THE APPLICATION OF MAP MATCHING METHOD IN GPS/INS INTEGRATED NAVIGATION SYSTEM

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ABSTRACT

Map matching method plays an important role in vehicle location and navigation systems. It employs the information in a digital map to compensate the positioning error. This paper presents a fuzzy-logic-based probabilistic map-matching algorithm used in GPS/INS integrated navigation systems, in which the reliability degree of map matching resolution is given explicitly as the decision basis in selecting matching road segment by utilizing the fuzzy comprehensive judgement. The results of experimental simulations have shown that the system performance gained significant enhancement by introducing this algorithm.

KEY WORDS

Map Matching, Fuzzy Logic, Global positioning system, Dead-reckoning, integrated navigation system.

INTRODUCTION

Map matching method plays an important role in vehicle location and navigation systems. It employs the information in a digital map to compensate the positioning error. A good map-matching algorithm can significantly enhance the location accuracy of a vehicle on road networks. The purpose of this paper is to introduce the reader a fuzzy-logical-based probabilistic map-matching algorithm used in GPS/INS integrated navigation systems. The basic idea of this algorithm is to get a proper matching result by integrating the position information provided by GPS and dead-reckoning positioning module through a fussy-logic-based inference algorithm. Global Positioning System and Inertial Navigation technologies are the two most widely used positioning methods in land-vehicle navigation systems. The GPS is a satellite-based radio navigation system, which provides a practical and affordable means of determining position, velocity and time around the global. In order to compute its location in three-dimension space, a GPS receiver must be able to lock onto signals from at least four different satellites. For this reason, GPS position fix may be unavailable in urban areas near tall buildings or heavily foliated environments. Inertial Navigation, which can also be refereed to as Dead reckoning, is a typical stand-alone technology, whose reliability is free of the affection of environmental situation. When GPS position fix become unavailable, using dead-reckoning sensors alone can continuously position a vehicle for a short time period. But due to the affection of accumulated error, the error in the dead-reckoning position estimation grows without bound after long periods of time. Thus, Dead reckoning module can not be used alone without an occasional calibration provided by other position measurement such as GPS. It is clear that neither the GPS nor Dead reckoning module alone can provide completely vehicle position information. Therefore, multisensor integration is required in land-vehicle navigation systems. Basically, the errors that appear in GPS position fixes and in the outputs of dead-reckoning sensors are complementary in nature: dead-reckoning sensors can smooth out the short-term GPS errors, and GPS fixes can be used to calibrate the dead-reckoning sensor drift over long periods. Proper fusion of the GPS fixes with the dead-reckoning sensor data can take advantages of these complementary errors, and produce positioning performance which is better than that could be obtained with either type of data alone. To some extent, the map-matching algorithm presented in this paper can be described as a calibration of position result based on the fusion of GPS position fix and dead-reckoning sensor data. In the following section, the probabilistic method for defining positioning error region in GPS/INS integrated systems is introduced firstly. After this, the discussion will be focused on the fuzzy-logic-based road selection algorithm. At the end of this paper, we will present the realization scheme of the map-matching algorithm, and the simulation results that can examine the effectivity of this algorithm will be given.

ERROR REGION DEFINING METHOD FOR GPS/INS INTEGRATED SYSTEMS

The first step of map-matching process is to define an error region that may contains a vehicle's actual position based on the position estimation provided by positioning module. This error region is then used to extract the candidate matching roads from digital map databases. From statistical estimation theory, we know that the variance and covariance information of the input and output signals can be used to define error eclipses in a stochastic system. Suppose that the variance-covariance matrix of a position system can be modeled as

$$P = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{yx} & \sigma_y^2 \end{bmatrix} \qquad (1)$$

where σ_x and σ_y are the north and east standard deviations of the positioning sensor measurement errors, σ_x^2 and σ_y^2 are the variances, σ_{xy} and σ_{yx} are the covariances. Then the positioning error ellipse can be derived as

$$a = \hat{\sigma}_0 \sqrt{1/2(\sigma_x^2 + \sigma_y^2 + \sqrt{(\sigma_x^2 - \sigma_y^2)^2 + 4\sigma_{xy}^2})} \qquad (2)$$

$$b = \hat{\sigma}_0 \sqrt{1/2(\sigma_x^2 + \sigma_y^2 - \sqrt{(\sigma_x^2 - \sigma_y^2)^2 + 4\sigma_{xy}^2})} \qquad (3)$$

$$\Phi = \frac{\pi}{2} - \frac{1}{2}\arctan(\frac{2\sigma_{xy}}{\sigma_x^2 - \sigma_y^2}) \qquad (4)$$

where a is the length of the semi-major axis of ellipse, b is the length of the semi-minor axis of the ellipse, Φ is the orientation of the semi-major axis of the ellipse relative to North, and $\hat{\sigma}_0$ is the posteriori variance of unit weight, also known as the expansion factor. The center of the ellipse is the current vehicle location estimation (Figure 1.). The dimensions of the ellipse can be scaled to represent various confidence levels. Assuming that the distribution of measurement errors is a standard normal distribution, the standard ellipse ($\hat{\sigma}_0 = 1$) corresponds to a 39% confidence region, and an expansion factor $\hat{\sigma}_0$ of 2.15 can be used to obtain the 95% confident level.

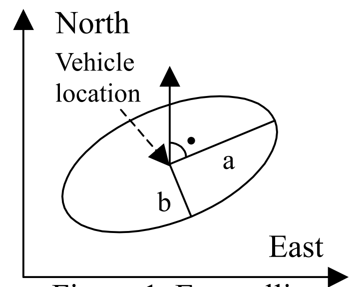

Figure 1. Error ellipse

As an absolute positioning system, GPS is free from error accumulation. For this reason, GPS position fix is suitable to be used to define error regions whenever it is available. For a GPS receiver that uses pseudorange measurement principle, its 3D position can be determined by the following equations:

$$\rho_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} + c(t_s - \delta t_i) \qquad (5)$$

where (x, y, z) is the unknown coordinate of the receiver, (x_i, y_i, z_i) is the known coordinate of a satellite, ρ_i is the measured pseudorange, and δt is the clock offset between receiver time and GPS time. If the receiver can locking on the signals from four or more different satellites, it can achieving enough equations to compute the unknown 3D coordinate. After linearization, the above equations can be written in a vector-matrix form as

$$Y = AX \qquad (6)$$

where Y is the known vector of measurements and X is the unknown vector. Linear algebra can be used to solve for the unknown vector X. A by-product of the computation is the cofactor matrix

$$P = (A^T A)^{-1} = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{xz} & \sigma_{xt_s} \\ \sigma_{yx} & \sigma_y^2 & \sigma_{yz} & \sigma_{yt_s} \\ \sigma_{zx} & \sigma_{zy} & \sigma_z^2 & \sigma_{zt_s} \\ \sigma_{t_s x} & \sigma_{t_s y} & \sigma_{t_s z} & \sigma_{t_s}^2 \end{bmatrix} \qquad (7)$$

For a 3D GPS solution, the cofactor matrix is a 4×4 matrix where three components are contributed by the receiver position (x, y, z) and one component by the receiver clock. Thus when GPS fix is available, the variances and covariances that used to define the map-matching error ellipse can be obtained directly from this cofactor matrix. Usually these parameters can be easily acquired from the outputs of many kinds of GPS receiver. In the case of GPS position failure, dead-reckoning sensor data must be used to continuously define the error ellipse based on the error model of INS module. Note that it is often appropriate to multiply the derived error region by an expansion factor in order to represent the affection of uncertain errors.

FUZZY-LOGICAL-BASED MAP-MATCHING ROAD SELECTION METHOD

Once the error region has been defined, candidate matching road segments can be extract from the digital map database. As discussed in preceding sections, the vehicle trajectory reported by a positioning module is often distorted or different from the actual route due to positioning errors. This often causes some difficulty in map-matching process. For an instance, when the vehicle is traveling in a city downtown area, there may be many road segments whose patterns matching the reported trajectory well in some aspects while different in other aspects. It is difficulty to distinguish precisely on which particular road the vehicle is traveling. Rather, the system may conclude that the vehicle is "more likely" to be on certain streets, and "less likely" to be on some certain other streets. In order to get an accurate matching position, this ambiguity needs to be solved. Fuzzy logical method has been demonstrated as an effective way to deal with such tasks. In this paper, fuzzy logic method is used to assign truth values for each of the candidate road segments based on positioning sensor signals, then road selection is made by applying comprehensive judgements. In order to assign truth values for each of the candidate road segments, the following rules are introduced firstly:

> Rule 1: If the difference between the current vehicle heading angel and the direction of the road segment (denoted by Δheading) is small, then the road segment's truth value is high.
> Rule 2: If the distance from current vehicle position estimation and the candidate road segment is small, then the road segment's truth value is high.
> Rule 3: If the difference between the vehicle trajectory reported by positioning sensors and the road segment's shape pattern is small, then the road segment's truth value is high.

The membership functions of "small" and "large" for Δheading can be defined as

$$\mu_{hh}(x) = \begin{cases} 1-|x|/60 & |x| \le 60 \\ 0 & |x| > 60 \end{cases} \quad (8) \qquad \mu_{hc}(x) = \begin{cases} |x|/60 & |x| \le 60 \\ 1 & |x| > 60 \end{cases} \quad (9)$$

where x is the difference between the current vehicle heading angel and the direction of the candidate road segment, $\mu_{hh}(x)$ is the truth value for "Δheading is small", and $\mu_{hc}(x)$ is the truth value for "Δheading is large". The membership functions of "small" and "large" for the distance from the vehicle position estimation and the road segment is defined as

$$\mu_{dh}(y) = \begin{cases} 1-y/20 & y \le 20 \\ 0 & y > 20 \end{cases} \quad (10) \qquad \mu_{dc}(y) = \begin{cases} y/20 & y \le 20 \\ 1 & y > 20 \end{cases} \quad (11)$$

where y is the Euclid distance between the current vehicle position estimation and its projection point in the road segment, $\mu_{dh}(y)$ and $\mu_{dc}(y)$ are the truth values for "distance is small" and "large". To define the membership function for Rule 3, dead reckoning estimation is used to generate the current vehicle moving trajectory because of its continuity and high short-time accuracy, from which the current vehicle position and heading angel can be determined by following equations

$$x_n = x_{n-1} + d_{n-1,n} cos\theta_{n-1} \quad (12)$$
$$y_n = y_{n-1} + d_{n-1,n} sin\theta_{n-1} \quad (13)$$
$$\theta_n = \theta_{n-1} + \omega_{n-1,n} \quad (14)$$

where (x_n,y_n) and (x_{n-1},y_{n-1}) are the coordinates of the vehicle positions at time t_n and t_{n-1}, θ_n and θ_{n-1} are the vehicle heading angel at time t_n and time t_{n-1}, $d_{n-1,n}$ is the distance traveled between time t_{n-1} and time t_n, $\omega_{n-1,n}$ is the angular velocity between time t_{n-1} and time t_n. Assumed the projection of the current vehicle position estimation in the candidate road segment as the vehicle position at time t_n in the above equations, and the direction of the road segment as the heading angel θ_n, we can work out a group of the assumed vehicle positions at previous time t_{n-1}, t_{n-2}, etc, given the data provided by dead-reckoning sensors. Then the resemblance between the short-time dead-reckoning trajectory and the shape pattern of the candidate road segment can be measured by the average Euclid distance (denoted by Δd) defined as

$$\Delta d = \sum_{i=1}^{k} \sqrt{(x_{n-i} - x'_{n-i})^2 + (y_{n-i} - y'_{n-i})^2} \,/\, k \quad (15)$$

where (x_{n-i}, y_{n-i}) and (x'_{n-I}, y'_{n-i}) is the assumed vehicle position at time t_{n-i} and its projection in the candidate road segment, k is the number of assumed positions. It is clearly that the smaller the average Euclid distance is, the more likely it is that the vehicle trajectory and the shape pattern of the candidate road segment are similar. Therefore, the membership function of "small" and "large" for "the difference between the vehicle trajectory and the shape pattern of the road segment" can be defined as follows

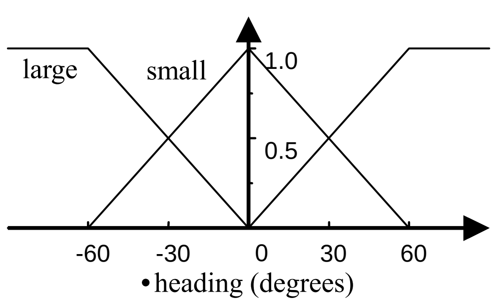

Figure 2. Membership function for Rule 1

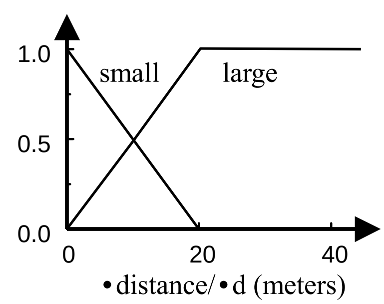

Figure 3. Membership functions for Rule2/Rule 3

$$\mu_{\Delta dh}(z) = \begin{cases} 1 - z/20 & y \le 20 \\ 0 & y > 20 \end{cases} \quad (16) \qquad \mu_{\Delta dc}(z) = \begin{cases} z/20 & y \le 20 \\ 1 & y > 20 \end{cases} \quad (17)$$

where z is the average Euclid distance defined above, $\mu_{\Delta dh}(z)$ and $\mu_{\Delta dc}(z)$ are the truth values of "small" and "large" for the resemblance between the vehicle trajectory and the shape pattern of the candidate road segment. The membership functions defined above are showed in Figure 2 and figure3. Base on these membership functions, we can assign a truth value from 0 to 1 for each of the candidate road segments by using following equations

$$Q = P \circ R = [p_1 \quad p_2 \quad p_3] \circ [R_1^T \quad R_2^T \quad R_3^T]^T \quad (18)$$

where $R_1 = [\mu_{hh}(x), \mu_{hc}(x)]$, $R_2 = [\mu_{dh}(y), \mu_{dc}(y)]$, and $R_3 = [\mu_{\Delta dh}(z), \mu_{\Delta dc}(z)]$, which are the fuzzy factor matrixes based on Rule 1, Rule 2, and Rule 3, P is the weight assigned matrix, and the sum of the three weight factors p_1, p_2 and p_3 is 1, and Q is the fuzzy truth value vector, the two factors of which are the truth value of "high" and "low" for "the degree of the resemblance between current vehicle trajectory and the candidate road segment is". Besides the degree of resemblance between the road pattern and the vehicle trajectory, the connectivity between the candidate road and the previously determined matching road must be considered. Therefore, a combined evaluation matrix $[Q, Q']$ and weight assigned vector $P' = [p_1' \quad p_2' \quad p_3' \quad p_4']$ are used to determine the fuzzy truth value finally given to a candidate road segment. Here Q is the fuzzy truth value vector assigned to the candidate road segment, Q′ is the connectivity vector, which is the truth value vector of the previously matching road segment when it is connected with the candidate road segment, otherwise it is zero. The sum of the four factors in P′ is 1. After that, we can calculate the truth value of the candidate road segment as

$$\mu = P' \circ [Q \quad Q']^T \quad (19)$$

where μ is the truth value of the candidate road's reliability degree, which gives a explicit decision basis in selecting matching road segment.

THE REALIZATION OF THE MAP-MATCHING ALGORITHM AND SIMULATION RESULTS

The flowchart of the fuzzy-logic-based map-matching algorithm is showed in Figure 4.

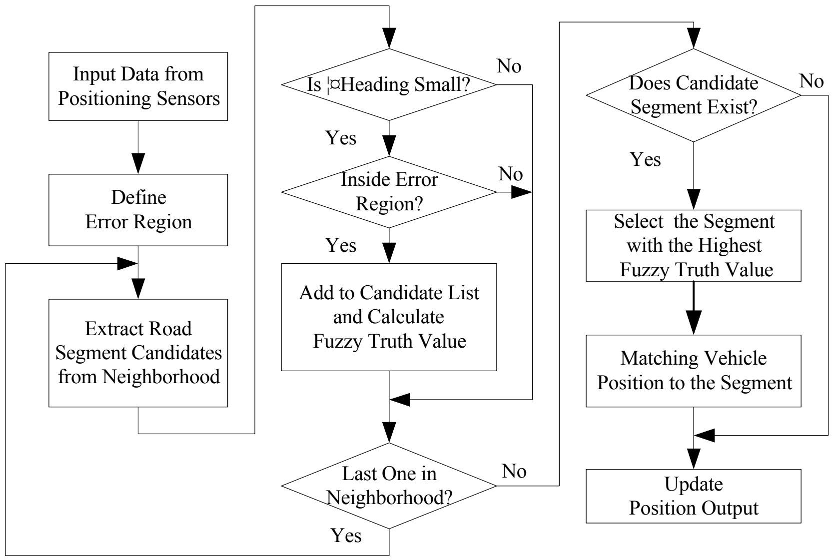

Figure 4. flowchart of the fuzzy-logic-based map-matching algorithm

Since ellipses are inconvenient for extracting candidate road segments, rectangle error regions are used in here. Then Rule 1 is introduced firstly to delete unreliable candidate road segments. After that, each of the remaining segments is evaluated and given a fuzzy truth value, and the road segment with the highest true value is chosen as the matching segment. A reliability threshold is kept in the algorithm, and the position matching process is made only when the highest truth value passes this threshold. In addition, if the highest truth value reaches a high level, such as 0.9 for a example, then not only the coordinates of the road segment are used to calibrate the vehicle position, but also the direction of which is used to calibrate the vehicle heading angel reported from dead-reckoning sensors.

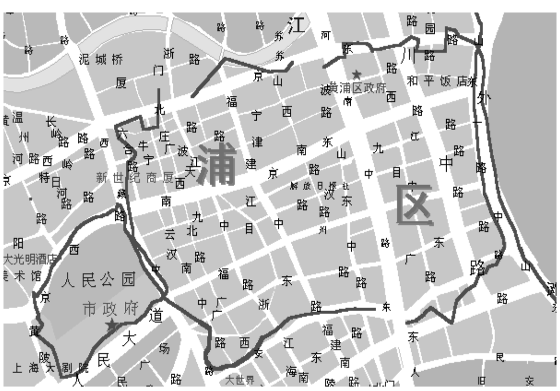

Figure 5. Vehicle trajectory measured by GPS

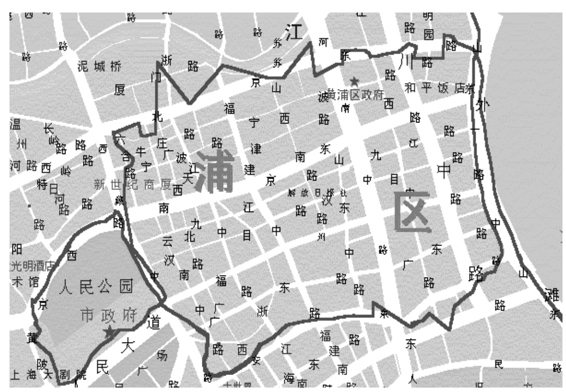

Figure 6. Vehicle trajectory measured by GPS/INS

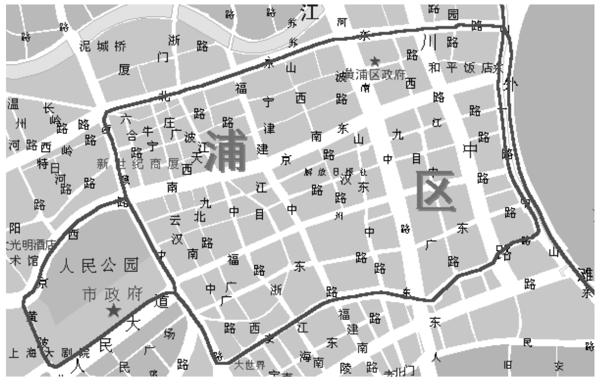

Figure 7 Vehicle trajectory calibrated by fuzzy-logic-based map-matching

To examine the effectivity of this fuzzy-logic-based map-matching method, we have used it to process some real-world positioning data. Figure 5 shows the GPS measured trajectory of a vehicle that moved in Shanghai's central metropolis areas. The trajectory contains many drift errors and has some broken segments due to the blocking of satellite signals caused by high buildings and other environmental factors. Figure 6 shows the estimated trajectory of the same vehicle reported by GPS/INS integrated system, from which we can see that all the broken segments has been complemented by dead-reckoning trajectory. But it is obviously that the bad dead-reckoning original vehicle position and heading angel provided by GPS have caused severely deterioration in the system performance. Figure 7 shows the trajectory that has been calibrated by introducing the fuzzy-logic-based map-matching algorithm. Here the weight assigned vector P is defined as [1/3, 1/3, 1/3], P′ is defined as [0.6, 0, 0.4, 0], the reliability threshold is 0.5. The position calibration is made by replacing the location estimation provided by positioning sensors with its nearest projection point in the matching road segment. The dead-reckoning heading angel calibration is made by using the direction of matching road segment when its fuzzy truth value is higher than 0.8. From this calibrated trajectory we can see that, almost all of the vehicle locations have been matched to the proper road segments, and the positioning performance has gained great enhancement.

CONCLUSION

From the above discussions we can get the following conclusions:

1. Map-matching method is an effective way to improve the positioning performance of vehicle location and navigation systems.
2. By introducing fuzzy logic method, the ambiguity in the matching road selection can be solved.
3. Simulation results have shown that, the utilization of the fuzzy-logic-based map-matching algorithm presented in this paper can bring significant accuracy amelioration for GPS/INS integrated positioning module.

The other important thing is that, fuzzy-logic-based map-matching method is relatively simple to realize, and it only burdens a small task on the on-vehicle navigation computer. Now this method has already been utilized in a certain type of autonomous vehicle location and navigation system.

REFERENCE

1. YiLin Zhao, Vehicle location and navigation systems, Artech House, Boston, 1996, pp. 83-103.
2. W. C. Collier, “In-vehicle route guidance systems using map matched dead-reckoning”, Proc. IEEE Position, Location and Navigation symp., 1990, pp. 359-363.
3. G. J. Klir and B. yuan, Fuzzy Sets and fuzzy Logic: Theory and Applications, pretence Hall, Upper saddle River, NJ, 1995.
4. L. J. Huang, W. W. Kao, H. Oshizawa, and M. Tomizuka, “A Fuzzy Logic Based Map-Matching Algorithm for Autonomous Navigation Systems”, Paper No.16, IEEE Roundtable Discussion on Fuzzy and Neural Systems, and Vehicle Applications, Nov. 1991.