

Weighted structured total least squares

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Total least squares

Consider an over-determined linear system of equations

$$AX \approx B, \quad \text{where } A \in \mathbb{R}^{m \times n} \text{ and } B \in \mathbb{R}^{m \times d}.$$

How to find an approximate solution? Two popular methods are:

Least squares method: **correct B**

$$\min_{\Delta B, X} \|\Delta B\|_F^2 \quad \text{subject to} \quad AX = B - \Delta B \quad (\text{LS})$$

Total least squares method: **correct both A and B**

$$\min_{\Delta A, \Delta B, X} \|\begin{bmatrix} \Delta A & \Delta B \end{bmatrix}\|_F^2 \quad \text{subject to} \quad (A - \Delta A)X = B - \Delta B \quad (\text{TLS})$$



Outline

- 1 Introduction: total least squares and extensions
- 2 Review of results on the structured TLS problem
- 3 New results on the weighted structured TLS problem
- 4 Conclusions



Weighted total least squares

- the TLS cost function $\|\begin{bmatrix} \Delta A & \Delta B \end{bmatrix}\|_F^2$ measures the correction size
- the Frobenius norm puts equal emphasis on all elements
- define $\|\Delta C\|_W^2 := \text{vec}^T(\Delta C^T) W \text{vec}(\Delta C^T)$, where $W > 0$ is given

Weighted total least squares method

$$\min_{\Delta A, \Delta B, X} \|\begin{bmatrix} \Delta A & \Delta B \end{bmatrix}\|_W^2 \quad \text{subject to} \quad (A - \Delta A)X = B - \Delta B \quad (\text{WTLS})$$



Structured total least squares

- the data matrix $C := \begin{bmatrix} A & B \end{bmatrix}$ was assumed unstructured
- in problems involving dynamic phenomena C is structured
- next we define a **TLS problem with structure constraint**

The structure is specified by an injective function $\mathcal{S} : \mathbb{R}^{n_p} \rightarrow \mathbb{R}^{m \times (n+d)}$.
 C is **\mathcal{S} -structured** if $C \in \text{image}(\mathcal{S})$, i.e., $C = \mathcal{S}(p)$, for some $p \in \mathbb{R}^{n_p}$.

Structured total least squares method

$$\min_{\Delta p, X} \|\Delta p\|^2 \quad \text{subject to} \quad \mathcal{S}(p - \Delta p) \begin{bmatrix} X \\ -I_d \end{bmatrix} = 0 \quad (\text{STLS})$$



Affine structured TLS

Let \mathcal{S} be affine, i.e., $\mathcal{S}(p) = S_0 + \sum_{i=1}^{n_p} S_i p_i$, for some $S_i \in \mathbb{R}^{m \times (n+d)}$.

Then the constraint $\mathcal{S}(p - \Delta p)X_{\text{ext}} = 0$ is **bilinear** in X and Δp .

$$\mathcal{S}(p - \Delta p)X_{\text{ext}} = 0 \iff G(X)\Delta p = r(X),$$

where

$$G(X) := [\text{vec}((S_1 X_{\text{ext}})^T) \quad \dots \quad \text{vec}((S_{n_p} X_{\text{ext}})^T)] \in \mathbb{R}^{md \times n_p},$$

and

$$r(X) := \text{vec}((\mathcal{S}(p)X_{\text{ext}})^T) \in \mathbb{R}^{md}.$$

The affine STLS problem is a **double minimization problem**

$$\min_X \left(\min_{\Delta p} \|\Delta p\|_2^2 \quad \text{subject to} \quad G(X)\Delta p = r(X) \right).$$



The topic of this talk: structured weighted TLS

Structured weighted total least squares method

Given a data matrix $C \in \mathbb{R}^{m \times (n+d)}$, $m > n$, structure specification $\mathcal{S} : \mathbb{R}^{n_p} \rightarrow \mathbb{R}^{m \times (n+d)}$, and weight matrix $W \in \mathbb{R}^{n_p \times n_p}$, $W > 0$, find

$$\hat{X} = \min_{\Delta p, X} \Delta p^T W \Delta p \quad \text{subject to} \quad \mathcal{S}(p) \begin{bmatrix} X \\ -I \end{bmatrix} = 0 \quad (\text{SWTLS})$$

- properties
- solution methods
- software



Equivalent unconstrained problem

The inner minimization has an analytic solution.

Theorem (Equivalent optimization problem for affine STLS)

Assuming that $n_p \geq md$, an affine STLS problem is equivalent to

$$\min_X f(X) \quad \text{where} \quad f(X) := r^T(X) \Gamma^\dagger(X) r(X) \quad \text{and} \quad \Gamma(X) := G(X)G^T(X).$$

- the constraint and the decision variable Δp are eliminated
- nonlinear least squares problem
- use classical optimization methods



Properties

Structure assumption

$\mathcal{S}(p) = [C^1 \ \dots \ C^q]$, where C^l , for $l = 1, \dots, q$, is block-Toeplitz, block-Hankel, unstructured, or exact.

Theorem (Structure of the weight matrix Γ)

If the structure assumption holds, the weight matrix $\Gamma(X)$ is

$$\Gamma(X) = \begin{bmatrix} \Gamma_0 & \Gamma_1^\top & \dots & \Gamma_s^\top & \mathbf{0} \\ \Gamma_1 & \ddots & \ddots & \ddots & \ddots \\ \vdots & \ddots & \ddots & \ddots & \ddots \\ \Gamma_s & \ddots & \ddots & \ddots & \ddots \\ \mathbf{0} & & \Gamma_s & \dots & \Gamma_1 & \Gamma_0 \end{bmatrix} \in \mathbb{R}^{md \times md}.$$

Equivalent unconstrained problem for (SWTLS)

The affine structured weighted TLS problem

$$\min_{\Delta p, X} \Delta p^\top W \Delta p \quad \text{subject to} \quad \mathcal{S}(p) \begin{bmatrix} X \\ -I \end{bmatrix} = 0 \quad (\text{SWTLS})$$

again can be solved partially by eliminating Δp .

Theorem (Equivalent optimization problem for weighted STLS)

The affine weighted STLS problem (SWTLS) is equivalent to

$$\min_X f_w(X) \quad \text{where} \quad f_w(X) := r^\top(X) \Gamma_w^\dagger(X) r(X) \\ \text{and} \quad \Gamma_w(X) := G(X) W^{-1} G^\top(X).$$

Efficient cost function and first derivative evaluation

From X to $f(X)$ and $f'(X)$

- cost function evaluation:

$$f(X) = r^\top(X) y(X), \quad \text{where} \quad \Gamma(X) y(X) = r(X)$$

the structure of Γ is exploited in solving for $y \rightsquigarrow O(m)$ flops

- $f'(X)$ can also be evaluated from $y(X)$ in $O(m)$ flops

From \mathcal{S} to Γ

$$\Gamma_k(X) = (I_K \otimes X_{\text{ext}}^\top) S_k (I_K \otimes X_{\text{ext}})^\top, \quad k = 0, 1, \dots, s,$$

where the matrices $S_k \in \mathbb{R}^{K(n+d) \times K(n+d)}$ depend on the structure \mathcal{S}

Properties of the weight matrix Γ_w

In general neither the block-Toeplitz nor the block-banded properties of $\Gamma = GG^\top$ are present in $\Gamma_w = GW^{-1}G^\top$.

Assumption: block-diagonal weight matrix W

Let the blocks C^l be parameterized by $p_l \in \mathbb{R}^{n_{p,l}}$, and let $p = \text{col}(p_1, \dots, p_q)$. In addition, W is assumed to be block-diagonal

$$W = \text{diag}(W^1, \dots, W^q), \quad \text{where} \quad W^l \in \mathbb{R}^{n_{p,l} \times n_{p,l}}.$$

The assumption forbids cross-weighting among the parameters of the blocks C^1, \dots, C^q .

Main result

Define $V := W^{-1}$ and $V^l := (W^l)^{-1}$.

Lemma

Under the structure and weight matrix assumptions, if all blocks V^l are Toeplitz, then $\Gamma_w = GVG^\top$ is Toeplitz.

Lemma

Under the structure and weight matrix assumptions, if W is banded with bandwidth p , then $\Gamma_w = GVG^\top$ is banded with bandwidth $s + p$, where s is the bandwidth in the unstructured case.



Conclusions

- main question: properties of Γ in the equivalent problem
- unstructured problems: Γ block-Toeplitz and banded
- structured problems with W block-diagonal: Γ banded
- this implies $O(m)$ computational complexity of the algorithm
- software is available at
<http://www.esat.kuleuven.be/~imarkovs>



Implication of the main result

Under the structure and weight matrix assumptions, if W is banded the cost function and first derivative can still be evaluated in $O(m)$ flops.

Therefore this type of problems can still be solved efficiently.

The only difference with the unweighted case is that now

$$\Gamma_{ij}(X) = (I_K \otimes X_{\text{ext}}^\top) S_{ij} (I_K \otimes X_{\text{ext}}^\top)^\top,$$

where

$$S_{ij} := \begin{cases} \text{diag}(V_i^1, \dots, V_i^q) S_{i-j} & \text{if } 0 \leq i-j \leq s \\ S_{ji}^\top & \text{if } -s \leq i-j < 0 \\ 0 & \text{otherwise} \end{cases}$$

