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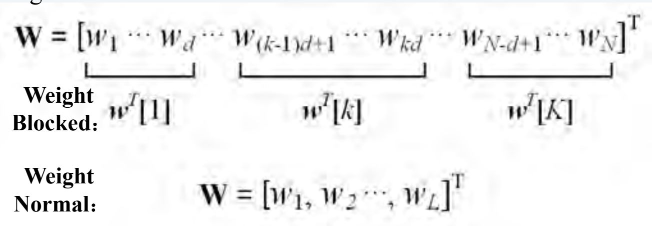
# Generalized Correntropy Induced Metric Based Block Sparse Memory Improved Proportionate Affine Projection Sign Algorithm

ShengWei Xie[1], Ji Zhao[1], Qiang Li[1], Hongbin Zhang[2]

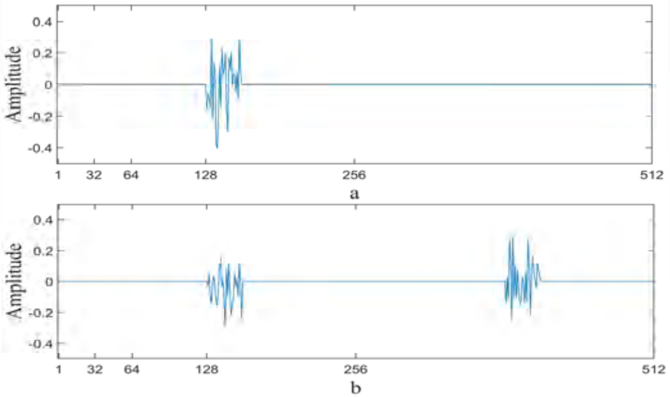
[1]School of Information Engineering, Southwest University of Science and Technology [2]School of Information and Communication, University of Electronic Science and Technology of China, Chengdu, 611731, China

## Abstract

In this paper, by combining the block sparse memory improved proportionate affine projection sign algorithm (BS-MIP-APSA) and the generalized correntropy induced metric(GCIM), we have proposed two block sparse adaptive filteringalgorithms, named as GCIM-BS-MIP-APSA-I and GCIM-BS-MIP-APSA-II, by directly using GCIM to measure the sparse information and treating GCIM as a function of block weight vector, respectively, for identification of sparse systems. Based on the good characteristic of GCIM approximating the $l_0$-norm,the proposed algorithms, especially GCIM-BS-MIP-APSA-II, can achieve improved filtering accuracy and faster convergence rate when the identified system is block sparse. We also have analyzed the system computational complexity of proposed algorithms. Some simulation results are conducted to demonstrate the efficiency of GCIM-BS-MIP-APSAs compared with other competing algorithm.




## Block-sparse systems:




## The Proposed Algorithm

**Initialization:**

parameters: $\boldsymbol{w}(0)=\mathbf{0}$, $\varepsilon>0$ $\varepsilon_2>0$, $\mu>0$, $a\in\{0.5,0\}$, $B>0$, $K>0$, $\lambda>0$, $\alpha>0$

**Computation:**

**while** $\{\boldsymbol{x}(i),\, d(i)\}$ $(i\geq 1)$ available **do**

1) $\boldsymbol{y}(i)=\boldsymbol{X}(i)^T\boldsymbol{w}(i-1)$

2) $\boldsymbol{e}(i)=\boldsymbol{d}(i)-\boldsymbol{y}(i)$

3) for $j\in\{0,1,\cdots,N-1\}$ do

4) GCIM-BS-MIP-APSA-I:

$$g_j(i-1)=\frac{1-a}{2L}+\frac{(1+a)\|\boldsymbol{w}_j(i-1)\|_0}{2B\sum_{k=0}^{N-1}\|\boldsymbol{w}_k(i-1)\|_0+\varepsilon_2}$$

or

GCIM-BS-MIP-APSA-II:

$$g_j(i)=\frac{1-a}{2L}+\frac{(1+a)f(\boldsymbol{w}_j(i-1))}{2B\sum_{k=0}^{N-1}f(\boldsymbol{w}_k(i-1))+\varepsilon_2}$$

5) end for

6) $\boldsymbol{g}(i)=\left[g_0(i)\mathbf{1}_B^T, g_1(i)\mathbf{1}_B^T,\cdots,g_{N-1}(i)\mathbf{1}_B^T\right]^T$

7) $\boldsymbol{P}(i)=[\boldsymbol{g}(i)\odot\boldsymbol{x}(i),\boldsymbol{P}_{-1}(i-1)]$

8) $\mathrm{sgn}(\boldsymbol{e}(i))=[\mathrm{sgn}(e(i)),\mathrm{sgn}(e(i-1)),\cdots,\mathrm{sgn}(e(i-K+1))]^T$

9) $\boldsymbol{x}_{ps}(i)=\boldsymbol{P}(i)\mathrm{sgn}(\boldsymbol{e}(i))$

10) $\boldsymbol{w}(i)=\boldsymbol{w}(i-1)+\mu\frac{\boldsymbol{x}_{gs}(i)}{\sqrt{\boldsymbol{x}_{gs}^T(i)\boldsymbol{x}_{gs}(i)+\varepsilon}}$

**end while**

**GCIM-BS-MIP-APSA-I**

$$\|\boldsymbol{w}\|_0\sim GCIM(\boldsymbol{w},0)=\frac{\gamma}{N}\left(1-\sum_{k=1}^{N}\exp(-\lambda|w_k|^\alpha)\right)$$

$$g_j(i-1)=\frac{1-a}{2L}+\frac{(1+a)\,\|w_j(i-1)\|_0}{2B\sum_{k=0}^{N-1}\|w_k(i-1)\|_0+\varepsilon_1}$$

$$\boldsymbol{w}(i)=\boldsymbol{w}(i-1)+\mu\frac{\boldsymbol{P}(i)\,\mathrm{sgn}(\boldsymbol{e}(i))}{\sqrt{\boldsymbol{P}(i)\,\mathrm{sgn}(\boldsymbol{e}(i))^T\,\boldsymbol{P}(i)\,\mathrm{sgn}(\boldsymbol{e}(i))+\varepsilon}}$$

**Apply GCIM-I To MIP-APSA: key equations**

**GCIM-BS-MIP-APSA-II**

$$f(\boldsymbol{w}_k(i-1))=1-\exp(-\lambda\|\boldsymbol{w}_k(i-1)\|_p^\alpha)$$

$$g_j(i-1)=\frac{1-a}{2L}+\frac{(1+a)f(\boldsymbol{w}_k(i-1))}{2B\sum_{k=0}^{N-1}|f(\boldsymbol{w}_k(i-1))+\varepsilon_2}$$

$$\boldsymbol{w}(i)=\boldsymbol{w}(i-1)+\mu\frac{\boldsymbol{P}(i)\mathrm{sgn}(\boldsymbol{e}(i))}{\sqrt{\boldsymbol{P}(i)\mathrm{sgn}(\boldsymbol{e}(i))^T\boldsymbol{P}(i)\mathrm{sgn}(\boldsymbol{e}(i))+\varepsilon}}$$

**Apply GCIM-II To MIP-APSA: key equations**

## Simulation Results

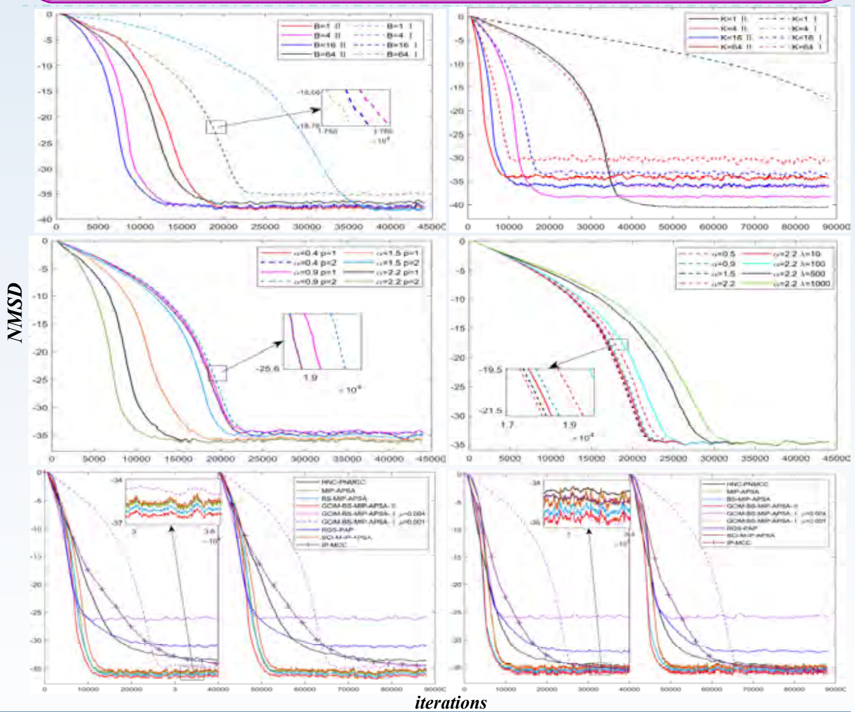
**Object:** System Identification

**Model:** $\boldsymbol{d}(i)=\boldsymbol{X}(i)^T\boldsymbol{w}(i)+\boldsymbol{v}(i)$

**Parameters: Gau-noise with** 0 **mean and SNR =** 40 **dB BG-noise with** P[b(i)=1]=0.1 **and SINR =** 0 **dB**

**Gau- kernel size** $\alpha=2.2$ **Reg- factor** $\lambda=1000$ **Block size** $B=16$

$\boldsymbol{u}(i)=[x(i),x(i-1),\ldots,x(i-511)]^T$ $\boldsymbol{w}=[w_1,w_2,\ldots,w_{512}]^T$




## Conclusion

In this paper, based on the generalized correntropy induced metric, we have proposed two different block saprse memory improved proportionate APSA algorithms for block-sparse system identification. Some simulations are conducted to test the filtering performances of proposed algorithms. From these results, we can conduct that directly using GCIM to replace the $l_2$-norm of block weight vector cannot enhance the filtering accuracy and convergence rate of BS-MIP-APSA. Furthermore, treating CGIM as a function of the $l_p$-norm of block weight vector leads to the improved BS-MIP-APSA, namely, GCIM-BS-MIP-APSA-II, which achieves smaller steady-state misadjustment and faster convergence rate.