Blind Localization of 3G Mobile Terminals in Multipath Scenarios

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Abstract – Locating mobile terminals in cellular radio networks offers a variety of new applications in everyday live and, moreover, is very valuable in emergency cases. We consider to tackle the localization task with help of a smart antenna at the base station. We propose a blind localization approach in multipath scenarios which needs only further information about the locations of the main scattering objects, e.g. buildings. We use the additional information from a 2-D electronic data base of the environment and combine it with simple ray-tracing elements.

1 Introduction and Boundary Conditions

Our research aims at estimating the locations of individual mobile users. For the problem of geolocating mobile units within a cellular infrastructure a numerous of position location algorithms are presented in [1],[2]. However, here we focus on the blind case, i.e. we do not exploit mobile system specific information contained in the signals. The localization task will be carried out with one observation station which is equipped with an antenna array, e.g. described in detail in [3], allowing to estimate the Directions of Arrival (DoA) and the relative delays of the incoming signals from the mobile terminals. The urban scenario affected by the multipath propagation and the blind observation complicates the localization task. This results in the following boundary conditions:

- The transmitted signals (as well as training sequences) are unknown. This leads to a blind estimation problem concerning the channel parameters.
- The blind case implies no synchronization between the observation and mobile stations. Therefore, we have no information about the absolute delay and range respectively.
- The considered mobile communication system uses CDMA as multiple access technology [4]. This causes an unknown multi-user interference.
- The signal amplitudes of different mobile stations differ at the observation station due to the power management.

The treatment of the blind estimation problem is not the topic of our discussion. We assume to receive the estimated multipath parameters from some kind of blind estimator. In the following we limit ourselves to the discussion of only one mobile station, i.e. we assume some kind of preprocessing in order to separate the individual signals.

2 Classification of Measurement Scenarios

Multipath propagation in urban scenarios aggravates the blind localization task drastically. We distinguish two kinds of multipath scenarios where reflected, scattered or diffracted waves called multipath components arrive at the antenna: In the first case there exists a Line-Of-Sight (LOS) connection and possibly further multipath components. In the second case there are only Non-Line-Of-Sight (NLOS) connections. Two typical multipath scenarios with a total number of three rays are shown in Fig. 1 and Fig. 2. In order to have the same number of components for both scenarios we generated three NLOS-path in Fig. 2 since the LOS path is shadowed.

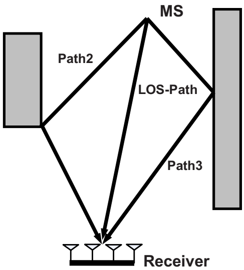

Fig. 1 LOS-scenario

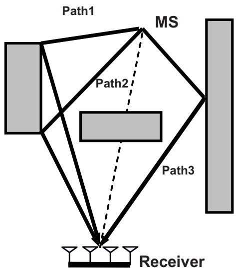

Fig. 2 NLOS-scenario

The problem of localization in cooperative scenarios with NLOS-connections has been discussed in a number of publications [11], [2]. They declare severe degradation in positioning accuracy in the NLOS-case, whereas the localization under LOS-conditions in a cooperative scenario seems to be the trivial one since the estimated DoA and absolute delay of the LOS-component are sufficient to estimate the position of the mobile station.

As we are dealing with the blind localization task we have no information about the absolute delay. Therefore the localization procedure for the cooperative case under LOS-conditions can not be applied to the blind case.

The unknown transmitter position is the origin of every incoming multipath component. Therefore we propose to extract information about the transmitter position from the measured multipath components. In radio channel modeling, each multipath component is characterized by its delay, DoA, and complex valued path weight [5]. Every estimated DoA corresponds to an obstacle or to a transmitter lying in the field of view of the receiver, whereas the delay refers to the propagation path length. The multipath components can be mapped onto a DoA-Delay-plane. This results in a distribution that is typical for each scenario and contains geometrical information related to the environment. Fig. 3 shows an example of such a distribution for the scenario with three multipaths.

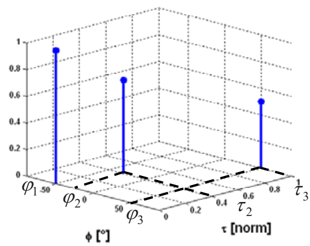

Fig. 3 Relative delay-DoA distribution for a scenario with 3 multipaths

As we have mentioned above we can not estimate the absolute delays of the multipaths but the delay differences referred to as the relative delays in a blind scenario. Geometrically, it means that we estimate the differences of the length of the multipaths. Because the delay of the first incoming multipath is unknown we estimate only two relative delays in the scenario with three multipaths.

Additionally, we have three DoA's for each multipath. Hence we obtain five parameters for the measurement scenario with three multipaths.
We want to find out how many degrees of freedom are required to solve the blind positioning problem and compare it with the information extracted from the multipaths. Therefore we take a closer look at Fig. 1 and Fig. 2 and define every kind of interaction of the radiated wave with the obstacles as interaction points. We specify the position of each interaction point, of the transmitter, and the receiver by two coordinates in the two-dimensional space. We assume that the receiver position is known. The positions of the interaction points and the transmitter position are unknown. For the LOS case in Fig. 1 we obtain six unknown coordinates and for the NLOS case in Fig. 2 eight unknown coordinates. If we assume a multiple bounce scattering then we will have more interaction points and obviously even more unknowns. It was shown that the corresponding number of the known parameters for the scenario with three measured multipaths is five. Hence the information included in the measured multipath parameters is not sufficient to solve the non-cooperative problem. We need additional sources of information.

3 Proposed Localization Algorithm

We propose to retrieve the additional information from the positions of the major interaction points in the environment. One way to solve the localization problem could be to use auxiliary range measurement between significant interaction points and the observation station with some ranging device [6]. Another possibility is to exploit the motion of the observation station. These two techniques have one weak point in common. They assume a single bounce scattering. From the experimental measurements with the channel sounder it is known that the probability for multiple bounce scattering in urban scenarios is not negligible [5]. Hence we don't follow these approaches, instead we calculate a probability density function for the position of the transmitter given the measured parameters and a priori information about the environment [8],[9].
In the first step of the proposed positioning approach we simulate the environment by 2D-objects representing buildings which allows us to generate the path parameters for arbitrary transmitter positions. As a generating mechanism we use a ray-optical wave propagation tool. In the second step we define the likelihood function and propose a method to compare the generated path parameters with the estimated path parameters. In the next subsections we would like to explain the above-mentioned processing steps in more detail.

3.1 2D-Ray-Tracing Modeling Approach

The basic principle of the implemented ray-tracing modeling approach was taken from [7]. However it was simplified and adjusted to our problem. We take into account such propagation phenomena like multiple reflections and diffractions. We use only two dimensions to describe the environment in the model for the following two reasons:

1. The information about the height of the buildings in the operational area is mostly not available since we will use only 2D aerial photos and urban maps as additional information sources.
2. Due to real-time system requirement it is preferable to use the small dimensionality of the problem.

At the current level of development we do not calculate the electromagnetic parameters of the waves e.g. the transmitted signal power. It will be the topic of future research.

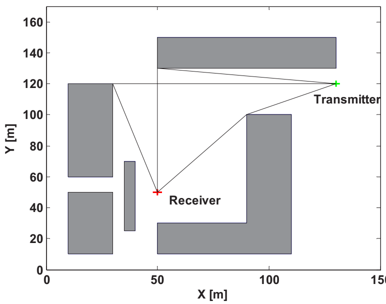

Fig. 4 Result of the ray-tracing tool for interaction order of one

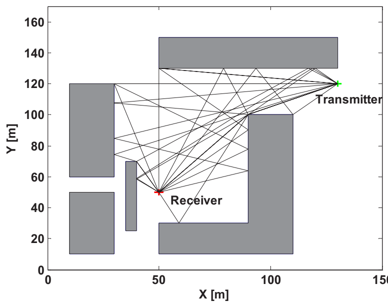

Fig. 5 Result of the ray-tracing tool for interaction order of two

Fig. 4 presents a simple environment and ray-tracing results with an interaction order of one. That means that each wave train connecting the observation station, called receiver, with the mobile station, referred to as transmitter, impinges at most one time on an obstacle. In Fig. 5 we increased the interaction order to two. The number of detected paths rises up to 15.

In our simulations the ray-tracing modeling approach serves for the position estimation procedure as well as for generating the estimated path parameter. The generation of the estimated parameters consists of two operations: give additive noise to the exact path parameters and then we remove the absolute delay.

3.2 Likelihood Function

In this section we want to define the likelihood function which incorporates the proximity between the generated path parameters with the ray-tracing algorithm from an arbitrary transmitter position and the estimated path parameters from measurements with the antenna array. In the calculation of the proximity between the calculated and measured path parameters we consider on the one hand errors in the measured path parameters and on the other hand modeling errors within the ray-tracing approach which may produce a different number of multipath components depending on the accuracy of modeling the environment.

We arrange the estimated path parameters in a parameter vector which has the following form:

$$\mathbf{z} = \left[\tau_1 \ldots \tau_P \quad \varphi_1 \ldots \varphi_P\right]^{\mathrm{T}}, \tag{1}$$

where $P \in \mathrm{N}$ is the number of estimated multipaths. Each multipath $p = 1 \ldots P$ is characterized by its relative delay $\tau_p \in \left[0 \quad \ldots \quad \tau_{\max}\right]$ and the azimuthal direction of arrival $\varphi_p \in \left[-\pi \quad \ldots \quad \pi\right]$. Each estimated parameter has a corresponding standard deviation which implies the uncertainties due to the finite sampling rate, the calibration errors at the receiver, the given signal-to-noise ratio, and due to the errors of the blind estimation algorithm. We collect the standard deviations in the vector:

$$\boldsymbol{\sigma} = \left[\sigma_{\tau_1} \ldots \sigma_{\tau_P} \quad \sigma_{\varphi_1} \ldots \sigma_{\varphi_P}\right]^{\mathrm{T}}, \tag{2}$$

whereby σ_{τ_p} corresponds to τ_p and σ_{φ_p} corresponds to φ_p respectively. Now we assume a transmitter position:

$$\mathbf{s} = \left[x \quad y\right]^{\mathrm{T}}, \tag{3}$$

specified by two Cartesian coordinates. For the assumed transmitter position $\mathbf{s}$ we generate the corresponding parameter vector:

$$\tilde{\mathbf{g}}(\mathbf{s}) = \begin{bmatrix} \tilde{\tau}_1 \ldots \tilde{\tau}_M & \varphi_1^* \ldots \varphi_M^* \end{bmatrix}^{\mathrm{T}}, \tag{4}$$

by means of the ray-tracing approach. M is the number of generated multipaths, $\varphi_m^* \in [-\pi \;\ldots\; \pi]$ with $m = 1 \ldots M$ is the generated azimuthal direction of arrival, and $\tilde{\tau}_m \in [\tilde{\tau}_{\min} \;\ldots\; \tilde{\tau}_{\max}]$ is the generated absolute delay since we obtain the whole path length from the ray-tracer. In order to obtain the relative delays we subtract the absolute delay of the first incoming generated multipath component from the multipath delays in (4) in the following way:

$$\tau_m^* = \tilde{\tau}_m - \tilde{\tau}_{\min}, \tag{5}$$

and define the vector with generated parameters corresponding to the transmitter position $\mathbf{s}$:

$$\mathbf{g}^*(\mathbf{s}) = \begin{bmatrix} \tau_1^* \ldots \tau_M^* & \varphi_1^* \ldots \varphi_M^* \end{bmatrix}^{\mathrm{T}} \tag{6}$$

with $\tau_m^* \in [0 \ldots \tau_{\max}^*]$.

Now we want to derive the statistical weight which expresses the probability that the estimated multipath components have been radiated from the assumed transmitter position $\mathbf{s}$. Therefore we compare the generated parameter vector $\mathbf{g}^*(\mathbf{s})$ with the estimated parameter vector $\mathbf{z}$. Since their dimensions can be different we propose to match them "path wise". Therefore we define the following bivariate Gaussian distribution to describe the proximity between the estimated multipath p and the generated path m:

$$N\left(\boldsymbol{\mu}_m^*(\mathbf{s}); \boldsymbol{\mu}_p, \mathbf{C}_p\right) = \frac{1}{\sqrt{|2\pi \mathbf{C}_p|}} \exp\left\{-\frac{1}{2}\left(\boldsymbol{\mu}_p - \boldsymbol{\mu}_m^*(\mathbf{s})\right)^{\mathrm{T}} \mathbf{C}_p^{-1}\left(\boldsymbol{\mu}_p - \boldsymbol{\mu}_m^*(\mathbf{s})\right)\right\}, \tag{7}$$

$\boldsymbol{\mu}_p = \begin{bmatrix} \varphi_p & \tau_p \end{bmatrix}^{\mathrm{T}}$ is the mean value, which contains the estimated DoA and the relative delay of the p-th multipath. The related covariance matrix $\mathbf{C}_p = \begin{bmatrix} \sigma_{\varphi_p}^2 & 0 \\ 0 & \sigma_{\tau_p}^2 \end{bmatrix}$ contains the estimated standard deviations of the DoA and the relative delay related to the p-th multipath defined in (2). $\boldsymbol{\mu}_m^*(\mathbf{s}) = \begin{bmatrix} \varphi_m^* & \tau_m^* \end{bmatrix}^{\mathrm{T}}$ is the parameter pair of the m-th generated multipath.

Ideally there is exactly one generated multipath m which corresponds to the estimated multipath p. It is obvious that the maximum value of (7) indicates the most probable combination of the estimated and generated multipath. We propose the following method in order to find the unique and most probable association between the estimated and generated paths. We calculate:

$$\nu_{m,p} = N\left(\boldsymbol{\mu}_m^*(\mathbf{s}); \boldsymbol{\mu}_p, \mathbf{C}_p\right), \tag{8}$$

for all index values of m and p and define the matrix:

$$\mathbf{W} = \begin{bmatrix} \nu_{1,1} & \cdots & \nu_{1,P} \\ \vdots & \ddots & \vdots \\ \nu_{M,1} & \cdots & \nu_{M,P} \end{bmatrix}, \tag{9}$$

In the next step we search for the maximum value of all matrix elements in $\mathbf{W}$:

$$\eta_1 = \nu_{m,p} = \max(\mathbf{W}). \tag{10}$$

We store the individual weight η_1 of the estimated multipath p and eliminate the m-th row and the p-th column from $\mathbf{W}$ in order to achieve the unique association between the estimated and generated parameter pairs. Then we repeat the maximum search with the reduced matrix $\mathbf{W}$ in which the m-th generated multipath and the p-th measured multipath have been removed. After P search iterations we obtain P individual weights $\eta_r(\mathbf{s})$ with $r = 1 \ldots P$. We should mention that we can always fulfil the condition $M \geq P$ by increasing the interaction order. We define the total likelihood function as the sum over the individual multipath weights:

$$w(\mathbf{s}) = \sum_{r=1}^{P} \eta_r(\mathbf{s}). \tag{11}$$

We have rejected the conventional product formulation for the complete cost function because in this case a single multipath component calculated with the ray-tracer from the exact transmitter position which is wrong due to modelling errors of the environment, yields a vanishing individual weight $\eta_p(\mathbf{s})$ and hence would decrease drastically the joint weight even if the remaining individual weights are significant.

4 Simulation Results

In Fig. 6 we demonstrate our approach within a two-dimensional scenario with a certain transmitter and receiver position and the corresponding normalized grey-coded likelihood function calculated at 1000 points **s**. Hereby we have used the same noise level for all estimated multipaths of $\sigma_\varphi = 2°$ and $\sigma_\tau = \frac{10\,\mathrm{m}}{c_{light}}$, where c_{light} is the speed of light. The number of the estimated paths was eight. We can observe the multimodal character of the likelihood function, however the maximum lies close to the true transmitter position

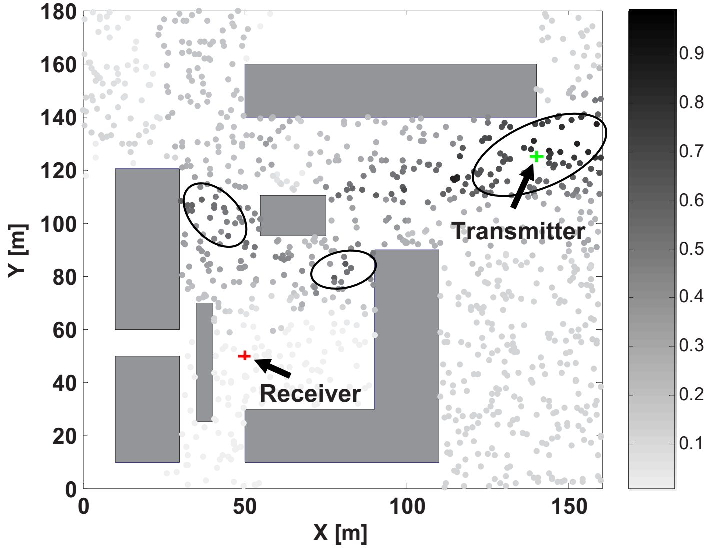

Fig. 6 First example of the likelihood function

Fig. 7 shows the same scenario but a different transmitter position. Furthermore we changed the noise level to $\sigma_\varphi = 5°$ and $\sigma_\tau = \frac{15\,\text{m}}{c_{light}}$. The number of the estimated paths was five. We can see that the maximum of the likelihood function does not agree with the true transmitter position. We have found that the performance of the position estimation depends on the number of the estimated parameters, their accuracy and the scenario.

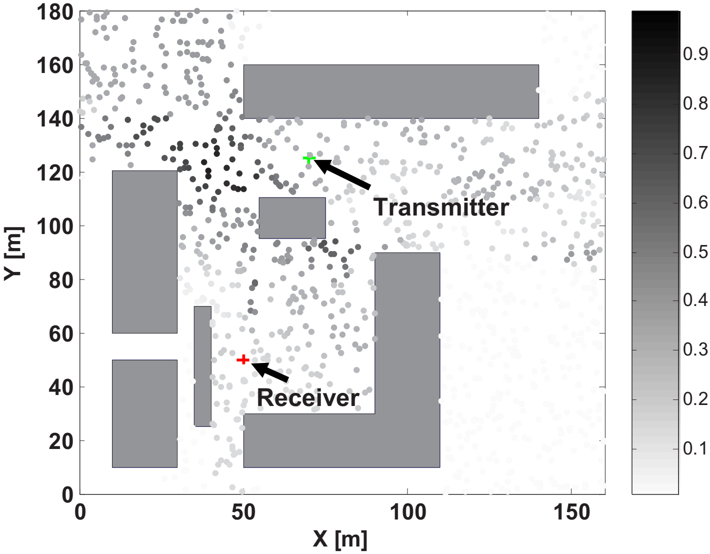

Fig. 7 Second example of the likelihood function

5 Conclusions

We presented an approach to locate mobile terminals with help of an antenna array in urban areas, which are dominated by multipath propagation. On the basis of a 2D model of the urban area all multipath components from arbitrary transmitter position to the observation station were computed with a ray-tracing algorithm. A measure was defined which characterizes how well the parameters of the calculated multipath components emanating from transmitter position **s** coincide with the measured path parameters. In this approach we incorporated measurement errors at the receiving station as well as possible modeling mismatches of the 2D-scenario resulting in over-/underestimation of the number of multipath components.

In simulations we showed examples of the likelihood function which has its maximum close to the estimated transmitter position. In future work the approach will be extended to moving sources. Therefore we will apply sequential Bayesian localization and tracking techniques [8], [9]. For the numerical realisation we will use well established particle filtering techniques [10].

6 References

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