ROBUST SUBSPACE TRACKING BASED BLIND CHANNEL IDENTIFICATION IN IMPULSIVE NOISE ENVIRONMENT

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ABSTRACT

Subspace-based robust blind channel identification algorithm[1] using sign covariance matrix has recently been proposed to mitigate the adverse effect of impulsive noise. Since batch eigen-decomposition, which is computationally very expensive, needs to be implemented to estimate subspace of the sign covariance matrix for channel vector estimation, a subspace-tracking-based channel identification scheme is naturally more preferable to reduce complexity. Unfortunately, conventional RLS-based subspace tracking algorithms[4], which has much lower computational complexity though, are widely known to be sensitive to impulse noise in nature. In order to overcome this dilemma, we herein propose a robust channel identification scheme based on robust statistics subspace tracking algorithm. This scheme is shown to be able to further improves the robustness of channel identification in impulsive ambient noise in comparison with it's sign covariance matrix based counterpart, while it's computational complexity is substantially lower than that of latter. Moreover, even if the estimation of sign covariance matrix can be carried out recursively in a symbol-by-symbol fashion and then adapt to the variance of channel coefficients, our simulation results show that the robust approach we propose in this paper has comparable tracking capability in term of tracking speed, but smaller steady state error resulting from it's higher robustness, for both sudden change and slow time-varying channel with impulsive noise.

1. INTRODUCTION

Blind channel identification using second order statistics has received considerable attention recently because of its potential application in communications and other signal processing problems. An effective approach is the subspace-based blind identification method [2,3], where oversampling is used to convert the single-input and single-output (SISO) linear time-invariant channel to an equivalent Single-Input Multi-Output (SIMO) model for identification. The signal and noise subspaces of the covariance matrix of the channel outputs can then be used to determine the channel coefficients, under mild condition. The signal and noise subspaces are usually computed from the eigen-decomposition of the covariance matrix. Most recently, the problem of robust channel identification in non-Gaussian noise with impulsive characteristic was studied, due to their practical importance in communications. The adverse effect of the impulse noise is suppressed by replacing the covariance matrix with a sign covariance matrix. Simulation results showed that the sign covariance matrix based channel identification scheme is more robust than the conventional covariance matrix approach. Both methods, however, involve batch eigen-decomposition of the covariance or sign covariance matrices of received sample vectors, which is known to be very computationally expensive. It is natural to consider using fast subspace tracking algorithms for tracking the signal or noise subspaces, if lower computational complexity is desired. The PAST and PASTd algorithm [4] are two such algorithms employing a recursive least squares (RLS)-liked algorithm. Although the PAST and PASTd algorithm have an arithmetic complexity of order O(*Nr*), where *N* is the dimension of the matrix and *r* is the number of signal eigenvectors to be tracked, they are extremely vulnerable to impulse noise. Simulation results in [12] showed that the estimation errors of the RLS-based PAST and PASTd algorithms increase significantly when the ambient noise is corrupted by additive impulse noise. Hence, blind channel identification employing these and similar *RLS*-based subspace tracking algorithms are very likely to suffer from the same problem. This motivates us to consider in this paper subspace tracking based blind channel identification algorithms that require substantially lower computational complexity than the sign covariance matrix method, while sharing it's immunity to impulse noise. In particular, a new correlation matrix, based on robust statistics [13], is proposed to suppress the adverse effect of the impulse noise. The robust PAST algorithm that we have previously proposed in [12] is then employed for tracking the signal subspace. This robust PAST algorithm is similar to the robust statistic based adaptive filters in [5,7-11,13], where those impulse-corrupted data vectors are detected using robust *M*-estimator and are prevented from corrupting the subspace estimate. Simulation results show that the proposed robust subspace channel identification method can more effectively mitigate the adverse effect of the impulse. And, its tracking ability and response to sudden change of channel coefficients are comparable to that of the sign covariance matrix based method, if recursive updating of sign covariance matrix and batch eigen-decomposition are employed in the latter.

The layout of the paper is as follows: Section 2 is a brief description of the blind channel identification problem. Section 3 introduces the subspace-based channel identification method and the PAST subspace tracking algorithm [4]. The proposed robust subspace tracking algorithm and its corresponding channel identification scheme are introduced in Section 4. Simulation results and comparison with the covariance approach are presented in Section 5. The conclusions are drawn in Section 6.

2. SIGNAL MODEL

Consider a base-band channel identification problem where the information symbols $s(n)$ are emitted by the digital source at time nT, where T is the duration of symbol. Let $h(t)$ be the overall impulse response of the channel due to pulse shaping, channel response, modulation and demodulation. The received continuous baseband signal is given by

$$x(t) = \sum_{m=-\infty}^{\infty} s(m)h(t-mT) + v(t)\,, \tag{1}$$

where $v(t)$ is an additive noise, which is assumed to be Gaussian distributed and is independent from the symbols transmitted. Eqn. (1) can be converted to an equivalent SIMO model by oversampling the signal received, by a factor of *P* say. Let $\underline{x}(n)$ be a (*P*x1) column vector with its elements those samples taken at the n-th interval of period *T*. We have

$$\underline{x}(n) = \sum_{k=0}^{L} \underline{h}(k)s(n-k) + \underline{v}(n)\,, \tag{2}$$

where $\underline{x}(n) = [x(nT), x(nT-(T/P)),..., x(nT-(T(P-1)/P))]^T$; $\underline{h}(k)$, L, and $\underline{v}(n)$ are, respectively, the channel impulse response, the channel order, and the additive white Gaussian noise vector (AWGN) with power spectral density σ^2. Stacking $N+1$ successive samples of the received signal into one column vector, i.e., $\underline{X}(n) = [\underline{x}^T(n), \underline{x}^T(n-1),..., \underline{x}^T(n-N)]^T$, we obtain,

$$\underline{X}(n) = \boldsymbol{H}_N \cdot \underline{S}(n) + \underline{V}(n)\,, \tag{3}$$

where $\underline{S}(n) = [s(n), s(n-1),..., s(n-N-L)]^T$,

$\underline{V}(n) = [\underline{v}^T(n), \underline{v}^T(n-1),..., \underline{v}^T(n-N)]^T$,

and $\boldsymbol{H}_N$ is the channel convolution matrix given by

$$\boldsymbol{H}_N = \begin{bmatrix} \underline{h}(0) & \underline{h}(1) & ... & \underline{h}(L) & 0 & ... & 0 \\ 0 & \underline{h}(0) & \underline{h}(1) & ... & \underline{h}(L) & ... & 0 \\ ... & ... & ... & ... & ... & ... & ... \\ 0 & ... & 0 & \underline{h}(0) & \underline{h}(1) & ... & \underline{h}(L) \end{bmatrix}.$$

3. SIGNAL SUBSPACE BASED CHANNEL IDENTIFICATION

Subspace-based blind channel identification was first introduced in [3] by exploiting the structure of the filtering matrix $\boldsymbol{H}_N$. It is based on the covariance matrix $\boldsymbol{R}_X$ of the received sample vector $\boldsymbol{X}(n)$ which is given by

$$\boldsymbol{R}_X = E[\underline{X}(n)\cdot\underline{X}^H(n)] = \boldsymbol{H}_N\cdot\boldsymbol{R}_S\cdot\boldsymbol{H}_N^H + \boldsymbol{R}_V, \tag{4}$$

where $E[\bullet]$ denote the mathematical expectation, $\boldsymbol{R}_S = E[\underline{S}(n)\cdot\underline{S}^H(n)]$, $\boldsymbol{R}_V = E[\underline{V}(n)\cdot\underline{V}^H(n)]$ are, respectively, the covariance matrix of transmitted symbol vector $\underline{S}(n)$ and noise vector $\underline{V}(n)$. We assume the transmitted symbol vectors are i.i.d. for successive symbol intervals, and the noise covariance matrix is given by $\boldsymbol{R}_V = \sigma^2\cdot\boldsymbol{I}$. To ensure channel identifiably, the sub-channels resulting from the SIMO model are assumed to have no common zeros. We also assume that we have prior knowledge about the maximum channel order L. It can be seen that the signal and noise subspaces can be separated by performing an eigen-decomposition of the matrix $\boldsymbol{R}_X$. Let λ_i and $\underline{u}_i$ be the eigenvalue and its eigenvector of $\boldsymbol{R}_X$. If the eigenvalues are arranged in descending order of their magnitudes such that $\lambda_1 \ge \ldots \ge \lambda_K \ge \lambda_{K+1} = \ldots = \lambda_n = \sigma^2$, then the corresponding column span of eigenvectors: $\boldsymbol{U}_s = [\underline{u}_1,\ldots,\underline{u}_K]$ and $\boldsymbol{U}_n = [\underline{u}_{K+1},\ldots,\underline{u}_M]$ constitute, respectively, the signal subspace and noise subspace, and we have

$$\boldsymbol{R}_X = \boldsymbol{U}\Sigma\boldsymbol{U}^H = [\boldsymbol{U}_s \quad \boldsymbol{U}_n]\cdot\begin{bmatrix}\Lambda_s & \\ & \Lambda_n\end{bmatrix}\cdot\begin{bmatrix}\boldsymbol{U}_s^T \\ \boldsymbol{U}_n^T\end{bmatrix}, \tag{5}$$

where $\boldsymbol{U} = [\underline{u}_1,\ldots,\underline{u}_M]$, $\Sigma = diag(\lambda_1,\ldots,\lambda_M)$, $\Lambda_s = diag(\lambda_1,\ldots,\lambda_K)$, and $\Lambda_n = diag(\lambda_{K+1},\ldots,\lambda_M)$, $K = L+N+1$ is the dimension of signal subspace, and $M = P\cdot(N+1)$ is the dimension of $\boldsymbol{R}_X$. Let's partition the signal subspace eigenvector as

$$\underline{u}_i = [\underline{u}_0^{(i)T}, \underline{u}_1^{(i)T}, \ldots, \underline{u}_N^{(i)T}]^T \tag{6}$$

and define the following matrix $\boldsymbol{Q}$

$$\boldsymbol{Q} = \sum_{i=1}^{K}\boldsymbol{q}_i\cdot\boldsymbol{q}_i^H \tag{7}$$

where $\boldsymbol{q}_i$ is the filtering matrix of $\underline{u}_i$ given by

$$\boldsymbol{q}_i = \begin{bmatrix} \underline{u}_0^{(i)} & \underline{u}_1^{(i)} & \cdots & \underline{u}_N^{(i)} & 0 & \cdots & 0 \\ 0 & \underline{u}_0^{(i)} & \underline{u}_1^{(i)} & \cdots & \underline{u}_N^{(i)} & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & \underline{u}_0^{(i)} & \underline{u}_1^{(i)} & \cdots & \underline{u}_N^{(i)} \end{bmatrix}. \tag{8}$$

It was proved in [3] that the channel vector $\underline{h} = [\underline{h}^T(0), \underline{h}^T(1),\ldots,\underline{h}^T(L)]^T$ can be estimated from the eigenvector of $\boldsymbol{Q}$ having the maximum eigenvalue, and the solution is unique except for a scaling by a multiplicative constant.

In order to efficiently estimate the subspace parameters, subspace tracking algorithms such as the PAST and it's deflation version PASTd [4] can be employed. The PAST algorithm [4] is a *RLS-based* algorithm which can be summarized as follows

PAST Algorithm

Initialize $\boldsymbol{P}(0)$ and $\boldsymbol{W}(0)$

FOR $i = 1,2,\ldots$ **DO**

$\underline{y}(i) = \boldsymbol{W}^H(i-1)\underline{X}(i)$, $\underline{h}(i) = \boldsymbol{P}(i-1)\underline{y}(i)$,

$\underline{g}(i) = \underline{h}(i)/[\beta + \underline{y}^H(i)\underline{h}(i)]$,

$\boldsymbol{P}(i) = \frac{1}{\beta}Tri\{\boldsymbol{P}(i-1) - \underline{g}(i)\underline{h}^H(i)\}$,

$\underline{e}(i) = \underline{X}(i) - \boldsymbol{W}(i-1)\underline{y}(i)$,

$\boldsymbol{W}(i) = \boldsymbol{W}(i-1) + \underline{e}(i)\underline{g}^H(i)$.

The superscript ^{H} denotes Hermitian transpose and the operator $Tri\{\cdot\}$ indicates that only the upper (or lower) triangular part of the matrix argument is calculated and its Hermitian transposed version is copied to the lower (or upper) triangular part. For each input vector $\underline{X}(i)$, the algorithm computes a new estimate of the signal subspace $\boldsymbol{W}(i)$ ($\hat{\boldsymbol{U}}_s$) from the previous estimate $\boldsymbol{W}(i-1)$. β is the forgetting factor. As mentioned earlier, the performance of this algorithm, like the *RLS* algorithm, is extremely sensitive to the impulse noise. Suppose that $n(i)$ is modeled as a contaminated Gaussian noise given by $\underline{n}(i) = \underline{n}_g(i) + b(i)\cdot\underline{n}_i(i)$, where $\underline{n}_g(i)$ and $\underline{n}_i(i)$ are uncorrelated zero mean white Gaussian processes with covariance matrices $\sigma\boldsymbol{I}_M$ and $\sigma_i\boldsymbol{I}_M$, respectively. $\underline{n}_i(i)$ represents the impulsive component with $\sigma_i >> \sigma$. $b(i)\in\{0,1\}$ is a random binary sequence independent of $\underline{n}_i(i)$, which indicates the presence (absence) of an impulse at time i if $b(i) = 1$ (0). It can be shown that the correlation matrix $\boldsymbol{R}_X$ in (4) becomes $\boldsymbol{R}_X = E[\underline{X}\cdot\underline{X}^H] = \boldsymbol{H}_N\cdot\boldsymbol{R}_S\cdot\boldsymbol{H}_N^H + \sigma^2\boldsymbol{I}_M + E[b^2(i)]\sigma_i^2\boldsymbol{I}_M$. Any subspace tracking or eigen-decomposition methods for estimating the subspaces from $\boldsymbol{R}_X = E[\underline{X}\cdot\underline{X}^H]$ will be significantly affected by the impulsive component $E[b^2(i)]\sigma_i^2\boldsymbol{I}_M$. Here, we define the robust correlation matrix $\boldsymbol{R}_X^\rho = E[\rho_X\cdot\underline{X}\cdot\underline{X}^H]$, where ρ_X is a weight function which should ideally be zero when an impulse is detected in vector $\underline{X}$ and 1 otherwise. Under this assumption, $\boldsymbol{R}_X^\rho \approx \boldsymbol{H}_N\cdot\boldsymbol{R}_S\cdot\boldsymbol{H}_N^H + \sigma^2\boldsymbol{I}_M$, which stabilizes the subspace estimation. The definition of $\boldsymbol{R}_X^\rho$ can be justified more formally using maximum likelihood estimation. The details are omitted here due to page limitation. We shall show in next section that the weight function ρ_X can be derived from the error in the PAST algorithm so that a more robust algorithm against impulse noise can be developed [12].

4. ROBUST SUBSPACE TRACKING AND CHANNEL IDENTIFICATION ALGORITHMS

We see in section 3 that the conventional correlation matrix and hence the PAST algorithm is extremely sensitive to impulse noise in the data vector $\underline{X}(i)$. In the PAST algorithm, the measure $J(\boldsymbol{W}) = E\|\underline{X} - \boldsymbol{W}\boldsymbol{W}^H\underline{X}\|^2 = E\|\underline{e}\|^2$ is minimized using the *RLS* algorithm. It can be seen from the PAST algorithm given in the previous section that $\underline{y}(i)$, $\underline{h}(i)$, $\underline{g}(i)$, $\boldsymbol{P}(i)$, $\underline{e}(i)$, and $\boldsymbol{W}(i)$ will be affected in turn by an impulse in $\underline{X}(i)$. The corrupted matrices, $\boldsymbol{P}(i)$ and $\boldsymbol{W}(i)$, will be used to compute the new $\boldsymbol{P}(i)$'s and $\boldsymbol{W}(i)$'s, causing hostile effects on the subspace estimate and requires many iterations to recover, especially when β is close to one. We now consider the proposed robust PAST algorithm using robust statistic. First of all, we note that the purpose of ρ_X in the robust correlation matrix estimate $\boldsymbol{R}_X^\rho$ is to de-emphasis the impulse-corrupted observation $\underline{X}(i)$. A similar approach can be applied to the PAST algorithm by defining a robust distortion measure $J_\rho(\boldsymbol{W}) = E\|\rho(\|\underline{e}\|_F - \mu_e)\cdot\underline{e}\|^2$, where $\rho(\cdot)$ is the weight function of an M-estimator [13]. For the Huber *M*-estimate that will be used in this paper, $\rho(e)$ =1 when $|e| < T$ and 0 otherwise, where T is a threshold to be estimated continuously. μ_e is the robust location or mean estimator of $\|\underline{e}\|_F$. It can be seen that if $\underline{X}(i)$ is corrupted by impulses, the Frobenius norm of the error vector $\underline{e}(i)$, $\|\underline{e}(i)\|_F$, will become very large. $\rho(\|\underline{e}\|_F - \mu_e)$ will become zero and the impulse-corrupted measurement is prevented from entering into the minimization. A similar approach has been successively applied to develop robust adaptive filters under impulse noise [5,7-11]. We now consider the estimation of the threshold T and the robust mean estimator μ_e (for simplicity, the subscript *e* in μ_e will be dropped in the subsequent discussion). Though the exact distribution of $\|\underline{e}(i)\|_F$ is unknown, for simplicity, it is assumed to be Gaussian distributed but corrupted by additive impulse noise (note also that $\|\underline{e}(i)\|_F$ is always positive). Specifically, the probability that $|\Delta e_\mu(i)| = \left|\|\underline{e}(i)\|_F - \hat{\mu}(i)\right|$ is greater than a given threshold $T(i)$ is

$$p_T = P_r\{|\Delta e_\mu(i)| > T(i)\} = erfc\left(T(i)/\hat{\sigma}(i)\right), \qquad (9)$$

where $erfc(r) = (2/\sqrt{\pi})\int_r^\infty e^{-x^2}dx$ is the complementary error function. $\hat{\mu}(i)$ and $\hat{\sigma}(i)$ are the estimated mean and standard deviation of the Frobenius norm of the "impulse free" error vector. Using different threshold parameters *T(i)*, we can detect the presence of the impulse noise with different degrees of confidence. In this work, p_T is chosen to be 0.05 so that we have 95% confidence in saying that the current error vector is corrupted by impulse noise. The corresponding threshold parameter $T(i)$ is determined to be $T(i) = 1.96 \cdot \hat{\sigma}(i)$. A commonly used estimate for $\hat{\sigma}^2(i)$ and $\hat{\mu}(i)$ are respectively: $\hat{\sigma}^2(i) = \lambda_\sigma \hat{\sigma}^2(i-1) + (1-\lambda_\sigma)(\Delta e_\mu(i))^2$ and $\hat{\mu}(i) = \lambda_\mu \hat{\mu}(i-1) + (1-\lambda_\mu)\|\underline{e}(i)\|_F$, where λ_μ and λ_σ are some forgetting factors. It is, however, not robust to impulse noise. In fact, a single impulse with large amplitude can substantially increase the value of $\hat{\sigma}(i)$ and $\hat{\mu}(i)$, and hence the values of $T(i)$. Better estimates for $\hat{\sigma}^2(i)$ and $\hat{\mu}(i)$ are [6]

$$\hat{\sigma}^2(i) = \lambda_\sigma \hat{\sigma}^2(i-1) + 1.483\left(1 + \frac{5}{N_w - 1}\right)(1-\lambda_\sigma)\,\mathrm{med}\left(A((\Delta e_\mu(i))^2)\right) \qquad (10a)$$

and
$$\hat{\mu}(i) = \lambda_\mu \hat{\mu}(i-1) + (1-\lambda_\mu)\,\mathrm{med}\left(A(\|e(i)\|_F)\right), \qquad (10b)$$

where $A(x(i)) = \{x(i), \cdots, x(i - N_w + 1)\}$, N_w is the length of the estimation window, and med(.) is the median operation. λ_μ and λ_σ are the forgetting factors. In practice N_w varies from 5 to 11 so that the operations required by the median operations are quite reasonable. For large values of N_w, the pseudo median instead of the median can be computed to reduce the arithmetic complexity. Therefore, the arithmetic complexity of the proposed robust PAST algorithm is comparable to that of the conventional PAST algorithm.

Robust PAST Algorithm

Initialize $\boldsymbol{P}(0)$, $\boldsymbol{W}(0)$, $\hat{\sigma}^2(0)$, and $\hat{\mu}(0)$

FOR $i = 1,2,....$ **DO**

$\underline{y}(i) = \boldsymbol{W}^H(i-1)\underline{X}(i)$, $\underline{h}(i) = \boldsymbol{P}(i-1)\underline{y}(i)$,

$\underline{g}(i) = \underline{h}(i)/[\beta + \underline{y}^H(i)\underline{h}(i)]$,

$\boldsymbol{P}(i) = \frac{1}{\beta}Tri\{\boldsymbol{P}(i-1) - \underline{g}(i)\underline{h}^H(i)\}$,

$\underline{e}(i) = \underline{X}(i) - \boldsymbol{W}(i-1)\underline{y}(i)$,

$$\boldsymbol{P}(i) = (1 - \rho(|\Delta e_\mu(i)|))\boldsymbol{P}(i-1) + \rho(|\Delta e_\mu(i)|)\frac{1}{\beta}Tri\{\boldsymbol{P}(i-1) - \underline{g}(i)\underline{h}^H(i)\},$$

$\boldsymbol{W}(i) = \boldsymbol{W}(i-1) + \rho(|\Delta e_\mu(i)|)\underline{e}(i)\underline{g}^H(i)$,

update $\hat{\sigma}^2(i)$ and $\hat{\mu}(i)$ using (11),

$T(i) = 1.96 \cdot \hat{\sigma}(i)$,

END

Our robust PAST algorithm updates $T(i) = 1.96 \cdot \hat{\sigma}(i)$, $\hat{\sigma}^2(i)$ and $\hat{\mu}(i)$ at each iteration. If $|\Delta e_\mu(i)| > T(i)$, both signal subspace $\boldsymbol{W}(i)$ and the intermediate matrix $\boldsymbol{P}(i)$ will not be updated, preventing the impulse from affecting the subspace estimate. Using the weight function: $\rho(|\Delta e_\mu(i)|) = 1$ when $|\Delta e_\mu(i)| < T(i)$, and 0 otherwise, the above robust PAST algorithm that minimizes $J_\rho(\boldsymbol{W})$ is obtained.

5. SIMULATION RESULTS

The performance of proposed robust channel identification algorithm is investigated under the ε-contamination noise model, and compared with channel identification methods based on covariance matrix and sign covariance matrix. The probability density function (pdf) of the ε-contamination noise model is defined as

$$f = (1-\varepsilon)N(0,\sigma^2) + \varepsilon N(0,\sigma_I{}^2), \qquad (11)$$

where $0 \le \varepsilon \le 1$, $N(0,\sigma^2)$ is the pdf of the Gaussian background noise, $N(0,\sigma_I{}^2)$ is the pdf of the impulse noise. In our simulation, the impulse noise occurrence probability ε is set to 0.1, and with $10 \cdot \log_{10}\frac{\sigma_I{}^2}{\sigma^2} = 30dB$. The transmitted symbols are equally distributed random $4-QAM$ signal, which are independent between sample durations. The noise is uncorrelated with the transmitted symbols and is i.i.d. for different symbols. To facilitate the performance comparison between the proposed algorithm and the conventional covariance and sign covariance matrix based algorithms [1], the same channel setting as in [1] is employed in the following simulation: the number of virtual channel is $P = 4$, the length of temporal window is $N = 10$, the order of channel ISI is $L = 4$. The channel coefficients are:

$$\underline{h}_0^T = [(-0.049+0.359j),(0.443-0.0364j), (-0.221-0.322j),(0.417+0.030j)]$$

$$\underline{h}_1^T = [(0.482-0.569j),(1),\ (-0.199+0.918j),(1)]$$

$$\underline{h}_2^T = [(-0.556+0.587j),(0.921-0.194j),\ (1),(0.873+0.145j)]$$

$$\underline{h}_3^T = [(1),(0.189-0.208j),\ (-0.284-0.524j),(0.285+0.309j)]$$

$$\underline{h}_4^T = [(-0.171+0.061j),(-0.087-0.054j), (0.136-0.19j),(-0.049+0.161j)]$$

The power of the Gaussian background noise is 20dB lower than that of the signal of interest. The median filter length N_w is set to be 9, and the forgetting factors λ_μ, λ_σ, and β are all set equal to 0.97. The initial value $\boldsymbol{P}(0)$, $\boldsymbol{W}(0)$ are chosen to be identity matrices or their leading submatrices. Both $\hat{\sigma}^2(0)$ and $\hat{\mu}(0)$ are set to 10, a relatively large number to their normal value, to initialize system adaptation. The canonical angle between the estimated channel vector $\hat{\underline{h}}$ and it's true value $\underline{h}$ is adopted as performance measure, which is defined as $\sphericalangle(\underline{h},\hat{\underline{h}}) \equiv a\cos\left(abs\left[\frac{\hat{\underline{h}}^H\underline{h}}{\|\hat{\underline{h}}\|\cdot\|\underline{h}\|}\right]\right)$, where $\|\bullet\|$ denotes the Euclidean norm. The MSE of the estimated channel is defined as $MSE = \frac{1}{N_m}\sum_{i=1}^{N_m}\sphericalangle(\underline{h},\hat{\underline{h}}_i)^2$ where N_m is the number of Monte-Carlo trials, and $\hat{\underline{h}}_i$ is the estimated channel vector of the i th trial. The performance of the proposed algorithm and its covariance matrix based counterpart are compared in Figures 1 to 3. In Fig.1, the individual and consecutive impulse noise intrudes the system from the 200th symbol. It can be clearly observed in Fig.1 that the covariance matrix based method is significantly affected by the impulsive noise, while the sign covariance matrix based method is also affected, but to a smaller extent. Whereas, the robust subspace tracking based scheme remain largely unaffected, suggesting that it is much more robust to the presence of impulsive noise than the former two algorithms. In Fig.2, the individual and consecutive impulse noise intrudes the system from the 100th symbol, and the channel coefficients are suddenly changed at the 200th symbol duration when the channel vector $\underline{h}$ changes from

$\underline{h}=[\underline{h}_0^T,\underline{h}_1^T,\underline{h}_2^T,\underline{h}_3^T,\underline{h}_4^T]^T$ to $\underline{h}^{'}=[\underline{h}_1^T,\underline{h}_0^T,\underline{h}_2^T,\underline{h}_3^T,\underline{h}_4^T]^T$. It is evident from Fig.2 that, from the 100^{th} to 200^{th} symbol, the proposed algorithm manifest its much higher robustness than the other two algorithms after impulse noise intrude the channel; from 200^{th} to 400^{th} symbol, the propose algorithm is shown to have a comparable adaptation speed to sudden channel change in impulse noise environment when compared with the other two algorithms; and furthermore from 400^{th} to 600^{th} symbol, it is shown to have smaller steady state error than both the covariance and sign covariance matrix based method after they re-converge again, which suggesting it's robustness and adaptation capability to sudden channel change in impulse noise environment. For slowly time-varying channel in Fig.3, the channel vector is set to be rotating in its vector space at a fixed but low angle velocity from the 100^{th} symbol, and impulse noise intrude the channel from the 300^{th} symbol. Fig. 3 clearly demonstrates that the tracking capability of the proposed scheme in slowly time-varying channel is also comparable to that of the other two algorithms from the 100^{th} to 300^{th} symbol, but more robust than the other two algorithms when tracking channel coefficients in impulse noise environment after the 300^{th} symbol. The data presented in Figs. 1 to 3 are generated by averaging over 100 independent Monte-Carlo trials.

6. CONCLUSION

A new robust channel identification scheme based on robust PAST algorithm is presented in this paper. A systematic method, using the robust statistic concept, is used to detect the impulse in the input data vector and prevent them from corrupting the signal subspace for further tracking. Simulation results using the blind subspace-based channel identification show that the proposed scheme, using the robust subspace tracking algorithm, performs more robustly than the conventional covariance matrix and sign covariance matrix approaches in impulse noise environment, while it's computational complexity is much lower than that of the latter two. The adaptation capability of the proposed scheme in sudden changed channel and slow time-varying channel with impulse noise is also found to be comparable to that of covariance matrix based approaches, while it is shown to have smaller steady state error, which suggesting higher robustness, than it's covariance matrix based counterparts when tracking and adapting in impulsive noise environment.

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Curve A: Covariance Matrix Based Approach
Curve B: Sign Covariance Matrix Based Approach
Curve C: Robust Subspace Tracking Based Approach

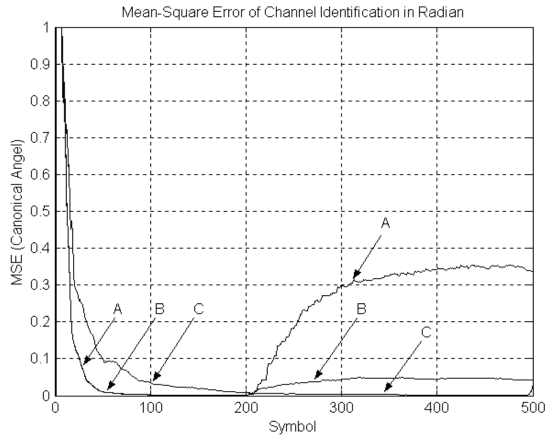

Fig. 1. MSE of Channel Identification in impulse noise

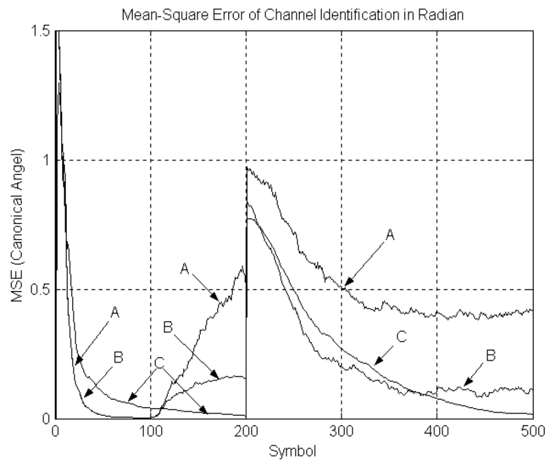

Fig. 2. MSE of Channel Identification in sudden change channel

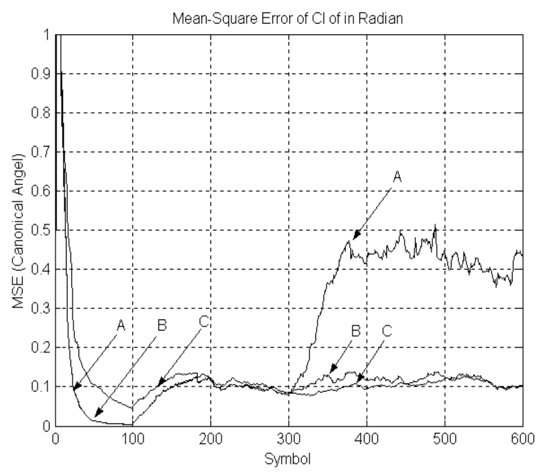

Fig. 3. MSE of Channel Identification in slow time-varying channel