

## In search for useful extensions of the STLS: problems the method can solve and problems we aim at

Ivan Markovsky

### Promoters

Sabine Van Huffel and Bart De Moor

Brain storming meeting, Leuven, 16 June 2003

## About my PhD

topic: errors-in-variables (EIV) estimation problems

includes: system identification, filtering, TLS, STLS

motivation: consider measurement errors on the available data

equation error and measurement error in the linear model  $Ax = b$

$Ax = b + e$ ,  $e$  equation error,  $b$  is noisy, but  $A$  is exact  
( $A + \tilde{A}$ ) $x = b + \tilde{b}$ ,  $\tilde{A}$ ,  $\tilde{b}$  measurement noises, all the data  $[A \ b]$  is noisy

tools: linear algebra, optimization, systems theory, statistics

collaborations: A. Kukush (Kiev), A. Premoli (Milano), M-L. Rastello (Torino)  
P. Rapisarda (Univ. Maastricht), R. Pintelon (VUB)

current financing: research council scholarship

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1

## Problems and publications

- Linear parametric design
  - “Linear parametric design”, TR#01-39
  - “H2-optimal linear parametric design”, TR#01-40
  - “Multi-model system parameter estimation”, TR#02-40, *SMC 2002*
- Estimation in bilinear EIV model  $AXB \approx C$ 
  - “Consistent estimation in the bilinear multivariate EIV model”, TR#01-72, *Metrika*
  - application in computer vision: fundamental matrix estimation
  - “Consistent fundamental matrix estimation in a quadratic measurement error model arising in motion analysis”, TR#01-64, *CSDA*
- Ellipsoid estimation
  - “Consistent estimation in an implicit quadratic measurement error model”, TR#02-115
  - “Consistent least squares fitting of ellipsoids”, TR#02-116, *Numerische Mathematik*

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2

## Problems and publications (cont.)

- Element-wise weighted total least squares problem
  - “The element-wise weighted total least squares problem”, TR#02-48
- Errors-in-variables Kalman filtering
  - “Continuous-time Errors-in-variables Filtering”, TR#02-41, *CDC 2002*
  - “Linear dynamic filtering with noisy input and output”, TR#02-191, *SYSID 2003*
- Structured total least squares
  - “Consistency of the STLS estimator in a multivariate EIV model”, TR#02-192
  - “On the computation of the structured total least squares estimator”, TR#02-203
- Stability of reduced order models in subspace identification

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3

## Methodologies and algorithms

- adjusted least squares

inspired by consistency consideration

results in **simple and reliable** computational method (just as LS)

requires Gaussian noise model with **known covariance matrix**

**noise variance estimation** is possible but results in iterative methods

**less efficient** than the maximum likelihood method

- maximum likelihood estimation

nice properties but results in **nonconvex optimization problem**

develop efficient **local optimization methods**

- subspace methods

**robust and efficient** computation

**less efficient** than the maximum likelihood method

## The structured total least squares problem

$$\min_{\Delta A, \Delta B, X} \left\| \begin{bmatrix} \Delta A & \Delta B \end{bmatrix} \right\|_F^2 \quad \text{s.t.} \quad (A - \Delta A)X = B - \Delta B$$

(1)

and  $\begin{bmatrix} \Delta A & \Delta B \end{bmatrix}$  has the same structure as  $\begin{bmatrix} A & B \end{bmatrix}$

assume **affine structured** data matrix  $C := \begin{bmatrix} A & B \end{bmatrix}$

$$C = \mathcal{S}(p) := S_0 + \sum_{l=1}^{n_p} S_l p_l$$

then (1) becomes the following optimization problem

$$\min_{X, \Delta p} \left\| V^{-1/2} \Delta p \right\|_2^2 \quad \text{s.t.} \quad \mathcal{S}(p - \Delta p) \begin{bmatrix} X \\ -I_d \end{bmatrix} = 0$$

## Previous work in SISTA on the STLS problem

- B. De Moor, Rimmanian SVD approach

"Structured total least squares and  $L_2$  approximation problems"

gives **many applications**

- Ph.D. thesis P. Lemmerling

overview of computational methods

algorithm for deconvolution, the structure of  $C$  is  $\begin{bmatrix} T & U \end{bmatrix}$

algorithm for speech compression,  $C$  is **Hankel**

- Ph.D. thesis N. Mastronardi

efficient (meaning  $O(m)$ ,  $m$  sample size) computational algorithms

## Errors-in-variables system identification

STLS problem with two blocks structured data matrix  $C = \begin{bmatrix} T & T \end{bmatrix}$

with **noise-free** input or output,  $C$  is  $\begin{bmatrix} T & F \end{bmatrix}$

for **MIMO** systems,  $C$  has **block-Toeplitz/Hankel** blocks

in order to cover these (and other) problems, we consider data matrices

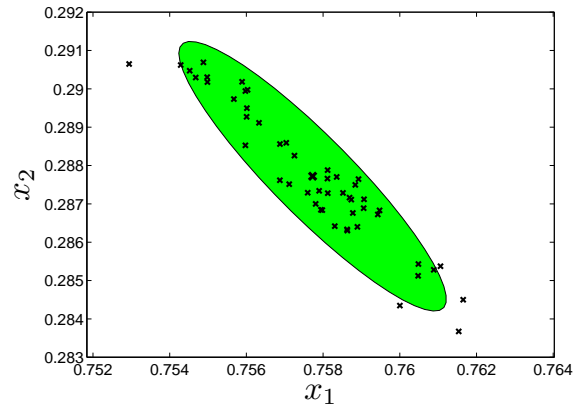
$$C = \mathcal{S}(p) = \begin{bmatrix} C_1 & \cdots & C_q \end{bmatrix}$$

where  $C_i$  is **Toeplitz** (T), **Hankel** (H), **unstructured** (U), or **noise free** (F)

efficient computation is still possible using an alternative approach,  
see TR#02-203

## Other extensions

- **regularized STLS** needed in, e.g., image deblurring
- **computation of confidence ellipsoids**, useful additional information



## Other extensions and application

the following extensions are more difficult:

- treat **known initial conditions** of the time-series model
- allow for **more general** weighting matrix  $V$   
motivation: different input and output noise variances
- design of **optimized algorithms** for particular structures

applications:

- improvement of the **balanced model reduction/subspace estimate**
- **image deblurring**