A NON-LINE-OF-SIGHT MITIGATION TECHNIQUE BASED ON ML-DETECTION

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ABSTRACT

[1]Geolocation in Non Line of Sight (NLOS) environments is an important issue in wireless communication networks. In several recent publications related with the nature and magnitude of the NLOS phenomenon it is concluded that this is the major source of error in position estimators based on time measurements. This article presents a new approach to ameliorate the effect of the NLOS exploiting the redundant time measurements in scenarios with more than the minimum number of base stations (BSs). This redundant data allows to formulate the problem as a test of hypothesis performing a hard decision to discard the BS considered to be in a NLOS scenario. Numerical simulations show that the proposed algorithm can discard the NLOS errors in certain scenarios. The algorithm is also compared with some other existing methods to show the advantage of the new approach.

1. INTRODUCTION

A problem of growing importance in mobile communication networks is estimating the mobile position since the international commissions announced the minimum requirements in location for the next wireless generations. One of the most common approaches to get the position is to measure several Time-of-arrival (TOA) or Time-difference-of-arrival (TDOA) measurements among a set of BSs. Performance is limited by the errors added to the measurements caused mainly by the multipath effect. Several recent papers as [1] have analyzed that the most important source of error is the NLOS phenomenon. These kind of errors occur when the direct path between the mobile and the BS is blocked, for instance by a building, and a constant positive bias is added to the measurements. This is known as a NLOS scenario and the involved BS is usually named a NLOS-BS.

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Several simulations in recent literature have found that the position error in the location estimators increases linearly with the increase in the NLOS errors ([2]). This killer effect has been recognized by others and several NLOS mitigation algorithms have been presented. One of the most common approaches consists of exploiting the fact that the variance of the TOA measurements is significantly increased in NLOS scenarios ([3] and [2]). These algorithms try to detect the NLOS-BSs by comparing the estimated variance of the measurements with an a-priori known variance. This last variance cannot normally be provided because it depends on the environment conditions (rural, urban or suburban). Another approach is to use a fixed scatter model to obtain an improved TOA estimate from a set of TOA measurements corrupted by multipath errors ([4]). Although these approaches can ameliorate the effect of the multipath, they cannot detect constant NLOS error in short observation windows.

Finally, another approach consists of exploiting the redundant information present in the measurements to detect and drop the NLOS errors. The most relevant previous contribution in this direction was presented in [5] where the problem was formulated in terms of hypotheses, where each hypothesis corresponded to a set of BS considered under NLOS scenarios. The algorithm presented there was based on a weighted combination of the partial position estimates associated to each hypothesis. Unfortunately, this combination presents poor performance if the NLOS error presented in the TOA measurement is high.

This paper presents a new algorithm to detect the NLOS-BSs using the redundant information present in the TOA measurements when more than the minimum number of BSs are present (2 BSs in 2D location and 3 BSs in a 3D location). In this case, several hypotheses of the set of BSs under NLOS scenarios are formulated and, on the basis of the ML-detection principle [6], the most suitable hypothesis can be selected. The main contribution of this paper is applying a sound detection principle for the selection of the best hypothesis, instead of averaging the results of all possible hypothesis based on heuristic arguments, as in previous approaches.

Numerical simulations show that, with a high enough NLOS error, the algorithm is able to discard perfectly the BSs under a NLOS scenario, clearly improving the mean performance of the classical location algorithms. Although the mathematical development presented in this paper and the simulations have been performed with TOA measurements, both can be, in a straightforward way, extended to the TDOA measurements case.

2. ML DETECTION APPLIED TO NLOS PROBLEM

In this section, the general principles of the ML-detection technique [6] are applied to the NLOS detection case based on TOA measurements. In the next section, the specific mathematical developments for this application are presented.

Let us assume that M TOA measurements are available for each one of the K BS under visibility. The common static model used to express the m-th TOA measurement (in time) of the k-th BS is:

$$t_{k,m} = f_k(\mathbf{x}) + n_{k,m} + b_k = \|\mathbf{x} - \mathbf{x}_k\| + n_{k,m} + b_k \quad (1)$$

where $n_{k,m}$ is a zero-mean gaussian noise term independent in time and independent for each BS ($E[n_{k,m}n_{k',m'}] = \sigma_k^2 \delta_{k,k'}\delta_{m,m'}$), $\mathbf{x}$ is the true position of the mobile, $\mathbf{x}_k$ is the position of the k-th BS, b_k is the possible NLOS bias error (assumed constant along the time window), $\| \ \|$ is the common norm operator and $\delta_{k,k'}$ is the Kronecker delta function. The gaussian assumption of the term $n_{k,m}$ is a common hypothesis used in location-related publications as in [3].

Under this assumption, the conditional density function (p.d.f.) of the $M-th$ TOA measurement of the k-th BS ($\mathbf{t}_k = [t_{k,1}, \ldots, t_{k,M}]^T$) can be expressed as follows:

$$p_k^{NLOS}(\mathbf{t}_k|\mathbf{x}, b_k) = \prod_{m=1}^{M} \frac{1}{\sqrt{2\pi}\sigma_k} e^{-\frac{1}{2}\left(\frac{t_{k,m} - f_k(\mathbf{x}) - b_k}{\sigma_k}\right)^2} \quad (2)$$

$$p_k^{LOS}(\mathbf{t}_k|\mathbf{x}) = \prod_{m=1}^{M} \frac{1}{\sqrt{2\pi}\sigma_k} e^{-\frac{1}{2}\left(\frac{t_{k,m} - f_k(\mathbf{x})}{\sigma_k}\right)^2} \quad (3)$$

Note that the two previous expressions correspond to the assumption that the k-th BS *is* or *is not* under a NLOS scenario.

The proposed algorithm is based on considering different hypothesis characterized by the subset of BSs that are assumed to be under a NLOS scenario. The number of hypothesis considered depends on the number of available TOA measurements (K) and the maximum number of possible NLOS-BSs considered. If we only want to consider that single NLOS-BS may be present, the number of hypothesis will be $N_{hyp} = \binom{K}{0} + \binom{K}{1} = 1 + K$. If two possible NLOS-BSs are considered, the number of hypothesis grows up to $N_{hyp} = \binom{K}{0} + \binom{K}{1} + \binom{K}{2} = 1 + K + K \cdot (K-1)/2$ and so on. Logically, the complexity of the algorithm will grow with the number of considered hypothesis and a trade-off between the capacity to detect (maximum number of BS considered under NLOS) and the performance in the absence of NLOS errors becomes a key aspect to be analyzed.

In general the l-th hypothesis can be characterized by the set of BSs assumed to be under a NLOS scenario (S_l^{NLOS}) and the complementary set of BSs that are assumed to be under a LOS scenario (S_l^{LOS}). Then, the conditional p.d.f. of the KM TOA measurements associated to the l-th hypothesis can be expressed as:

$$q_l\left(\mathbf{t}|\mathbf{x}, \mathbf{b}_{S_l^{NLOS}}\right) = \prod_{k \in S_l^{NLOS}} p_k^{NLOS}(\mathbf{t}_k|\mathbf{x}, b_k) \prod_{k \in S_l^{LOS}} p_k^{LOS}(\mathbf{t}_k|\mathbf{x}) \quad (4)$$

where $\mathbf{t} = \left[\mathbf{t}_1{}^T, \mathbf{t}_2{}^T, \cdots, \mathbf{t}_K{}^T\right]^T$ is the vector formed with the KM TOA measurements and $\mathbf{b}_{S_l^{NLOS}}$ is the vector formed with the NLOS error bias (b_k) presented in (1) of the BSs assumed to be under NLOS in this hypothesis.

It can be noted, that the conditional p.d.f. of each hypothesis depends on a different subset of unknown parameters. These are the true position of the mobile ($\mathbf{x}$) and the set of bias (produced by the NLOS effect) of the assumed NLOS-BSs ($\mathbf{b}_{S_l^{NLOS}}$). The basic principle of the ML-detection technique is finding the ML estimation of the unknown parameters of each hypothesis before comparing them using the classic likelihood ratio test. Hence, we maximize the conditioned l-th hypothesis p.d.f. with respect to the set of parameters of the l-th hypothesis as follows:

$$q_l^{ML}(\mathbf{t}) = \max_{\mathbf{x}, \mathbf{b}_{S_l^{NLOS}}} q_l\left(\mathbf{t}|\mathbf{x}, \mathbf{b}_{S_l^{NLOS}}\right) \quad (5)$$

Note that the p.d.f. associated to each hypothesis does not depend now on any unknown parameter, so the selected hypothesis can be chosen as follows:

$$\widehat{l} = arg \ \max_{l} \ \gamma_l \cdot q_l^{ML}(\mathbf{t}) \quad (6)$$

where the constants γ_l are assigned according to each a-priori probability of the hypothesis. If no knowledge of the probability of each hypothesis is given, a reasonable selection would be $\gamma_l = 1, \forall\ l$.

3. PROPOSED ALGORITHM

This section shows the specific expressions of the proposed algorithm developed in the previous section.

The maximum difficulty in the proposed algorithm is the maximization process needed in (5). In this maximization process, we have to find the position of the mobile $\mathbf{x}$ and a subset of biases $\mathbf{b}_{S_l^{NLOS}}$ that best jointly fit the p.d.f. of the available TOA measurements. Despite this joint nature of the maximization process, both position and biases estimates can be expressed separately after non-trivial mathematical manipulations ([7]) as:

$$\widehat{\mathbf{x}}_l = \arg\max_{\mathbf{x}} \prod_{k\in S_l^{LOS}} p_k^{LOS}(\mathbf{t}_k|\mathbf{x}) \quad (7)$$

$$\widehat{b}_{k,l} = \frac{1}{M}\sum_{m=1}^{M} t_{k,m} - f_k(\widehat{\mathbf{x}}_l) \quad (8)$$

where $\widehat{b}_{k,l}$ is the bias estimate of the k-th BS. Logically, the k-th BS represents all BS under a NLOS scenario in the l-th hypothesis.

These previous expressions are indicating that the ML estimate of the position under the l-th hypothesis is the ML estimation of the position only using the TOA measurements corresponding to BSs assumed to be under a LOS scenario. Coherently, the biases estimates are the exact difference between the correspondent TOA measurement and the theoretical TOA value taking the position estimate obtained before ($\widehat{\mathbf{x}}_l$). Note that this result is only valid under the gaussian assumption explained in section (2).

After this result, the ML-detection algorithm presented in the first section is quite simple because the ML procedure to compute the position using free-of-bias TOA measurements has been widely studied in wireless location literature ([8]). Concretely, it has been applied in the simulation a modified version of the efficient algorithm presented in ([9]), but similar results are obtained when standard ML location methods are used.

In order to find more compact expressions, let us continue applying the natural logarithm to (6) as follows:

$$\widehat{l} = \arg\max_{l}\left[\ln\gamma_l + \ln q_l^{ML}(\mathbf{t})\right] = arg\max \Gamma_l \quad (9)$$

where Γ_l, defined in a trivial way, is commonly called the hypothesis-ratio.

If we now apply the definition of the individual p.d.f. associated at each BS ((2) and (3)), the hypothesis ratio presented is simplified as follows:

$$\Gamma_l = C + \ln\gamma_l + \max_{\mathbf{x},\mathbf{b}_{S_l^{NLOS}}} \Theta\Big(\mathbf{t},\mathbf{x},\mathbf{b}_{S_l^{NLOS}}\Big) \quad (10)$$

$$\Theta = \sum_{m=1}^{M}\left[\sum_{k\in S_l^{NLOS}} \frac{(t_{k,m} - f_k(\mathbf{x}) - b_k)^2}{-2\sigma_k^2} + \sum_{k\in S_l^{LOS}} \frac{(t_{k,m} - f_k(\mathbf{x}))^2}{-2\sigma_k^2}\right] \quad (11)$$

In these expressions, C is an irrelevant constant and the parameters of Θ have been removed in the second equation for space reasons. Now, if we apply the previous results of the maximization process presented in (7) and (8), the first term of Θ vanishes and Γ_l become:

$$\Gamma_l = C + \ln\gamma_l + \sum_{m=1}^{M}\sum_{k\in S_l^{LOS}} \frac{(t_{k,m} - f_k(\widehat{\mathbf{x}}_l))^2}{-2\sigma_k^2} \quad (12)$$

In order to simplify the notation, we can define $\left[\widehat{\sigma_k^2}\right]_l$ as the estimated variance of the M TOA measurements associated to the k-th BS (under the l-th hypothesis).

$$\left[\widehat{\sigma_k^2}\right]_l = \frac{1}{M}\sum_{m=1}^{M}(t_{k,m} - f_k(\widehat{\mathbf{x}}_l))^2 \quad (13)$$

Then, using (12) and (13) in (9), the decision-rule becomes:

$$\widehat{l} = \arg\min_{l}\left[\ln\gamma_l^{-1} + \sum_{k\in S_l^{LOS}} \frac{M}{2}\left(\frac{\left[\widehat{\sigma_k^2}\right]_l}{\sigma_k^2}\right)\right] \quad (14)$$

Observing this last expression, the procedure to compute the metric (or hypothesis-ratio) for each hypothesis can be summarized in two steps: first, compute the ML-estimation of the position using only the BSs that are assumed to be under a LOS scenario and second, using this previous position estimate, compare the theoretical variances with the estimated ones. Note that only the BSs under LOS have to be used again in this second step.

Finally, once the hypothesis has been selected using (14), the final position estimate corresponds to the partial position estimate ($\widehat{\mathbf{x}}_{\widehat{l}}$) of the selected hypothesis.

4. NUMERICAL SIMULATIONS

This section shows the numerical simulation conducted to evaluate the performance of the algorithm. Concretely, the scenario consists in five BS that provide four TOA measurements in a LOS situation and one in a NLOS. The proposed algorithm is tested (10000 trials) with different values for the NLOS-bias in order to evaluate the performance in scenarios with a soft or hard NLOS phenomenon. BSs are distributed uniformly in a circumference of 5 Km radius centered at the position of the mobile in order to avoid singular geometry problems. The variance of all TOA measurements is assumed constant (σ).

The proposed algorithm is compared with the two limit cases: the *worst* algorithm that computes the ML-estimate of the position using always the five TOA measurements, and the *best* algorithm that uses only the four BSs under LOS conditions (unless when the NLOS bias error is zero, in which case, all measurements are used). Logically, this second algorithm is impossible to be implemented and is only presented as a benchmark against which to compare the proposed algorithm. The algorithm is also compared

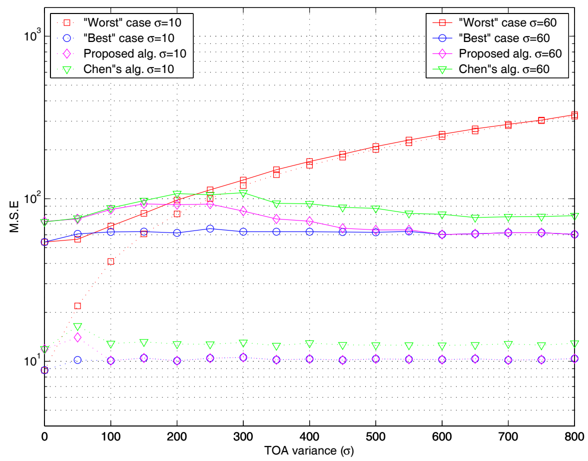

Fig. 1. Performance of the proposed ML-detection algorithm

with the Chen's algorithm [5] that consists of weighted average of the position estimate associated to all possible hypotheses.

The simulated algorithms compute a 2D position assuming that the mobile is placed at the same plane as that of the BSs and the ML-detection algorithm only takes as hypothesis the possibility of a single NLOS-BS, so the number of hypotheses is $N_{hyp} = 1 + K = 6$.

The conclusion is that with a high enough NLOS error, the proposed ML-detector can completely discard the NLOS-BS and compute exactly the same position as the *best* algorithm. Note also that with small NLOS errors the performance of the algorithm is a little poorer than not implementing any NLOS mitigation technique. This presents a clear trade-off that can be adjusted with a proper selection of the coefficients γ_l in (6). The performance of the Chen's algorithm is quite similar to the proposed one for low values of the NLOS-bias. However, in scenarios with a higher NLOS-bias, the proposed method, clearly, outperforms that of Chen's.

Finally, it can be observed in the figure that the detection is much more difficult for high values of σ because the same NLOS bias is not as easily detectable as for low values.

5. CONCLUSIONS

This paper has shown a new technique to mitigate the NLOS effect in location estimators based on TOA measurements. Concretely, the proposed algorithm exploits the redundant information present in available data when more than the minimum number of BSs are available. This can be seen as an improvement of the classical ML position estimation technique (widely studied in recent literature) by adding the hypothesis presented in this paper to detect the NLOS situations. The proposed algorithm is based on the formulation of hypothesis associated to different subsets of BSs considered to be in a NLOS scenario. A hard decision algorithm is presented applying the ML-detection principle to decide the subset of NLOS-BTs.

Numerical simulations show that for high values for the NLOS-bias error, the algorithm is able to discard the BSs under a NLOS scenario performing a near optimum position estimation. Simulations also prove that the performance of the proposed ML-detection algorithm depends on the variance of the TOA measurements. This is, low values of σ_k allow the algorithm to detect more clearly the NLOS-bias added to some TOA measurements. Finally the algorithm has been compared with the most relevant existing methods in order to show the advantages of the proposed approach.

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