Interference Prediction Using IMM Estimator in Broadband Wireless Packet Networks

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Abstract–*An interference prediction scheme is proposed for power control in packet-switched TDMA wireless networks. The prediction scheme is based on the interacting multiple model (IMM) estimator, and it is adaptive to a wide range of nonstationary dynamic characteristics of the interference power. Compared to Leung's scheme, it can predict the interference power more accurately and allow us to adjust the transmit power more efficiently in achieving a desired signal-to-interference-plus-noise ratio (SINR).*

Keywords–*Interference prediction, Power control, IMM estimator.*

I. Introduction

One of techniques to mitigate the effects of cochannel interference is to adaptively control the transmission power level of all the users in the wireless network. Maintaining the transmission power of a user at its minimum level which is allowed under current channel conditions, it is possible to minimize the power consumption for the user and eliminate unnecessary interference to other users. Recently, attempts have been made to predict the interference power using a Kalman filter and to control the transmission power, based on the prediction, to achieve a desired level of signal-interference-plus-noise ratio (SINR) [1], [2]. The objective of this work is to present an interference prediction scheme, which is based on the interacting multiple model (IMM) estimator [3], [4], for power control in wireless packet-switched TDMA networks. Notice that the IMM estimator has been applied to blind equalization of time-varying channels in [5].

II. IMM Estimator

The IMM estimator is known to be one of the most cost-effective and simple scheme for estimating the state of a dynamic system with several behavior (or postulated) modes which can switch from one to another. The estimator is implemented based on a set of multiple Kalman filters, each set up for each behavior mode, and a finite state Markov chain that governs the transition between the modes. The design parameters of the IMM estimator include the set of models for the Kalman filters and the transition probabilities of the Markov chain.

The innovation in IMM is that the hypotheses reduction step is replaced by a mixing step which is performed before the prediction. The merging technique keeps the number of hypotheses constant. The input to the mixing step are the estimates made in the previous time step:

$$\hat{x}_i(k-1) \stackrel{\text{def}}{=} E[x(k-1)|M_i(k-1), Z^{k-1}],\ 1 \le i \le N.$$

The approximation introduced here is that the conditional distribution $p(\hat{x}(k-1)|M_i(k-1), Z^{k-1})$ is Gaussian:

$$p(\hat{x}(k-1)|M_i(k-1), Z^{k-1}) \sim N(\hat{x}_i(k-1), C_i(k-1)).$$

where $C_i(k-1)$ is the error covariance associated with $\hat{x}_i(k-1)$. The output is again N estimates

$$x_j^0(k-1) \stackrel{\text{def}}{=} E[x(k-1)|M_j(k-1), Z^{k-1}],\ 1 \le j \le N$$

with the corresponding covariances. The estimates are the basis of prediction and measurement update by Kalman filters under the set of hypotheses $\{M_j(k) : 1 \le j \le N\}$ which result in the updated estimates:

$$\hat{x}_j(k) = E[x(k)|M_j(k), Z^k].$$

Thus, in the IMM we have only N hypotheses to be checked at every stage. The final output is given by

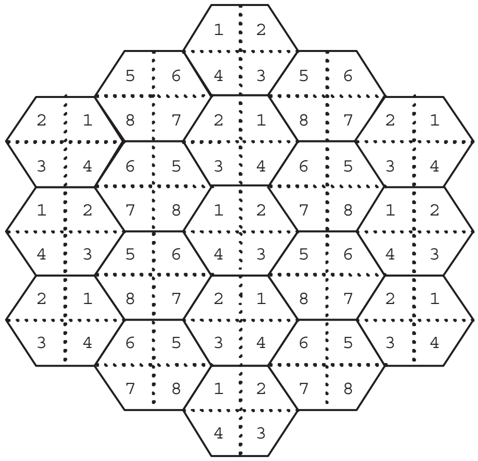

Fig. 1 A four-sector cell layout [1].

combining the model conditioned estimates as follows:

$$\hat{x}(k)=E[x(k)|Z^k]=\sum_{j=1}^{N}E[x(k)|M_j(k),Z^k]P(M_j(k)|Z^k)$$
$$=\sum_{j=1}^{N}\hat{x}_j(k)P(M_j(k)|Z^k).$$

$$\begin{aligned}\hat{x}(k+1|k) &= E[x(k+1)|Z^k]\\ &= \sum_{i=1}^{N}\sum_{j=1}^{N}E[x(k+1)|M_i(k+1),M_j(k),Z^k]\\ &\quad \cdot P(M_i(k+1)|M_j(k),Z^k)P(M_j(k)|Z^k).\end{aligned}$$

The IMM estimator is autonomous and adaptively adjusts its bandwidth according to the mode changes of the system dynamics. More details on the IMM estimator can be found in [3], [4]. In this work, we adopt the IMM estimator to predict the interference power in packet-switched TDMA wireless networks.

III. Network Model and Interference Dynamics Modeling

Our wireless packet network model is briefly described in this section, which is the same as the one presented in [1]. More details on the network model can be found in the reference. Our IMM-based scheme is designed for power control of this network model. The cell layout and interleaved channel assignment (ICA) are shown in Fig.1. Each cell in the hexagonal layout is divided into four sectors. Each sector is serviced by a base station located at the center of the cell. The label number in each sector in Fig.1 indicates the channel assigned to the sector by the ICA scheme. The sector is serviced by a base station antenna which has a parabolic beam pattern with 60 degree beamwidth. Terminals are assumed to be uniformly distributed over each sector. Message length is assumed to have a discrete form of Pareto distribution with average message length L. We consider the cell at the center of the layout. Cell radius is 1 km. It is further assumed that, after a terminal transmits a message, the base station immediately schedules another randomly chosen terminal in the same sector to start a new transmission in the next time slot. It is also assumed that interference power in one time slot can be measured and used to determine the transmit power for the next slot.

We adopt an ARMAX model [6] for the interference dynamics modeling. The first-order ARMAX was accurate enough for our modeling such that

$$I(k+1)=\alpha I(k)+\beta I_{avg}+F(k) \qquad (1)$$

where $I(k)$ is the interference and noise power received at the base station at slot k and I_{avg} is the average interference and noise power, both in dBm unit. $F(k)$ is the process noise with mean zero and variance Q. The parameters α, β and Q are dependent on the average message length L. We obtained α and β for each L by using the least squares method [6] that minimizes

$$f(\alpha,\beta)=\sum_{k=1}^{N}(I(k+1)-\alpha I(k)+\beta I_{avg})^2, \qquad (2)$$

where $I_{avg}=\sum_{k=1}^{N}I(k)/N$. The least squares method yields

$$\begin{aligned}\alpha &= \frac{\sum_{k=1}^{N}I(k)I(k+1)-I_{avg}\sum_{k=1}^{N}I(k+1)}{\sum_{k=1}^{N}I^2(k)-I_{avg}\sum_{k=1}^{N}I(k)}\\ \beta &= \frac{1}{NI_{avg}}\sum_{k=1}^{N}I(k+1)-\alpha\sum_{k=1}^{N}I(k).\end{aligned}$$

These parameters can be approximated as

$$\begin{aligned}\alpha &\approx \frac{\sum_{k=1}^{N}I(k)I(k+1)-NI_{avg}^2}{\sum_{k=1}^{N}I^2(k)-NI_{avg}^2}\\ \beta &\approx 1-\alpha. \end{aligned} \qquad (3)$$

We obtained α for a random interference sequence of 5,000 data points. We also obtained the variance Q of the process noise $F(k)$ by using the sample variance of $I(k+1)-\alpha I(k)-\beta I_{avg}$ for the data points. These parameters are listed in Table I for the case that the traffic load (denoted as ρ) is unity.

To validate our model, we obtained the mean of the process noise $F(k)$ by using the sample mean (denoted as m_F) of $I(k+1)-\alpha I(k)-\beta I_{avg}$ for the data points. The results are also presented in Table I, where we can see that the mean is close to zero. We tested the whiteness of $F(k)$ by using as a test statistic the following function of the time-average

Table I Parameters α and Q, sample mean m_F, and test statistic ζ_N for $\rho = 1$.

L	α	Q	m_F	ζ_N
1	0.016	19.57	1.23×10^{-4}	2.28
2	0.417	15.70	6.88×10^{-4}	2.21
3	0.643	11.88	-2.68×10^{-4}	1.03
4	0.718	8.87	4.24×10^{-4}	1.41
5	0.791	7.51	1.29×10^{-4}	1.73
10	0.892	3.65	-6.69×10^{-4}	1.20
15	0.924	2.58	4.46×10^{-4}	0.79
20	0.944	2.21	-1.18×10^{-3}	2.44
40	0.962	1.36	-7.45×10^{-5}	0.15

sample autocorrelation for $F(k)$ one-step apart [6]:

$$\zeta_N = \frac{N\left(\sum_{k=1}^{N} F(k)\, F(k+1)\right)^2}{\left(\sum_{k=1}^{N} F^2(k)\right)^2}. \qquad (4)$$

Under the assumption that $F(k)$ is white, the statistic ζ_N should be asymptotically chi-square distributed with one degree of freedom. The statistic for each L is shown in Table I which is evaluated for those 5,000 data points. The upper limit of the acceptance region of ζ_N is 3.84 for the significance test at a significance level of 0.05, and the table shows that the whiteness hypothesis of $F(k)$ is acceptable. Notice that the model Leung [1] adopted assumes that $\alpha = 1$ and $\beta = 0$, regardless of the average message length.

IV. IMM-Based Interference Prediction and Performance Comparison

Two IMM estimators were implemented to predict the interference-plus-noise power, and their prediction performances were compared with Leung's scheme [1]. First, we implemented the IMM estimator (called IMM-2A) using a bank of two Kalman filters matched to the models with $L = 1$ and $L = 10$. The diagonal and off-diagonal elements of the Markov transition probability matrix were chosen to be 0.96 and 0.04, respectively. The IMM estimator (called IMM-3A) was also implemented using a bank of three Kalman filters matched to the models with $L = 1, 3$, and $L = 15$. The diagonal and off-diagonal elements of the Markov transition probability matrix were chosen to be 0.96 and 0.02, respectively. In both of the estimators, I_{avg} was set to the measured interference-plus-noise power averaged over the last 30 slots.

The transmission power level is adjusted at each slot to achieve a target SINR. Let γ denote the target SINR, $p(k)$ the transmission power at slot k, and $g(k)$ the channel gain from the transmitting terminal to the base station at the slot. Also let $i(k)$ and $\bar{i}(k)$ denote, respectively, the true and predicted values of the interference power both in mW unit. We assume that $g(k)$ is accurately estimated. The terminal is requested via a control channel on the downlink to transmit at slot k with transmit power

$$p(k) = \gamma \frac{\bar{i}(k)}{g(k)}. \qquad (5)$$

Table II RMS Prediction Errors of Interference Power (dB).

	IMM-2A	IMM-3A	Leung's scheme
L=1	4.93	4.95	7.44
L=5	4.22	4.15	5.79
L=10	3.88	3.82	5.41
L=20	3.32	3.31	5.16

Table III RMS SINR Deviations (dB).

	IMM-2A	IMM-3A	Leung's scheme
L=1	5.97	5.99	7.68
L=5	5.78	5.74	6.72
L=10	5.61	5.58	6.51
L=20	5.35	5.35	6.30

Table IV Average Transmission Power (Watts).

	IMM-2A	IMM-3A	Leung's scheme
L=1	0.228	0.229	0.276
L=5	0.254	0.253	0.285
L=10	0.232	0.232	0.279
L=20	0.261	0.261	0.302

Table V Packet Error Rate.

	IMM-2A	IMM-3A	Leung's scheme
L=1	7.47×10^{-2}	7.45×10^{-2}	1.24×10^{-1}
L=5	5.78×10^{-2}	5.67×10^{-2}	8.84×10^{-2}
L=10	5.06×10^{-2}	4.98×10^{-2}	8.29×10^{-2}
L=20	4.35×10^{-2}	4.35×10^{-2}	7.82×10^{-2}

We performed a Monte Carlo simulation of 500 runs to compare the interference prediction and power control performances of the IMM-based schemes and of Leung's scheme [1] for the average message length L having values of 1, 5, 10 and 20. In the simulation, the SINR target γ is set to 17dB and the maximum transmission power is limited to 1 Watts. The rms prediction errors in dB are presented in Table II. The table shows that, compared to Leung's scheme, both of the IMM-based schemes can predict the interference power much more accurately. The advantage in the prediction accuracy is most significant for $L = 1$. This is the case where the temporal correlation of the interference is weaker and that Leung's model (Eq.(1) with $\alpha = 1$ and $\beta = 0$) is most poorly matched to the interference dynamics. Notice that IMM-2A is comparable to IMM-3A in prediction performance.

The true SINR at the base station for the transmission power determined by (5) is $\gamma(k) = p(k)g(k) \,/\, i(k)$. The rms values of SINR deviation from the SINR target (17dB) are presented in Table III, and the average transmission power in Table IV. Assuming that the trasmission power is adjusted according to (5), we evaluate the packet error rates and list the results in Table V. In the evaluation, we used the packet error rate model employed in [1], which maps each SINR into a packet error rate. The tables indicate that the IMM-based power control can track the target SINR more accurately than Leung's scheme. Both IMM-2A and IMM-3A allocate the transmit power 10-18 percent less than Leung's scheme, while keeping the packet error rates about 40 percent lower. The MATLAB code was run on a 2-GHz Pentium IV (800 Mflops) to evaluate the interference prediction. The computational times were 0.19 μsec (148 flops) and 0.35 μsec (276 flops), respectively, for IMM-2A and IMM-3A. Considering that IMM-2A is comparable to IMM-3A in interference prediction and it is computationally advantageous, it seems reasonable to choose IMM-2A as the interference prediction scheme.

V. Conclusions

We proposed an interference prediction scheme based on the IMM estimator for power control in wireless packet-switched TDMA networks. Compared to Leung's scheme, IMM-based schemes can predict the interference power much more accurately. The IMM-based power control can track the target SINR more efficiently. As a consequence, it was possible to maintain the packet error rates significantly lower than Leung's scheme, while spending less transmit power.

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