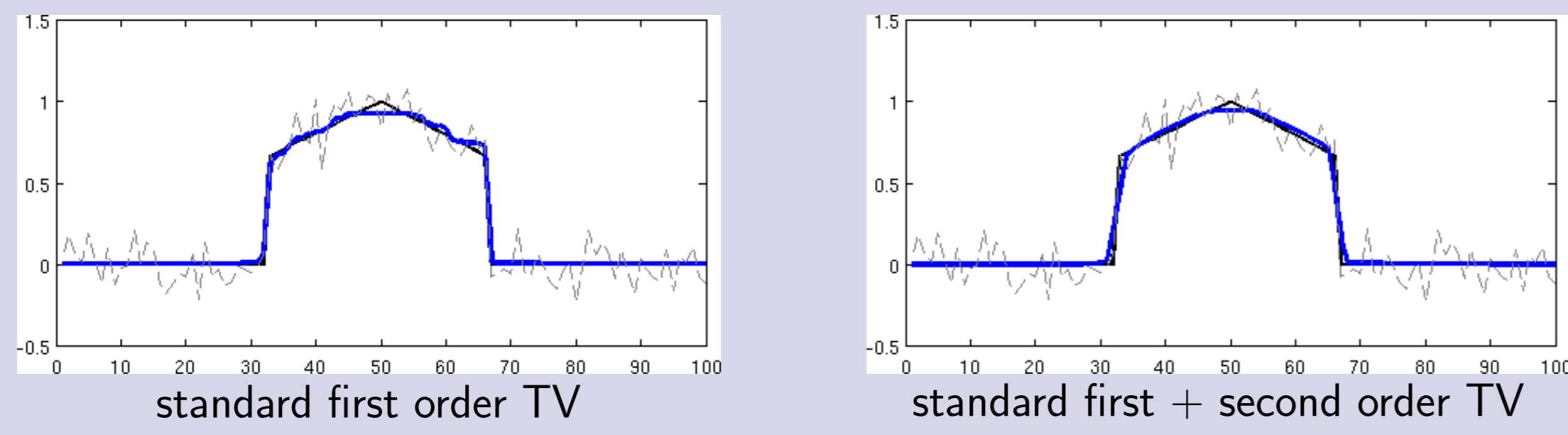


## Overview

We propose an improved first- and second-order anisotropic total variation (TV) regularization, which in particular reduces smoothing across edges and slope discontinuities. The epigraph of the data is investigated with a special structure tensor to detect slope discontinuities.

## Motivation

Example (1D):



- Standard TV suffers from stair-casing and flattening of the ridge.
- Second order TV avoids stair-casing, but smooths edges and ridge.

## Detecting Edges

We follow the *standard approach* utilizing the structure tensor

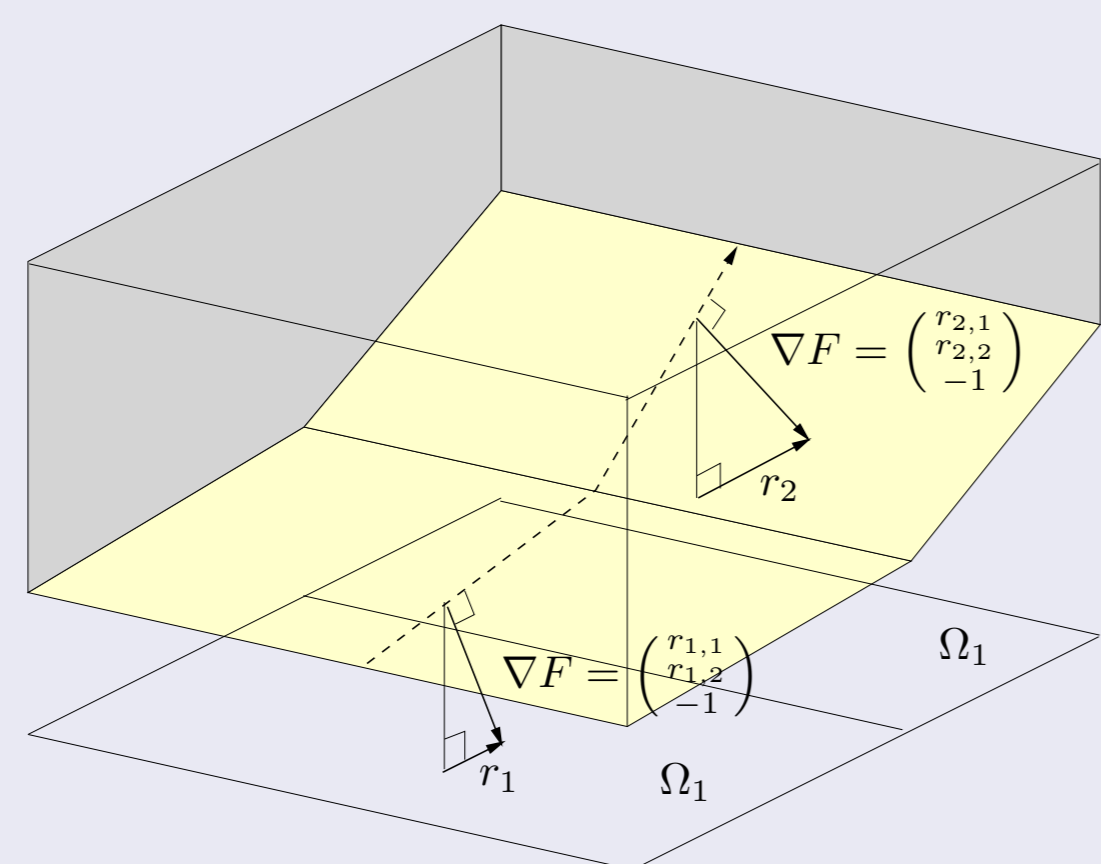
$$S_u(\mathbf{x}) = (\nabla u_{\sigma}(\mathbf{x}) \nabla u_{\sigma}(\mathbf{x})^{\top})_{\rho} \quad (1)$$

of image  $u : \Omega \rightarrow \mathbb{R}$ .  $(\cdot)_{\sigma}$  and  $(\cdot)_{\rho}$  denote the convolution with Gaussian kernels with std. deviation  $\sigma, \rho > 0$ .

- eigenvalues:  $\lambda_1^S \geq \lambda_2^S \geq 0$
- eigenvectors  $v_1^S, v_2^S$
- edge indicator function:  $E^S(\mathbf{x}) := \min\{c \cdot (\lambda_1^S(\mathbf{x}) - \lambda_2^S(\mathbf{x})), 1\}$ ,  $c > 0$

## Detecting Slope Discontinuities

Assumption:  $u$  is continuous and piecewise affine, with one discontinuity of  $\nabla u$  along a line.



example of a slope discontinuity

- graph of  $u$ :  $\Gamma = (x, y, u(x, y))^{\top}$ .
- epigraph of  $u$ : super-level set  $\{(x, y, z) \mid F(x, y, z) \geq 0\}$  of  $F(x, y, z) := u(x, y) - z$ .
- to detect edges of the graph, we propose to apply the three-dimensional structure tensor to  $F$ :

$$((\nabla F(x, y, z))(\nabla F(x, y, z))^{\top})_{\rho} \quad (2)$$

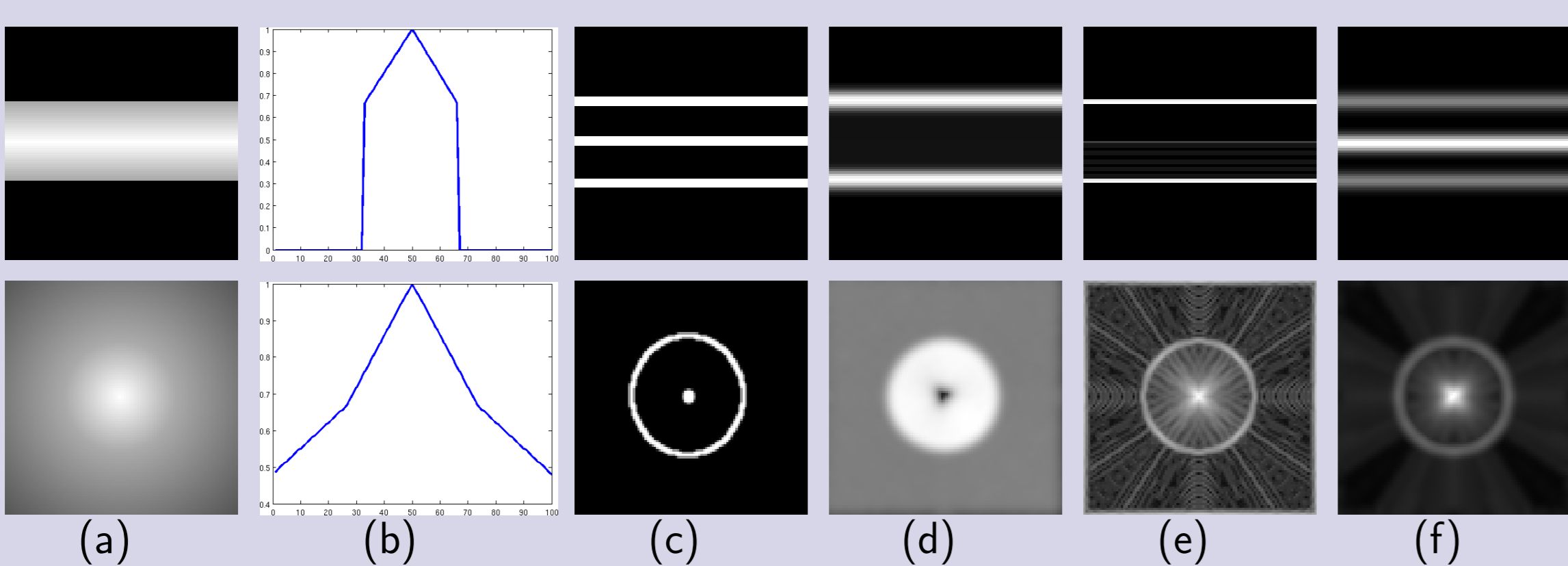
- restrict this structure tensor to  $\Gamma$ :

$$T_u(x, y) := ((\nabla \tilde{F}(x, y))(\nabla \tilde{F}(x, y))^{\top})_{\rho}, \quad (3)$$

where  $\nabla \tilde{F}(x, y) := \nabla F(x, y, u(x, y))$ .

- eigenvalues:  $\lambda_1^T \geq \lambda_2^T \geq \lambda_3^T \geq 0$ .

- define indicator function for slope discontinuities:  $E^T(\mathbf{x}) := \min\{c\lambda_2^T(\mathbf{x}), 1\}$



Detecting slope discontinuities: (a) test images, (b) cross-section, (c) ideal result, (d) standard structure tensor, (e) curvature based approach, (f) proposed method.

## Approach: Anisotropic Second Order TV

Variational approach:

$$\mathcal{F}(u) := \frac{1}{2} \|u - f\|_{L^2}^2 + \mathcal{R}_1(u) + \mathcal{R}_2(u) \quad u \in BV^2(\Omega) \quad (4)$$

First order

$$\mathcal{R}_1(u) := \int_{\Omega} (\nabla u^{\top}(\mathbf{x}) A(\mathbf{x}) \nabla u(\mathbf{x}))^{\frac{1}{2}} dx, \quad (5)$$

with

$$A(\mathbf{x}) = \begin{pmatrix} v_1^S(\mathbf{x}) & v_2^S(\mathbf{x}) \\ v_1^S(\mathbf{x}) & v_2^S(\mathbf{x}) \end{pmatrix} \begin{pmatrix} \alpha_1(\mathbf{x}) & 0 \\ 0 & \alpha_2(\mathbf{x}) \end{pmatrix} \begin{pmatrix} (v_1^S(\mathbf{x}))^{\top} \\ (v_2^S(\mathbf{x}))^{\top} \end{pmatrix}. \quad (6)$$

Second order

For  $u \in C^{\infty}(\Omega)$

$$\mathcal{R}_2(u) = \int_{\Omega} \beta_1 \|(Hu)v^S\|_2 + \beta_2 \|(Hu)(v^S)^{\perp}\|_2 dx, \quad (\text{with } H = \text{Hessian of } u). \quad (7)$$

Generalization to  $u \in L^1(\Omega)$

$$\mathcal{R}_2(u) := \sup \left\{ \int_{\Omega} (\text{div}^2 \varphi) u dx \mid \varphi \in \mathcal{C} \right\}, \quad \text{with} \quad (8)$$

$$\mathcal{C} := \{C_c^{\infty}(\Omega; \mathbb{R}^4), \forall \mathbf{x} \in \Omega : \langle \varphi(\mathbf{x}), w_1(\mathbf{x}) \rangle^2 + \langle \varphi(\mathbf{x}), w_2(\mathbf{x}) \rangle^2 \leq (\beta_1(\mathbf{x}))^2, \langle \varphi(\mathbf{x}), w_3(\mathbf{x}) \rangle^2 + \langle \varphi(\mathbf{x}), w_4(\mathbf{x}) \rangle^2 \leq (\beta_2(\mathbf{x}))^2\}, \quad (9)$$

with suitably chosen  $w_i(\mathbf{x}) : \Omega \rightarrow \mathbb{R}^4$  depending on  $v^S$ .

**Theorem:** Assume that  $\alpha_i(\mathbf{x}), \beta_i(\mathbf{x})$ ,  $i = 1, 2$ , are bounded from below and above by positive constants. Then there exists a unique minimizer of (4).

*Proof:* see SSVM paper.

## Choice of $\alpha_i(\mathbf{x}), \beta_i(\mathbf{x})$ :

Let

$$E(\mathbf{x}) := \max\{E^S(\mathbf{x}), E^T(\mathbf{x})\} \in [0, 1]. \quad (10)$$

The indicator functions  $E^S, E^T$  are calculated from the structure tensors  $S_f$ , and  $T_f$  applied to data  $f$ .

$$\alpha_1(\mathbf{x}) := E(\mathbf{x})\alpha_{min} + (1 - E(\mathbf{x}))\alpha_{max}, \quad \alpha_2(\mathbf{x}) := \alpha_{max}, \quad (11)$$

$$\beta_1(\mathbf{x}) := E(\mathbf{x})\beta_{min} + (1 - E(\mathbf{x}))\beta_{max}, \quad \beta_2(\mathbf{x}) := \beta_{max},$$

with suitable  $\alpha_{min}, \alpha_{max}, \beta_{min}, \beta_{max} > 0$ .

## Related approaches: adaptive TGV / infimal convolution

Infimal convolution (IC) [Setzer et al. 2011]:

$$\min_u \frac{1}{2} \|u - f\|_2^2 + \inf_{\{u_1, u_2 \mid \nabla u = u_1 + u_2\}} \alpha \|u_1\|_1 + \beta \|Du_2\|_1. \quad (12)$$

TGV [Bredies et al. 2010]:

$$TGV^2(u) := \sup\{u \text{ div}^2 \varphi dx \mid \varphi \in C_c^2(\Omega, Sym^2), |\varphi| \leq \alpha, |\text{div} \varphi| \leq \beta \text{ a.e.}\}. \quad (13)$$

Adaptive variants of IC and TGV:

$$\alpha(\mathbf{x}) := E(\mathbf{x})\alpha_{min} + (1 - E(\mathbf{x}))\alpha_{max}, \quad \beta(\mathbf{x}) := E(\mathbf{x})\beta_{min} + (1 - E(\mathbf{x}))\beta_{max}, \quad (14)$$

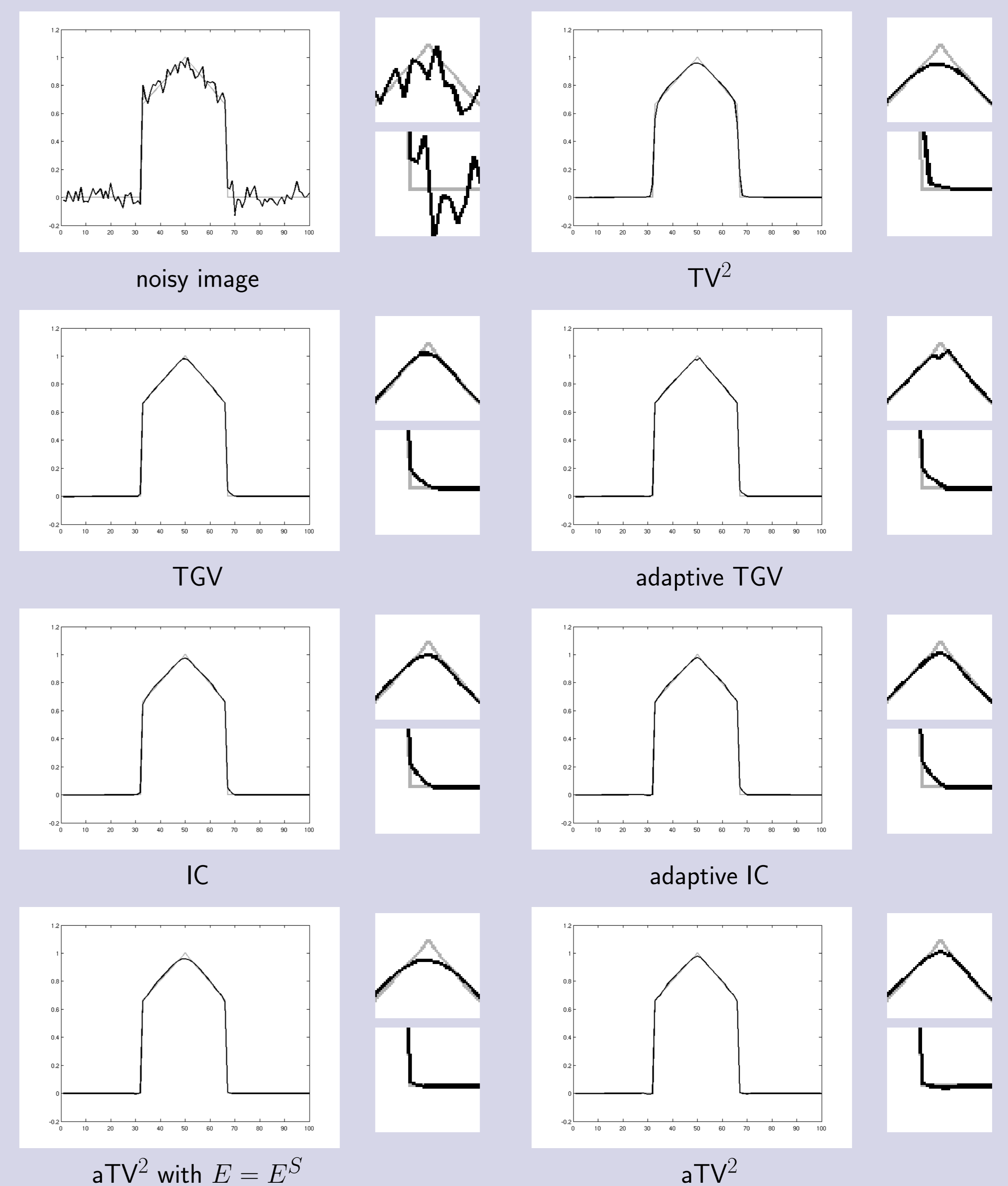
with suitable  $\alpha_{min}, \alpha_{max}, \beta_{min}, \beta_{max}$  and  $E$  as defined in (10).

## Results

Methods to compare:

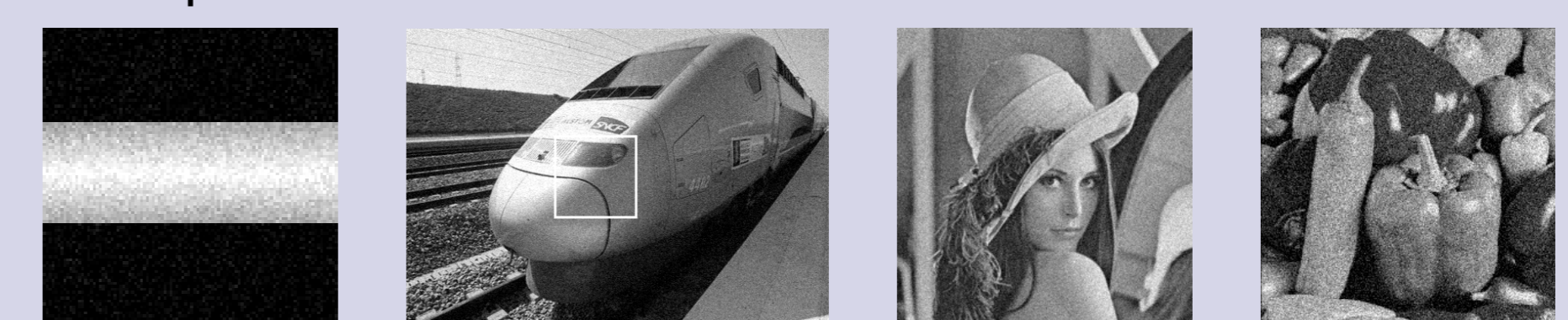
- $TV^2$  – standard second-order TV
- IC – infimal convolution (standard/adaptive)
- TGV (standard/adaptive)
- $aTV^2(E = E^S)$  – proposed approach using  $E = E^S$
- $aTV^2$  – proposed approach ( $E$  as in (10)).

## Qualitative comparison



Cross-sections of the results (back lines) of TGV, IC, their adaptive variants and the proposed method. Noise-free data shown in gray.

## Quantitative comparison



test images used for comparison.

Example	Roof	Train (part)	Lena	Peppers
$aTV^2(E = E^S)$	4.6946e-4	2.4249e-4	1.0703e-4	1.8858e-4
TGV	0.8857e-4	2.3644e-4	0.9362e-4	1.3883e-4
Adaptive TGV	0.8703e-4	2.3364e-4	0.8985e-4	1.3258e-4
IC	1.0405e-4	2.3968e-4	0.9519e-4	1.3822e-4
Adaptive IC	0.9861e-4	2.3693e-4	0.9205e-4	1.3589e-4
<b><math>aTV^2</math></b>	<b>0.5703e-4</b>	<b>2.2560e-4</b>	<b>0.8749e-4</b>	<b>1.2997e-4</b>

Mean squared errors (MSE) to the noise-free image for the different methods. Approximate optimal parameters for each method were retrieved by grid search.

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