Mobile Terminal Tracking in Urban Scenarios Using Multipath Propagation.

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Abstract: Locating mobile terminals is an important requirement not only for offering location based services but also for handling emergency cases of non-subscribed users, and radio surveillance. We propose a blind localization approach which takes advantage of multipath propagation by using additional information about the known locations of the main scattering objects, e.g. buildings. This information is processed by means of a simple ray tracing technique based on a 2D geographic data base. We assume a single observation station equipped with multiple antennas which is able of estimating the directional and relative temporal structure of the received multipath components. Exploiting the parameters of the multipath components we propose a mobile terminal tracking algorithm based on particle filtering technique.

1 Introduction

Various methods have been proposed for estimating the location of mobile terminals for example in cellular networks. Most of them are based on trilateration utilizing the Received Signal Strength (RSS), Time of Arrival (ToA), Time Delay of Arrival (TDoA), Angle of Arrival (AoA) of the signal as well as diverse combinations [SC05]. Those methods presume close cooperation between the network infrastructure and the Mobile Station (MS) and Line-of-Sight (LoS) connection.

However, there are many relevant application scenarios where no cooperation between the terminal and the network infrastructure can be exploited. These include nonsubscribed MS localization for emergency and security aspects [KS06]. In this case, no a-priori information about the transmitted signal and the timing reference is available. Therefore, we need “blind” detection methods. Moreover, single station localization is preferred which means that there is only one multi-antenna observing station (OS) which is capable of AoA estimation.

It is well known that urban scenarios are affected by multipath propagation. Furthermore, the LoS connection between the base and mobile station is not always available. Whereas missing LoS detrimentally affects trilateration techniques, there are methods which can take advantage of the multipath structure of wave propagation. So-called fingerprint methods [SC05] belong to this class of algorithms. They are based on the comparison (correlation) of measured radio parameters, e.g. DoA's, to pre-calculated or pre-measured reference data. This, however, needs an extensive and accurate database which is not always available, especially for the applications considered here. A modified version which includes an on-site calculation of spatial fingerprints by 3D ray tracing was proposed in [KS06]. This method uses a detailed 3D geographic data-base and relies on a single elevated base station.

An alternative localization method which uses the proximity between the measured and predicted multipath parameters has been defined in [AD06], and in [AK06] the verification of this method on the measurement data has been carried out. Hereby, instead of 3D terrain data 2D terrain data have been exploited which is justified by the low height of both, OS and MS, on street level. On the other hand, access to 2D data is much easier and algorithm complexity which is essential for the real-time requirements is considerably reduced. Moreover, the electromagnetic properties of the propagating waves like the signal strength have not been used since the material information of the surrounding buildings is not available. Due to the remarkable differences the term geometrical modeling approach (GMA) instead of ray-tracing prediction model has been submitted in [AK06] in order to avoid the confusion. Other than the method proposed in [KS06] it was furthermore assumed that blind space-time-filtering techniques [Wi04] can be used to obtain the spatial and temporal characteristics of the radio channel even without prior information about the transmitted signal. Still we should take into account that the "blind case" implies missing temporal synchronization between OS and MS resulting in loss of base delay information. That is, we possess only excess (or relative to LoS) delays and DoA's of multipath components.

Recording the OS measurements made at different positions and fusing them by means of the Bayesian theory in [AK06] we achieved a better localization accuracy of the MS. In this contribution we focus on the problem of tracking of a single moving MS using a single static OS. Hereby, we apply the particle filtering techniques and analyze the performance in synthetic urban scenarios. In the second section we present the dynamic model with an implemented particle filter and in the third we will show some simulation results.

2 Dynamic model, particle filtering

In this section we will define a simple dynamic model for the moving MS and static OS. Let us introduce the state vector

$$\mathbf{x}_k = \begin{bmatrix} x_k & y_k & \dot{x}_k & \dot{y}_k \end{bmatrix}^{\mathrm{T}} \in \mathrm{R}^4, \tag{1}$$

where R is a set of real numbers, $k \in \mathrm{N}$ is the time index and N is a set of natural numbers. x_k and y_k are the Cartesian coordinates of the MS and $\dot{x}_k$ and $\dot{y}_k$ specify it's speed along the x - and y - axis respectively. The position of the OS is assumed to be known and constant $\mathbf{r}_0 = \begin{bmatrix} x_0 & y_0 \end{bmatrix}^{\mathrm{T}}$. We assume that the target state evolves according to the following discrete-time linear stochastic model:

$$\mathbf{x}_k = \mathbf{f}_{k-1}(\mathbf{x}_{k-1}, \mathbf{v}_{k-1}) = \mathbf{\Phi} \cdot \mathbf{x}_{k-1} + \mathbf{v}_{k-1}, \tag{2}$$

where $\mathbf{v}_{k-1} = \begin{bmatrix} \frac{T^2}{2} v_{\ddot{x},k-1} & \frac{T^2}{2} v_{\ddot{y},k-1} & T \cdot v_{\ddot{x},k-1} & T \cdot v_{\ddot{y},k-1} \end{bmatrix}^{\mathrm{T}}$ is the process noise sequence according to [BR01] and $\mathbf{\Phi} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$ is the system matrix. Whereas $v_{r,k-1} \sim N(0, \sigma_r^2)$ with $r = \ddot{x}, \ddot{y}$ and T is the sampling interval. The measurements are related to the target state via the nonlinear measurement equation:

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k, \mathbf{r}_0) + \mathbf{w}_k. \tag{3}$$

The measurement vector $\mathbf{z}_k$ has the following structure:

$$\mathbf{z}_k = \begin{bmatrix} \tau_1 \ldots \tau_P & \varphi_1 \ldots \varphi_P \end{bmatrix}^{\mathrm{T}}, \tag{4}$$

where τ_p is the excess/relative delay of the i -th multipath component ($p = 1 \ldots P$) and φ_p it's DoA. P is the number of detected multipaths. $\mathbf{h}(\mathbf{x}_k, \mathbf{r}_0)$ is the measurement function, which depends on the position of the MS and the OS. We would like to emphasize that $\mathbf{h}(\mathbf{x}_k, \mathbf{r}_0)$ is a nonlinear function since the number and the values of the multipath parameters depend in a nonlinear fashion on the position of the MS and OS. The measurement noise sequence $\mathbf{w}_k = \begin{bmatrix} \omega_{\tau_1} \ldots \omega_{\tau_P} & \omega_{\varphi_1} \ldots \omega_{\varphi_P} \end{bmatrix}^{\mathrm{T}}$ consists of realizations from the Gaussian distributions $\omega_{\tau_p} \sim N(0, \sigma_{\tau_p}^2)$ and $\omega_{\varphi_p} \sim N(0, \sigma_{\varphi_p}^2)$.

In general, the modelled parameter values $\tilde{\mathbf{z}}_k$ from the output of the GMA cannot be identical to the observed values $\mathbf{z}_k$ for two reasons: measurement uncertainties and model imperfections. Here we assume that we have no modelling mismatch, that means e.g. that the real measurement environment is perfectly reproduced by the GMA, the measurement is influenced only by additive noise, so there are no other disturbing factors which can produce e.g. the "virtual" multipaths. The modelling mismatch issue will be an object of our future investigation.

The dynamic model is now complete and we proceed to the tracking part of the algorithm. Since the measurement equation is nonlinear we propose to use particle filtering, which is able to cope with such types of problems. Particle filtering is a sequential

Monte Carlo method where densities are approximated by a weighted set of samples. There is a rich variety of particle filters. We selected the auxiliary sampling importance resampling (ASIR) filter and will use the notation proposed in [RA04] in the sequel. Its basic idea is to perform the resampling step at time $k-1$ (using the available measurement at time k), before the particles are propagated to time k. In a first step of every iteration, all weights are updated using the actual measurement $\mathbf{z}_k$ and the likelihood function $p\left(\mathbf{z}_k \mid \boldsymbol{\mu}_k^i\right)$ according to $w_k^i = p\left(\mathbf{z}_k \mid \boldsymbol{\mu}_k^i\right) \cdot w_{k-1}^i$, whereby we choose $\boldsymbol{\mu}_k^i = \mathrm{E}\left[\mathbf{x}_k \mid \mathbf{x}_{k-1}^i\right]$. The likelihood function is defined in [AD06] and its maximum corresponds to the most probable position of the MS. In the second step we normalize the weights and resample using the algorithm described in [RA04]. Between the normalization and resampling we calculate the mean and covariance of the state estimate. The resampling eliminates the samples with low importance weights, multiplies the samples with high importance weights, and stores the index of their parents, denoted by i^j. In the third step we generate the new set of particles according to this index $\mathbf{x}_k^j \sim p\left(\mathbf{x}_k \mid \mathbf{x}_{k-1}^{i^j}\right)$ and calculate the new weights using $w_k^j = p\left(\mathbf{z}_k \mid \mathbf{x}_k^j\right) \big/ p\left(\mathbf{z}_k \mid \boldsymbol{\mu}_k^{i^j}\right)$ (see [RA04]). Finally, we normalize the weights and propagate to the next iteration. In the next section we present the simulation results.

3 Simulation Results

In this section we present some Monte Carlo simulation results of the previously explained tracking algorithm. We used a synthetic scenario depicted in Figure 1 with the OS located at $\mathbf{r}_0 = \left[60 \quad 40\right]^{\mathrm{T}}\,\mathrm{m}$. We have generated 40 MS trajectories according to the following dynamic parameters and initial values. The initial positions of the MS were uniformly drawn from 2 $5\mathrm{m} \times 5\mathrm{m}$ rectangular regions centred at $\left[130 \quad 120\right]^{\mathrm{T}}\,\mathrm{m}$ and $\left[80 \quad 40\right]^{\mathrm{T}}\,\mathrm{m}$ respectively. The initial value of the velocity was set to $\left[\dot{x}_0 \quad \dot{y}_0\right]^{\mathrm{T}} = \left[-4 \quad 0\right]^{\mathrm{T}}\,\mathrm{m/s}$ for the first region and $\left[\dot{x}_0 \quad \dot{y}_0\right]^{\mathrm{T}} = \left[0 \quad 4\right]^{\mathrm{T}}\,\mathrm{m/s}$ for the second region. The sample interval T was assumed as 1s and the measurement period was limited to 50s, so $k = 1,\ldots,50$. The process noise, which models the acceleration along the x - and y - axis, was represented by 2 independent white Gaussian sequences with equal standard deviations (STD's) of $\sigma_{\ddot{x}} = \sigma_{\ddot{y}} = 0{,}5\mathrm{m/s}^2$ (see (2)). The measurements consisting of the multipath parameters corrupted by additive noise are also assumed to be white Gaussian processes (see (3)). The noise level of the delay and DoA parameters of all multipaths among each other was identical during the same simulation run. Each trajectory was tracked with different combinations of measurement noise STD values of $\sigma_{\tau_p} / c_{light} = 1{,}3{,}7\mathrm{m}$ for path length and $\sigma_{\varphi_p} = 1{,}3{,}5°$ for DoA. Furthermore, the multipaths with a single bounce scattering were considered and the number of detected multipaths lied between 3 and 12. The number of particles was 300.

Figure 2 shows the mean position error over all 40 trajectories for all possible combinations of path length and DoA STD values. We observe that the cases with higher STD lead to a larger position error. A very important issue in every filter design is the consistency test. There are three consistency criteria defined in [BR01], however we test only the first one accepted to be the most important. It demands that the state errors should have zero mean and magnitude corresponding to the state covariance as yielded by the filter. We have tested the trajectories starting in the first region separately from those starting in the second region. It was observed that in the first case the consistency criterion was fulfilled whereas in the second case the consistency could not be accepted. The reason for this behaviour could be the distinct multimodality of the likelihood function resulting in the filter mismatch for certain MS tracks. That means that further investigations on this topic are required [Ko01].

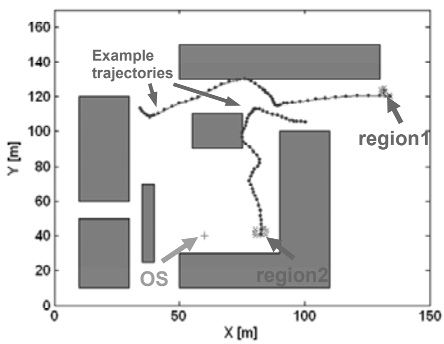

Figure 1: Measurement scenario

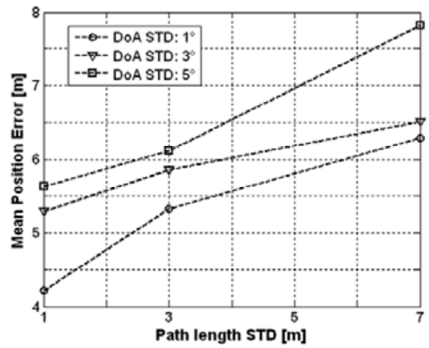

Figure 2: Mean position error

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