

# Frequency domain subspace-based identification of discrete-time power spectra from uniformly spaced measurements

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- 3 Identification algorithm
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  - Linear matrix inequalities
  - Non-linear least squares

*A subspace algorithm proposed by Van Overche et al. (1997) to identify state space models from given uniformly spaced power spectrum measurements.*

- When spectrum samples are on a uniform grid of frequencies, the inverse discrete-Fourier transform (IDFT) of the given power spectrum can be expressed in terms of the state-space parameters of the spectral factor.
- A realization theory based on McKelvey *et al.*:1996 is then devised to obtain the system matrices from this IDFT.
- Two methods ensuring positivity of the identified spectrum are proposed.

Consider the  $l \times l$  dimensional square discrete time system:

$$\begin{aligned}x_{k+l} &= Ax_k + Bu_k, \\y_k &= Cx_k + Du_k\end{aligned}\tag{1}$$

with  $A \in \mathbf{R}^{n \times n}$ ,  $B \in \mathbf{R}^{n \times l}$ ,  $C \in \mathbf{R}^{l \times n}$  and  $D \in \mathbf{R}^{l \times l}$  nonsingular. The vector sequences  $u_k, y_k \in \mathbf{R}^l$  are the input and output sequences, respectively.

- (1)–(2) stable and strictly minimum phase: all eigenvalues of  $A$  and  $A - BD^{-1}C$  strictly inside the unit circle.
- $\{A, B\}$  and  $\{A, C\}$  controllable and observable.
- $A$  non-singular.

The system (1)–(2) is thus a minimal stochastic system.

The transfer function of the system:

$$G(z) = D + C(zI_n - A)^{-1}B.$$

The power spectrum associated with (1)–(2):

$$S(z) = G(z)G^T(z^{-1}). \quad (2)$$

The system (1)–(2) is the innovation form, unity variance, minimum phase spectral factor associated with  $S(z)$ .

- (2) satisfies the positive realness condition

$$S(z) > 0, \quad |z| = 1.$$

imposing positivity constraints on the spectrum samples as well as on the identified power spectrum.

- Splitting of the power spectrum (Caines:1988)

$$S(z) = H(z) + H^T(z^{-1})$$

where

$$H(z) = \Lambda_0/2 + C(zI_n - A)^{-1}G,$$

$$\Lambda_0 = CPC^T + DD^T,$$

$$G = APC^T + BD^T,$$

$$P = APA^T + BB^T \text{ (discrete-time Lyapunov equation).}$$

- The IDFT  $v_k$  of a given complex signal  $V_k = V(e^{j2\pi k/2N})$ ,  $k = 0, \dots, 2N - 1$  is defined by

$$v_k = \frac{1}{2N} \sum_{r=0}^{2N-1} V_r e^{j2\pi rk/2N}.$$

The problem treated can now be stated as follows:

*Given*

$N + 1$  matrices  $S_k \in \mathbf{C}^{l \times l}$  of the power spectrum  $S(z)$  evaluated at  $N + 1$  equidistant points over the unit circle:

$$S_k = S(e^{j2\pi k/2N}), \quad k = 0, \dots, N,$$

*Find*

- The system matrices  $A, G, C, \Lambda_0$  describing the power spectrum.
- The system matrices  $A, B, C, D$  describing the spectral factor (1)–(2).

Expand the  $N + 1$  given points  $S_k$  to  $2N$  points as follows:

$$S_{N+k} = S_{N-k}^*, \quad k = 1, \dots, N - 1.$$

From now on,  $S_k$  denotes this signal of length  $2N$ .

**Theorem 1** (Inverse discrete Fourier transform). With  $M = (I_n - A^{2N})^{-1}$ , the IDFT  $s_k \in \mathbf{R}^{l \times l}$  of the given power spectrum  $S_k$  is given by

$$\begin{aligned} s_0 &= \Lambda_0 + CA^{2N}MG + G^T(A^T)^{2N}M^T C^T, \\ s_k &= CA^{k-1}MG + G^T(A^T)^{2N-k-1}M^T C^T, \quad 1 \leq k < 2N. \end{aligned}$$

- The proof of this theorem is based on McKelvey *etal.*:1996.



The extended observability matrix  $\Gamma_q \in \mathbf{R}^{lq \times n}$  and reversed extended observability matrix  $\tilde{\Gamma}_r \in \mathbf{R}^{lr \times n}$  are defined as

$$\Gamma_q = \begin{pmatrix} C \\ \vdots \\ CA^{q-1} \end{pmatrix}, \quad \tilde{\Gamma}_r = \Pi \Gamma_r$$

where  $\Pi \in \mathbf{R}^{lN \times lN}$  is the permutation matrix given by

$$\Pi = \begin{pmatrix} 0 & \cdots & I_l \\ \vdots & \ddots & \vdots \\ I_l & \cdots & 0 \end{pmatrix}$$

The extended controllability matrix  $\Delta_r \in \mathbf{R}^{n \times lr}$  and reversed extended controllability matrix  $\tilde{\Delta}_q \in \mathbf{R}^{n \times lq}$  are defined as

$$\Delta_r = (G \ \cdots \ A^{r-1}), \quad \tilde{\Delta}_q = \Delta_q \Pi.$$

- Since (1)–(2) is minimal, the matrices  $\Gamma_q, \tilde{\Gamma}_r$  and  $\Delta_r, \tilde{\Delta}_q$  are respectively of full column and row rank  $n$ .

Let

$$\mathcal{S} = \begin{pmatrix} \mathbf{s}_1 & \cdots & \mathbf{s}_r \\ \vdots & \ddots & \vdots \\ \mathbf{s}_q & \cdots & \mathbf{s}_{q+r-1} \end{pmatrix}$$

with  $q, r \geq 2n, r + q < 2N$ .

**Theorem 2** The block-Hankel matrix  $\mathcal{S}$  can be decomposed as

$$\mathcal{S} = \begin{pmatrix} \Gamma_q & \tilde{\Delta}_q^T \end{pmatrix} \begin{pmatrix} M & 0 \\ 0 & M^T \end{pmatrix} \begin{pmatrix} \Delta_r \\ \tilde{\Gamma}_r^T \end{pmatrix}$$

which leads to the following results:

- $\text{rank}(\mathcal{S}) = 2n$ .
- The column space of  $\mathcal{S}$  can be expressed in terms of the system matrices as  
 column space  $\mathcal{S} = \text{column space } (\Gamma_q \tilde{\Delta}_q^T)$ .
- The row space of  $\mathcal{S}$  can be expressed in terms of the system matrices as

$$\text{row space } \mathcal{S} = \text{row space } \begin{pmatrix} \Delta_r \\ \tilde{\Gamma}_r^T \end{pmatrix}$$

- $A$  is determined by a procedure similar to in Akçay and Türkay:2004 (SVD followed by eigen decomposition).
- $G$ ,  $C$ , and  $A$  are determined in the same step of Van Overschee *etal.*:1997 whereas  $G$ ,  $C$ , and  $\Delta_0$  are estimated from  $S_k$  by an LS procedure in Akçay and Türkay:2004.
- With  $M = (I_n - A^{2N})^{-1}$ ,

$$\Delta_0 = s_0 - CA^{2N-1}MG - G^T(A^T)^{2N-1}M^T C^T.$$

- $B$  and  $D$  are determined as in Akçay and Türkay:2004.
- Consistency follows from McKelvey *etal.*:1996.

When  $S_k$  are not generated by a finite dimensional linear system or noise corrupted, there is no guarantee that the identified power spectrum, which is determined by  $A$ ,  $G$ ,  $C$ , and  $\Lambda_0$  will be positive real.

- When the identified sequence is not positive real, the Riccati equation has no positive definite solution and the spectral factor cannot be computed.
- Two possible solutions to this problem are presented.
  - Both of these solutions start from given matrices  $A$  and  $C$ . The solutions then state how  $G$  and  $\Lambda_0$  are determined through the solution of an optimization problem which guarantees a positive real identified power spectrum.

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Given  $A$  and  $C$ , a positive real identified spectrum can be guaranteed by solving the following optimization problem:

Given the known transfer matrix

$$L(z) = \left( C(zI_n - A)^{-1} \quad I_l \right),$$

solve

$$\min_{Q,S,R} \sum_{k=0}^{2N-1} \|S_k - L(e^{j2\pi k/2N}) \begin{pmatrix} Q & S \\ S^T & R \end{pmatrix} L(e^{-j2\pi k/2N})\|_F^2$$

constrained to

$$\begin{pmatrix} Q & S \\ S^T & R \end{pmatrix} \geq 0.$$

- The system matrices  $G$  and  $\Lambda_0$  can then be found by solving the set of equations:

$$P = APA^T + Q, \quad (3)$$

$$G = APC^T + S, \quad (4)$$

$$\Lambda_0 = CPC^T + R. \quad (5)$$

- The constraint guarantees that the resulting identified quadruple  $A, G, C, \Lambda_0$  leads to a positive real spectrum.
- This optimization problem can be converted to an LMI.
- The drawback: the LMI software is not suited for large  $N$ .



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Given  $A$  and  $C$ , a positive real identified spectrum can be guaranteed by solving the following NLS optimization:

$$\min_{B,D} \sum_{k=0}^{2N-1} \|S_k - L(e^{j2\pi k/2N}) \begin{pmatrix} B \\ D \end{pmatrix} (B^T \ D^T) L(e^{-j2\pi k/2N})\|_F^2.$$

- To insure a minimum phase model, (3)–(5) can be solved for  $G$  and  $\Lambda_0$ , after which a new  $B$  and  $D$  (guaranteeing a minimum phase model) can be computed through the solution of the Riccati equation.

## Initial guesses of $B$ and $D$

“Perturb  $\Lambda_0$  to  $\tilde{\Lambda}_0$  so that the the power spectrum associated with the resulting quadruple  $\{A, G, C, \tilde{\Lambda}_0\}$  is positive real”

$$\tilde{\Lambda}_0 = \Lambda_0 + \tau I_l, \quad \tau > 0.$$

- Taking  $\tau$  large will trivially ensure positive realness of the power spectrum. However, we would like to keep  $\tau$  as small as possible, which can be posed as an LMI:

$$\begin{aligned} \min \quad & \tau \quad \text{subject to } \tau > 0, \quad P > 0, \\ & \begin{pmatrix} P - APA^T & G - APC^T \\ G^T - CPA^T & \Lambda_0 - CPC^T + \tau I_l \end{pmatrix} > 0. \end{aligned}$$

- A general perturbation model  $\tilde{\Lambda}_0 = \Lambda_0 + \tau$  where the Frobenius norm of  $\tau$  is to be minimized can be introduced.
- The Riccati equation associated with  $\{A, G, C, \tilde{\Lambda}_0\}$  can now be solved. This leads to matrices  $B^0$  and  $D^0$  which can serve as initial guesses for the NLS optimization problem.
- Both methods can be used with data sampled on a non-uniform grid of frequencies.
- The identification algorithm and the methods ensuring positivity of the spectrum are further studied in Hinnen *etal.*:2005.