New Algorithms Based on Sigma Point Kalman Filter Technique for Multi-sensor Integrated RFID Indoor/Outdoor Positioning

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***Abstract*— The demand for seamless positioning has been significantly high. The methods of providing continuous indoor/outdoor positions seamlessly and the algorithms for smoothly transferring the estimation of positions from multiple positioning systems have attracted a great interest in the Location Based Services (LBS) research community. Most seamless positioning techniques are based on integrated methods, which usually contain nonlinear relationships in observation models. In this paper, the developments for integrating the measurements in nonlinear systems based on the Sigma Point Kalman Filter (SPKF) are introduced in order to solve the complex nonlinear problems efficiently and effectively. These developments are implemented for both vehicle navigation and pedestrian positioning applications. Recent research has suggested that continuous and metre-level position solutions can be achieved using multi-sensor integrated RFID positioning systems based on SPKF related algorithms. The Iterated Reduced SPKF (IRSPKF) using a sequential approach proposed in this paper can provide more accurate positioning results with less computational cost than other SPKF based algorithms. The potential capabilities using this new algorithm developed in multi-sensor integrated RFID positioning systems for indoor/outdoor positioning applications have been demonstrated.**

***Keywords*—RFID; GPS; Sigma Point Kalman Filter; Indoor; Integration**

I. INTRODUCTION

The demand for seamless positioning has significantly increased since the introduction of 'ubiquitous computing' (Weiser, 1991) in the late 1980s. Positional information has become more and more important since it is needed almost everywhere all the time. Consequently, the methods of providing continuous indoor/outdoor positions seamlessly and the algorithms for smoothly transferring the estimation from one outdoor system, like GPS, to another system indoor, like Radio Frequency Identification (RFID) system, has attracted a great interest in the Location Based Services (LBS) community [1, 2].

Most seamless positioning techniques are based on an integrated method, such as the integration of GPS and Micro-Electro-Mechanical Systems (MEMS) Inertial Navigation System (INS). The relationships between the integrated techniques are usually nonlinear. Normally, the Extended Kalman Filter (EKF) is the preferred algorithm for integrating the measurements in nonlinear systems. However, it approximates the dynamic models and observation models by linearization and noises are ignored in these models. Apparently, these approximations may cause divergence of the filter in the complex nonlinear systems.

In this paper, the developments for integrating the measurements in nonlinear systems based on the Sigma Point Kalman Filter (SPKF) are introduced in order to solve the complex nonlinear problems efficiently and effectively. These developments are implemented in the multi-sensor integrated RFID positioning systems both for the vehicle navigation and pedestrian positioning applications.

II. SEQUENTIAL APPROACH IN ITERATED REDUCED SIGMA POINT KALMAN FILTER

In order to compensate for the limitations in the EKF, the SPKF was introduced in the mid-1990's [3]. This algorithm transforms a set of sample points nonlinearly, which are cited as sigma-points, instead of using the linearised functions in the EKF.

A. *Sigma Point Kalman Filter*

The sigma-points are determined by the following equations.

$$\mathbf{X}_i^x = \begin{cases} \bar{x} & i = 0 \\ \bar{x} + \zeta \cdot (\sqrt{\underset{\sim}{P}})_i & i = 1, \dots, N \\ \bar{x} - \zeta \cdot (\sqrt{\underset{\sim}{P}})_i & i = N+1, \dots, 2N \end{cases} \tag{1}$$

where $\mathbf{X}_i^x$ is the i th sigma-point of the state; $\bar{x}$ is the mean of the state; $\underset{\sim}{P}$ is the error covariance matrix of the state; ζ is a scalar scaling factor that determines the spread of the sigma-points and N is the dimension.

$$\mathbf{X}_i^w = \begin{cases} \bar{w} & i = 0 \\ \bar{w} + \zeta \cdot (\sqrt{\underset{\sim}{Q}})_i & i = 1, \dots, N \\ \bar{w} - \zeta \cdot (\sqrt{\underset{\sim}{Q}})_i & i = N+1, \dots, 2N \end{cases} \tag{2}$$

where $\mathbf{X}_i^w$ is the i th sigma-point of the state; $\overline{w}$ is the mean of the process noise and $\underset{\sim}{Q}$ is the error covariance matrix of the process noise.

$$\mathbf{X}_i^v = \begin{cases} \overline{v} & i = 0 \\ \overline{v} + \zeta \cdot (\sqrt{\underset{\sim}{R}})_i & i = 1, \ldots, N \\ \overline{v} - \zeta \cdot (\sqrt{\underset{\sim}{R}})_i & i = N+1, \ldots, 2N \end{cases} \tag{3}$$

where $\mathbf{X}_i^v$ is the i th sigma-point of the state; $\overline{v}$ is the mean of the measurement uncertainties and $\underset{\sim}{R}$ is the error covariance matrix of the measurement uncertainty.

Accordingly, the time update equations of the SPKF can be expressed as follows:

$$\mathbf{X}_{i,k|k-1}^x = f(\mathbf{X}_{i,k-1}^x, \mathbf{X}_{i,k-1}^w) \tag{4}$$

$$\hat{x}_k^- = \sum_{i=0}^{2N} w_i^m \cdot \mathbf{X}_{i,k|k-1}^x \tag{5}$$

$$\underset{\sim}{P}_{x_k}^- = \sum_{i=0}^{2N} \sum_{j=0}^{2N} w_{ij}^c \cdot (\mathbf{X}_{i,k|k-1}^x) \cdot (\mathbf{X}_{i,k|k-1}^x)^T \tag{6}$$

The measurement update equations of the SPKF are:

$$\mathbf{Z}_{i,k|k-1} = h(\mathbf{X}_{i,k|k-1}^x, \mathbf{X}_{i,k}^v) \tag{7}$$

$$\hat{z}_k^- = \sum_{i=0}^{2N} w_i^m \cdot \mathbf{Z}_{i,k|k-1} \tag{8}$$

$$\underset{\sim}{P}_{\tilde{z}_k} = \sum_{i=0}^{2N} \sum_{j=0}^{2N} w_{ij}^c \cdot (\mathbf{Z}_{i,k|k-1}) \cdot (\mathbf{Z}_{i,k|k-1})^T \tag{9}$$

$$\underset{\sim}{P}_{x_k z_k} = \sum_{i=0}^{2N} \sum_{j=0}^{2N} w_{ij}^c \cdot (\mathbf{X}_{i,k|k-1}^x) \cdot (\mathbf{Z}_{i,k|k-1})^T \tag{10}$$

$$\underset{\sim}{\overline{K}}_k = \underset{\sim}{P}_{x_k z_k} \cdot \underset{\sim}{P}_{\tilde{z}_k}^{-1} \tag{11}$$

$$\hat{x}_k^+ = \hat{x}_k^- + \underset{\sim}{\overline{K}}_k \cdot (z_k - \hat{z}_k^-) \tag{12}$$

$$\underset{\sim}{P}_{x_k}^+ = \underset{\sim}{P}_{x_k}^- - \underset{\sim}{\overline{K}}_k \cdot \underset{\sim}{P}_{\tilde{z}_k} \cdot \underset{\sim}{\overline{K}}_k^T \tag{13}$$

where w_0^m is the weight of the sigma-point of the measurements; w^c is the weight of the sigma-point of the covariance and $\underset{\sim}{\overline{K}}_k$ is the Kalman gain.

By implementing the SPKF, the major limitations in the EKF, including the complicities and the instabilities of the linearised Jacobian approximations, can be satisfactorily resolved. In addition, this algorithm can be made more robust by using the iterative method [4]. However, computational burden can be a limitation for implementation [5].

B. *The Reduced Sigma Points*

The Reduced SPKF (RSPKF) is based on the theory that the number of points used for constructing the largest possible affinely independent set is $N+1$ (see Fig. 1). The RSPKF then reduces the number of sigma-points required from $2N+1$ in the standard SPKF to $N+2$ [6].

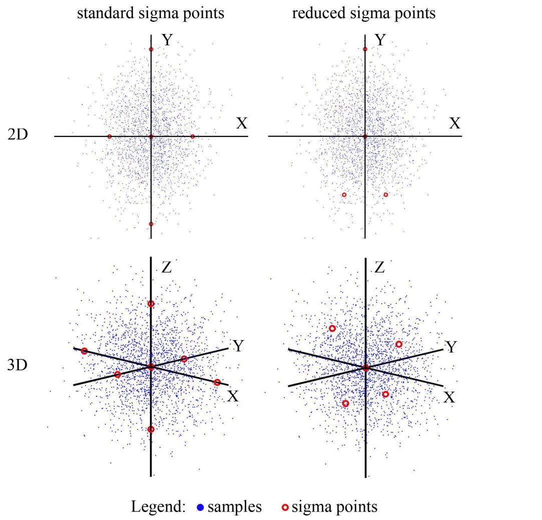

Figure 1. A schematic plot of the fundamentals in the reduced sigma points theory

(the top two plots show the standard sigma points (5 points) and reduced sigma points (4 points) in 2-D and the bottom two plots show the standard sigma points (7 points) and reduced sigma points (5 points) in 3-D)

C. *RSPKF using Iterated Approach*

Using a similar idea of the iterated SPKF, RSPKF method is developed [7]. The objective of the new development was to obtain an updated measurement as an approximate maximum of a posterior estimate via the Gauss-Newton iterative method [8]. The algorithm repeats the process of the RSPKF at every epoch until the results meet the terminal conditions using the Gauss-Newton iterative method (see Equ. 14).

$$\left\| \hat{x}_{k(i+1)}^+ - \hat{x}_{k(i)}^+ \right\| \leq \varepsilon \text{ or } i \leq M \tag{14}$$

where i is the number of the iteration; M is the maximum number of the iteration; ε is the threshold of the distance between state vectors in the adjacent iterations and $\hat{x}_{k(i)}^+$ is the k th state vector in the i th iteration.

D. *IRSPKF using Sequential Approach*

In practice, the components of the observation vector can be considered as a sequence of scalar measurements and their measurement noises are uncorrelated. As a result, the measurement update stage can be implemented in a sequential processing approach rather than a block processing approach. The sequential approach, therefore, can be used to further restrain the noises from observations and increase the computational speed. For example, Fig. 2 shows a significant improvement in the computational speed by using the sequential approach and the reduced sigma points (SRSPKF) rather than other kinds of SPKF algorithms, such as the standard SPKF, RSPKF and SPKF using sequential approach (SSPKF).

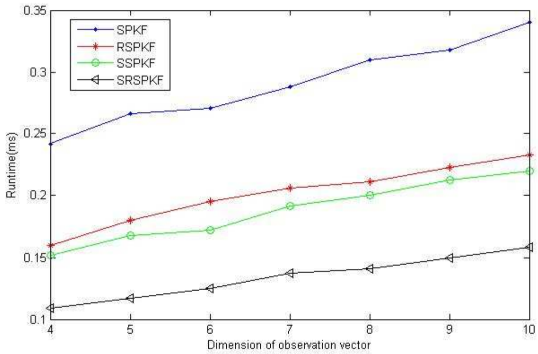

Figure 2. A schematic plot of the runtimes using various SPKF algorithms

III. EXPERIMENTS AND RESULTS

The experiments both for the vehicle navigation using GPS/RFID integrated techniques and for the pedestrian positioning using MEMS INS/GPS/RFID integrated techniques were conducted in order to evaluate the SPKF based algorithms developed. In all the experiments, the centimetre-level positions measured by the GPS RTK technique were used as references for the evaluation.

A. *Positioning Systems*

The positioning system used in the experiments for vehicle navigation includes a *Trimble R8* GPS receiver (for pseudorange measurements) and an RFID system. The other positioning system for pedestrian positioning includes a *MinimaxX* (for MEMS INS measurements and GPS positions based on C/A code measurements) and an RFID system.

The RFID system used in this research is an intelligent long range RFID system developed by *Identec Solutions*. It consists of an *i-Card III* interrogator (reader) and *i-Q* transponders (tags) (see Fig. 3). It works on 915MHz and claims a reading range of 100m in a free space [9].

The *MinimaxX* used in this research is a portable MEMS INS/GPS integrated device. It contains a tri-axis accelerometer, three gyroscopes, a tri-axis magnetometer and a low-cost GPS [10].

B. *Vehicle Navigation in Urban Areas*

Experiments for evaluating the SPKFs for vehicle navigation were conducted at Site A (see Fig. 4). In the open areas, the pseudorange measurements from a GPS receiver were used for positioning. In the GPS blocked areas, which are in the north-east corner of the circuit, an RFID tag array was placed along the roads in order to provide additional distance measurements. The SPKFs developed were used to integrate the measurements for seamless positioning.

Figure 3. RFID interrogator and transponder used in the research

(*i-Card III* interrogator (left) and *i-Q* transponder (right) of the *Identec Solutions* long range active RFID system)

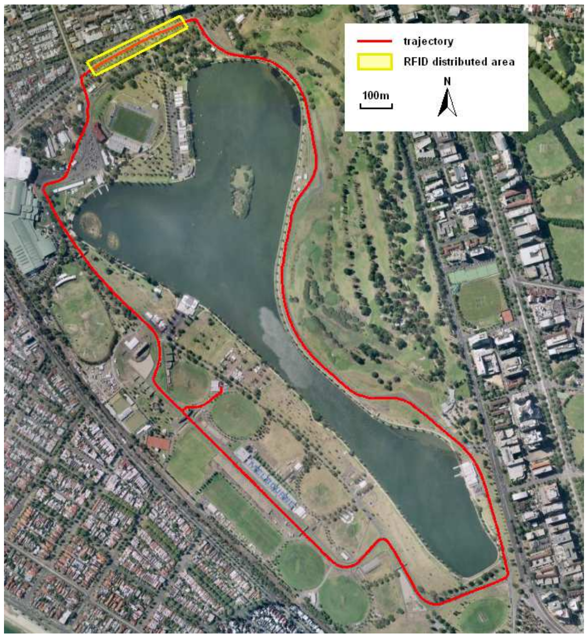

Figure 4. The experimental site and the trajectory for evaluating the iterated reduced SPKF for the GPS/RFID integrated positioning technique

(The tested trajectory is along Site A. In the north-east corner partial GPS signals were blocked by the buildings nearby the roads. The RFID tags were placed in those areas to provide additional distance measurements. The satellite image in the background is taken from *Google Earth*.)

According to the experiments, the continuous positions can be achieved by using the GPS/RFID integrated technique. The positioning RMSE was 2.923m using RSPKF. It can be reduced to 1.357m by using the IRSPKF developed and 1.353m by using the sequential approach in IRSPKF (see Fig. 5) respectively.

C. *Indoor/Outdoor Positioning for Pedestrians*

The pedestrian positioning experiments were conducted at Site B. A complicated environment setting was chosen. This includes the indoor areas experiments in a house that was mainly constructed of timber, the canopy covered areas outside the house and outdoor open areas (see Fig. 6). Eleven RFID tags were placed outdoors to provide additional observations in the blocked GPS signal areas. Another four RFID tags were placed along the corridor in the house for indoor positioning experiments.

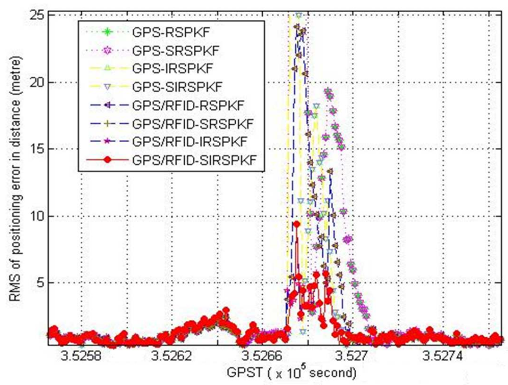

Figure 5. The positioning errors of vehicle navigation experiments using various positioning methods

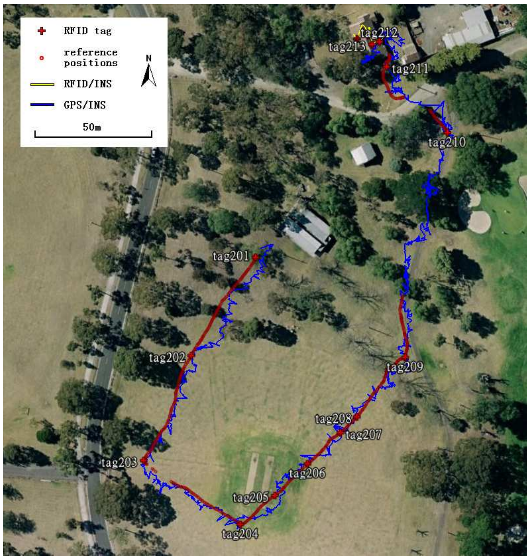

Figure 6. The experimental results for pedestrian positioning

(The experiments, including indoor and outdoor pedestrian positioning, were conducted at Site B. The satellite image in the background is taken from *Google Earth*.)

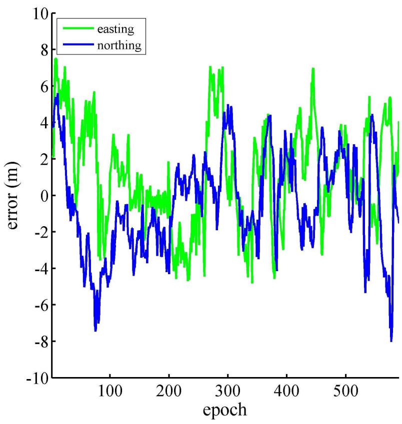

Figure 7. The positioning errors of pedestrian positioning experiments

(The positioning references are based on the GPS RTK measurements.)

The experiments showed that the Iterated Reduced SPKF (IRSPKF) using the sequential approach can be applied for indoor/outdoor pedestrian positioning using multi-sensor integrated RFID positioning technique too. Metre-level positioning accuracy and seamless positions are achieved (see Fig. 7).

IV. CONCLUSION

In summary, the IRSPKF is developed for solving the complex nonlinear problems in the multi-sensor integrated positioning scenarios and the sequential approach is introduced to improve the efficiency and the effectiveness of the algorithm developed. The experiments conducted in Site A and Site B show that the multi-sensor integrated RFID positioning techniques are suitable for the vehicle navigation and pedestrian positioning applications. Continuous and metre-level positions can be achieved using the SPKF based algorithms developed. The IRSPKF using the sequential approach proposed in this paper can provide more accurate positioning results with less computational cost than other SPKF based algorithms investigated. It has demonstrated the potential of the new algorithm developed in multi-sensor integrated RFID positioning systems for indoor/outdoor positioning applications.

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