# Methods for inverse problems: V. Kaczmarz and Expectation Maximization methods

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#### overview

- 1 Problem setting: System of nonlinear operator equations
- 2 Gradient type Kaczmarz methods
- Newton type Kaczmarz methods
  - Levenberg-Marquardt type Kaczmarz methods
  - IRGNM type Kaczmarz methods
- 4 EM algorithms

# System of nonlinear operator equations

Instead of  $\mathbf{F}(x) = \mathbf{y}$  consider systems of operator equations

$$F_0(x) = y_0$$
  
 $F_1(x) = y_1$   
 $F_2(x) = y_2$   
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Example: EIT

$$\begin{cases} \nabla \cdot (\sigma \nabla u_i) = 0 & \text{in } \Omega \\ \nu \cdot (\sigma \nabla u_i) = j_i, & u_i = v_i & \text{on } \partial \Omega \end{cases} \qquad i = 0, \dots, N-1$$

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$$F_i(x) = y_i, \quad i = 0, \dots, N-1,$$

noisy data

$$||y_i^{\delta}-y_i||\leq \delta\,,\quad i=0,\ldots,N-1\,,$$

e.g. x... coefficient in a PDE,  $\mathbf{F}(x) = (F_0(x), \dots, F_{N-1}(x))$ ... discr. Dirichlet-to Neumann map Kaczmarz methods (algebraic reconstruction technique): cyclic iteration over subproblems [Kaczmarz'93], [Natterer'97]

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+ perform iterations for several smaller subproblems  $F_i(x) = y_i$  instead of one large problem  $\mathbf{F}(x) = \mathbf{y}$ 

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Gradient type Kaczmarz methods

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#### Discrepancy principle:

stop the iteration as soon as  $\|\mathbf{F}(x_k^\delta) - \mathbf{y}^\delta\| \leq au\delta \leadsto k_* \sim \delta^{-1}$ 

Nonlinearity condition:

$$\|\mathbf{F}(\tilde{x}) - \mathbf{F}(x) - \mathbf{F}'(x)(\tilde{x} - x)\| \le \eta \|\mathbf{F}(\tilde{x}) - \mathbf{F}(x)\|$$

Convergence Results:

$$x_{k+1}^\delta = x_k^\delta - \mathbf{F}'(x_k^\delta)^*(\mathbf{F}(x_k^\delta) - \mathbf{y}^\delta)$$

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• monotonicity of the error and <sup>2</sup> summability of the residuals:  $||x_{k+1}^{\delta} - x^*||^2 < ||x_k^{\delta} - x^*||^2 - c||\mathbf{F}(x_k^{\delta}) - \mathbf{v}^{\delta}||^2$ 

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#### Landweber Kaczmarz iteration

$$x_{k+1}^{\delta} = x_k^{\delta} - F'_{[k]}(x_k^{\delta})^* (F_{[k]}(x_k^{\delta}) - y_{[k]}^{\delta})$$

 $[k] = k \mod N$ 

Discrepancy principle:

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Nonlinearity condition:

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$$\begin{aligned} x_{k+1}^{\delta} &= x_k^{\delta} - \omega_k F_{[k]}'(x_k^{\delta})^* (F_{[k]}(x_k^{\delta}) - y_{[k]}^{\delta}) \\ \omega_k &:= \begin{cases} 1 & \text{if } \|F_{[k]}(x_k^{\delta}) - y_{[k]}^{\delta}\| \ge \tau \delta \\ 0 & \text{otherwise} \end{cases}. \end{aligned}$$

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Choice of 
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: (inexact Newton)  $\rho \in (0,1)$   $\|\mathbf{F}'(x_k^{\delta})(x_{k+1}^{\delta}(\alpha) - x_k^{\delta}) + \mathbf{F}(x_k^{\delta}) - y^{\delta}\| = \rho \|\mathbf{F}(x_k^{\delta}) - y^{\delta}\|$ 

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#### Convergence Results

- monotonicity of the error and <sup>2</sup> summability of the residuals
- convergence with exact/noisy data [Hanke'96], [Rieder'99]
- convergence rates [Hanke'09] (optimal)

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## Levenberg-Marquardt Kaczmarz iteration

$$x_{k+1}^{\delta} = x_k^{\delta} + (F'_{[k]}(x_k^{\delta})^* F'_{[k]}(x_k^{\delta}) + \alpha_k I)^{-1} F'_{[k]}(x_k^{\delta})^* (y_{[k]}^{\delta} - F_{[k]}(x_k^{\delta}))$$

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- convergence with exact data and  $\alpha_k \equiv \alpha$  [Burger BK'04], [Baumeister BK Leitão'09]

## Example 1

#### Reconstruction from Dirichlet-Neumann Map:

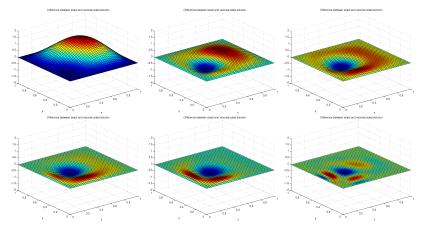
Estimate space-dependent coefficient  $q \geq 0$ 

$$-\Delta u + qu = 0, \quad \text{in } \Omega,$$
  
$$u = f \quad \text{on } \partial \Omega,$$

from *N* Dirirchlet-Neumann pairs  $(f_i, \frac{\partial u_i}{\partial \nu}|_{\partial \Omega})$ .

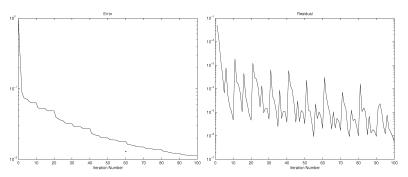
$$\Omega = (0,1)^2$$
 $f_i \approx \delta(\cdot - x^i)$ ,  $x^i$  uniformly spaced on  $\partial\Omega$ 
 $N = 20$ 
 $q^* = 3 + 5\sin(\pi x)\sin(\pi y)$ 
 $q_0 \equiv 3$ 

# Results with Levenberg-Marquardt-Kaczmarz



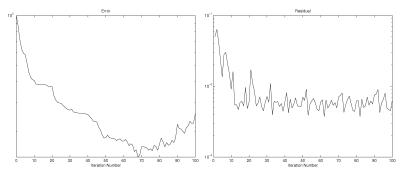
Difference  $q^* - q_k$  at iterates 1, 2, 3, 5, 10, and 100.

# Convergence with exact data



Semi-logarithmic plot of error (left) and residual (right) vs. iteration number

# Semiconvergence with noisy data



Semi-logarithmic plot of error (left) and residual (right) vs. iteration number,  $\delta=1\%$ 

$$\begin{split} x_{k+1}^{\delta} \; &= \; x_k^{\delta} + \omega_k (F_{[k]}'(x_k^{\delta})^* F_{[k]}'(x_k^{\delta}) + \alpha I)^{-1} F_{[k]}'(x_k^{\delta})^* (y_{[k]}^{\delta} - F_{[k]}(x_k^{\delta})) \\ \omega_k \; &:= \; \begin{cases} 1 & \text{if } \|F_{[k]}(x_k^{\delta}) - y_{[k]}^{\delta}\| \geq \tau \delta \\ 0 & \text{otherwise} \end{cases} \,. \end{split}$$

stop the iteration as soon as 
$$\|F_i(x_k^\delta) - y_i^\delta\| \le \tau \delta \ \forall i$$
 i.e.,  $k_*^\delta := \min\{jN \in \mathbb{N} : x_{jN}^\delta = x_{jN+1}^\delta = \cdots = x_{jN+N}^\delta\}$ 

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stop the iteration as soon as 
$$||F_i(x_k^{\delta}) - y_i^{\delta}|| \le \tau \delta \quad \forall i$$
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$$||F_i(\tilde{x}) - F_i(x) - F_i'(x)(\tilde{x} - x)|| \le \eta ||F_i(\tilde{x}) - F_i(x)|| \quad \forall i$$

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- monotonicity of the error and <sup>2</sup> summability of the residuals
- convergence with exact/noisy data
   [Baumeister BK Leitão'09]

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## Inverse doping problem for semiconductor devices

(drift-diffusion equations, equilibrium at vanishing applied potential U) Reconstruct  $\gamma=e^{V_0}$  ( $V_0...$  potential) in

from *N* Dirirchlet-Neumann pairs  $(U_i, \Lambda(U_i))$  where

$$\Lambda(U) = \int_{\Gamma_1} (\mu_n \gamma \hat{u}_{\nu} - \mu_p \gamma^{-1} \hat{v}_{\nu}) ds$$

 $\hat{u}$ ,  $\hat{v}$  ....concentrations of electrons and holes, U ... applied potential,  $\mu_n$ ,  $\mu_p$  ... (known) electron and hole mobilities.

The doping profile C can then be determined from  $C(x) = \gamma(x) - \gamma^{-1}(x) - \lambda^2 \Delta(\ln \gamma(x)), x \in \Omega$ .

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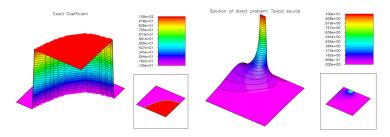
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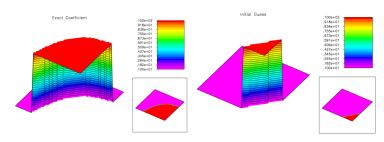
## Exact coefficient and PDE solution for one voltage source

$$\begin{split} &\Omega = (0,1)^2, \qquad N = 9 \\ &\Gamma_1 := \{(x,1); \ x \in (0,1)\}, \ \Gamma_0 := \{(x,0); \ x \in (0,1)\}, \\ &\partial \Omega_N := \{(0,y); \ y \in (0,1)\} \cup \{(1,y); \ y \in (0,1)\}, \\ &U_i(x) := \left\{ \begin{array}{ll} 1, & |x-x_i| \leq 2^{-4} \\ 0, & \text{else} \end{array} \right., \ x_i = \frac{2i+1}{2M} \ i = 0, \dots, M-1. \end{split}$$



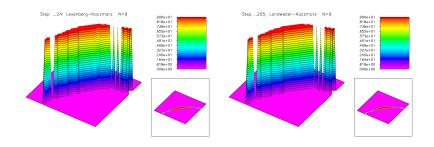
exact coefficient  $\gamma$  to be identified (left); typical voltage source  $U_i$  and corresponding solution  $\hat{u}$  (right)

## Exact coefficient and initial guess



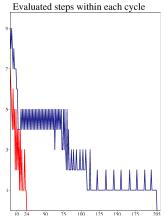
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# Comparison of loping Levenberg-Marquardt-Kaczmarz with Landweber-Kaczmarz



Numerical experiment with noisy data (5%): error obtained with L-LMK after 24 cycles (left); error obtained with L-LWK after 205 cycles (right)

# Comparison of loping Levenberg-Marquardt-Kaczmarz with Landweber-Kaczmarz



Numerical experiment with noisy data (5 per cent): number of non-loped inner steps in each cycle for  $\rm L\text{-}LMK$  (solid red) and  $\rm L\text{-}LWK$  (dashed blue), respectively.

$$\begin{aligned} x_{k+1}^{\delta} &= x_0 - G_{\alpha_k}(\mathbf{F}'(x_k^{\delta}))(\mathbf{F}(x_k^{\delta}) - \mathbf{y}^{\delta} - \mathbf{F}'(x_k^{\delta})(x_k^{\delta} - x_0)) \\ \text{e.g., } G_{\alpha}(K) &= (K^*K + \alpha I)^{-1} \\ \text{Choice of } \alpha_k &: \quad \alpha_k = \alpha_0 q^k \\ \text{Discrepancy principle:} \end{aligned}$$

stop the iteration as soon as  $\|\mathbf{F}(x_k^\delta) - \mathbf{y}^\delta\| \le au\delta \leadsto k_* \sim |\log \delta|$ 

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#### Nonlinearity condition:

$$\mathbf{F}'(\tilde{x}) = \mathbf{R}_{\tilde{x}}^{\mathsf{x}} \mathbf{F}'(x)$$
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#### Convergence Results:

- convergence with exact/noisy data
- convergence rates
   [Bakushinski'92], [BK Neubauer Scherzer'94], [Hohage'99]

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convergence + rates in Banach space
 [BK Schöpfer Schuster'09], [BK Hofmann'09]

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- convergence with exact/noisy data
- convergence rates[BK '97]

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convergence with exact/noisy data [Burger BK '06]

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## Nonlinearity conditions

$$\mathbf{F}'(\tilde{x}) = \mathbf{F}'(x)\mathbf{R}_{\tilde{x}}^{\times}, \quad \|\mathbf{R}_{\tilde{x}}^{\times} - I\| \leq C_{R}\|\tilde{x} - x\|, \quad \tilde{x}, x \in \mathcal{B}_{\rho}(x^{*})$$

$$\Longrightarrow ( \text{ with } R_{i\tilde{x}}^{\times} := \mathbf{R}_{\tilde{x}}^{\times} )$$

$$F'_{i}(\tilde{x}) = F'_{i}(x)R_{i\tilde{x}}^{\times}, \quad \|R_{i\tilde{x}}^{\times} - I\| \leq C_{R}\|\tilde{x} - x\|, \quad \tilde{x}, x \in \mathcal{B}_{\rho}(x^{*}) \quad (*) \text{ for all } i$$

i.e., range invariance of all individual  $F_i$  is a weaker condition than range invariance of collection  ${\bf F}$ 

#### Lemma

Let X, Y, Z be Hilbert spaces, and let  $L_i \in \mathcal{L}(Z_i, Y_i)$ . Moreover, let  $H_i: X_i \to Z_i$ ,  $i = 0, \dots, p-1$  be continuously Fréchet differentiable. Then,

$$\forall i : H_i \text{ satisfies } (*) \Rightarrow \forall i : F_i = L_i \circ H_i \text{ satisfies } (*)$$

Moreover,

$$\exists C_i, (\forall x \in \mathcal{B}_{\rho}(x^*), : ||H'_i(x)^{-1}|| \leq C_i)$$
 and  $H'_i$  Lipschitz  $\Rightarrow H_i$  satisfies  $(*)$ 

## Nonlinearity conditions

$$\mathbf{F}'(\tilde{x}) = \mathbf{F}'(x)\mathbf{R}_{\tilde{x}}^{\times}, \quad \|\mathbf{R}_{\tilde{x}}^{\times} - I\| \leq C_{R}\|\tilde{x} - x\|, \quad \tilde{x}, x \in \mathcal{B}_{\rho}(x^{*})$$

$$\Longrightarrow ( \text{ with } R_{i\tilde{x}}^{\times} := \mathbf{R}_{\tilde{x}}^{\times})$$

$$F'_{i}(\tilde{x}) = F'_{i}(x)R_{i\tilde{x}}^{\times}, \quad \|R_{i\tilde{x}}^{\times} - I\| \leq C_{R}\|\tilde{x} - x\|, \quad \tilde{x}, x \in \mathcal{B}_{\rho}(x^{*}) \quad (*) \text{ for all } i$$

i.e., range invariance of all individual  $F_i$  is a weaker condition than range invariance of collection  ${\bf F}$ 

#### Lemma

Let X, Y, Z be Hilbert spaces, and let  $L_i \in \mathcal{L}(Z_i, Y_i)$ . Moreover, let  $H_i: X_i \to Z_i$ ,  $i = 0, \dots, p-1$  be continuously Fréchet differentiable. Then,

$$\forall i : H_i \text{ satisfies } (*) \Rightarrow \forall i : F_i = L_i \circ H_i \text{ satisfies } (*)$$

Moreover,

$$\exists C_i, (\forall x \in \mathcal{B}_{\rho}(x^*), : \|H'_i(x)^{-1}\| \leq C_i)$$
 and  $H'_i$  Lipschitz  $\Rightarrow H_i$  satisfies  $(*)$ 

## Example 1

#### Reconstruction from Dirichlet-Neumann Map:

Estimate space-dependent coefficient  $q \geq 0$ 

$$-\Delta u + qu = 0, \quad \text{in } \Omega,$$
  
$$u = f \quad \text{on } \partial\Omega,$$

from *N* Dirichlet-Neumann pairs  $(f_i, \frac{\partial u_i}{\partial \nu}|_{\partial \Omega})$ .

 $L: u \mapsto \frac{\partial u}{\partial \nu}|_{\partial \Omega}$  ... trace operator

 $H_i:q\mapsto u_i$  ... parameter-to-solution map for PDE with Dirichlet data  $f_i$ 

## Example 2

#### Reconstruction from multiple sources:

Estimate space-dependent coefficient  $q \ge 0$ 

$$\begin{array}{rcl} -\Delta u + qu & = & h, & \quad \text{in } \Omega, \\ \frac{\partial u}{\partial \nu} & = & 0 & \quad \text{on } \partial \Omega, \end{array}$$

from N source-Dirichlet pairs  $(h_i, u_i)$ .

 $L: u \mapsto u|_{\partial\Omega}$  ...trace operator

 $H_i: q \mapsto u_i \dots$  parameter-to-solution map for PDE with source  $h_i$ ,

SPECT: Reconstruct source f and coefficient  $a \ge 0$  in

$$\theta_i \cdot \nabla u_i + au_i = f$$
 in  $\Omega \subset \mathbb{R}^d$ ,

from N pairs  $(\theta_i, u_i|_{\Gamma_i^+})$ where  $\theta_i \in S(0, 1)$ ,  $\Gamma_i^+ := \{x \in \partial\Omega : \nu(x) \cdot \theta_i \geq 0\}$ , and  $u_i|_{\partial\Omega \setminus \Gamma_i^+} = 0$ .

Ultrasound tomography: Reconstruct f in

$$\Delta v_i + k^2 (1 - f) v_i = k^2 f e^{ikx \cdot \theta_i}$$
 in  $\Omega$ ,  
 $\frac{\partial v_i}{\partial \nu} = B v_i$  on  $\partial \Omega$ ,

from N pairs  $(\theta_i, u_i|_{\partial\Omega})$ where  $\theta_i \in S(0, 1)$ ,  $u_i = e^{ikx \cdot \theta_i} + v_i$ 

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. . .

(see [Natterer'96], [Burger BK'06])

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(see [Natterer'96], [Burger BK'06])

## Example 2

#### Reconstruction from multiple sources:

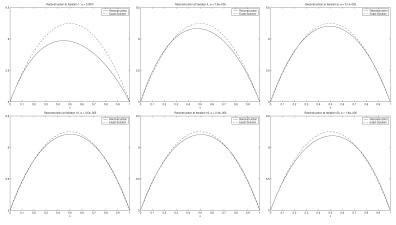
Estimate space-dependent coefficient  $q \geq 0$ 

$$\begin{array}{rcl} -\Delta u + qu & = & h, & \quad \text{in } \Omega, \\ \frac{\partial u}{\partial \nu} & = & 0 & \quad \text{on } \partial \Omega, \end{array}$$

from N source-Dirichlet pairs  $(h_i, u_i)$ .

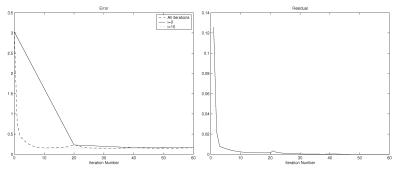
$$\Omega = (0,1)$$
 $h_i \approx \delta(\cdot - x^i)$ ,  $x^i$  uniformly spaced in  $\Omega$ 
 $N = 20$ 
 $q^* = 5 + 5x(1-x)$ 
 $q_0 \equiv 5$ 

## Results with IRGNM-Kaczmarz (exact data)



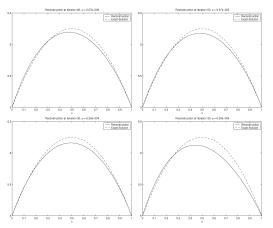
Reconstructions  $q_k$  at iterates 1, 4, 8, 12, 16, and 20.

## Convergence of IRGNM-Kaczmarz (exact data)



Plot of error (left) and residual (right) vs. iteration number

## Results with IRGNM-Kaczmarz (noisy data)



Reconstructions  $q_k$  for noise levels  $\delta=0.5\%$  (top left),  $\delta=1\%$  (top right),  $\delta=3\%$  (bottom left),  $\delta=5\%$  (bottom right).

## Expectation Maximization (EM) algorithms

## EM (Richardson-Lucy) algorithm for linear problems

for image reconstruction with nonnegativity constraints:

[Bertero 1998], [Natterer&Wuebbeling 2001], [Dempster&Laird&Rubin 1977]

 $F: L^1(\Omega) \to L^1(\Sigma)$  linear operator

$$x_{k+1}^{\delta} = x_k^{\delta} F^* \left( \frac{y^{\delta}}{F x_k^{\delta}} \right). \tag{1}$$

→ multiplicative fixed-point scheme.

well-suited for multiplicative noise models (e.g. Poisson models)

 $F,\ F^*$  positivity preserving,  $x_0^\delta \geq 0,\ y^\delta \geq 0 \ \Rightarrow \ \forall k \in \mathbb{N}:\ x_k^\delta \geq 0$ 

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#### Derivation

$$x_{k+1}^{\delta} = x_k^{\delta} F^* \left( \frac{y^{\delta}}{F x_k^{\delta}} \right). \tag{2}$$

is descent method for the functional

$$J(x) := \int_{\Sigma} \left[ y^{\delta} \log \left( \frac{y^{\delta}}{Fx} \right) - y^{\delta} + Fx \right] d\sigma,$$

Kullback-Leibler divergence (relative entropy) between Fx and  $y^{\delta}$ . optimality condition

$$x\left(-F^*\left(\frac{y^\delta}{Fx}\right)+F^*1\right)=0.$$

with operator scaling  $F^*1 = 1 \iff (2)$ 

## Idea of convergence proof

[Mülthei&Schorr89], [Natterer&Wuebbeling 2001], [Resmerita&Engl&Iusem 2007], [Bissantz&Mair&Munk]

similar to Landweber with  $\|\cdot\|^2 \leftrightarrow \text{Kullback-Leibler divergence}$ 

$$KL(x, \tilde{x}) = \int_{\Omega} \left[ x \log \frac{x}{\tilde{x}} - x + \tilde{x} \right],$$

For  $x^{\dagger}$  with  $Fx^{\dagger} = y$  by convexity

$$KL(x^{\dagger}, x_{k+1}) + J(x_k) \leq KL(x^{\dagger}, x_k)$$
.

 $\Rightarrow$ 

$$\mathit{KL}(x^{\dagger}, x_k) + \sum_{j=0}^{k-1} J(x_j) \leq \mathit{KL}(x^{\dagger}, x_0),$$

 $\Rightarrow$  boundedness of  $KL(x^{\dagger}, x_k)$  and summability of  $J(x_j)$ .

## EM algorithm for nonlinear problems

nonlinear operator  $F: L^1(\Omega) \to L^1(\Sigma)$ , no scaling  $\leadsto$  fixed-point equation

$$xF'(x)^*1 = xF'(x)^*\left(\frac{y^{\delta}}{Fx}\right).$$

nonlinear EM algorithm

$$x_{k+1}^{\delta} = \frac{x_k^{\delta}}{F'(x_k^{\delta})^* 1} F'(x_k^{\delta})^* \left(\frac{y^{\delta}}{F(x_k^{\delta})}\right).$$

[Haltmeier&Leitao&Resmerita 2009]