AN ADAPTIVE VITERBI DETECTOR, BASED ON SINUSOID MODELLING OF FADING MOBILE RADIO CHANNELS

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Parameters of time-varying systems are often estimated with adaptive algorithms, by discounting old data. We may then face a dilemma: use of a short data window (or, equivalently, a large adaptation gain) gives noisy estimates. With a long data window (small gain), time–varying parameters are tracked with a considerable delay. A satisfactory compromise can be hard to find, if it exists at all.

These problems are, for example, encountered in the design of adaptive equalizers. Consider the North American digital mobile radio standard. In this time division-multiple access (TDMA) system, bursts of 168 complex symbols are transmitted, with interval 40 μs, using $\pi/4$ DQPSK [1]. The first 14 symbols of each burst constitute a known training sequence. In discrete time, the channel is well described by a two ray Rayleigh fading model

$$y(n) = b_0(n)d(n) + b_1(n)d(n-1) + v(n) \quad . \tag{1}$$

Here, $\{y(n)\}$ is the received complex baseband sequence, $\{d(n)\}$ is the transmitted sequence, while $\{v(n)\}$ is zero mean white noise. The SNR is 15-25 dB [2]. The goal is to estimate $\{d(n)\}$ from $\{y(n)\}$. Real and imaginary parts of the unknown time–varying coefficients $b_0(n), b_1(n)$ are independent. If vertically polarized antennas are used, their spectra have pronounced peaks at the Doppler frequency f_d [1]. (For a mobile with velocity v, at carrier frequency f_c (= 900 MHz), $f_d = vf_c/c$.) The time–variations will be significant during one data burst: a burst time of 168x40μs = 6.8ms is half a Doppler period, if $v = 100$ km/h. Thus, adaptive equalization is required.

If we regard an adaptive channel estimator in combination with the Viterbi algorithm [2], the obvious first choice is, perhaps, Recursive Least Squares (RLS)–tracking, to update the channel coefficients $b_0(n), b_1(n)$. For this system, it results in large parameter errors and an unsatisfactory performance, for all choices of forgetting factor. Our alternative is based on (1), where we parametrize the coefficients by

$$\begin{aligned} b_0(n) &= [\ell_1 + k_1 \sin(\omega_1 n + \varphi_1)] + i[\ell_2 + k_2 \sin(\omega_2 n + \varphi_2)] \\ b_1(n) &= [\ell_3 + k_3 \sin(\omega_3 n + \varphi_3)] + i[\ell_4 + k_4 \sin(\omega_4 n + \varphi_4)] \quad . \end{aligned} \tag{2}$$

This model structure is easily generalized to m–ray models. It has adequate flexibility to describe the variations during up to one period of f_d, i.e. for one burst at velocities up to $v = 200$ km/h. The 16 parameters in (2) are estimated using *four separate recursive prediction error algorithms* [3], one for each parameter vector

$$\Theta_j = (k_j, \omega_j, \varphi_j, \ell_j) \quad ; \quad j = 1 \ldots 4 \quad . \tag{3}$$

These recursions perform stochastic quasi–Newton optimization of Θ_j. Each of them requires slightly more computation time than RLS for four parameters.

[1] Disregarding the $\pi/4$–shift for simplicity, we can regard each symbol as belonging to the set $\{1+i, 1-i, -1+i, -1-i\}$. The *difference* between two consecutive symbols encode two bits of data.

[2] Due to continuous–time pre–sampling filtering, the corresponding continuous–time carrier to interference ratio $E_b/N_0 \approx$ SNR - 5dB. Thus, SNR $\in [15dB ... 25dB]$ corresponds to $E_b/N_0 \in [10dB ... 20dB]$.

In an initial **Phase I**, $\{y(n)\}_1^{14}$ and the known training sequence $\{d(n)\}_1^{14}$ is used. Two separate robustified RLS algorithms are used, repeatedly, on these data to estimated *linear trend models* of $b_0(n)$ and $b_1(n)$. (We here substitute n for $\sin(\omega_j n + \varphi_j)$ in (2).)

All 16 parameters are adapted in the following **Phase II**, using $\{y(n)\}_{15}^{168}$ The unknown input $d(n), n > 14$, is estimated by a Viterbi detector. As the data sequence is traversed, the model is improved. (See Figure 1, a simulation for SNR=20dB, $f_d = 83$Hz.) The latest improved model is, in its turn, used in the Viterbi detector (Figure 2). Note, that the model (1),(2) can be extrapolated in time. This is of use in the Viterbi algorithm.

No forgetting of old data is used. The model (1)–(3) will thus be based on *the whole data sequence*, up to the latest utilized $y(n)$. This provides higher accuracy, compared to RLS–tracking of $b_0(n), b_1(n)$ with a short data window. See Figures 3 and 4. They summarise simulations of two extremes of a range of situations to be expected in practice. [3] Compared to Viterbi detection combined with channel estimation by RLS–tracking, our approach reduces the bit error rate by a factor of ≈ 2. The price to be paid is that the total computational effort increases by a factor of ≈ 3.

We have modelled a time–varying system by estimating the parameters of *deterministic functions*, which describe the time variations. We strongly believe that this seldomly used concept deserves more attention in system identification.

[3] Based on simulation of 1000 bursts (350 000 unknown bits) at 15, 20 and 25 dB SNR. Time–varying coefficients were generated by filtering white noise. We generated 10 batches of 100 bursts each. It was ascertained that the level–crossing statistics for *each* batch corresponded closely to the Rayleigh fading model. This reduced the variance of the results significantly. With RLS–tracking, the best performance, shown in the figures, was achieved with forgetting factor 0.7, i.e. a data window of ≈ 4 samples !

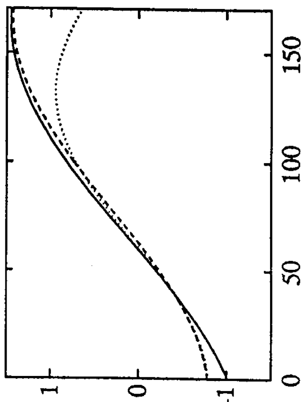

Figure 1. True Re($b_0(n)$) (solid), model at n=60 (dotted), n=168 (dashed).

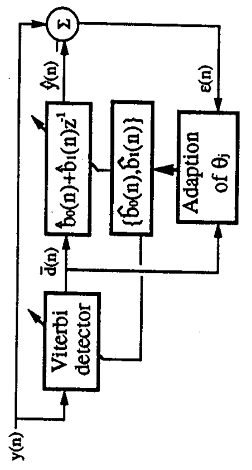

Figure 2. The adaptive equalizer, in Phase II.

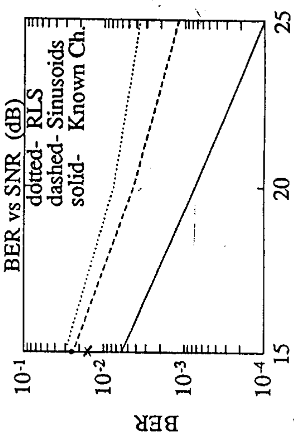

Figure 3. Performance of equalizers, when $E|b_1(n)|^2 = E|b_0(n)|^2$

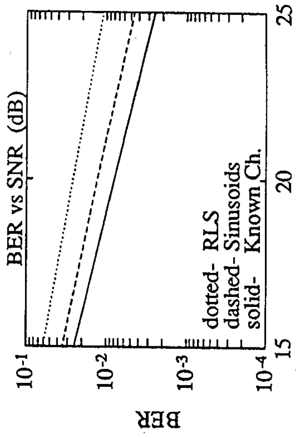

Figure 4. Performance of equalizers, when $b_1(n) = 0$.

References

[1] W. C. Jakes, Ed., *Microwawe Mobile Communication*, Wiley, New York, 1974.

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[3] L. Ljung and T. Sderstrm, *Theroy and Practice of Recursive Identification*, MIT Press, Cambridge, Mass, 1983.