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A State Space Approach to Propagation Path Parameter Estimation and Tracking

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A State Space Approach to Propagation Path Parameter Estimation and Tracking

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Abstract

In this paper we address the problem of propagation path parameter estimation in channel sounding. Our approach is based on a state-space model that describes the dynamics of the channel parameters in time. The method builds on the work presented in TD(04)124, where it has been shown that the performance of propagation path parameter estimators can be improved if the correlation of the radio channel parameters in time is exploited by a maximum likelihood estimator. The proposed state-space based approach has lower computational complexity than the previous method and allows the tracking of the desired time varying parameters as well. Since the dimension of the state, i.e., the number of model parameters, is significantly smaller than the dimension of a channel observation by applying the matrix inversoin lemma we are able to reduce the computational complexity of the extended Kalman filter. The performance of the proposed technique is investigated using channel sounding measurements.

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 [1]. 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 [2]. On the other hand, there is a growing interest in exploiting multiple antennas at both the BS and MS site. These MIMO (multiple-input-multiple-output) transmission systems promise a considerable increase in capacity [3]. Parametric MIMO channel models are required not only to evaluate the performance of generic transmission systems, e.g. in terms of MIMO capacity [4], but also for realistic link-level simulation of a specific algorithm in detail [5]. Prediction of the long term channel parameter variation can also help to control of the modem signal processing at the down-link. Powerful channel models are also needed in network planning.

A real-time channel sounder delivers a sequence of channel observations. From each of these observations (snapshots) a set of channel parameters is estimated. A simple approach is to consider the subsequent estimates as independent. However, it can be observed that the specular part of the channel response contains propagation paths which persist over a certain number of snapshots. These paths are characterized by a series of estimates with static or slowly changing parameters. In [6], a deterministic maximum likelihood estimator was proposed to exploit the correlation of the structural parameters such as time-delay of arrival, direction of departure (DoD) and/or direction of arrival (DoA). It was shown that the proposed method outperforms the maximum likelihood estimator which does not exploit the strong correlation, i.e, predictability of the structural parameters over time [6]. Besides the reduced estimation error, it has been shown that a propagation path can be tracked over time even if it is shadowed or if its parameters intersect with the parameters of another path (path crossover). The main drawback of the proposed maximum likelihood estimator for parameter tracking [6] is its high computational complexity. This is due to the fact that the maximum likelihood estimator operates in a block manner, independently from the previous estimates which may not be feasible for tracking the parameters over time.

In this paper we propose a state-space based method for parameter tracking in order to estimate the propagation paths. The method stems from the maximum likelihood parameter estimation procedure (RIMAX) which was introduced in [7], [8]. In addition, tracking ideas resemble the approach used in Multiple Target Tracking (MTT) in radar. Propagation parameter tracking can considerably increase path parameter pairing over time. This can be used to answer more precisely the questions of path lifetime in different measurement scenarios. It also allows detailed investigation of the parameter statistics of scattering clusters which, in a microscopic sense, may be composed of a number of paths. If the parameters of a propagation path are tracked over time we are able to estimate the amplitude variation, Doppler shift and delay/angular variance of the individual parameter. However, a prerequisite for any post-processing of the parameter estimates is that the parameter estimator provides an estimate of the error covariance matrix of the estimated channel parameters.

The state-space model derived in this paper maps the dynamic propagation path parameters to the channel observations. The estimation and tracking is done by using the Extended Kalman Filter (EKF), since the function mapping the channel parameter vector to the observation vector is nonlinear. The benefits of the method are twofold, first we obtain a lower complexity than using the ML algorithm. This is due to the fact that EKF is a recursive estimator, whereas ML needs to perform several iterations for the same received observation vector in order to converge. Moreover, by applying the matrix inversion lemma the complexity of EKF can be further reduced. The second advantage is the tracking capability of EKF, which can give us an insight of the time evolution of the propagation parameters. This information is not available when using ML.

In the following section we present the data model for a channel observation. In Section III we formulate the state-space model which describes the dynamics of our parameters and present the Kalman filter recursions. In Section IV we present some estimation results of the implemented parameter estimator and draw conclusions in Section V.

II. Data Model for a Channel Observation

We use the data model introduced in [9], [8] to describe the structured wideband MIMO channel. This data model is based on the assumption that every specular propagation path can be described by a R_p-dimensional (5-D) shift operator on the transmit signal. It shifts the Tx-signal in the 4 independent angular domains: transmit azimuth φ_T and elevation ϑ_T, receive azimuth φ_R and elevation ϑ_R, as well as in the time-delay domain τ. Furthermore, it is assumed that the 5 related aperture domains (frequency and antenna array apertures) are finite. The periodic excitation signal is band-limited, and the aperture of antenna arrays is determined by their size, which is limited too. Finally, the parameters are or can be treated as bounded parameters. All angles are bounded by $(-\pi, \pi)$, and the time-delay is bounded by $(0, \tau_{max})$ where τ_{max} is a function of transmit power, free space loss, and receiver noise. Under these constraints and considering that a shift in one domain can also be expressed by the multiplication with a complex exponential in the related aperture domain, the family of exponential functions is sufficient to construct a data model for a specular propagation path.

For notational convenience we replace the shift-parameters of propagation path (component) p from the physical model using normalized shift parameters $\mu_p^{(r)}$, which are related to their physical counterparts $\varphi_{T,p}$, $\vartheta_{T,p}$, $\varphi_{R,p}$, $\vartheta_{R,p}$, and τ_p by a unique projection. We collect all structural parameters $\mu_p^{(r)}$ belonging to one propagation path p to the vector $\boldsymbol{\mu}_p = \left[\mu_p^{(1)} \cdots \mu_p^{(R_p)}\right]^{\mathrm{T}}$. Let

$$\mathbf{a}\left(\mu_p^{(r)}\right) = \tfrac{1}{\sqrt{N_r}} \left[\begin{array}{ccccc} \mathrm{e}^{-j\mu_p^{(r)} \frac{N_r - 1}{2}} & \dots & 1 & \dots & \mathrm{e}^{+j\mu_p^{(r)} \frac{N_r - 1}{2}} \end{array} \right]^T \in \mathbb{C}^{M \times 1} \tag{1}$$

be the vector valued complex exponential related to the shift parameter $\mu_p^{(r)}$ in the dimension r of component p with dimension N_r. Then the R-dimensional shift then $\mathbf{a}\left(\boldsymbol{\mu}_k\right) = \mathbf{a}\left(\mu_p^{(R)}\right) \otimes \mathbf{a}\left(\mu_p^{(R-1)}\right) \otimes \ldots \otimes \mathbf{a}\left(\mu_p^{(1)}\right)$ is a vector valued function mapping the real shift parameters $\boldsymbol{\mu}_p$ to a complex vector in $\mathbb{C}^{N \times 1}$ with unit length and size $N = N_1 N_2 \cdot \ldots \cdot N_{R_p}$. Here $\otimes$ denotes the Kronecker product. Introducing the four transformation matrices $\mathbf{G}_{HH}, \mathbf{G}_{HV}, \mathbf{G}_{VH}, \mathbf{G}_{VV}$ describing the linear measurement system and H, V referring to polarization we can express the noise-free observation $\mathbf{s}\left(\boldsymbol{\theta}_p\right) \in \mathbb{C}^{M \times 1}$ of a single specular propagation path by

$$\mathbf{s}\left(\boldsymbol{\theta}_p\right) = \mathbf{G}_{HH}\mathbf{a}\left(\boldsymbol{\mu}_p\right)\gamma_{HH,p} + \mathbf{G}_{HV}\mathbf{a}\left(\boldsymbol{\mu}_p\right)\gamma_{HV,p} + \mathbf{G}_{VH}\mathbf{a}\left(\boldsymbol{\mu}_p\right)\gamma_{VH,p} + \mathbf{G}_{VV}\mathbf{a}\left(\boldsymbol{\mu}_p\right)\gamma_{VV,p} \tag{2}$$

with the parameter vector

$$\boldsymbol{\theta}_p = \left[\begin{array}{ccccccccc} \boldsymbol{\mu}_p^T & \Re\{\gamma_{HH,p}\} & \Im\{\gamma_{HH,p}\} & \Re\{\gamma_{HV,p}\} & \Im\{\gamma_{HV,p}\} & \Re\{\gamma_{VH,p}\} & \Im\{\gamma_{VH,p}\} & \Re\{\gamma_{VV,p}\} & \Im\{\gamma_{VV,p}\} \end{array} \right]^{\mathrm{T}}. \tag{3}$$

Let us clarify the meaning of the system matrices $\mathbf{G}_{HH}, \mathbf{G}_{HV}, \mathbf{G}_{VH}, \mathbf{G}_{VV}$ by an example. We assume the narrowband radio channel has been measured using three-dimensional antenna arrays at both the Tx- and the Rx-site with M_T and M_R antenna elements respectively. The radio channel is measured in the spectral domain with a broadband-signal of M_f equally spaced lines about the carrier frequency f_c. Furthermore, we assign the normalized shift parameters to the physical parameters in the following way

$$\begin{aligned}\mu^{(\tau)} = \mu^{(1)} = 2\pi \tfrac{\tau}{\tau_{max}},\\ \mu^{(\varphi_T)} = \mu^{(2)} = \varphi_T,\\ \mu^{(\vartheta_T)} = \mu^{(3)} = \vartheta_T,\\ \mu^{(\varphi_R)} = \mu^{(4)} = \varphi_R,\\ \mu^{(\vartheta_R)} = \mu^{(5)} = \vartheta_R,\end{aligned} \tag{4}$$

For simplicity, we will assume narrowband measurements in that sense, that it is sufficient in terms of the measurement accuracy to describe the directional characteristics of the antenna arrays at the carrier frequency, and that the Nyquist sampling theorem is strictly adhered to in all five dimensions. Using the fact that the far-field beam-pattern of an antenna-array is the two-dimensional Fourier-transform of its effective aperture distribution function [10], [9] we can express the relation between the signals at the antenna array ports and the element beam-patterns using the effective aperture distribution functions. Collecting the EADFs of the Tx- and Rx-array row-wise in the matrices $\mathbf{G}_{T_H}, \mathbf{G}_{T_V}$ and $\mathbf{G}_{R_H}, \mathbf{G}_{R_V}$, respectively, we can use

$$\begin{aligned}\mathbf{b}_{T_H}\left(\mu^{(2)}, \mu^{(3)}\right) = \mathbf{G}_{T_H}\left(\mathbf{a}\left(\mu^{(3)}\right) \otimes \mathbf{a}\left(\mu^{(2)}\right)\right),\\ \mathbf{b}_{T_V}\left(\mu^{(2)}, \mu^{(3)}\right) = \mathbf{G}_{T_V}\left(\mathbf{a}\left(\mu^{(3)}\right) \otimes \mathbf{a}\left(\mu^{(2)}\right)\right),\\ \mathbf{b}_{R_H}\left(\mu^{(4)}, \mu^{(5)}\right) = \mathbf{G}_{R_H}\left(\mathbf{a}\left(\mu^{(5)}\right) \otimes \mathbf{a}\left(\mu^{(4)}\right)\right),\\ \mathbf{b}_{R_V}\left(\mu^{(4)}, \mu^{(5)}\right) = \mathbf{G}_{R_V}\left(\mathbf{a}\left(\mu^{(5)}\right) \otimes \mathbf{a}\left(\mu^{(4)}\right)\right)\end{aligned} \tag{5}$$

to express the relation between the signals on the antenna array ports and a far-field point source or drain in a fixed distance. Furthermore we use the usually diagonal matrix $\mathbf{G}_f$ to describe the frequency response of the measurement system. Altogether the matrices

$$\begin{aligned}\mathbf{G}_{HH} = \mathbf{G}_{R_H} \otimes \mathbf{G}_{T_H} \otimes \mathbf{G}_f\\ \mathbf{G}_{HV} = \mathbf{G}_{R_V} \otimes \mathbf{G}_{T_H} \otimes \mathbf{G}_f\\ \mathbf{G}_{VH} = \mathbf{G}_{R_H} \otimes \mathbf{G}_{T_V} \otimes \mathbf{G}_f\\ \mathbf{G}_{VV} = \mathbf{G}_{R_V} \otimes \mathbf{G}_{T_V} \otimes \mathbf{G}_f\end{aligned} \tag{6}$$

describe the linear measurement system.

In [11], [8] it has been shown, that the observed radio channel consists not only of specular components but also of dense multipath components (DMC). So by assuming that the radio channel is a linear system, we approximate the observation $\mathbf{y} \in \mathbb{C}^{M \times 1}$ with the superposition of a finite number P of specular propagation paths and the realization of a stochastic process. With the complex vector $\mathbf{n}_d$ drawn from a multivariate circular Gaussian process $\mathcal{N}_c(\mathbf{0}, \mathbf{R}_d) \in \mathbb{C}^{M \times 1}$ describing the distribution of the observed dense multipath components, and the zero mean circular Gaussian measurement noise $\mathbf{n}_m \sim \mathcal{N}_c(\mathbf{0}, \mathbf{I}) \in \mathbb{C}^{M \times 1}$ the model for a channel observation is

$$\mathbf{y} = \sum_{p=1}^{P} \mathbf{s}(\boldsymbol{\theta}_p) + \mathbf{n}_d + \mathbf{n}_m. \tag{7}$$

For a discussion about the structure of the covariance matrix $\mathbf{R}_d$ of the process $\mathbf{n}_d$, see [11], [8]. Combining the independent circular Gaussian processes $\mathbf{n}_d$ and $\mathbf{n}_m$ in $\mathbf{n}_y = \mathbf{n}_d + \mathbf{n}_m$ yields

$$\mathbf{y} = \sum_{p=1}^{P} \mathbf{s}(\boldsymbol{\theta}_p) + \mathbf{n}_y. \tag{8}$$

To derive a compact expression for the channel model we introduce the parameter vector

$$\boldsymbol{\mu}^{(r)} = \begin{bmatrix} \mu_1^{(r)} & \cdots & \mu_P^{(r)} \end{bmatrix}^{\mathrm{T}}$$

and collect the related complex exponentials in the matrix valued function

$$\mathbf{A}_r\left(\boldsymbol{\mu}^{(r)}\right) = \begin{bmatrix} \mathbf{a}_r\left(\mu_1^{(r)}\right) & \cdots & \mathbf{a}_r\left(\mu_P^{(r)}\right) \end{bmatrix} \tag{9}$$

. For notational convenience, we drop the dependency of $\mathbf{A}_r\left(\boldsymbol{\mu}^{(r)}\right)$ on $\boldsymbol{\mu}^{(r)}$ and write $\mathbf{A}_r$ in the following. Using the parameter vector

$$\boldsymbol{\mu} = \begin{bmatrix} \left(\boldsymbol{\mu}^{(1)}\right)^{\mathrm{T}} & \left(\boldsymbol{\mu}^{(2)}\right)^{\mathrm{T}} & \cdots & \left(\boldsymbol{\mu}^{(R_p)}\right)^{\mathrm{T}} \end{bmatrix} \tag{10}$$

describing the structural parameters of all specular propagation paths the yields the full parameter vector as

$$\boldsymbol{\theta} = \left[\begin{array}{ccccccccc} \boldsymbol{\mu}^{\mathrm{T}} & \Re\{\boldsymbol{\gamma}_{HH}^{\mathrm{T}}\} & \Im\{\boldsymbol{\gamma}_{HH}^{\mathrm{T}}\} & \Re\{\boldsymbol{\gamma}_{HV}^{\mathrm{T}}\} & \Im\{\boldsymbol{\gamma}_{HV}^{\mathrm{T}}\} & \Re\{\boldsymbol{\gamma}_{VH}^{\mathrm{T}}\} & \Im\{\boldsymbol{\gamma}_{VH}^{\mathrm{T}}\} & \Re\{\boldsymbol{\gamma}_{VV}^{\mathrm{T}}\} & \Im\{\boldsymbol{\gamma}_{VV}^{\mathrm{T}}\} \end{array} \right]^{\mathrm{T}} \tag{11}$$

With the weight vector

$$\boldsymbol{\gamma} = \left[\begin{array}{cccc} \boldsymbol{\gamma}_{HH}^{\mathrm{T}} & \boldsymbol{\gamma}_{HV}^{\mathrm{T}} & \boldsymbol{\gamma}_{VH}^{\mathrm{T}} & \boldsymbol{\gamma}_{VV}^{\mathrm{T}} \end{array} \right]^{\mathrm{T}}. \tag{12}$$

and the matrix valued function

$$\mathbf{A}\left(\boldsymbol{\mu}\right) = \mathbf{A}_R \diamond \mathbf{A}_{R-1} \diamond \cdots \diamond \mathbf{A}_1, \tag{13}$$

where $\diamond$ denotes the Khatri-Rao product, the contribution of the specular propagation paths can be expressed by

$$\mathbf{s}\left(\boldsymbol{\theta}\right) = \left[\begin{array}{cccc} \mathbf{G}_{HH}\mathbf{A}\left(\boldsymbol{\mu}\right) & \mathbf{G}_{HV}\mathbf{A}\left(\boldsymbol{\mu}\right) & \mathbf{G}_{VH}\mathbf{A}\left(\boldsymbol{\mu}\right) & \mathbf{G}_{VV}\mathbf{A}\left(\boldsymbol{\mu}\right) \end{array} \right] \boldsymbol{\gamma} \in \mathbb{C}^{M\times 1}. \tag{14}$$

The Jacobian matrix, i.e, the matrix of the first order derivatives of the data model to the model parameters $\boldsymbol{\theta}$ is given by

$$\mathbf{D}\left(\boldsymbol{\theta}\right) = \frac{\partial}{\partial \boldsymbol{\theta}^{\mathrm{T}}}\mathbf{s}\left(\boldsymbol{\theta}\right) = \left[\begin{array}{ccc} \frac{\partial}{\partial \theta_1}\mathbf{s}\left(\boldsymbol{\theta}\right) & \cdots & \frac{\partial}{\partial \theta_{LP}}\mathbf{s}\left(\boldsymbol{\theta}\right) \end{array} \right] \tag{15}$$

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III. State Space Model and Estimation

In order to allow the estimation of our parameter we first have to build the state-space model. The parameters of interest are collected into a vector, which is the state in our model. In this paper we use four parameters which are the delay $\tau_{k,p}$, the path weight γ which is split into real $\gamma_{k,p}^{Re}$ and imaginary parts $\gamma_{k,p}^{Im}$. However, this model can be extended to contain other structural parameters. The state vector of for each path p is given by:

$$\boldsymbol{\theta}_{k,p} = \left[\mu_{k,p}^{(\tau)} \;\; \mu_{k,p}^{(\varphi)} \;\; \gamma_{k,p}^{Re} \;\; \gamma_{k,p}^{Im}\right]^T \tag{16}$$

and has the dimension $L \times 1$, where L is the number of parameters of interest, in this case $L = 4$. All the vectors $\boldsymbol{\theta}_{k,p}$ are stacked into a vector $\boldsymbol{\theta}_k$ that contains the parameters infromation at time k for all the paths and has the dimension $LP \times 1$ and has the form as in equation (11). The state space model is given by:

$$\boldsymbol{\theta}_{k+1} = \boldsymbol{\Phi}_k \boldsymbol{\theta}_k + \mathbf{v}_k \tag{17}$$

$$\mathbf{y}_k = \mathbf{s}\left(\boldsymbol{\theta}_k\right) + \mathbf{n}_{y,k}, \tag{18}$$

where the nonlinearity $\mathbf{s}\left(\boldsymbol{\theta}_k\right)$ is mapping the state vector $\boldsymbol{\theta}_k$ onto the observations $\mathbf{y}_k$ of dimension $M \times 1$. The state transition matrix $\boldsymbol{\Phi}$ is assumed to have spectral radius less than unity to ensure stability. The state and observation noise sequences are assumed to be white and Gaussian, uncorrelated with each other and uncorrelated with the state. The covariance matrix of the state noise is given by $\mathbf{Q}_{\boldsymbol{\theta}}$ and is a diagonal matrix containing on the diagonal the corresponding noise variance of each parameter. For example, for one path and four parameter to be estimated we have $\mathbf{Q}_{\boldsymbol{\theta}} = diag\{\sigma^2_{\mu^{(\tau)}} \;\; \sigma^2_{\mu^{(\varphi)}} \;\; \sigma^2_{\gamma^{Re}} \;\; \sigma^2_{\gamma^{Im}}\}$. The covariance matrix of the observation noise is given by $\mathbf{R}_d$. In the case of the $L = 4$ parameters to be estimated, the nonlinear function for one path p is:

$$\mathbf{s}\left(\boldsymbol{\theta}_k\right) = \left[\mathbf{a}(\mu_p^{(\tau)}) \otimes \mathbf{a}(\mu_p^{(\varphi)})\right] \left(\gamma_{k,p}^{Re} + j\gamma_{k,p}^{Im}\right) \tag{19}$$

with $\mathbf{a}(\mu_p^{(\tau)})$ and $\mathbf{a}(\mu_p^{(\varphi)})$ expressed as in (1). In order to apply EKF one has to compute the Jacobian $\partial \mathbf{s}/\partial \boldsymbol{\theta}$. In our example of $L = 4$ parameters, for one path we obtain:

$$\mathbf{D}_p = \frac{\partial \mathbf{s}}{\partial \boldsymbol{\theta}_{k,p}} = \left[\mathbf{a}(\mu_p^{(\varphi)}) \otimes \mathbf{a}(\mu_p^{(\tau)}) \;\; j\left(\mathbf{a}(\mu_p^{(\varphi)}) \otimes \mathbf{a}(\mu_p^{(\tau)})\right) \;\; \left[\mathbf{a}(\mu_p^{(\tau)}) \otimes \frac{\partial \mathbf{a}(\mu_p^{(\tau)})}{\partial \mu_p^{(\tau)}}\right] \boldsymbol{\gamma}_p \;\; \left[\frac{\partial \mathbf{a}(\mu_p^{(\tau)})}{\partial \mu_p^{(\tau)}} \otimes \mathbf{a}(\mu_p^{(\varphi)})\right] \boldsymbol{\gamma}_p\right] \tag{20}$$

where $\gamma_p = (\gamma_{k,p}^{Re} + j\gamma_{k,p}^{Im})$. For p paths we have the structure given by (15).

The dimension of the state equation is equal with $LP \times 1$ while the observation vector at time k is having the dimension $M \times 1$, where $M >> LP$ (for example, in case we track 4 parameters on 200 paths, the state is of dimension 800×1 while the observation is of dimension 5128×1, in the case when an array with 8 elements is used). The main computational burden is in computing the matrix inversion in the Kalman gain in equation (23). The matrix to be inverted being of dimension $M \times M$. In order to reduce the complexity we apply the matrix inversion lemma. Consequently, only matrix of dimension $PL \times PL$ needs to be inverted. This provides significant savings in computational complexity in this application. In the example stated above the numerical complexity for the matrix inversion is reduced by approximately a factor of 250. Taking into account that the estimated parameters are real-valued and applying the matrix inversion lemma, the EKF equations are:

$$\hat{\boldsymbol{\theta}}_{(k|k-1)} = \boldsymbol{\Phi}\hat{\boldsymbol{\theta}}_{(k-1|k-1)} \tag{21}$$

$$\mathbf{P}_{(k|k-1)} = \boldsymbol{\Phi}\mathbf{P}_{(k-1|k-1)}\boldsymbol{\Phi}^{T} + \mathbf{Q}_{\boldsymbol{\theta}} \tag{22}$$

$$\mathbf{K}_{(k)} = \mathbf{P}_{(k|k-1)}\left[\mathbf{I} - \mathbf{J}(\hat{\boldsymbol{\theta}},\mathbf{R}_d)\left(\mathbf{J}(\hat{\boldsymbol{\theta}},\mathbf{R}_d) + \mathbf{P}^{-1}_{(k|k-1)}\right)^{-1}\right]\left[\begin{array}{c}\Re\left\{\mathbf{R}_d^{-1}\mathbf{D}_{(k)}\right\}\\ \Im\left\{\mathbf{R}_d^{-1}\mathbf{D}_{(k)}\right\}\end{array}\right]^{\mathrm{T}}, \tag{23}$$

$$\mathbf{P}_{(k|k)} = \left(\mathbf{J}(\hat{\boldsymbol{\theta}},\mathbf{R}_d) + \mathbf{P}^{-1}_{(k|k-1)}\right)^{-1} \tag{24}$$

$$\hat{\boldsymbol{\theta}}_{(k|k)} = \hat{\boldsymbol{\theta}}_{(k|k-1)} + \mathbf{K}_{(k)}\left[\begin{array}{c}\Re\left\{\mathbf{y}_k - \mathbf{s}\left(\hat{\boldsymbol{\theta}}_{(k|k-1)}\right)\right\}\\ \Im\left\{\mathbf{y}_k - \mathbf{s}\left(\hat{\boldsymbol{\theta}}_{(k|k-1)}\right)\right\}\end{array}\right] \tag{25}$$

where $\mathbf{J}(\hat{\boldsymbol{\theta}},\mathbf{R}_d) = \Re\left\{\mathbf{D}^{H}_{(k)}\mathbf{R}_d^{-1}\mathbf{D}_{(k)}\right\}$ is the observed Fisher information, $\mathbf{P}_{(k|k-1)}$ is the prediction error covariance matrix, $\mathbf{P}_{(k-1|k-1)}$ is the filtering error covariance matrix and K is the Kalman gain.

The initialization and the values of the state transition matrix and state noise covariance matrix are sensitive issues when applying Kalman filter. In order to have an accurate initialization we run the ML estimator for the first 11 data vectors. The state transition matrix is kept fixed and since the parameters in the state are decoupled, it is a diagonal matrix with entries close to one. The observation noise covariance matrix $\mathbf{R}_d$ is again estimated using the ML algorithm. However, it has a structure that allows a low complexity inverse calculation as well. The state noise covariance matrix and state transition matrix are selected by trial and error for now.

IV. Estimation Results

During summer 2001 a measurement campaign has been carried out in the major street Chuo-Dori (Chuo-Avenue) downtown Tokyo, which can be characterized as an urban environment with a regular street grid and high-rise buildings at both sides of the street. The street is situated in the district Nihonbashi. A measurement with a static BS position and a moving MS was conducted. Figure 1 shows a view to the scenario through the BS antenna array. Figure 2 shows the parameter tracking results for the direct path in a time variant scenario. The path was tracked over a time of approximately 30 seconds. The blue circles denote the maximum likelihood estimates of RIMAX, i.e., without parameter tracking. The red line shows the estimated TDoA of the direct path tracked by the Kalman filter.

In the second estimation example, Figure 3, the tracking capability of the estimator of weak propagation paths, i.e., with a low SNR is shown. The maximum likelihood estimator without tracking is clearly unable to determine parameter estimates when the individual SNR of a propagation path is to low in a observation. The Kalman filter, on the other hand, is able to pair the parameter estimates using information gathered from the prior estimates.

V. Conclusion

In this paper we have presented a recursive technique for propagation path parameter estimation and tracking. A low complexity algorithm with respect to existing ML techniques has been introduce. The first parameter estimation results show that by applying a recursive technique path parameter pairing over time can be done.

Further research work will involve a carefull investigation of the parameter estimation methods for the Kalman filter state space model. More detailed investigations of Kalman performance will be performed (for example ensuring the whiteness of the innovation sequence).

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Fig. 1. View from the base station to the scenario

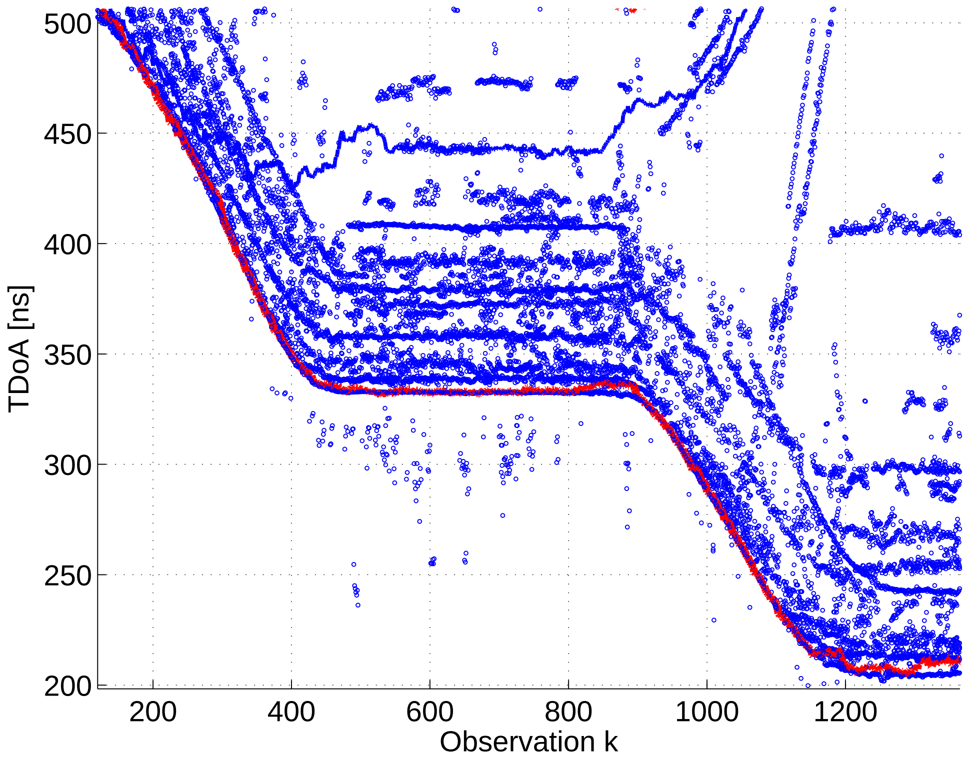

Fig. 2. Parameter tracking results for the direct path. The blue circles denote the parameter estimates of RIMAX, i.e., without parameter tracking. The red line shows the estimated TDoA of the direct path tracked by the Kalman filter

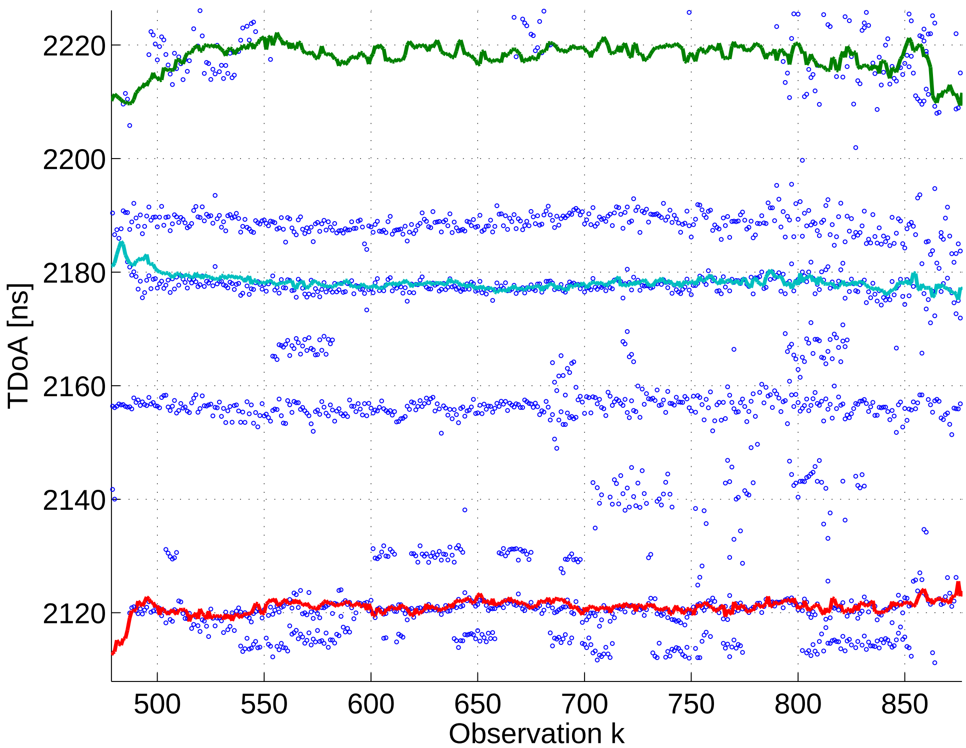

Fig. 3. Tracking of weak propagation paths. The blue circles denote the parameter estimates of RIMAX, i.e., without parameter tracking. The lines show the Kalman filter estimates of the TDoA

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