UPPSALA UNIVERSITET

Channel Estimation and Prediction for Adaptive OFDM Downlinks

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Summary

Topic

Accurate estimation and prediction of the channel parameters in mobile radio communications are essential for attaining high transmission quality. We investigate the estimation performance of a computationally low complexity general constant-gain (GCG) algorithm and compare it with an ideal Kalman filter.

We also compare the power prediction performance of the Kalman filter and the GCG filter.

System

The system used in this work is an adaptive OFDM multiuser system. Users adaptively allocates subchannels and use different modulation formats depending on need and channel quality.

Conclusion

Estimation : The GCG performance is *close* to Kalman performance.
Prediction : The GCG performance is *equal* to Kalman performance.

The OFDM Downlink

The adaptive OFDM multiuser downlink has the following properties :

- Equal spacing between subcarriers and time samples suitable for vehicular user in urban environments.
- Base stations allocate bins (=120 time-frequency symbols) to users depending on predicted channel quality.
- Eight uncoded modulation formats are available.

These properties require each user to

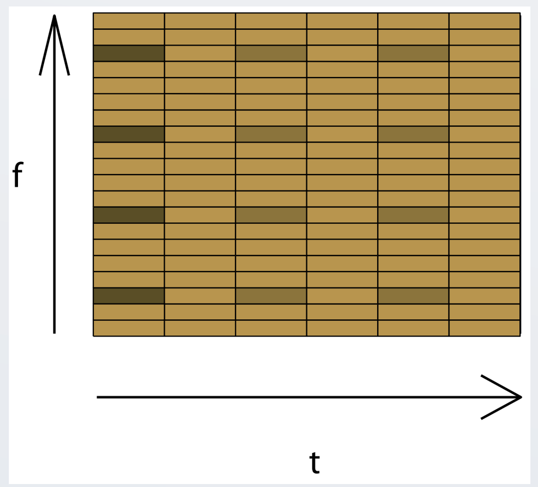
- *Predict* the *power* for scheduling purposes
- *Estimate* the *complex taps* for payload data detection purposes.

Bins consist of 120 symbols. Syncronization issues demand some of the symbols to be known :

- 4 symbols in each bin are known QPSK symbols. We denote them *pilot* symbols.
- 8 symbols in each bin are used for downlink information (user assignment etc). Their values are unknown but they are known to be QPSK symbols and may therefore be used in decision-directed mode.

This leaves 108 out of 120 symbols for payload data. Each symbol may at best represent 8 bits, giving the system a maximum spectral efficiency of 6.48 bps/Hz.

Each user may be assigned one or more 200 KHz-by-667 microseconds time-frequency bins. The bins are divided into 20 by 6 time-frequency symbols. Four of these 120 symbols are known QPSK pilot symbols (dark brown), and eight are unknown QPSK downlink data symbols



Kalman Channel Estimation

The measured signal y for a certain time t and a certain subcarrier n is affected by the complex channel tap h, the transmitted symbol s and the measurement noise v in the following manner :

$$y_{n,t} = s_{n,t} h_{n,t} + v_{n,t}$$

Tap behaviour are described by

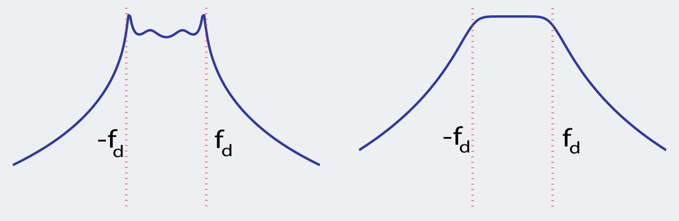
$$x_{t+1} = F x_t + G e_t$$
$$h_t = H x_t$$
$$y_t = \phi_t^* h_t + v_t$$

Tracking may be done by Kalman recursions. Each iteration produces both the filter estimates $\hat{h}_{t|t}$ and the one-step predictions $\hat{h}_{t+1|t}$ of the taps.
The filter only operates on the pilots and the downlink data symbols, i.e every 2[nd] and every 5[th] symbol transmitted over the OFDM downlink.
Both time- and frequency correlation are built into the model :

- *time* : 4[th] order autoregressive fading model
- *frequency* : process noise correlation matrix

Two different fading statistics are used depending on the channel :

Doppler spectra for the two different fading models



Jakes statistics *Robust statistics*

N number of subchannels are tracked in parallel. The regressor matrix ϕ_t^* is contructed from the transmitted QPSK symbols s_1-s_N :

$$\phi_t^* = \begin{pmatrix} s_1 & & \\ & \ddots & \\ & & s_N \end{pmatrix}$$

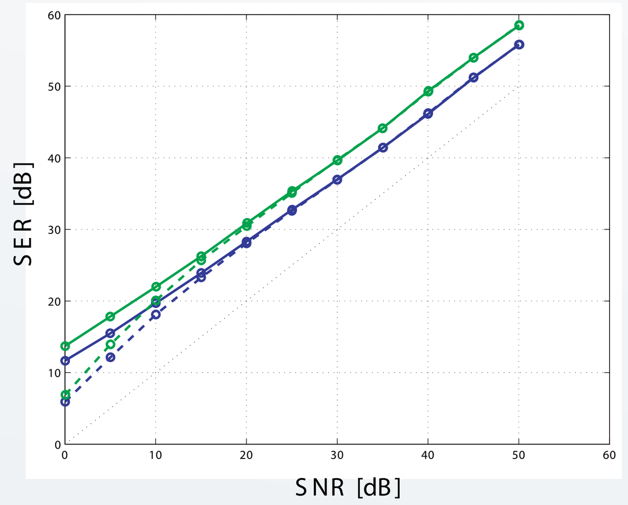
The values of s_1 through s_N are constructed in either of two ways :

- Known pilot symbols (33 %)
- Detected QPSK downlink symbols (67 %)

The latter is calculated with aid of the one-step prediction from the last iteration :

$$\hat{s}_{n,t} = \text{detectQPSK}(y_{n,t}/\hat{h}_{n,t|t-1})$$

The hat indicates that s is an estimate that may or may not be correct.
Using estimates for regressors means that the filter is decision directed. Wrong decisions will severely influence the performance of the filter as seen below.



Channel signal to estimation error ratio (SER) versus SNR for a Jakes flat fading channel. Using estimated values of regressors (dashed) makes the filter perform worse than if correct regressors are used (solid) due to erroneous decisions. Blue line shows performance for filter width N=4. Doubling the filter width (green, N=8) increases performance by 3 dB for a flat fading channel.

The GCG Algorithm

The general constant gain algorithm (GCG) is derived by first defining

$$R = E\phi_t^* \phi_t$$
$$Z_t = \phi_t^* \phi_t - R$$
$$\eta_t = Z_t (h_t - \hat{h}_{t|t-1}) + \phi_t^* v_t$$
$$f_t = R h_t + \eta_t$$

Since the regressors in ϕ_t^* are all QPSK symbols and hence have modulo one, it follows that $Z_t = 0$ for this particular application. This reduces the expressions for the gradient noise to

$$\eta_t = \phi_t^* v_t$$

We now have a new set of state and measurement equations :

$$x_{t+1} = F x_t + G e_t$$
$$h_t = H x_t$$
$$f_t = R h_t + \eta_t$$

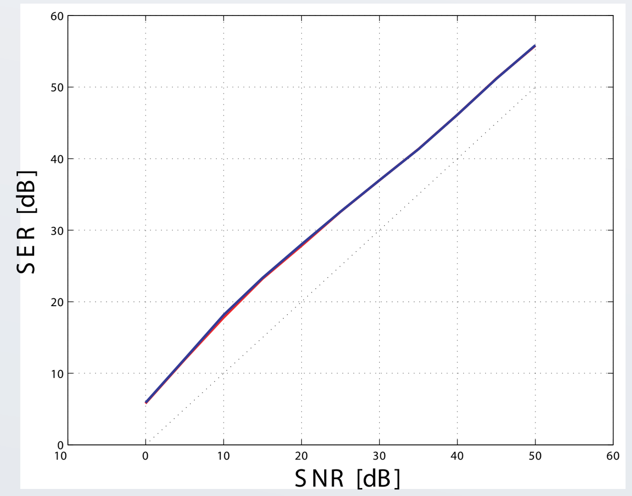
This transforms the measurement equations form one with a time-*in*variant regressor matrix and stationary measurement noise, to one with a time-variant regressor matrix and *non*-stationary measurement noise :

Kalman : $y_t = \phi_t^* h_t + v_t$ (time-variant, stationary)
GCG : $f_t = R h_t + \eta_t$ (time-invariant,non-stationary)

A *constant* steady-state filter gain matrix K is calculated via an algebraic Riccati equation. This needs to be recalculated only when the system parameters, such as Doppler frequency, change. The filter gain is used for updating the states through

$$\hat{x}_{t|t} = F \hat{x}_{t-1|t-1} + K(f_t - R\hat{h}_{t|t-1})$$

Below are a few comparisons between the estimation performance of the Kalman filter and the GCG filter.



Channel signal to error ratio (SER) versus SNR for a Jakes flat fading channel. The Kalman filter (red) and the GCG filter (blue) perform equally well (the graphs almost completely overlap). Four parallel

Channel Prediction

Prediction of the channel power is necessary for allowing the base station to schedule resources among users.

Prediction of the taps L steps ahead is done by

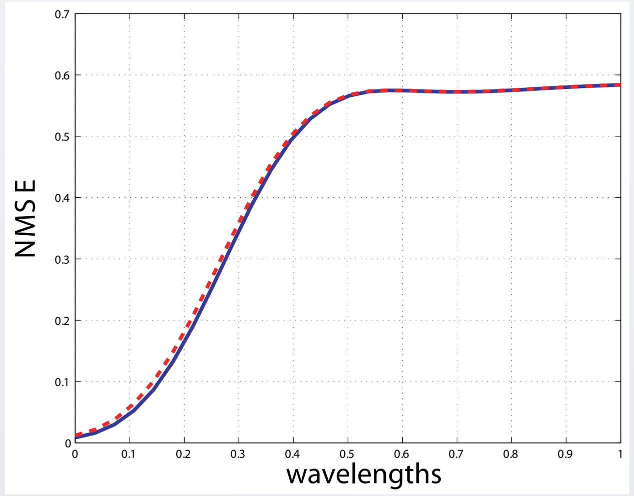
$$\hat{h}_{t+L|t} = H F^L \hat{x}_{t|t}$$

$\hat{x}_{t|t}$ is the filter estimate of the states. Since the filters operate on every 2[nd] time sample, L is in units of 0.222 milliseconds.

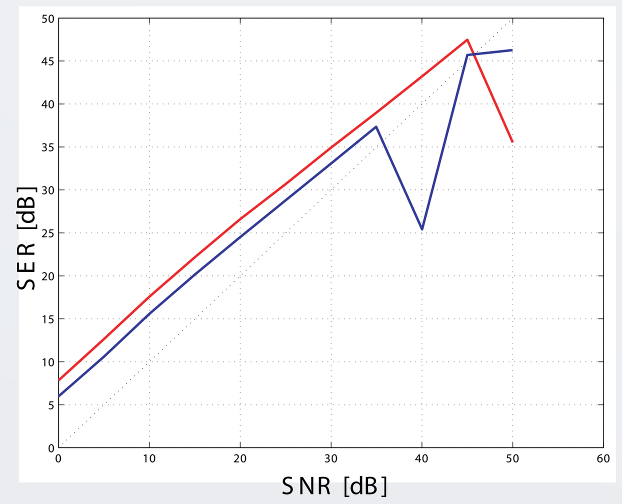
We compare the prediction performance of the Kalman filter and the GCG filter in terms of *Normalized Mean Square Error* (NMSE). It is defined as

$$\text{NMSE} = \frac{E||h_{n,t}|^2 - |\hat{h}_{n,t|t-L}|^2 - \sigma_h^2 + \sigma_{\hat{h}}^2|^2}{E|h_{n,t}|^4}$$

As seen below there are no noticeable difference between the performance of the two filters.



Normalized Mean Square Error (NMSE) versus prediction horizon for the Kalman filter (solid blue) and the GCG filter (red dashed) for channel tap data based on real measurements. There are no significant difference between the two.



Channel signal to error ratio (SER) versus SNR for channel tap data based on real measurements. The Kalman filter (red) performs somewhat better than the GCG algorithm (blue). Four parallel subcarriers were tracked at a time. The strange behaviour of the graphs at high SNR is due to the filters sensitivity to erroneous estimates of the downlink QPSK symbols when the noise is expected to be low.