

# Iteratively Reweighted Flexible Krylov methods for Sparse Reconstruction

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We are interested in the solution of

$$Ax + e = b, \quad A \in \mathbb{R}^{M \times N}, \quad b \in \mathbb{R}^M, \quad e \in \mathbb{R}^M$$

coming from suitable discretization of

$$\int_{\Omega} k(s, t) f(t) dt + \varepsilon(s) = g(s).$$

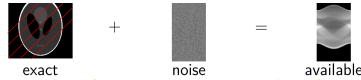
Modeling inverse problems:

- the process  $k$  (resp.  $A$ ), the output  $g$  (resp.  $b$ ) are known;
- the input  $f$  (resp.  $x$ ) is unknown.

Image deblurring and denoising.



Tomography reconstruction and denoising.



## Iterative Regularization: Krylov Subspace Methods

[Saad, Iterative Methods for Sparse Linear Systems, SIAM, 2003]

Common framework for Krylov Subspace methods for

$$\arg \min_{x \in \mathbb{R}^N} \|Ax - b\|_2.$$

At step  $k$ :

- Expand the solution (Krylov) subspace:
 
$$\mathcal{R}(V_k) = \mathcal{K}_k(C, d) = \text{span}\{d, Cd, \dots, C^{k-1}d\},$$
 by updating a partial decomposition of  $A$  of the form:
 
$$AV_k = U_{k+1}H_k, \quad \text{with } H_k \in \mathbb{R}^{(k+1) \times k}.$$
- Consider the approximation  $x_k = V_k y_k$ .
- Solve the projected LS:
 
$$y_k = \arg \min_{y \in \mathbb{R}^k} \|b - AV_k y\|_2 = \arg \min_{y \in \mathbb{R}^k} \|d_k - H_k y\|_2$$

## Sparsity enforcing $\ell_p$ regularisation term

[P. Rodriguez and B. Wohlberg. An efficient algorithm for sparse reconstructions with  $\ell^p$  data term. In Proc. of the 4th IEEE Annapolis Technical Conf. (ANDESCON), 2008.]

For  $\lambda, p > 0$

$$\arg \min_{x \in \mathbb{R}^N} \|Ax - b\|_2^2 + \lambda \|x\|_p^p = \arg \min_{x \in \mathbb{R}^N} \|Ax - b\|_2^2 + \lambda \|W^{(p)}(x) x\|_2^2$$

$$W^{(p)}(x) = \text{diag}(\{|x_i|^{p-2}\}_{i=1, \dots, N})$$

Approximate by a sequence:

$$x_k = \arg \min_{x \in \mathbb{R}^N} \|Ax - b\|_2^2 + \lambda \|W_k x\|_2^2 + c_k, \quad W_k = W^{(p)}(x_{k-1})$$

or, equivalently,

$$\tilde{x}_k = \arg \min_{x \in \mathbb{R}^N} \|AW_k^{-1}x - b\|_2^2 + \lambda \|x\|_2^2, \quad \text{so } x_k = W_k^{-1}\tilde{x}_k.$$

## Iterative Regularization: FGMRES and FLSQR

[Saad. A flexible prec. GMRES. SISC, 1993.]

[Chung, Gazzola. Flexible Krylov Methods for  $\ell_p$  regularization. SIAM J. Sci. Comput., 2019.]

At step  $k$ :

- Expand a search (Flexible Krylov) subspace:
 
$$\mathcal{R}(Z_k) = \text{span}\{W_k^{-1}v_1, W_k^{-1}v_2, W_k^{-1}v_3, \dots\}$$
 expanding the decomposition

$$AZ_k = V_{k+1}H_k, \quad \text{with } H_k \in \mathbb{R}^{(k+1) \times k}$$

- Consider the approximation  $x_k = Z_k y_k$ .
- Solve the projected LS:

$$y_k = \arg \min_{y \in \mathbb{R}^k} \|b - AZ_k y\|_2 = \arg \min_{y \in \mathbb{R}^k} \|d_k - H_k y\|_2$$

$$\min_{x \in \mathbb{R}^N} \|Ax - b\|_2^2$$

$$\min_{x \in \mathbb{R}^N} \|Ax - b\|_2^2 + \lambda \|W_k x\|_2^2$$

$$\min_{y \in \mathbb{R}^k} \|AZ_k y - b\|_2^2 + \lambda \|W_k Z_k y\|_2^2$$

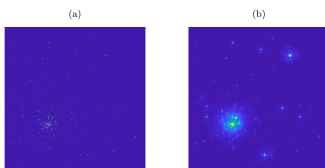


Fig. 1: Setting for the star\_cluster test problem. (a) True image  $x_{\text{true}}$ . (b) Noisy measurement  $b$ .

Define

$$T^{(p)}(x) = \|Ax - b\|_2^2 + \lambda \|W^{(p)}(x) x\|_2^2$$

**Lemma** The sequence  $(T^{(p)}(x_k))_{k \geq 0}$  for  $0 < p \leq 2$ , where  $x_k$  is the approximated solution computed after  $k$  steps of the IRW-FGMRES or the IRW-FLSQR methods, is decreasing monotonically and it is bounded from below by zero.

**Theorem** The sequence  $(x_k)_{k \geq 1}$ , where  $x_k$  is the approximated solution computed after  $k$  steps of IRW-FGMRES or IRW-FLSQR with  $p > 0$ , is such that

$$\lim_{k \rightarrow \infty} \|x_k - x_{k-1}\|_2 = 0.$$

Moreover, it converges to a stationary point of  $T^{(p)}$  and, if  $p \geq 1$ , this is the unique minimizer of  $T^{(p)}$ .

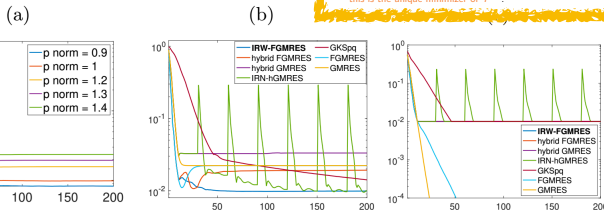


Fig. 2: star\_cluster test problem tested with the discrepancy principle. (a) history of the relative error norms (i.e., relative error norm against iteration number) for the new IRW-FGMRES and different  $p$  norms. (b) history of the relative error norms for the new IRW-FGMRES and other Krylov-based solvers. (c) history of the relative residual norms (i.e., relative residual norm against iteration number) for the new IRW-FGMRES and other Krylov-based solvers

