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Survey for Wavelet Bayesian Network Image Denoising

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Abstract
In now days, wavelet-based image denoising method, which extends a recently emerged "geometrical" Bayesian framework. The new scheme combines three criteria for distinctive theoretically useful coefficients from noise: coefficient magnitudes, their advancement across scales and spatial clustering of bulky coefficients close to image edges. These three criteria are united in a Bayesian construction. The spatial clustering properties are expressed in a earlier model. The statistical properties regarding coefficient magnitudes and their development crossways scales are expressed in a joint conditional model. We address the image denoising difficulty, where zero-mean white and homogeneous Gaussian additive noise is to be uninvolved from a given image. We employ the belief propagation (BP) algorithm, which estimates a coefficient based on every one the coefficients of a picture, as the maximum-a-posterior (MAP) estimator to derive the denoised wavelet coefficients. We illustrate that if the network is a spanning tree, the customary BP algorithm can achieve MAP estimation resourcefully. Our research consequences show that, in conditions of the peak-signal-to-noise-ratio and perceptual superiority, the planned approach outperforms state-of-the-art algorithms on a number of images, mostly in the textured regions, with a range of amounts of white Gaussian noise.
Keywords— Bayesian network, Bayesian estimation, Image denoising, Image restoration, Wavelet transform.

I. INTRODUCTION

The class of natural images that we encounter in daily life is only a small subset of the set of all possible images. This subset is called an image manifold. Digital image processing applications are becoming increasingly important and they all start with a mathematical representation of the image. In Bayesian restoration methods, the image manifold is encoded in the form of prior knowledge that express the probabilities that specified combinations of pixel intensities can be experiential in an image.

Because image spaces are high-dimensional, one often isolates the manifolds by decomposing images into their components and by fitting probabilistic models on it [1], [2]. The construction of a Bayesian network involves prior knowledge of the probability relationships between the variables of interest. Learning approaches are widely used to construct Bayesian networks that best represent the joint probabilities of training data. In practice, an optimization process based on a heuristic search technique is used to find the best structure over the space of all possible networks. However, the approach is computationally intractable because it must explore several combinations of dependent variables to derive an optimal Bayesian network. The difficulty is resolved in this paper by representing the data in wavelet domains and restricting the space of possible networks by using certain techniques, such as the "maximal weighted spanning tree". Three wavelet properties - sparsity, cluster, and motion - can be oppressed to reduce the computational complexity of learning a Bayesian network [3]-[7]. During the last decades, multi resolution image representations, like wavelets, have received much attention for this purpose, due to their sparseness which manifests in highly non-Gaussian statistics for wavelet coefficients. Marginal histograms of wavelet coefficients are typically leptokurtotic and have heavy tails [8], [9]. In literature, many wavelet-based image denoising methods have arisen exploiting this property, and are often based on simple and elegant shrinkage rules. In addition, joint histograms of wavelet coefficients have been studied in. Taking advantage of correlations between wavelet coefficients either across space, scale or orientation, additional improvement in denoising performance is obtained. The Gaussian Scale Mixture (GSM) model, in which clusters of coefficients are modeled as the artifact of a Gaussian random vector and a positive scaling variable, has been shown to produce outcome that are appreciably better than marginal models [10]. Image restoration aims to construct an estimate sharing the significant features still present in the degraded image, but with the artifacts censored.

II. PROBLEM FORMULATION

In our construction, we use image patches to take into account complex spatial interactions in images. In contrast to exemplar-based approaches for image modeling . An unsupervised method that uses no collection of image patches and no computational intensive training algorithms. Our adaptive smoothing works in the joint spatial-range domain as the nonlocal means filter but have a more powerful adaptation to the local structure of the data since the size of windows and control parameters are estimated from local image statistics [11]. We create the presentation of the proposed denoising algorithm by first introducing how sparsity and redundancy are brought to exploit. We do that via the beginning of the Sparse land reproduction Once this is set, we will talk about how local management on image patches turns into a global prior in a Bayesian rebuilding framework. The second part of the paper attempts to further validate recent claims that lossy compression can be used for denoising. The Bayes Shrink threshold can aid in the parameter selection of a coder designed with the intention of denoising, and thus achieving concurrent denoising and looseness. Specifically, the zero-zone in the quantization step of compression is analogous to the threshold value in the thresholding function. The left behind coder design parameters are selected based on a criterion derived from Rissanen's minimum description length (MDL) theory [12]. Experiments show that this compression method does indeed remove noise extensively, especially for great noise power. although it introduces quantization noise and should be used only if bit rate were an additional concern to denoising. In meticulous, the transform-domain denoising methods normally assume that the true signal can be well approximated by a linear combination of few basis elements. That is, the signal is sparsely represent in the transform domain. thus, by preserving the few high-magnitude transform coefficients that convey typically the accurate-signal energy and discarding the rest which are mainly due to noise, the correct signal can be successfully estimated. The sparsity of the representation depends on both the transform and the true-signal's properties. The multi resolution transforms can achieve first-class sparsity for spatially localized fine points, for instance edges and singularities. When this prior-learning plan is combined with sparsity and redundancy, it is the glossary to be used that we target as the learned set of parameters [13].

III. IMAGE DENOISING

Image denoising is an important image processing assignment, both as a process itself, and as a module in other processes. Very several ways to denoise an image or a set of records exists. The main properties of an excellent image denoising model are that it will eliminate noise while preserving edges. Generally linear models have been used. One common technique is to use a Gaussian filter, or homogeneously solving the heat-equation with the noisy image as input-data, i.e. a linear, 2nd order PDE-reproduction. For some purposes this kind of denoising is sufficient. One large advantage of linear noise removal models is the speed. But a reverse draw of the linear models is that they are not able to preserve edges in a excellent way: edges, which are recognized as discontinuities in the image, are dirty out. Nonlinear models on the other hand can handle edges in a much better way than linear models can. This filter is very good at preserving edges, but smoothly unstable regions in the input image are transformed into piecewise constant regions in the output image. Using the TV-filter as a denoiser leads to solve a 2nd order nonlinear PDE. because smooth regions are transformed into piecewise constant regions when using the TV-filter, it is desirable to generate a model for which smoothly changeable regions are transformed into smoothly unreliable regions, and yet the edges are preserved. This can be done for example by solving a 4th order PDEd instead of the 2nd order PDE from the TV-filter. result show that the 4th order filter produces greatly better results in smooth regions, and unmoving preserves edges in a very excellent way.

IV. IMAGE DENOISING TECHNIQUES

Image denoising algorithms may be the oldest in image processing. various methods, in spite of implementation, share the similar basic plan noise reduction through image blurring. Blurring can be done nearby, as in the Gaussian smoothing model or in anisotropic filtering; by calculus of variations; or in the frequency domain, such as Weiner filters. but a universal "best" approach has yet to be found.

A) Patch-Based Image Denoising

A novel adaptive and patch-based approach is proposed for image denoising and representation. The method is based on a point wise selection of small image patches of fixed size in the variable neighborhood of each pixel. Our involvement is to associate with each pixel the weighted sum of data points within an adaptive neighborhood, in a manner that it balances the exactness of approximation and the stochastic error, at each spatial location. This method is general and can be applied under the assumption that there exist repetitive patterns in a local neighborhood of a point. By introducing spatial adaptively, we expand the work earlier described by Buades *et al.* which can be measured as an addition of bilateral filtering to image patches. Finally, we recommend a nearly parameter-free algorithm for image denoising. The scheme is applied to both artificially despoiled (white Gaussian noise) and real images and the performance is extremely close to, and in some cases yet surpasses, that of the already published denoising schemes. A novel adaptive and exemplar-based approach is proposed for image restoration and representation. The method is based on a point wise selection of small image patches of fixed size in the variable neighbourhood of each pixel. The core idea is to associate with each pixel the weighted sum of data points within an adaptive neighbourhood. This method is general and can be applied under the assumption that the image is a locally and fairly stationary process. In this paper, we spotlight on the problem of the adaptive neighbourhood selection in a manner that it balances the accuracy of approximation and the stochastic error, at each spatial location. Thus, the new proposed point wise estimator mechanically adapts to the degree of underlying smoothness which is unidentified with minimal a priori assumptions on the function to be recovered [14].

B) Wavelet Based Image Denoising

Wavelet-based image denoising method, which extends a newly emerged "geometrical" Bayesian framework. The new method merges three criteria for distinguishing supposedly valuable coefficients from noise: coefficient magnitudes, their development across scales and spatial clustering of large coefficients close to image edges. These three criteria are pooled in a Bayesian construction. The spatial clustering properties are expressed in a prior model. The statistical properties regarding coefficient magnitudes and their progression across scales are expressed in a joint conditional model. The three middle novelties with respect to related approaches are

1) The inter scale-ratios of wavelet coefficients are statistically characterized and different local criteria for distinguishing valuable coefficients from noise are evaluated.
2) A joint provisional model is introduced.
3) A novel anisotropic Markov random field prior model is designed. The results demonstrate an enhanced denoising performance over related earlier techniques [15].

Figure1: Left: reference images: 1: "Lena," 2: "Goldhill," 3: "Fruits," and 4: "Barbara." Right: reference edge positions for vertical orientation of details at resolution scale.

Several issues were addressed to improve Bayesian image denoising using prior models for spatial clustering. A new MRF prior model was introduced to preserve image details better. A joint significance measure, which combines coefficients magnitudes and their evolution through scales, was introduced. For the resulting, joint conditional model a simple practical realization was proposed and motivated via Simulations. The advantage of the joint conditional model in terms of noise suppression performance was demonstrated on different images and for different amounts of noise. Some aspects that were analyzed in this paper may be useful for other denoising schemes as well: the realistic conditional densities of interscale ratios obtained via simulations and objective criteria for evaluating noise suppression performance of different significance measures [15].

C) Sparse And Redundant Representations Based Image Denoising

We address the image denoising difficulty, where zero-mean white and homogeneous Gaussian additive noise is to be detached from a given image. The move toward taken is based on sparse and redundant representations over trained dictionaries. Using the K-SVD algorithm, we achieve a dictionary that describes the image content effectively. Two training options are measured: using the corrupted image itself, or training on a amount of high-quality image database. Since the K-SVD is limited in management small image patches, we expand its deployment to arbitrary image sizes by defining a global image prior that forces sparsity over patches in every location in the image. We illustrate how such Bayesian treatment leads to a simple and effective denoising algorithm. This lead to a state-of-the-art denoising presentation, equivalent and sometimes surpassing recently published leading alternative denoising methods. Image denoising, leading to state-of-the-art presentation, equivalent to and sometimes surpassing recently published leading alternatives denoising methods. The planned method is based on local operations and involves sparse decompositions of each image block under one fixed over-complete dictionary, and a simple average calculation. The content of the dictionary is of main importance for the denoising method we have shown that a dictionary trained for natural real images, as well as an adaptive glossary trained on patches of the noisy image itself, both present very well [16].

D) Adaptive Wavelet Thresholding for Image restoration (denoising)

An adaptive, data-driven threshold for image denoising via wavelet soft-thresholding. The threshold is derivative in a Bayesian framework, and the previous used on the wavelet coefficients is the generalized Gaussian distribution (GGD) widely used in image processing applications. The anticipated threshold is simple and closed-form, and it is adaptive to each sub band because it depends on data-driven estimates of the parameters. Investigational results show that the proposed method, called *BayesShrink*, is usually within 5% of the MSE of the best soft-thresholding benchmark with the image assumed known. It also outperforms Donohue and Johnston's *Sure Shrink* most of the time. The subsequent part of the paper attempt to further validate recent claims that lossy compression can be used for denoising. The *BayesShrink* threshold can serve in the parameter selection of a coder designed with the intention of denoising, and thus achieving instantaneous denoising and compression. particularly, the zero-zone in the quantization step of compression is analogous to the threshold value in the thresholding function. The residual coder design parameters are chosen based on a criterion derived from Rissanen's minimum description length (MDL) principle. Experiments show that this compression scheme does indeed remove noise considerably, especially for huge noise power. However, it introduces quantization noise and should be used only if bitrates were an additional concern to denoising. is often corrupted by noise in its acquisition or transmission. The goal of denoising is to eliminate the noise while retaining as much as possible the important signal features. Conventionally, this is achieved by linear processing such as Wiener filtering. A vast literature has emerged freshly on signal denoising using nonlinear techniques, in the location of additive white Gaussian noise [17].

Figure 2: shows the wavelet based Adaptive Wavelet Thresholding for Image Denoising [17].

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E) Image Denoising By Sparse 3D Transform-Domain Collaborative Filtering

Image denoising strategy based on an enhanced sparse representation in transform domain. The improvement of the sparsity is achieved by grouping similar 2D image fragments (e.g. blocks) into 3D data arrays which we call "groups". Collaborative filtering is a special procedure developed to deal with these 3D groups. We appreciate it using the three successive steps: 3D transformation of a group, reduction of the transform band, and inverse 3D transformation. The result is a 3D approximate that consists of the together filtered grouped image blocks. By attenuating the noise, the simultanious filtering reveals even the finest details shared by grouped blocks and at the same time it preserves the essential unique features of each character block. The filtered blocks are returned to their original locations. since these blocks are overlapping, for each pixel we obtain several different estimates which need to be combined. Aggregation is a particular averaging process which is exploited to take advantage of this redundancy. A important improvement is obtained by a specially developed collaborative Wiener filtering. An algorithm based on this description denoising approach and its efficient implementation is presented in full detail; an extension to color-image denoising is also developed. The experimental results display that this computationally scalable algorithm achieves state-of-the-art denoising performance in terms of both peak signal-to-noise ratio and subjective visual quality [18].

F) Image Denoising Using Mixtures of Projected Gaussian Scale Mixtures

A new statistical model for image restoration in which neighborhoods of wavelet sub bands are modeled by a discrete mixture of linear projected Gaussian Scale Mixtures . In each projection, a lower dimensional approximation of the local neighborhood is obtained, thus modeling the strongest correlations in that neighborhood. The model is a generalization of the just developed Mixture of GSM (MGSM) model that offers a significant improvement both in PSNR and visually compared to the current state-of-the-art wavelet techniques. Though the computation cost is very high this hampers its use for practical purposes. We present a quick EM algorithm that takes advantage of the projection bases to speed up the algorithm. The results explain that, when foretelling on a fixed data-independent basis, even computational advantages with a imperfect loss of PSNR can be obtained with respect to the BLS-GSM denoising method, although data-dependent bases of Principle Components offer a higher denoising presentation, both visually and in PSNR compared to the current wavelet-based state-of-the-art denoising methods. The Mixtures of Projected Gaussian Scale Mixtures (MPGSM) as a means to further improve upon the recently proposed MGSM model. The new model is a generalization of the existing SVGSM, OAGSM and MGSM techniques and allows for a lot of flexibility with regard to the neighborhood size, spatial adaptation and even when modeling dependencies between different wavelet sub bands. We developed a fast EM algorithm for the model training, based on the "winner-take all" approach, taking benefit of the Principal Component bases. We discussed how this technique can also be used to speed up the denoising itself. We discussed how data independent projection bases can be constructed to allow flexible neighborhood structures, offering computational savings compared to the GSM-BLS method which can be useful for real-time denoising applications. Finally we showed the PSNR improvement of the complete MPGSMBLS method compared to recent wavelet-domain state-of the- art methods [19].

G) Bayesian Network Image Denosing

From the perspective of the Bayesian approach, the denoising problem is basically a prior probability modeling and estimation task. In this paper, we suggest an approach that exploits a hidden Bayesian system, constructed from wavelet coefficients, to model the previous probability of the original image. Then, we use the belief propagation (BP) method, which estimates a coefficient based on all the coefficients of an image, as the maximum-a-posterior (MAP) estimator to develop the denoised wavelet coefficients. We explain that if the network is a spanning tree, the standard BP algorithm can execute MAP estimation competently. Our experiment results demonstrate that, in conditions of the peak-signal-to-noise-ratio and perceptual quality, the projected approach outperforms state-of-the-art algorithms on various images, particularly in the textured regions, with various amounts of white Gaussian noise [20].

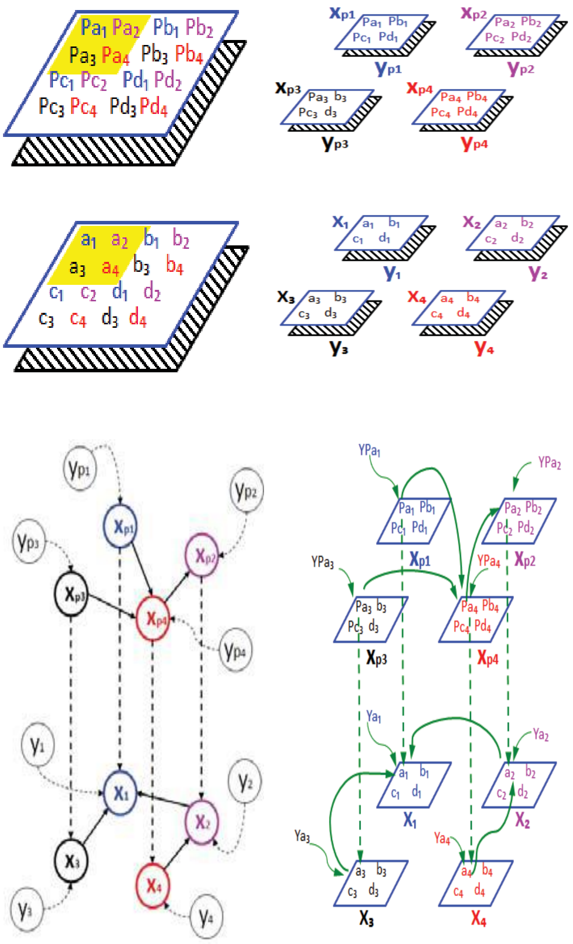

Figure 3: Bayesian Network Image Denoising [20].

V. CONCLUSION

Bayesian image denoising using prior models for spatial clustering. A new MRF prior model was introduced to preserve image details better. A joint significance measure, which combines coefficients magnitudes and their evolution through scales, was introduced. For the resulting, joint conditional model a simple practical realization was proposed and motivated via simulations. We have described a novel adaptive denoising algorithm where patch-based weights and variable window sizes are jointly used. An advantage of the method is that internal parameters can be easily chosen and are relatively stable. The algorithm is able to denoise both piecewise-smooth and textured natural images since they contain enough redundancy. Actually, the performance of our algorithm is very close, and in some cases still surpasses, to that of the previously published denoising methods. Also we just mention that the algorithm can be easily parallelized since at iteration, each pixel is processed independently. However, some problems may occur when the texture sample contains too many Texel's making hard to find close matches for the locality context window.

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