A NEW BEAMFORMING METHOD USING SECOND ORDER STATISTICS-BASED BLIND CHANNEL IDENTIFICATION

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Abstract- **This paper proposes a new beamforming method, which calculates and adjusts the weights of adaptive antenna array elements using second order statistics-based blind channel identification. We show the performance of the proposed system in a static two-ray multipath channel encountered in indoor wireless environments, and discuss the attainable bit error rate (BER) in comparison with some beamformers such as constant modulus algorithm (CMA). We also discuss the advantage, disadvantage, applicability and feasibility of the blind technique in wireless communications systems.**

I. Introduction

Looking at the history of development of wireless communications systems from the view point of multiple access scheme, we have been so far successful in making effective use of frequency orthogonality, time orthogonality and code orthogonality in FDMA, TDMA and CDMA, respectively. Recently, Space Division Multiple Access (SDMA), which utilizes space orthogonality, has been drawing much attention as an essential access scheme to provide multimedia services in fourth generation wireless communications systems. At present, space resources are not made good use of in wireless communications systems, therefore, their efficient use has a dramatic potential to break through the system performance. This is the reason why now spatial and temporal signal processing is a hot topic of research.

Beamforming, which plays an important role in SDMA realization, is a technique which tries to receive only incoming desired signal and to suppress undesired signals, by appropriately adjusting the weights of antenna array elements. Performance of beamformer depends on the criterion used in the weights calculation algorithm, and several weight calculation algorithms such as constant modulus algorithm (CMA)[1], have been proposed in order to obtain better transmission performance. We have been proposing a beamforming method for indoor high speed wireless multimedia communications systems[2], where the beamformer calculates and adjusts the weights of adaptive array elements using suppressed spread spectrum (SS) pilot signals. The SS pilot signals are parallelly transmitted with data signal with the power suppressed enough, therefore, the receiver can handle only the pilot channel, independent of the data channel. After estimating the instantaneous impulse response at each antenna element with the suppressed SS signals, the weights are adjusted so as to maximize the signal to noise plus interference ratio (SNIR) before signal demodulation process.

On the other hand, blind channel identification methods, which are based only on calculation of second order statistics of received signal, recently have been proposed by different research groups, such as Moulines, Duhamel, Cardoso and Mayrargue[3], and Tong, Xu and Kailath[4]. It was known that blind channel identification can be done by employing higher order statistics (HOS) of received signal because higher order statistics of stationary signals have channel phase information. The most serious limitation of HOS-based blind algorithms is slow rate of convergence. It is because HOS-based estimation requires a much larger sample size[5]. However, the above two research groups showed that second order statistics is enough for channel identification if employing cyclostationarity of digital signals. This implies that second order statistics-based blind channel identification requires much less signal processing. Although a lot of discussions have been made from the mathematical point of view, however, the applicability and feasibility have never been fully discussed in wireless communications applications.

In this paper, we discuss a beamforming method employing second order statistics-based blind channel identification, where we take Moulines' approach. Combining the blind technique into our already-proposed beamforming method based on SNIR maximization, our method is now free from the transmission of SS-pilot signal, therefore, it is applicable to

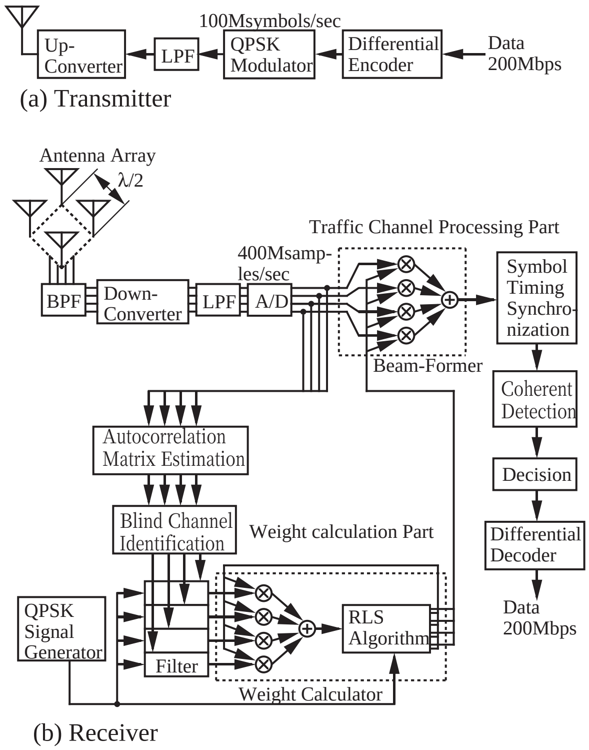


Fig. 1. Transmitter/Receiver Structure

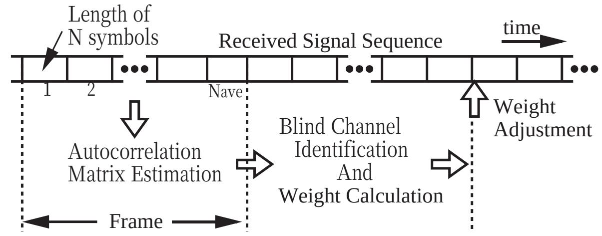


Fig. 2. Signal Frame Structure

any kinds of wireless communications systems.

We show the estimation error and attainable bit error rate performance for the proposed blind beamformer in a static two-ray multipath channel encountered in indoor wireless environments. We compare the transmission performance among the CMA-based beamformer, the pilot-assisted beamformer and the blind beamformer, and discuss the advantage, disadvantage, applicability and feasibility of the blind technique in wireless communications systems.

II. System Configuration

It is assumed that the proposed beamformer is applied to down link of wireless LAN(Local Area Network) system, where a base station with an omnidirectional antenna communicates with n half-fixed terminals each having an adaptive antenna array. Fig.1 shows the transmitter/receiver structure.

In the transmitter, data sequence (200Mbit/sec) is first differentially encoded, and then it is converted into QPSK waveform(100Msymbol/sec). The baseband signal passes through the LPF (Low Pass Filter), i.e., emission filter, and finally is transmitted from an omnidirectional antenna after up-conversion.

In the receiver, the incoming signal is received by an antenna array which consists of $N_{ary}(=4)$ sensors arranged in the position of the vertex of a square, where the sensor spacing is the half of carrier wavelength. The received signal undergoes the BPF (Band Pass Filter), the down-converter, the LPF (matched filter), and the A/D converter. The BPF is used for the suppression of the adjacent channel interference and noise as well as for the extraction of the spectrum around desired signal. The sampling rate of the A/D converter is four times the symbol rate. Next, the received signal is processed in the traffic channel processing part and in the weight calculation part independently.

In the traffic channel processing part, the outputs from the matched filter are multiplied by the weights of the beamformer which are calculated in the weight calculation part. After symbol timing synchronization and coherent demodulation, the data are finally differentially decoded.

In the weight calculation part, the ensemble-averaged autocorrelation matrix of the received signal is replaced by the time averaged one. Using this correlation matrix, the complex instantaneous impulse response of the channel at each antenna element is estimated by performing second order statistics-based blind channel identification. Details of the channel identification algorithm are discussed in section IV. Next, a QPSK signal is generated in the receiver and is fed into the filter whose tap coefficients are the same as the estimated complex instantaneous impulse response of the channel. Based on the pseudo-received signal made from the estimated impulse response and the generated QPSK signal and noise, the weights of antenna elements are calculated. Details of the weights calculation algorithm are discussed in section V.

III. Signal Frame Structure

Fig.2 shows the signal frame structure of the proposed system. The length of one frame is N(the number of symbols used in calculation of the autocorrelation matrix) times N_{ave}(the number of averaging times of autocorrelation matrix estimation) symbols. The autocorrelation matrix of the received signal is estimated using the received signal in the first frame, and during the next frame, the blind channel identification and the calculation of the weights with RLS algorithm are performed. Finally, at the end of the frame, the weights of beamformer are adjusted.

IV. Blind Channel Identification

The algorithm described here is mainly based on the method proposed by Moulines et al. However, we give a modification to apply it to practical wireless communications situations.

In what follows, we assume that the channel at the jth sensor can be modeled as an FIR filter whose impulse response is $h_j(t)$. Note that, $h_j(t)$ includes the effect of the emission filter, the channel response, the antenna response, and matched filter.

Let T, d_n, and $v_j(t)$ denote the symbol duration, the symbol emitted by the digital source at time nT and additive noise at the jth sensor, respectively. The output of LPF(matched filter) at $x_j(t)$ is given by

$$x_j(t) = \sum_{m=-\infty}^{\infty} d_m h_j(t-mT) + v_j(t). \quad (1)$$

For the blind channel identification based on the second order statistics, several measurements have to be made during sampling period T. This requirement can be satisfied by oversampling the incoming signal which is received by antenna array.

A. Oversampling of Received Signal

Oversampling $x_j(t)$ with a sampling period $\Delta(= t/4)$ constructs a set of $L \times N_{ary}(L = T/\Delta)$ sequences according to $x_n^{(i,j)} = x_j(t_0 + i\Delta + nT)$ for $0 \leq i \leq L-1$, $1 \leq j \leq N_{ary}$. Assuming that the channel can be modeled FIR filter, $h_j(t)$ has finite duration M. We can write $x_n^{(i,j)}$ in the form,

$$x_n^{(i,j)} = \sum_{m=0}^{M} d_{n-m} h_m^{(i,j)} + v_n^{(i,j)}, \quad (2)$$

where

$$v_n^{(i,j)} = v_j(t_0 + i\Delta + nT), \quad (3)$$

$$h_n^{(i,j)} = h_j(t_0 + i\Delta + nT). \quad (4)$$

Using $h_j^{(i)}(n)$, we can write the discrete-time channel impulse response which we want to estimate in the vector form,

$$H = [H_0, \cdots, H_{N_{ary}}]^T, \quad (5)$$

$$H_j = [H_j^{(0)}, \cdots, H_j^{(L-1)}]^T, \quad (6)$$

$$H_j^{(i)} = [h_0^{(i,j)}, \cdots, h_M^{(i,j)}]^T, \quad (7)$$

where $[\cdot]^T$ denotes the transpose. If we gather N successive samples of $x_n^{(i,j)}$, we will have a matrix formulation:

$$X_n^{(i,j)} = \mathcal{H}_N^{(i,j)} D_n + V_n^{(i,j)}, \quad (8)$$

where

$$X_n^{(i,j)} = [x_n^{(i,j)}, \cdots, x_{n-N+1}^{(i,j)}]^T, \quad (N \times 1) \quad (9)$$

$$D_n = [d_n, \cdots, d_{n-N-M+1}]^T, \ ((N+M) \times 1) \quad (10)$$

$$V_n^{(i,j)} = [v_n^{(i,j)}, \cdots, v_{n-N+1}^{(i,j)}]^T, \quad (N \times 1) \quad (11)$$

$$\mathcal{H}_N^{(i,j)} = \begin{bmatrix} h_0^{(i,j)} & \dots & h_M^{(i,j)} & & 0 \\ & \ddots & & \ddots & \\ 0 & & h_0^{(i,j)} & \dots & h_M^{(i,j)} \end{bmatrix}. \quad (12)$$
$$(N \times (N+M))$$

Putting a set of L sequences together will yield

$$X_n^{(j)} = \mathcal{H}_N^{(j)} D_n + V_n^{(j)}, \quad (13)$$

where

$$X_n^{(j)} = [X_n^{(0,j)T}, \cdots, X_n^{(L-1,j)T}]^T, \quad (NL \times 1) \quad (14)$$

$$V_n^{(j)} = [V_n^{(0,j)T}, \cdots, V_n^{(L-1,j)T}]^T, \quad (NL \times 1) \quad (15)$$

$$\mathcal{H}_N^{(j)} = [\mathcal{H}_N^{(0,j)T}, \cdots, \mathcal{H}_N^{(L-1,j)T}]^T. \quad (NL \times (N+M)) \quad (16)$$

Furthermore, putting a set of N_{ary} matrices together will yield

$$X_n = \mathcal{H}_N D_n + V_n, \quad (17)$$

where

$$X_n = [X_n^{(0)T}, \cdots, X_n^{(N_{ary}-1)T}]^T, \quad (NLN_{ary} \times 1) \quad (18)$$

$$V_n = [V_n^{(0)T}, \cdots, V_n^{(N_{ary}-1)T}]^T, \quad (NLN_{ary} \times 1) \quad (19)$$

$$\mathcal{H}_N = [\mathcal{H}_N^{(0)T}, \cdots, \mathcal{H}_N^{(N_{ary}-1)T}]^T. \quad (20)$$
$$(NLN_{ary} \times (N+M))$$

B. Whitening of Filtered Noise

Second-order Statistics based blind identification algorithms include subspace decomposition of autocorrelation matrix R_x of vector X_n. R_x can be described as

$$\begin{aligned} R_x &= E[X_n X_n^H] \\ &= \mathcal{H}_N R_d \mathcal{H}_N^H + R_v, \quad (21) \end{aligned}$$
$$(NLN_{ary} \times NLN_{ary})$$

where $R_d = E[D_n D_n^H]$ $((N+M) \times (N+M))$ and $R_v = E[V_n V_n^H]$ $(NLN_{ary} \times NLN_{ary})$. In the equation above, $E[\cdot]$ and $[\cdot]^H$ denote the ensemble average and Hermitian transposition, respectively. R_v denotes the autocorrelation matrix of additive noise vector V_n and is noise part of R_x. This noise part has to be in the shape of (constant) $\times I$ ($NLN_{ary} \times NLN_{ary}$ identity matrix) in order to decompose R_x into subspace. However, in practical wireless communication system, the noise obtained at the matched filter output is no longer white. In this case, pre- and post-multiplying the noise whitening matrix $W_v (= R_v^{-1/2})$ leads to

$$\begin{aligned} W_v R_x W_v^H &= W_v \mathcal{H}_N R_d \mathcal{H}_N^H W_v^H + W_v R_v W_v^H \\ &= W_v \mathcal{H}_N R_d \mathcal{H}_N^H W_v^H + \sigma^2 I, \end{aligned} \quad (22)$$

where σ^2 denotes a variance of additive noise at the front end of the receiver. Let $\underline{R}_x = W_v R_x W_v^H$, $\underline{\mathcal{H}}_N = W_v \mathcal{H}_N$, then we have

$$\underline{R}_x = \underline{\mathcal{H}}_N R_d \underline{\mathcal{H}}_N^H + \sigma^2 I. \quad (23)$$

This is a desired form. Using Eq.(23), the estimation of the discrete time channel impulse response can be accomplished with Moulines's approach.

V. Proposed Beamforming Method

Now that the estimate of discrete time channel impulse response at each antenna element is available, we can calculate the weights of the beamformer. Let $\hat{h}_j(\tau)$ $(1 \le j \le 4, 0 \le \tau \le NL)$ denote the estimated discrete time channel impulse response at the jth sensor.

In our algorithm, we first search for a path with the maximum power. In other words, defining

$$\sigma(\tau) = \sum_{j=1}^{N_{ary}} |\hat{h}_j(\tau)|^2 \quad (24)$$

as the total power at τ, we search for $\tau = \tau_{max}$ such that $\sigma(\tau)$ is maximum. Then, we calculate the coefficients of the filter which is used for beamforming. Using τ_{max}, we can write the coefficients $f_j(k)$ as

$$f_j(k) = \hat{h}_j(\tau_{max} + kT), \quad (1 \le j \le 4), \quad (25)$$

which has a non-zero value for k satisfying $0 \le \tau_{max} + kT \le NL$ and zeros otherwise.

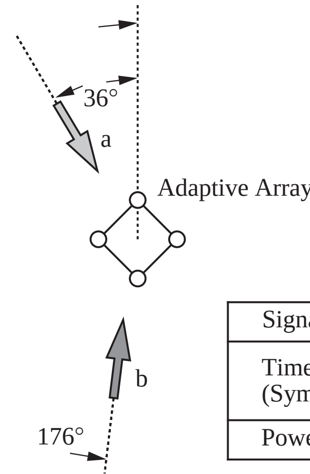
Using a QPSK signal $d'(k)$ which is generated in the receiver, the pseudo-received signal $x'_j(k)$ is given by

$$x'_j(k) = d'(k) * f_j(k) + n'_j(k), \quad (26)$$

where $*$ denotes the convolution. $n'_j(k)$ is also the generated noise, whose power is equal to that of the noise in the channel. Using this quasi-received signal, we calculate the weights.

As a weight calculation algorithm for our beamforming method, we adopt RLS algorithm.

RLS algorithm is as follows:



Signal	a	b
Time Delay (Symbol Time)	0	4
Power Ratio	1	1

Fig. 3. Channel Model

1. initial condition
   $w(0) = 0$
   $P(0) = p^{-1} I$ (p : minute positive number, I : $N_{ary} \times N_{ary}$ identity matrix)

2. RLS algorithm

   (a) $k = 1$

   (b) calculation of kalman gain

   $$K(k) = \frac{P(k-1)x'(k)}{\mu + x'^{*T} P(k-1) x'(k)}$$

   (c) $y(k) = x'^T w(k-1)$

   (d) calculation of error

   $$\epsilon(k) = y(k) - d'(k)$$

   (e) renewal of the weights

   $$w(k) = w(k-1) - K^*(k)\epsilon(k)$$

   (f) renewal of inverse covariance matrix

   $$P(k) = \frac{1}{\mu} P(k-1) - K(k) x'^{*T}(k) P(k-1)$$

   (g) $k = k + 1$, return to (b)

where μ and $(\cdot)^*$ denote the forgetting factor and the complex conjugate, respectively.

VI. Computer Simulation

A. Channel Model

Fig.3 shows the channel model discussed in this paper. This is a static two ray multipath channel

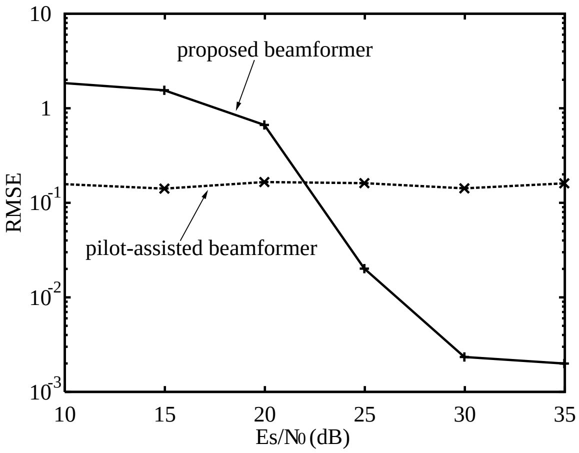


Fig. 4. Estimation Error versus Es/No

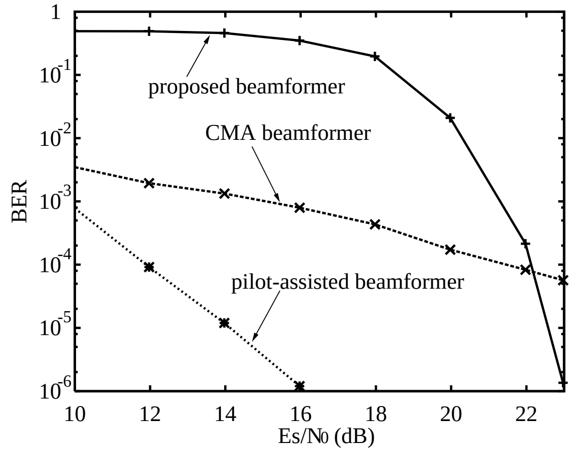


Fig. 5. Bit Error Rate Performance

model where there are a preceding wave and a four-symbol delayed wave. The power ratio of these two incoming signals is the same.

B. Parameter

In the proposed beamformer, we adopt a root nyquist filter with roll off factor 0.5 as the LPF in the transmitter and receiver. The window width N is chosen to be 15 and the length of FIR filter (the channel) to be 9. The number of averaging times of correlation matrix is equal to 272, that is, the length of one frame becomes 4080 symbols, and in the estimation of the correlation matrix, the time averaging is performed over 4080 symbols.

The number of repetitions, p, and μ in the RLS algorithm are chosen to be 50, 1.0×10^{-8}, and 1.0, respectively.

On the other hand, the pilot assisted system, employs the maximum-length shift register (M-) sequence with length of 256.

C. Normalized Root-Mean-Square Error

Fig.4 shows the root mean square error (RMSE) of the proposed blind channel estimation, versus the signal to noise energy ratio per symbol(E_s/N_0). Defining $f_j(k)$ and $\hat{f}_j^l(k)$ as the true and the estimated impulse responses of the channel of at the jth antenna element in the lth trial, respectively, the RMSE is defined as

$$RMSE = \frac{1}{\sum_{i=0}^{N_{ary}-1} ||f_i(k)||} \times \sqrt{\frac{1}{N_{trial}} \sum_{l=0}^{N_{trial}-1} ||\hat{f}_j^l(k) - f_j(k)||^2}, \quad (27)$$

where $||\cdot||$ and N_{trial} denote the Euclidean norm and the number of trials (100 in this simulation).

The RMSE of the pilot assisted system does not depend on E_s/N_0. This is because the noise is almost negligibly small in this E_s/N_0 region, and the autocorrelation property of the M-sequence limits the estimation.

On the other hand, the RMSE of the blind estimater decreases suddenly around $E_s/N_0 = 20dB$. Therefore the performance of the blind system could be superior to that of the pilot assisted system when E_s/N_0 becomes over 23dB.

D. Bit Error Rate

Fig.5 shows the bit error rate (BER) performance versus the E_s/N_0. For the sake of the comparison, the BER performance of the pilot assisted beamformer and CMA beamformer is also plotted.

The CMA beamformer, which also works in a blind manner, suffers from slow rate of convergence. Therefore, once the sample size for weight calculation is determined, it severely affects the performance. In this computer simulation, we chose a small sample size for the CMA, so the performance is worse than that of the pilot assisted beamformer, and the BER improves more slowly as E_s/N_0 increases.

The pilot assisted beamformer can achieve the best performance among the three beamformers, however, it requires a special transmission format.

The performance of the proposed blind beamformer is the poorest. However, as expected Fig.4, it could outperform the pilot assisted beamformer for E_s/N_0 >23dB.

VII. Conclusions and Discussions

In this paper, we have proposed a new blind beamforming method using second order statistics-based blind channel identification. This beamformer requires no pilot signals and can estimate the channel impulse response to adjust the weights of array elements only with the incoming signals. We have shown the root mean square error of the channel impulse response estimation and the attainable bit error rate performance in a static two-ray multipath channel. We believe that we could show the applicability of second order statistics-based blind technique to a practical wireless system, however, it has a lot of problems. They are as follows:

- the performance of the blind beamformer is very poor as compared with that of pilot assisted and CMA beamformers. Relatively high E_s/N_0 is required to achieve a better bit error rate.
- the knowledge of the length of the channel impulse response is required for estimation.
- Hard matrix computation is still required. Better performance in low E_s/N_0 environment results in larger matrix size.

Consequently, we need a lot of modifications and reconsiderations of second order-based blind technique, which is matured in academic point of view, to make it applicable to practical wireless systems. It has a lot of problems mentioned above, however, we believe we can solve them.

Appendix

I. Autocorrelation Matrix of Filtered Noise

This appendix shows the autocorrelation matrix R_v of additive noise which has passed through the matched filer.

Since $R_v = E[V_n V_n^H]$ (V_n is defined in Eqs.(11), (15), (19)), you can easily verify that the (p,q) component of R_v is $E[v^{(\alpha,\beta)}_{p-N\alpha-NL\beta+n-1} v^{(\gamma,\delta)*}_{q-N\gamma-NL\delta+n-1}]$ where α, β, γ, and δ denote the integer parts of $(p-NL\beta)/N$, $p/(NL)$, $(q-NL\delta)/N$, and $q/(NL)$, respectively. Therefore, we will calculate the value of $E[v_p^{(i,j)} v_q^{(k,l)*}]$.

We assume that the additive noise is white at the input of the matched filter. Let $w_j(t_0 + i\Delta + nT)$ denotes the white noise at the $j$the antenna element and $s(t_0 + i\Delta + nT)$ denotes the impulse response of the matched filter. The components of R_v can be calculated as followings:

$$
\begin{aligned}
& E[v_p^{(i,j)} v_q^{(k,l)*}] \\
= \; & E[v_j(t_0 + i\Delta + pT) v_l^*(t_0 + k\Delta + qT)] \\
= \; & E[\sum_{a=-\infty}^{\infty} w_j(a\Delta) s(t_0 + i\Delta + pT - a\Delta) \\
& \cdot \sum_{b=-\infty}^{\infty} w_l^*(b\Delta) s^*(t_0 + k\Delta + qT - b\Delta)] \\
= \; & \sum_{a=-\infty}^{\infty} \sum_{b=-\infty}^{\infty} s(t_0 + i\Delta + pT - a\Delta) \\
& \cdot s^*(t_0 + k\Delta + qT - b\Delta) E[w_j(a\Delta) w_l^*(b\Delta)] \\
= \; & \sigma^2 \sum_{a=-\infty}^{\infty} s(i\Delta + pT - a\Delta) s^*(j\Delta + qT - a\Delta),
\end{aligned}
$$

where σ^2 denotes the variance of white noise. Though it is a matter of course, the components of R_v depends only on the impulse response of matched filter. In general, since we have the knowledge of the matched filter, we can calculate the noise autocorrelation matrix R_v, a prior.

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