Visual Computing: Blending

SS 2016

IVD - Institut für Visualisierung und Datenanalyse

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Karlsruhe Institut für Technologie

We solved matting

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Kind of :)

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- And now for something completely different: blending

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Overview

Image compositing as 'reverse matting' problem

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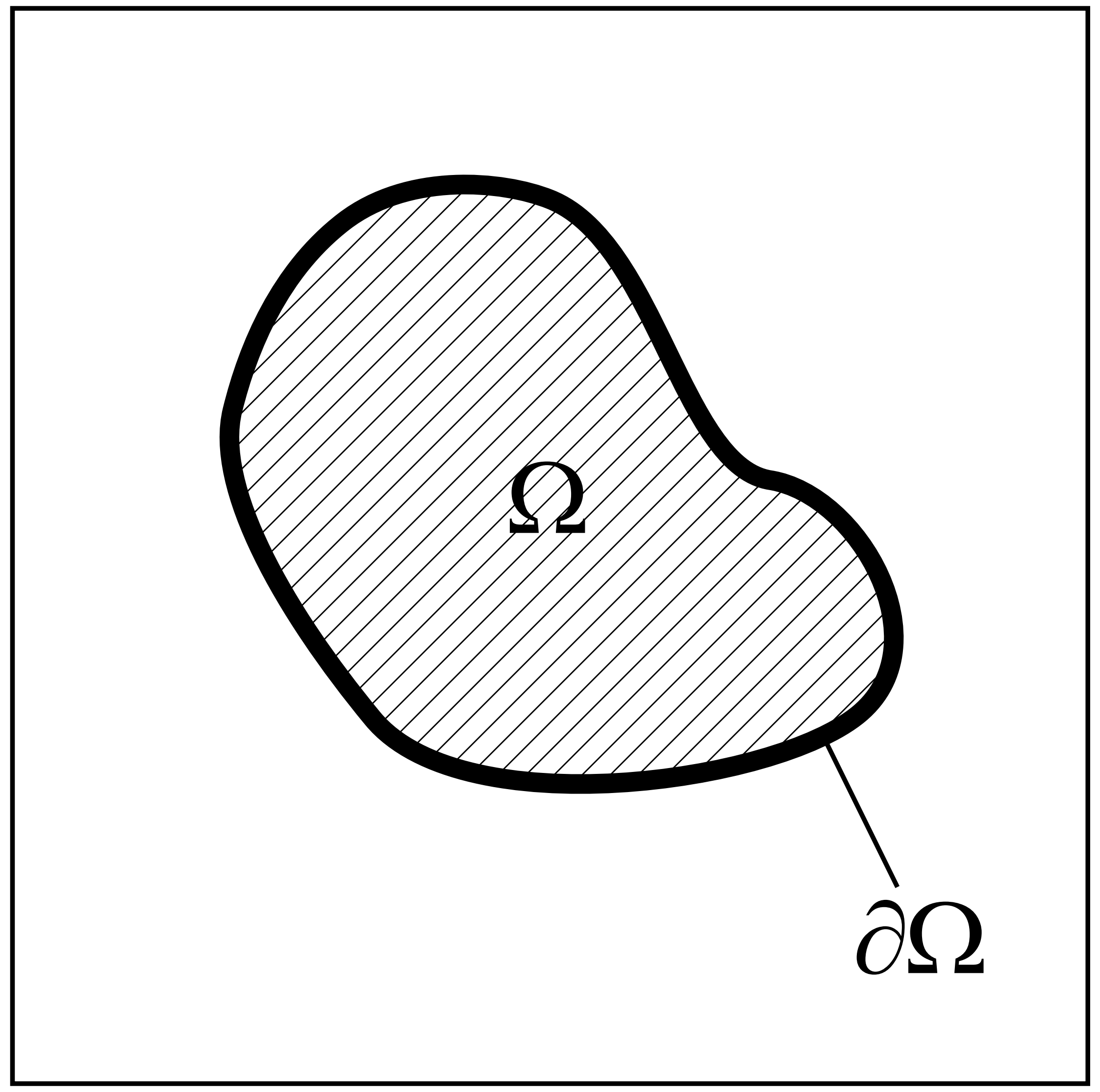
- Compositing hard edge image regions
- Gradient domain blending
- Graph cut compositing (cannot be solved by matting equation)

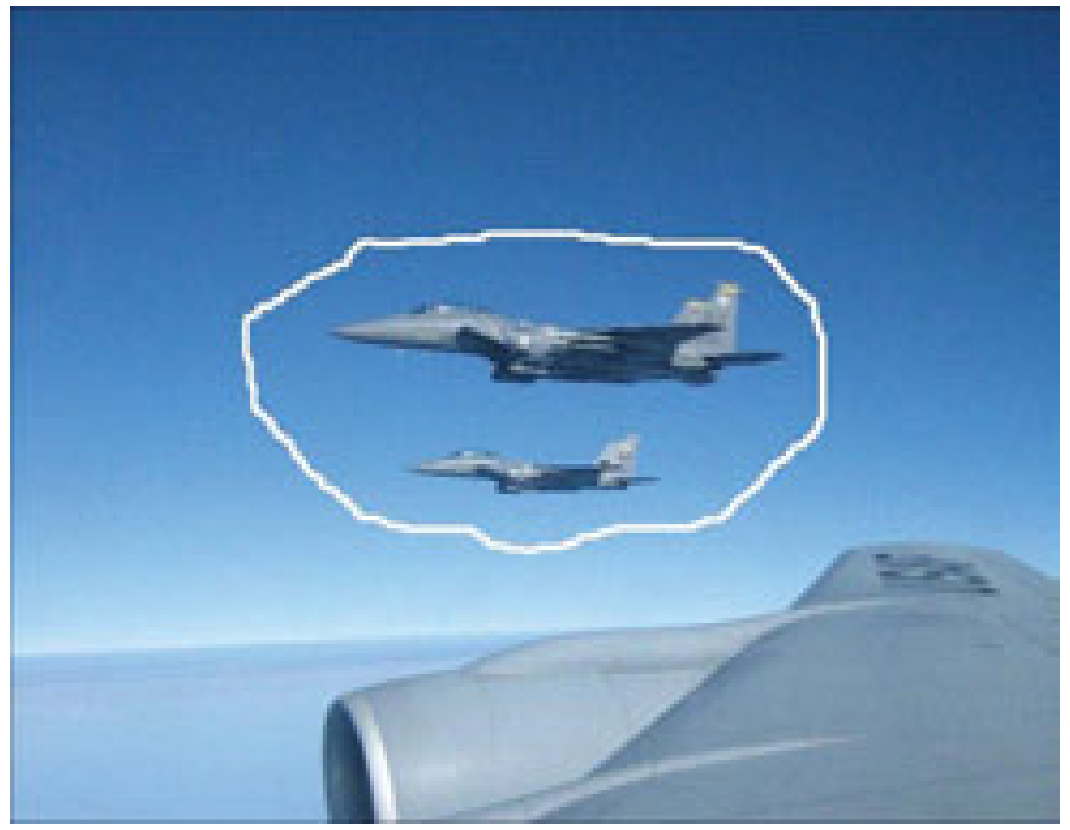
Overview: Hard Edge Regions

Overview: Hard Edge Regions

Overview: Gradient Domain Blending



(a)



Overview: Graph Cut Compositing

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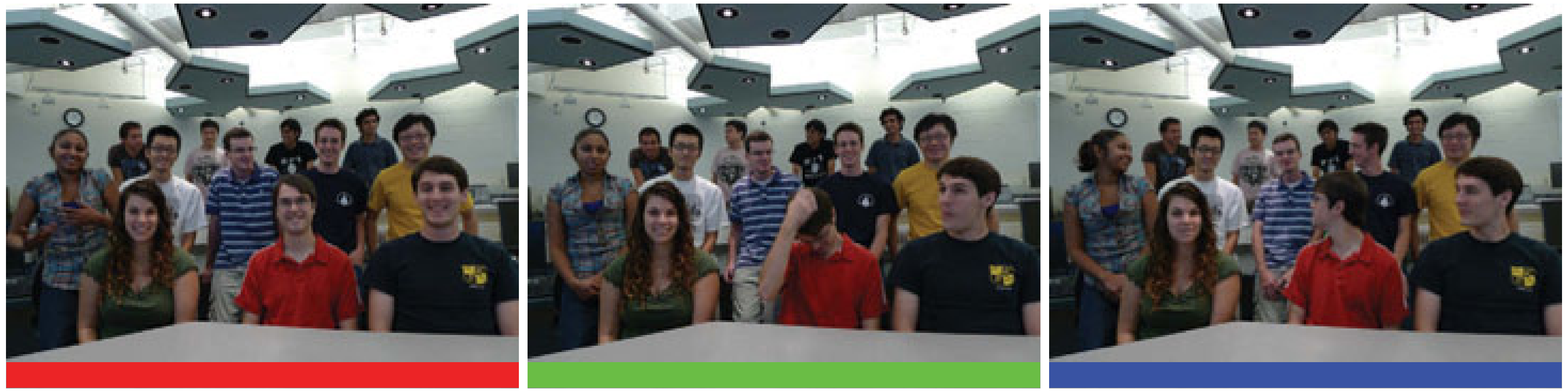

(a)

Overview: Graph Cut Compositing

(a) (b)

Matting/Blending Eq.

$$I = \alpha F + (1 - \alpha) B$$

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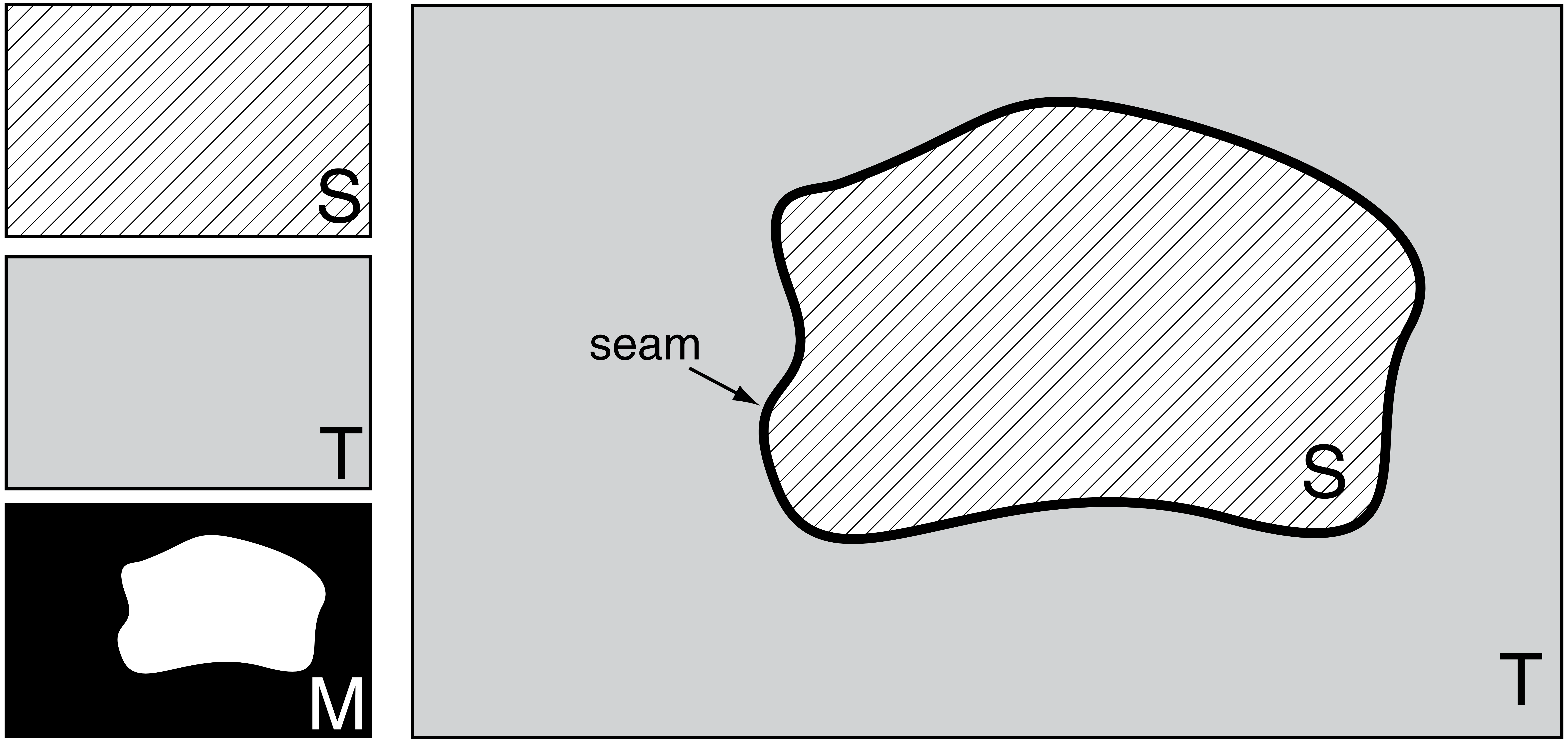
$$I = \alpha F + (1 - \alpha) B$$

$$I(x,y) = \begin{cases} F(x,y) \text{ where } \alpha = 1 \\ B(x,y) \text{ where } \alpha = 0 \end{cases}$$

Terminology

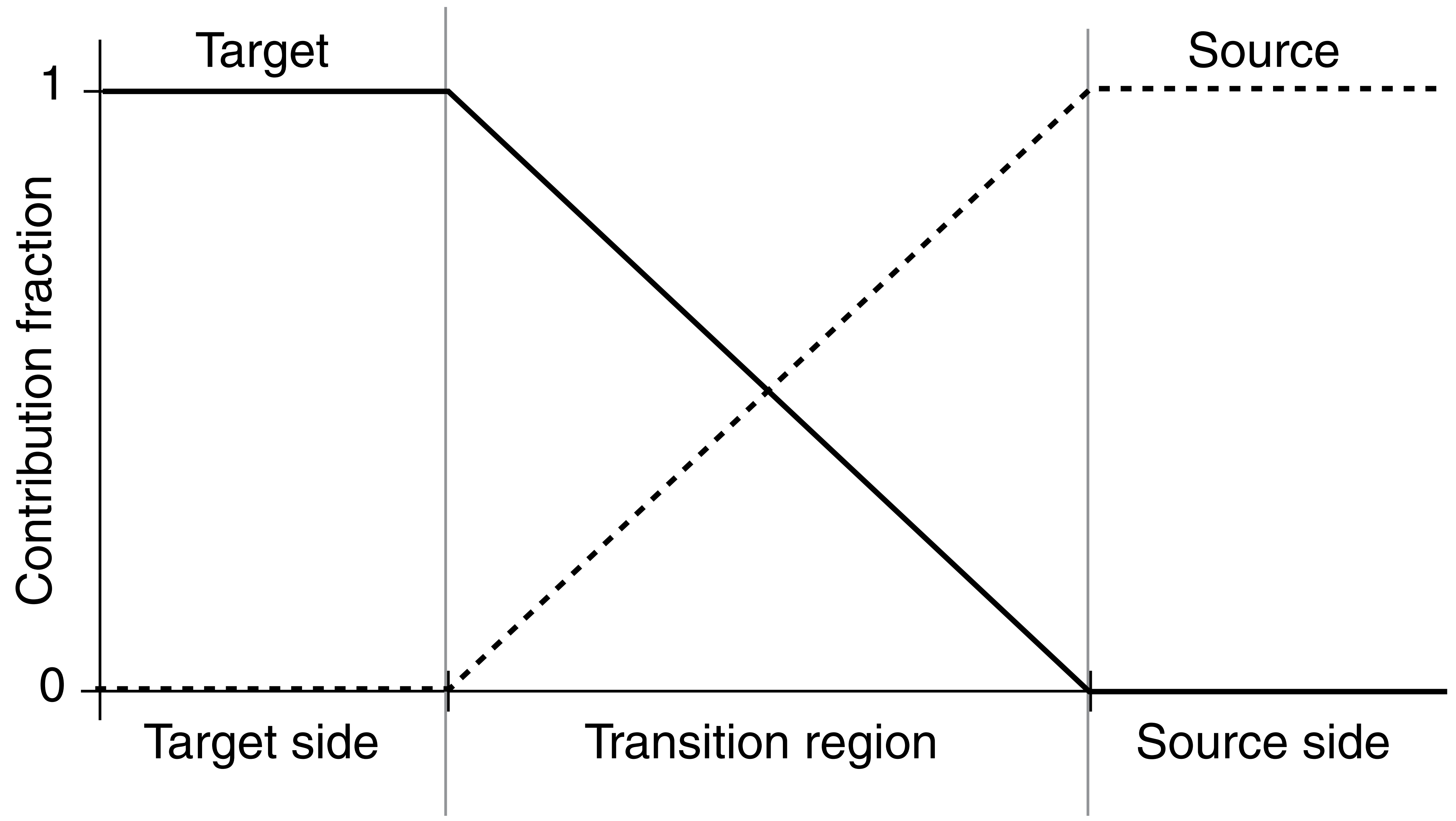


S: source image, T: target image, M: binary mask

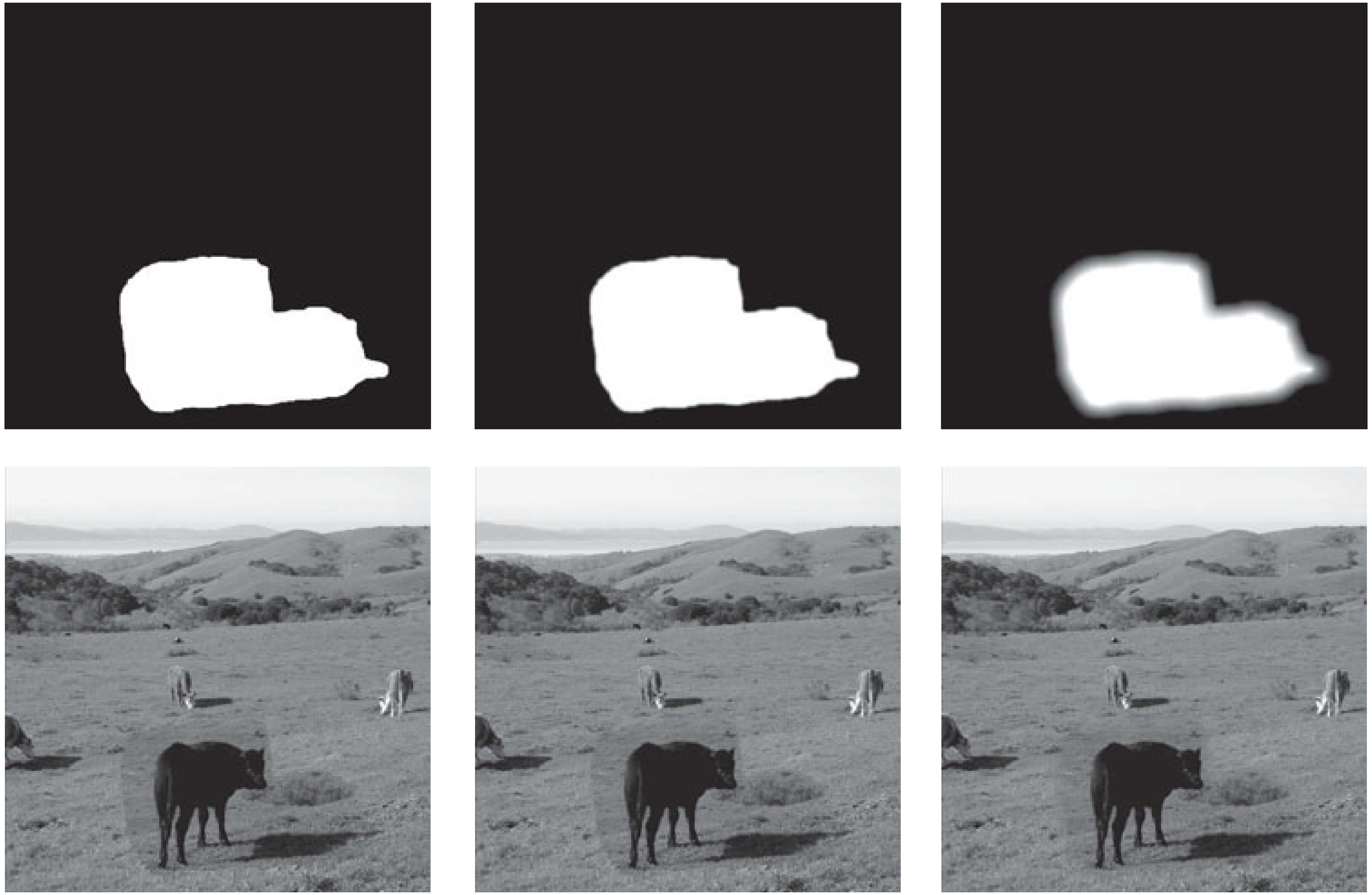
Visible Seams

Visible Seams

Transition Regions



Different Transition Region Widths



Matte Painting

Matte Painting

Burt and Adelson

Burt and Adelson

- Blend **low-frequency** changes across **wide** transition regions.

Burt and Adelson

- Blend **low-frequency** changes across **wide** transition regions.
- Blend **high-frequency** changes across **narrow** transition regions.

RESEARCH CONTRIBUTIONS

A Multiresolution Spline With Application to Image Mosaics

PETER J. BURT and EDWARD H. ADELSON
RCA David Sarnoff Research Center

We define a multiresolution spline technique for combining two or more images into a larger image mosaic. In this procedure, the images to be splined are first decomposed into a set of band-pass filtered component images. Next, the component images in each spatial frequency band are assembled into a corresponding band-pass mosaic. In this step, component images are joined using a weighted average within a transition zone which is proportional in size to the wave lengths represented in the

Peter J. Burt and Edward H. Adelson. 1983. A multiresolution spline with application to image mosaics. ACM Trans. Graph. 2, 4 (October 1983), 217-236. DOI=http://dx.doi.org/10.1145/245.247

THE STEERABLE PYRAMID: A FLEXIBLE ARCHITECTURE FOR MULTI-SCALE DERIVATIVE COMPUTATION

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ABSTRACT

We describe an architecture for efficient and accurate linear decomposition of an image into scale and orientation subbands. The basis functions of this decomposition are directional derivative operators of any desired order. We describe the construction and implementation of the transform. [1]

"steerable pyramid", as developed in [5, 6]. Similar representations have been developed by Perona [7]. In this linear decomposition, an image is subdivided into a collection of subbands localized in both scale and orientation. The scale tuning of the filters is constrained by a recursive system diagram (described below). The orientation tuning is constrained by the property of steerability [5].

E. P. Simoncelli and W. T. Freeman. 1995. The steerable pyramid: a flexible architecture for multi-scale derivative computation. In Proceedings of the 1995 International Conference on Image Processing (Vol. 3)-Volume 3 - Volume 3 (ICIP '95), Vol. 3. IEEE Computer Society, Washington, DC, USA, 3444-.

Gaussian Pyramid

Gaussian Kernel (blurring kernel)

$$K = [-0.05,\ 0.25,\ 0.6,\ 0.25,\ -0.05]^\top\ [-0.05,\ 0.25,\ 0.6,\ 0.25,\ -0.05]$$

$$G_i = (K * G_{i-1})_{\downarrow 2}, \quad i = 1, \dots, N$$

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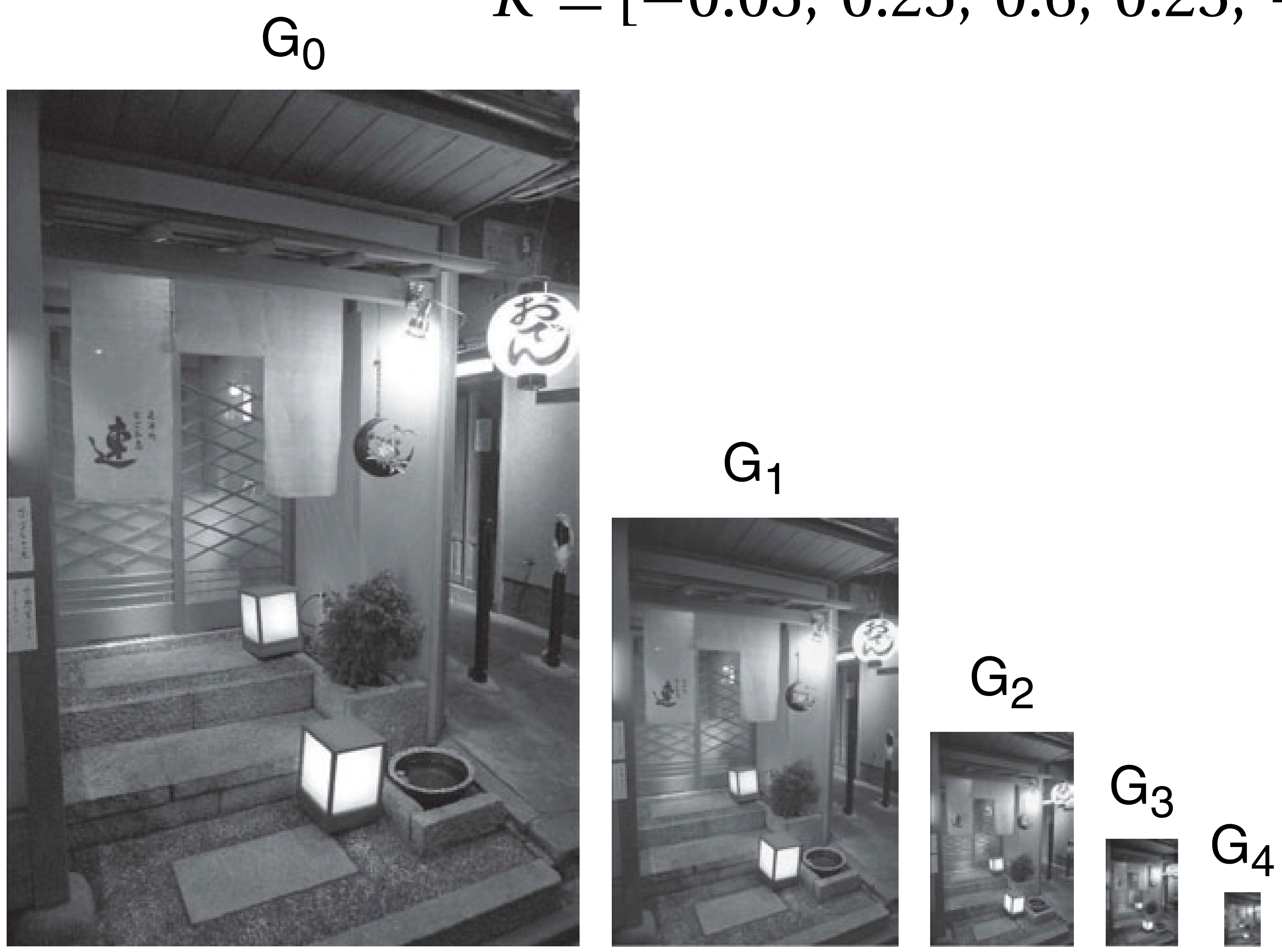

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Karlsruhe Institute of Technology

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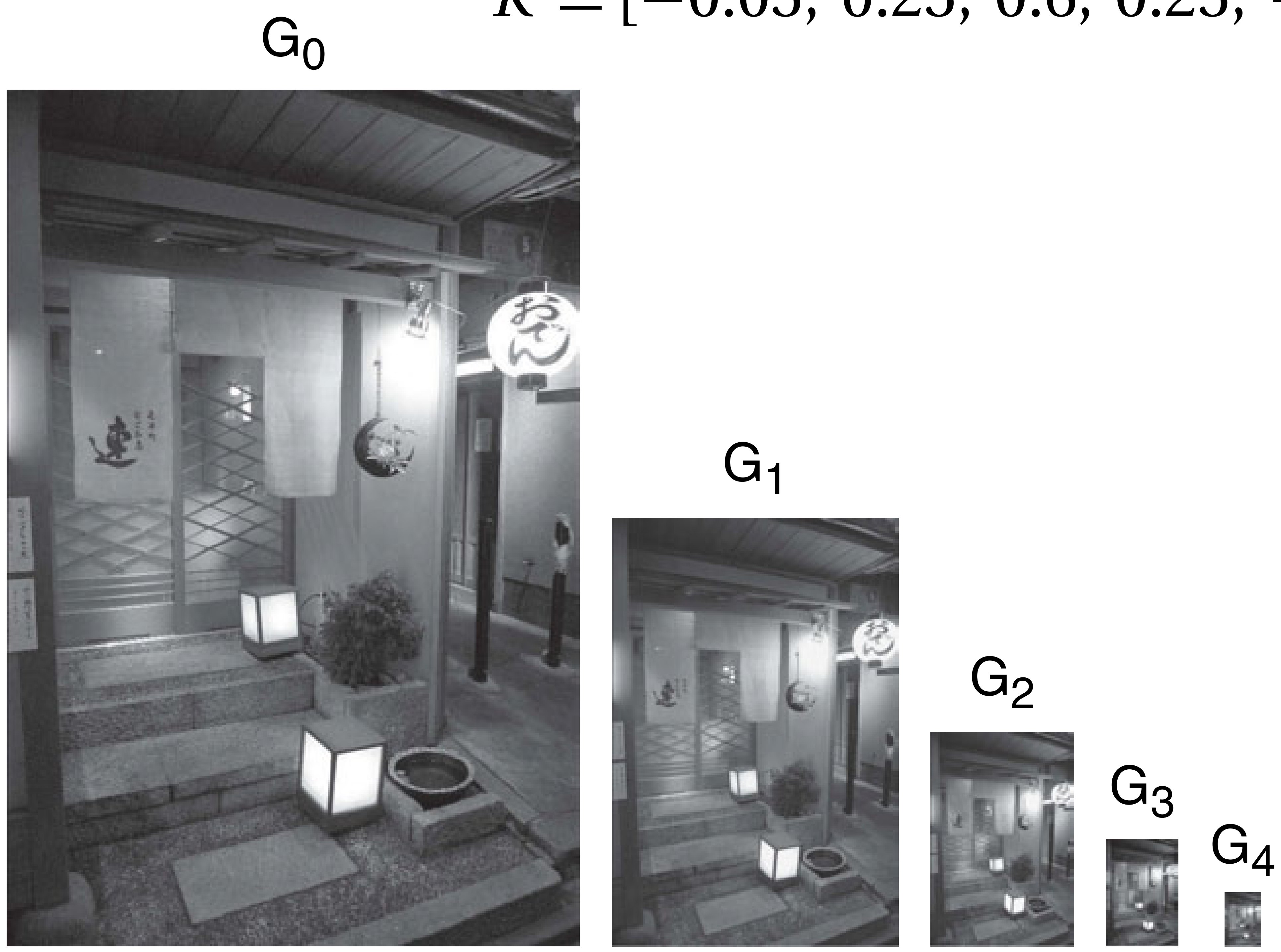

$$G_0 * K$$

$$G_i = (K * G_{i-1})_{\downarrow 2}, \quad i = 1, \ldots, N$$

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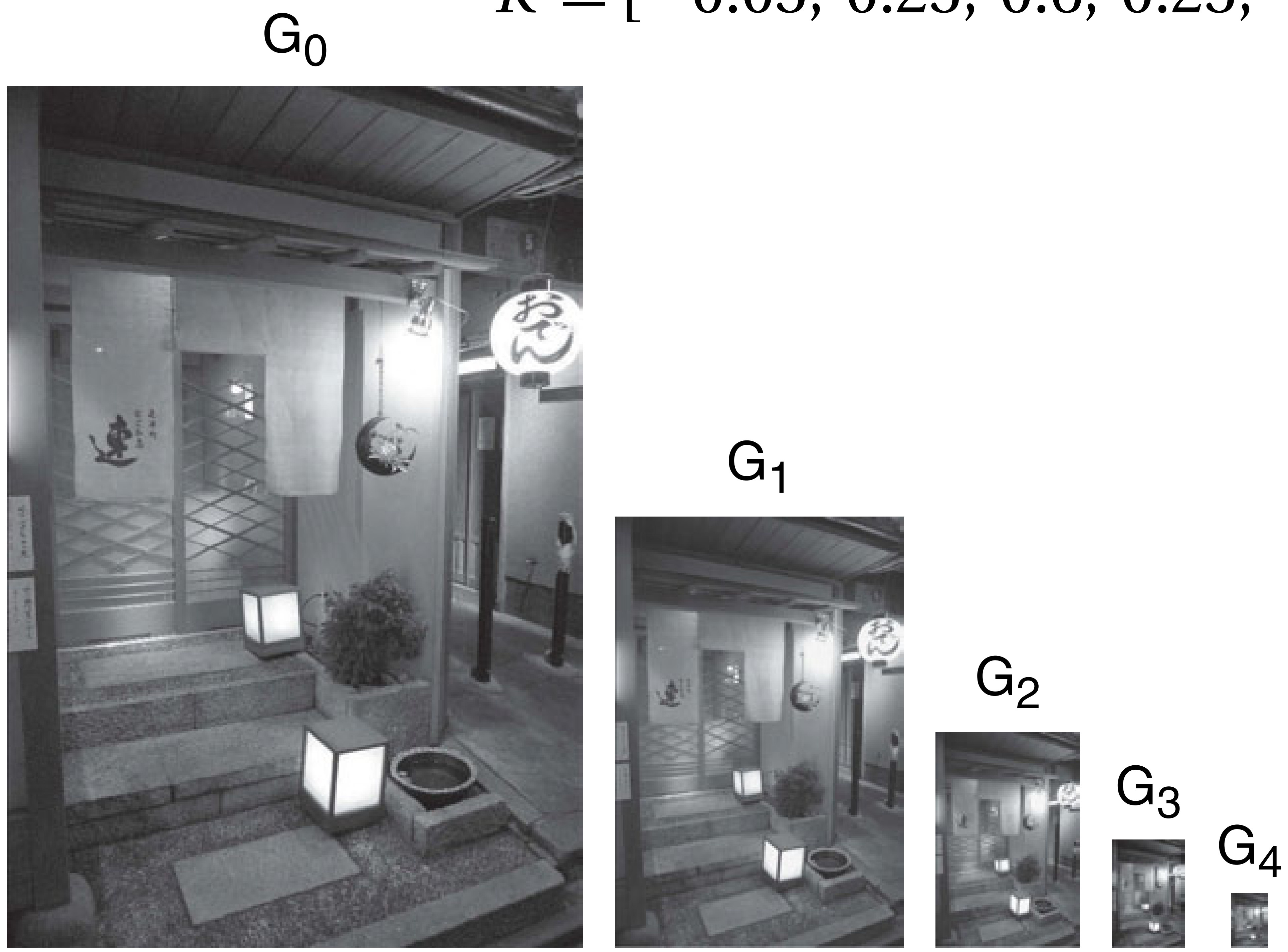

$$G_0 * K$$

$$G_1 = (G_0 * K)_\downarrow$$

$$G_i = (K * G_{i-1})_{\downarrow 2}, \quad i = 1, \ldots, N$$

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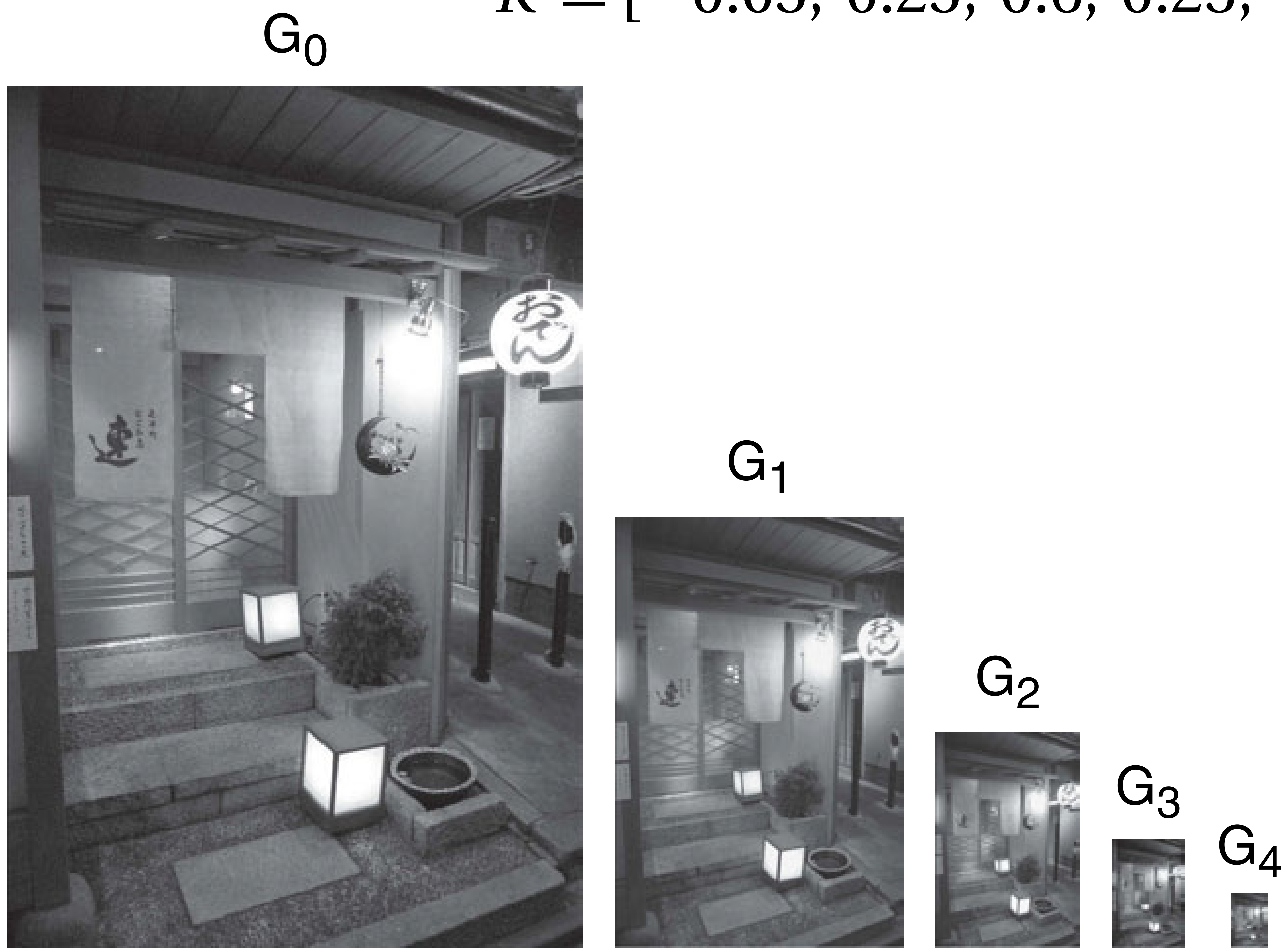


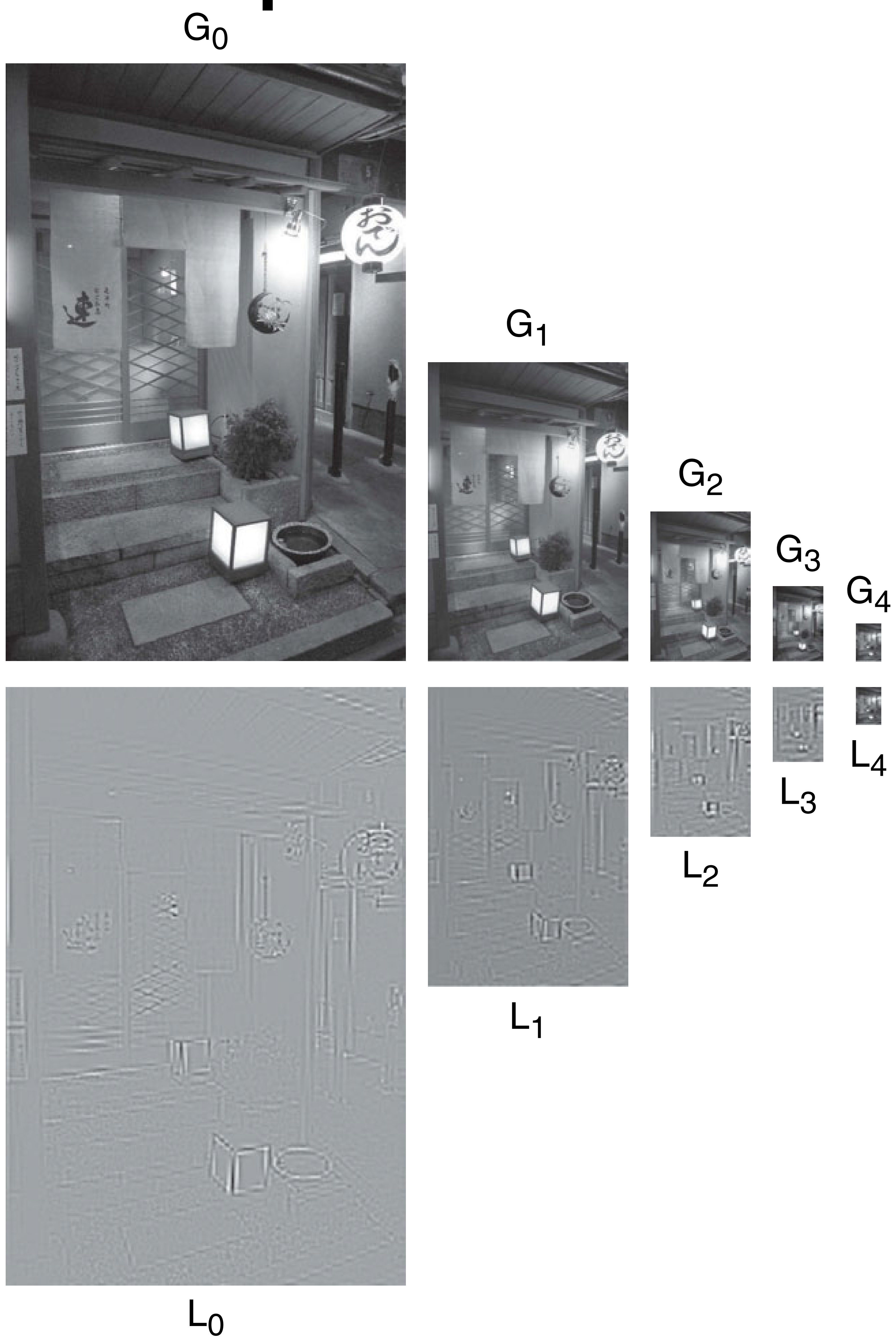
$$G_0 * K$$

$$G_1 = (G_0 * K)_\downarrow$$

$$G_i = (K * G_{i-1})_{\downarrow 2}, \quad i = 1, \dots, N$$

$$L_i = G_i - (K * G_i), \quad i = 0, \dots, N-1$$

Laplacian Pyramid



$$I = \sum_{i=0}^{N} L_{i\uparrow}$$

Multiresolution Blending

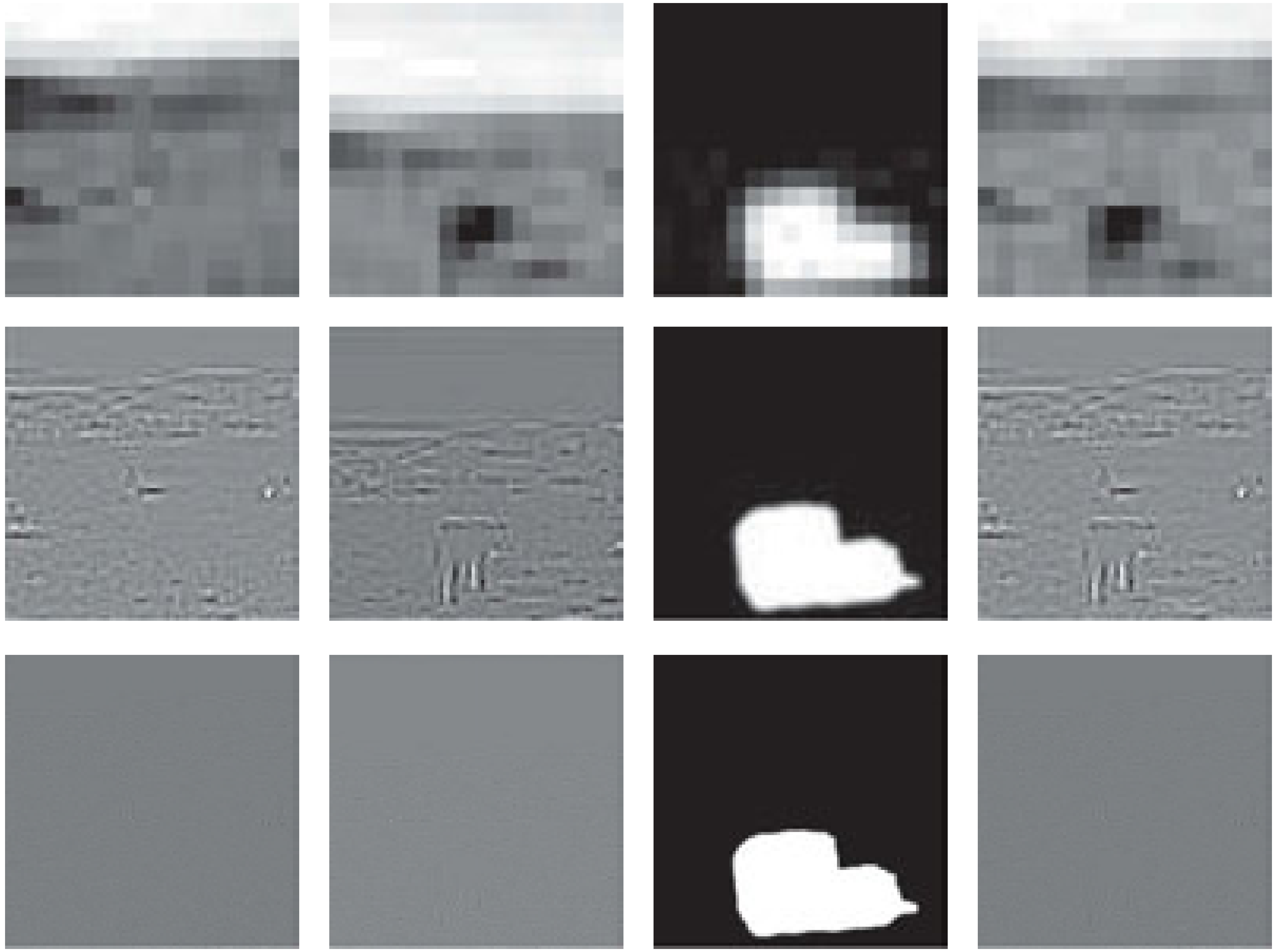
build Laplacian pyramid for composite image
with Gaussian of Map M and Laplacians of Source S and Target T:

$$L_0^C = G_0^M L_0^S + (1 - G_0^M) L_0^T$$
$$\vdots$$
$$L_N^C = G_N^M L_N^S + (1 - G_N^M) L_N^T$$

combine upsampled Laplacians to final composite image:

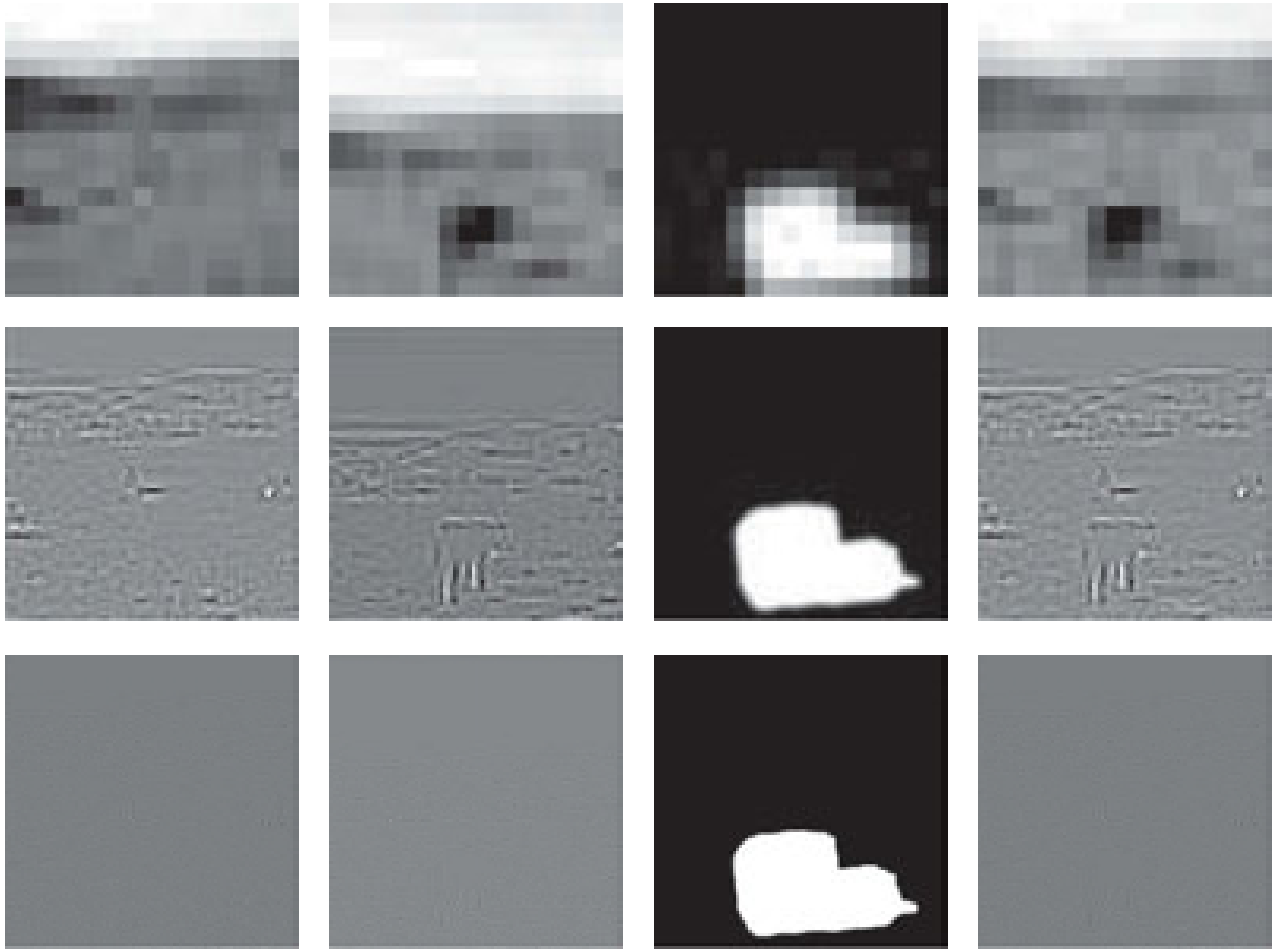
$$I^C = \sum_{i=0}^{N} (L_i^C)_\uparrow$$

Multiresolution Blending



(c) (d) (e) (f)

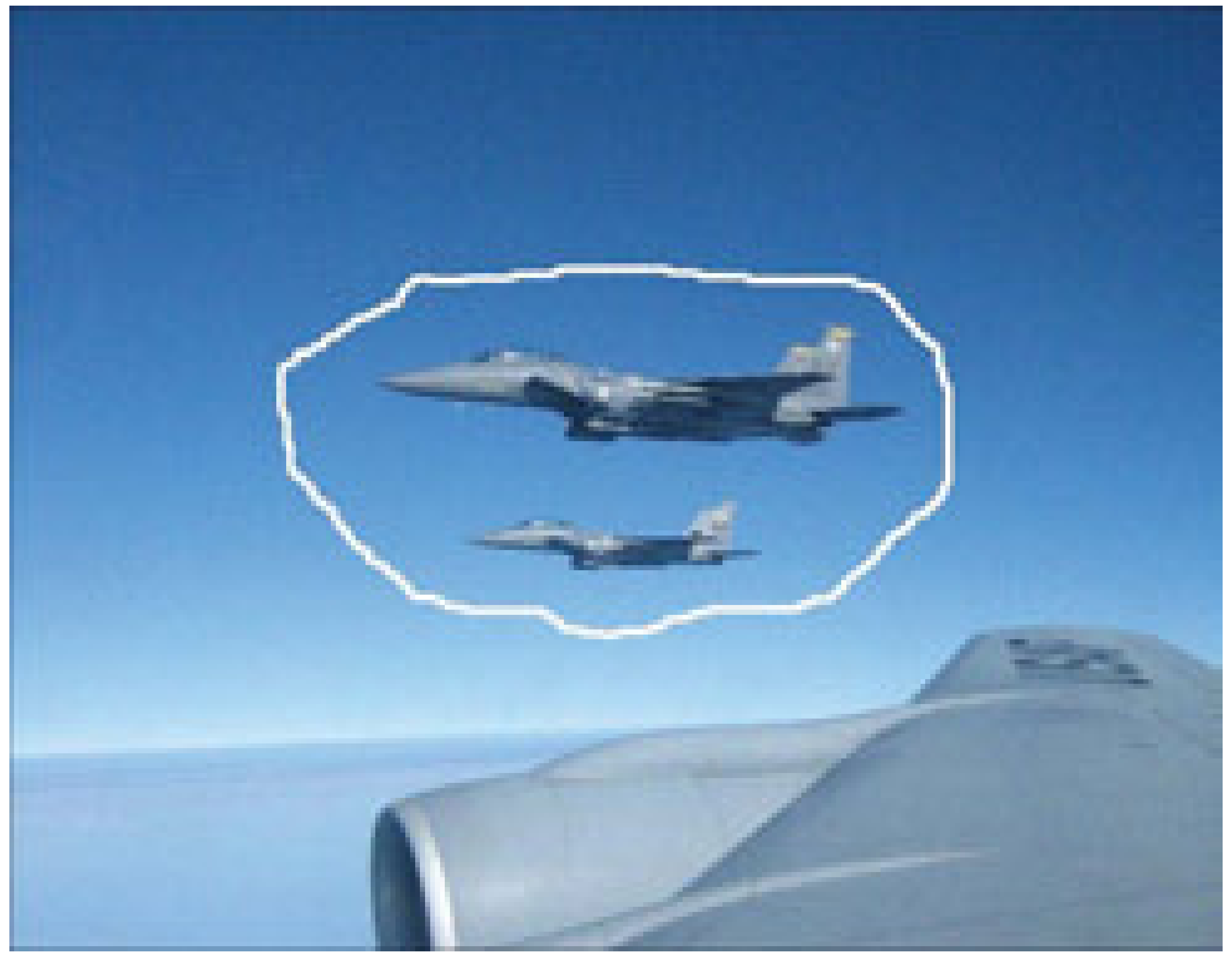
Multiresolution Blending



(c) (d) (e) (f)

Difficult Example

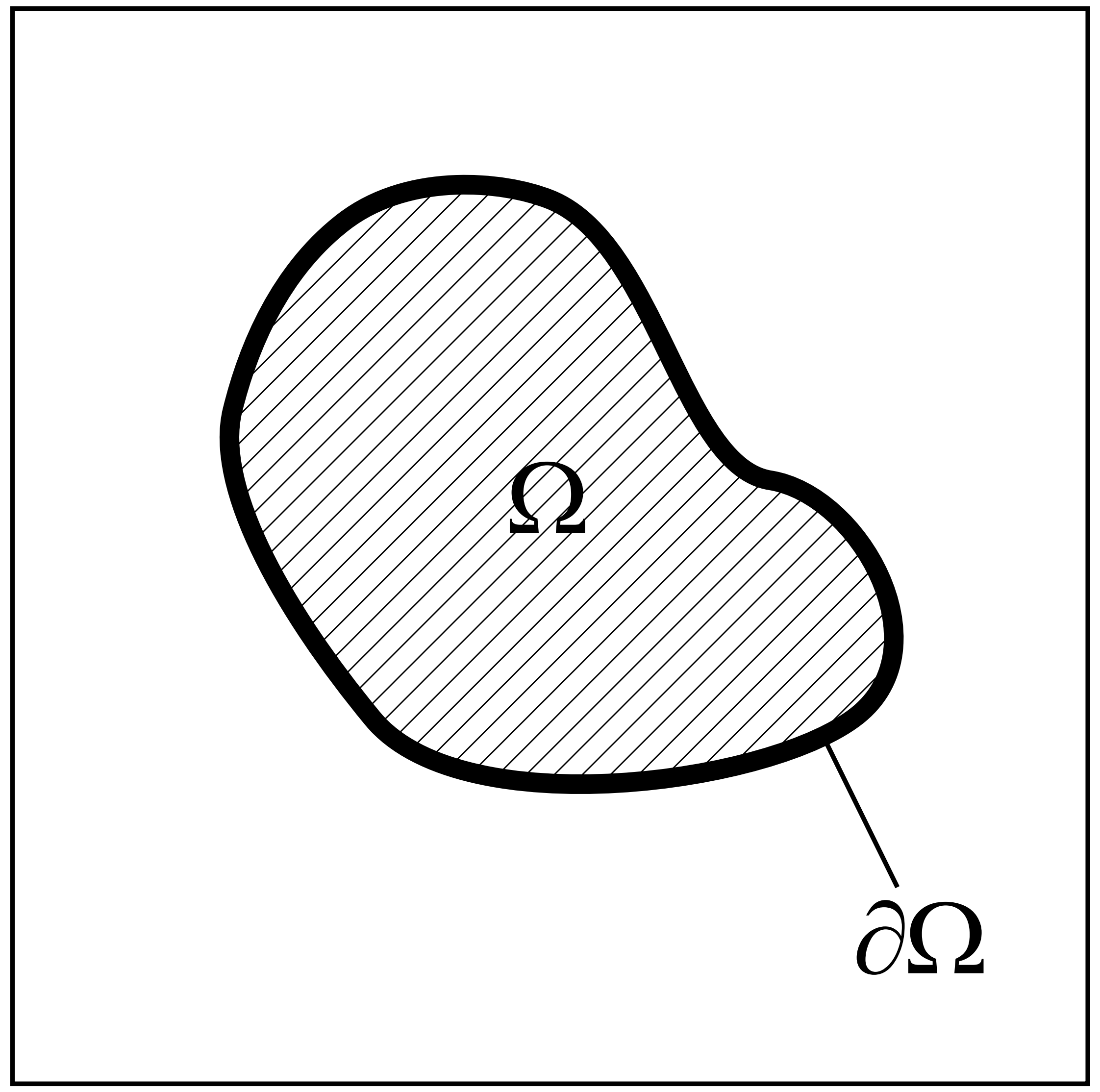
(a)



(b)

(c)

Poisson/Gradient domain



Problem Formulation

$$\min_{I(x,y)\in\Omega} \iint_{\Omega} \|\nabla I(x,y) - \nabla S(x,y)\|^2 \, dx\, dy$$

$$s.t.\ \ I(x,y) = T(x,y) \ \text{ on } \partial\Omega$$

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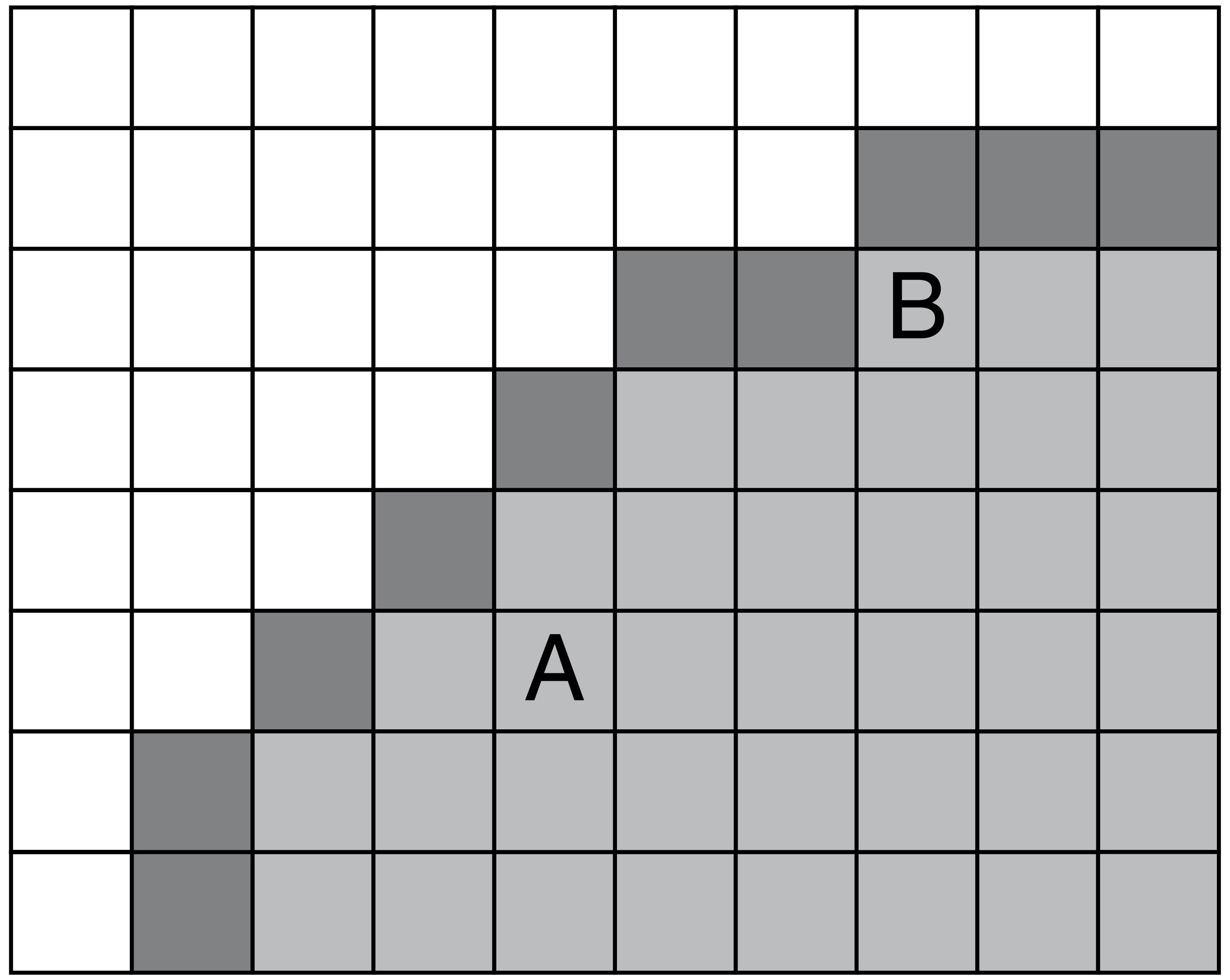
$$s.t.\ \ I(x,y) = T(x,y) \ \text{ on } \partial\Omega$$

$$\nabla^2 I(x,y) = \nabla^2 S(x,y) \ \text{ in } \Omega$$

$$s.t.\ \ I(x,y) = T(x,y) \ \text{ on } \partial\Omega$$

Problem Formulation

$$I(x+1,y)+I(x-1,y)+I(x,y+1)+I(x,y-1)-4I(x,y)$$
$$= S(x+1,y)+S(x-1,y)+S(x,y+1)+S(x,y-1)-4S(x,y) \quad (3.14)$$



$$\left(\sum_{q\in\mathcal{N}(p)\cap\Omega} I(q)\right)+\left(\sum_{q\in\mathcal{N}(p)\cap\partial\Omega} T(q)\right)-4I(x,y)$$
$$= S(x+1,y)+S(x-1,y)+S(x,y+1)+S(x,y-1)-4S(x,y)$$

Results

Problem