Blind Joint Equalization of Multiple Synchronous Mobile Users Using Oversampling and/or Multiple Antennas

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Abstract

We consider multiple (p) users that operate on the same carrier frequency and use the same linear digital modulation format. We consider $m > p$ antennas receiving mixtures of these signals through multipath propagation (equivalently, oversampling of the received signals of a smaller number of antenna signals could be used). We consider conditions on the matrix channel response for the existence of a Zero-Forcing Equalizer (ZFE) (which cancels inter-symbol and inter-user interference). In the noisefree case, we show how a ZFE can be obtained from linear prediction and the channel matrix itself can also be determined as a byproduct. The problem is one of signal and noise subspaces and we show a convenient way of solving the deterministic maximum likelihood problem using a minimal linear parameterization of the noise subspace. This parameterization is found as a byproduct in the linear prediction problem.

1 Matrix Channels

Consider linear digital modulation over a linear channel with additive Gaussian noise. Assume that we have p transmitters at a certain carrier frequency and m antennas receiving mixtures of the signals. We shall assume throughout that $m > p$. The received signals can be written in the baseband as

$$y_i(t) = \sum_{j=1}^{p}\sum_{k} a_j(k)h_{ij}(t-kT) + v_i(t) \qquad (1)$$

where the $a_j(k)$ are the transmitted symbols from source j, T is the common symbol period, $h_{ij}(t)$ is the (overall) channel impulse response from transmitter j to receiver antenna i. Assuming the $\{a_j(k)\}$ and $\{v_i(t)\}$ to be jointly (wide-sense) stationary, the processes $\{y_i(t)\}$ are (wide-sense) cyclostationary with period T. If $\{y_i(t)\}$ is sampled with period T, the sampled process is (wide-sense) stationary. Sampling in this way leads to an equivalent discrete-time representation. We could also obtain multiple channels in the discrete time domain by oversampling the continuous-time received signals, see [1],[2],[3].

We assume the channels to be FIR. In particular, after sampling we assume the (vector) impulse response from source j to be of length N_j. Without loss of generality, we assume the first non-zero vector impulse response sample to occur at discrete time zero, and we can assume the sources to be ordered so that $N_1 \geq N_2 \geq \cdots \geq N_p$. Let $N = \sum_{j=1}^{p} N_j$. The discrete-time received signal can be represented in vector form as

$$\begin{aligned}
\mathbf{y}(k) &= \sum_{j=1}^{p}\sum_{i=0}^{N_j-1} \mathbf{h}_j(i)a_j(k-i) + \mathbf{v}(k)\\
&= \sum_{i=0}^{N_1-1} \mathbf{h}(i)\mathbf{a}(k-i) + \mathbf{v}(k)\\
&= \sum_{j=1}^{p} \mathbf{H}_{j,N_j}A_{j,N_j}(k) + \mathbf{v}(k) = \mathbf{H}_N\mathbf{A}_N(k) + \mathbf{v}(k),
\end{aligned}$$

$$\mathbf{y}(k) = \begin{bmatrix} y_1(k)\\ \vdots \\ y_m(k)\end{bmatrix}, \mathbf{v}(k) = \begin{bmatrix} v_1(k)\\ \vdots \\ v_m(k)\end{bmatrix}, \mathbf{h}_j(k) = \begin{bmatrix} h_{1j}(k)\\ \vdots \\ h_{mj}(k)\end{bmatrix}$$

$$\mathbf{H}_{j,N_j} = [\mathbf{h}_j(N_j-1)\cdots\mathbf{h}_j(0)], \mathbf{H}_N = [\mathbf{H}_{1,N_1}\cdots\mathbf{H}_{p,N_p}]$$
$$\mathbf{h}(k) = [\mathbf{h}_1(k)\cdots\mathbf{h}_p(k)], \mathbf{a}(k) = \left[a_1^H(k)\cdots a_p^H(k)\right]^H$$
$$A_{j,N_j}(k) = \left[a_j^H(k-N_j+1)\cdots a_j^H(k)\right]^H$$
$$\mathbf{A}_N(k) = \left[A_{1,N_1}^H(k)\cdots A_{p,N_p}^H(k)\right]^H \qquad (2)$$

where superscript ^{H} denotes Hermitian transpose.

2 FIR Zero-Forcing (ZF) Equalization

We consider a structure of equalizers as in Fig. 1 to not only cancel the intersymbol interference for every source separately, but also cancel the interference between different sources. We assume the equalizer filters to be FIR of length L: $F_{ji}(z) = \sum_{k=0}^{L-1} f_{ji}(k)z^{-k}$, $j = 1,\ldots,p$, $i = 1,\ldots,m$. We introduce $\mathbf{f}_j(k) = [f_{j1}(k)\cdots f_{jm}(k)]$, $\mathbf{f}(k) = \left[\mathbf{f}_1^H(k)\cdots\mathbf{f}_p^H(k)\right]^H$, $\mathbf{F}_{j,L} = [\mathbf{f}_j(L-1)\cdots\mathbf{f}_j(0)]$, $\mathbf{F}_L = [\mathbf{F}_{1,L}^H\cdots\mathbf{F}_{p,L}^H]^H$, $\mathbf{H}(z) = \sum_{k=0}^{N_1-1}\mathbf{h}(k)z^{-k}$ and

$\mathbf{F}(z)=\sum_{k=0}^{L-1}\mathbf{f}(k)z^{-k}$. The condition for the equalizer to be ZF is $\mathbf{F}(z)\mathbf{H}(z) = \operatorname{diag}\{z^{-n_1}\cdots z^{-n_p}\}$ where $n_j \in \{0,1,\ldots,N_j+L-2\}$. The ZF condition can be written in the time-domain as

$$\mathbf{F}_L\ \mathcal{T}_{L,p}(\mathbf{H}_N) = \begin{bmatrix} 0\cdots 0\ 1\ 0\cdots 0 & \cdots & 0\cdots 0 \\ \vdots & \ddots & \vdots \\ 0\cdots 0 & \cdots & 0\cdots 0\ 1\ 0\cdots 0 \end{bmatrix} \tag{3}$$

where $\mathcal{T}_{M,p}(\mathbf{H}_N) = [\mathcal{T}_M(\mathbf{H}_{1,N_1})\cdots\mathcal{T}_M(\mathbf{H}_{p,N_p})]$ and $\mathcal{T}_M(\mathbf{x})$ is a banded block Toeplitz matrix with M block rows and $[\mathbf{x}\ 0_{n\times(M-1)}]$ as first block row (n is the number of rows in $\mathbf{x}$). (3) is a system of $p(N+p(L-1))$ equations in Lmp unknowns. To be able to equalize, we need to choose the equalizer length L such that the system of equations (3) is exactly or underdetermined. Hence

$$L \geq \underline{L} = \left\lceil \frac{N-p}{m-p} \right\rceil \tag{4}$$

We assume that $\mathbf{H}_N$ has full rank if $N \geq m$. If not, it is still possible to go through the developments we consider below. But lots of singularities will appear and the non-singular part will behave in the same way as if we had a reduced number of channels, equal to the row rank of $\mathbf{H}_N$. Reduced rank in $\mathbf{H}_N$ can be detected by inspecting the rank of $\mathrm{E}\mathbf{y}(k)\mathbf{y}^H(k)$. If a reduced rank in $\mathbf{H}_N$ is detected, the best way to proceed (also when quantities are estimated from data) is to preprocess the data $\mathbf{y}(k)$ by transforming them into new data of dimension equal to the row rank of $\mathbf{H}_N$.

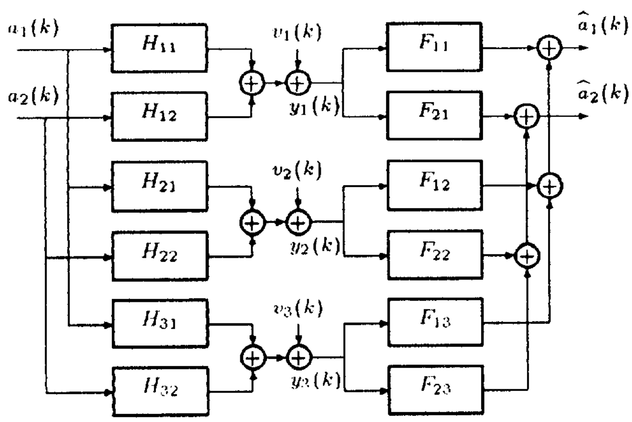

Figure 1: Channel and linear equalizer for $m = 3$ channels and $p = 2$ sources.

The matrix $\mathcal{T}_{L,p}(\mathbf{H}_N)$ is a block Toeplitz block matrix. It can be shown that for $L \geq \underline{L}$ it has full column rank if the following assumptions are satisfied

(A1) $\operatorname{rank}(\mathbf{H}(z)) = p$, $\forall z$ and $\operatorname{rank}(\mathbf{h}(0)) = p$. In this case, $\mathbf{H}(z)$ is called irreducible in systems theory,

(A2) $\operatorname{rank}([\mathbf{h}_1(N_1-1)\cdots\mathbf{h}_p(N_p-1)]) = p$, in which case $\mathbf{H}(z)$ is called column reduced, see [4].

Assuming $\mathcal{T}_{L,p}(\mathbf{H}_N)$ to have full column rank, the nullspace of $\mathcal{T}^H_{L,p}(\mathbf{H}_N)$ has dimension $L(m-p)-N+p$. If we take the entries of any vector in this nullspace as equalizer coefficients, then the equalizer output is zero, regardless of the transmitted symbols.

To find a ZF equalizer (corresponding to some delays n_j), it suffices to take an equalizer length equal to $\underline{L}$. We can arbitrarily fix $\underline{m} = \underline{L}(m-p)-N+p$ equalizer coefficients (e.g. take $\underline{m}$ equalizer filters of length $\underline{L}-1$ only). The remaining $p(p(\underline{L}-1)+N)$ coefficients can be found from (3). This shows that for $m > p$, a FIR equalizer suffices for ZF equalization (and interference cancellation)!

3 Channel Identification from Second-order Statistics: Frequency Domain Approach

Consider the noise-free case and let the sources be temporally white but possibly correlated among themselves with $p \times p$ covariance matrix $R_{\mathbf{a}}$. Then the power spectral density matrix of the stationary vector process $\mathbf{y}(k) = \mathbf{H}(z)\mathbf{a}(k)$ is

$$S_{\mathbf{yy}}(z) = \mathbf{H}(z)\,R_{\mathbf{a}}\mathbf{H}^H(z^{-*})\,. \tag{5}$$

The following spectral factorization result has been brought to our attention by Loubaton [5]. Let $\mathbf{K}(z)$ be a $m \times p$ rational transfer function that is causal and stable. Then $\mathbf{K}(z)$ is called minimum-phase if $\mathbf{K}(z) \neq 0$, $|z| > 1$. Let $S_{\mathbf{yy}}(z)$ be a rational $m \times m$ spectral density matrix of rank p. Then there exists a rational $m \times p$ transfer matrix $\mathbf{K}(z)$ that is causal, stable, minimum-phase, unique up to a unitary $p \times p$ constant matrix, of (minimal) McMillan degree $\deg(\mathbf{K}) = \frac{1}{2}\deg(S_{\mathbf{yy}})$ such that

$$S_{\mathbf{yy}}(z) = \mathbf{K}(z)\,\mathbf{K}^H(z^{-*})\,. \tag{6}$$

In our case, $S_{\mathbf{yy}}$ is polynomial (FIR channel) and $\mathbf{H}(z)$ is minimum-phase since we assume $\operatorname{rank}(\mathbf{H}(z)) = p$, $\forall z$. Hence, the spectral factor $\mathbf{K}(z)$ identifies the channel

$$\mathbf{K}(z) = \mathbf{H}(z)R_{\mathbf{a}}^{1/2}\Phi \tag{7}$$

where $R_{\mathbf{a}}^{1/2}$ is any particular (e.g. triangular) matrix square-root of $R_{\mathbf{a}}$ and Φ is a $p \times p$ unitary matrix. So the channel identification from second-order statistics is simply a multivariate MA spectral factorization problem. The remaining factors $R_{\mathbf{a}}^{1/2}$ and Φ can be identified by exploiting higher-order moments (see [6] and references therein) or the discrete distribution nature of the sources [7].

4 Gram-Schmidt Orthogonalization, Triangular Factorization and Linear Prediction

UDL Factorization of the Inverse Covariance Matrix

Consider a vector of zero mean random variables $Y = [y_1^H\ y_2^H \cdots y_M^H]^H$. We shall introduce the notation $y_{1:M} = Y$. Consider Gram-Schmidt orthogonalization of the components of Y. We can determine the linear least-squares (lls) estimate $\widehat{y}_i$ of y_i given $y_{1:i-1}$ and the associated estimation error $\widetilde{y}_i$ as

$$\begin{aligned} \widehat{y}_i &= \widehat{y}_i|_{y_{1:i-1}} = R_{y_i y_{1:i-1}} R^{-1}_{y_{1:i-1} y_{1:i-1}} y_{1:i-1} , \\ \widetilde{y}_i &= \widetilde{y}_i|_{y_{1:i-1}} = y_i - \widehat{y}_i \end{aligned} \tag{8}$$

where $R_{ab} = \mathrm{E}ab^H$ for two random column vectors a and b. The Gram-Schmidt orthogonalization process consists of generating consecutively $\widetilde{Y} = [\widetilde{y}_1^H\ \widetilde{y}_2^H \cdots \widetilde{y}_M^H]^H$ starting with $\widetilde{y}_1 = y_1$. We can write the relation

$$L\,Y = \widetilde{Y} \tag{9}$$

where L is a unit-diagonal lower triangular matrix. The first $i-1$ elements in row i of L are $-R_{y_i y_{1:i-1}} R^{-1}_{y_{1:i-1} y_{1:i-1}}$. From (9), we obtain

$$\mathrm{E}(LY)(LY)^H = \mathrm{E}\widetilde{Y}\widetilde{Y}^H \Rightarrow L R_{YY} L^H = D = R_{\widetilde{Y}\widetilde{Y}} . \tag{10}$$

D is indeed a diagonal matrix since the $\widetilde{y}_i$ are decorrelated. Equation (10) can be rewritten as the UDL triangular factorization of R^{-1}_{YY}

$$R^{-1}_{YY} = L^H D^{-1} L . \tag{11}$$

If Y is filled up with consecutive samples of a random process, $Y = [y^H(k)\ \ y^H(k-1) \cdots\ y^H(k-M+1)]^H$, then the $\widetilde{y}_i$ become backward prediction errors of order $i-1$, the corresponding rows in L are backward prediction filters and the corresponding diagonal elements in D are backward prediction error variances. If the process is stationary, then R_{YY} is Toeplitz and the backward prediction errors filters and variances (and hence the UDL factorization of R^{-1}_{YY}) can be determined using a fast algorithm, the Levinson algorithm. If Y is filled up in a different order, *i.e.* $Y = [y^H(k)\, y^H(k+1) \cdots y^H(k+M-1)]^H$, then the backward prediction quantities become forward prediction quantities, which for the the prediction error filters and variances are the same as the backward quantities if the process $y(.)$ is scalar valued.

If the process $\mathbf{y}(.)$ is vector valued, we shall still carry out the Gram-Schmidt orthogonalization scalar component by scalar component. In the time-series case, this is multichannel linear prediction with sequential processing of the channels. If the matrix $R_{\mathbf{YY}}$ is singular, then there exist linear relationships between certain components of $\mathbf{Y}$. As a result, certain components y_i will be perfectly predictible from the previous components and their resulting orthogonalized version $\widetilde{y}_i$ will be zero. The corresponding diagonal entry in D will hence be zero also. For the orthogonalization of the following components, we don't need this y_i. As a result, the entries under the diagonal in the coresponding column of L can be taken to be zero (minimum-norm choice for the prediction filters in those rows). The (linearly independent) row vectors in L that correspond to zeros in D are vectors that span the null space of $R_{\mathbf{YY}}$. The number of non-zero elements in D equals the rank of $R_{\mathbf{YY}}$.

LDU Factorization of a Covariance Matrix

Assume at first that $R_{\mathbf{YY}}$ is nonsingular. Since the $\widetilde{y}_i$ form just an orthogonal basis in the space spanned by the y_i, $\mathbf{Y}$ can be perfectly estimated from $\widetilde{\mathbf{Y}}$. Expressing that the covariance matrix of the error in estimating $\mathbf{Y}$ from $\widetilde{\mathbf{Y}}$ is zero leads to

$$\begin{aligned} 0 &= R_{\mathbf{YY}} - R_{\mathbf{Y}\widetilde{\mathbf{Y}}} R^{-1}_{\widetilde{\mathbf{Y}}\widetilde{\mathbf{Y}}} R_{\widetilde{\mathbf{Y}}\mathbf{Y}} \Rightarrow \\ R_{\mathbf{YY}} &= R_{\mathbf{Y}\widetilde{\mathbf{Y}}} R^{-1}_{\widetilde{\mathbf{Y}}\widetilde{\mathbf{Y}}} R_{\widetilde{\mathbf{Y}}\mathbf{Y}} = U^H D^{-1} U \end{aligned} \tag{12}$$

where D is the same diagonal matrix as in (10) and $U = L^{-H}$ is a unit-diagonal upper triangular matrix. (12) is the LDU triangular factorization of $R_{\mathbf{YY}}$. In the stationary multichannel time-series case, $R_{\mathbf{YY}}$ is block Toeplitz and the rows of U and the diagonal elements of D can be computed in a fast way using a sequential processing version of the multichannel Schur algorithm.

When $R_{\mathbf{YY}}$ is singular, then D will contain a number of zeros, equal to the dimension of the nullspace of $R_{\mathbf{YY}}$. Let J be a selection matrix (the rows of J are rows of the identity matrix) that selects the nonzero elements of D so that JDJ^H is a diagonal matrix that contains the consecutive non-zero diagonal elements of D. Then we can write

$$R_{\mathbf{YY}} = (JU)^H (JD^{-1}J^H)(JU) \tag{13}$$

which is a modified LDU triangular factorization of the singular $R_{\mathbf{YY}}$. $(JU)^H$ is a modified lower triangular matrix, its columns being a subset of the columns of the lower triangular matrix U^H. A modified version of the Schur algorithm to compute the generalized LDU factorization of a singular block Toeplitz matrix $R_{\mathbf{YY}}$ has been recently proposed in [8].

5 Signal and Noise Subspaces

Consider now the measured data with additive independent white noise $\mathbf{v}(k)$ with zero mean and assume $\mathrm{E}\mathbf{v}(k)\mathbf{v}^H(k) = \sigma_v^2 I_m$ with unknown variance σ_v^2 (in the complex case, real and imaginary parts are assumed to be uncorrelated, colored noise with known correlation structure but unknown variance could equally well be handled). A vector of L measured data can be expressed as

$$\mathbf{Y}_L(k) = \mathcal{T}_{L,p}(\mathbf{H}_N)\, A_{N+p(L-1)}(k+L-1) + \mathbf{V}_L(k) \tag{14}$$

where $\mathbf{Y}_L(k) = \left[\mathbf{y}^H(k) \cdots \mathbf{y}^H(k+L-1)\right]^H$ and $\mathbf{V}_L(k)$ is defined similarly. Therefore, the structure of the covariance matrix of the received signal $\mathbf{y}(k)$ is

$$\mathrm{R}^{\mathbf{y}}_L = \mathcal{T}_{L,p}(\mathbf{H}_N)\, \mathrm{R}^a_{N+p(L-1)} \mathcal{T}^H_{L,p}(\mathbf{H}_N) + \sigma_v^2 I_{mL} \quad (15)$$

where $\mathrm{R}^a_{N+p(L-1)} = \mathrm{E} A_{N+p(L-1)}(k) A^H_{N+p(L-1)}(k)$. We assume R^a_M to be nonsingular for any M. For $L \geq \underline{L}$, and assuming (A1), (A2), $\mathcal{T}_{L,p}(\mathbf{H}_N)$ has full column rank and σ_v^2 can be identified as the smallest eigenvalue of $\mathrm{R}^{\mathbf{y}}_L$. Replacing $\mathrm{R}^{\mathbf{y}}_L$ by $\mathrm{R}^{\mathbf{y}}_L - \sigma_v^2 I_{mL}$ gives us the covariance matrix for noise-free data. Given the structure of $\mathrm{R}^{\mathbf{y}}_L$ in (15), the column space of $\mathcal{T}_{L,p}(\mathbf{H}_N)$ is called the signal subspace and its orthogonal complement the noise subspace.

Consider the eigendecomposition of $\mathrm{R}^{\mathbf{y}}_L$ of which the real positive eigenvalues are ordered in descending order:

$$\begin{aligned} \mathrm{R}^{\mathbf{y}}_L &= \sum_{i=1}^{N+p(L-1)} \lambda_i V_i V_i^H + \sum_{i=N+p(L-1)+1}^{mL} \lambda_i V_i V_i^H \\ &= V_{\mathcal{S}} \Lambda_{\mathcal{S}} V_{\mathcal{S}}^H + V_{\mathcal{N}} \Lambda_{\mathcal{N}} V_{\mathcal{N}}^H \end{aligned} \quad (16)$$

where $\Lambda_{\mathcal{N}} = \sigma_v^2 I_{(m-p)L-N+p}$ (see (15)). The sets of eigenvectors $V_{\mathcal{S}}$ and $V_{\mathcal{N}}$ are orthogonal: $V_{\mathcal{S}}^H V_{\mathcal{N}} = 0$, and $\lambda_i > \sigma_v^2$, $i = 1, \ldots, N+p(L-1)$. We then have the following equivalent descriptions of the signal and noise subspaces

$$Range\{V_{\mathcal{S}}\} = Range\{\mathcal{T}_{L,p}(\mathbf{H}_N)\}, \; V_{\mathcal{N}}^H \mathcal{T}_{L,p}(\mathbf{H}_N) = 0. \quad (17)$$

6 The Instantaneous Mixture Case

We shall consider the noiseless case and we can assume w.l.o.g. that the first p rows of $\mathbf{h}(0)$ are linearly independent (the ordering of the channels can always be permuted to achieve this). The covariance matrix of $\mathbf{y}(k) = \mathbf{h}(0)\mathbf{a}(k)$ is $\mathrm{R}^{\mathbf{y}}_1 = \mathbf{h}(0) R_{\mathbf{a}} \mathbf{h}^H(0)$. By carrying out the Gram-Schmidt orthogonalization of the components of $\mathbf{y}(k)$, we obtain the triangular factorizations we discussed above. In particular

$$\begin{aligned} & L \mathrm{R}^{\mathbf{y}}_1 L^H = D = blockdiag\left\{D_p, 0_{(m-p)\times(m-p)}\right\} \\ & \Rightarrow \mathrm{R}^{\mathbf{y}}_1 = U_p^H D_p^{-1} U_p \end{aligned} \quad (18)$$

where U_p^H is a $m \times p$ matrix of the generalized lower triangular form we discussed above. Taking $R_{\mathbf{a}}^{1/2}$ to be triangular, we arrive at

$$\mathbf{h}(0) = U_p^H D_p^{-1/2} \Phi R_{\mathbf{a}}^{-1/2} \quad (19)$$

where Φ is a $p \times p$ unitary matrix. Φ and $R_{\mathbf{a}}^{1/2}$ represent $\frac{1}{2}p(p-1)$ and $\frac{1}{2}p(p+1)$ degrees of freedom respectively. If we don't know $R_{\mathbf{a}}$, we can determine $\mathbf{h}(0)$, using the LDU factorization of $\mathrm{R}^{\mathbf{y}}_1$, as $U_p^H D_p^{-1/2}$, up to p^2 degrees of freedom. If $R_{\mathbf{a}}$ is known, e.g. $R_{\mathbf{a}} = \sigma_a^2 I_p$, then $U_p^H D_p^{-1/2}$ determines $\mathbf{h}(0)$ up to only Φ, *i.e.* up to only $\frac{1}{2}p(p-1)$ degrees of freedom.

In general, if $\mathbf{h}(0)$ is determined using subspace techniques from U_p^H, then the only part of $\mathbf{h}(0)$ that can be determined uniquely from $\mathrm{R}^{\mathbf{y}}$ is $\mathbf{h}(0)T = \mathbf{h}'(0) = [I_p \;\; *]^H$ which is related to $\mathbf{h}(0)$ by a nonsingular $p \times p$ matrix T, representing p^2 degrees of freedom. Note also that $L U_p^H = [I_p \;\; 0]^H$. Hence

$$\tilde{\mathbf{y}}(k) = L\mathbf{y}(k) = L\mathbf{h}(0)\mathbf{a}(k) = \begin{bmatrix} I_p \\ 0 \end{bmatrix} D_p^{-1/2} \Phi R_{\mathbf{a}}^{-1/2} \mathbf{a}(k) \quad (20)$$

or $\tilde{y}_{1:p}(k)$ is just a linear transformation of $\mathbf{a}(k)$.

7 Blind Equalization and Channel Identification from Second-order Statistics by Multichannel Linear Prediction

ZF Equalizer and Noise Subspace Determination

We consider again the noiseless covariance matrix or equivalently assume noisefree data: $v(t) \equiv 0$. We shall also assume the transmitted symbols to be uncorrelated, $\mathrm{R}^{\mathbf{a}}_M = R_{\mathbf{a}} \otimes I_M$, though the noise subspace parameterization we shall obtain also holds when the transmitted symbols are correlated.

Consider now the Gram-Schmidt orthogonalization of the consecutive (scalar) elements in the vector $\mathbf{Y}_L(k)$. We start building the UDL factorization of $\mathrm{R}^{\mathbf{y}}_L$ and obtain the consecutive prediction error filters and variances. No singularities are encountered until we arrive at block row $\underline{L}$ in which we treat the elements of $\mathbf{y}(k+\underline{L}-1)$. From the full column rank of $\mathcal{T}_{\underline{L},p}(\mathbf{H}_N)$, we infer that we will get $\underline{m} \in \{0, 1, \ldots, m-p-1\}$ singularities. If $\underline{m} > 0$, then the following scalar components of $\mathbf{Y}$ become zero after orthogonalization: $\tilde{y}_i(k+\underline{L}-1) = 0$, $i = m+1-\underline{m}, \ldots, m$. So the corresponding elements in the diagonal factor D are also zero. We shall call the corresponding rows in the triangular factor L singular prediction filters.

For $L = \underline{L}+1$, $\mathcal{T}_{\underline{L}+1,p}(\mathbf{H}_N)$ has m more rows than $\mathcal{T}_{\underline{L},p}(\mathbf{H}_N)$ but only p more columns. Hence the (column) rank increases by p. As a result $\tilde{y}_i(k+\underline{L})$, $i = 1, \ldots, p$ are not zero in general while $\tilde{y}_i(k+\underline{L}) = 0$, $i = p+1, \ldots, m$. Furthermore, since $\mathcal{T}_{\underline{L},p}(\mathbf{H}_N)$ has full column rank, the orthogonalization of $y_{1:p}(k+\underline{L})$ w.r.t. $\mathbf{Y}_{\underline{L},p}(k)$ is the same as the orthogonalization of $y_{1:p}(k+\underline{L})$ w.r.t. $A_{N+p(\underline{L}-1)}(k+\underline{L}-1)$. Hence, since the $\mathbf{a}(k)$ are assumed to be uncorrelated, only the components of $y_{1:p}(k+\underline{L})$ along $\mathbf{a}(k+\underline{L})$ remain: $\tilde{\mathbf{y}}(k+\underline{L})|_{\mathbf{Y}_{\underline{L},p}(k)} = \mathbf{h}(0)\mathbf{a}(k+\underline{L})$ and for the rest of the details of the orthogonalization of the components of $\mathbf{y}(k+\underline{L})$, we can refer to section 6. In particular, $\tilde{y}_{1:p}(k+\underline{L})$ are just a linear transformation of $\mathbf{a}(k+\underline{L})$.

This means that the corresponding (p outputs) prediction filter is (proportional to) a ZF equalizer! Since the prediction error is white, a further increase in the length of the prediction span will not improve the prediction. Hence $\widetilde{\mathbf{y}}(k+L) = \mathbf{h}(0)\mathbf{a}(k+L)$, $L \geq \underline{L}$ and the (block of m) prediction filters in the corresponding block row $L+1$ will be appropriately shifted versions of the (block) prediction filter in (block) row $\underline{L}+1$. In particular also for the prediction errors that are zero, a further increase of the length of the prediction span cannot possibly improve the prediction. Hence $\widetilde{y}_i(k+L) = 0$, $i = p+1, \ldots, m$, $L \geq \underline{L}$. The singular prediction filters further down in the triangular factor L are appropriately shifted versions of the first $m-p$ singular prediction filters. Furthermore, the entries in these first $m-p$ singular prediction filters that appear under the 1's ("diagonal" elements) are zero for reasons we explained before in the general orthogonalization context. So we get a (rank p) white prediction error with a finite prediction order. Hence the channel ouput process $\mathbf{y}(k)$ is *autoregressive*. Due to the structure of the remaining rows in L being shifted versions of the first ZF equalizer and the first $m-p$ singular prediction filters, after a finite "transient", L becomes a banded lower triangular block Toeplitz matrix.

Consider now $L > \underline{L}$ and let us collect all consecutive singular prediction filters in the triangular factor L into a $((m-p)(L-\underline{L})+\underline{m}) \times (mL)$ matrix $\mathcal{G}_L$. The row space of $\mathcal{G}_L$ is the (transpose of) the noise subspace. Indeed, every singular prediction filter belongs to the noise subspace since $\mathcal{G}_L \mathcal{T}_{L,p}(\mathbf{H}_N) = 0$, all rows in $\mathcal{G}_L$ are linearly independent since they are a subset of the rows of a unit-diagonal triangular matrix, and the number of rows in $\mathcal{G}_L$ equals the noise subspace dimension. $\mathcal{G}_L$ is a banded block Toeplitz matrix of which the first $m-p-\underline{m}$ rows have been omitted. $\mathcal{G}_L$ is in fact parameterized by the first $m-p$ singular prediction filters. Let us collect the nontrivial entries in these $m-1$ singular prediction filters into a column vector G_N. So we can write $\mathcal{G}_L(G_N)$. The length of G_N can be calculated to be $Nm - p^2$ which equals the number of degrees of freedom in $\mathbf{H}_N$ for identification with a subspace technique (in which case we can only identify $\mathbf{h}(k)T = \mathbf{h}'(k)$ where T is such that $\mathbf{h}'(0) = [I_p \;\; *]^H$). So $\mathcal{G}_L(G_N)$ represents a minimal linear parameterization of the noise subspace.

Channel Identification

From the discussion above, it is now not difficult to see that in the LDU factorization of $\mathrm{R}^{\mathbf{y}}$, the lower triangular factor $(JU)^H$ is banded and becomes block Toeplitz after a finite transient. Indeed, for $L \geq \underline{L}$, the $L+1^{\text{st}}$ block column of $(JU)^H$ is $\mathrm{E}\, \mathbf{y}(k:\infty)\widetilde{y}_{1:p}^H(k+L) =$

$$\left[0_{mL\times p}^H \; \mathbf{h}^H(0) \cdots \mathbf{h}^H(N_1-1) \; 0 \cdots\right]^H \; \mathrm{E}\mathbf{a}(k+L)\widetilde{y}_{1:p}^H(k+L) \tag{21}$$

which hence contains the channel impulse response, apart from a multiplicative factor.

Channel Estimation from Data using Deterministic ML

See [3] for channel estimation from an estimated covariance sequence by subspace fitting for $p = 1$. That approach can straightforwardly be extended to the case of general p. The details for deterministic maximum likelihood have been worked out in [9] for $p = 1$. Basically, we use $P^{\perp}_{\mathcal{T}_{M,p}(\mathbf{H}_N)} = P_{\mathcal{G}_M^H(G_N)}$. The essential number of degrees of freedom in $\mathbf{H}_N$ and G_N is $mN-p^2$ for both. So $\mathbf{H}_N$ can be uniquely determined from G_N and vice versa. Due to the (almost) block Toeplitz character of $\mathcal{G}_M$, the product $\mathcal{G}_M \mathbf{Y}_M(k)$ represents a convolution. Due to the commutativity of convolution, we can write $\mathcal{G}_M(G_N)\mathbf{Y}_M(k) = \mathcal{Y}_N(\mathbf{Y}_M(k))[1 \;\; G_N^H]^H$ for some properly structured $\mathcal{Y}_N(\mathbf{Y}_M(k))$. This leads us to formulate the DML problem as

$$\min_{G_N} \begin{bmatrix} 1 \\ G_N \end{bmatrix}^H \mathcal{Y}_N^H(\mathbf{Y}_M(k)) \left(\mathcal{G}_M^H(G_N)\mathcal{G}_M(G_N)\right)^{-1} \mathcal{Y}_N(\mathbf{Y}_M(k)) \begin{bmatrix} 1 \\ G_N \end{bmatrix} \tag{22}$$

which can be solved iteratively in the IQML fashion.

References

[1] L. Tong, G. Xu, and T. Kailath. "A New Approach to Blind Identification and Equalization of Multipath Channels". In *Proc. of the 25th Asilomar Conference on Signals, Systems & Computers*, pages 856–860, Pacific Grove, CA, Nov. 1991.

[2] D.T.M. Slock. "Blind Fractionally-Spaced Equalization, Perfect-Reconstruction Filter Banks and Multichannel Linear Prediction". In *Proc. ICASSP 94 Conf.*, Adelaide, Australia, April 1994.

[3] D.T.M. Slock and C.B. Papadias. "Blind Fractionally-Spaced Equalization Based on Cyclostationarity". In *Proc. Vehicular Technology Conf.*, Stockholm, Sweden, June 1994.

[4] T. Kailath. *Linear Systems*. Prentice-Hall, NJ, 1980.

[5] Ph. Loubaton. "Egalisation autodidacte multicapteurs et systèmes multivariables". GDR 134 (Signal Processing) working document, february 1994, France.

[6] B. Laheld and J.-F. Cardoso. "Adaptive Source Separation with Uniform Performance". In *Proc. EUSIPCO-94, SIGNAL PROCESSING VII: Theories and Applications*, pages 183–186, Edinburgh, Scotland, Sept. 13-16 1994.

[7] S. Talwar, M. Viberg, and A. Paulraj. "Blind Estimation of Multiple Co-Channel Digital Signals Using an Antenna Array". *IEEE Signal Processing Letters*, SPL-1(2):29–31, Feb. 1994.

[8] P. Van Dooren. "Regularization of Low-Rank Toeplitz and Quasi-Toeplitz Matrices". In *Proc. 3rd International Workshop on SVD and Signal Processing*, Leuven, Belgium, Aug. 22-25 1994.

[9] D.T.M. Slock. "Subspace Techniques in Blind Mobile Radio Channel Identification and Equalization using Fractional Spacing and/or Multiple Antennas". In *Proc. 3rd International Workshop on SVD and Signal Processing*, Leuven, Belgium, Aug. 22-25 1994.