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Image de-noising with subband replacement and fusion process using bayes estimators,☆,☆☆

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A B S T R A C T

A hybrid image de-noising framework with an automatic parameter selection scheme is proposed to handle substantially high noise with an unknown variance. The impetus of the framework is to preserve the latent detail information of the noisy image while removing the noise with an appropriate smoothing and feasible sharpening. The proposed method is executed in two steps. First, the sub-band replacement and fusion process based on accelerated version of the Bayesian non local means method are implemented to enhance the weak edges that often result in low gradient magnitude and fade out during the de-noising process. Then, a truncated beta-Bernoulli process is employed to infer an appropriate dictionary of the edge enhanced data to obtain de-noising results precisely. Numerical simulations are performed to substantiate the restoration of the weak edges through sub-band replacement and fusion process. The proposed de-noising scheme is validated through visual and quantitative results using well established metrics.

1. Introduction

Restoration of images affected by inevitable noise is an important task in digital image processing. The main challenge in image de-noising is to eliminate noise effectively from a corrupted image by reconstructing an approximation of the clean image while preserving its latent information such as corners and edges [1–3]. The algorithms that fail to distinguish latent features from noise produce blurry outputs with de-noising artifacts [3]. The non-local means (NLM) based techniques, such as *Bayesian NLM filtering*, often perform well in maintaining sharp edges and corners (see for instance [4]). However, an

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Table 1
Comparison of image de-noising methods for House image based on PSNR values for mismatched estimations of σ.

σ	10/28.13			15/24.61			20/22.11			25/20.18		
Methods	σ_{+5}	σ_t	σ_{-5}	σ_{+5}	σ_t	σ_{-5}	σ_{+5}	σ_t	σ_{-5}	σ_{+5}	σ_t	σ_{-5}
OBNL	35.58	35.75	35.49	34.06	34.07	33.79	32.82	32.81	32.56	31.72	31.73	31.54
K-SVD	35.19	35.98	33.57	34.01	34.32	32.60	33.00	33.20	31.84	32.06	32.15	31.15
BM3D	35.60	36.71	30.42	34.44	34.94	30.92	33.52	33.70	31.30	32.72	**32.86**	31.26
BPFA	36.28	36.30	36.28	34.49	34.51	34.53	33.26	33.25	33.24	32.23	32.24	32.25
Proposed	**36.70**	**36.72**	**36.72**	**35.03**	**35.05**	**35.07**	**33.91**	**33.90**	**33.89**	**32.86**	**32.86**	**32.87**

important drawback of these algorithms is that the image is not processed if no similar patches are found. Moreover, the estimation of noise parameters is very delicate [5].

Optimization based methods have been effective in removing noise while preserving image structure (see, for example, [1,2]). Among those, *K-means singular value decomposition* (K-SVD) has demonstrated significant advantages [7]. It uses an over-complete learned dictionary matched to the images of interest. This works effectively on de-noising as the learned dictionaries render more adaptive priors for Bayesian estimation [4]. Unfortunately, the K-SVD algorithm is conditional since it applies only to the cases where the error parameter matches the *ground truth* [8]. In uncertainty an appropriate setting for finding K-SVD does not possess the adaptive dictionary of the similar pixel matching values in general. Therefore, the setting of either a sparsity level and a predefined dictionary size or an error threshold is required to determine the patch-specification. Other well known recent methodologies include *block-matching 3D filtering* (BM3D) [9], *learned simultaneous sparse coding* (LSSC) [10], *trainable nonlinear reaction diffusion* (TNRD) [11], *non-locally centralized sparse representation* (NCSR) [12], *weighted nuclear norm minimization* (WNNM) [14], *patch group prior based de-noising* (PGPD) [17], and *shrinkage fields* [18]. These methods show good performance in cases where an error parameter matches to the *ground truth* in the form of an exact noise variance [8]. However, their performance is significantly affected if the settings do not agree with the *ground truth*. The interested readers are referred, for instance, to [5] and Table 1 for further details.

In order to mitigate the aforementioned problem of matching the ground truth, a Bayesian non-parametric method, coined as *beta process factor analysis* (BPFA), has been suggested by Zhou et al. [5]. The beta process is derived by an underlying Poisson process, and its properties as a stochastic process for Bayesian modeling are well understood [19]. The purpose of using such a non-parametric Bayesian approach based on beta Bernoulli process is to infer the relative information in a non-parametric fashion. Besides, in BPFA method, the automatic inference of the sparsity level of the coefficients has been performed [5]. However, experimental results of the BPFA method in terms of *peak signal-to-noise ratio* (PSNR) do not correlate with outputs of related algorithms to achieve a state of the art performance [2]. Since the weak edges have low gradient magnitude and are similar to the background structure of noisy image, they are often corrupted by false or degraded edge formations during usual de-noising processes [2,8].

The aim of this article is to design a hybrid image de-noising framework with an integrated parameter selection scheme to handle substantially high noise having unknown variance. The main motivation behind this investigation is to design a hybrid Bayesian technique that benefits from the non-local property in keeping the latent features intact while availing the advantages of the dictionary learning with adaptive priors in removing the idiosyncratic noise from the corrupted image. The central idea is to effectively work in uncertainty of noise parameters where contemporary de-noising techniques often show compromised performance, and to substantiate that the dictionary redundancy performance of the dictionary learning system can be improved [7].

Towards this end, a two-step strategy is adopted. The first step consists of applying an optimized Bayesian NLM filtering using two different sets of parameters to noisy image followed by a sub-band replacement and fusion process. This hybrid application to the given noisy image provides the processed data with enhanced edges and corners. In the second step, dictionary learning is performed using adaptive patch size with a non-parametric Bayesian estimation.

The application of the NLM algorithm on noisy image, with appropriately tuned pairs of regularization parameters, patch sizes and search window sizes, furnishes two processed images, one with enhanced smooth regions (i.e. enhanced low frequency contents) and one with enhanced sharp regions (i.e. enhanced high frequency contents). Then a sub-band replacement is performed since the image with enhanced smooth regions (respectively sharp regions) may have degraded high (respectively low) frequency contents. These contents are replaced with those of the noisy image to obtain first stage processed images. The basic role of the proposed sub-band replacement is to preserve the salient features of the noisy image. The band splitting is achieved using multi-resolution wavelet transform [13,15,16]. The first stage processed images are then *fused* with the given noisy image for balancing the relevant information that may have been gotten out of place during the replacement procedure. The combining parameters in the fusion process are the weights estimated in terms of the *Shannon* entropy of the first stage processed images and the estimated noise variance of the noisy image. The process of fusion then provides two second stage processed images. We once again use NLM filtering to further refine the second stage images in order to remove the artifacts appeared because of sub-band replacement and fusion with the noisy image. The resulting images are then fused together furnishing the final stage processed data. In the second step of the de-noising framework a model based on truncated beta-process factor analysis [5] is invoked to separate the salient covariance configuration of the