AN UNSCENTED KALMAN FILTER BASED MAXIMUM LIKELIHOOD RATIO FOR NLOS BIAS DETECTION IN UMTS LOCALIZATION

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ABSTRACT

In this paper, a new location tracker for cellular networks in mixed line-of-sight (LOS)/non-line-of-sight (NLOS) environments is presented. NLOS situations result in biased UMTS measurements such as Time of Arrival (TOA) or Angle of Arrival (AOA), hence in erroneous position estimates. We propose to consider NLOS as abrupt changes affecting the UMTS system which can be identified by fault detection and isolation (FDI) algorithms such as the generalized likelihood ratio (GLR) or the marginalized likelihood ratio (MLR). As the measurements depend on the mobile location in a non linear way, we present an Unscented Kalman filter based MLR to jointly identify the biased measurements and track the mobile position. Numerical results show that the developped method improves localization accuracy with a reasonable computational cost.

1. INTRODUCTION

The rapid development of wireless communications leads to more and more integrated services for the user. Among them, radiolocation has received a great deal of interest over the past few years. As an alternative to the Global Positioning System (GPS), cellular networks can be directly used to provide localization services. In such a case, the position of a mobile user in a geographical area is estimated through parameter measurements of signals propagated between the mobile and a set of cellular base stations (BS). The propagation parameters can be received signal strength (RSS), angles of arrival (AOA), times of arrival (TOA), time differences of arrival (TDOA), or their combination.

Because of their sensibility to the considered path loss attenuation model, the RSS-based approaches have been proved to be less accurate than TOA or TDOA approaches in high dynamic systems [10]. The TOA method exploits the measurement of the line-of-sight propagation delay. The transmitter/receiver distance is obtained by multiplying this time measurement by the speed of the light. To avoid the communication of the BS location to the mobile and to eliminate the clock bias, one can take TDOA measures, which are related to the relative distances between the mobile and several BS. Nevertheless, the performance of these two latter methods depends mainly on the synchronization accuracy. As an alternative, the AOA technique estimates the mobile location by first measuring the AOA of a signal from the mobile at several BS by using antenna arrays. Contrary to the above-mentioned methods which require at least three BS, two BS for positioning suffices for AOA-based positioning.

On the basis of these measurements, the mobile location is then obtained by trilateration. In the case of TOA for instance, the distance measurements define a circle around each BS. When the measures are noise-free, these circles intersect at a unique point which represents the mobile location. However, in pratice, only noisy measurements are available and one has only access to the location that best fits the measurements. When the signal follows a direct path between the mobile and the BS, the noise is a white Gaussian random variable. However, most of the time, no direct path exists. This leads to non-line-of-sight (NLOS) positive additive biases which corrupt the mobile location estimates. To mitigate Universal Mobile Telecommunications System (UMTS) positioning errors, several NLOS identification techniques have been investigated.

Among them, Woo et al. [5] have proposed to identify NLOS errors by comparing the standard deviation of range measurements with a detection threshold. Another method presented in [6] consists of carrying out a time-history based hypothesis test by considering a consecutive sequence of range measurements. More effective hypothesis tests have been developped based on measurement error models. Thus, in Borras et al. [7], the NLOS error is modeled as a non-zero mean Gaussian random variable (RV) and a decision theoretical framework for NLOS identification is presented based on a likelihood ratio test. However, all these approaches assume that a great number of measurements corresponding to the same hypothesis, namely LOS or NLOS, are available. Besides, the range variation between these measurements has to be negligible.

To avoid imposing a NLOS error distribution, Chen et al. [8] have developped a residual weighting algorithm respectively for an AOA and a TOA location system. This approach requires to compute the weighted residuals from the least-square location estimates over each range measurement combination. The final location estimate is the linear combination of the least-square location estimates weighted inversely to their residuals. However, this heuristic method needs a great number of BS and need to consider all the possible range measurement combinations.

More recently, Grosicki et al. [1] have proposed to select the most reliable set of three TOA measurements in the sense of the minimisation of a criterion. This latter is chosen as the square error between all the BS distance measurements and their least-square estimates from each possible 3-uplet of TOA measurements. This method has the advantage of requiring less BS than the above-mentioned ones, but does not take into account information from the past measurements.

To take advantage of the measurement time-history, Najar et al. [3] introduce a state model for the mobile location. As the TOA measurements depend on the mobile location in a non linear way, they propose a tracking method based on an Extended Kalman filter (EKF). The main contribution of this work is the joint estimation of both the position unknown and the bias on the measurements. More recently, Huerta et al. [2] have proposed a joint tracker of the NLOS situation and the mobile position by a Rao-Blackwellized Particle filter.

In this paper, the NLOS errors are considered as mean jumps affecting the measurements. Therefore, we apply a sequential Fault Detection and Isolation (FDI) technique to jointly identify the measures in NLOS and track the mobile position. Similary to [3] and [2], we make use of the measurement correlation through time to improve detection, but we do not estimate the NLOS error amplitude. Most FDI algorithms apply to linear dynamic system such as the well-known Generalized Likelihood Ratio (GLR) first presented in [13] and more recently the Marginalized Likelihood Ratio (MLR) presented by Gustafsson [14]. Such methods have been extended to weakly non linear systems by carrying out local linearizations. As an alternative, the use of particle filtering for FDI has also been investigated lately but turns out to be quite costly [11]. This work proposes an Unscented Kalman filtering (UKF) based MLR approach to jointly identify the NLOS measurements and track the mobile position.

The remainder of the paper is organized as follows. The system model is detailed in section 2. In section 3, the UKF-based FDI method is described. Finally, in section 4, the relevance of the proposed algorithm is illustrated by simulation results.

2. SYSTEM DESCRIPTION

Let us focus our attention on the localization of a mobile on a wideband CDMA cellular system. We assume that an adaptive antenna array is available at all the N_B BS and that these latter are synchronized between them and with the mobile to be located. At any time, this mobile can receive pilot signals from its home BS and at least two neighboring BS. We consider two types of measurements for location purposes :

- The TOA can be measured as the position of the first peak of the autocorrelation function of the propagation channel coefficients. The latter are classically provided by the RAKE receiver which carries out intercorrelations of the received signal with delayed versions of the pilot sequence. In pratice, with respect to Nokia measurement results, the TOA are corrupted by estimation noises with a standard deviation equal to 150m [6].
- As for the AOA, the BS steers its adaptive antenna spot beam to track the dedicated pilot signal from the mobile for improved reception. This provides the arriving azimuth angle of the signal from the mobile. In a macrocell environment, the AOA measurements can be obtained with an accuracy of a few degrees [9].

Under these considerations, the generalized location observation equation in matrix form is given by:

$$z(t) = f\left(p(t)\right) + n(t) + \nu(t) \tag{1}$$

where $z(t) = [z_1(t) \cdots z_{N_B}(t)]^T$ denotes the $N_B \times 1$ measurement vector stacking the measurements obtained from the N_B BS. The vector $p(t) = [x_M(t)\ y_M(t)]^T$ is composed of the two-dimensional mobile coordinates in a planar frame of reference. $f\left(p(t)\right)$ is a non linear function of the mobile coordinates. $n(t) = [n_1(t) \cdots n_{N_B}(t)]^T$ is the zero-mean Gaussian noise vector of covariance matrix $Q = \sigma^2 I_{N_B \times N_B}$ and $\nu(t) = [\nu_1(t) \cdots \nu_{N_B}(t)]^T$ is the NLOS error vector. If the l^{th} BS is in LOS, then $\nu_l(t) = 0$, otherwise $\nu_l(t)$ is a time-correlated RV [2].

- For TOA measurements, denoted $\{\tau_l(t)\}_{l=1,\,\cdots,\,N_B}$, one has:

$$z_l(t) = c\tau_l(t) = \sqrt{(x_M(t)-x_l)^2 + (y_M(t)-y_l)^2} + n_l(t) + \nu_l(t), \tag{2}$$

with c the speed of light and $\{x_l,\ y_l\}$ are the l^{th} BS coordinates.

- For AOA measurements, denoted $\{\theta_l\}_{l=1,\,\cdots,\,N_B}$, one has:

$$z_l(t) = \theta_l(t) = \arctan\left(\frac{y_M(t)-y_l}{x_M(t)-x_l}\right) + n_l(t) + \nu_l(t) \tag{3}$$

In addition to these observation equations, a state model is required to use a sequential estimation algorithm such as a Kalman or a particle filter. The choice of the model directly depends on the kinetics of the mobile user. Classical motion models used in navigation and tracking are presented for instance in [15]. In a general manner, they can be written:

$$x(t) = Ax(t-1) + u(t), \tag{4}$$

where $x(t)$ is the so-called state vector, the components of which are the parameters of interest, A is a square matrix, and $u(t)$ is the state noise, assumed white and Gaussian with covariance matrix Σ.

If the mobile user moves slowly, a 1^{st} order model can be used and $x(t) = p(t)$. If its velocity $v(t)$ changes through time, it is appended to the state vector and $x(t) = \left[p(t)^T, v(t)^T\right]^T$, resulting in a 2^{nd} order model.

In equations (2) and (3), the TOA and AOA measurements are related to the position in a non linear way. Therefore, a particle filter could be used to track the mobile position, but the associated computational cost is considered excessive. A low-cost solution consists in linearizing the system by using an EKF. Nevertheless, this method involves the calculation of derivatives and is only accurate to the 1^{st} order. The EKF solution may diverge when the system is highly non linear. A better approximation can be obtained by combining Kalman filter equations with the Unscented transform (UT) to propagate the mean and the covariance through the non-linearities [4]. Contrary to the EKF, this so-called Unscented Kalman filter (UKF) is accurate to 2^{nd} order with a similar computational cost. The principle of this method is recalled in the next section.

3. UKF STATE ESTIMATION

Similarly to the EKF, the UKF computes a Gaussian approximation of the distribution of the state vector conditionnally upon the observations $p\left(x(t)|z_{1:t}\right)$, where in the sequel $z_{l:p} = [z(l) \ldots z(p)]^T$. However, the UKF directly estimates the mean and covariance matrix of this distribution by using the Unscented Transform (UT).

3.1 UT principle

The UT is a deterministic sampling technique whereby a finite set of carefully chosen sample points are used to capture the statistics of a RV. The principle is the following. Assume X is a random vector of dimension L which is transformed into the vector Y:

$$Y = g(X),$$

where g is a non linear mapping.

If X is Gaussian and $\bar{X}$ and P_X denote its mean and covariance matrix respectively, the sigma points describing the distribution of X are obtained as:

$$\begin{aligned}
\chi_i &= \bar{X}, \text{ for } i = 0, \\
\chi_i &= \bar{X} + \left((L+\lambda)P_X\right)_i, \text{ for } i = 1, \ldots, L \\
\chi_i &= \bar{X} - \left((L+\lambda)P_X\right)_i, \text{ for } i = L+1, \ldots, 2L,
\end{aligned}$$

with λ is a scaling parameter the purpose of which is to refine the approximation of the higher order moments.

The corresponding UT weights are computed as :

$$\begin{aligned}
W_0^m &= \lambda/(L+\lambda), \\
W_0^c &= \lambda/(L+\lambda) + (1-\alpha^2+\beta), \\
W_i^c &= W_i^m = 1/\left\{2(L+\lambda)\right\},
\end{aligned}$$

where the choice of α and β is an open problem discussed for instance in [4].

Two sets of weights are required, one to compute mean estimates and the other dedicated to covariance estimates. Then, these sigma points are propagated through g to yield the *posterior* sigma points $\Upsilon_i = g(\chi_i)$ for $i = 1, \ldots, 2L+1$. Finally, the 1^{st} and 2^{nd} order statistics of Y can be approximated as:

$$\begin{aligned}
\bar{Y} &= \sum_{i=0}^{2L} W_i^c \Upsilon_i, \\
P_Y &= \sum_{i=0}^{2L} W_i^m \left(\Upsilon_i - \bar{Y}\right)\left(\Upsilon_i - \bar{Y}\right)^T.
\end{aligned}$$

3.2 Application of UKF to UMTS localization

The UKF can be viewed as a recursive application of the UT to a RV composed both of the state vector components and the measurement and state noises: $X(t) = [x(t), u(t), n(t)]$ in our case. The mean and covariance matrices computed this way are then incorporated to the standard Kalman filter equations to obtain the UKF formulation.

Thus, assuming the NLOS bias vector is known, the UKF provides at each time step a Gaussian approximation of the state distribution:

$$p\left(x(t)|z_{1:t}, \nu_{1:t}\right) \simeq \mathcal{N}\left(\bar{x}^{\nu}(t), P_{xx}^{\nu}(t)\right), \qquad (5)$$

with $\bar{x}^{\nu}(t)$ the state estimate at time t and $\mathcal{N}(\mu, \Sigma)$ is a Gaussian distribution the mean and the covariance of which are respectively equal to μ and Σ.

In the meantime, the UKF estimates the probability of observing measurement $z(t)$ conditionnal upon the values of the bias $\nu_{1:t}$ and the previous observations $z_{1:t-1}$:

$$p\left(z(t)|z_{1:t-1}, \nu_{1:t}\right) \simeq \mathcal{N}\left(\bar{z}^{\nu}(t), P_{zz}^{\nu}(t)\right). \qquad (6)$$

We describe hereafter a FDI approach based on these statistics to cope with the NLOS biases.

4. UKF BASED FDI

4.1 Problem formulation

In this paper, we propose to consider NLOS as mean jumps affecting the UMTS localization measurements, either TOA or AOA. Detection of the induced biases is performed by deciding between multiple competing hypotheses at each time step t:

$$\begin{aligned} \mathrm{H}_0(t) &: \text{ all BS are in LOS} \\ \mathrm{H}_1(t,k) &: \text{ some of the BS are in NLOS from time } k \leq t \end{aligned}$$

In accordance with the previous notations, the bias vector $\nu(t)$ is null under $\mathrm{H}_0(t)$ hypothesis whereas at least one of its components has taken a strictly positive value otherwise. This formulation allows delayed detection of small biases which would gradually drag off the UKF estimates.

In a general manner, FDI is made difficult for the available measurements depending on the unknown system state vector. Existing approaches in the litterature proceed either by marginalization or estimation. When the studied dynamic system is linear Gaussian, the marginalization is analytically tractable leading to various approaches which monitors the residuals of the estimation filter. One of the most popular algorithm is the Generalized Likelihood Ratio (GLR) which applies when the system state is estimated by a Kalman filter. This algorithm uses the KF innovations as residuals to carry out hypothesis testing. In [14], Gustafsson has proposed the marginalized likelihood ratio (MLR) as an alternative more robust to modeling errors. Such methods have been extended to weakly non linear systems by applying local linearization schemes. An Extended Kalman filter is then used in place of the classical Kalman filter for state estimation. This work extends the MLR to non linear systems by taking advantage of UKF techniques to avoid the linearization step. The proposed algorithm is detailed hereafter.

The MLR makes decisions on the basis of the following log-likelihood ratio (LLR) in accordance with Neyman-Pearson lemma:

$$T(t,k) = -2\ln\frac{p\left(z_{1:t}|\mathrm{H}_1(t,k)\right)}{p\left(z_{1:t}|\mathrm{H}_0\right)}. \qquad (7)$$

By applying Bayes rule, this LLR can be written in a more compact manner:

$$T(t,k) = -2\ln\frac{p\left(z_{k:t}|\mathrm{H}_1(t,k), z_{1:k-1}\right)}{p\left(z_{k:t}|\mathrm{H}_0, z_{1:k-1}\right)}. \qquad (8)$$

One of the difficulty to compute this quantity is the unknown bias value ν under H_1 hypothesis. It can be reasonably assumed that the detection delay is small enough so that the bias is constant during time interval $[k,t]$. The GLR substitutes this nuisance parameter for its ML estimate. One of the original idea of the MLR is to eliminate ν by marginalization. More precisely:

$$p(z_{k:t}|\mathrm{H}_1(t,k), z_{1:k-1}) \simeq \int p(z_{k:t}|\nu, k, z_{1:k-1})p(\nu)d\nu, \qquad (9)$$

where $p(z_{k:t}|\nu, k, z_{1:k-1})$ is the likelihood function for a bias ν affecting the observation vector from time k to t.
The decision rule then takes the form:

- Selection of the best change time candidate

$$\hat{k} = \arg\max_{k} T(t,k), \qquad (10)$$

- Thresholding

$$s_t = T(t,\hat{k}) \underset{H_0}{\overset{H_1}{\gtrless}} h, \qquad (11)$$

where s_t is the so-called test statistic and h is the hypothesis test threshold, the choice of which is commented in the sequel.

In the framework of linear Gaussian systems which undergo a mean jump, the impact of ν on the filter residuals can be made explicit. Thus, an analytical expression can be derived for $T(t,k)$ when a convenient prior is chosen for ν. The problem at hand is made more difficult by the non linear measurement equation. The contributions of this paper are twofold. First, we propose to take advantage of the UT to approximate the likelihood function appearing in (9). Second, we run a bank of UKF to yield Gaussian approximations of the predicted measurement distributions under each candidate hypothesis.

4.2 Application of UT to FD

The key idea of the proposed approach is to use UKF to have Gaussian distributed test variables even if the studied system is non linear. Besides, the MLR test statistic computation requires an integration over all possible values of ν, which cannot be performed analytically. As an alternative, we propose to make use of the UT as follows. Assume a set of sigma points associated to the bias RV ν has been generated. If they are denoted $N = \{N_i\}_{i=1:N_\nu}$ and $W_{N_i}^c$ or $W_{N_i}^m$ are the corresponding weights, then the following approximation of expression (9) can be used:

$$p(z_{k:t}|\mathrm{H}_1(t,k), z_{1:k-1}) = \sum_{i=1}^{N_\nu} W_{N_i}^m p(z_{k:t}|N_i, k, z_{1:k-1}), \qquad (12)$$

where $p(z_{k:t}|N_i, k, z_{1:k-1})$ is the probability of observing $z_{k:t}$ if a mean jump of amplitude N_i occurs at time k.

The choice of convenient sigma points is commented later. It should be noted that they can be generated off-line at once before running the FDI algorithm. Assuming k is known and $\nu = N_i$, a Gaussian approximation of the distributions appearing in (12) can be obtained by using UKF. A straightforward solution to compute the test statistic $T(t,k)$ then consists in running as many UKF as bias sigma points and possible values for the NLOS time of occurrence k. Such an approach, though exhaustive, results in an exponentially increasing computational complexity. Similarly to the GLR, we suggest limiting the search to a finite-length window $t - L_w < k \leq 0$.

When implementing the described method, numerical difficulties arise from the direct computation of the LLR. To prevent such difficulties, the mixture of Gaussian distribution in (12) can be merged in a single Gaussian distribution as in the IMM algorithm developped by Bar-Shalom [16]. If applied, this merging provides a simple expression of $T(t,k)$ in the form of:

$$\begin{aligned} \widehat{T}(t,k) = \sum_{p=k}^{t} &(z(p) - \bar{z}^0(p))^T \left(P_{zz}^0(p)\right)^{-1} (z(p) - \bar{z}^0(p)) \\ &- (z(p) - \bar{z}^1(p))^T \left(P_{zz}^1(p)\right)^{-1} (z(p) - \bar{z}^1(p)) + K, \end{aligned} \qquad (13)$$

where :
- K is a constant independant of the observations,
- $\bar{z}^0(p)$ and $P_{zz}^0(p)$ are the predicted observation vector and its associated covariance matrix computed by the UKF under the null

hypothesis,
- $\bar{z}^1(p)$ and $P^1_{zz}(p)$ result from the merging process:

$$\bar{z}^1(p) = \sum_{i=1}^{N_v} W^m_{N_i} \bar{z}^{N_i}(p),$$

$$P^1_{zz}(p) = \sum_{i=1}^{N_v} W^c_{N_i} \left(P^{N_i}_{zz}(p) + (\bar{z}^{N_i}(p) - \bar{z}^1(p))(\bar{z}^{N_i}(p) - \bar{z}^1(p))^T \right),$$

with $\bar{z}^{N_i}(p)$ and $P^{N_i}_{zz}(p)$ the predicted observation vector and its associated covariance matrix when $v = N_i$ as denoted in section 2.

4.3 Application of UT to FI

Along with FD comes FI which consists of identifying the BS in NLOS to pursue navigation with a non-erroneous set of measurements. In this paper, we propose to perform simultaneously FD and FI by taking into account not only the times of appearance of the NLOS biases but also their directions. To study one after the other all the possible LOS/NLOS combinations, we use specific v-sigma points with a limited number of non-zero components corresponding to the considered NLOS directions. By sake of simplicity, we assume only one of the BS can switch from a LOS to an NLOS situation, or reversely, at a given time step. Note that this is a classical hypothesis in the fault diagnosis literature which is satisfied provided NLOS biases do not appear simultaneously on different measurements and provided the detection delay is short enough. Hence, the following families of sigma points are generated:

$$N_{ij} = (0, \ldots, v_i, \ldots, 0)^T, \text{for } i = 1, \ldots, N_v \text{ and } j = 1, \ldots, N_B, \quad (14)$$

where only the j$^{\text{th}}$ component is non zero.
The possible values of v_i are generated by applying the UT sampling technique considering a scalar truncated Gaussian distribution of strictly positive mean. Three different values are thus obtained.
To make identification possible, one LLR is then computed for each possible NLOS direction by restricting the sum in (12) to the j$^{\text{th}}$ subset of sigma-points $\{N_{ij}\}$, for $i = 1, \ldots, N_v$. The resulting test variable, denoted $T_j(t,k)$, stands for the hypothesis of a mean jump affecting the j$^{\text{th}}$ measurement from time k to t. In a second step, before making the decision (11), we select both the best change time candidate and its associated direction j as follows:

$$(\hat{k}, \hat{j}) = \arg\max_{k,j} T_j(t,k).$$

The corresponding test variable $s_t = T_{\hat{j}}(t, \hat{k})$, is finally compared to the test threshold to decide if there is actually a NLOS situation. In this case, measurement j is excluded, at least temporarily since the LOS/NLOS situation evolves very quickly.

5. SIMULATION RESULTS

In this section, we study the relevance of the proposed algorithm on simulated data. A two-dimensional trajectory corresponding to a mobile user moving onto an horizontal plane at a velocity varying around 60 km/h has been generated. This setting corresponds to a classical urban car scenario. The mobile is assumed to communicate with four neighboring BS. The TOA and AOA measurements all along this trajectory have been computed by considering the following noise specifications.

- As for the TOA, the noise has been generated as a zero mean white Gaussian process of standard deviation equal to 150 meters. One measurement is corrupted by a NLOS error from the 24^{th} time step. The amplitude of this introduced bias is chosen to be equal to 1300 meters. These values are coherent with [6].
- When using AOA, the noise is modeled as a zero-mean white Gaussian process with a standard deviation equal to 5 degrees. A NLOS bias of amplitude equal to 20 degrees appears on one measurement from the 24^{th} time step in accordance with [9].

The choice of the test threshold as well as the mean and covariance of the NLOS *a priori* bias distribution deserves further comments. The threshold for a hypothesis test is classically set as a function of a given false detection probability. However, due to the non linear measurement equation, the distribution of the test variable under H_0 hypothesis does not admit a closed-form expression. To overcome this problem, we have estimated the cumulative probability density function of T by running extensive Monte Carlo (MC) simulations corresponding to different realizations of the measurement noise for the reference urban trajectory. The obtained plot for TOA measurements is represented in Figure 1, a similar cumulative probability function has been obtained when dealing with AOA measurements. By using these results, the threshold has been set to ensure a false alarm probability of 0.05.
As for the sigma points N_{ij}, they have been generated according to a truncated non-centered Gaussian distribution $\mathcal{N}(2000, 2000^2/9)$ and $\mathcal{N}(40, 40^2/9)$ for TOA and AOA measurements respectively.

In the following, the proposed results have been obtained by averaging 1000 MC runs. The fault detection/isolation performance is presented in Table 1 in terms of probability of good isolation (P_{GI}), probability of good detection and estimation of the NLOS time of occurrence (P_{GDGE}), probability of good estimation of the NLOS time of occurrence but with a delayed detection (P_{DDGE}), probability of a delayed estimation and detection of the NLOS error time of occurrence (P_{DDDE}) , probability of false detection (P_{FD}) and mean detection delay for the two types of measurements. The proposed FDI algorithm shows good performance in terms of mean detection delay and fault isolation. In particular, the interest of the delayed detection appears for the AOA measurements where it takes on average 1.08s to detect a NLOS error but the time of occurrence is properly recovered 870 out of the 1000 runs.

Finally, the Root Mean Square error (RMSE) for the considered trajectory is illustrated in Figure 2 when considering TOA measurements and in figure 3 when considering AOA ones. The on-line detection/exclusion of the BS in NLOS appears to significantly decrease the estimation error obtained without applying a detection/exclusion procedure (cf. Figures 4 and 5). It should be noted that the RMSE changes through time due to the varying mobile/BS geometry. In addition, the AOA performance can be greatly impaired by sudden changes of dynamics as shown by the rmse peak at time 40 s.

	TOA mesurements	AOA mesurements
P_{GI}	0.988	0.9980
P_{GDGE}	0.892	0.0620
P_{DDGE}	0.0080	0.870
P_{DDDE}	0.0020	0
P_{FD}	0.098	0.0680
mean delay	0.09s	1.0800s

Table 1: Performance of the proposed FDI algorithm.

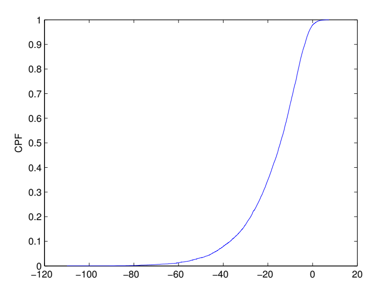

Figure 1: Empirical Cumulative Probability Function (CPF) for T when considering TOA measurements.

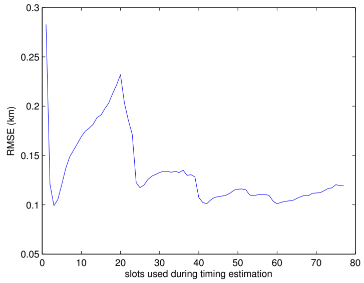

Figure 2: RMSE of the tracking algorithm during the considered trajectory with detection of NLOS TOA errors

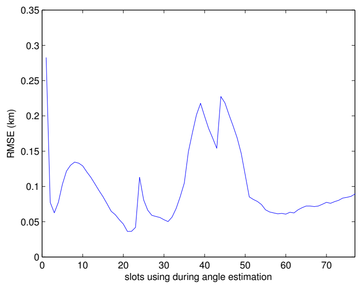

Figure 3: RMSE of the tracking algorithm during the considered trajectory with detection of NLOS AOA errors

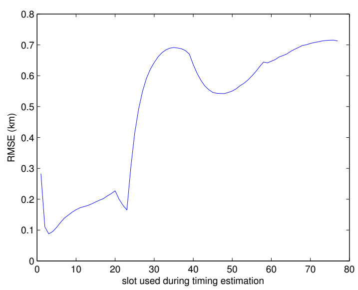

Figure 4: RMSE of the tracking algorithm during the considered trajectory without detection of NLOS TOA errors

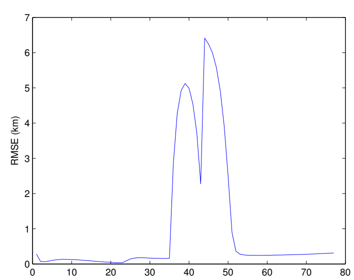

Figure 5: RMSE of the tracking algorithm during the considered trajectory without detection of NLOS AOA errors

6. CONCLUSION

In this paper, a new MLR algorithm based on the UT has been proposed to mitigate NLOS errors in a UMTS positioning system. The developped algorithm has the advantage of simultaneously detecting and correcting the NLOS biases and estimating the mobile dynamics. The on-line procedure is shown in particular to prevent positioning error accumulation. As a perspective, the method should be extended to handle several NLOS errors at a time.

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