NLOS MITIGATION BASED ON A TRELLIS SEARCH FOR WIRELESS LOCATION

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ABSTRACT

Wireless location using Time of Arrival (TOA) and Time-Difference-Of-Arrival (TDOA) measurements has received considerable attention over the last years to be the best selection for cell phone location. The major problem related with these types of measurements is the Non-Line-Of-Sight problem (NLOS) that happens when the direct path between the Base Stations (BSs) and the mobile is blocked. This paper presents a new technique to mitigate the NLOS effect in dynamic scenarios based on a Trellis search of the NLOS state. Numerical simulation shows that the proposed technique outperforms the previous contributions because it is able to detect and reject the NLOS measurements.

1. INTRODUCTION

Wireless location has received considerable attention in the last decades. This is partially motivated by the fact that location algorithms will be mandatory for public cell networks, and partially motivated by the interesting market in position-based services as car-routing or position-based publicity. Another interesting feature is the possible optimization of the network planning based on the position of the terminals.

To estimate the position of the mobile, several techniques have been proposed during the last years. The most successful technique seems to be based on timing measurements such as TOA or TDOA. The advantages of using these observations are that the accuracy achieved is in the order of tens of meters, that is what is required for emergency calls, and that the investments needed could be assumed.

The main obstacle between the use of TOA or TDOA observations towards an accurate location system is the Non-Line-Of-Sight effect. This effect mentioned as the *killing effect* in [1], is by far the most important cause of big errors in the positioning algorithms based on timing measurements. Note that NLOS errors can be in the order of hundreds of meters.

Good algorithms to mitigate the NLOS effect have been presented in the previous literature. One of the first approaches presented was based on the observation that the timing measurements captured in a NLOS channel are normally corrupted with a stronger noise, i.e. bigger variance. Using this concept, [2] and [3] proposed to discard the timing measurements with bigger variances using a certain detection criteria. The main problem here is that the variance of a timing observation in a LOS scenario depends strongly on the type of scenario, i.e. urban, suburban or rural. Another problem is that the detection process could take some time estimating the variance of the incoming observation, so this approach is not very suitable for high dynamic scenario.

Other papers, like [4] are based on the idea that the NLOS process could be intermittent. This means that the BSs can be in LOS or in NLOS in an intermittent way. This model is intuitively correct when we are talking about in-car applications where the mobile is supposed to be moving and seeing the BSs in LOS or NLOS intermittently. The idea proposed in [4] consists in exploiting this intermittent effect of the NLOS to discard the NLOS measurements. The problem here is that in [4] it is assumed that the mobile is static during the observation period, which is contradictory with the hypothesis that the NLOS is intermittent.

Also based on the idea that the NLOS effect can be intermittent, other papers like [5] and [6] try to pre-filter the timing measurements to, somehow, eliminate the effect of the NLOS from the measurements. The techniques used are a biased Kalman filter in [5] and a filter based on a certain scattering model in [6]. Obviously, the authors in these last papers made assumptions about the nature of the NLOS errors, so the performance of such algorithms is logically based on how well the real measurements errors fit this model. On the other side, this type of approaches does not use the relationship between the measurements captured simultaneously from different BSs. This is, all the timing measurements coming from a certain BS are pre-filtered independently from the rest of measurements, not exploiting the relationship between them.

In this direction, [7] tries to exploit the relationships between three TOA measurements captured simultaneously from different BSs, trying to mitigate the NLOS errors. However, it is difficult to extent the proposed algorithm to more TOA measurements or even other types of measurements. Maybe the most significant contributions in this direction are [8] and [9]. In both articles, the authors formulate all the possible hypothesis of LOS/NLOS for a specific instant of time, i.e. each hypothesis is characterized by which BSs are under LOS and which BSs are under NLOS. Latter on, the ML position estimates are obtained for each hypothesis. Finally the solution presented in [8] consists in a linear weighted combination of the partial position estimates associated to each hypothesis. The algorithm presented in [9] tries to identify what is the most likely hypothesis using the incoming timing measurements based on the application of the ML detection principle. The major problem with these last approaches is that they exploit only the relationship between timing measurements captured at the same time (one snapshot), but they do not exploit the relationship between the timing measurements along the time axis as in [5] and [6].

This paper tries to extend the work presented in [9] to dynamic scenarios, exploiting also the relationship between the timing observations among different snapshots of measurements. In this sense the new algorithm exploits the relationship between measurements in both directions: inside the snapshot and along the time axis. The proposed algorithm assumes, like previous ap-

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proaches [4], that the NLOS effect is intermittent, but it is coherent also with assuming that the mobile is in a dynamic scenario. No specific assumption of the NLOS error is done, so the proposed algorithm exploits only the coherence between the incoming timing measurements using certain assumptions about the mobile trajectory. As it will be seen, the natural extension of [9] for dynamic scenarios leads to an unafordable complexity, so a Trellis-based search algorithm is proposed to track the state (LOS or NLOS) of the BSs.

A model for the intermittent effect of the NLOS is also presented to simulate the proposed algorithm. Simulation results will show that the proposed algorithm outperforms the previous approaches and it is near to the optimum that is ideally defined as the ML estimator that only uses the timing measurements under LOS.

2. SIGNAL MODEL

Let us assume an scenario where L BSs are under the visibility of the mobile. In this scenario, the mobile can periodically obtain snapshots of L TOA measurements associated to each one of the BSs or $L-1$ independent TDOA measurements associated to all the independent pairs between the reference BSs and the neighbor BSs. To unify the notation of the development for the case of TOA and TDOA observations, let us define K as the number of measurements we have at each instant of time (each snapshot), i.e. K=L for TOA measurements and K=$L-1$ for TDOA measurements. These K measurements will be referred to as *sources* (because they produce a new measurement at each instant of time) indicating single BSs for the TOA case and pairs of BSs for TDOA case.

Let us define the K observations (k=[1,K]) taken at the n-th instant of time as:

$$t_{k,n} = g_k\left(\mathbf{x}_n\right) + w_{k,n} + l_{k,n} \tag{1}$$

where $w_{k,n}$ is the noise term caused by the additive noise and the multipath effect in the TOA/TDOA estimation, $l_{k,n}$ is the error caused by the NLOS effect and $g_k\left(\mathbf{x}_n\right)$ is the non-linear function relating the observations and the parameter of interest, i.e. $\mathbf{x}_n$ that is the position of the mobile at the n-th instant of time.

The non-linear function $g_k\left(\mathbf{x}_n\right)$ in (1) does not depend on the temporal subindex n and it is defined specifically for the type of measurement as:

$$\begin{aligned} g_k^{TOA}\left(\mathbf{x}_n\right) &= \parallel \mathbf{x}_n - \mathbf{x}_k^{BS} \parallel & (2)\\ g_k^{TDOA}\left(\mathbf{x}_n\right) &= \parallel \mathbf{x}_n - \mathbf{x}_{k+1}^{BS} \parallel - \parallel \mathbf{x}_n - \mathbf{x}_1^{BS} \parallel & (3)\end{aligned}$$

where $\mathbf{x}_k^{BS}$ is the known position of the k-th BS.

If the mobile captures N snapshots of measurements at a constant rate of r snapshots per second, we would like to model the evolution of the mobile position at each instant of time as a function of a finite number of parameters as:

$$\mathbf{x}_n = \mathbf{h}_n\left(\mathbf{x},\mathbf{u}\right) \tag{4}$$

where $\mathbf{h}_n\left(\mathbf{x},\mathbf{u}\right)$ does not depend on the source subindex k and shows the mobile position at the n-th instant of time based on the position $\mathbf{x}$ at the end of the observed window and the rest of movement parameters included in $\mathbf{u}$ such as speed, acceleration,etc. For instance, for a constant speed linear trajectory, we have:

$$\mathbf{h}_n\left(\mathbf{x},\mathbf{u}\right) = \mathbf{x} + (n-N)\mathbf{s} \tag{5}$$

where $\mathbf{u}=\mathbf{s}$ is the constant unknown speed vector of the mobile.

A common assumption in wireless location is that the multipath terms $w_{k,n}$ are independent in time among sources, and Gaussian distributed with known variance as:

$$E\left[w_{k,n}w_{k',n'}\right] = \sigma_k^2\delta_{k-k'}\delta_{n-n'} \tag{6}$$

where δ_p is the Kronecker Delta. For a generalization with unknown variance, we refer the reader to [10].

The model for the NLOS term $l_{k,n}$ is not as standard as the previous one but three common assumptions are done in previous publications [4] [11] [6]:

- **(a)** The NLOS term for each source (subindex k) is independent from that of the other sources.
- **(b)** In NLOS conditions, a significant bias will be added to the measurement and this bias will be positive for TOA measurements. The distribution for this bias is usually assumed as uniform but no standard models have been presented so they will be assumed to be completely unknown.
- **(c)** The NLOS effect in dynamic scenarios is intermittent, so the NLOS term will be zero when the measurement is under LOS conditions and will be more or less constant in consecutive NLOS instants of time.

3. SINGLE SNAPSHOT ESTIMATION

This section presents the ML estimation of the position at the n-th instant of time, $\mathbf{x}_n$, using only a single snapshot of K measurements as shown in (1). The goal here is to obtain the ML estimation of $\mathbf{x}_n$ being robust against the NLOS effect. This represents an introduction to the multiple snapshot case and a review of previous contributions in the field.

If we have K measurements that can be in LOS or in NLOS, there are $Q=2^K$ possible hypothesis regarding the NLOS state. For the q-th hypothesis, we can define γ_q^{LOS} and γ_q^{NLOS} as the vectors containing the subindex of the sources that are supposed to be in LOS and NLOS respectively.

Under the q-th hypothesis, we can divide the K original samples $t_{k,n}$ in two subvectors $\mathbf{t}_{n,q}^{LOS}$ and $\mathbf{t}_{n,q}^{NLOS}$ associated with the measurements that are in LOS and NLOS respectively as follows:

$$\begin{aligned} t_{k,n} \in \mathbf{t}_{n,q}^{LOS} &\quad\Leftrightarrow\quad k \in \gamma_q^{LOS} & (7)\\ t_{k,n} \in \mathbf{t}_{n,q}^{NLOS} &\quad\Leftrightarrow\quad k \in \gamma_q^{NLOS} & (8)\end{aligned}$$

In a coherent way we can define also the non-linear functions associated to the previous vectors as

$$\begin{aligned} g_k\left(\mathbf{x}_n\right) \in \mathbf{g}_{n,q}^{LOS}(\mathbf{x}_n) &\quad\Leftrightarrow\quad k \in \gamma_q^{LOS} & (9)\\ g_k\left(\mathbf{x}_n\right) \in \mathbf{g}_{n,q}^{NLOS}(\mathbf{x}_n) &\quad\Leftrightarrow\quad k \in \gamma_q^{NLOS}. & (10)\end{aligned}$$

In the same direction, we can divide the original K variances σ_k^2 in two diagonal matrices containing the variance associated with the measurements that are supposed to be in LOS and NLOS respectively under the q-th hypothesis as follows:

$$\begin{aligned} \sigma_k^2 \in \mathrm{diag}\left(\mathbf{R}_\mathrm{q}^\mathrm{LOS}\right) &\quad\Leftrightarrow\quad k \in \gamma_q^{LOS} & (11)\\ \sigma_k^2 \in \mathrm{diag}\left(\mathbf{R}_\mathrm{q}^\mathrm{NLOS}\right) &\quad\Leftrightarrow\quad k \in \gamma_q^{NLOS} & (12)\\ & & (13)\end{aligned}$$

and finally, we can define the vector containing all the unknown NLOS errors as follows:

$$l_{k,n} \in \mathbf{l}_{n,q} \Leftrightarrow k \in \gamma_q^{NLOS} \tag{14}$$

Using these definitions, we can define the ML estimation of the position $\mathbf{x}_n$ and the unknown NLOS biases $\mathbf{l}_{n,q}$ under the q-th hypothesis ($\widehat{\mathbf{x}}_{n,q}$ and $\widehat{\mathbf{l}}_{n,q}$ respectively) as follows:

$$\widehat{\mathbf{x}}_{n,q}, \widehat{\mathbf{l}}_{n,q} = \arg \min_{\mathbf{x}_n, \mathbf{l}_{n,q}} \left[\Psi_{n,q}^{LOS}\left(\mathbf{x}_n\right) + \Psi_{n,q}^{NLOS}(\mathbf{x}_n, \mathbf{l}_{n,q}) \right] \tag{15}$$

where

$$\Psi_{n,q}^{LOS}\left(\mathbf{x}_n\right) = \phi\left(\mathbf{t}_{n,q}^{LOS} - \mathbf{g}_{n,q}^{LOS}(\mathbf{x}_n), \mathbf{R}_q^{LOS}\right)$$
$$\Psi_{n,q}^{NLOS}(\mathbf{x}_n, \mathbf{l}_{n,q}) = \phi\left(\mathbf{t}_{n,q}^{NLOS} - \mathbf{g}_{n,q}^{NLOS}(\mathbf{x}_n) - \mathbf{l}_{n,q}, \mathbf{R}_q^{NLOS}\right)$$
$$\phi\left(\mathbf{m}, \mathbf{R}\right) = \ln|\mathbf{R}| + \mathbf{m}^T\mathbf{R}^{-1}\mathbf{m} \tag{16}$$

As shown in [11], under the assumtion that $\mathbf{x}_n$ is known, the ML estimation of $\mathbf{l}_{n,q}$ can be obtained from (15) as:

$$\widehat{\mathbf{l}}_{n,q}\left(\mathbf{x}_n\right) = \mathbf{t}_{n,q}^{NLOS} - \mathbf{g}_{n,q}^{NLOS}(\mathbf{x}_n) \tag{17}$$

and now using (17) in (15), the compressed ML estimation of $\mathbf{x}_n$ becomes:

$$\widehat{\mathbf{x}}_{n,q} = \arg\min_{\mathbf{x}_n} \left[\Psi_{n,q}^{LOS}\left(\mathbf{x}_n\right) + \Psi_{n,q}^{NLOS}\left(\mathbf{x}_n, \widehat{\mathbf{l}}_{n,q}\left(\mathbf{x}_n\right)\right) \right] \tag{18}$$
$$\widehat{\mathbf{x}}_{n,q} = \arg\min_{\mathbf{x}_n} \Psi_{n,q}^{LOS}\left(\mathbf{x}_n\right) \tag{19}$$

that can be solved using a closed form algorithm like in [12] or [13]. Note that the second term in (18) becames constant with respect to $\mathbf{x}_n$ and can be removed from the minimization. This last expression (19) basically demonstrates that, if we do not have any knowledge of the NLOS biases, the ML position estimator is obtained only using the measurements that are supposed to be under LOS.

Another conclusion from (19) is that the covariance matrix of $\widehat{\mathbf{x}}_{n,q}$, $\mathbf{C}_{n,q} = E\left[\left(\widehat{\mathbf{x}}_{n,q} - \mathbf{x}_n\right)\left(\widehat{\mathbf{x}}_{n,q} - \mathbf{x}_n\right)^T\right]$ can be approximated as follows:

$$\mathbf{C}_{n,q} \approx \left[\mathbf{G}_{n,q}^T\left(\widehat{\mathbf{x}}_{n,q}\right)\left(\mathbf{R}_q^{LOS}\right)^{-1}\mathbf{G}_{n,q}\left(\widehat{\mathbf{x}}_{n,q}\right)\right]^{-1} \tag{20}$$

where matrix $\mathbf{G}_{n,q}\left(\mathbf{x}_n\right) = \left[\begin{array}{cc} \frac{\partial \mathbf{g}_{n,q}^{LOS}(\mathbf{x}_n)}{\partial [\mathbf{x}_n]_1} & \frac{\partial \mathbf{g}_{n,q}^{LOS}(\mathbf{x}_n)}{\partial [\mathbf{x}_n]_2} \end{array}\right]$.

Until now, we have Q possible position estimates $\widehat{\mathbf{x}}_{n,q}$, $q = 1, \cdots, Q$ corresponding to the ML position estimates under the Q possible hypothesis regarding the NLOS state. In order to obtain a final position estimate considering the Q possible hypothesis, two approaches have been proposed to solve this last step. Pi-Chun Chen proposed in [8] to obtain the estimations as a combination of the Q partial estimates as follows:

$$\widehat{\mathbf{x}}_n = \left[\sum_{q=1}^{Q} \exp\left(-\Psi_{n,q}^{LOS}\left(\widehat{\mathbf{x}}_{n,q}\right)\right)\right]^{-1} \sum_{q=1}^{Q} \exp\left(-\Psi_{n,q}^{LOS}\left(\widehat{\mathbf{x}}_{n,q}\right)\right)\widehat{\mathbf{x}}_{n,q} \tag{21}$$

In [9], the authors proposed just to extend the ML search into the hypothesis domain applying the ML detection principle as follows:

$$\widehat{\mathbf{x}}_n \ , \ \widehat{q} = \arg\min_{\mathbf{x}_n, q} \left[\Psi_{n,q}^{LOS}\left(\mathbf{x}_n\right) + \ln\Gamma_q^{-1}\right] \tag{22}$$

where Γ_q are some tuning parameters to modify the a-priori probability of each hypothesis and to compensate for the different number of unknown parameters in each hypothesis.

As exposed in [9], this second alternative obtains better performance, specially in severe NLOS scenarios since it is able to detect and remove the NLOS.

4. MULTIPLE SNAPSHOT ESTIMATION

The goal now is to extend the work presented in [9] to the multiple snapshot case using the movement model presented in (4). The major drawback in [9] was that the decisions about the LOS/NLOS hypothesis were taken instantaneously at each instant of time as shown in (22), non exploiting the high correlation between the position in two consecutive instants of time shown in (4) or (5) nor the high correlation in time of the NLOS phenomena.

The goal now is not estimating the mobile position at each instant of time in an independent way, but also estimating the mobile position at the end of the observed window $\mathbf{x}$ and the movement parameters $\mathbf{u}$ shown in (4).

Taking into account that we have Q possible simple hypothesis regarding the NLOS state for each instant of time, now we have $P = Q^N$ global hypothesis regarding the NLOS state for the entire observation window of N consecutive snapshots of measurements. Let us define $\mathbf{q}_p$ as the vector containing the simple hypothesis for each instant of time under the p-th global hypothesis. This is, its n-th element, $\mathbf{q}_p\left(n\right) \in [1, Q]$, is the simple hypothesis selected for the n-th instant of time under the p-th ($p \in [1, P]$) global hypothesis.

Under this p-th global hypothesis we have as unknowns, the position at the end of the observation window $\mathbf{x}$, the movement parameters $\mathbf{u}$ and the set of unknown NLOS biases for each instant of time defined as:

$$\mathbf{l}_p = \left[\mathbf{l}_{1,\mathbf{q}_p(1)}^T, \ldots, \mathbf{l}_{N,\mathbf{q}_p(N)}^T\right]^T \tag{23}$$

.

Analogously to the previous section, the ML formulation of all the unknown parameters under the p-th hypothesis can be formulated as:

$$\widehat{\mathbf{x}}_p, \widehat{\mathbf{u}}_p, \widehat{\mathbf{l}}_p = \arg\min_{\mathbf{x},\mathbf{u},\mathbf{l}_p} \chi_p\left(\mathbf{x}, \mathbf{u}, \mathbf{l}_p\right) \tag{24}$$

$$\chi_p\left(\mathbf{x}, \mathbf{u}, \mathbf{l}_p\right) = \tag{25}$$
$$\sum_n \Psi_{n,\mathbf{q}_p(n)}^{LOS}\left(\mathbf{h}_n\left(\mathbf{x}, \mathbf{u}\right)\right) + \Psi_{n,\mathbf{q}_p(n)}^{NLOS}\left(\mathbf{h}_n\left(\mathbf{x}, \mathbf{u}\right), \mathbf{l}_{n,\mathbf{q}_p(n)}\right)$$

where $\Psi_{n,q}^{LOS}\left(\mathbf{x}_n\right)$ and $\Psi_{n,q}^{NLOS}(\mathbf{x}_n, \mathbf{l}_{n,q})$ are defined in (16).

Again, as shown in [11] and assuming that all the unknown parameters included in $\mathbf{l}_p$ are independent, we can obtain the ML estimation $\mathbf{l}_p$ and compress the ML function $\chi_p\left(\mathbf{x}, \mathbf{u}, \mathbf{l}_p\right)$. Concretely, the ML estimation of $\mathbf{l}_p$, $\widehat{\mathbf{l}}_p = \left[\widehat{\mathbf{l}}_{1,\mathbf{q}_p(1)}^T, \ldots, \widehat{\mathbf{l}}_{N,\mathbf{q}_p(N)}^T\right]$ is obtained as:

$$\widehat{\mathbf{l}}_{n,\mathbf{q}_p(n)} = \mathbf{t}_{n,\mathbf{q}_p(n)}^{NLOS} - \mathbf{g}_{n,\mathbf{q}_p(n)}^{NLOS}(\mathbf{h}_n\left(\mathbf{x}, \mathbf{u}\right)) \tag{26}$$

and the compressed ML estimations of $\mathbf{x}$ and $\mathbf{u}$ are obtained as:

$$\widehat{\mathbf{x}}_p, \widehat{\mathbf{u}}_p \quad = \quad \arg\min_{\mathbf{x},\mathbf{u}} \chi_p\left(\mathbf{x}, \mathbf{u}, \widehat{\mathbf{l}}_p\right) \tag{27}$$
$$\widehat{\mathbf{x}}_p, \widehat{\mathbf{u}}_p \quad = \quad \arg\min_{\mathbf{x},\mathbf{u}} \sum_n \Psi_{n,\mathbf{q}_p(n)}^{LOS}\left(\mathbf{h}_n\left(\mathbf{x}, \mathbf{u}\right)\right) \tag{28}$$

Here, we obtain a similar result: the mobile position $\mathbf{x}$ and the movement parameters $\mathbf{u}$ are obtained as if we had only the available LOS measurements (under the p-th hypothesis).

Finally, if we apply the same idea shown in (22), we can select the most likely hypothesis as:

$$\widehat{\mathbf{x}}, \widehat{\mathbf{u}}, \widehat{p} = \arg\min_{\mathbf{x},\mathbf{u},p} \left[\sum_n \Psi_{n,\mathbf{q}_p(n)}^{LOS}\left(\mathbf{h}_n\left(\mathbf{x}, \mathbf{u}\right)\right) + \ln\Gamma_{\mathbf{q}_p(n)}^{-1}\right] \tag{29}$$

5. PROPOSED ALGORITHM

It is clear that the complexity associated with the last expression makes it useless for a real implementation since it is not possible to test $P = 2^{K \cdot N}$ global hypothesis to select the best one. This section presents the proposed simplification for a real implementation. The proposed idea is inspired in the coding theory based on Trellis Coded Modulation (TCM), where it is not possible to evaluate the likelihood of all possible paths, so only the most likely paths survive at each iteration. While in TCM schemes we try to extract the codified source information, here we try to extract the NLOS state at each iteration. While in TCM schemes there are forbiden transitions, here we have low probability transitions (i.e. all NLOS to all LOS). Finally, while in TCM schemes we extract information from the received signal to, somehow, estimate the probability of each state based on the previous probability of all the states, here we do exactly the same.

First of all, note that (28) shows the ML estimation of the position $\mathbf{x}$ and model parameters $\mathbf{u}$ using only the LOS measurements we have at different instants of time defined by the p-th global hypothesis. This estimation can be approximated in a two-steps estimation process. In the first step, partial position estimates are obtained for each instant of time using only the LOS we have. In the second step the partial position estimates are fused using the movement model shown in (4). This two steps estimation process can be mathematically expressed as follows:

$$\widehat{\mathbf{x}}_p, \widehat{\mathbf{u}}_p = \arg\min_{\mathbf{x},\mathbf{u}} \sum_n \phi\left(\widehat{\mathbf{x}}_{n,\mathbf{q}_p(n)} - \mathbf{h}_n(\mathbf{x},\mathbf{u}), \mathbf{C}_{n,\mathbf{q}_p(n)}\right) \tag{30}$$

where $\widehat{\mathbf{x}}_{n,q}$ is the partial estimate under the q-th hypothesis for the n-th instant of time as defined in (19) and $\mathbf{C}_{n,q}$ is its approximate covariance matrix defined in (20).

Under this approximation, we can redefine the hypothesis selection criteria defined in (29) as:

$$\widehat{\mathbf{x}}, \widehat{\mathbf{u}}, \widehat{p} = \arg\min_{\mathbf{x},\mathbf{u},p}\left[\sum_n \phi\left(\widehat{\mathbf{x}}_{n,\mathbf{q}_p(n)} - \mathbf{h}_n(\mathbf{x},\mathbf{u}), \mathbf{C}_{n,\mathbf{q}_p(n)}\right) + \ln\Gamma^{-1}_{\mathbf{q}_p(n)}\right] \tag{31}$$

where it can be seen that all the P hypothesis are based on the $Q \cdot N$ partial position estimates and their covariance matrices. This is, the $P = Q^N$ global hypothesis are all the ways to combine the Q partial position estimates that we have per each one of the N instants of time.

For clarity reasons, let us isolate the hypothesis selection in (31) as:

$$\widehat{p} = \arg\min_p \Xi(\mathbf{q}_p, N) \tag{32}$$

where

$$\Xi(\mathbf{q}, M) = \min_{\mathbf{x},\mathbf{u}} \sum_{n=1}^{M}\left[\phi\left(\widehat{\mathbf{x}}_{n,\mathbf{q}(n)} - \mathbf{h}_n(\mathbf{x},\mathbf{u}), \mathbf{C}_{n,\mathbf{q}(n)}\right) + \ln\Gamma^{-1}_{\mathbf{q}_p(n)}\right] \tag{33}$$

The cost function $\Xi(\mathbf{q}, M)$ shows the likelihood of a certain hypothesis expressed by the vector $\mathbf{q}$. This includes the simple hypothesis for the M instants of time.

Note that (32) is just showing that we decide the hypothesis p based on the likelihood of the possible P global hypothesis using all the N available snapshots of measurements.

The idea we propose is to limit the search over the entire P possible hypothesis, iteration by iteration as in TCM.

The proposed technique consists in only considering Q partial hypothesis at each iteration. A partial hypothesis is a collection of simple hypothesis associated to all the instants of time until the current iteration. These Q partial hypothesis will be the most likely hypothesis that end with a particular NLOS state.

At the M-th instant of time, these Q partial hypothesis are defined by the vectors $\boldsymbol{\beta}_q^M$, $q = 1, \cdots, Q$. These vectors contain the simple hypothesis for each instant of time until the current instant of time indicated by M, this is $\boldsymbol{\beta}_q^M(n) \in [1, Q]$ $n \leq M$, the n-th element of $\boldsymbol{\beta}_q^M$, is the simple hypothesis considered for the n-th instant of time.

Coherently with the definition, the last element inside the vector $\boldsymbol{\beta}_q^M$ has to be q, this is $\boldsymbol{\beta}_q^M(M) = q$. Note that $\boldsymbol{\beta}_q^M$ is a M-length vector since it contains only the simple hypothesis selected for the first M instants of time. Note also, that each partial hypothesis corresponds to a family of the P global hypothesis since the partial hypothesis shows only the simple hypothesis selected until the M-th instant of time.

Let us assume then that we are at the M-th instant of time and that we have Q partial hypothesis defined by the vectors $\boldsymbol{\beta}_q^M$. It is clear that initially, we can form $Q \cdot Q$ partial hypothesis as follows:

$$\boldsymbol{\beta}_{q,q'}^M = \left[\boldsymbol{\beta}_q^M, q'\right] \quad q' = 1, \cdots, Q \;\; q = 1, \cdots, Q \tag{34}$$

Generically, $\boldsymbol{\beta}_{q,q'}^M$ contains all the simple hypothesis considered until the M-th instant of time by $\boldsymbol{\beta}_q^M$ and the new assumption about the NLOS state for the $M+1$-th instant of time.

Since we have Q new vectors that end with a certain hypothesis q', these are $\boldsymbol{\beta}_{q,q'}^M \forall q$, we have to select the most likely one using a simplified version of (32). Concretelly we implement this hypothesis selection as:

$$\boldsymbol{\beta}_{q'}^{M+1} = \boldsymbol{\beta}_{q_{sel},q'}^M \tag{35}$$

$$q_{sel} = \arg\min_q \Xi\left(\boldsymbol{\beta}_{q,q'}^M, M+1\right) \tag{36}$$

Note that the search for each state (q') is only over the Q possibilities consisting in the transitions between all the previous state and the new one. It is clear that the unafordable complexity of (32) has been dramatically reduced since here we implement a search of Q candidates instead of the Q^M candidates that we had in the generic ML detection approach.

Finally, it can be seen that the minimization over the position $\mathbf{x}$ and movement parameters $\mathbf{u}$ in (33) can be implemented iteratively with a linear Kalman filter reducing the complexity of evaluating the minimization at each iteration.

6. NUMERICAL SIMULATIONS

Numerical simulations have been performed in a scenario with five BSs uniformly distributed in a circle of radius 2 Km centered in the origin of coordinates. The mobile is moving with a constant speed of $\mathbf{s} = \begin{bmatrix} 10 & 5 \end{bmatrix}$ meters per second crossing the origin of coordinates in the middle of the time observed window. The measurement rate is $r = 1$ snapshot of TOAs per second and the length of the observed window is $N = 100$ snapshots.

Joining the assumptions **(a)**, **(b)** and **(c)** shown in section 2 about the NLOS effect, we have simulated the NLOS effect of each BS as an independent process. The NLOS phenomena for each BS is modelled with a Markov Chain with two states: LOS and NLOS. There is a transition at each instant of time with the following changing probabilities:

$$p_{LOS \to NLOS} = 0.015 \qquad p_{NLOS \to LOS} = 0.04$$

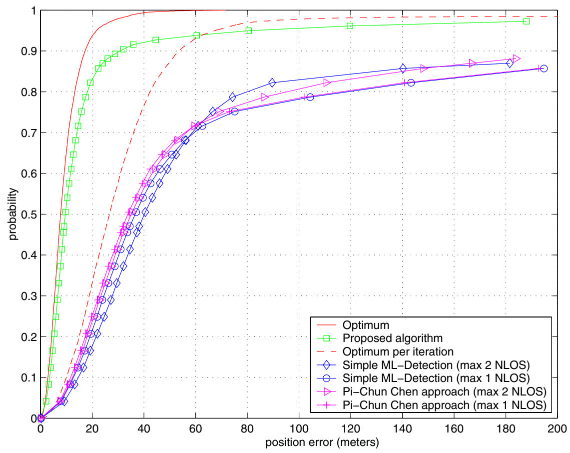

Fig. 1. C.D.F. of the position error with σ_k=30 meters

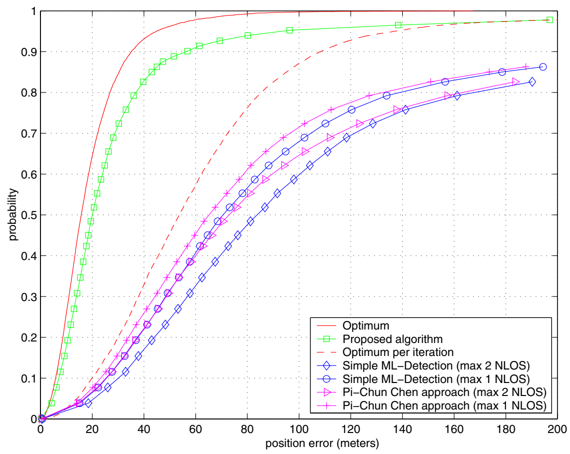

Fig. 2. C.D.F. of the position error with σ_k=60 meters

Each time there is a transition from LOS to NLOS, a new bias is selected for the samples $l_{k,n}$ using a uniform distribution in the range [200,400] meters. This bias is used in all the consecutive iterations until the next transition from NLOS to LOS.

Figures (1) and (2) show the sample cumulative density function (CDF) of the position error of the proposed technique when the standard deviation of the TOA measurements is $\sigma_k = 30meters$ and $\sigma_k = 60meters$ repectivelly.

In the same figure, two theoretical limits have been plotted for comparison. We can see the *Optimum per iteration* limit consisting in selecting always the LOS measurements at each iteration and compute the position $\mathbf{x}_n$ iteration by iteration. On the other hand, we can also see the *Optimum* limit consisting in selecting always the LOS measurements and compute the mobile position $\mathbf{x}$ and the movement parameters $\mathbf{u}$ exploiting the movement model presented in (5). Logically, both limits can not be implemented since it is not possible to guess the NLOS state.

For comparison, we also present the performance of the algorithm presented in (22) [12] as *simple-ML-detection* and the algorithm presented in (21) [8] as *Pi-Chun Chen* algorithm. In both cases, we have limited the NLOS hypothesis search to 1 or 2 NLOS. It can be seen how the proposed algorithm clearly outperforms the previous contributions since it is able to exploit a movement model over the intermittent effect of the NLOS.

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