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Adaptive Image Denoising by Targeted Databases

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Abstract— **The 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 bedfor a variety of image processing tasks in our proposed system proposes the data-dependent denoising procedure to restore noisy images. Different from existing denoising algorithms which search for patches from either the noisy image or a generic database, the new algorithm finds patches from a database that contains relevant patches. In our project contain two steps they are First, we determine the basis function of the denoising filter by solving a group sparsity minimization problem. The optimization formulation generalizes existing denoising algorithms and offers systematic analysis of the performance. Improvement methods are proposed to enhance the patch search process. Second, we determine the spectral coefficients of the denoising filter by considering a localized Bayesian prior. The localized prior leverages the similarity of the targeted database, alleviates the intensive Bayesian computation, and links the newmethod to the classical linear minimum mean squared error estimation. Finally our experimental result show the our proposed algorithm is better and also it overcome existing methods problem.**

Index Terms— **Image denoising, Localized Prior, Group Sparsity**

I. Introduction

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption.

Image denoising is a classical signal recovery problemwhere 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 bedfor a variety of image processing tasks.Among the numerous contributions in image denoising inthe literature, the most highly-regarded class of methods, todate, is the class of *patch-based image denoising* algorithms.

For any patch-based denoising algorithm, the denoising performance is intimately related to the reference patchesp1, . . . , pk. Typically, there are two sources of these patches:the noisy image itself and an external database of patches.
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 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 showed that in the limit, the theoretical minimum mean squared error of denoising is achievable using an infinitely large externaldatabase. Recently 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.

II. EXISTING SYSTEM

In our existing system use the *patch-based image denoising* algorithms for denising.The idea of a patch-based

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denoising algorithm issimple: Given a √d×√d patch q ∈ Rd from the noisy image,the algorithm finds a set of reference patches p1, . . . , pk ∈ Rdand applies some linear (or non-linear) function Φ to obtainan estimate p of the unknown clean patch p .For any patch-based denoising algorithm, the denoising performance is intimately related to the reference patchesp1, . . . , pk. Typically, there are two sources of these patches:the noisy image itself and an external database of patches.

Drawback:

- It is fails for rare patches— patches that seldom recur in an image.
- It cannot be achieve better performance.

III. PROPOSED SYSTEM

In our proposed system propose the adaptive image denoising algorithm using a *targeted* external database instead of a *generic* database. Here, a targeted database refers to a databasethat contains images *relevant* to the noisy image only. The targeted external databases could be obtained in many practical scenarios, suchas text images (*e.g.*, newspapers and documents), human faces(under certain conditions), and images captured by multiviewcamera systems. Other possible scenarios include images oflicense plates, medical CT and MRI images, and images oflandmarks.In our project contain two steps they are First, we determine the basis function of the denoising filter by solving a group sparsity minimization problem. The optimization formulation generalizes existing denoising algorithms and offers systematic analysis of the performance. Improvement methods are proposed to enhance the patch search process. Second, we determine the spectral coefficients of the denoising filter by considering a localized Bayesian prior. The localized prior leverages the similarity of the targeted database, alleviates the intensive Bayesian computation, and links the new method to the classical linear minimum mean squared error estimation.

For fixed U, it is not difficult to show that the optimal denoised patch is

$$\widehat{\boldsymbol{p}} = \boldsymbol{U}\left(\mathrm{diag}\left\{\frac{(\boldsymbol{u}_1^T\boldsymbol{p})^2}{(\boldsymbol{u}_1^T\boldsymbol{p})^2+\sigma^2},\ldots,\frac{(\boldsymbol{u}_n^T\boldsymbol{p})^2}{(\boldsymbol{u}_n^T\boldsymbol{p})^2+\sigma^2}\right\}\right)\boldsymbol{U}^T\boldsymbol{q}.$$

Our proposed method takes into account of the uncertainty of the initial estimate p when estimating Λ. The idea is to assume a prior distribution of the patch p and minimize the Bayesian mean squared error (BMSE) over Λ:

$$\mathrm{BMSE} = \mathbb{E}_{\boldsymbol{p}}\left[\mathbb{E}_{\boldsymbol{q}|\boldsymbol{p}}\left[\left\|\boldsymbol{U}\boldsymbol{\Lambda}\boldsymbol{U}^T\boldsymbol{q}-\boldsymbol{p}\right\|_2^2 \;\middle|\; \boldsymbol{p}\right]\right].$$

Here, we assume that the exact expression of f(p) is unknown, but the mean μ and covariance Σ of f(p) can be reasonably estimated. Consequently, for a given μ and Σ, the minimum BMSE is achieved at where the division is element-wise. We do not need a specific form for f(p) except the knowledge of μ and Σ. To define μ and Σ, we first note that μ is the desired mean of the prior and Σ is the covariance measuring the uncertainty. Based on the set of k similar patches p1 , . . . , pk , we define

$$\mu = \sum_{i=1}^{k} \omega_i p_i, \quad \Sigma = \sum_{i=1}^{k} \omega_i (p_i - \mu)(p_i - \mu)^T$$

μ is the best-k non-local mean solution of the patches, and Σ is the covariance of the patches. Christo Ananth et al. [6] proposed a system which uses intermediate features of maximum overlap wavelet transform (IMOWT) as a pre-processing step. The coefficients derived from IMOWT are subjected to 2D histogram Grouping. This method is simple, fast and unsupervised. 2D histograms are used to obtain Grouping of color image. This Grouping output gives three segmentation maps which are fused together to get the final segmented output. This method produces good segmentation results when compared to the direct application of 2D Histogram Grouping. IMOWT is the efficient transform in which a set of wavelet features of the same size of various levels of resolutions and different local window sizes for different levels are used. IMOWT is efficient because of its time effectiveness, flexibility and translation invariance which are useful for good segmentation results.

We evaluate the performance of the proposed method by comparing to several existing algorithms. The methods we considered in the comparison include BM3D, BM3D-PCA, LPG-PCA, NLM and EPLL. Except for EPLL, all other four methods are re-implemented so that patches can be searched over multiple images. The experiment considers denoising face images using a dataset. We simulate the denoising task by adding noise to a randomly chosen image and use other images in the database for denoising. The faces are not pre-processed, and so they have different expressions and alignments. However, even in the presence of this degree of image variations, the proposed method still performs satisfactorily over a range of noise levels.

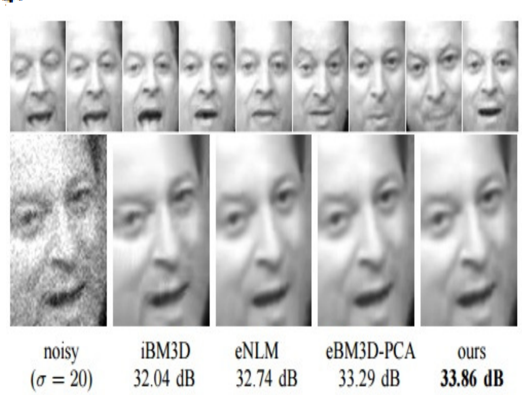

Fig.1. Performance of Proposed System over a range of noise levels

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IV. CONCLUSION

The 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 bedfor a variety of image processing tasks in our proposed system proposes the data-dependent denoising procedure to restore noisy images. Different from existing denoising algorithms which search for patches from either the noisy image or a generic database, the new algorithm finds patches from a database that contains relevant patches. In our project contain two steps they are First, we determine the basis function of the denoising filter by solving a group sparsity minimization problem. The optimization formulation generalizes existing denoising algorithms and offers systematic analysis of the performance. Improvement methods are proposed to enhance the patch search process. Second, we determine the spectral coefficients of the denoising filter by considering a localized Bayesian prior. The localized prior leverages the similarity of the targeted database, alleviates the intensive Bayesian computation, and links the newmethod to the classical linear minimum mean squared error estimation. Finally our experimental result show the our proposed algorithm is better and also it overcome existing methods problem.

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