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A GRADIENT BASED ALGORITHM FOR PATH PARAMETER TRACKING IN CHANNEL SOUNDING

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A Gradient Based Algorithm for Path Parameter Tracking in Channel Sounding

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***Abstract*—We are describing an algorithm for channel parameter tracking for application in channel sounding measurement. At first, we derive a data model for so called block-wise estimation. For the parameter estimation we use a coordinate-wise optimization for the global search and a gradient based algorithm for the local search. Moreover, the Fisher-information matrix which is calculated throughout the optimization procedure, provides a variance estimate of the parameters. In contrast to known channel parameter estimators, the proposed algorithm additionally yields an estimation of the dynamic parameters, e.g. variation of time delay and azimuth angle. Block-wise channel parameter estimation considerably improves parameter tracking and, thus, enhances the accuracy and robustness of path parameter analysis. It gives also more information on the dynamic channel parameter characteristics and allows investigation of the microscopic path statistics.**

***Index Terms*—Parameter estimation, mobile radio channel, Maximum Likelihood estimation, gradient based optimization.**

I. Introduction

The interest in the multidimensional structure of the mobile radio channel is growing rapidly. The initial motivation was the investigation of the space-time structure at the base station (BS). In the recent time the double-directional modelling of the radio channel has attracted a lot of interest [4]. This is mainly due to two reasons. At one hand, double directional channel measurements gives a better physical insight into the wave propagation mechanism in real radio environments since it provides an enhanced multi-path resolution and it has the ability to remove the measurement antenna influence from the channel observation [5]. On the other hand, there is a growing interest in the exploitation of multiple antennas at both the BS and MS site. These MIMO (multiple-input-multiple-output) transmission systems promise a considerable increase in capacity [6]. Parametric MIMO channel models are required not only to evaluate the performance of generic transmission systems, e.g. in terms of MIMO capacity [7], but also for realistic link-level simulation of a specific algorithm in detail [8]. Prediction of the long term channel parameter variation can also help to control of the modem signal processing at the down-link.

A real-time channel sounder delivers a sequence of instantaneous channel observations. From each of these snapshots a set of channel parameter is estimated. The simplest approach is to consider the snapshot estimates as independent. It can, however, easily be observed that the specular part of the channel response contains wave propagation paths which persist along a certain number of snapshots. These paths are characterized by a continuous series of estimates with static or slowly changing parameters. Figure 1 shows the estimated time delay (resp. the path length) during an observed time of 40 s. A path track is identified by a uniquely assigned path number. In Figure 1 the path numbers are indicated by different colors. The path identification number assignment is carried out by applying a simple genetic transfer role which takes no advantage of the path persistence. Hereby the snapshots are taken as independent. Obviously, there arise ambiguities in assigning the path identification. Primarily at "crossovers" of the estimated path trajectories the path track is lost. Such crossover scenarios take place when the estimates of at least two paths come closer in the multidimensional parameter space than Rayleigh resolution ([9], [10]).

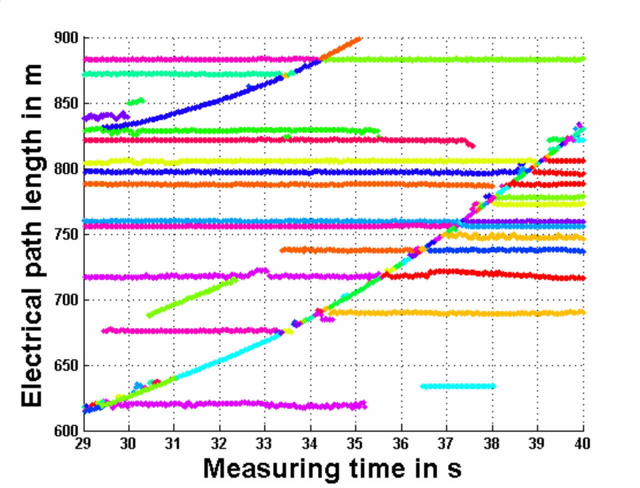

Figure 1: Estimated time delay vs. observation time of an example mobile radio channel.

An enhanced path tracking algorithm should take advantage of the similarity of subsequent estimates. Here we propose a procedure which calculates a block-wise estimate from a predefined number of snapshots. From this data blocks we estimate so-called static parameters which describe the mean path time delays (Time Delay of Arrival, TDoA) and angles (Direction of Arrival, DoA, and Direction of Departure, DoD). Moreover, dynamic parameters are estimated which describe the mean variation rate of TDoA, DoA, DoD variation resp. Parameter tracking based on the block estimation can considerably enhance the path number assignment and, thus, reduce problem with path parameter pairing. This can be used to answer more precisely the questions of path lifetime duration in different measurement scenarios. This also allows detailed investigation of the parameter statistics of scattering clusters which, in a microscopic sense, may be composed of a number of paths. We can estimate the amplitude variation, Doppler shift and delay/angular variance of the individual parameter estimates. Hereby it is very important to distinguish the estimated parameter variance from the variance error of the parameter estimator. The Maximum likelihood parameter estimation procedure follows the RIMAX framework which was introduced in [2].

In the following section we present the data model for parameter estimation, in section III we formulate the optimization problem. In section IV we explain the structure of the developed algorithm for parameter tracking of the mobile radio channel and finally, in the last section we present some estimation results of the implemented tracking algorithm.

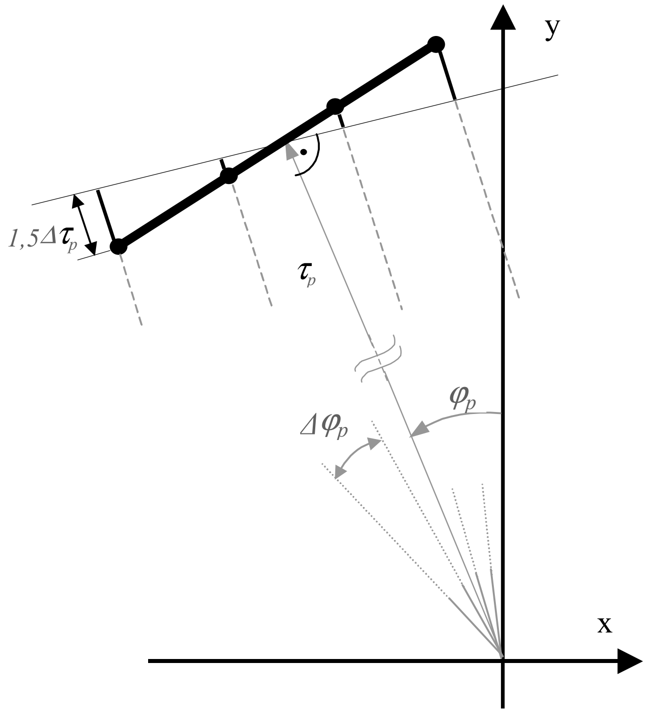

Figure 2: Block data model

II. Data Model

We use the well known base-band representation of the double directional channel model that approximates the narrow-band radio channel by the superposition of a finite number of propagation paths.

At first, the meaning of the term "snapshot" is explained. This term describes an instantaneous observation of the radio channel at one point of time. The proposed procedure uses a sequence of *N* snapshots and, thus, performs block-wise parameter estimation. This is a basically different approach compared with the single snapshot estimation, where each snapshot is analyzed separately and independently from the other. We assume piecewise linear and uniform motion. Hence the trajectories can be approximated by a set of line sections.

The parameter vector to be defined contains 2*R* real values that describe the mean static and dynamic structural parameters of each block. In this example, the number *R* of the structural parameter dimension is two since we have time delay and receiver azimuth. Furthermore, there are 2 *N* real values for the real- and imaginary parts of the complex path weights of the *N* snapshots. These parameters depend linearly on the measured data. Obviously, the model can be extended for other structural parameters, e.g. the transmit angles in azimuth and elevation or the Doppler-shift. Also full polarimetric path weight factors can be included.

So we have four structural parameters in this example which are the mean time delay τ, the mean time delay variation $\Delta\tau$, the mean azimuth angle of arrival φ and the mean azimuth angle variation $\Delta\varphi$. Thereby τ and φ are static and $\Delta\tau$, $\Delta\varphi$ are typically dynamic parameters. The detailed meaning of each of them is given below:

1. The azimuth angle of arrival φ is given between the direction to central point of a trajectory line and the perpendicular of the array aperture. φ is bounded by $\left[-\pi/2;\pi/2\right]$.
2. τ is the normalized time delay of the signal between the central point of a trajectory line and the central antenna element. Is bounded by $[0;1]$.
3. $\Delta\tau$ corresponds to the mean time delay variation between two consecutive snapshots. $\Delta\tau$ depends on the velocity of the transmitter (receiver) and/or the velocity of the reflecting objects as well as on the measurement rate of the system. This parameter is related to the velocity of the reflecting object and characterizes the dynamics of the mobile scenario.
4. $\Delta\varphi$ is the mean azimuth angle variation between two consecutive snapshots.

(1) describes the parameter vector for specular components:

$$\boldsymbol{\theta}_{sp,p} = \left[\tau_p \quad \Delta\tau_p \quad \varphi_p \quad \Delta\varphi_p \quad \gamma_{1,p}^{\mathrm{Re}} \quad \gamma_{1,p}^{\mathrm{Im}} \quad \cdots \quad \gamma_{N,p}^{\mathrm{Re}} \quad \gamma_{N,p}^{\mathrm{Im}}\right] \tag{1}$$

whereby $\gamma_{1,p}^{\mathrm{Re}}$ is the real part of the first of *N* path weights in the block of the p-th path. All structural parameters belonging to one propagation path p are collected in the vector $\boldsymbol{\mu}_p$, so we can use the following notation:

$$\boldsymbol{\theta}_{sp,p} = \begin{bmatrix} \boldsymbol{\mu}_p & \gamma_{1,p}^{\text{Re}} & \gamma_{1,p}^{\text{Im}} & \cdots & \gamma_{N,p}^{\text{Re}} & \gamma_{N,p}^{\text{Im}} \end{bmatrix} \quad (2)$$

We can construct the vector-valued basis function $\mathbf{a}_{i,n,p}$ for one propagation path using aperture sizes of the particular parameter domain M_i ($i = 1,\ldots,R$) as well as it's static $\mu_p^{(2i-1)}$ and it's dynamic $\mu_p^{(2i)}$ parameter:

$$\mathbf{a}_{i,n,p} = \frac{1}{\sqrt{M_i}} \cdot \begin{bmatrix} e^{-j2\pi\cdot f\left(\mu_p^{(2i-1)},\mu_p^{(2i)}\right)\left(-\frac{(M_i+1)}{2}\right)} \\ \vdots \\ e^{-j2\pi\cdot f\left(\mu_p^{(2i-1)},\mu_p^{(2i)}\right)\left(\frac{(M_i+1)}{2}\right)} \end{bmatrix} \in \mathbb{C}^{[M_i\times 1]} \quad (3)$$

whereby $n = \left(-\frac{(N-1)}{2};\ldots;\frac{(N-1)}{2}\right)$ is a snapshot index within a block. The argument of the basis function for the time-delay domain is than:

$$f_\tau(\tau,\Delta\tau) = (\tau_p + n\cdot\Delta\tau_p) \in \mathbb{R}^{[M_1\times 1]} \quad (4)$$

and for the angular domain (azimuth):

$$f_\alpha(\varphi,\Delta\varphi) = \frac{d}{2}\sin(\varphi_p + n\cdot\Delta\varphi_p) \in \mathbb{R}^{[M_2\times 1]} \quad (5)$$

respectively. With the symbol $\Diamond$ we define the Kathri-Rao product, thus $\left(\mathbf{a}_{R,n,p}\Diamond\ldots\Diamond\mathbf{a}_{1,n,p}\right)$ is a vector-valued function mapping the real shift parameters from $\mathbb{R}^{2\cdot R}$ to a complex vector in $\mathbb{C}^M$ with unit length and size $M = M_1\cdot M_2\cdot\ldots\cdot M_R$. The following expression describes the frequency response for p-th propagation path at the measurement point n:

$$\mathbf{s}\left(\boldsymbol{\theta}_{sp,n,p}\right) = \left(\mathbf{a}_{R,n,p}\Diamond\ldots\Diamond\mathbf{a}_{1,n,p}\right)\cdot\gamma_{n,p} \quad (6)$$

$$\mathbf{S}\left(\boldsymbol{\theta}_{sp,p}\right) = \left[\mathbf{s}\left(\boldsymbol{\theta}_{sp,1,p}\right) \;\; \cdots \;\; \left(\mathbf{s}\left(\boldsymbol{\theta}_{sp,N,p}\right)\right)\right] \in \mathbb{C}^{[M\times N]} \quad (7)$$

Taking into account that the radio channel is a linear system, we can say that the observation is up to a certain accuracy a superposition of a finite number P of propagation paths plus a complex matrix

$$\mathbf{D}_{dds} = \left[\mathbf{d}_{dds,1} \;\; \cdots \;\; \mathbf{d}_{dds,N}\right] \in \mathbb{C}^{[M\times N]} \quad (8)$$

describing the distribution of the observed dense diffuse scattered components. We define the decomposition of the covariance matrix $\mathbf{R}(\boldsymbol{\theta}_{dds})$ by:

$$\mathbf{L}(\boldsymbol{\theta}_{dds})\cdot\mathbf{L}^{\text{H}}(\boldsymbol{\theta}_{dds}) = \mathbf{R}(\boldsymbol{\theta}_{dds}). \quad (9)$$

So the realization of the distributed diffuse components at the n-th measurement point looks like:

$$\mathbf{d}_{dds,n} \sim \mathbf{L}(\boldsymbol{\theta}_{dds})\cdot\left(\mathcal{N}\left(0,\tfrac{1}{2}\mathbf{I}\right) + j\cdot\mathcal{N}\left(0,\tfrac{1}{2}\mathbf{I}\right)\right). \quad (10)$$

The matrix

$$\mathbf{W} = \left[\mathbf{w}_1 \;\; \cdots \;\; \mathbf{w}_N\right] \in \mathbb{C}^{[M\times N]} \quad (11)$$

with

$$\mathbf{w}_i \sim \mathcal{N}\left(0,\frac{\sigma^2}{2}\cdot\mathbf{I}\right) + j\cdot\mathcal{N}\left(0,\frac{\sigma^2}{2}\cdot\mathbf{I}\right) \quad (12)$$

describes the measurement noise. $\mathbf{R}(\boldsymbol{\theta}_{dds})$ is a function of the parameter vector $\boldsymbol{\theta}_{dds}$ with its parameters defined in [2]. We assume that these parameters are stationary during one snapshots block. So we can write:

$$\mathbf{R}(\boldsymbol{\theta}_{dds}) = \mathbf{I}^{[M_2\times M_2]} \otimes \mathbf{R}_f(\boldsymbol{\theta}_{dds}) \quad (13)$$

where $\mathbf{I}$ is the identity matrix and M_2 the aperture of an antenna array and $\otimes$ denotes a Kronecker product.
Using (7) the block observation $\mathbf{X}\in\mathbb{C}^{[M\times N]}$, containing N realizations $\mathbf{x}_1,\ldots,\mathbf{x}_N$ can be expressed by:

$$\mathbf{X} = \mathbf{S}(\boldsymbol{\theta}_{sp}) + \mathbf{D}_{dds} + \mathbf{W} = \sum_{p=1}^{P}\mathbf{S}(\boldsymbol{\theta}_{sp,p}) + \mathbf{D}_{dds} + \mathbf{W}. \quad (14)$$

III. Maximum Likelihood Estimation

We will make use of the Maximum-Likelihood-Principle in order to formulate the optimization problem. For this reason we express the conditional density function of the n-th observation $\mathbf{x}_n$ in the block as follows:

$$\text{pdf}\left(\mathbf{x}_n \mid \boldsymbol{\theta}_{sp},\boldsymbol{\theta}_{dds}\right) = \frac{1}{\pi^M\cdot\det(\mathbf{R}(\boldsymbol{\theta}_{dds}))} e^{-\left(\mathbf{x}_n - \mathbf{s}(\boldsymbol{\theta}_{sp})_n\right)^{\text{H}}\cdot\mathbf{R}(\boldsymbol{\theta}_{dds})^{-1}\left(\mathbf{x}_n - \mathbf{s}(\boldsymbol{\theta}_{sp})_n\right)}. \quad (15)$$

The related log-likelihood function is

$$L\left(\mathbf{x}_n \mid \boldsymbol{\theta}_{sp},\boldsymbol{\theta}_{dds}\right) = -M\cdot\ln(\pi) - \ln(\det(\mathbf{R}(\boldsymbol{\theta}_{dds}))) - \left(\mathbf{x}_n - \mathbf{s}(\boldsymbol{\theta}_{sp})_n\right)^{\text{H}}\cdot\mathbf{R}(\boldsymbol{\theta}_{dds})^{-1}\left(\mathbf{x}_n - \mathbf{s}(\boldsymbol{\theta}_{sp})_n\right). \quad (16)$$

We get the complete Likelihood function if we consider all snapshots within the measurement block in the following way:

$$\text{pdf}\left(\mathbf{X} \mid \boldsymbol{\theta}_{sp},\boldsymbol{\theta}_{dds}\right) = \prod_{n=1}^{N}\text{pdf}\left(\mathbf{x}_n \mid \boldsymbol{\theta}_{sp},\boldsymbol{\theta}_{dds}\right). \quad (17)$$

The related complete log-likelihood function is:

$$L\left(\mathbf{X} \mid \boldsymbol{\theta}_{sp},\boldsymbol{\theta}_{dds}\right) = \sum_{n=1}^{N}\Big(-M\cdot\ln(\pi) - \ln(\det(\mathbf{R}(\boldsymbol{\theta}_{dds}))) - \left(\mathbf{x}_n - \mathbf{s}(\boldsymbol{\theta}_{sp})_n\right)^{\text{H}}\cdot\mathbf{R}(\boldsymbol{\theta}_{dds})^{-1}\left(\mathbf{x}_n - \mathbf{s}(\boldsymbol{\theta}_{sp})_n\right)\Big). \quad (18)$$

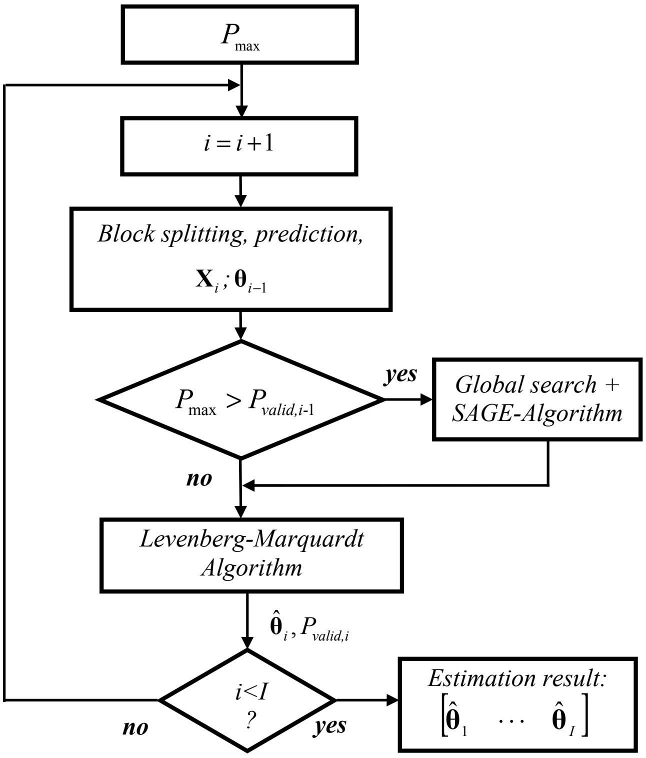

Figure 3: Flow chart of the tracking algorithm

The parameters of the diffuse, distributed scattering ($\boldsymbol{\theta}_{dds}$) components and of the discrete ($\boldsymbol{\theta}_{sp}$) components are assumed to be uncorrelated. So, according to EM-algorithm, we use sequential space alternating parameter optimization. Let us now define some basic steps in the optimization routine. The alternating procedure requires two different formulation of the optimization problem. The estimation of the discrete components is our main concern here. The first and the second terms in equation (16) doesn't depend on the parameters $\boldsymbol{\theta}_{sp}$, hence the function to minimize is (19):

$$\hat{\boldsymbol{\theta}}_{sp} = \arg\min_{\boldsymbol{\theta}_{sp}} \left(\sum_{n=1}^{N} \left(\left(\mathbf{x}_n - \mathbf{s}(\boldsymbol{\theta}_{sp})_n \right)^{\mathrm{H}} \cdot \mathbf{R}(\boldsymbol{\theta}_{dds})^{-1} \cdot \left(\mathbf{x}_n - \mathbf{s}(\boldsymbol{\theta}_{sp})_n \right) \right) \right) \qquad (19)$$

The result belongs to the well-known category of optimization tasks called Weighted-Least-Squares and there are many search strategies available in the literature.

IV. TRACKING ALGORITHM

The proposed tracking algorithm consists of two steps. Figure 3 presents it's flow chart. For the initialization of the parameters the tracking algorithm uses at first the estimated angles and delays of the previous observation and estimates the linear parameters (path weights) for the actual observation. In the second initializing step a coordinate (parameter)-wise search algorithm (SAGE-type) is applied to search for raw parameter estimates of new propagation paths in the scenario.

At the next step, the initial solution determined by the global search algorithm is improved by the local search method. The gradient based line-search method of Levenberg-Marquardt is used for the local search. It is an iterative procedure that optimizes a non-linear function $F(\hat{\boldsymbol{\theta}}_i)$:

$$F(\hat{\boldsymbol{\theta}}_i) = \sum_{n=1}^{N} \left(\left(\mathbf{x}_n - \mathbf{s}(\hat{\boldsymbol{\theta}}_i)_n \right)^{\mathrm{H}} \cdot \mathbf{R}(\boldsymbol{\theta}_{dds})^{-1} \cdot \left(\mathbf{x}_n - \mathbf{s}(\hat{\boldsymbol{\theta}}_i)_n \right) \right) \qquad (20)$$

along a feasible descent search direction $\boldsymbol{\Delta}\hat{\boldsymbol{\theta}}_i$

$$\boldsymbol{\Delta}\hat{\boldsymbol{\theta}}_i = \left(\mathbf{H}(\hat{\boldsymbol{\theta}}_i) + \lambda \cdot \mathbf{I} \right)^{-1} \cdot \mathbf{g}(\hat{\boldsymbol{\theta}}_i) \qquad (21)$$

where $\mathbf{H}(\hat{\boldsymbol{\theta}}_i)$ is the Hessian, $\mathbf{g}(\hat{\boldsymbol{\theta}}_i)$ is the gradient vector, $\mathbf{I}$ is an identity matrix and λ is a scalar value. The parameter update equation for the $(i+1)$-th iteration is:

$$\hat{\boldsymbol{\theta}}_{i+1} = \hat{\boldsymbol{\theta}}_i + \boldsymbol{\Delta}\hat{\boldsymbol{\theta}}_i \,. \qquad (22)$$

The multiplier λ has to be chosen such that

$$F(\hat{\boldsymbol{\theta}}_{i+1}) < F(\hat{\boldsymbol{\theta}}_i). \qquad (23)$$

There are 3 stopping criteria for the algorithm:

1. Stop by exceeding the maximal number of iterations.

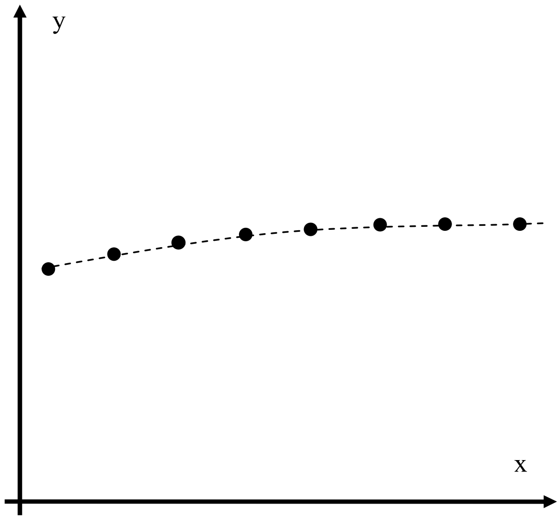

Figure 4: Measured path trajectory

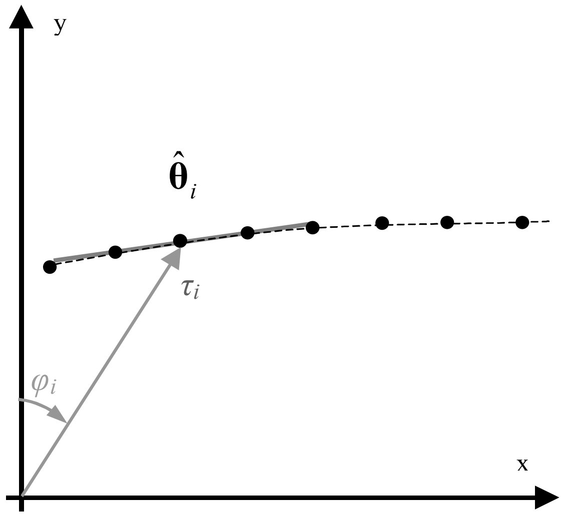

Figure 5: i-th block parameter estimation

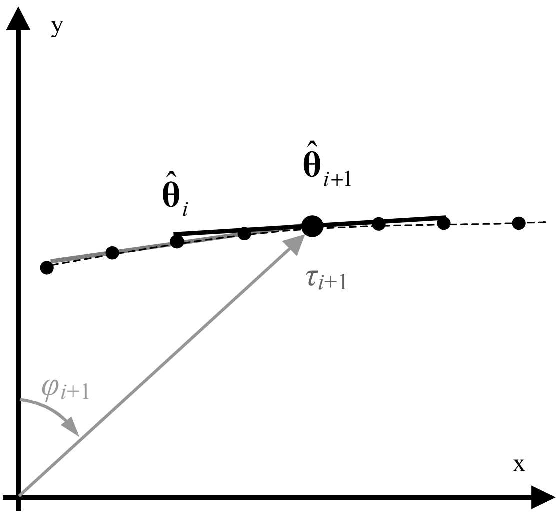

Figure 6: Overlapped block-wise estimations

2. Stop if the weighted least squared error $F(\hat{\boldsymbol{\theta}}_i)$ doesn't changes with further iterations.
3. Stop if $\lambda \to \infty$ or the search direction is $\Delta\hat{\boldsymbol{\theta}}_i$ identical zero.

One feature of the RIMAX parameter estimation framework is to submit the reliability of the estimated path parameters. This function is implemented as part of the Levenberg-Marquardt procedure. It is well- known that the variances of the channel parameters are defined by the diagonal elements of the Fisher-Information-Matrix (FIM). Using this information we assume, that the propagation paths with a high variance value of the respective path weight are not reliable and have to be deleted from the parameter set. The estimation of the FIM is given by the covariance matrix of the first order derivatives of the observed data vector with respect to the parameters $\boldsymbol{\theta}$ of the P paths. Thus the FIM is equal to the Gauß-Newton approximation of the Hessian $\mathbf{H}(\hat{\boldsymbol{\theta}}_i)$ except for a constant factor. So the information on reliability of the propagation paths results from the Hessian without any additional calculating complexity.

Now we introduce the prediction procedure which is one of the most important parts of every tracking algorithm. The Figure 4 presents a fragment of the motion trajectory of the virtual source. As already mentioned, the main idea of the tracking algorithm is the assumption that each trajectory in the certain mobile scenario can be approximated with the set of the line sections. The length of these sections is chosen depending on the mobile scenario and the snapshot rate of the measuring system. Each line section connects a fixed number of measurement points to one snapshot block. In this example we set the size of the snapshot block to 5 snapshots. Figure 5 presents the estimation of the i-th snapshot block in the Cartesian coordinate system. Now, we can predict the location of the (i+1)-th snapshot block. We can use for example the parameters of the last snapshot in the i-th snapshot block to predict the location of the subsequent snapshot block. The result is shown in the Figure 6. This approach is applied to the remaining snapshots as well.

Because of snapshot block overlapping we get two estimations for each measurement point. The equation (16) is linear in the parameters $[\gamma_{1,p}^{\mathrm{Re}} \quad \gamma_{1,p}^{\mathrm{Im}} \quad \cdots \quad \gamma_{N,p}^{\mathrm{Re}} \quad \gamma_{N,p}^{\mathrm{Im}}]$, hence we can calculate their estimates using a closed form solution.

V. Estimation Results

In this chapter we present some estimation results of the developed tracking algorithm. For the estimation we have used data of the measuring campaign in Tokyo, Japan. The measurement, which took place in a street scenario was made by using the RUSK Channel Sounder. The transmitter and the receiver were fixed during the measurement and there were many mobile and immobile reflectors.

Figure 7: Street scenario in Tokio

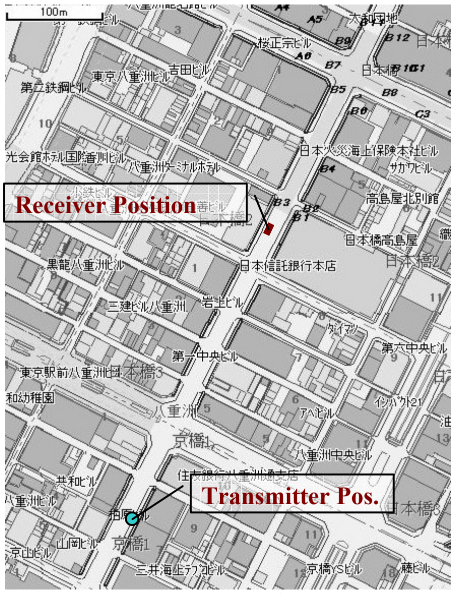

Figure 8: Map of Tokio

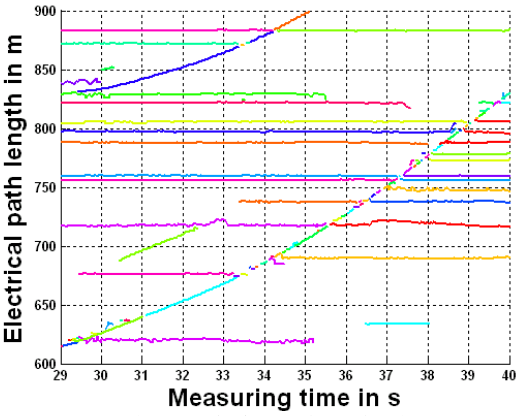

Figure 9: Single snapshot estimation

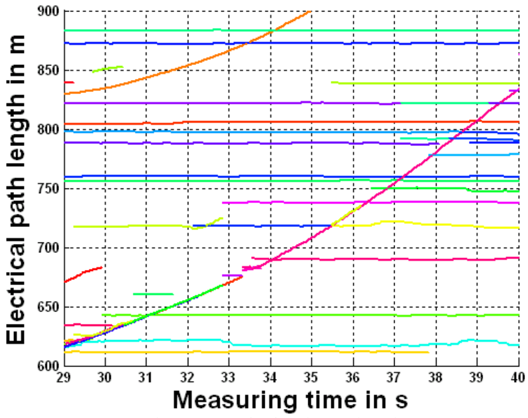

Figure 10: Block-wise estimation

The Figure 7 and Figure 8 shows the measuring environment and the map of the city district.

Figure 9 and Figure 10 show the time delay estimation results of the implemented tracking algorithm. Figure 9 is the single snapshot estimation, Figure 10 presents the block-wise estimation. Each path is indicated by a different color. The curved trajectories correspond to the mobile reflectors. It's obvious, that the block-wise estimation algorithm achieves a better performance concerning the parameter tracking. The most of path losses occur at the path cross-over situations. Figure 11 presents the azimuth angle estimation of the implemented tracking algorithm. Most of the paths impinge to the receiver array from the front side direction. This is caused by the special measuring scenario. The walls of the houses lead the radiated waves in the same direction, so the variation of the angle of arrival at the receiver array is small. The components with wider angular variation are caused by the reflecting objects on the right and on the left side of the receiving antenna (see Figure 7). They are associated with short delay.

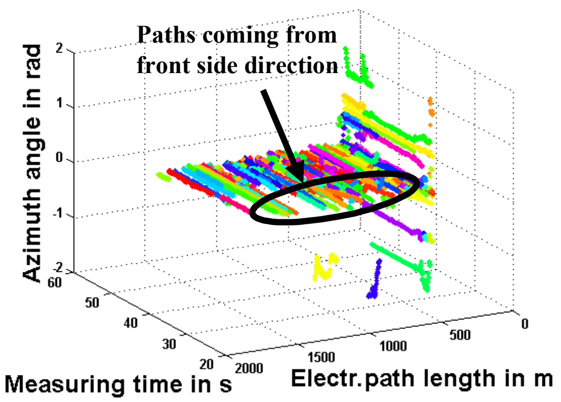

Figure 11: Azimuth and time delay angle estimation

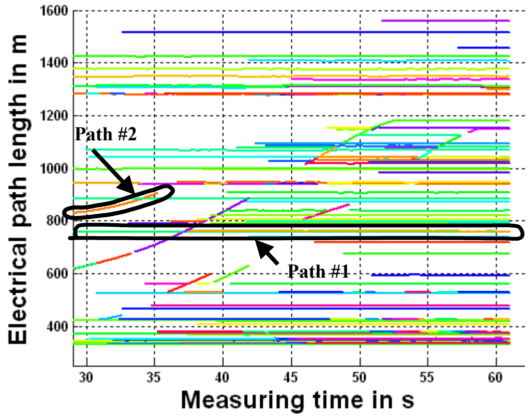

Figure 12: Selected paths

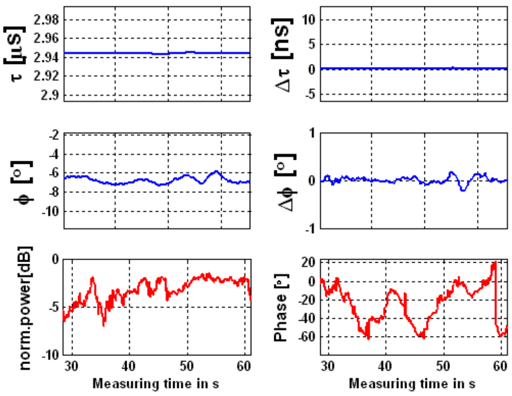

Figure 13: Estimated parameters of the 1st path

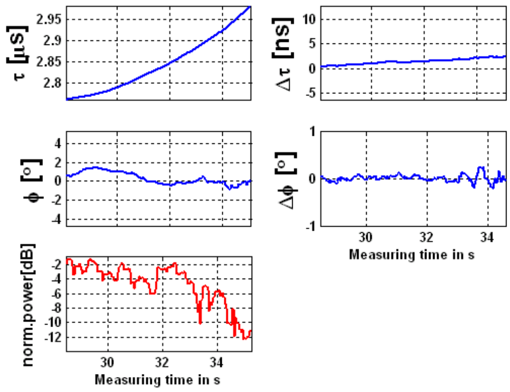

Figure 14: Estimated parameters of the 2nd path

Figure 12 presents a block-wise estimation results of two selected propagation paths for microscopic path variance analysis. The first path corresponds to the stationary reflector and the second one to the mobile reflector. Figure 13 and Figure 14 show the estimated structural parameters as well as estimated normalized received power for each of the selected paths. The variation of the first path weight is low since it is a static path. The path weight of second path changes much more since it results from a moving reflector. The received power variation is limited in the first case by 5 dB and in the second case by 25 dB. The time delay τ of the varying path appears to be quadratic. For the static path in Fig. 13 also the phase response of the complex path weight is given. The slow phase slope could be a result of an imperfect synchronization of the Tx/Rx reference oscillators whereas the small-scale variation of the phase may be introduced by the oscillating mast of the antenna. The equivalent phase diagram was omitted for the dynamic path in Fig. 14 since in this case the measurement rate of the sounder was not chosen high enough to reproduce the phase response in the Nyquist sense.

Figure 15 and Figure 16 depict the variation of the number of the estimated propagation paths for two different snapshot block lengths. This raises the question of path number estimation. Here the number of the paths is adaptively calculated for every snapshot block. The procedure is as follows. At first we estimate the maximum path number. It is calculated from the mean value of the path number of the last 5 previous block estimates. To allow a moderate growing number of paths, this number is increased by, e.g., 3 paths. In the next step the paths parameters are initialized by using the parameters from the previous block. The prediction mechanism is indicted in Figure 4-Figure 6. The dynamic parameters are directly taken from the previous block estimate of the corresponding path and the static parameters are corrected by using the dynamic parameters. This gives a favorable starting position for the parameter optimization. The parameters of new paths are initialized by a coordinate-wise global search algorithm. The resulting parameter vector is then optimized by the gradient search algorithm. In a third step, the variance of the estimated parameters is evaluated. If the estimated parameters are indicted as unreliable, the corresponding propagation path is canceled. This procedure reduces the number of the paths and preserves only the significant estimates. In the next block the path number can again increase according to the adaptation rule described.

Comparing Figure 15 and Figure 16 we can see that the mean number of path depends on the length of the snapshot block, it is reduced when the block length is increasing. The reason is that for longer blocks only those paths are preserved which exist of a longer time interval.

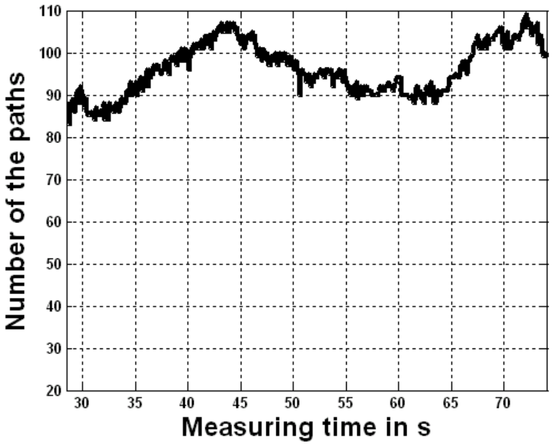

Figure 15: Variation of the estimated path number. Block length 7

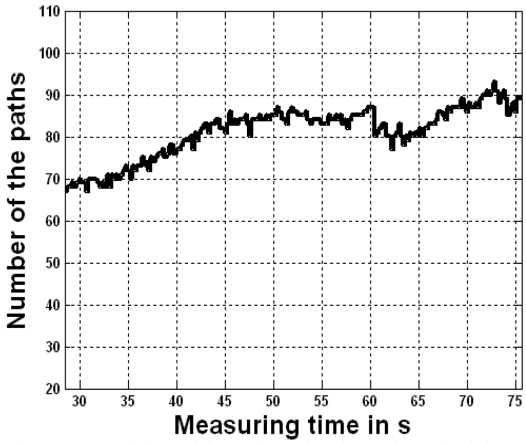

Figure 16: Variation of the estimated path number. Block length 15

VI. Conclusion

We have presented an algorithm for estimation and tracking of the parameters of the radio channel. The proposed algorithm yields the dynamic model parameters which contain information about the time variation of the channel. Another feature is the reliability estimation which allows adaptively control the path number throughout the measuring time. Since the parameters are jointly estimated for blocks of measured snapshots, there are no difficulties with estimation association. The path parameters can by easily identified and separated in the estimated data sets and are easily manageable e.g. for the purpose of detailed statistical analysis. The tracking algorithm has been tested on a static SIMO scenario in an urban environment. Its performance should be proved further on data records from dynamic scenarios with different antenna structures.

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