia and Portage Counties, respectively, would correctly snap approximately 98% of the DGPS data points. An example is presented to show the incorrect performance of the map-matching algorithm when bidirectional roadways are present.

Sensitivity analyses for a number of variables are needed to verify the performance of the simple map-matching algorithm. Some of these variables are buffer size, temporal resolution, spatial data accuracy, speed tolerance, and number of consecutive DGPS data points. Further research should include addressing cases that involve violation of network topology (e.g., vehicles traveling against allowed directions of travel), topological disconnects (e.g., roadway centerlines not connected at county boundaries), and DGPS data points off the represented roadway network.

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