A Vehicle Tracking System Based on WSN

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Outline

Motivation

- The project carried on in the Master thesis is covered by the regional XALOC project, an e-infraestructure project in the framework INFOREGIO program funded by the Autonomous Government of Catalonia and led by World Sensing.
- The XALOC project develops a system to Manage Public Parking and Localization based on WSN.

Objectives

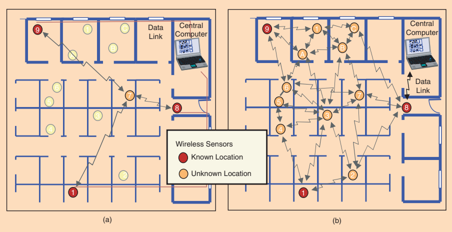
- The study and theoretical development of tracking techniques that can be useful for WSN applications. → A Matlab based simulator is implemented.
- Practical development of a Java-based navigator to indicate the real-time position of a driver looking for a free parking spot. Implementation of a Kalman Filter taking real position measurements from the WSN.

Outline

Introduction to WSN

- Wireless Sensor Networks: a large-scale wireless network with several nodes interconnected.
- Classification: Cooperative/Non-cooperative, centralized/distributed.

Wireless Sensor Network



- measuring a physical value
- processing data
- wireless communication

Embedded Systems

- small processing power (KHz)
- small memory (KBs)
- powered by AA, AAA or watch batteries.

Localization in WSN

- What is "localization"?
  - Determining where a given node is physically located in a network.

What we need to perform localization in a WSN?:

- few anchor nodes with known coordinates obtained by either GPS or manually configured.
- several unknown nodes without known coordinates.
- A ranging metric or signal metric to estimate the distance between nodes.

Ranging metrics

These schemes estimated the distance to the transmitter by measuring some metrics of the received signal. These metrics are the following:

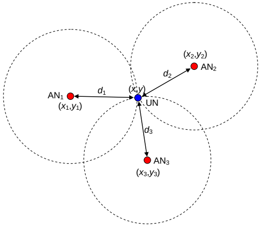
- ToA(*Time of Arrival*): this metric estimates the distance from the LoS (*Line of Sight*) signal propagation delay.
- TDoA(Time Difference of Arrival): this metric obtains the unknown coordinates by measuring the time difference of arrival of different signals.
- RToA *(Round Trip Time of Arrival*): this metric measures the round trip time between the transmitter and the receiver. It avoids synchronized clocks.
- AoA(*Angle of Arrival*): this metric finds the direction of arrival of a signal by using an array of antennas.
- RSSI(*Received Signal Strength Indicator*): this metric corresponds to the received power which is dependent on the distance as:

  $$RSSI = P_o - 10\gamma log_{10}(d)$$

  ,where P_o is the measured RSSI at $1m$. Thus, isolating d we can obtain an estimation of the distance.

Multilateration

- Multilateration is a technique that uses the estimated distances to a set of anchor nodes to find the unknown coordinates (x, y). The minimum number of anchor nodes is three. The accuracy increases with the number of anchor nodes.



The idea is to solve the following unconstrained cost function, being w_i positive weights(1/0) that enphasize the most reliable links.

$$(\hat{x}, \hat{y}) = \underset{x,y}{argmin} \sum_{i=1}^{N} w_i \left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - d_i \right)^2$$

Outline

Tracking in Wireless Sensor Networks

- When the node is moving then tracking techniques must be used to follow the trajectory of the sensor node. The most common tracking methods which are the next follow a state space model (or dynamic state model):

Tracking techniques

- Kalman Filter (KF) used when the trajectories' dynamic state model is linear.
- Extended Kalman Filter (EKF) used when the trajectories' dynamic model is nonlinear. Then a linealization of the model is taken into account.
- Interacting Multiple Model (IMM) used when several models appear in the trajectory. The IMM combines these models to produce an accurate estimate.

KF versus EKF

- In KF the Kalman gains as well as the predicted/updated process covariance can be computed off-line.
- In EKF the Kalman gains as well as the predicted/updated process covariance must be computed on-line since all of them depend on the Jacobian of the nonlinear function f over each of the states in $\hat{x}(k|k)$:

$$\mathbf{F}(k) = \frac{\partial f(k)}{\partial x} \Big|_{\mathbf{x}=\hat{\mathbf{x}}(k|k)}$$

Outline

KF with the nearly constant velocity model

KF Process and observation equations

$$\mathbf{x}(k+1) = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}(k) + \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \end{bmatrix} \mathbf{u}(k) \quad k \geq 0 \quad (1)$$

$$\mathbf{Q} = \mathbf{G}(k)\sigma_u^2 \mathbf{I} \mathbf{G}(k)', \quad (2)$$

$$\mathbf{z}(k+1) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \mathbf{x}(k+1) + \mathbf{w}(k+1) \quad (3)$$

- $\mathbf{x} = [x \; v_x \; y \; v_y]^T$ and $\mathbf{u} \sim \mathcal{N}(0, \sigma_u^2)$ where σ_u^2 is the acceleration variance that depends upon the scenario. Typical values can be for instance $\sigma_u^2 = 0.1 m/s^2$, $2 m/s^2$.

Outline

EKF with the nearly CT model

- Now the state vector is extended with one more row: $\mathbf{x} = [x\ v_x\ y\ v_y\ \Omega]^T$

EKF Process and observation equations

$$\mathbf{x}(k+1) = \begin{bmatrix} 1 & \frac{sin\Omega(k)T}{\Omega(k)} & 0 & -\frac{1-cos\Omega(k)T}{\Omega(k)} & 0 \\ 0 & cos\Omega(k)T & 0 & -sin\Omega(k)T & 0 \\ 0 & \frac{1-cos\Omega(k)T}{\Omega(k)} & 1 & \frac{sin\Omega(k)T}{\Omega(k)} & 0 \\ 0 & sin\Omega(k)T & 0 & cos\Omega(k)T & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}(k) + \begin{bmatrix} \frac{1}{2}T^2 & 0 & 0 \\ T & 0 & 0 \\ 0 & \frac{1}{2}T^2 & 0 \\ 0 & T & 0 \\ 0 & 0 & T \end{bmatrix} \mathbf{u}(k) \tag{4}$$

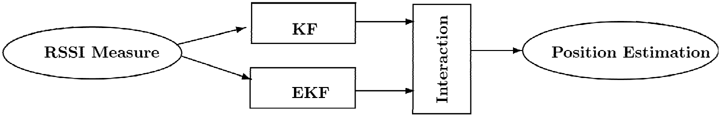
$$\mathbf{z}(k+1) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \mathbf{x}(k+1) + \mathbf{w}(k+1) \tag{5}$$

Outline

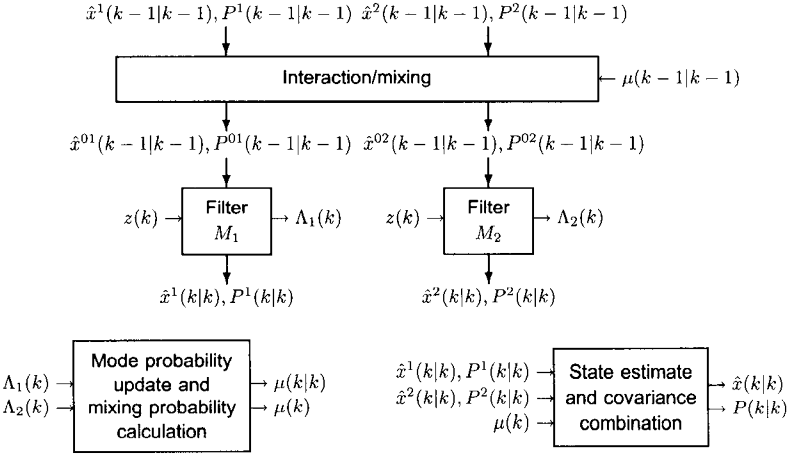
The Interacting Multiple Model (IMM) (I)

IMM

- Either KF or EKF alone are not suitable to track a trajectory composed by both stretchs and turns.
- The solution: IMM which functionallity is the weighted combination based on the likelihoods of each filter between the produced estimations by all the interacting models.



The Interacting Multiple Model (II)



Outline

Matlab-based simulator

- A simulator based on Matlab is implemented to test and compare the developed IMM algorithm with both KF and EKF in urban environments.

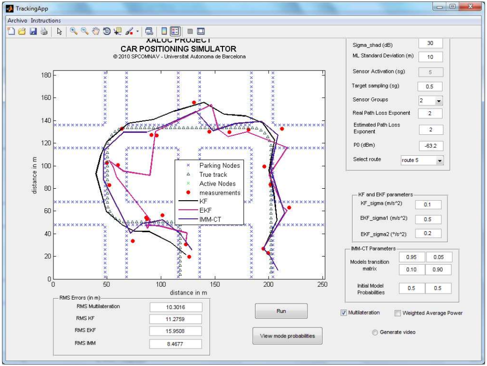
Tracking Simulations (I)

Simulation cases

1. Impact of σ^2_{shad} and σ_z variation.
2. $\mathbf{U}_{KF}$ and $\mathbf{U}_{EKF}$ adaptation.

Tracking Simulations (II): Impact of σ^2_{shad} and σ_z variation

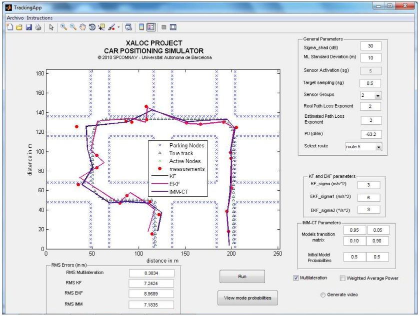
- In real scenarios high shadowing implies high position errors. Next we show for $\sigma_z = 10\,m$ and $\sigma^2_{shad} = 30\,dB$.



$RMSE_z\,(m)$	10.3016
$RMSE_{KF}\,(m)$	11.2759
$RMSE_{EKF}\,(m)$	15.9508
$RMSE_{IMM}\,(m)$	8.4677

Tracking Simulations (III): $\mathbf{U}_{KF}$ and $\mathbf{U}_{EKF}$ adaptation

- When the system noise is high it is necessary to adjust the tracking filters with its process covariance. The criteria to follow is: larger process covariance ⇒less belief to the model.

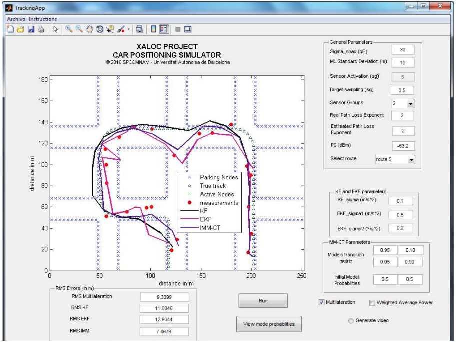


$$\mathbf{U}_{\mathbf{KF}} = \begin{bmatrix} 3 & 0 \\ 0 & 3 \end{bmatrix} \quad \mathbf{U}_{\mathbf{EKF}} = \begin{bmatrix} 6 & 0 & 0 \\ 0 & 6 & 0 \\ 0 & 0 & 3 \end{bmatrix} \quad (6)$$

$RMSE_z\,(m)$	8.3834
$RMSE_{KF}\,(m)$	7.2424
$RMSE_{EKF}\,(m)$	8.9689
$RMSE_{IMM}\,(m)$	7.1835

Tracking Simulations (IV): Adaptation of IMM parameters

- Next we show the behaviour of IMM under **p**: the models transition matrix.



$$\mathbf{p} = \mathbf{p}' = \begin{bmatrix} 0.95 & 0.10 \\ 0.05 & 0.90 \end{bmatrix} \quad (7)$$

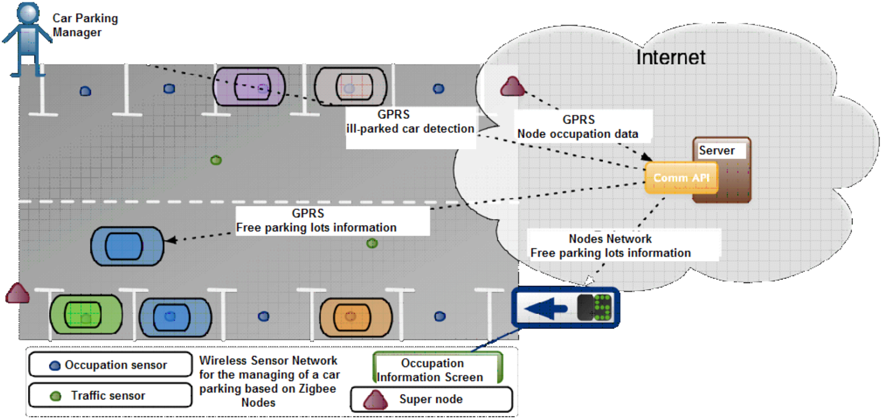
$RMSE_z\,(m)$	9.3399
$RMSE_{KF}\,(m)$	11.8046
$RMSE_{EKF}\,(m)$	12.9044
$RMSE_{IMM}\,(m)$	7.4678

Outline

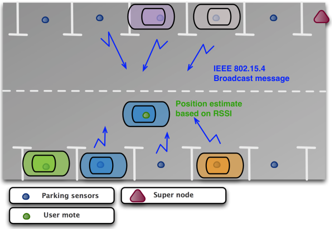
Goal

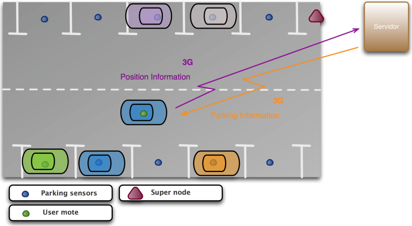
- Implementation of a real time vehicle localization system tested during a live demonstration on 7^{th} July at the fire's department of the UAB campus.
- Since the live demonstration was carried out by considering a straight road, the system was based on linear KF.
- Besides, some improvements were introduced to the system in order to cope with real scenario impairments.

Scenario Description



Nodes Communication





- The sensor on-board the vehicle measures the RSSI from all parking sensors (reference nodes).
- Position Information is obtained from the coordinates of the parking sensors and the measured RSSIs.

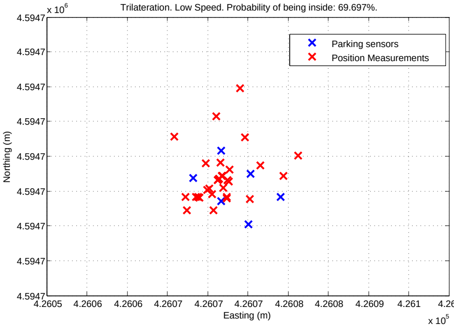
Scenario Location

The live demonstration was carried out at the fire's department parking of the Universitat Autonoma de Barcelona, Spain.

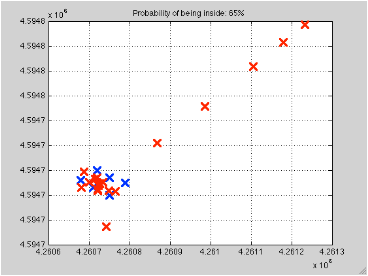
Outline

Multilateration in practice

First multilateration is tested in a real scenario, where the vehicle is moving at both low and high speed.



Multilateration at low speed



Multilateration at higher speed

Weighted Average Power Method (I)

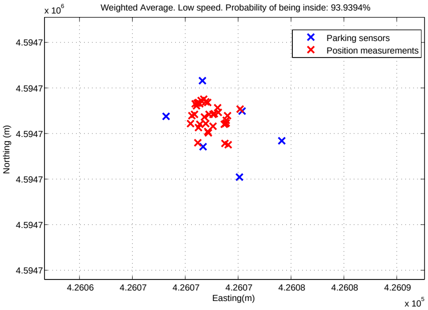
New positioning technique to combat the multipath effect: $\Rightarrow$ **Weighted Average Power Method** (WAPM).

Weighted Average Power Method

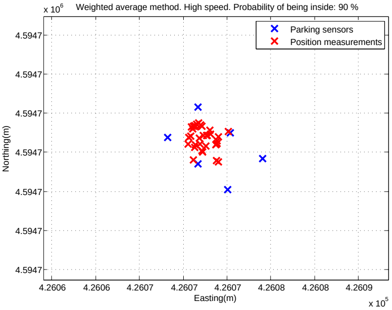
$$(\hat{x}, \hat{y}) = \mathbf{A} \cdot \alpha$$

$$\alpha = \frac{RSSI_n}{\sum_{i=1}^{N} RSSI_i}, \; n = 1, \ldots, N_{anchors}$$

Weighted Average Power Method (II)



WAPM at low speed



WAPM at high speed

Application of the Kalman Filter (I)

- One dimensional KF with a nearly constant velocity model is used to follow the linear trajectory of the vehicle.

Dynamic state model and observation model

$$\mathbf{x}(k+1) = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \mathbf{x}(k) + \begin{bmatrix} T^2/2 \\ T \end{bmatrix} \mathbf{u}(k) \quad n = 1, 2, \dots \tag{8}$$

$$\mathbf{z}(k+1) = \begin{bmatrix} 1 & 0 \end{bmatrix} \mathbf{x}(k+1) \tag{9}$$

$$\mathbf{x} = \begin{bmatrix} d \\ v \end{bmatrix} \tag{10}$$

Application of the Kalman Filter (II)

- Note that the vehicle does not move along the longitudinal axes but it moves along a diagonal projection straight line:

Projection straight line

$$\begin{pmatrix} x_p \\ y_p \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} + \left(\frac{(b - a_1 x - a_2 y)}{a_1^2 + a_2^2} \right) \begin{pmatrix} a_1 \\ a_2 \end{pmatrix}, \tag{11}$$

,
where

$$m = \frac{y_1 - y_0}{x_1 - x_0} \tag{12}$$

$$b = y_0 - x_0 m \tag{13}$$

$$a_1 = -m \tag{14}$$

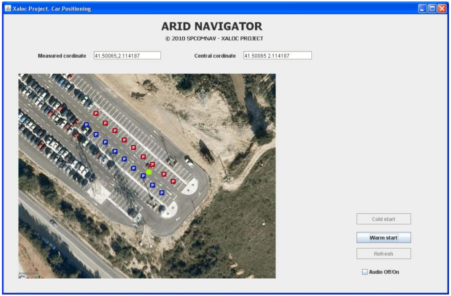
$$a_2 = 1, \tag{15}$$

Outline

ARID NAVIGATOR

Navigator components

- User Terminal: netbook+base station+3G USB dongle
- Navigator Application: Java Programming language+tinyOS



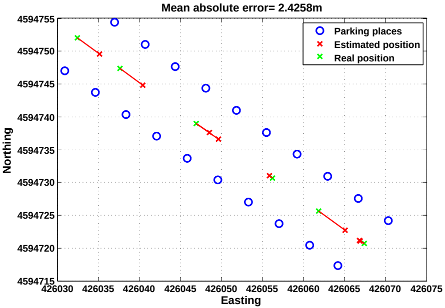
Outline

Experimental validation (I)

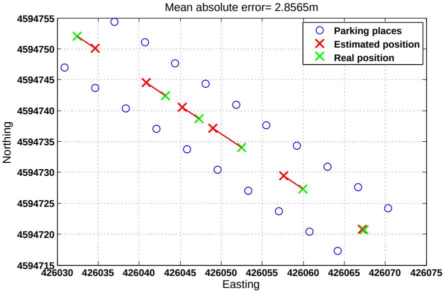
Experimental Validation

- 20 sensors placed in 20 parkings in an area of dimensions $80\,x\,70\ m^2$.
- The car was moving along a diagonal road, i.e. the projection line.
- Two considerations:
  - Tracking of the car's position that is moving at a constant speed of $10\ Km/h$
  - Tracking of the car's position that is moving at a constant speed of $20\ Km/h$.
- The following Kalman parameters obtained through several campaign measurements provides minimum position error :
  - $\sigma_u^2 = 3\ m/s^2$
  - $\mathbf{R}$ (KF Measurement noise covariance) $= 10\ m$

Experimental Validation (II): car moving at 10 Km/h



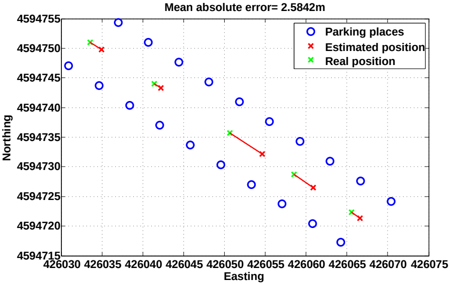
First realization. Mean absolute error = 2.4258 m



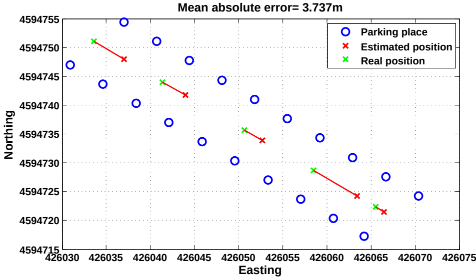
Second realization. Mean absolute error = 2.8565 m

Mean absolute error $= 2.6412\, m$.

Experimental Validation (III): car moving at 20 Km/h



First realization. Mean absolute error = 2.5842 m



Second realization. Mean absolute error = 3.737 m

Mean absolute error = 3.1606 m.

Summary

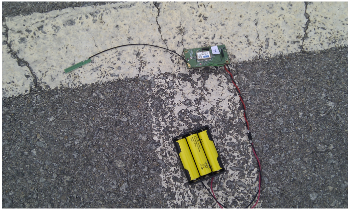
Summary

- Multilateration performance is not robust in real scenarios, appearing large position errors in the order of 30 *m*.
- New position technique called as Weighted Average Power Method is used to make sure that the estimated car's position is inside the measurement field.
- The experimental validation demonstrates position errors in the average $2 - 3\,m$.
- A Java-based navigator called ARID NAVIGATOR is developed to show the real time position to the driver on a map downloaded from GoogleMaps.
- The navigator is validated during the live demonstration carried on 7^{th} 2010.

Conclusions and Future Work

- The carried work has dealt with the theoretical validation of different tracking algorithms for WSN as well as the experimental development of a tracking system in a Wireless Sensor Network.
- The theoretical validation demonstrates that the novel IMM algorithm as a combination of a uniform motion model and a coordinated turn model provides a lower average position error.
- The experimental development has dealt with the development of a Java-based navigator that tracks the car's position by using a Kalman Filter. A novel position technique known as Weighted Average Power Method combined with the projection and a Kalman Filter provides lower position error than multilateration when the car is moving.
- Future work is intended apply distributed (collaborative) algorithms such as
    - distributed localization
    - distributed tracking

Some photos...



Thanks

Thanks for your attention

Any Questions?