Abstract :

Many algorithms are proposed for Sparse System Identification. In this project the NNC-NLMAT (Non-Uniform Constraint) introduced in [1] will be implemented with an addition of set-membership and proportionate probabilities for weights in the filter as proposed in the PNLMS algorithm [2],will be implemented
The NNC-NLMAT, NNC-PNLMAT, SM-NNC-PNLMAT will be compared.

Inputs :-

Sparse System h = a random sparse vector .
X - input to the filter being estimated :

X = A + v

A is the noise
v is the input proper

A and v are assumed to be uncorrelated (can be expanded to correlated too.)

A - impulsive noise + white gaussian noise

V = 1)Gaussian rp 2)Rayleigh rp 3)

Outputs : W(the weights of filte),MSD,EMSE

Number of Iterations - 3000;

Algorithm :NNC-NLMAT , NNC-PNLMAT,SM-NNC-PNLMAT;

Non-Uniform Constraint :

The integration of p-norm like constraint will unavoidably cause an estimation bias at the same time of achieving sparsity exploitation [7]. While the introduction of p-norm like enables the optimization of norm constraint via the adjustment of p parameter, as (7) indicates, the p parameter affects the estimation bias as well as the intensity of sparsity correction equally, therefore it cannot be directly adopted to seek a tradeoff between them.
To address this problem,split the definition of the classic p-norm like in (3) into a non-uniform p-norm like definition which uses a different value of p for each of the L entries in w(n),as :

||w(n)|| pp,L =
L

$i=1p$
$|w_i(n)|_i, 0 \le p_i \le 1$

Set-Membership Constraint :

The model space in which includes input–output vector pairs is defined as Θ. A upper bound of estimated error is γ. The criterion of set-membership is to seek the optimization subject to

$| e (n)|^2 \le \gamma^2 .$
(8)

When $\hat{w}(n)$ does not belong to Θ, the problem of solving optimization of the SM-PNLMS can be described as

$\min \| \hat{w}(n) - \hat{w}(n-1) \|_2^2$ s.t. $d(n) - x^T(n)\hat{w}(n) = \gamma.$
(9)

The updating equation of the SM-PNLMS is

$\hat{w}(n) = \hat{w}(n-1) +$
where
(
$\mu_{SM} =$
$1 -$
$\mu_{SM}\, x(n)\, Q(n-1)\, e(n)$
,
T
$x(n)\, Q(n-1)\, x(n) + \varepsilon_{SM}$
γ
, if $| e(n)|$
$| e(n)|$
$> \gamma$
0, otherwise
.
(10)
(11)

Herein, the matrix $Q(n-1)$ is the same as Equation (4). The role of ε_{SM} in Equation (10) is the same as that of ε in Equation (3).

Proportionality :

The updating equation of the PNLMS algorithm can be described as

$\mu x(n) Q(n-1) e(n)$
$\hat{w}(n) = \hat{w}(n-1) + T$
,
(3)
$x(n) Q(n-1) x(n) + \varepsilon$
where μ is an overall step size, and ε is a small regularization parameter. $Q(n-1)$ is the step size
assignment matrix, which is diagonal and can be described as
$Q(n-1) = \text{diag}\{q_0(n-1), q_1(n-1), \ldots, q_{N-1}(n-1)\}$.
(4)
The elements in $Q(n-1)$ are calculated by
$q_j(n-1) =$
$\alpha_j(n-1)$
,0
$N-1$
$\sum \alpha_i(n-1)$
$i=0$
$\leq j \leq N-1,$

where
$\alpha_j(n-1) = \max\{\rho \max\{\delta, |\hat{w}_0(n-1)|, |\hat{w}_1(n-1)|, \cdots, |\hat{w}_{N-1}(n-1)|\}, \hat{w}_j(n-1)$
.
(6)

Herein, ρ is a positive constant of which range is usually $N\ 1 \sim N\ 5$, and its purpose is to avoid $\hat{w}_j(n-1)$ stalling in the case of it being much smaller than the largest element. δ is a regularization
parameter, and it is used to avoid the updating stopping when all of the taps are zeros at beginning

Objectives :

1.Understand NLMAT algorithm and why it works better than NNC-LMS for non-Gaussian Inputs.

2.Understand NNC,SM and P constraints and how they help to exploit sparsity and their effect on NLMAT algorithm.

3. Suggest explanaions for observed results
Expected Results :

Algorithm that integrates all three constraints I expect to give better results but I am not sure. But all of them should perform at least as good as the NNC_NLMAT descibed in [1].

References:

[1]Robust Sparse Normalized LMAT Algorithms for Adaptive
System Identification Under Impulsive Noise Environments
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[2]An Improved Set-Membership Proportionate
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[3]Non-Uniform Norm Constraint LMS Algorithm for
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F. Y. Wu, Student Member, IEEE, and F. Tong, Member, IEEE