Table 1: Mean±standard deviation of parameters of simulation example for different data lengths

	N = 1024		N = 2048	
Estimation algorithms	b(1) = -2.333	b(2) = 0.667	b(1) = 2.333	b(2) = 0.667
LS-method 1	-1.3791±0.5749	0.2924±0.3335	-1.8309±0.4639	0.3262±0.3140
LS-method 2	2.0107±0.7793	0.5696±0.5225	-2.3121±0.5938	0.6296±0.4136
[3]	-0.7713±1.1865	0.2181±0.2936	-1.3466±1.0388	0.1840±0.3156
[4]	-1.1696±0.7496	0.4916±0.7524	-1.4461±0.7463	0.4199±0.4872

SNR = 0dB and 100 Monte Carlo runs

Table 1 and Fig. 1 appear to indicate that both LS-method 2 and LS-method 1 are more robust to additive coloured Gaussian noise. LS-method 2 produces the best estimates of the two in terms of bias and standard deviation in a highly noisy environment, which demonstrates the potential of equations using third- and fourth-order cumulant statistics to estimate the parameters of NMP models in the presence of additive Gaussian noise.

Conclusions: A new set of equations which link third- and fourth-order cumulants for an MA model have been presented and applied to an NMP FIR system identification. Simulation results indicate that these two methods, and especially LS-method 2, perform better than other published cumulant-based linear methods in the coloured Gaussian noise case. This improvement of the results is basically due to the fact that the proposed methods make use of more cumulant information, since they use more third cumulant slices than [4] does and also make use of fourth-order cumulants, and that unlike [3] they do not make use of correlation information, strongly degraded in the coloured Gaussian noise case.

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Macrodiversity cochannel interference analysis

L.-C. Wang and C.-T. Lea

Indexing terms: Diversity reception, Interference (signal), Cellular radio

A cochannel interference analytical model to evaluate the performance of $S + I$-macrodiversity to combat shadowing is presented. It was found that the performance difference between the $S + I$-macrodiversity and S/I-macrodiversity is significant, but the performance with S-macrodiversity is close to the case of $S + I$-macrodiversity.

Introduction: Macrodiversity, also known as base-station diversity, is a form of large-scale selection space diversity. In a system with macrodiversity, a mobile unit will be served by several base stations simultaneously and the branch with the best quality will be chosen. Macrodiversity is a powerful technique to combat the shadowing effect in cellular mobile communications networks. In this Letter the performance of macrodiversity will be evaluated in terms of cochannel interference (CCI) probability, which is defined as the probability that the desired signal level is less than the required receiver threshold due to excessive interference.

To evaluate the performance of CCI probability, three kinds of selection diversity have been reported in the literature: (i) S/I-diversity: the signal/interference ratio (S/I) is constantly computed and the branch with the largest S/I is selected and the signal of which is sent to the input of the receiver; (ii) S-diversity: the signal power (S) is constantly measured and the branch with the largest S is selected; (iii) $S + I$-diversity: the signal mixed with interference, i.e. $S + I$, is constantly measured and the branch with the largest $S + I$ is selected. Obviously each technique requires a different degree of implementation complexity. For example, $S + I$-macrodiversity is the easiest to implement. Only the received signal ($S + I$) is monitored. S-macrodiversity, however, requires that the interference be separated from the received signal, which is obviously not practical. However, S-macrodiversity can be considered as an approximation for the $S + I$ case. The most desirable type, of course, is S/I-macrodiversity, however this is also the most difficult to implement.

Past work on the CCI analysis for $S + I$ selection diversity, however, is focused on the microscopic diversity, i.e. with consideration of only Rayleigh fading [1, 2] or Nakagami fading [3]. Considering the shadowing effect, Yeh and Wilson and Schwartz [4] analysed the performance of S-macrodiversity. In this Letter we present a cochannel interference analytical model for $S + I$-macrodiversity and compare all three forms of macrodiversity.

S-macrodiversity: In [4], the CCI probability of S-macrodiversity is expressed as

$$\begin{aligned}F_S(\lambda_{th}) &= \mathrm{Prob}(\max(S_1, S_2, ..., S_L)/I_i \le \lambda_{th})\\ &= 1 - L\int_0^\infty \left[\int_{-\infty}^{\frac{x}{\lambda_{th}}} \frac{1}{\sqrt{2\pi}\sigma_I y} \exp\left[\frac{-(\ln y - \ln \Upsilon_I)^2}{2\sigma_I^2}\right] dy\right]\\ &\left[1 - Q\left(\frac{\ln x - \ln \Upsilon_k}{\sigma_k}\right)\right]^{L-1} \frac{1}{\sqrt{2\pi}\sigma_k x} \exp\left[\frac{-(\ln x - \ln \Upsilon_k)^2}{2\sigma_k^2}\right] dx \end{aligned} \tag{1}$$

where $Q(x) = \int_x^\infty [1/\sqrt{2\pi}]\exp(-x^2/2)dx$, σ_k is the shadowing spread, and Υ_k is the area mean power of the log-normal distributed desired signal. By using the approach in [5], we characterise the sum of multiple log-normal interfering signals by another log-normal random variable I_i with variance σ_I and area mean Υ_I.

S/I-macrodiversity: Assume S/I in each branch (S_k/I_k, $k = 1,...,L$) are i.i.d. random variables. In addition, the total interference power in each branch is approximated by the same technique as in eqn. 1. Then the CCI probability with S/I-macrodiversity is

$$\begin{aligned}F_{S/I}(\lambda_{th} &= \mathrm{Prob}(\max(S_1/I_1, S_2/I_2, ..., S_L/I_L)/I_i \le \lambda_{th})\\ &= [\mathrm{Prob}(S_k/I_k \le \lambda_{th})]^L\\ &= \left[Q\left(\frac{\ln \frac{\Upsilon_k}{\lambda_{th}\Upsilon_I}}{\sqrt{\sigma_k^2 + \sigma_I^2}}\right)\right]^L \end{aligned} \tag{2}$$

Note that $\mathrm{Prob}(S_k/I_k \le \lambda_{th})$ is just the CCI probability with no diversity. Because the CCI probabilities with no diversity are the same for the S-diversity, S/I-diversity, and $S + I$-diversity, $\mathrm{Prob}(S_k/I_k \le \lambda_{th})$ can be obtained by letting $L = 1$ in eqn. 1.

S + I-macrodiversity: In [1], the CCI probability with L-branch $S + I$ selection diversity is written as

$$\begin{aligned}&F_{S+I}(\lambda_{th}) =\\ &1 - \sum_{i=1}^{L} \mathrm{Prob}(S_i/I_i \ge \lambda_{th} | S_i + I_i \ge S_j + I_j, j = 1, ..., L, j \ne i)\\ &\mathrm{Prob}(S_I + I_i \ge S_j + I_j, j = 1, ..., L, j \ne i)\\ &= 1 - L\int_0^\infty \int_{\lambda_{th}}^\infty f_{U,V}(u, v)[\mathrm{Prob}(S_i + I_i \le v)]^{L-1} du dv \end{aligned} \tag{3}$$

Note that $f_{U,V}(u,v)$ is the composite PDF of random variables $U = S_i + I_i$ and $V = S_i/I_i$. The relation between $f_{U,V}(u,v)$ and the composite PDF of random variables S_i and I_i is

$$f_{U,V}(u,v) = \frac{v}{(u+1)^2} f_{S_i,I_i}\left(\frac{uv}{u+1}, \frac{v}{u+1}\right) \qquad (4)$$

We now apply eqns. 3 and 4 to study the shadowing effect. As in [4], the log-normal random variable I_i with area mean Υ_I and logarithmic variance σ_I is the approximate composite PDF of the sum of multiple log-normal interferers. Let σ_k and Υ_k be the shadowing spread and area mean of the desired signal S_k, respectively. Assuming that S_k and I_k are independent, we then express eqn. 4 as

$$f_{U,V}(u,v) = \frac{1}{2\pi\sigma_k\sigma_I uv} \exp\left[-\frac{\left(\ln\frac{uv}{(u+1)\Upsilon_k}\right)^2}{2\sigma_k^2}\right] \times \exp\left[-\frac{\left(\ln\frac{v}{(u+1)\Upsilon_I}\right)^2}{2\sigma_I^2}\right] \qquad (5)$$

Next we use a log-normal random variable with area mean Υ_c and logarithmic variance σ_c to approximate $S_j + I_j$, since both S_j and I_j are log-normal distributed. Then

$$\mathrm{Prob}(S_j + I_j \le v) = 1 - Q\left(\frac{\ln(v/\Upsilon_c)}{\sigma_c}\right) \qquad (6)$$

Substituting eqns. 5 and 6 into eqn. 3, we express the CCI probability in Hermite form as follows:

$$F_{S+I}(\lambda_{th}) = 1 - \int_{\infty}^{\infty} f(w)\exp(-w^2)dw = 1 - \sum_{i=1}^{i=n} f(w_i)h_i \qquad (7)$$

where w_i and h_i are the roots and weight factors of the nth-order Hermite polynomial, and

$$f(w) = \frac{L}{\pi}\int_{\frac{\ln\lambda_{th}}{\sqrt{2}\sigma_k}}^{\infty} \exp\left[-\left(z - \frac{\ln\Upsilon_k/\Upsilon_I}{\sqrt{2}\sigma_k} + \sigma_I w/\sigma_k\right)^2\right] \left[1 - Q\left(\frac{\ln(\exp(\sqrt{2}\sigma_k z)+1) - \ln\Upsilon_c/\Upsilon_I + \sqrt{2}\sigma_I w}{\sigma_c}\right)\right]^{L-1} dz \qquad (8)$$

Numerical results and conclusions: Consider a dual-slope path-loss model, $P_r/P_t = 1/r^a(1 + g/r)^b$, where P_r/P_t is the ratio of received power to the transmitted power, r is the distance, $a = b = 2$ and $g = 0.6$ times the cell radius in our case. Assume that the receiver is located at the cell boundary R and the interferers are $4.6R$ away. Fig. 1 compares S-macrodiversity, $S + I$-macrodiversity and S/I-macrodiversity (i.e. eqns. 1, 2 and 7) in the presence of a single 8dB log-normal interferer. It is shown that, at the 5% CCI probability, the threshold of the receiver's power can be set at 15dB for two-branch S/I-macrodiversity; that is, the probability that the receiver's S/I is 15dB is 0.95. For S- and $S + I$-macrodiversity, the threshold of the receiver's S/I has to be set at 11dB and 10dB under the same 5% CCI probability. From this result, we see that the difference between S- and $S + I$ -macrodiversity is small, which means that the analytical model based on S-macrodiversity is a good approximation for $S + I$-macrodiversity. We also see that the difference between S/I-macrodiversity and $S + I$-macrodiversity is significant. These results also hold for the case of multiple interferers. Fig. 1 also shows the effect of number of diversity branches on the performance in the presence of two interferers. At the 5% CCI probability, two-branch $S + I$-macrodiversity has 5dB gain over the case of no diversity; three-branch $S + I$-macrodiversity has 8dB gain over no diversity. Fig. 2 shows how the performance of a macrodiversity cellular system is affected by the number of interferers. The case we study is a channel with three-branch $S + I$-macrodiversity. Compared to the case of one interferer, two interferers degrade the performance by 1.7dB, and three interferers degrade the performance by 4.5dB.

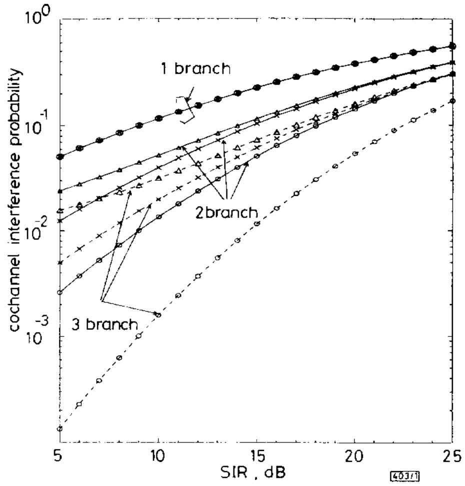

Fig. 1 *Performance comparison of S/I-macrodiversity, S-macrodiversity and S + I-macrodiversity in presence of one log-normal shadowing interferer, where shadowing spread for desired signal and interferer is 8dB*

O *S/I* selection
× *S* selection
△ *S + I* selection

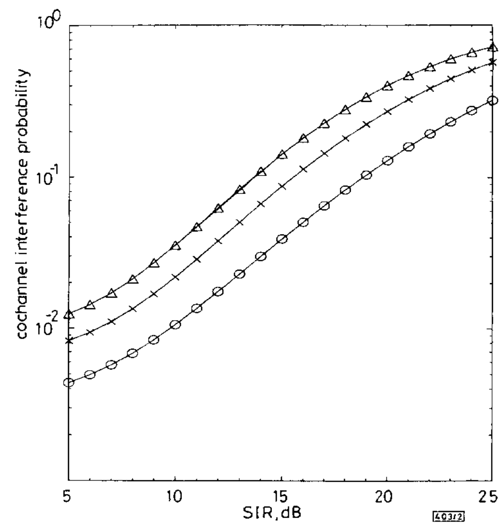

Fig. 2 *Effects of number of interferers on performance of three-branch S + I-macrodiversity, where shadowing spread for desired signal and interferer is 6dB*

O 1 interferer
× 2 interferers
△ 3 interferers

Finally, we would like to point out that the analytical models developed in the Letter can be applied to macrodiversity cases with more branches and interferers. They are a useful tool for studying the performance of cellular systems with macrodiversity.

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Representation of hidden Markov model for noise adaptive speech recognition

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Indexing terms: Hidden Markov models, Speech recognition

The state parameters of the hidden Markov model are represented by the autocorrelation coefficients of a context window that can be adaptively transformed to cepstral and delta cepstral coefficients according to the environmental noise. Experimental results show that it can significantly improve the speech recognition rate under noisy environments.

Introduction: The application of speech recognition systems under noisy environments should take into account the effect of noise. The spectral subtraction proposed by Boll [1] is a widely used technique for removing the effect of noise. Van Hamme introduced the autoregressive domain spectral subtraction [2]. Mansour and Juang proposed a family of distortion measures for robust speech recognition [3]. Lee *et al.* investigated the nonlinear adaptation of cepstral coefficients for noisy speech recognition [4]. In this Letter a new representation of the hidden Markov model (HMM) that allows the adaptation of both cepstral and delta cepstral coefficients is proposed for noisy speech recognition. In this new approach, a state or a mixture component of a state is indirectly represented by the autocorrelation coefficients of a content window that can be adaptively transformed to cepstral and delta cepstral coefficients according to the environmental noise. Experimental results show that it can significantly improve the speech recognition rate under noisy environments.

New representation of HMM: In this study, a feature vector **v** consists of cepstral vector **c**, delta cepstral vector **d**, and delta log-energy e. In the conventional continuous hidden Markov model, the output feature vector of a state S (or a mixture component of a state) is often represented as a multivariate Gaussian random vector $X_S \approx N(\mathbf{v}_S, \Sigma_S)$, where $\mathbf{v}_S^T = [\mathbf{c}_S^T\ \mathbf{d}_S^T\ e_S]$ is the mean vector and Σ_S is the covariance matrix. Since the mapping between clean and noisy cepstral feature vectors is nonlinear [4] and the mapping between clean and noisy delta cepstral vectors could be even more complex, it is difficult to adapt the reference parameters to meet a noisy environment for this kind of representation. In our new approach, the cepstral and delta cepstral parts of the mean vectors of a state are indirectly represented by the autocorrelation vectors of a five-frame context window, $[\mathbf{r}_{S,-2}, \mathbf{r}_{S,-1}, \mathbf{r}_{S,0}, \mathbf{r}_{S,1}, \mathbf{r}_{S,2}]$ where $\mathbf{r}_{S,c} = [r_{S,c}(1), r_{S,c}(2), ..., r_{S,c}(P)]^T$ is the LPC analysis order; $c = 0$ stands for the instantaneous frame; $c = -1, -2$ are the left context frames, $c = 1, 2$ are the right context frames, and the autocorrelation coefficients are normalised such that $r_{S,c}(0) = 1$. The corresponding LPC vectors $\mathbf{a}_{S,c}$ of the instantaneous and context frames can be derived from these autocorrelation vectors by the following equation using the Durbin algorithm:

$$\mathbf{a}_{S,c} = \mathbf{R}_{S,c}^{-1}\mathbf{r}_{S,c} \qquad c = -2, ..., 2$$

where $\mathbf{R}_{S,c}$ is the corresponding autocorrelation matrix. The cepstral vectors $\mathbf{c}_{S,c}$ can be calculated using LPC to the cepstrum conversion formula. Therefore, the mean cepstral vector $\mathbf{c}_S$ of state S can be taken as $\mathbf{c}_{S,0}$ and the delta cepstral vector $\mathbf{d}_S$ can be calculated by the following formula:

$$\mathbf{d}_S = \sum_{k=-2}^{k=2} k\mathbf{c}_{S,c} \Big/ \sum_{k=-2}^{k=2} k^2$$

Note that only the mean vectors of cepstral and delta cepstral coefficients are indirectly represented by autocorrelation vectors; the other parts of the state parameters remain unchanged.

Parameter estimation for new representation: First, a conventional HMM was trained from a clean speech database by using the segmental k-means algorithm. Then, each frame of the training data was labelled with the state and mixture identity by using the Viterbi decoding procedure based on the conventional HMM model. The normalised autocorrelation vectors corresponding to the same label along with those autocorrelation vectors of their context frames were averaged to obtain the new, indirect representation. For example, the autocorrelation vectors of a state S (or a mixture component S of some state) can be obtained by

$$[\mathbf{r}_{S,-2}, \mathbf{r}_{S,-1}, \mathbf{r}_{S,0}, \mathbf{r}_{S,1}, \mathbf{r}_{S,2}] = \sum_{u,t}[\mathbf{r}_{t-2}^u, \mathbf{r}_{t-1}^u, \mathbf{r}_t^u, \mathbf{r}_{t+1}^u, \mathbf{r}_{t+2}^u]/N_S$$

where $\mathbf{r}_t^u$ represents the normalised autocorrelation vector of the tth frame of the uth utterance, the summation indices run over all frames t of utterance u that are labelled S, and N_S is the total number of frames belonging to S.

Adaptation of cepstral and delta cepstral vector: In this Letter we consider additive stationary white Gaussian noise that is uncorrelated to speech. The maior effect of noise is to add the noise energy η to the zeroth autocorrelation coefficient of speech. Hence, the noisy version of the autocorrelation coefficients $\tilde{\mathbf{r}}_{S,c}(k)$, $k = 0, ..., P, c = -2, ..., 2$, of a state of the reference model can be obtained by first scaling them to meet the energy of the input utterance and then adding the estimated noise energy $\hat{\eta}$ to their zeroth autocorrelation coefficients, i.e.

$$\tilde{r}_{S,c}(0) = r_{t,c}(0) + \hat{\eta}$$

$$\tilde{r}_{S,c}(k) = r_{t,c}(0)r_{S,c}(k) \qquad k = 1, ..., P$$

where $\mathbf{r}_{t,c}(0)$ is the estimated speech energy of the input utterance. The noisy version of the reference LPC vector, cepstral vector and delta cepstral vector can then be calculated, using $\tilde{\mathbf{r}}_{S,c}(k)$ instead of $\mathbf{r}_{S,c}(k)$.

Table 1: Experimental results

SNR	Baseline	Projection measure	Cepstrum adaptation	Cepstrum and delta cepstrum adaptation
Clean	98.8	98.6	98.5	98.2
20dB	80.8	94.5	95.4	95.9
15dB	66.5	85.1	91.6	92.3
10dB	48.7	69.8	82.1	84.8
5dB	26.6	49.8	66.9	74.1
0dB	10.9	30.2	46.8	49.9

Experiments and conclusions: A multispeaker (50 males and 50 females) isolated Mandarin digit recognition [4] under noisy environments was conducted to check the validity and noise compensation of this new representation. The white Gaussian noise was generated by computer and added to speech with the desired signal/noise ratio. The feature vector consisted of 12 LPC derived cepstral coefficients, 12 delta cepstral coefticients, and delta log-energy. A conventional continuous-density HMM was used as the baseline system. The state output was modelled as a four-mixture Gaussian distribution of feature vectors. The model parameters of the baseline system were trained by using clean speech data. The parameters of the new representation were then obtained as described in the preceding Sections. The noise energy was estimated by taking the frame of the minimum energy in an input utterance as the noise frame. All the frames were then biased by this noise energy. The proposed noise adaptation method was applied to the cepstral and delta cepstral mean vector of the reference model; the other parameters of the baseline model were kept