
Nonlinear Scale Space Analysis in Image Processing

by

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Abstract

The objective of this work is to develop and analyze robust and fast image segmentation algorithms. They must be robust to pervasive, large-amplitude noise, which cannot be well characterized in terms of probabilistic distributions. This is because the applications of interest include synthetic aperture radar (SAR) segmentation in which speckle noise is a well-known problem that has defeated many algorithms. The methods must also be robust to blur, because many imaging techniques result in smoothed images. For example, SAR image formation has a natural blur associated with it, due to the finite aperture used in forming the image. We introduce a family of first-order multi-dimensional ordinary differential equations with discontinuous right-hand sides and demonstrate their applicability to segmenting both scalar-valued and vector-valued images, as well as images taking values on a circle. An equation belonging to this family is an inverse diffusion everywhere except at local extrema, where some stabilization is introduced. For this reason, we call these equations “stabilized inverse diffusion equations” (“SIDEs”). Existence and uniqueness of solutions, as well as stability, are proven for SIDEs. A SIDE in one spatial dimension may be interpreted as a limiting case of a semi-discretized Perona-Malik equation [49,50], which, in turn, was proposed in order to overcome certain shortcomings of Gaussian scale spaces [72]. These existing techniques are reviewed in a background chapter. SIDEs are then described and experimentally shown to suppress noise while sharpening edges present in the input image. Their application to the detection of abrupt changes in 1-D signals is also demonstrated. It is shown that a version of the SIDEs optimally solves certain change detection problems. Its relations to the Mumford-Shah functional [44] and to linear programming are discussed. Theoretical performance analysis is carried out, and a fast implementation of the algorithm is described.

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This thesis is dedicated to the memory of my
mother, Tamara B. Skomorovskaya (1935-1997).

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After spending eight years at MIT, all in the same group and in the same office, I have the dubious distinction of having been in the Stochastic Systems Group (SSG) longer than any current (and, I suspect, past) member except our leader Alan Willsky¹. I have seen many people go through the group: dozens of graduate students, six secretaries, numerous post-docs, research scientists, and visitors—sufficient to staff an Electrical Engineering department of a medium-size college, and still have enough administrative assistants left over to sustain “Murphy Brown” for at least a couple of seasons.

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¹Despite this fact, I probably hold another dubious record—namely, having the shortest dissertation. I think there have been people in the group whose theses had sentences longer than this whole document.

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Introduction

IN this chapter, we introduce the problem of segmentation and change detection addressed in this thesis, and describe the organization of the thesis.

■ 1.1 Problem Description and Motivation

To segment a 1-D or 2-D signal means, roughly speaking, to partition the domain of its definition into several regions in such a way that the signal is homogeneous within each region and changes abruptly between regions. The exact meaning of the word “homogeneous” depends on the application: most often it means smoothly varying or constant intensity (this case is addressed in Chapters 3 and 4), or uniform texture (Chapters 4 and 5).

The objective of this thesis is to develop and analyze robust and fast image segmentation algorithms. They must be robust to pervasive, large-amplitude noise, which cannot be well characterized in terms of probabilistic distributions. This is because the applications of interest are exemplified by synthetic aperture radar (SAR) segmentation in which speckle noise is a well-known problem that has defeated many algorithms. (A prototypical SAR log-magnitude image of two textural regions—forest and grass—is shown in Figure 1.1.) The methods must also be robust to blur, because many imaging techniques result in smoothed images. For example, SAR image formation has a natural blur associated with it, due to the finite aperture used in forming the image.

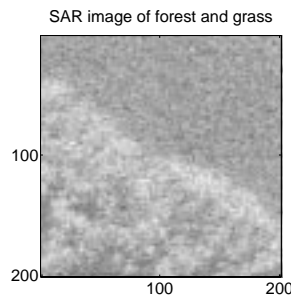


Figure 1.1. SAR image of trees and grass.

Image segmentation is closely related to restoration, that is, the problem of estimating an image based on its degraded observation. Indeed, the solution to one of these problems makes the other simpler: estimation is easier if the boundaries of homogeneous image regions are known, and vice versa, segmentation is easier once a good estimate of the image has been computed. It is therefore natural that many segmentation algorithms are related to restoration techniques, and in fact some methods combine the two, producing estimates of both the edge locations and image intensity [36, 44], as we will see in Chapter 2.

In describing any restoration or segmentation technique, the notion of *scale* is very important. Any such technique incorporates a scale parameter—either directly in the computation procedure, or implicitly as a part of the image model—which controls the smoothness of the estimate and/or sizes of the segmented regions. The precise definitions of scale, in several contexts, are given in Chapters 2 and 3; intuitively, changing the parameter from zero to infinity will produce a so-called *scale space*, i.e. a set of increasingly coarse versions of the input image. There are two approaches to generating a scale space: one starts with a probabilistic model, the other starts with a set of “common-sense” heuristics. The difference between the two is conceptual: they both may lead to the same algorithm [39, 44], producing the same scale space. In the former case, one would build a probabilistic model of images of interest [6, 32, 39] and proceed to derive an algorithm for computing the solution which is, in some probabilistic sense, optimal. For example, one could model images as piecewise constant functions with additive white Gaussian noise, and the edges (i.e. the boundaries separating the constant pieces of the function) as continuous curves whose total length is a random variable with a known distribution. Assigning larger probabilities to the occurrence of edges would correspond to larger scales in such a model, which will be illustrated in Chapter 4. Given a realization of this random field, the objective could be to compute the maximum likelihood estimates [66] of the edge locations. The main shortcoming of this approach is that a good model is unavailable in many applications, and that usually any realistic model yields a complicated objective functional to be optimized. Obtaining the optimal solution is therefore not computationally feasible, and one typically settles for a local maximum [6, 63]. An alternative to such probabilistic methods of generating scale spaces is to devise an algorithm using a heuristic description of images of interest. Stabilized Inverse Diffusion Equations (SIDEs), which are the main topic of this thesis, belong to this latter category.

SIDEs are motivated by the great recent interest in using evolutions specified by partial differential equations (PDE’s) as image processing procedures for tasks such as restoration and segmentation, among others [1, 12, 35, 46, 49, 50, 55–57, 72]. The basic paradigm behind SIDEs, borrowed from [1, 35, 49, 72], is to treat the input image as the initial data for a diffusion-like differential equation. The unknown in this equation is usually a function of three variables: two spatial variables (one for each image dimension) and the scale—which is also called *time* because of the similarity of such equations to evolution equations encountered in physics. In fact, one of the starting points of this

line of investigation was the observation [72] that smoothing an image with Gaussians of varying width is equivalent to solving the linear heat diffusion equation with the image as the initial condition. Specifically, the solution to the heat equation at time t is the convolution of its initial condition with a Gaussian of variance $2t$. Gaussian filtering has been used both to remove noise and as a pre-processor for edge detection procedures [9]. It has serious drawbacks, however: it displaces and removes important image features, such as edges, corners, and T-junctions. (An example of this behavior will be given in Chapter 2 (Figure 2.1).) The interpretation of Gaussian filtering as a linear diffusion led to the design of other, nonlinear, evolution equations, which better preserve these features [1, 46, 49, 55–57]. For example, one motivation for the work of Perona and Malik in [49, 50] is achieving both noise removal and edge enhancement through the use of an equation which in essence acts as an unstable inverse diffusion near edges and as a stable linear-heat-equation-like diffusion in homogeneous regions without edges.

The point of departure for the development of our SIDEs are the anisotropic diffusions introduced by Perona and Malik and described in the next chapter. In a sense that we will make both precise and conceptually clear, the evolutions that we introduce may be viewed as a conceptually limiting case of the Perona-Malik diffusions. These evolutions have discontinuous right-hand sides and act as inverse diffusions “almost everywhere” with stabilization resulting from the presence of the discontinuities in the right-hand side. As we will see, the scale space of such an equation is a family of segmentations of the original image, with larger values of the scale parameter t corresponding to segmentations at coarser resolutions.

Since “segmentation” may have different meanings in different contexts, we close this section by further clarifying which segmentation problems are addressed in this thesis and which are not. This also gives us an opportunity to mention four important application areas.

Automatic Target Recognition. Segmentation problems arise in many aspects of image processing for automatic target recognition. Some examples are the identification of tree-grass boundaries in synthetic aperture radar images [18] (an example given in the beginning of this section will be further treated in Chapter 3), the localization of hot targets in infrared radar [15], and the separation of foreground and background in laser radar (see [23] and references therein). Due to high rates of data acquisition, it is desirable for some of these problems that the algorithm be fast, in addition to being robust. As shown in Chapters 3 and 4, the algorithms presented in this thesis outperform existing segmentation algorithms in speed and/or robustness.

Segmentation of medical images. Given an image or a set of images resulting from a medical imaging procedure—such as ultrasound [13], magnetic resonance imaging [2, 64], tomography [6, 27], dermatoscopy [19, 60]—it is necessary to extract certain objects of interest, e. g. an internal organ, a tumor, or a boundary between

the gray matter and white matter. The main challenges of the segmentation problem depend on the object and on the imaging modality. For example, ultrasound imaging introduces both significant blurring and speckle noise [8, 22, 70], and so the corresponding segmentation algorithms must be robust to such degradations. Robustness of the algorithm introduced in this thesis is experimentally demonstrated in Chapters 3 and 4; Chapter 4 also contains its theoretical analysis.

Detection of abrupt changes in 1-D signals [3]. Application areas include analysis of electrocardiograms and seismic signals, vibration monitoring in mechanical structures, and quality control. Several synthetic 1-D examples are considered in Chapters 3 and 4.

Computer vision. In the computer vision literature, the term “segmentation” often refers to finding the contours of objects in natural images—i.e., photographic pictures of scenes which we are likely to see in our everyday life [16]. This is an important problem in low-level vision, because it has been universally accepted since [71] that segmenting the perceived scene plays an important role in human vision. However, noise and other types of degradation are usually not as significant here as in the medical and radar images; the main challenge is the variety of objects, shapes, and textures in a typical picture. This problem is therefore not directly addressed in the present thesis; applying the algorithms developed here to this problem is a topic for future research.

■ 1.2 Summary of Contributions and Thesis Organization

Chapter 2 is a review of several methods of image restoration and segmentation, each of which has important connections to the main contribution of this thesis, namely Stabilized Inverse Diffusion Equations (SIDEs). We mentioned in the previous section that SIDE evolutions produce nonlinear scale spaces, similarly to the equations in [1, 49]. What sets SIDEs apart from other frameworks is the form of their right-hand sides which results in improved performance. This is shown in Chapter 3, both through experiments confirming the SIDEs’ speed and robustness, and through proving a number of their useful properties, such as stability with respect to small changes in the input data. It is also explained how the SIDEs are related to several existing methods, such as Perona-Malik diffusions [49], shock filters [46], total variation minimization [6, 46, 58], the Geman-Reynolds functional [21], and region merging [43].

The main drawback of the methods which are based on heuristic descriptions of images of interest (rather than on probabilistic models) is that it is usually unclear how they perform on noisy images; experimentation is the most popular way of demonstrating robustness [5, 49, 56, 63]. This has been the case with diffusion-based methods: they are complicated nonlinear procedures, and therefore theoretical analysis of what happens when a random field is subjected to such a procedure is usually impossible. Unlike their predecessors, SIDEs turn out to be amenable to some probabilistic analysis, which

is carried out in Chapter 4. It is shown that a specific SIDE finds in $N \log N$ time the maximum likelihood solutions to certain binary classification problems. The likelihood function for one of these problems is essentially a 1-D version of the Mumford-Shah functional [44]. Thus, an interesting link is established between diffusion equations, Mumford and Shah’s variational formulation, and probabilistic models. The robustness of the SIDE is explained by showing that, in a certain special case, it is optimal with respect to an H_∞ -like criterion—which, roughly speaking, means that the SIDE achieves the minimum worst-case error. The performance is also analyzed by computing bounds on the probabilities of errors in edge location estimates. To summarize, the main contribution of Chapter 4 is establishing a connection between diffusion-based methods and maximum likelihood edge detection, as well as extensive performance analysis.

Chapter 5 extends SIDes to vector-valued images and images taking values on a circle. We argue that most of the properties derived in Chapter 3 carry over. These results are applicable to color segmentation, where the image value at every pixel is a three-vector of red, green, and blue values. We also apply our algorithm to texture segmentation, in which the vector image to be processed is formed by extracting features from the raw texture image, as well as to segmenting orientation images.

Possible directions of future research are proposed in Chapter 6.