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# PREDICTION OF RECEIVED SIGNAL POWER IN CDMA CELLULAR SYSTEMS

Jarno M. A. Tanskanen[1], Aiping Huang[1,2], Timo I. Laakso[3], and Seppo J. Ovaska[4]

[1]Laboratory of Signal Processing and Computer Technology
Helsinki University of Technology
FIN-02150 Espoo, Finland

[2]Inst. of Detection Tech. & Intelligent Instrument
Dep. of Scientific Instrument
Zhejiang University
310027 Hangzhou
China

[3]Signal Processing Group / SEMSE
University of Westminster
115 New Cavendish Street
W1M 8JS London, UK
(on leave from NOKIA Research Center
Helsinki, Finland)

[4]Electronics Laboratory
Lappeenranta University of Technology
P. O. Box 20
FIN-53851 Lappeenranta
Finland

**Abstract—In this paper, prediction of signal power in Code Division Multiple Access (CDMA) systems in urban radio channels is investigated. We focus on the processing of the measured input signal for power control purposes in a mobile station receiver. Predictive filtering based on a polynomial signal model is proposed, and a class of FIR-type polynomial filters is investigated with simulations. Two alternative schemes are examined; direct prediction of the squared power signal, and prediction of the in-phase and quadrature signal components separately.**

**The simulations show that FIR polynomial predictors can provide smoothed signal power samples with the signal-to-noise ratio (SNR) improved by ca. 5 dB, without any delaying of the signal. The results show that polynomial prediction is a highly potential tool for delayless filtering of additive noise and smoothing of fast fading of the signal.**

## I. INTRODUCTION

As the CDMA systems are inherently interference limited, it is of paramount importance to keep the transmission power of each mobile user as low as possible [1]. This is crucial in the uplink transmission (from mobile to base station), where all the mobile units need to be controlled by the base station to keep the *received power level* from each mobile unit constant in the average. The need for power control has been widely studied, and the capacity of a CDMA system is found to greatly depend on the power control function [1], [2]. The mobile transmitter power control is achieved through a closed power control loop for which it is necessary to estimate the received power level. This paper proposes a method for compensating the delay caused by the power estimator itself and the other processing stages of the signal power estimate. A CDMA power control loop with predictive power level estimation is illustrated in Fig. 1.

The function of predictive filtering is twofold: to predict future values of the power signal, and to reduce the additive noise and interferences corrupting the power signal. Usually, the latter function is more important, i.e., *delayless smoothing* of the power signal. An additional requirement in a control application like this is that the control loop should remain *stable* in all conditions; this sets explicit requirements for the predictive filter as well. Our paper does not consider the power control problem itself but addresses the prediction approach of the received signal power as seen by the base station without power control.

The noisy fading power signal and the predictors are introduced in Sections II and III, respectively. Section IV discusses some important aspects of signal power prediction. The simulation results are presented in Section V, and the summarizing conclusions are drawn in Section VI.

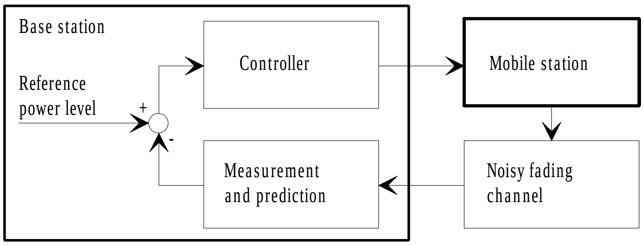


Fig. 1. Power control loop in a CDMA system.

## II. NOISY FADING POWER SIGNAL

### A. Channel model

A simulation model for a Rayleigh fading channel was introduced by Jakes in [3]. Our simulator assumes a superposition of plane waves whose arrival angels are uniformly distributed. Different plane waves are associated with different Doppler shifts ranging from the minimum to the maximum specified by the mobile speed. The simulator consists of low frequency oscillators at these Doppler shift frequencies. The frequency distribution results in a satisfactory approximation of the Rayleigh fading spectrum of the simulated signal. In-phase and quadrature components are formed by summing the appropriately weighted oscillator outputs. These provide for uniformly distributed random phase of the complex output. After multiplication with corresponding carrier components, the signal is centered at the carrier frequency. Our carrier frequency was 1800 MHz, the sampling rate of the unmodulated in-phase and quadrature

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components was 1 kHz, and the applied vehicle speeds were 5 km/h and 50 km/h. The simulator is depicted in Fig. 2, and examples of noiseless and noisy power signal simulations are presented in Fig. 3. Increasing the mobile speed has a similar effect to decreasing sampling rate. Also, the bandwidth of the signal is directly proportional to the vehicle speed.

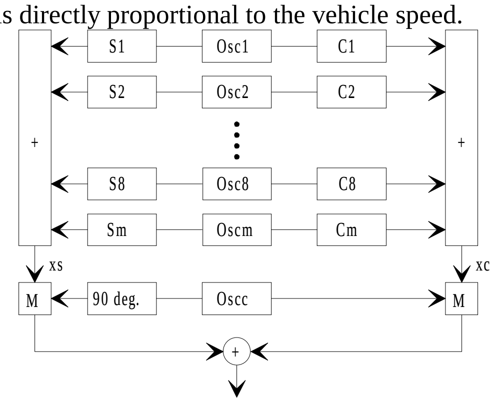


Fig. 2. Rayleigh fading channel simulator. Adapted from [3]. Oscm is the maximum Doppler shift frequency oscillator, Osc1... Osc8 are the Doppler shift frequency oscillators with appropriate frequency distribution, and Oscc is the carrier oscillator. Appropriate oscillator phase shifts are obtained by the choice of coefficients {S1, ...,S8}, and {C1, ..., C8}. M is the carrier modulator.

It is not desirable for a power control system to follow very fast fading, and normally the system also introduces some physical performance limits to the response speed of the power control. To take this into account, the reference fading power signal for SNR calculations was lowpass filtered to produce a 'slow fading' part of the power signal. It is not possible to separate the actual slow fading and the fast fading with one fixed cut-off frequency purely on the physical basis as the slow fading may also occasionally contain high frequency components usually encountered in fast fading signals. For this reason the cut-off frequency is to be chosen based on the power control system. We set the cut-off frequency at the maximum Doppler shift frequency encountered at the mobile speed of 5 km/h, and filtered the reference power signal with the sixth order Butterworth lowpass filter with this cut-off frequency. The filtering was performed as zero-phase forward and reverse filtering resulting in the effective filter order of twelve.

Another Rayleigh fading channel model was used for comparisons. The model generates a Rayleigh fading signal by shaping noise to form the signal components which are then squared and summed to produce the power response. The model used approximated a channel power response as seen by a receiver with a vertical monopole antenna [4]. Visually the power response closely resembled that of Jakes' model in Fig. 3.

### *B. Noise*

The noise used was zero mean white Gaussian noise that was independently added to the in-phase and quadrature components, xc and xs in Fig. 2, respectively. The power

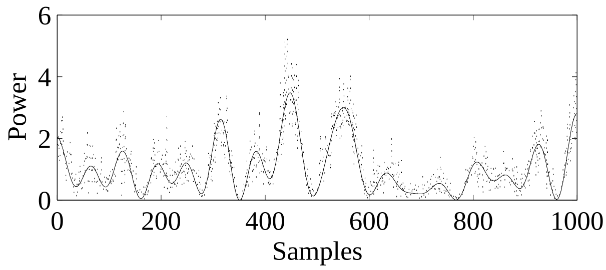


Fig. 3. Noisy (dotted) and noiseless (solid) power signal simulations of one second at 5 km/h using Jakes' model.

level of the components was derived from the model, and the noise sequence was added to obtain the desired SNR within components. As power measurements encountered in practice are usually noisy, the component SNRs 10 dB and 0 dB were chosen to be analyzed, to illustrate typical 'good' and 'bad' channels.

## III. OVERVIEW OF PREDICTOR DESIGN TECHNIQUES

With reference to the noiseless power signal in Fig. 3, it is easy to see that a piecewise polynomial model can be expected to suit well for modeling of the narrow-band power signal. The polynomial signal model is given by

$$\tilde{y}(n) = \nu_0 + \nu_1 n + \ldots + \nu_{L-1} n^{L-1} + \nu_L n^L + e(n) \tag{1}$$

where $n$ is the index of a discrete-time sequence, $\tilde{y}(n)$ is the value of the polynomial at $n$, $e(n)$ is an additive noise term, $\nu_i$ are the weighting coefficients with $i$=0, 1, ..., $L$, and $L$ is the degree of the polynomial model selected.

Polynomial prediction, used in this paper, is based on approximating signals as low degree polynomials whose future values are estimated from a measured sample history. Generally, a one-step-ahead predicted signal value at time $n$ is given by a finite sum of weighted past signal values

$$\hat{y}(n) = \sum_{i=1}^{k} h(i) y(n-i) . \tag{2}$$

The noise gain $NG$ of this predictor in both time and frequency domains is defined by

$$NG = \sum_{i=-\infty}^{\infty} |h(i)|^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} \left| H\left(e^{j\omega}\right) \right|^2 d\omega \tag{3}$$

where $H\left(e^{j\omega}\right)$ is the transfer function of the predictor.

### *A. Heinonen-Neuvo prediction*

One important class of polynomial predictors are Heinonen-Neuvo (H-N) predictors [5]. They are FIR type predictors which, in addition to exact prediction of a polynomial signal of given order, use the remaining degrees of freedom to minimize the noise gain (3) of the filters. They are derived to provide for unbiased prediction. The predictors have low computational cost when implemented using the Campbell-Neuvo structure [6], which provides for im-

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plementation of any H-N predictor of given degree using a fixed number of arithmetic operations. Since H-N predictors are optimized for polynomial signals, they were expected to perform equally well with both Jakes' and noise shaping channel models.

Closed form solution of the optimal one-step-ahead predictor coefficients exist [5]. For the first and second degree polynomials they are given by

$$h_1(i) = \frac{4k - 6i + 2}{k(k-1)} \tag{4}$$

$$h_2(i) = \frac{9k^2 + (9 - 36i)k + 30i^2 - 18i + 6}{k^3 - 3k^2 + 2k}, \tag{5}$$

respectively, where $k$ is the length of the predictor, $i$=1, ..., $k$, and the subscript of $h$ denotes the degree $L$ of the polynomial to be predicted.

Magnitude responses for the first and second degree H-N predictors of lengths 20 and 50 are plotted in Fig. 4. The lowpass nature of H-N predictors is clearly visible with the passband bandwidth and the passband gain decreasing along with the increasing predictor length. For equal passband bandwidths or peak gains, higher degree predictors have to be longer than the corresponding lower degree predictors.

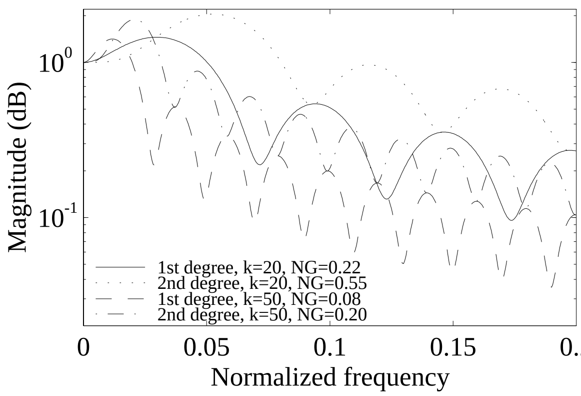


Fig. 4. Magnitude responses of some H-N predictors.

### B. Prefilter prediction

IIR filters are more efficient for processing narrow-band signals, like low-order polynomials, than FIR filters. With an appropriate lowpass-type recursive prefilter, the overall predictor can be designed to meet the noise gain requirements by lower implementation costs than by using a pure FIR predictor. An analytical method for designing an optimized FIR postfilter for any stable prefilter is derived in [7]. The optimal FIR is designed to provide for unbiased prediction and minimized overall noise gain. With prefilter transfer function equal to unity, the prefiltering approach reduces to the H-N approach.

### C. Recursive linear smoothed Newton prediction

Recursive linear smoothed Newton predictor (RLSN) [8] is an enhanced version of the classical Newton predictor. The enhancement is that the predicted estimate of the current input sample is fed back and added with weighting to the weighted input sample. This sum is then added to the sum of smoothed successive differences. The difference operators get their inputs directly without prescaling. Being recursive of nature, the RLSN predictors can offer much better noise attenuation characteristics than the H-N predictors with an equal computational burden. The RLSN, and the prefiltered prediction, would be other natural choices for power prediction applications.

## IV. Power Prediction Techniques

The received signal is a real-valued high-frequency bandpass signal. It is transformed to equivalent lowpass complex-valued signal by demodulation. The lowpass signal consists of a noisy real component and a noisy imaginary component, i.e., of the in-phase and quadrate components, as described in Section II a. The corresponding power signal is the sum of squares of these two components. If the bandwidth of the components is $F$, the bandwidth of the power signal is $2F$ because squaring (multiplication) in time domain implies convolution in the frequency domain.

There exist two approaches for power signal prediction: 1) direct prediction of the noisy power signal which has been calculated from the noisy components, Fig. 5(a), and 2) getting the predictive estimate of the power signal as the sum of squared predictions of the components, Fig. 5(b). In Fig. 5, $y_c$ and $y_s$ are the noisy in-phase and quadrature components, respectively.

In the first approach, although the noisy power signal is always positive, the values of its estimate might be negative when a predictor with a long impulse response is used and the noisy input signal approaches zero. This is unnatural for the feedback loop. In the second approach the predictive power estimate is guaranteed to be strictly positive because of the final squaring operations. Detailed statistical analysis of the approaches is presented in [9].

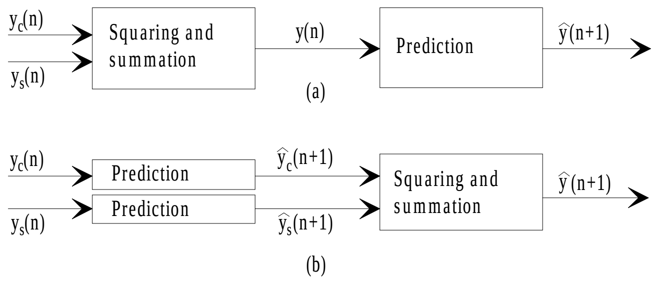


Fig. 5. Block diagrams of the two prediction schemes.

Noticing the variation of signal bandwidths before and after squaring, the second approach provides a possibility of reducing the prediction error by using more narrowband predictors and removing most of the noise as early as possible. The computational costs of the first and second approach may be different since they demand one or two predictors, respectively.

Simulation results presented in this paper are based on one-step-ahead predictions of both the power signal and its in-phase and quadrature components.

## V. Simulation Results

Several H-N predictors were used with the Jakes' channel model with theoretical SNRs 10 dB and 0 dB in the in-phase and quadrature components. The most interesting results are plotted in Figs. 6 - 9. It is to be kept in mind that the first and second degree H-N predictors for practical use, i.e., $NG < 1$, are of lengths not less than 6 and 13, respectively. The input power signal SNR was defined to be equal to the output power signal SNR without filtering and prediction. They were estimated from the sample sequences as

$$SNR_{out} = \frac{\sum_n \left[ \left( f\left( x_c(n+1)^2 + x_s(n+1)^2 \right) \right)^2 \right]}{\sum_n \left[ \hat{y}(n) - \left( f\left( x_c(n+1)^2 + x_s(n+1)^2 \right) \right)^2 \right]} \tag{6}$$

$$SNR_{in} = \frac{\sum_n \left[ \left( f\left( x_c(n)^2 + x_s(n)^2 \right) \right)^2 \right]}{\sum_n \left[ \left( y_c(n)^2 + y_s(n)^2 - f \left( x_c(n)^2 + x_s(n)^2 \right) \right)^2 \right]} \tag{7}$$

where $\hat{y}(n)$ is an output power sample, $n$ spans over the sample sequence used for computing the SNRs, $x_c(n)$ and $x_s(n)$ are noiseless input samples, and $f$ produces the Butterworth lowpass filtered sample of the signal whose corresponding sample is the argument of $f$. $f(\cdot)$ provides for the SNR measure that takes the desired smoothing of the fast fading into account. The SNR gains, shown in Figs. 6 - 9, were calculated as

$$\text{SNR gain } (dB) = SNR_{out}(dB) - SNR_{in}(dB) \tag{8}$$

For each case least-squares optimal (LS) FIRs [10] were designed to give some "upper bound" for performance comparisons. These were designed using a noisy power signal as input and the corresponding noiseless one-step-ahead predicted lowpass filtered power signal as the desired output. The same sample sequences used for designing the LS FIRs were filtered with respective filters to produce "the best possible nonadaptive prediction." It is noted that longer LS FIRs cannot adapt to the time varying signal properties significantly better than shorter LS FIRs. An adaptive filter would be needed to further improve the prediction. The calculation of LS FIR coefficients is very much more tedious than computing the H-N coefficient, since it requires knowledge of the signal spectrum, and solving of a possibly large system of equations.

From Fig. 6, it can be seen that in low noise conditions at slow speeds the prediction in components requires longer predictors to reach the same SNR gain as the direct prediction of the power signal. In such cases, the prediction should be done directly from the power signal. It is also noticed that the output SNR gain gets worse after reaching a maximum as the filter length increases. This is due to the fact that while high-order predictors have smaller noise gain they also have a more narrow prediction bandwidth than low-order predictors. Also, longer filters are needed to match the narrower signal bandwidth in the case of component prediction than in the direct power prediction.

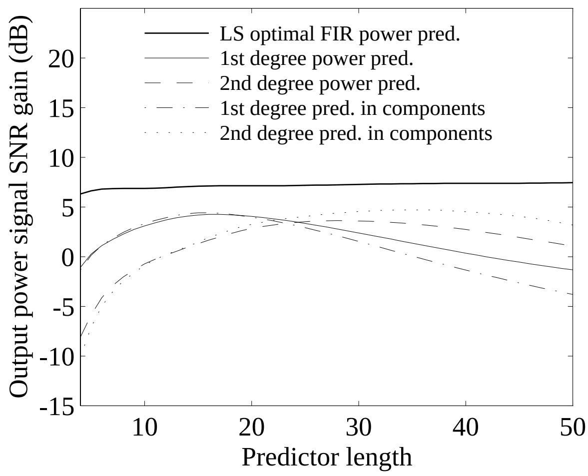


Fig. 6. Output SNR gains of H-N predictors as functions of the predictor length. (Theoretical component input SNR 10 dB, speed 5 km/h.)

Under high noise conditions at low speeds, Fig. 7, prediction in components exhibits clearly better noise attenuation than the direct prediction of the power signal. In these cases the prediction should be done in components. As in the component prediction the signal to be predicted is of narrower bandwidth, the actual signal is better preserved than with the direct power prediction. Also, with much higher noise content, it is easier to improve the overall SNR than in the low noise conditions.

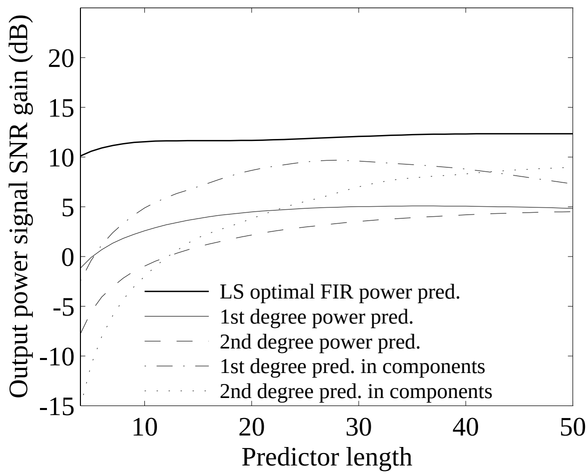


Fig. 7. Output SNR gains of H-N predictors as functions of the predictor length. (Theoretical component input SNR 0 dB, speed 5 km/h.)

From Fig. 8, it can be concluded that again in the low noise conditions the direct prediction of the power signal performs better than the prediction of components. At 50 km/h the SNR curves exhibit some nonmonotonic behavior.

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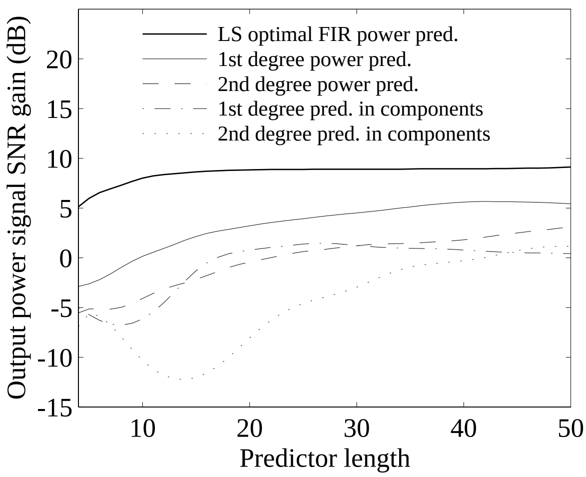


Fig. 8. Output SNR gains of H-N predictors as functions of the predictor length. (Theoretical component input SNR 10 dB, speed 50 km/h.)

In Fig. 9, the results are similar to those of Fig. 7, i.e., under high noise conditions the maximum SNR gain is achieved by using prediction in components. Figs. 8 and 9 reflect also smoothing out some fast fading as desired, as the lowpass filtered reference was used for SNR calculations. The fact that the second degree predictors have higher noise gain than the first degree predictors of the same length is evident in all Figs. 6 - 9.

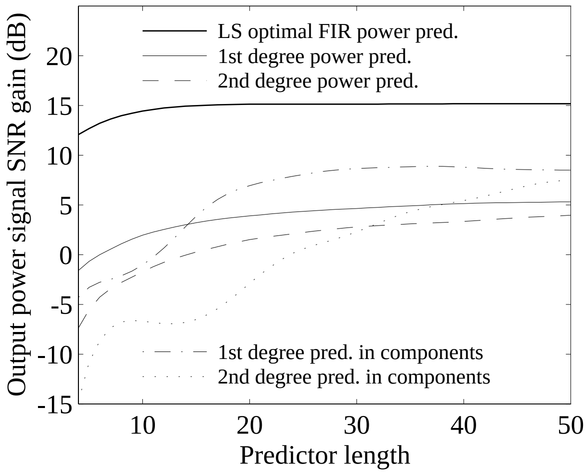


Fig. 9. Output SNR gains of H-N predictors as functions of the predictor length. (Theoretical component input SNR 0 dB, speed 50 km/h.)

## VI. Conclusions

Our conclusion is that with simple 10 - 20 tap polynomial predictors the SNR of the power signal can be improved by upto 5 - 9 dB, while introducing no delay in the signal. At higher speeds, suitable H-N predictors may be successfully used to average out short-term fading. The results shown using Jakes' Rayleigh fading power response are similar to results obtained using the noise shaping Rayleigh fading.

In the presence of considerable noise, the power estimate is more accurate if it is calculated from the separate predictions of in-phase and quadrature components. In these cases implementation cost may be reduced by predicting the components even though two predictors are needed instead of one as shorter predictors are required in order to achieve the same SNR gain.

In summary, predictive filtering is a highly potential tool for power control in the uplink transmission of CDMA systems. These results encourage to carry out a thorough analysis of the proposed prediction schemes in a real power control loop. Apart from the advantages for short-term power control, predictive techniques may also be useful in forecasting the longer-term power level for control of handovers from one base station to another.

Our future work includes; more detailed applicability studies of IIR predictors, modeling of the power control loop of Fig. 1, and evaluating different prediction methods with power controlled channel response simulations. As the choice for the best predictor depends on the noise content of the signal and on the vehicle speed, an adaptive approach should be considered. Also, the studies are to be extended to include long-term prediction for use in handling handovers.

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