MOBILE TRACKING USING UKF, TIME MEASURES AND LOS-NLOS EXPERT KNOWLEDGE

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ABSTRACT

The main difficulty for the location of terminals in wireless communications systems is the Non Line Of Sight (NLOS) situation caused by obstacles in the transmitted signal path, between the base stations and the user equipment. This NLOS situation biases TDOA measures, resulting in a biased final position. However, not all of the base stations may be in NLOS. Determining which base stations are in LOS can improve the accuracy of the system. It is feasible to estimate the reliability of the measures through the study of signal parameters like the delay spread, received power or previous position estimates. The objective of this paper is to analyze the improvements in positioning accuracy by tracking the terminal with an unscented Kalman filter (UKF) incorporating knowledge of NLOS-LOS situation. The evaluation of the approach has been carried out with measures taken in real scenarios.[1]

1. INTRODUCTION

The objective is to estimate the position of the mobile using the pilot signals sent by several base stations. We assume that all base stations transmit the pilot signal synchronously, or that they are non-synchronized base stations but the delay between transmitting times is known. The mobile is not synchronized with the BS, so this transmitting time is unknown by the terminal. Using the high resolution timing estimator presented in [1][2], the relative time of arrival (RTOA) can be estimated combating the multipath problem, but not the NLOS. The simplification of this problem to TDOA measures, subtracting two RTOA measurements, has been widely studied [3][4][5]. Normally the observation errors of different TDOA measurements sharing the same BS are assumed independent, but they aren't. In this paper we consider another point of view. We estimate, jointly with the position, the transmitting time, so all RTOA measurements can be considered as TOA estimates, thus avoiding the TDOA problem because each TOA estimate is truly independent from others.

The position and transmitting time are tracked using an unscented Kalman filter (UKF) [6]. This linearization method has a complexity of the order of the extended Kalman filter (EKF), but is more suitable for non-linear systems. The most important innovation of this document is the addition of expert knowledge of LOS-NLOS to the UKF. Alternative approaches are based on Monte Carlo methods (particle filters), which can provide a better solution, at the cost of a much higher computational effort [7][8].

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2. MODEL

The model is composed by the state and observation equations. The only restriction for using the UKF is that all the random variables must be Gaussian (GRV) [6]. The linearity of the state and observation equations doesn't matter.

2.1. State Equation

The state vector is composed of:

$$\mathbf{s}_k = \left[p_x(k) \quad p_y(k) \quad v_r(k) \quad v_\varphi(k) \quad \tau_0(k) \right]^T \tag{1}$$

where p_x and p_y are the coordinates of the mobile position; v_r and v_φ are the radial and angular velocity respectively; and τ_0 is the pilot signal transmitting time.

The state equations are:

$$\begin{aligned} v_r(k+1) &= v_r(k) + n_r(k+1) \\ v_\varphi(k+1) &= v_\varphi(k) + n_\varphi(k+1) \\ \tau_0(k+1) &= \tau_0(k) + n_\tau(k+1) \\ p_x(k+1) &= p_x(k) + v_r(k+1)\cos\left(v_\varphi(k+1)\right) \\ p_y(k+1) &= p_y(k) + v_r(k+1)\sin\left(v_\varphi(k+1)\right) \end{aligned} \tag{2}$$

where n_r, n_φ and n_τ are GRV. All these state equations are summarized in:

$$\mathbf{s}_{k+1} = \mathbf{f}_s\left(\mathbf{s}_k, n_r, n_\varphi, n_\tau\right) \tag{3}$$

where $\mathbf{f}_s(\cdot)$ is a non-linear function.

2.2. Observation Equation

The observation vector is composed of the RTOA measurements for each base station:

$$\mathbf{y}_k = \left[y_1(k) \quad \cdots \quad y_N(k) \right]^T \tag{4}$$

The equation for each measurement is:

$$y_i(k) = F\left(m_i(k)\right) + \tau_0(k) + \sqrt{\left(X_i - p_x(k)\right)^2 + \left(Y_i - p_y(k)\right)^2} \tag{5}$$

where y_i is the measured RTOA in equivalent meters; X_i and Y_i are the base station coordinates; m_i is a GRV (mean 0, variance 1) that determines the observation error; and $F(\cdot)$ is a function that accommodates the pdf of the noise to the LOS-NLOS situation and the timing estimator used. The result $F(m_i(k))$ is in fact a non-gaussian random variable, but the use of this function is needed because the UKF assumes the gaussianity of the input variables [6].

The set of all observation equations can be summarized in:

$$\mathbf{y}_k = \mathbf{f}_0(\mathbf{s}_k, m_1, \ldots, m_N) \quad (6)$$

where $\mathbf{f}_0(\cdot)$ is a non-linear function.

The complete noise vector is:

$$\mathbf{n}_k = \begin{bmatrix} n_r(k) & n_\varphi(k) & n_\tau(k) & m_1(k) & \cdots & m_N(k) \end{bmatrix}^T \quad (7)$$

2.3. The F function

The $F(\cdot)$ function varies depending if the base station is in LOS or NLOS and the RTOA estimator used. For the timing estimator used [1] we determined empirically (from real data) the pdf's corresponding to these two cases. More important than the function itself is the PDF of $F(m_i(k))$ where $m_i(k)$ is a GRV (mean 0, variance 1).

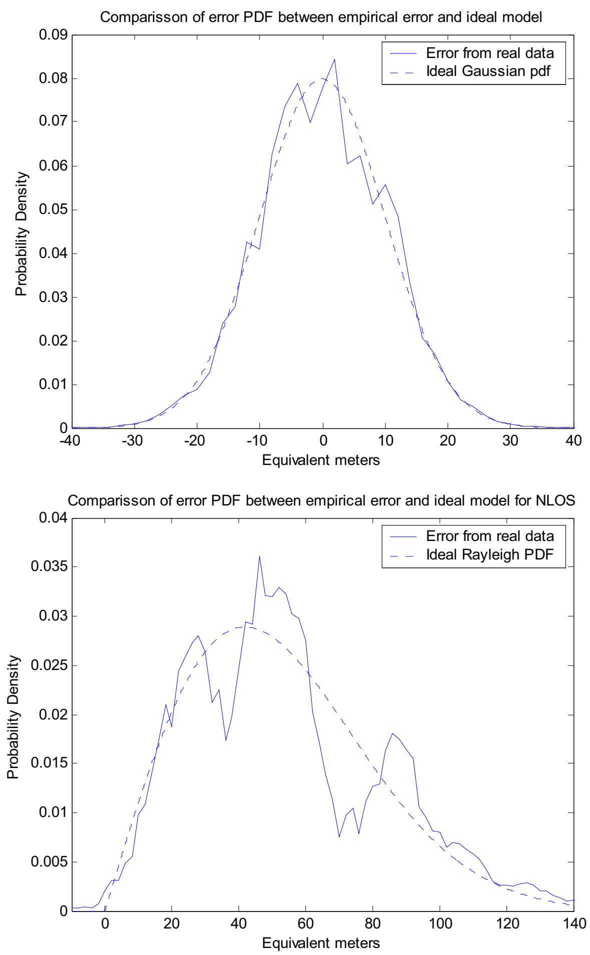

Figure 1. Representation of the F function pdf for the NLOS and LOS cases.

For the LOS case, the pdf selected is gaussian, with mean 0, thus the F function is only a scalar factor. The variance depends on the SNR. For the NLOS case the pdf selected is Rayleigh:

$$P_{F_{NLOS}(n_i)}(\tau) = \frac{\tau e^{-\tau^2/2s^2}}{s^2} \quad (8)$$

and the parameter s depends on the propagation scenario. For our experiments with real data we established $s = 42$. Figure 1 compares the selected pdf's and a histogram of the RTOA estimation error in both LOS and NLOS cases, obtained from real data.

These functions are determined for our environment (mainly suburban) and our estimator. Other environments or other estimators, may have different pdf's associated.

3. STANDARD UKF

We present a brief description of the UKF based on [6] for better understanding of the document.

Let the general vector be:

$$\mathbf{x}_k = \begin{bmatrix} \mathbf{s}_k \\ \mathbf{n}_k \end{bmatrix} \quad (9)$$

All the random variables contained in this vector are GRV. The objective is to obtain the prediction of the observation vector $\mathbf{y}_k$ from $\mathbf{x}_k$. The unscented transformation is a method that allows us to calculate the statistics of a random variable which undergoes a non-linear transformation $\mathbf{y}_k = g(\mathbf{x}_k)$. The methods consists on calculating the set of sigma points $\boldsymbol{\mathcal{X}}_k$ associated with $\mathbf{x}_k$; obtain the observation sigma set from $\boldsymbol{\mathcal{Y}}_k = g(\boldsymbol{\mathcal{X}}_k)$; and finally estimate the statistics of $\mathbf{y}_k$.

3.1. Form of the sigma set

Assume $\mathbf{x}_k$ has mean $\bar{\mathbf{x}}_k$ and covariance $\mathbf{P}_{\mathbf{x}_k}$. The associated sigma set $\boldsymbol{\mathcal{X}}_k$ is a matrix composed of $2L+1$ column vectors $\mathcal{X}_{k,i}$, called sigma points, according to the following:

$$\begin{aligned} \mathcal{X}_{k,0} &= \bar{\mathbf{x}}_k \\ \mathcal{X}_{k,i} &= \bar{\mathbf{x}}_k + \left(\sqrt{(L+\lambda)\mathbf{P}_{\mathbf{x}_k}}\right)\Big|_i \qquad i = 1,\ldots,L \\ \mathcal{X}_{k,i} &= \bar{\mathbf{x}}_k - \left(\sqrt{(L+\lambda)\mathbf{P}_{\mathbf{x}_k}}\right)\Big|_{i-L} \qquad i = L+1,\ldots,2L \end{aligned} \quad (10)$$

where $\lambda = \alpha^2 L - L$ is a scaling parameter. α determines the spread of the sigma points. We use $\alpha = 10^{-3}$. This transform is represented as:

$$\left\langle \bar{\mathbf{x}}_k, \mathbf{P}_{\mathbf{x}_k} \right\rangle \xrightarrow{UT} \boldsymbol{\mathcal{X}}_k \quad (11)$$

In the case of independent noise variables, the covariance of each one only affects two sigma points as stated in (10). So the pdf of each variable is characterized by only three sigma points, two from the covariance, and one from the mean.

3.2. Obtain the statistics from a sigma set

The previous sigma set can be passed through a non-linear function, obtaining a new sigma set $\boldsymbol{\mathcal{Y}}_k$. The mean and covariance of the associated $\mathbf{y}_k$, are computed from the sigma points weighted by:

$$\begin{aligned} W_0^{(m)} &= \lambda/(L+\lambda) \\ W_0^{(c)} &= \lambda/(L+\lambda) + (3-\alpha^2) \\ W_i^{(m,c)} &= 1/\left(2(L+\lambda)\right) \quad , \quad i \neq 0 \end{aligned} \quad (12)$$

So, the result is:

$$\bar{\mathbf{y}}_k = \sum_{i=0}^{2L} W_i^{(m)} \mathcal{Y}_{k,i}$$
$$\mathbf{P}_{\mathbf{y}_k} = \sum_{i=0}^{2L} W_i^{(c)} \left(\mathcal{Y}_{k,i} - \bar{\mathbf{y}}_k\right)\left(\mathcal{Y}_{k,i} - \bar{\mathbf{y}}_k\right)^T \tag{13}$$

This operation is represented as:

$$\boldsymbol{\mathcal{Y}}_k \xrightarrow{UT^{-1}} \left\langle \bar{\mathbf{y}}_k, \mathbf{P}_{\mathbf{y}_k} \right\rangle \tag{14}$$

3.3. UKF equations (initialization)

The previous statistics are:

$$\bar{\mathbf{s}}_0 = E\{\mathbf{s}_0\}$$
$$\mathbf{P}_{\mathbf{s}_0} = E\left\{\left(\mathbf{s}_0 - \bar{\mathbf{s}}_0\right)\left(\mathbf{s}_0 - \bar{\mathbf{s}}_0\right)^T\right\} \tag{15}$$
$$\mathbf{P}_{\mathbf{n}} = E\left\{\mathbf{n}\mathbf{n}^T\right\}$$

Then we obtain the initial statistics as:

$$\bar{\mathbf{x}}_0 = \begin{bmatrix} \bar{\mathbf{s}}_0^T & \mathbf{0} \end{bmatrix}^T$$
$$\mathbf{P}_0 = \begin{bmatrix} \mathbf{P}_{\mathbf{s}_0} & \mathbf{0} \\ \mathbf{0} & \mathbf{P}_{\mathbf{n}} \end{bmatrix} \tag{16}$$

It is possible to compute the sigma set associated with this vector.

3.4. UKF equations (loop)

For each iteration we compute the sigma set as:

$$\left\langle \bar{\mathbf{x}}_{k-1}, \mathbf{P}_{k-1} \right\rangle \xrightarrow{UT} \boldsymbol{\mathcal{X}}_{k-1} \tag{17}$$

The sigma set can be expressed as:

$$\boldsymbol{\mathcal{X}}_{k-1} = \begin{bmatrix} \boldsymbol{\mathcal{X}}_{k-1}^{\mathbf{s}} \\ \boldsymbol{\mathcal{X}}_{k-1}^{\mathbf{n}} \end{bmatrix} \tag{18}$$

separating the parts of the state vector and the noise vector.

Now the Kalman filter must be computed over the sigma set. First, predict the next state from the previous state:

$$\boldsymbol{\mathcal{X}}_{k|k-1}^{\mathbf{s}} = \mathbf{f}_s\left(\boldsymbol{\mathcal{X}}_{k-1}\right)$$
$$\boldsymbol{\mathcal{X}}_{k|k-1}^{\mathbf{s}} \xrightarrow{UT^{-1}} \left\langle \bar{\mathbf{s}}_{k|k-1}, \mathbf{P}_{\mathbf{s}_{k|k-1}} \right\rangle \tag{19}$$

Second, predict the observation from the state:

$$\boldsymbol{\mathcal{Y}}_{k|k-1} = \mathbf{f}_o\left(\boldsymbol{\mathcal{X}}_{k|k-1}^{\mathbf{s}}, \boldsymbol{\mathcal{X}}_{k-1}^{\mathbf{n}}\right)$$
$$\boldsymbol{\mathcal{Y}}_{k|k-1} \xrightarrow{UT^{-1}} \left\langle \bar{\mathbf{y}}_{k|k-1}, \mathbf{P}_{\mathbf{y}_{k|k-1}} \right\rangle \tag{20}$$

Third, compute the Kalman gain matrix:

$$\mathbf{P}_{\mathbf{sy}_{k|k-1}} = \sum_{i=0}^{2L} W_i^{(c)} \left(\mathcal{X}_{k|k-1,i}^{\mathbf{s}} - \bar{\mathbf{s}}_{k|k-1}\right)\left(\mathcal{Y}_{k|k-1,i} - \bar{\mathbf{y}}_{k|k-1}\right)^T$$
$$\mathcal{K} = \mathbf{P}_{\mathbf{sy}_{k|k-1}} \mathbf{P}_{\mathbf{y}_{k|k-1}}^{-1} \tag{21}$$

Finally, estimate the statistics of the state, and the general vectors:

$$\bar{\mathbf{s}}_k = \bar{\mathbf{s}}_{k|k-1} + \mathcal{K}(\mathbf{y}_k - \bar{\mathbf{y}}_{k|k-1}) \quad \bar{\mathbf{x}}_k = \begin{bmatrix} \bar{\mathbf{s}}_k^T & \mathbf{0} \end{bmatrix}^T$$
$$\mathbf{P}_{\mathbf{s}_k} = \mathbf{P}_{\mathbf{s}_{k|k-1}} - \mathcal{K}\mathbf{P}_{\mathbf{y}_{k-1}}\mathcal{K}^T \qquad \mathbf{P}_k = \begin{bmatrix} \mathbf{P}_{\mathbf{s}_k} & \mathbf{0} \\ \mathbf{0} & \mathbf{P}_{\mathbf{n}} \end{bmatrix} \tag{22}$$

3.5. Observation function

The $F(\cdot)$ function, contained in $\mathbf{f}_0(\cdot)$ (5), must be defined. This function depends on the LOS-NLOS situation. There are two easy solutions:

1. Predict the LOS-NLOS situation in absolute terms, and apply the corresponding function.
2. Predict the percentage of LOS-NLOS probability and combine the two functions according to this percentage.

The first solution is very easy to implement. However it is not normally easy to determine the LOS or NLOS situation. The second solution is not as easy to implement, but is much more accurate. The problem is that the $F(\cdot)$ function becomes too complex to be characterized with only three sigma points (10), because it only depends on one random variable: $m_i(k)$, as stated in (5).

4. IMPROVED UKF

To avoid the $F(\cdot)$ characterization problem, we propose to create a pseudo-sigma set with twice the number of sigma points, providing a better resolution.

Separate the $\mathbf{f}_0(\cdot)$ function (6) into its components:

$$\mathcal{Y}_{k|k-1}^{(i)} = f_{o_i}(\boldsymbol{\mathcal{X}}_{k|k-1}^{\mathbf{s}}, \boldsymbol{\mathcal{X}}_{k-1}^{\mathbf{n}}) \tag{23}$$

where $\mathcal{Y}_{k\backslash k-1}^{(i)}$ is the i row vector of $\boldsymbol{\mathcal{Y}}_{k|k-1}$.

Let's consider $f_{o_i}^{(LOS)}(\cdot)$ the function associated with the LOS case, and $f_{o_i}^{(NLOS)}(\cdot)$ the NLOS one. Let's form a double sized sigma set like:

$$\mathcal{Y}_{k|k-1}^{(LOS)(i)} = W_{i,k}^{(LOS)} f_{o_i}^{(LOS)}(\boldsymbol{\mathcal{X}}_{k|k-1}^{\mathbf{s}}, \boldsymbol{\mathcal{X}}_{k|k-1}^{\mathbf{n}})$$
$$\mathcal{Y}_{k|k-1}^{(NLOS)(i)} = W_{i,k}^{(NLOS)} f_{o_i}^{(NLOS)}(\boldsymbol{\mathcal{X}}_{k|k-1}^{\mathbf{s}}, \boldsymbol{\mathcal{X}}_{k|k-1}^{\mathbf{n}}) \tag{24}$$
$$\mathcal{Y}_{k|k-1}^{(i)} = \begin{bmatrix} \mathcal{Y}_{k|k-1}^{(LOS)(i)} & \mathcal{Y}_{k|k-1}^{(NLOS)(i)} \end{bmatrix}$$

where $W_{(i)}^{(LOS)}$ is the probability of LOS for the i base station. The new sigma set $\boldsymbol{\mathcal{Y}}_{k|k-1}$ is not strictly a sigma set, in the sense that its rows are previously weighted and it has twice the sigma points. In order to perform the inverse unscented transform for this particular pseudo-sigma set, the weights from 0 to $2L$ are the same as in (12), and from $2L+1$ to $4L+2$ are:

$$W_i^{(c,m)} = W_{i-2L+1}^{(c,m)} \tag{25}$$

From (13), the result of the inverse unscented transform is:

$$\bar{\mathbf{y}}_{k|k-1} = \sum_{i=0}^{4L+2} W_i^{(m)} \mathcal{Y}_{k|k-1,i}$$
$$\mathbf{P}_{\mathbf{y}_{k|k-1}} = \sum_{i=0}^{4L+2} W_i^{(c)} \left(\mathcal{Y}_{k|k-1,i} - \bar{\mathbf{y}}_{k|k-1}\right)\left(\mathcal{Y}_{k|k-1,i} - \bar{\mathbf{y}}_{k|k-1}\right)^T \tag{26}$$

The result is to obtain six sigma points to determine the $F(\cdot)$ function, three associated with the LOS case and three associated with the NLOS case, providing a better characterization of the $F(\cdot)$ function.

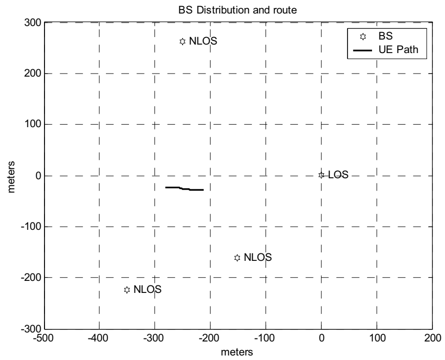

Figure 2. Base Stations distribution.

5. EVALUATION IN REAL SCENARIO

To finally evaluate the presented approach, it was tested in a real UMTS scenario. The measurement equipment is composed of transmitters and receiver working at the 1.8 GHz band, bandwidth of 5 MHz. A GPS is used in the mobile to provide an offline comparison measure.

The transmitted signal is a constant power pilot signal, composed of 256 chips shaped with a root-raised cosine. The number of channels estimates is around 800 per second (determined by the test-bed DSP capacity).

The received SINR can be determined as:

$$SINR(dB) = S_{pilot}(dBm) + \alpha(dB) - S_{other}(dBm) \qquad (27)$$

where S_{pilot} is the received pilot signal power, α a processing gain factor and S_{other} the intracell and intercell total interfering power. The α gain factor depends on the number of slots used for the channel estimation [9]:

Slots used	4	2	1	½	¼
$\alpha(dB)$	35	32	29	26	23

Extra noise is added in order to emulate the effect of interfering signals (S_{other}).

Figure 2 shows the base station distribution and the mobile path for our experiments with real data. The BS's marked with NLOS are in this situation for more than 80 % of the time.

Figure 3 compares the proposed approach, a basic UKF and a EKF. The four considered cases are:

1. The improved UKF approach with LOS-NLOS expert knowledge.
2. The basic UKF with expert LOS-NLOS knowledge.
3. A basic EKF solution where its noise variances are determined from the LOS-NLOS expert knowledge. This EKF implementation is explained in [3].
4. A static MSE estimator solution without tracking.

Due to the non-linear nature of the state and measurement equations, the EKF may diverge. To obtain the RMSE of Figure 3 the diverging solutions have been discarded, because of their aberrant nature. It's important to point that the EKF diverges on 30 % of the experiments in front of a never diverging UKF.

The RMSE and standard deviance have been computed as:

$$RMSE = \sqrt{E\left\{\|\boldsymbol{\varepsilon}\|_2^2\right\}}$$
$$\sigma_\varepsilon = \sqrt{E\left\{\left(\|\boldsymbol{\varepsilon}\|_2 - RMSE\right)^2\right\}} \qquad (28)$$

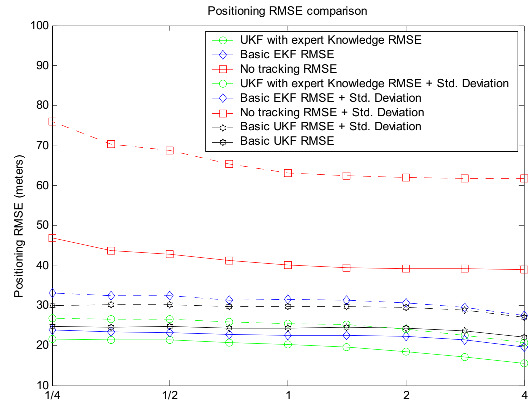

Figure 3: Comparison between different tracking algorithms.

6. CONCLUSIONS

In this paper a mobile location system with LOS-NLOS expert knowledge has been proposed and evaluated in real UMTS scenarios. RTOA measures are estimated from the pilot channel using a high resolution timing method. A novel UKF has been presented to track the source and benefit from the expert knowledge of LOS-NLOS situation. The method has a better behavior than EKF or UKF tracking, demonstrating a non-divergent and more accurate solution with the same computational cost.

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