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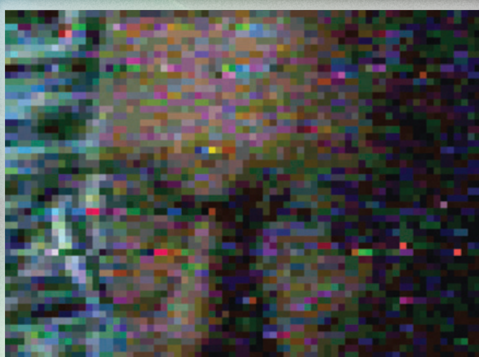
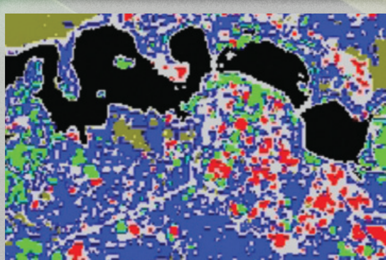
Image Restoration

Fundamentals and Advances





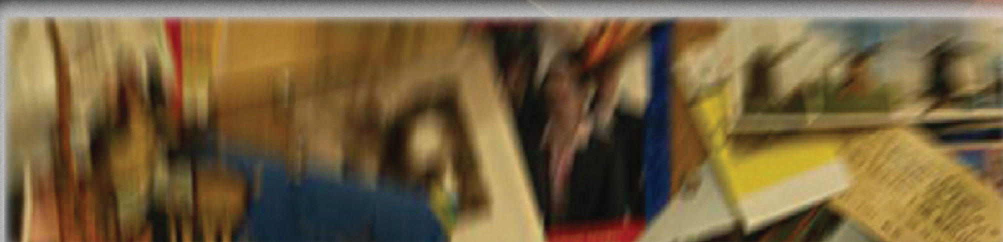


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Image Restoration

Fundamentals and Advances

Digital Imaging and Computer Vision Series

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Preface

Image restoration refers to the recovery of an unknown *true* image from its degraded measurement. The degradation may occur during image formation, transmission, and storage; and it may be in a number of forms, including additive noise, space invariant or variant blur, aliasing, and compression artifact. With the advances in imaging, computing, and communication technologies over the past decades, image restoration has evolved into a field at the intersection of image processing, computer vision, and computational imaging. Its derivatives include image denoising (also known as noise removal/reduction), image deblurring/deconvolution (including optical/motion deblurring), image inpainting (also called image completion), image interpolation (including super resolution and color demosaicking), image reconstruction (including computed tomography and compressed sensing), and image deblocking/deringing (also referred to as compression artifact removal). Apparently, image restoration techniques have become a fundamental tool to support low-level vision tasks arising from various scientific and engineering fields.

As two mid-career researchers in the field of image processing, it occurred to us that many reference books devoted to image restoration were published over twenty years ago, and more recent works on image restoration have been scattered around in the literature. There is a significant gap between what we can learn from standard image processing textbooks and what the current state-of-the-art is in image restoration. This book was conceived to fill in this gap, at least to some extent. We understand there are already monographs on similar topics such as sparse representation and super resolution. Therefore, we have chosen to edit a book featured by (1) focusing on algorithms rather than theories or applications, and (2) striking a good balance between fundamentals and advances.

Image restoration algorithms are important not only because they serve a wide range of real-world applications (e.g., astronomical imaging, photo editing, medical imaging, and so on), but also due to their intrinsic connection with underlying image models/representations. Breakthroughs in algorithm development often bring novel insights into fundamental properties of image sources—for example, Shapiro's [36] embedded zerotree wavelet (EZW) coding reshaped our thinking about the importance of modeling location uncertainty for images, Portilla et al.'s [23] Gaussian scalar mixture (GSM) denoising polished our understanding about variance estimation for wavelet coefficients, and Dabov et al.'s [27] block-matching 3D (BM3D) denoising challenged the conventional wisdom of modeling image signals from a local view. Meantime, the reproducibility of published works on algorithms makes it easier for other researchers to build upon each other's work, which often benefits the vitality of the technical community as a whole. For this reason, we have attempted to make this book as experimentally reproducible as possible. The source codes accompanying many chapters of this book can be downloaded from its homepage: http://www.csee.wvu.edu/~xinl/IRFA.html.

This book is neither a textbook nor a monograph, but it attempts to connect with a wider range of audience. For young minds entering the field of image processing, we recommend the first two chapters as a starting point. For image processing veterans, any individual chapter and its associated bibliography can serve as a quick reference. As with any edited book, we do acknowledge that our contributors have varying styles of writing and reasoning, but hopefully they also reflect the intellectual understanding of similar topics from diverse perspectives. Please feel free to challenge the claims and models contained in this book and use the released research codes to jump-start your own research.

To facilitate readers, we have organized the chapters as follows. The first three chapters (Chapters 1–3) serve as introductory chapters presenting the fundamentals of image denoising and blurring. Chapter 1 provides an overview of the image denoising field with an intuitive development of ideas and methods; Chapter 2 provides comprehensive coverage of image deconvolution methods, focusing on linear space-invariant systems; and Chapter 3 goes beyond linear space-invariant systems and discusses blind image restoration under space-varying blur. Chapters 4 through 6 concentrate on two important ideas that have been developed recently: nonlocality and sparsity. Chapter 4 reviews the image restoration methods that use the nonlocality idea; Chapter 5 focuses on the idea of sparsity and its extension from local to nonlocal representations; and Chapter 6 focuses on a specific prior driven by the sparsity idea. Chapters 7 and 8 are on super resolution image restoration. Chapter 7 briefly surveys the super resolution methods and presents a learning-based method; Chapter 8 demonstrates super resolution restoration in multispectral imaging with a new Bayesian approach. The final three chapters (Chapters 9–11) extend the treatment of the topic further. Chapter 9 deals with restoration of color images; Chapter 10 exemplifies the importance and variety of image formation modeling with the restoration of document images; and finally, Chapter 11 demonstrates that hybrid imaging systems may bring new possibilities in image restoration.

Last but not least, we want to thank CRC Press/Taylor & Francis for endorsing this book project. We are also grateful to all our colleagues and their collaborators for contributing their work to this book.

BAHADIR K. GUNTURK
XIN LI

Editors

Bahadir K. Gunturk

Bahadir K. Gunturk received his B.S. degree from Bilkent University, Turkey, and his Ph.D. degree from the Georgia Institute of Technology in 1999 and 2003, respectively, both in electrical engineering. Since 2003, he has been with the Department of Electrical and Computer Engineering at Louisiana State University, where he is an associate professor. His research interests are in image processing and computer vision. Dr. Gunturk was a visiting scholar at the Air Force Research Lab in Dayton, Ohio, and at Columbia University in New York City. He is the recipient of the Outstanding Research Award at the Center of Signal and Image Processing at Georgia Tech in 2001, the Air Force Summer Faculty Fellowship Program (SFFP) Award in 2011 and 2012, and named as a Flagship Faculty at Louisiana State University in 2009.

Xin Li

Xin Li received his B.S. degree with highest honors in electronic engineering and information science from the University of Science and Technology of China, Hefei, in 1996, and his Ph.D. degree in electrical engineering from Princeton University, Princeton, New Jersey, in 2000. He was a member of the technical staff with Sharp Laboratories of America, Camas, Washington, from August 2000 to December 2002. Since January 2003, he has been a faculty member in the Lane Department of Computer Science and Electrical Engineering at West Virginia University. He is currently a tenured associate professor at West Virginia University. His research interests include image/video coding and processing. Dr. Li received a Best Student Paper Award at the Visual Communications and Image Processing Conference in 2001; a runner-up prize of Best Student Paper Award at the IEEE Asilomar Conference on Signals, Systems and Computers in 2006; and a Best Paper Award at the Visual Communications and Image Processing Conference in 2010.

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Chapter 1

Image Denoising: Past, Present, and Future

XIN LI
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1.1 Introduction

Image denoising refers to the restoration of an image contaminated by additive white Gaussian noise (AWGN). Just like AWGN has served as the simplest situation in modeling channel degradation in digital communication, image denoising represents the simplest task in image restoration and therefore has been extensively studied by several technical communities. It should be noted that the study of the more general problem of signal denoising dates back to at least Norbert Wiener in the 1940s. The celebrated Wiener filter provides the optimal solution to the recovery of Gaussian signals contaminated by AWGN. The derivation of Wiener filtering, based on the so-called orthogonality principle, represents an elegant solution and the only known situation where constraining to linear solutions does not render any sacrifice on the performance. Therefore, at least in theory the problem of image denoising can be solved if we can reduce it to a problem that satisfies the assumptions behind the Wiener filtering theory. The challenge of image denoising ultimately boils down to the art of modeling images.

As George Box once said, "All models are wrong; but some are useful." Under the context of image denoising, the usefulness of models heavily depends on the class of images of interest. The class of photographic images (a.k.a. natural images) are likely to be the most studied in the literature of image coding and denoising. Even though denoising research has been co-evolving with coding research, image models developed for one do not lend themselves directly to the other. The bit rate constraint and accessibility to the original image define the boundary of image coding differently from that of image denoising. Taking an analogy, image denoising behaves more like a source decoding instead of an encoding one — for example, the role played by the redundancy of signal representation is diametrically different in denoising and coding scenarios. An overcomplete representation — often undesirable and deemed "wrong" in image coding — turns out to be a lot more "useful" in image denoising.

Image models underlying all existing image denoising algorithms, no matter explicitly or implicitly stated, can be classified into two categories: deterministic and statistical. Deterministic models include those studied in functional analysis (e.g., Sobolov and Besov-space functions) and partial differential equations (PDE); statistical models include Markov Random Field (MRF), conditional random field (CRF), Gaussian scalar mixture (GSM) and so on. Despite the apparent difference at the surface, deterministic and statistical models have intrinsic connections (e.g., the equivalence between wavelet shrinkage and total variation diffusion). The subtle difference between deterministic and statistical models is highlighted by Von Neumann's famous quote on randomness, "Anyone who considers arithmetical methods of producing random digits is, of course, in a state of sin." Indeed, a theoretically optimal denoising algorithm (though of little practical value) is to recognize the deterministic procedure of simulating AWGN on digital computers. By reverse-engineering the noise simulation process, one can always perfectly remove it and reach zero errors!

The above reasoning raises another issue that has not received as much attention from the image processing community as image modeling — mathematical modeling of *noise*. Even though computer simulation of AWGN has become the gold standard of image denoising, there is little justification that the contaminating noise in real-world images satisfies the AWGN assumption. In fact, noise sources in the physical world are often non-additive (e.g., multiplicative) and non-Gaussian (e.g., Poisson). Nevertheless, algorithms developed for AWGN can often be twisted to match other types of noise in more general restoration tasks (e.g., involving motion or optical blur). As regularization strategies aim at incorporating a priori knowledge about either the image or noise source into the solution algorithms, we expect that mathematical modeling of the noise source is going to play a more important role in the recovery of images contaminated by real-world noise in the future.

The rest of this chapter is organized as follows. We first provide a historical review of image denoising in Section 1.2, especially its revival in the past decade. Due to space limitation, our review is concise and attempts to complement existing ones (e.g., [1]). Then we will work with a pair of popular test images — $lena$ and $barbara$ — and walk through a series of representative denoising algorithms in Sections 1.3 through 1.5. These two images — one abundant with regular edges and the other regular textures — serve to illustrate the effectiveness of incorporating complementary priori knowledge such as local smoothness and nonlocal similarity. Fully reproducible experimental results will be reported to help young minds entering the field get acquainted with the current state-of-the-art algorithms yet maintain a healthy skepticism toward authoritative models. We make some concluding remarks and discuss future research directions in Section 1.6.

1.2 Historical Review of Image Denoising

Signal denoising dates back to the pioneering work of Wiener and Kolmogorov in the 1940s. The Wiener–Kolmogorov filtering theory was the first rigorous result of designing statistically optimal filters for the class of stationary Gaussian processes. Its long-lasting impact has been witnessed in the past six decades, as we will elaborate next. In the 1950s, Peter Swerling — one of the most influential radar theoreticians — made significant contributions to the optimal estimation orbits and trajectories of satellites and missiles at the RAND Corporation, while the Soviet mathematician Ruslan Stratonovich solved the problem of optimal nonlinear filtering based on his theory of conditional Markov processes in 1959–1960. The next milestone was marked by Rudolf Kalman's adaptive filtering, which extends the Wiener–Kolmogorov theory from a stationary to a nonstationary process. The capability of tracking changes of local statistics by Kalman filtering has led to a wide range of applications in space and military technology.

In the 1970s, two-dimensional signals such as digital imagery started to attract more attention. To the best of our knowledge, image denoising was first studied as a problem of statistical image enhancement by Nasser Nahi and Ali Habibi of the University of Southern California in [2, 3]. Test images used in their study are apparently oversimplified from today's standard, but given the limited computing power and memory resources, those early works were still visionary and it is not surprising that the USC image database is likely the most popular since then. By contrast, theoretic extension of Kalman filtering from 1D to 2D (e.g., [4]) had received relatively less attention partially due to the practical limitations at that time. The full potential of 2D Kalman filtering had to wait until advances in computing technology caught up in 1980s to make its implementation more feasible. The highly cited work of Jong-Sen Lee [5] on image enhancement/noise filtering by local statistics is a standard implementation of 2D Kalman filtering — namely, through the estimation of local mean/variance from a centralized window (the origin of image patches). Nevertheless, [5] was the first algorithmic achievement of applying local Wiener filtering to image denoising, and its conceptual simplicity (in contrast to mathematically more demanding state-space formulation in 2D Kalman filtering) greatly contributed to its impact on engineering applications.

The history of image denoising took an interesting turn in the late 1980s as wavelet theory was established independently by applied mathematicians, computer scientists, and electrical engineers [54]. Wavelet transforms rapidly became the favorite tool for various image processing tasks from compression to denoising. Simple ideas such as wavelet shrinkage/thresholding [7] became the new fashion; while orthodox approaches of applying local Wiener filtering in the wavelet domain (e.g., [8–12]) found themselves in an awkward position — they had to prove they work better than ad-hoc shrinkage techniques (e.g., [7, 13–16]). Not to mention that some more sophisticated models in the wavelet domain (e.g., hidden Markov model [17, 18] and Markov random field [19–21]) often achieve modest performance gain over local Wiener filtering while at the price of prohibitive complexity. The rapid growth of wavelet-based image denoising algorithms from the late 1990s to early 2000s might be the consequence of a bandwagon effect (unfortunately this author was also caught during his Ph.D. study). Hindsight reveals that what is more important than the invention of a tool (e.g., wavelet transform [22]) are the novel insights it could bear to a fundamental understanding of the problem. Good localization property of wavelet bases does indicate a good fit with the strategy of local Wiener filtering (even its more sophisticated extension such as Gaussian scalar mixture [23]), but what makes it a success is often what blinds its vision from seeing further.

At the turn of the century, two influential works related to texture synthesis appeared: Efros and Leung's nonparametric resampling in the spatial domain [24] and Portilla and Simoncelli's parametric models in the wavelet domain [25]. Experimental results clearly show that the nonparametric approach is more favored, which for the first time suggests that clustering (e.g., nearest-neighbor in the patch space) might play a more fundamental role than transform. The ripple of nonparametric resampling initiated by the community of texture synthesis took five years to reach the community of image denoising. In the summer of 2005, when I was attending the Computer Vision and Pattern Recognition (CVPR) conference for the first time, I was intrigued by a talk on nonlocal means denoising [17], which received the Best Paper Award Honorable Mention. While I was reasoning with myself about this new idea of nonlocal and the existing fashion of transform, I accidentally ran into a conference version of the now-celebrated BM3D denoising that was first published at a SPIE conference in the winter of 2005–2006 [27]. The reported experimental results were so impressive that I immediately recognized the potential impact of nonlocal sparsity. The rest of the story is easy to tell; since the publication of the journal version of BM3D [18], there has been increasing interest in not only image denoising (please refer to a plot of citation record in Figure 1.1), but also other restoration tasks where nonlocal sparse representations could benefit (please refer to the chapter on sparse representation in this book).

Next, we will break the history of image denoising into three episodes and re-run them in fast-forward mode. Due to space limitation, we will only review the most representative

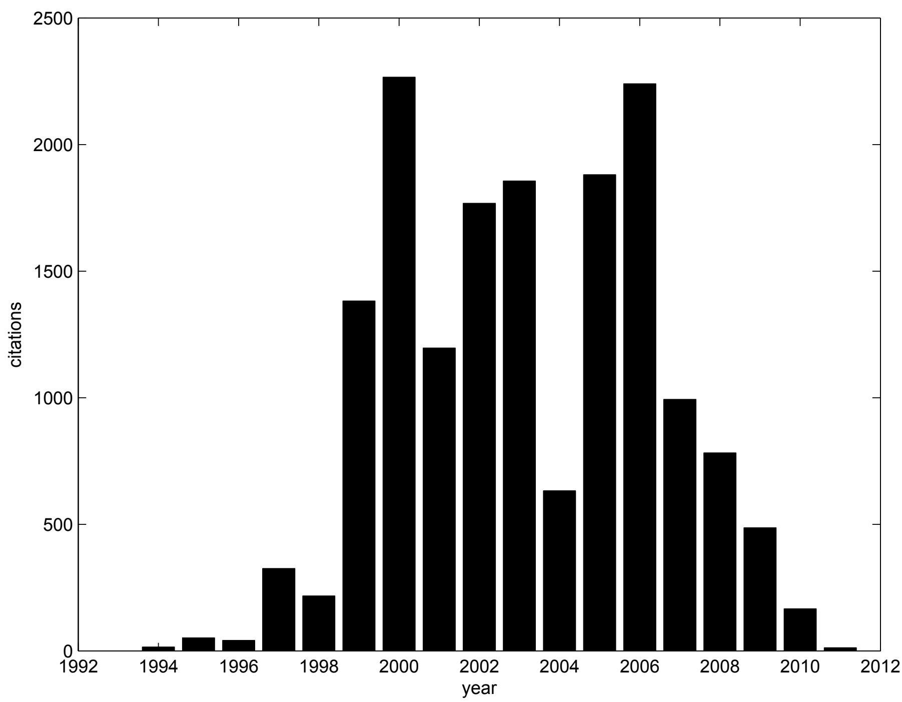

Figure 1.1 The evolutionary history of image denoising as measured by the total number of citations each year (as of May 2011 and based on *Publish or Perish*).

algorithms for each time period and report fully reproducible results for a pair of test images ($lena$ and $barbara$) and noise levels ($\sigma_w = 15, 50$). These two images from the University of Southern California (USC) data set — despite being less perfect — do contain the mixture of edges and textures and have been widely used in the literature on image denoising. The general message we deliver through these experiments is: as our understanding about image signals improves, we can achieve better denoising results, though at the price of increased computational complexity. Some idea might be rediscovered years later purely for the reason of waiting for computing technology to catch up. And not all bright ideas or new theories will pay off when applied to experimental validation.

1.3 First Episode: Local Wiener Filtering

What makes an image different from Gaussian noise? There are many possible lines of intuitive reasoning: any linear combination of two Gaussian noise processes is still Gaussian while the average of two photographic images does not produce a new legitimate one; random permutation of Gaussian noise does not change its statistical property (still iid Gaussian) while the random permutation of pixels usually destroys the image content for sure; AWGN is translation invariant or strongly stationary while the local statistics within an image often vary from region to region. There are two generic ways of turning intuitive reasoning into deeper understanding: mentally reproducible (i.e., through the use of mathematical models) and experimentally reproducible (i.e., through the design of computer algorithms). The boundary between these two lines is often vague: any mathematical model must be verified by experiments and the design of any image denoising algorithm inevitably involves some kind of mathematical model — explicitly or implicitly. We have opted to emphasize the line of experimentally reproducible attack here but the connections between an exemplar denoising algorithm and various theories/models will also be analyzed at least, at a conceptual level.

We first study the local Wiener filtering technique developed in [29]. Despite being published over thirty years ago, the basic idea behind the local estimation of mean and variance is still relevant and has been reused extensively in the literature of wavelet-based image denoising. Therefore, we deem it an appropriate baseline scheme to start with. As the formula of classical Wiener filtering suggests, an optimal filter for a Gaussian random variable contaminated by AWGN $y = x + w$ is given by

$$\hat{x} = \frac{\sigma_x^2}{\sigma_x^2 + \sigma_w^2} y, \tag{1.1}$$

where σ_x^2, σ_w^2 denotes the variance of signal and noise, respectively. In the presence of n noisy samples $y_1, ..., y_n$, a maximum-likelihood estimation of signal variance can be obtained by

$$\hat{\sigma}_x^2 = max[0, \frac{1}{n} \sum_{k=1}^{n} (y_k - \hat{m}_x)^2 - \sigma_w^2], \tag{1.2}$$

where $\hat{m}_x = \hat{m}_y = \frac{1}{n} \sum_{k=1}^{n} y_k$ is the mean of signal (under the zero-mean assumption of AWGN). Note that the optimality of Equation (1.1) is conditioned on the iid assumption

$MSE = 55.10$ $MSE = 219.33$ $MSE = 379.55$

$MSE = 234.71$ $MSE = 402.26$ $MSE = 575.22$

Figure 1.2 Comparison of denoised $lena$ (top) and $barbara$ (bottom) images at $\sigma_w = 15$ by local Wiener filtering (implemented by MATLAB® function $wiener2$) with different window sizes: left-$[3, 3]$, middle-$[11, 11]$, right-$[19, 19]$.

about $x_1, ..., x_n$. Because such an assumption is seldom satisfied by real-world images, the design of image denoising algorithms is intrinsically related to the modeling of image models, that is, to relax the strict assumption about $x_1, ..., x_n$ such that the Wiener filtering solution can better match the situation of real-world image data.

The key motivation behind local Wiener filtering is to recursively apply Equation (1.2) on a sliding-window basis. Therefore, the only user-defined parameter is the size of the local window $[T_1, T_2]$, decreasing/increasing the window size would reflect the assumption that local statistics change faster/slower from region to region. The algorithm of local Wiener filtering has been well documented in standard textbooks (e.g., [30]) and implemented by the $wiener2$ function in the MATLAB® image processing toolbox. Figures 1.2 and 1.3 include the comparison of denoised images at two different noise levels by local Wiener filtering with varying window sizes. It can be observed that (1) as the window size increases (i.e., the stationarity assumption underlying the image model goes from local to global), noise suppression is more effective but the denoised images appear more blurred; (2) as the noise level increases, larger window size is desirable for the purpose of obtaining a more accurate estimation of signal variance; (3) between $lena$ and $barbara$, the latter is a

Figure 1.3 Comparison of denoised $lena$ (top) and $barbara$ (bottom) images at $\sigma_w = 50$ by local Wiener filtering (implemented by MATLAB function $wiener2$) with different window sizes: left-$[3, 3]$, middle-$[11, 11]$, right-$[19, 19]$.

worse match for local Wiener filtering because its abundant textures tend to overshoot the estimated signal variance.

Just like the same physical law could admit seemingly different but deeply equivalent mathematical formulations, the intuitive idea of images being locally smooth can be characterized by different mathematical theories/tools. For example, the concept of local signal variance in Wiener filtering is connected with the smoothness of analytical functions in Sobolev space [31] and the definition of stabilizing operator in Tikhonov regularization [32]. Even though their rigorous connections in the sense of mentally reproducibility have remained elusive, we argue that what is more important and fundamental than tools themselves is what novel insights a new tool can bring about. Under the context of image denoising, a novel insight — if we put ourselves in the situation of the late 1980s — would be the characterization of local changes or transient events [5]. In other words, how to preserve singularities (edges, lines, corners, etc.) in photographic images would reshape our understanding of local Wiener filtering and its related tools.

1.4 Second Episode: Understanding Transient Events

The importance of preserving singularities such as edges and textures has been long recognized but it is the construction of wavelet theory in later 1980s that offers a principled solution. Intuitively, both singularities and noise involve changes but what distinguishes singularities from noise? Wavelet transforms are change-of-coordinates; they are carefully designed in such a way that signals of our interest (singularities) would be characterized by so-called heavy tails in the transform domain. The whole argument has a statistical flavor; it is possible that AWGN could produce some significant coefficient in the wavelet space; but the probability of such a rare event is so small that a conceptually simple strategy such as nonlinear thresholding is often sufficient to separate signals from noise.

1.4.1 Local Wiener Filtering in the Wavelet Space

In a nutshell, wavelet-based image denoising is nothing but the coupling of local Wiener filtering with wavelet transform. However, there are several technical subtleties that could guide us toward a deeper understanding of wavelet-based image denoising. First, the connection between nonlinear thresholding and local Wiener filtering, as pointed out in [8], suggests that wavelet thresholding can be viewed as a simplified version of Wiener filtering with reduced computational complexity. So it is often less fruitful to refine the strategy of thresholding than to improve the statistical model underlying signal variance estimation. Second, the redundancy of signal representation becomes relevant because it is desirable to have the estimator of signal variance to be invariant to the choice of basis functions. We argue that such a line of reasoning makes it easier to understand the idea behind so-called translation-invariant denoising [34]; the cycle-spin technique should be cast into the same category as the sliding windowing technique used in local Wiener filtering. Third, maximum-likelihood (ML) estimation of signal variance in Equation 1.2 represents an empirical Bayesian approach; there are plenty of tools developed by the statistical community to improve upon it. For example, there exists an iterative expectation-maximization (EM) based approach toward ML estimation of signal variance [35] and a fully Bayesian approach where signal variance is modeled by a hidden variable (e.g., in Gaussian scalar mixture [23]).

To illustrate how those ideas work, we continue our experimental studies as follows. Three wavelet-based image denoising algorithms are compared in this new experiment: TI-denoising [34] available from Wavelab tool box, local Wiener filtering[1] in the mrdwt domain (the implementation of mrdwt is taken from Rice Wavelet toolbox), and the famous BLS-GSM algorithm. Figures 1.4 and 1.5 include the subjective quality comparison of denoised images along with their objective measures in terms of MSE. It can be observed that (1) local Wiener filtering often offers a more principled approach than ad-hoc thresholding (to say the least, the theoretic formula for choosing the optimal threshold does not always match our empirical findings with practical data); (2) GSM offers further improvement over empirical Bayesian estimation of signal variance. The gain for $barbara$ is more

[1]In our released implementation, we have adopted an iterative ML estimation of signal variance as presented in [35] in contrast to the noniterative solution of Equation (1.2).

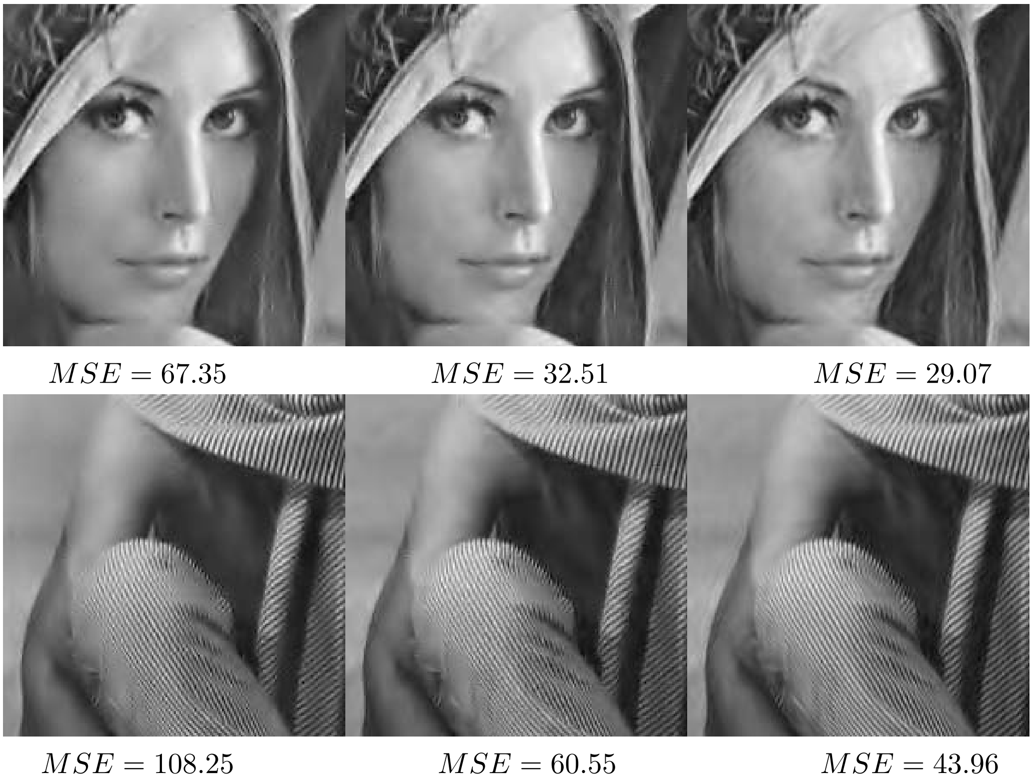

Figure 1.4 Comparison of denoised $lena$ (top) and $barbara$ (bottom) images at $\sigma_w = 15$ by three wavelet-based denoising algorithms: left - TI thresholding [34] (from Wavelab8.50), middle - local Wiener filtering in mrdwt domain [10] (from Rice Wavelet toolbox), right - BLS-GSM denoising [23].

significant than that for $lena$, which suggests that texture regions are where signal variance estimation falls apart in local Wiener filtering (we will revisit this issue in Section 1.5).

1.4.2 Wavelet vs. DCT Denoising

For a long time, there was debate about wavelet transform (as adopted by JPEG2000) and DCT (as adopted by JPEG) within the community of image coding. Despite the popularity and impact of wavelet-based image coders (e.g., EZW [32], SPIHT [37], and EBCOT [38]), their success seems to attribute more to the statistical modeling of wavelet coefficients than the wavelet transform itself. A comparative study [39] has clearly shown that the embedding coding strategy could also significantly boost DCT-based image coders. In fact, the choice between wavelet transform and DCT is also relevant to the task of image denoising. To the best of my knowledge, a comparative study between wavelet-based and DCT-based image denoising has not been undertaken in the open literature. Therefore, it seems a proper contribution for this review chapter to experimentally conduct such a comparison, which we hope will shed some insights into our understanding. As we elaborate next, the choice

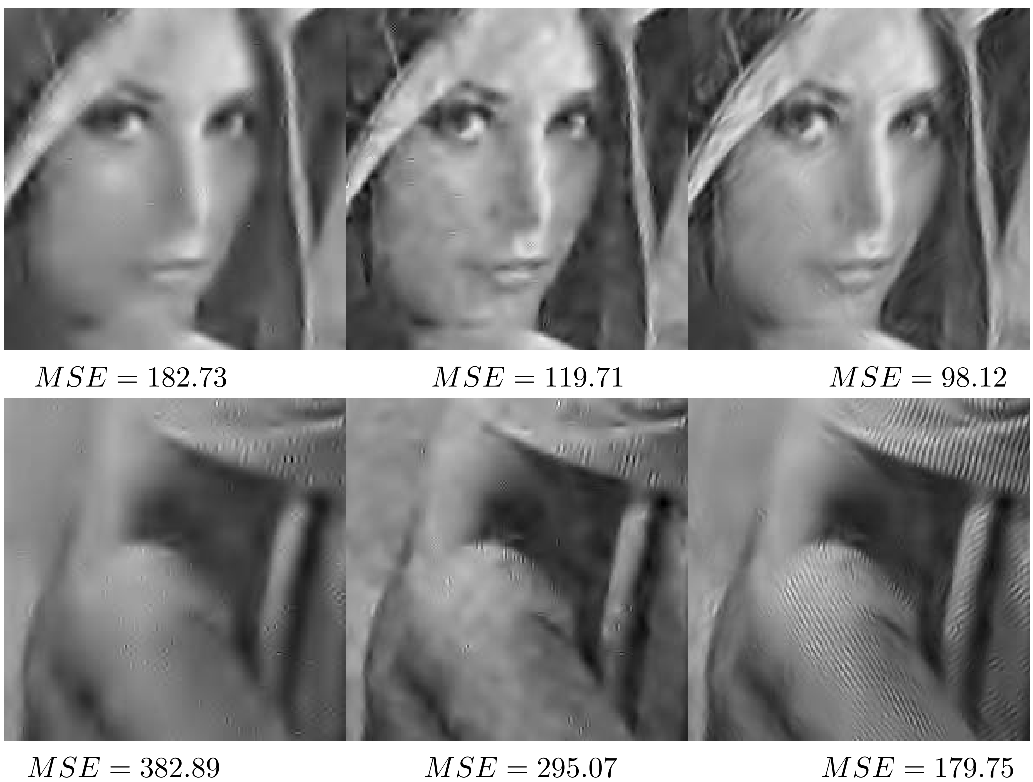

Figure 1.5 Comparison of denoised $lena$ (top) and $barbara$ (bottom) images at $\sigma_w = 50$ by three wavelet-based denoising algorithms: left - TI thresholding [34] (from Wavelab8.50), middle - local Wiener filtering in mrdwt domain [10] (from Rice Wavelet toolbox), right - BLS-GSM denoising [23].

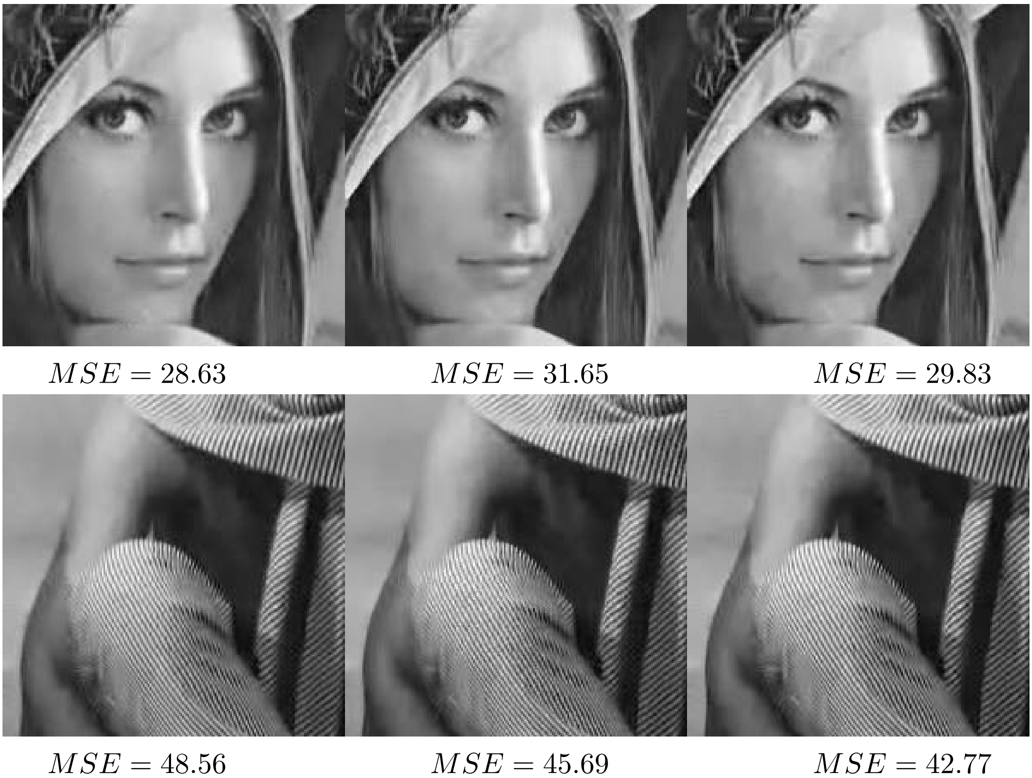

Figure 1.6 Comparison of denoised $lena$ (top) and $barbara$ (bottom) images at $\sigma_w = 15$ by three dictionary-based denoising algorithms: left - overcomplete DCT-based [41] (from KSVD toolbox), middle - Shape-Adaptive DCT [78] (from SA-DCT toolbox), right - weighted overcomplete-DCT denoising [42].

of transform or a fixed dictionary is secondary to the learning of dictionary and more fundamental issues related to the statistical modeling of photographic images such as locality.

We have tested three exemplar DCT-based denoising algorithms: (1) overcomplete-DCT denoising from KSVD toolbox [41]; (2) shape-adaptive DCT denoising [78]; (3) weighted overcomplete-DCT denoising [42]. Figures 1.6 and 1.7 include the comparison of denoising results for three DCT-based denoising techniques. Comparing them against Figures 1.4 and 1.5, we can observe that the best of DCT-based is indeed highly comparable to the best of wavelet based. Probably it is fair to say that DCT-based does not fall behind wavelet-based on $barbara$, an image with abundant textures (note that a similar observation was also made for the image coding task in [39]). Meanwhile, within the category of DCT-based denoising, we can see that sophisticated strategies such as shape adaptation [78] and weighed estimation [42] have their own merits but the gain is often modest.

In addition to DCT, we want to mention at least two other classes of attack on image denoising: geometric wavelets (e.g., curvelet [43] and contourlet [37]) and diffusion-based (e.g., total-variation diffusion [1, 46] and nonlinear diffusion [89]). Geometric wavelets have been shown to be particularly effective for a certain class of images such as finger-

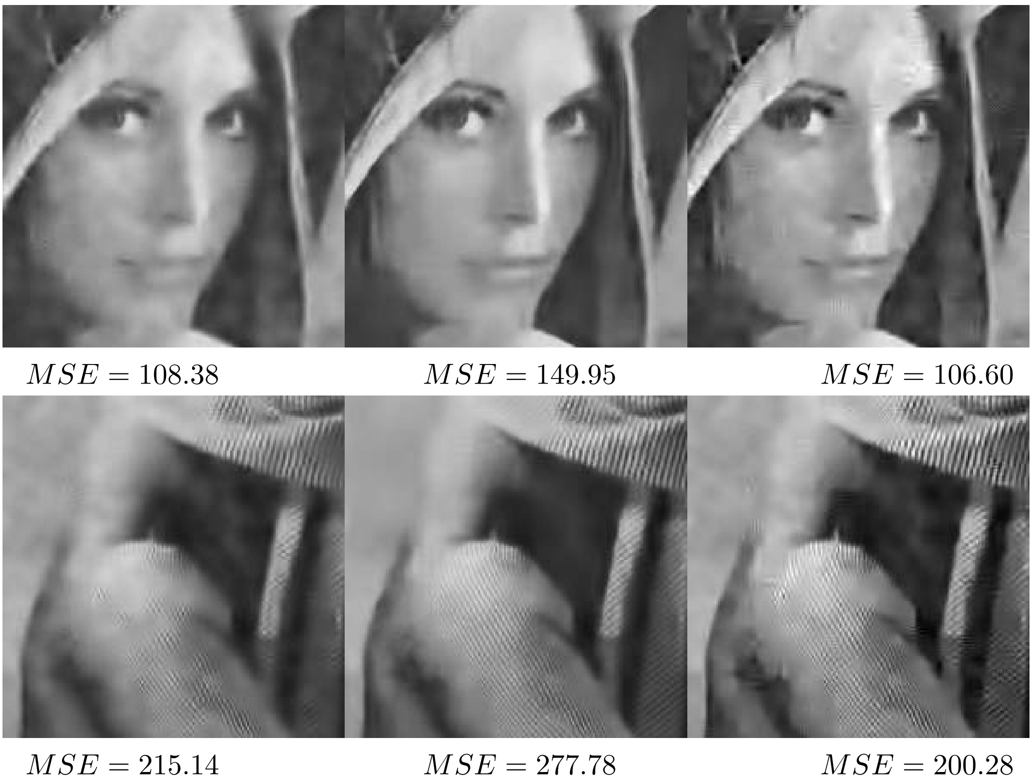

Figure 1.7 Comparison of denoised $lena$ (top) and $barbara$ (bottom) images at $\sigma_w = 50$ by three dictionary-based denoising algorithms: left - overcomplete DCT-based [41] (from KSVD toolbox), middle - Shape-Adaptive DCT [78] (from SA-DCT toolbox), right - weighted overcomplete-DCT denoising [42].

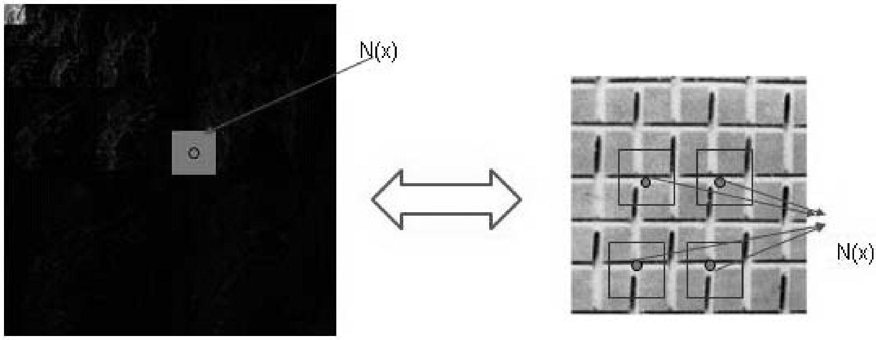

Figure 1.8 Local versus nonlocal neighborhood of a pixel x due to the relativity of defining $N(x)$.

prints with abundant ridge patterns, and diffusion-based models are often a good match with images containing piecewise constant content (e.g., cartoons). However, their overall performance on generic photographic images has not shown convincing improvement over wavelet or DCT-based approaches. It has also been shown that total-variation diffusion is mathematically equivalent to wavelet shrinkage with the simplest Haar filters [48]. Therefore we argue that those more sophisticated technical tools — nevertheless useful — fail to deliver new insights into the modeling of photographic images. What is more fundamental than discovering or polishing a tool is to gain a novel insight; can we think outside the box of transform-based image models?

1.5 Third Generation: Understanding Nonlocal Similarity

Second-generation image models based on wavelet transform or DCT attempt to characterize the a priori knowledge about photographic images by their local smoothness. For modeling transient events or singularities, such a local point of view is indeed appropriate. However, it is important to recognize that local variation and global invariance are two sides of the same coin. To define any change, we must first articulate the frame of reference for measuring such a change. For a pixel of interest within an image, it is often a default to speak of the change with respect to its local neighborhood but that does not imply that spatially adjacent pixels are the only possible frame of reference. For example, a texture image is often decomposed of self-repeating patterns originating from the joint interaction between local reaction and global diffusion [49]. Even for the class of regular edge structures, their geometric constraint implies the relativity of defining local variations — that is, the intensity field is homogeneous along the edge orientation.

It is more enlightening to understand the breakdown of locality assumption from a Wiener filtering perspective. The fundamental assumption underlying Equations (1.1) and (1.2) is that $\{y_1, ..., y_n\}$ belong to the same class (or associated with the same uncorrupted x). The locality principle assumes that $N(x) = \{y_1, ..., y_n\}$ are spatially adjacent pixels of x, no matter if it is in the pixel (first generation) or transform (second generation) domain. By contrast, self-repeating patterns in a texture image often dictate that $N(x)$ include spatially distant pixels (nonlocal neighbors) as shown in Figure 1.8. Such a seemingly simple observation has deep implications for the way we understand image signals, that is, image denoising is intrinsically connected with other higher-level vision tasks, including segmentation or even recognition. The connection between regression/denoising and classification/clustering offers novel insights beyond the reach of conventional image models in the Hilbert space (e.g., wavelet-based and DCT-based).

The idea of using data clustering techniques to solve the denoising problem has gained increased attention in the past five years. One of the earliest nonlocal denoising algorithms — nonlocal means (NLM) denoising [17, 50] — was largely motivated by the effectiveness of nonparametric sampling for texture synthesis [13] and adopted a weighted filtering strategy similar to spectral clustering [95]. It has inspired a flurry of patch-based nonlocal denoising algorithms (e.g., [52–54] and Total-Least-Square denoising [55]). Another pioneering work is KSVD denoising [41]; it generalizes the kmeans clustering algorithm and adaptive PCA denoising [56] by making a connection with matching pursuit-based sparsity optimization [57]. Various follow-up work includes K-LLD [43], learned simultaneous sparse coding (LSSC) [21], and stochastic approximation [60]. The breakthrough made by Finnish researchers — namely, BM3D denoising [18] — was based on a variation of k-Nearest-Neighbor clustering and a two-stage simplification of the EM-based estimation of signal variance as described in Equation (1.2). Despite the conceptual simplicity of BM3D, its outstanding performance (especially in terms of the trade-off between computational complexity and visual quality) has inspired renewed interest in the problem of image denoising (e.g., exemplar-based EM denoising [61], LPG-PCA denoising [62,67]). According to Google Scholar, [18] was the most often cited paper published by *IEEE Transactions on Image Processing* in 2007.

In our experimental study, we selected three exemplar nonlocal denoising algorithms whose implementations appear most robust and efficient: KSVD [41], nonlocal extension of MRF [64], and BM3D [18]. Figures 1.9 and 1.10 include the comparison of both subjective and objective quality comparisons for the two test images with low and high noise contaminations (all results are based on the authors' original source codes release without further parameter tuning). It can be observed that BM3D still outperforms others in all test scenarios and have also been confirmed by other experimental studies such as [64]. When compared with their local counterparts, we can see that nonlocal denoising algorithms can achieve at least comparable and often smaller MSE results.

As the field advances rapidly, one cannot help wondering: Is there any order in the jungle of nonlocal image denoising? We feel that the following two points are important, especially to those young minds entering the field. First, some clustering is more appropriate for denoising than others, if we extrapolate George Box's quoted above, "all clustering tools are wrong; some are useful." The usefulness of any data clustering technique depends on the task it serves. For image denoising, our experience suggests that outliers often have a negative impact on the sparsity of a signal representation and therefore it is desirable to use a clustering tool with minimum risk of outlier (e.g., kNN is preferred over kmeans). We suggest that denoising might be used as an evaluation tool for benchmarking clustering techniques; that is, an optimized clustering result should produce the most accurate estimation of signal variance and therefore the best denoising result. Second, the gap be-

Figure 1.9 Comparison of denoised $lena$ (top) and $barbara$ (bottom) images at $\sigma_w = 15$ by three nonlocal denoising algorithms: left - KSVD denoising [41] (from KSVD toolbox), middle - nonlocal regularization with GSM [64] (from NLR-GSM toolbox), right - BM3D denoising [18] (from BM3D toolbox).

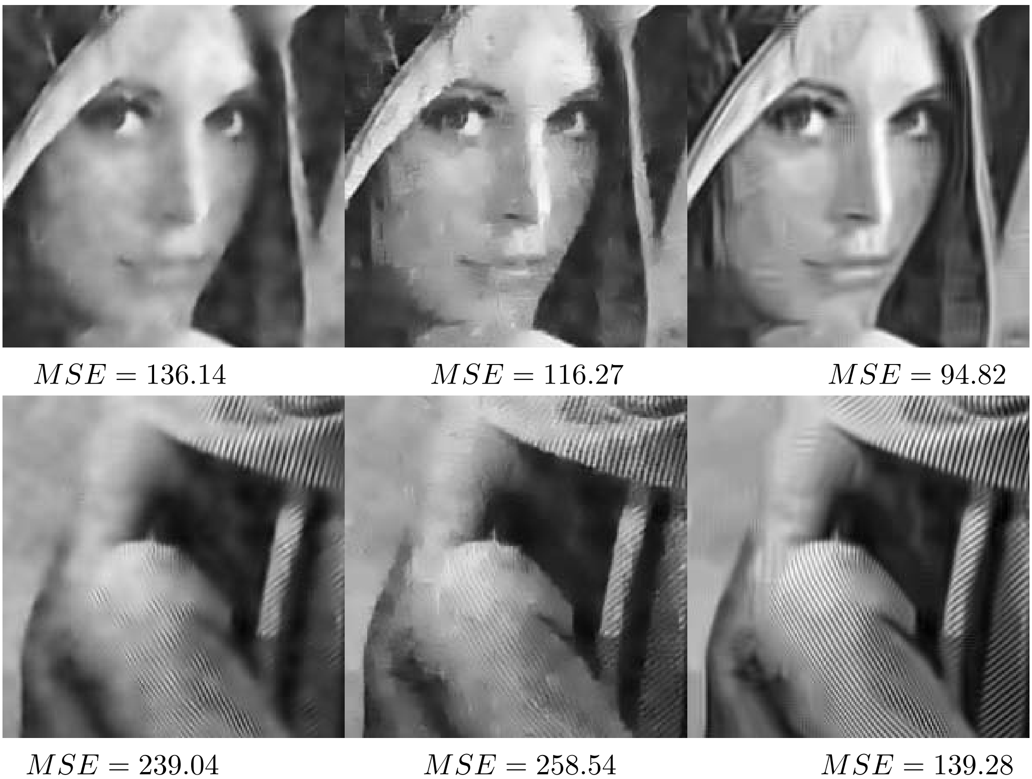

Figure 1.10 Comparison of denoised $lena$ (top) and $barbara$ (bottom) images at $\sigma_w = 50$ by three nonlocal denoising algorithms: left - KSVD denoising [41] (from KSVD toolbox), middle - nonlocal regularization with GSM [64] (from NLR-GSM toolbox), right - BM3D denoising [18] (from BM3D toolbox).

tween mentally reproducible and experimentally reproducible research is often the biggest challenge in image denoising research. A good and solid theory is mentally reproducible but does not always lead to better experimental results, while experimental breakthrough (e.g., BM3D) often suggests there is something missing in the existing theoretic framework, which calls for deeper logical reasoning. Our own recent work [61] attempts to fill in such a gap by deriving a nonlocal extension of Equation (1.2), but there is still a lot to explore (e.g., the extension from translational invariance to more generic invariant properties).

1.6 Conclusions and Perspectives

In this chapter, we have used extensive experiments to compare various image denoising techniques across three generations: local Wiener filtering, transform based, and nonlocal techniques. A cautious warning for readers who are eager to interpret the reported experimental results in an inductive fashion: we have only reported comparison results for two images at two different noise levels; it is likely that readers could easily find counterexamples for which KSVD outperforms BM3D or NLM-GSM falls behind GSM. We suggest that a sound interpretation of our reported experimental results here is that they have shown the general tendency or typical events (events with a high probability). There will always be exceptions at the “microscopic” level; but what matters more to both theoretic understanding and practical applications related to image denoising is the “macroscopic” behavior of different denoising algorithms. We conclude this chapter by making several comments about the role of representation and optimization in developing denoising algorithms and our own perspective about the evolutionary path of the field.

1.6.1 Representation versus Optimization

Representation is as important as optimization. Again taking BM3D as the example, its effectiveness is largely due to its right intuition and efficient implementation (the authors did not make serious claims about the optimization). In fact, it is possible to interpret the thresholding step and Wiener-filtering step in BM3D (they share lots of similarity) as the first two iterations of an EM-like algorithm. However, our experience has shown that more iterations do not always achieve further gain. Apparently, optimization is more successful in the non-blind scenario of lossy image coding [65] (where the original image is given) than the blind situation such as image denoising. A theoretically powerful tool such as Stein’s unbiased risk estimator (SURE) has only found limited success in wavelet-based [66] and nonlocal means [67] denoising. A deeper reason seems to be connected with the definition of randomness or determinism of Turing machines.

One might argue that it is possible to attack the denoising problem without the necessity of addressing the representational issue (e.g., learning-based [68–72]). On the surface, learning-based does appear to be an appealing framework as the alternative to model-based. As of today, learning-based image denoising has been less explored than model-based. However, we believe that the additional assumption about the availability of training data does not necessarily make the problem easier to solve. At least for Bayesians, training data simply “transforms” prior to posterior, so nothing has fundamentally changed. What is more, a pitfall with a learning-based approach is that it could be mathematically equivalent to many existing approaches unless we seriously attack learning as a separate problem on its own merit (i.e., from a neural computation perspective [73]).

1.6.2 Is Image Denoising Dead?

How much more room is left for image denoising research? Recent studies (e.g., [74]) have argued that there is often still plenty of room to improve for a wide range of generic images at certain noise levels. In fact, as long as we believe in the intrinsic connection between denoising and segmentation/recognition, the denoising problem will not be completely dead until others are solved. It is reasonable to expect that advances in image segmentation and object recognition could offer new insights into the way we define patch similarity and therefore really push the art of Wiener filtering to the next level. We also anticipate that the hierarchical representation in the Hilbert space (i.e., wavelet-based) could be generalized into nonlocal image representation (likely outside Hilbert space, e.g., metric space [75]).

Why should we still care about image denoising? Based on our own experience, a better denoising algorithm offers more than just a new tool. The new insights brought by BM3D have inspired many researchers (including this author) to revisit other conventional image processing tasks, including deblurring [22], interpolation [77], inpainting [78], and so on. Such leverage to other low-level vision tasks is almost a free lunch because they share the common objective of building a better image prior model. It might be more fruitful to leverage advances in image denoising to high-level tasks like the feedback connections in the human brain. Nevertheless, a higher SNR often implies more likelihood of object detection [79]; so it might be more rewarding to treat the problem of image denoising not as an isolated engineering problem but as one component in the bigger scientific picture of visual perception [80].

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