

# RFID Application for Vehicle Fusion Positioning in Completely GPS-denied Environments

Xiang Song, Xu Li, Weigong Zhang, and Wencheng Tang

**Abstract**—To realize accurate and reliable positioning in completely GPS-denied environments is the main challenge for land vehicles. A two-level extended Kalman filter (EKF)-based vehicle positioning strategy is proposed, which can fuse the data obtained from the radio frequency identification (RFID) and the in-vehicle sensors. First, the RFID-based preliminary positioning algorithm is developed. The received signal strength is used as an indicator to calculate the ranges between the RFID tags and reader, and then the vehicle's location is preliminary calculated by using the first level EKF. Further, to improve the positioning performance, the improved vehicle motion model is established, and the second level EKF algorithm is designed to fuse the preliminary positioning results and the in-vehicle sensors information. Finally, the proposed strategy is evaluated through experiments. The results validate the feasibility and effectiveness of the proposed strategy.

**Index Terms**—RFID, fusion positioning, EKF, in-vehicle sensors

## I. INTRODUCTION

FOR vehicle positioning, global positioning system (GPS) is the most widespread used technology [1],[2]. However, GPS may suffer from signal interruption or multipath [3] in GPS-denied environments which may decrease the positioning accuracy and reliability. To overcome the signal blockage of GPS, one common solution is that GPS is integrated with an inertial navigation system (INS) [4] or dead reckoning (DR) [5]. Owing to the measurement biases and integration processes, the INS and DR will accumulate large errors over time. These large errors may cause the rapid performance degradation during GPS outages. Other in-vehicle sensors such as vehicle motion sensors [6] can be used to compensate for the errors. However, the compensation effect is limited when GPS is in a long-time failure. The main reason is that the lack of the position

observation to correct the errors.

As an alternative, there has been rapid development of wireless location technologies [7], [8], [9] in recent years. Among them, Radio Frequency Identification (RFID) has attracted widely attention and become a possible solution to obtain object's location information in indoor environment [10], [11].

RFID can provide the location information in non-GPS environments. However, only the RFID cannot achieve high positioning performance for outdoor vehicle application due to the severe nonlinearities in vehicle operation process, i.e., both the accuracy and output frequency are not enough high to meet the requirement for many location-based applications. In addition, RFID can only provide the position information, but they cannot provide the speed or attitude information which is also important to the location-related vehicle services.

DR is a widely used vehicle positioning technology that uses the driving direction and speed to reckon the position of vehicle. DR has the advantage that it is totally self-contained. Consequently, it is always capable of providing the vehicle with an estimate of its position. However, this method suffers serious accumulative errors. These large errors are strongly time correlated and can cause the rapid performance degradation due to the lack of position observation.

To overcome the disadvantages and combine the advantages of RFID and DR method to achieve more accurate and reliable positioning performance, the multi-sensor fusion method [12], [13] provides us a viable solution. Due to the complementary natures of these two types of sensors, the RFID can be fused with several in-vehicle DR sensors to realize positioning in completely GPS-denied areas. In other words, RFID can provide the position observation to correct the accumulative integration errors of DR, and DR can provide speed and attitude information of vehicle to improve the positioning accuracy and output frequency of RFID. However, to the author's best knowledge, there has been little relevant research on the topic of fusion positioning specialized for vehicle by using RFID and in-vehicle sensors.

## II. PROBLEM DESCRIPTION AND RESEARCH METHODOLOGY

This paper aims to propose a fusion strategy for vehicle positioning based on RFID and in-vehicle sensors in completely GPS-denied environments. This strategy adopts a two-step approach, namely, the preliminary positioning based on the RFID and then the further fusion positioning.

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To obtain higher performance, the algorithms for both preliminary and fusion positioning are developed. The proposed fusion strategy is shown as Figure 1.

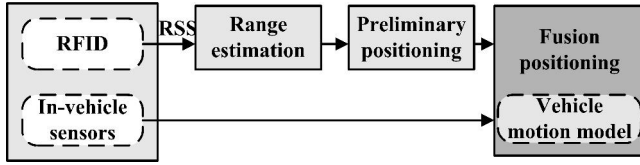


Fig. 1. Proposed vehicle positioning strategy.

The in-vehicle sensors include odometer, digital compass, two orthogonal accelerometers and a yaw gyro. In this paper, two-level extended Kalman filter (EKF) is developed to achieve positioning.

In the preliminary positioning, the received signal strength (RSS) of RFID is employed as the indicator to estimate the range from the vehicle to the RFID tags. Then the first level EKF is employed to preliminary compute the vehicle's location.

In the further fusion positioning, the low cost in-vehicle sensors are integrated with the preliminary positioning results utilizing the second level EKF. Due to the in-vehicle sensors, the positioning performance can be improved, i.e., the accuracy and output frequency are enhanced, the velocity and attitude information can be provided. Meanwhile, to describe the vehicle motion more accuracy, an improved vehicle motion model is established in the fusion process.

### III. PRELIMINARY POSITIONING

#### A. Range Estimation Algorithm

It seems that the first challenge of preliminary positioning is how to mathematically model the nonlinear relationship between the RSS and the range. Theoretically, under ideal environments, Friis transmission equation [11] can be applied to model the nonlinear correlation. However, in real applications, this model is not satisfied due to the environment effect. This paper proposes a least square support vector machine (LSSVM) algorithm [14], [15] to model the relationship. Compared with the propagation model, the proposed LSSVM algorithm has many advantages, such as high precision, high generalization ability and strong adaptability for different environments, which can significantly improve the subsequent positioning performance. The input of LSSVM is RSS, and the output is the range. The training data is collected through experiments in different situations. The training process is off-line, and then the trained LSSVM is used to estimate the range on-line.

Given a training set  $\{x_k, y_k\}_{k=1}^N$ , where  $x_k$  is input RSS vector,  $y_k$  is output range vector.  $x_k, y_k \in \mathbf{R}^1$ ,  $\mathbf{R}^1$  is the one-dimensional vector space. In feature space, the LSSVM model takes the form:

$$f(x) = \mathbf{w}^T \varphi(x) + b \quad (1)$$

where  $\mathbf{w} \in \mathbf{R}^{n_h}$  is an adjustable weight vector; the nonlinear

mapping  $\varphi(\cdot): \mathbf{R}^1 \rightarrow \mathbf{R}^{n_h}$  maps the input data into a higher dimensional feature space;  $b$  is the scalar threshold.

The optimization problem is

$$\min J(\mathbf{w}, b, e) = \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{1}{2} \gamma \sum_{k=1}^N e_k^2 \quad (2)$$

Due to the equality constraints:

$$y_k = \mathbf{w}^T \varphi(x_k) + b + e_k, k = 1, \dots, N \quad (3)$$

where  $e_k$  is the error variable and  $\gamma \geq 0$  is a regularization constant. To solve the optimization problem above-mentioned, the Lagrangian function is introduced:

$$L_{LS-SVM} = \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{1}{2} \gamma \sum_{k=1}^N e_k^2 - \sum_{k=1}^N \alpha_k \{ \mathbf{w}^T \varphi(\mathbf{X}_k) + b + e_k - y_k \} \quad (4)$$

where  $\alpha_k$  are the Lagrange multipliers, according to Karush Kuhn Tucker (KKT) optimization conditions which are illustrated in Equation (5):

$$\begin{cases} \frac{\partial L_{LS-SVM}}{\partial \mathbf{w}} = 0 \rightarrow \mathbf{w} = \sum_{k=1}^N \alpha_k \varphi(x_k) \\ \frac{\partial L_{LS-SVM}}{\partial b} = 0 \rightarrow \sum_{k=1}^N \alpha_k = 0 \\ \frac{\partial L_{LS-SVM}}{\partial e_k} = 0 \rightarrow \alpha_k = \gamma e_k, k = 1, \dots, N \\ \frac{\partial L_{LS-SVM}}{\partial \alpha_k} = 0 \rightarrow \mathbf{w}^T \varphi(x_k) + b + e_k - y_k = 0, k = 1, \dots, N \end{cases} \quad (5)$$

Eliminating  $\mathbf{w}$  and  $e_k$  will yield a linear system instead of a quadratic programming problem:

$$\begin{bmatrix} 0 & \mathbf{1}_N^T \\ \mathbf{1}_N & \mathbf{\Omega} + \mathbf{I}_N / \gamma \end{bmatrix} \begin{bmatrix} b \\ \mathbf{a} \end{bmatrix} = \begin{bmatrix} 0 \\ \mathbf{Y} \end{bmatrix} \quad (6)$$

where  $\mathbf{Y} = [y_1, \dots, y_N]^T$ ,  $\mathbf{1}_N = [1, \dots, 1]^T$  and  $\mathbf{a} = [\alpha_1, \dots, \alpha_N]^T$ .  $\mathbf{I}_N$  is a  $N \times N$  identity matrix.  $\mathbf{\Omega}$  is the kernel matrix defined by

$$\Omega_{ij} = \varphi(x_i)^T \varphi(x_j) = K(x_i, x_j), i, j = 1, \dots, N \quad (7)$$

The radial basis function (RBF) has been used here as the kernel function  $K(\cdot, \cdot)$ , which is given by

$$K(x, x_k) = \exp \left\{ -\frac{\|x - x_k\|_2^2}{2\sigma^2} \right\}, k = 1, \dots, N \quad (8)$$

where  $\|x - x_k\|_2^2$  is the squared Euclidean distance between the two feature vectors;  $\sigma$  is the width of RBF.

Further, the result of the LS-SVM model for function estimation becomes

$$f(x) = \sum_{k=1}^N \alpha_k K(x, x_k) + b \quad (9)$$

where  $\alpha_k$  and  $b$  are the solutions to Equation (6). The design values of  $\gamma$  and  $\sigma$  can be determined during the training of LSSVM.

After off-line training, Equation (9) can be used to on-line estimate the range between the tag and the reader according to the measured RSS.

### B. Positioning Algorithm

The first level EKF is developed to preliminary determine the position of vehicle by using the estimated ranges. Assumed that  $i$  tags with known coordinates  $(x_i, y_i)$  are detected by the reader at the time  $k$ , and the ranges from these tags to the vehicle are  $r_i$ . The state equation and measurement equation can be described as:

$$\begin{aligned}\mathbf{X}_R(k) &= \mathbf{A}_R \mathbf{X}_R(k-1) + \mathbf{W}_R(k-1) \\ \mathbf{Z}_R(k) &= \mathbf{h}_R(\mathbf{X}_R(k)) + \mathbf{V}_R(k)\end{aligned}\quad (10)$$

where  $k$  is the discrete-time step;  $\mathbf{X}_R(k) = [e(k) \ n(k)]^T$  indicates the state vector,  $e$  and  $n$  are the east and north coordinates of the vehicle; the state transition matrix  $\mathbf{A}_R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ ;  $\mathbf{W}_R$  and  $\mathbf{V}_R$  are the system and measurement noise and their covariance matrices are  $\mathbf{Q}_R$  and  $\mathbf{R}_R$ ;  $\mathbf{Z}_R = [r_1(k) \ \dots \ r_i(k)]^T$  is the observation vector and  $\mathbf{h}_R(k) = [h_1(k) \ \dots \ h_i(k)]^T$  is the corresponding observation function,

$h_i(k) = \sqrt{(e(k) - x_i(k))^2 + (n(k) - y_i(k))^2} + n_{fi}$ ,  $n_{fi}$  denotes the corresponding observation noise vector with the assumption of the zero-mean and Gaussian distribution.

Then the execution of EKF [16], [17] can be divided into time update stage and measurement update stage as follows:

Time update:

$$\hat{\mathbf{X}}_R(k, k-1) = \mathbf{A}_R \hat{\mathbf{X}}_R(k-1) \quad (11)$$

$$\mathbf{P}_R(k, k-1) = \mathbf{A}_R(k, k-1) \mathbf{P}_R(k-1) \mathbf{A}_R'(k, k-1) + \mathbf{Q}_R(k-1) \quad (12)$$

Measurement update:

$$\mathbf{K}_R(k) = \mathbf{P}_R(k, k-1) \mathbf{H}_R'(k) [\mathbf{H}_{\text{RFID}}(k) \mathbf{P}_R(k, k-1) \mathbf{H}_R'(k) + \mathbf{R}_R(k)]^{-1} \quad (13)$$

$$\hat{\mathbf{X}}_R(k) = \hat{\mathbf{X}}_R(k, k-1) + \mathbf{K}_R(k) [\mathbf{Z}_R(k) - \mathbf{h}_R(\hat{\mathbf{X}}_R(k, k-1))] \quad (14)$$

$$\mathbf{P}_R(k) = [\mathbf{I} - \mathbf{K}_R(k) \cdot \mathbf{H}_R(k)] \mathbf{P}_R(k, k-1) \quad (15)$$

where  $\mathbf{I}$  is an identity matrix,  $\mathbf{H}_R$  is the Jacobian matrix of the measurement function  $\mathbf{h}_R(\cdot)$  with respect to  $\mathbf{X}_R$

$$\mathbf{H}_R(k) = \begin{bmatrix} (e(k) - x_1(k))/D_1(k) & (n(k) - y_1(k))/D_1(k) \\ \dots & \dots \\ (e(k) - x_N(k))/D_N(k) & (n(k) - y_N(k))/D_N(k) \end{bmatrix}$$

$$D_i(k) = \sqrt{(e(k) - x_i(k))^2 + (n(k) - y_i(k))^2} \quad (i = 1, 2, \dots, N).$$

Since only the RFID is employed, this algorithm can only provide the position information, and the positioning accuracy and output frequency are not high enough, i.e., the output frequency is always no more than 1Hz.

## IV. FUSION POSITIONING

### A. Vehicle Motion Model

To describe the typical vehicle motion, an improved vehicle motion model is established. The state vector is

$$\mathbf{X}(k) = [e(k) \ n(k) \ v_e(k) \ v_n(k) \ \psi(k)]^T$$

where  $v_e(k)$  and  $v_n(k)$  denote the east and north speeds of the vehicle.  $\psi(k)$  is the yaw angle. The system input vector, i.e., the longitudinal and lateral accelerations  $a_x, a_y$ , and the yaw rate  $\omega_z$ , are measured by the accelerometers and yaw gyro. Defined  $a_e(k-1) = a_x \cos \psi(k-1) - a_y \sin \psi(k-1)$  and  $a_n(k-1) = a_x \sin \psi(k-1) + a_y \cos \psi(k-1)$ , the motion model is shown as:

$$\mathbf{X}(k, k-1) = \begin{bmatrix} e(k-1) + v_e(k-1)T + \frac{1}{2}[a_e(k-1)]T^2 \\ e(k-1) + [a_e(k-1)]T \\ n(k-1) + v_n(k-1)T + \frac{1}{2}[a_n(k-1)]T^2 \\ n(k-1) + [a_n(k-1)]T \\ \psi(k-1) + \omega_z T \end{bmatrix} \quad (16)$$

### B. Fusion Algorithm

The second level EKF is developed to fuse the data obtained from RFID and in-vehicle sensors for further positioning. Defined the observation vector  $\mathbf{Z} = [x_{\text{RFID}} \ y_{\text{RFID}} \ v_o \ \psi_c]^T$ , it can be seen that  $\mathbf{Z}$  comes from two sources, i.e.,  $x_{\text{RFID}}$  and  $y_{\text{RFID}}$  are the estimated vehicle's coordinates by first level EKF;  $v_o$  is the vehicle speed measured by odometer,  $\psi_c$  is the observed yaw angle from the compass.

$$\mathbf{Z} = \mathbf{h}[\mathbf{X}(k)] = \begin{bmatrix} e(k) + n_{pe} \\ n(k) + n_{pn} \\ v_e(k) \cos \psi(k) + v_n(k) \sin \psi(k) + n_v \\ \psi(k) + n_\psi \end{bmatrix} \quad (17)$$

where  $\mathbf{h}$  is the observation function.  $n_{pe}, n_{pn}, n_v$  and  $n_\psi$  are the observation noise vectors. By utilizing EKF algorithm as equation (11)-(15), the fusion positioning can be achieved.

## V. EXPERIMENTS AND RESULTS

The verification experiments were conducted in the simulated tunnel which was set in the outdoor open space. Only one experimental result is shown here as an instance because similar conclusions can be drawn by other tests. In the experiment, the output frequency of RFID hardware devices is 1Hz. The RSS range of tag is normalized to 0-255, and the maximum measured distance of tag is 9m.

Figure 2 shows the fitting results of the relationship between RSS and range in outdoor test site. For comparison, the propagation model-based algorithm utilizing Friis transmission equation is also investigated. It can be seen in Figure 2 that the LSSVM achieves better performance than the propagation model, which can provide the more accuracy range information and improve the performance of subsequent positioning algorithm.

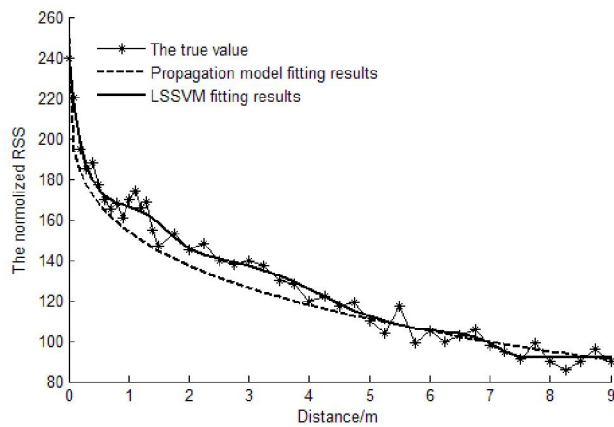


Fig. 2. The fitting results of the relationship

Figure 3 shows the trajectories of the vehicle, and Figure 4 illustrates the east position errors from preliminary and fusion positioning. For comparison, the widely used DR method is also investigated. Table I gives their performances, i.e., the output frequency, the speed and the statistics of Euclidean distance errors which contain the max value and the root mean square (RMS).

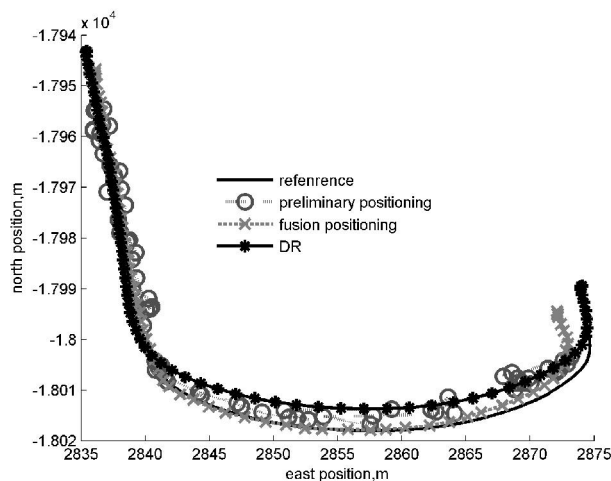


Fig. 3. The vehicle trajectories

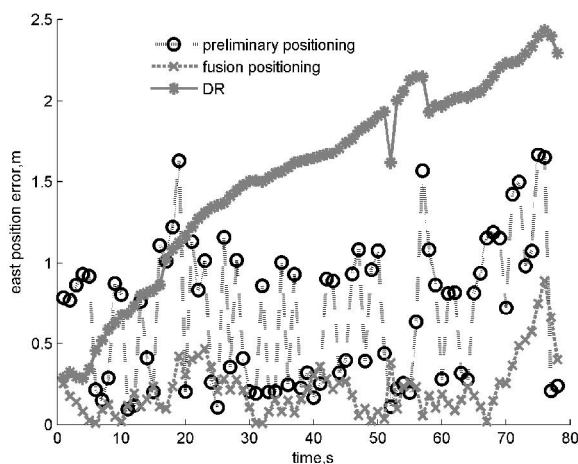


Fig. 4. The east positioning errors

TABLE I  
THE POSITIONING PERFORMANCE

| Method      | Euclidean distance error |        | Speed | Frequency (Hz) |
|-------------|--------------------------|--------|-------|----------------|
|             | MAX(m)                   | RMS(m) |       |                |
| Preliminary | 13.19                    | 4.47   | No    | 1              |
| Fusion      | 6.23                     | 3.78   | Yes   | 10             |
| DR          | 10.14                    | 5.21   | Yes   | 10             |

The reference trajectory was measured by high precision differential GPS. Figure 3, Figure 4 and Table I show that the fusion positioning performance is obviously better than preliminary positioning and DR. Compared with DR, the RMS value of Euclidean distance error of the proposed strategy is decreased to 3.78m, i.e., about 27% accuracy improvement over DR. It can be attributed that the RFID can provide the position observation to correct the accumulate errors of DR. Compared with the preliminary positioning algorithm, the RMS value of Euclidean distance error of the proposed strategy is reduced to 3.78m from the value 4.47m, and the output frequency is increased to 10Hz from the value 1Hz. Meanwhile, the speed and the attitude information can be provided. The main reason is that the in-vehicles sensors can provide accurate speed and attitude information to enhance the positioning accuracy and reliability,

Compared with the low-cost GPS which is most widely used in the vehicle, the proposed fusion positioning strategy has the approximation accuracy with higher frequency. Therefore, when GPS is completely unavailable, the proposed strategy can satisfy the common demand of vehicle positioning.

## VI. CONCLUSION

In this paper, RFID is employed to locate the vehicle in completely GPS-denied environments. Meanwhile, the in-vehicle sensors are introduced to improve the observability of RFID. A vehicle positioning strategy based on two-level EKF is proposed to fuse the data obtained from RFID and in-vehicle sensors. Experiments were performed to verify the effectiveness of the proposed strategy. The experimental results indicate that the proposed strategy achieves remarkable performance improvement in completely GPS-denied environments.

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