A Joint Perspective of Periodically Excited Efficient **NLMS Algorithm and Inverse Cyclic Convolution**



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Introduction: System Identification



Example: Fast measurements of HRTFs \rightarrow Different approaches exist

For static acoustic measurements: Inverse Cyclic Convolution (ICC) with Exponential Sweeps

For dynamic tracking of systems: *Normalized Least* Mean Square (NLMS)-type algorithms with socalled *Periodic Perfect Sequences* (PPSEQ)

Equivalence of ICC and NLMS for PPSEQ input [1], based on efficient NLMS implementation [2]





[2]

 $(0)_{0}$

[1]

 $p_i, i = 0, ..., N - 1$ exist.

Energy: $E_p = \mathbf{p}_0^{\mathrm{T}} \mathbf{p}_0$

with $\mathbf{p}_{n \mod N} = \mathbf{p}(n) = \mathbf{\breve{\Gamma}}(n)\mathbf{p}_0$

System Model

- System to be identified: $\mathbf{h}(n) = (h_0(n) \ h_1(n) \cdots h_{N-1}(n))^T$
- Excitation vector: $\mathbf{x}(n) = \left(x(n) \ x(n-1) \cdots x(n-N+1)\right)^{\mathsf{T}}$
- measurement noise $\rightarrow v(n)$ adaptation

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• Output of system: $d(n) = \mathbf{h}^{\mathrm{T}}(n) \cdot \mathbf{x}(n)$

correspondingly: $\hat{\mathbf{h}}(n)$, $\mathbf{d}(n)$, $\hat{\mathbf{d}}(n)$, $\mathbf{y}(n)$

Notation & Auxiliary Operators

 $\stackrel{\frown}{\times}$ Discrete Fourier Transform via DFT matrix \mathbf{F}

This work is a generalization of [1] showing the equivalence also for *arbitrary* periodic input signals for the NLMS implementation in [3]

Efficient NLMS Algorithm (eNLMS)[3] 3

Novel description of [3] see i $\mathbf{\hat{h}}_{eNLMS}(n) = \mathbf{F}^{-1} \operatorname{diag} \{ \mathbf{F} \mathbf{w}_0 \} \mathbf{F} \mathbf{\hat{c}}(n)$ Use NLMS algorithm for transformed coefficients:

- unit vector $\mathbf{e}_i = |1|_i$ $\mathbf{\hat{c}}(n+1) = \mathbf{\hat{c}}(n) + \mu \left(y(n) - \mathbf{\hat{c}}^{\mathrm{T}}(n) \cdot \mathbf{e}_{n \bmod N} \right) \mathbf{e}_{n \bmod N}^{\prime}$ step-size parameter μ



mati DFT: $\mathbf{X}(n) = \mathbf{F} \cdot \mathbf{x}(n)$ DFT IDFT: $\mathbf{x}(n) = \mathbf{F}^{-1} \cdot \mathbf{X}(n)$

$$= \begin{pmatrix} \omega^{0\cdot 0} & \omega^{0\cdot 1} & \cdots & \omega^{0\cdot (N-1)} \\ \omega^{1\cdot 0} & \omega^{1\cdot 1} & \cdots & \omega^{1\cdot (N-1)} \\ \vdots & \vdots & \ddots & \vdots \\ \omega^{(N-1)\cdot 0} & \omega^{(N-1)\cdot 1} & \cdots & \omega^{(N-1)\cdot (N-1)} \end{pmatrix}$$

with $\omega = \mathrm{e}^{-j \frac{2\pi}{N}}$

Permutation matrix $\Gamma(n)$ reorders elements of vector, beginning with *n*-th element going cyclically backwards through vector Example: N = 5, n = 2



Description

System

NLMS

- Goal: $\mathbf{w}_i^{\mathrm{T}} \mathbf{x}(n) = \begin{cases} 1 & \text{for } i = n \mod N \\ 0 & \text{otherwise} \end{cases}$
- To obtain basis \mathbf{w}_i :

 $\mathbf{w}_i = \frac{1}{E_p} \mathbf{F}^{-1} \operatorname{diag} \{ \mathbf{Fs} \}^{-1} \mathbf{Fp}_i$ equalization with s 'direction' of \mathbf{p}_i normalization to E_p

- \mathbf{w}_i form non-orthogonal basis of \mathbb{R}^N
- Output of system can be expressed as:

$$d(n) = \sum_{\substack{i=0\\N-1}}^{N-1} h_i(n) \mathbf{e}_i^{\mathrm{T}} \mathbf{x}(n), \quad h_i \text{ coeff. to basis } \mathbf{e}_i$$

$$= \sum_{\substack{i=0\\i=0}}^{N-1} c_i(n) \mathbf{w}_i^{\mathrm{T}} \mathbf{x}(n), \quad c_i \text{ coeff. to basis } \mathbf{w}_i$$

 $\rightarrow \mathbf{x}(n)$ appears as unit impulse excitation in transform domain

Current output sample matches exactly one coefficient: $d(n) = c_{n \mod N}(n)$ respectively $\mathbf{d}(n) = \mathbf{\Gamma}(n)\mathbf{c}(n)$

Inverse Cyclic Convolution (ICC) 4

Deconvolution in frequency domain by element-wise division:

 $\mathbf{\hat{h}}_{ICC}(n) = \mathbf{F}^{-1} [\operatorname{diag} \{ \mathbf{Fx}(n) \}^{-1} \mathbf{Fy}(n)]^* \longrightarrow \text{required to compensate}$ for mirroring of sequences $\mathbf{x}(n)$ and $\mathbf{y}(n)$

Equivalence of eNLMS and ICC 5

By alternative system description in $\ensuremath{\mathsf{3}}$ and $\ensuremath{\mathsf{4}}$, equivalence for $\mu=1$ 1 can be shown:

 $\mathbf{\hat{h}}_{eNLMS}^{\mu=1}(n) \stackrel{!}{=} \mathbf{\hat{h}}_{ICC}(n) \rightarrow \text{see paper}$

For arbitrary step-sizes μ , eNLMS yields: arbitrary

 $\mathbf{\hat{c}}(n+N) = \mathbf{\hat{c}}(n) + \mu(\mathbf{\Gamma}(n+N-1)\mathbf{y}(n+N-1) - \mathbf{\hat{c}}(n))$ $= (1 - \mu) \cdot \hat{\mathbf{c}}(n) + \mu \cdot (\mathbf{\Gamma}(n + N - 1)\mathbf{y}(n + N - 1))$

$$\mathbf{\hat{h}}_{\text{eNLMS}}(n+N) = (1-\mu) \cdot \mathbf{\hat{h}}_{\text{eNLMS}}(n) + \mu \cdot \mathbf{\hat{h}}_{\text{eNLMS}}^{\mu=1}(n+N)$$

•
$$\mathbf{h}(n) = \sum_{i=0}^{N-1} c_i(n) \mathbf{w}_i = \cdots = \mathbf{F}^{-1} \operatorname{diag} \{ \mathbf{F} \mathbf{w}_0 \} \mathbf{F} \mathbf{\Gamma}(n) \mathbf{d}(n)$$

Conclusion

- ICC and eNLMS are mathematical identical
- Bridged gap between ICC for static acoustic measurements and the eNLMS algorithm for dynamic system identification and tracking
- Enables transfer of knowledge from both approaches:
 - from ICC to eNLMS: regularization methods
 - from eNLMS to ICC: dynamic tracking properties and step-size control

As $\mathbf{\hat{h}}_{ ext{eNLMS}}^{\mu=1}(n) = \mathbf{\hat{h}}_{ ext{ICC}}(n)
ightarrow ext{recursive}$ averaging can be applied to ICC

Complexity is identical (see paper for detailed description)

References

[1] C. Antweiler, S. Kühl, B. Sauert, and P. Vary, "System Identification with Perfect Sequence Excitation – Efficient NLMS vs. Inverse Cyclic Convolution", in ITG Fachtagung Speech Communication, Erlangen, Germany, Sept. 2014.

[2] A. Carini, "Efficient NLMS and RLS Algorithms for Perfect Periodic Sequences," in Proc. of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Dallas, TX, USA, Mar. 2010, pp. 3746–3749.

[3] A. Carini, "Efficient NLMS and RLS Algorithms for Perfect and Imperfect Periodic Sequences", IEEE Transactions on Signal Processing, vol. 58, no. 4, pp. 2048-2059, Apr. 2010.

