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Energetic Image Denoising Scheme using Optimal Filtering Approach

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Abstract— We propose an information subordinate denoising technique to restore uproarious pictures. Not quite the same as existing denoising calculations which hunt down patches from either the boisterous picture or a nonexclusive images, the new calculation finds patches from an inputting image that contains applicable patches. We detail the denoising issue as an ideal channel plan issue and make two commitments. Initially, we decide the premise capacity of the solving so as to denoising channel a gathering sparsity minimization issue. The streamlining definition sums up existing denoising calculations and offers efficient examination of the execution. Change strategies are proposed to improve the patch look process. Second, we decide the unearthly coefficients of the considering so as to denoising channel a confined Bayesian prior. The limited past influences the similitude of the focused on image, lightens the serious Bayesian calculation, and joins the new strategy to the traditional direct least mean squared blunder estimation. We exhibit utilizations of the proposed system in an assortment of situations, including content pictures, multi-view pictures and confront pictures. As per the proposed scheme, the input image will be going to get noised by adding some suppressions bindings over the image. Once the image will get noised, we have to apply the optimal filtering rules to extract the image back from step by step strategies.

Index Terms— Denoising Technique, Boisterous Picture, Bayesian prior, Suppressions bindings

I. INTRODUCTION

Image denoising is a classical signal recovery problem where the goal is to restore a clean image from its observations. Although image denoising has been studied for decades, the problem remains a fundamental one as it is the test bed for a variety of image processing tasks. Among the numerous contributions in image denoising in the literature, the most highly-regarded class of methods, to date, is the class of patch-based image denoising algorithms.

For any patch-based denoising algorithm, the denoising performance is intimately related to the reference patches p1, . . . , pk. Typically, there are two sources of these patches: the noisy image itself and an external database of patches. The former is known as internal denoising, whereas the latter is known as external denoising. Internal denoising is practically more popular than external denoising because it is computationally less expensive. Moreover, internal denoising does not require a training stage, hence making it free of training bias. Furthermore, Glasner et al. showed that patches tend to recur within an image, e.g., at a different location, orientation, or scale. Thus searching for patches in the noisy image is often a plausible approach. However, on the downside, internal denoising often fails for rare patches—patches that seldom recur in an image. This phenomenon is known as "rare patch effect", and is widely regarded as a bottleneck of internal denoising. There are some works attempting to alleviate the rare patch problem. However, the extent to which these methods can achieve is still limited. External denoising is an alternative solution to internal denoising. Levin et al. showed that in the limit, the theoretical minimum mean squared error of denoising is achievable using an infinitely large external database.

Recently, Chan et al. developed a computationally efficient sampling scheme to reduce the complexity and demonstrated practical usage of large databases. However, in most of the recent works on external denoising, the databases used are generic. These databases, although large in volume, do not necessarily contain useful information to denoise the noisy image of interest. For example, it is clear that a database of natural images is not helpful to denoise a noisy portrait image.

A. ADAPTIVE IMAGE DENOISING

In this system, we propose an adaptive image denoising algorithm using a targeted external database instead of a generic database. Here, a targeted database refers to a database that contains images relevant to the noisy image only. As will be illustrated in later parts of this system, targeted external databases could be obtained in many practical scenarios, such as text images (e.g., newspapers and documents), human faces (under certain conditions), and images captured by multiview camera systems. Other possible scenarios include images of license plates, medical CT and MRI images, and images of landmarks. The concept of using targeted external databases has been proposed in various occasions. However, none of these methods are tailored for image denoising problems. The objective of this is to bridge the gap by addressing the following question: (Q): Suppose we are given a targeted external database, how should we design a denoising algorithm which can maximally utilize the database? Here, we assume that the reference patches p1, . . . , pk are given.

We emphasize that this assumption is application specific for the examples we mentioned earlier (e.g., text, multiview, face, etc), the assumption is typically true because these images have relatively less variety in content. When the reference patches are given, question (Q) may look trivial at the first glance because we can extend existing internal denoising algorithms in a brute-force way to handle external databases. For example, one can modify existing algorithms, so that the patches are searched from a database instead of the

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noisy image. Likewise, one can also treat an external database as a "video" and feed the data to multi-image denoising algorithms. However, the problem of these approaches is that the brute force modifications are heuristic. There is no theoretical guarantee of performance. This suggests that a straight-forward modification of existing methods does not solve question (Q), as the database is not maximally utilized. An alternative response to question (Q) is to train a statistical prior of the targeted database. The merit of this approach is that the performance often has theoretical guarantee because the denoising problem can now be formulated as a maximum a posteriori (MAP) estimation. However, the drawback is that many of these methods require a large number of training samples which is not always available in practice.

B. CONTRIBUTIONS

In view of the above seemingly easy yet challenging question, we introduced a new denoising algorithm using targeted external databases. Compared to existing methods, the method proposed achieves better performance and only requires a small number of external images. In this system, we extend by offering the following new contributions:

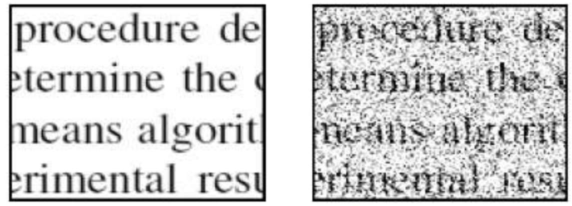
1) Generalization of Existing Methods. We propose a generalized framework which encapsulates a number of denoising algorithms. In particular, we show that the proposed group sparsity minimization generalizes both fixed basis and PCA methods. We also show (in Section IV-B) that the proposed local Bayesian MSE solution is a generalization of many spectral operations in existing methods.

2) Improvement Strategies. We propose two improvement strategies for the generalized denoising framework. In Section III-D, we present a patch selection optimization to improve the patch search process. We present a soft-thresholding and a hard-thresholding method to improve the spectral coefficients learned by the algorithm.

II. Problem Statement

In existing approaches there is a lacking in optimal filter strategies, all the developers try to get back the actual image by using regular Gaussian filters and other schemas according to their needs. So that the outcome of the image is only in compromised level not in the accepted level. The image will get recovered only if it is in the noise level σ is equal to 100 maximum. So if the image contains more than the level σ noise, there is no way to get back the actual image from noise. In this case all the researchers and developers needs a special filtering technique that is optimized for all the cases and produce the filtering with any level of noise sigma (σ).

- ✓ Regular filtering strategies like Gaussian rule applications
- ✓ Slow in Process
- ✓ Maximum process level of σ = 100 only
- ✓ Cost will be higher while it is implemented in practical applications such as passport verification scheme and other all image verification processes.



(a) clean (b) noisy $\sigma = 100$

Image Denoising has remained a fundamental problem in the field of image processing. Wavelets give a superior performance in image denoising due to properties such as sparsity and multiresolution structure. With Wavelet Transform gaining popularity in the last two decades various algorithms for denoising in wavelet domain were introduced. The focus was shifted from the Spatial and Fourier domain to the Wavelet transform domain. Ever since Donoho's Wavelet based thresholding approach was published in 1995, there was a surge in the denoising papers being published. Although Donoho's concept was not revolutionary, his methods did not require tracking or correlation of the wavelet maxima and minima across the different scales as proposed by Mallat. Thus, there was a renewed interest in wavelet based denoising techniques since Donoho demonstrated a simple approach to a difficult problem. Researchers published different ways to compute the parameters for the thresholding of wavelet coefficients. Data adaptive thresholds were introduced to achieve optimum value of threshold. Later efforts found that substantial improvements in perceptual quality could be obtained by translation invariant methods based on thresholding of an Undecimated Wavelet Transform. These thresholding techniques were applied to the nonorthogonal wavelet coefficients to reduce artifacts. Multiwavelets were also used to achieve similar results. Probabilistic models using the statistical properties of the wavelet coefficient seemed to outperform the thresholding techniques and gained ground. Recently, much effort has been devoted to Bayesian denoising in Wavelet domain. Hidden Markov Models and Gaussian Scale Mixtures have also become popular and more research continues to be published. Tree Structures ordering the wavelet coefficients based on their magnitude, scale and spatial location have been researched. Data adaptive transforms such as Independent Component Analysis (ICA) have been explored for sparse shrinkage. The trend continues to focus on using different statistical models to model the statistical properties of the wavelet coefficients and its neighbors. Future trend will be towards finding more accurate probabilistic models for the distribution of non-orthogonal wavelet coefficients.

The data-driven threshold for image denoising via wavelet soft-thresholding. The threshold is derived in a Bayesian framework, and the prior used on the wavelet coefficients is the generalized Gaussian distribution (GGD) widely used in image processing applications. The proposed threshold is simple and closed-form, and it is adaptive to each sub band because it depends on data-driven estimates of the parameters. Experimental results show that the proposed method, called

BayesShrink, is typically within 5% of the MSE of the best soft-thresholding benchmark with the image assumed known. It also outperforms Sure Shrink (Donoho and Johnstone 1994, 1995; Donoho 1995) most of the time. The second part of the paper attempts to further validate claims that lossy compression can be used for denoising. The BayesShrink threshold can aid in the parameter selection of a coder designed with the intention of denoising, and thus achieving simultaneous denoising and compression. Specifically, the zero-zone in the quantization step of compression is analogous to the threshold value in the thresholding function. The remaining coder design parameters are chosen based on a criterion derived from Rissanen's minimum description length (MDL) principle. Experiments show that this compression method does indeed remove noise significantly, especially for large noise power. However, it introduces quantization noise and should be used only if bitrate were an additional concern to denoising.

A novel wavelet-based image denoising algorithm under over complete expansion. In order to optimize the denoising performance, we make a systematic study of both signal and noise characteristics under over complete expansion. High-band coefficients are viewed as the mixture of non-edge class and edge class observing different probability models. Based on improved statistical modeling of wavelet coefficients, we derive optimal MMSE estimation strategies to suppress noise for both non-edge and edge coefficients. We have achieved fairly better objective performance than most recently-published wavelet denoising schemes.

III. PROPOSED SCHEME

In proposed system, an adaptive image denoising algorithm is implemented, using targeted external images instead of generic images. Here, a targeted image refers to a noisy image. Targeted external image could be obtained in many practical scenarios, such as text images (e.g., newspapers and documents), human faces (under certain conditions), and images captured by multi-view camera systems. Other possible scenarios include images of license plates, medical CT and MRI images, and images of landmarks. In addition Bayesian MSE rule generalization scheme is proposed to improve the quality of noisy images in any kind of sigma scenarios and it is not a restricted process as well.

ADVANTAGES

- Bayesian generalization and Optimal filtering strategies are used to obtain the actual image from noisy images.
- Performance and Processing time is comparatively good
- Maximum process level is up to n not restricted.
- Low Cost is enough to complete the practical implementations.

Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) as well as in terms of visual quality of the images. Many of the current techniques assume the noise model to be Gaussian. In reality, this assumption may not always hold true due to the varied nature and sources of noise. An ideal denoising

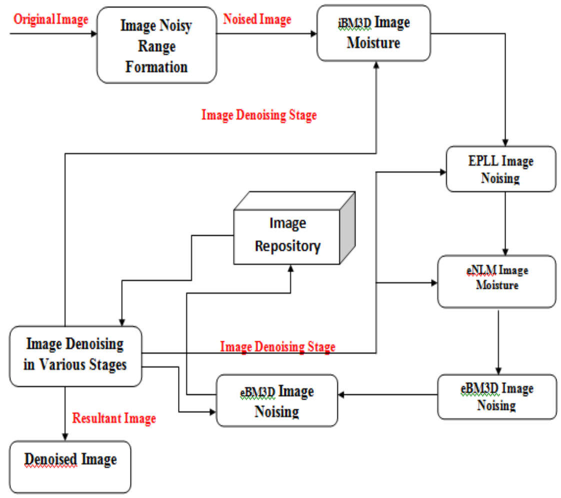


Fig.1 System Architecture

procedure requires a priori knowledge of the noise, whereas a practical procedure may not have the required information about the variance of the noise or the noise model. Thus, most of the algorithms assume known variance of the noise and the noise model to compare the performance with different algorithms. Gaussian Noise with different variance values is added in the natural images to test the performance of the algorithm. Not all researchers use high value of variance to test the performance of the algorithm when the noise is comparable to the signal strength. Use of FFT in filtering has been restricted due to its limitations in providing sparse representation of data. Wavelet Transform is the best suited for performance because of its properties like sparsity, multiresolution and multiscale nature. In addition to performance, issues of computational complexity must also be considered. Thresholding techniques used with the Discrete Wavelet Transform are the simplest to implement. Non-orthogonal wavelets such as UDWT and Multiwavelets improve the performance at the expense of a large overhead in their computation. HMM based methods seem to be promising but are complex. When using Wavelet Transform, Nason [40] emphasized that issue such as choice of primary resolution (the scale level at which to begin thresholding) and choice of analyzing wavelet also have a large influence on the success of the shrinkage procedure. When comparing algorithms, it is very important that researchers do not omit these comparison details. Several papers did not specify the wavelet used neither the level of decomposition of the wavelet transform was mentioned. It is expected that the future research will focus on building robust statistical models of non-orthogonal wavelet coefficients based on their intra scale and inter scale correlations. Such models can be effectively used for image denoising and compression.

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IV. METHODOLOGY

The major part of the project development sector considers and fully survey all the required needs for developing the project. Once these things are satisfied and fully surveyed, then the next step is to determine about the software specifications in the respective system such as what type of operating system the project would require, and what are all the necessary software are needed to proceed with the next step such as developing the tools, and the associated operations. Generally algorithms shows a result for exploring a single thing that is either be a performance, or speed, or accuracy, and so on. An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviors of the system. System architecture can comprise system components, the externally visible properties of those components, the relationships (e.g. the behavior) between them.

Following are the most frequently used project management methodologies in the project management practice:

A. Adaptive Image Denoising
B. Patch Selection Refinement
C. Denoising Text based Images
D. Denoising Multi-view Images and Human Faces

A. Adaptive Image Denoising

An adaptive image denoising module is implemented using a targeted external image instead of a generic image. Here, a targeted image refers to images which contain noisy levels in it. Targeted external images could be obtained via many practical scenarios, such as text images (e.g., newspapers and documents), human faces (under certain conditions), and images captured by multi-view camera systems. Other possible scenarios include images of license plates, medical CT and MRI images, and images of landmarks. The concept of using targeted external images has been proposed in various occasions. However, none of these methods are tailored for image denoising problems. This module of adaptive image denoising, we clearly tailor the problem of the given image and producing the denoising strategies over it as well as get back the perfect image from scenarios.

B. Patch Selection Refinement

The optimization problem suggests that the inputting image computed from the defined filtering schemes is the optimal basis with respect to the reference patches. However, one issue that remains is how to improve the selection of k patches from the original n patches. To gain more insight into it, the system has to first consider the special case when the image gets noised from the first pixel. We claim that, under this special condition, the solution of noisy image is equivalent to the original neighboring solution. This result is important, because neighboring pixel analysis is a fundamental building block of all patch based denoising algorithms. By linking neighboring pixel analysis scheme to the optimization formulation, we provide a systematic strategy to improve the neighboring pixel of images.

C. Denoising Text based Images

The first analysis of denoising noisy images considers denoising a image which contains text and animals in it. The purpose is to simulate the case where we want to denoise a noisy document with the help of other similar but non-identical texts. This idea can be easily generalized to other scenarios such as handwritten signatures, bar codes and license plates. To prepare this scenario, we capture randomly 8 regions of a documentary image and add noise. We then build the targeted external image set by analyzing many different arbitrary portions from a different neighboring pixels but with the same filtering rules and attain the result more better than the existing methodologies.

D. Denoising Multi-view Images and Human Faces

This module of denoising multi-view images experiment considers the scenario of capturing images using a multi-view camera system. The multi-view images are captured at different viewing positions. Suppose that one or more cameras are not functioning properly so that some images are corrupted with noise. Our goal is to demonstrate that with the help of the other clean views, the noisy view could be restored. The next strategy considers denoising human face images. In low light conditions, images captured are typically corrupted by noise. To facilitate other high-level vision tasks such as recognition and tracking, denoising is a necessary preprocessing step. This experiment demonstrates the ability of denoising face images.

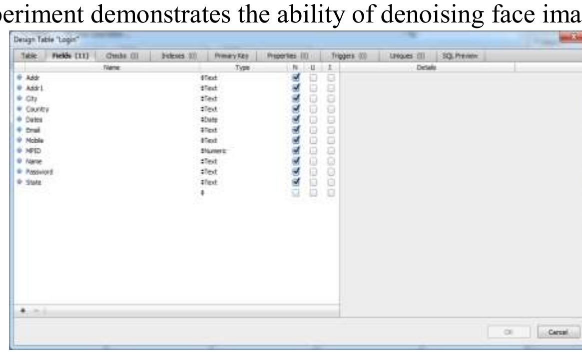

Fig.2 Database Table

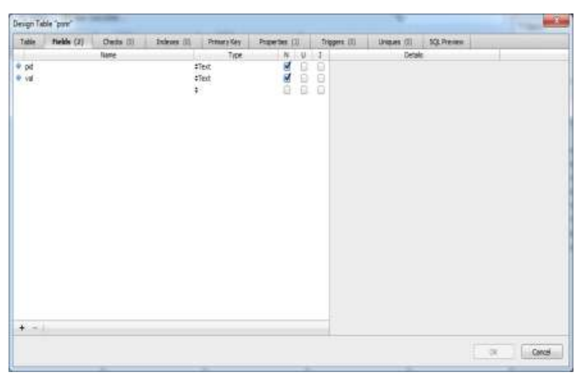

Fig.3 Database Table Design

V. CONCLUSION

Classical image denoising methods based on a single noisy input or generic databases are approaching their performance limits. We proposed an adaptive image denoising algorithm using targeted databases. The proposed method applies a group sparsity minimization and a localized prior to learn the basis matrix and the spectral coefficients of the optimal denoising filter, respectively. We show that the new method generalizes a number of existing patch-based denoising algorithms such as BM3D, BM3D-PCA, Shape-adaptive BM3D, LPG-PCA, and EPLL. Based on the new framework, we proposed improvement schemes, namely an improved patch selection procedure for determining the basis matrix and a penalized minimization for determining the spectral coefficients. For a variety of scenarios including text, multiview images and faces, we demonstrated empirically that the proposed method has superior performance over existing methods. With the increasing amount of image data available online, we anticipate that the proposed method is an important first step towards a data-dependent generation of denoising algorithms.

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