Dan ZHANG, Lei ZHAO, Duanqing XU, Dongming LU, 2022. Dual-constraint burst image denoising method. *Frontiers of Information Technology & Electronic Engineering*, 23(2):220-233. https://doi.org/10.1631/FITEE.2000353

Dual-constraint burst image denoising method

Key words: Image denoising; Burst image denoising; Deep learning

Corresponding author: Lei ZHAO
E-mail: cszhl@zju.edu.cn
ORCID: https://orcid.org/0000-0003-4791-454X

Motivation

1. Images are crucial information carriers that were developed for recording, sharing, and analyzing messages. Image denoising helps enhance the image quality, which directly determines our visual enjoyment and influences the efficiency and reliability of image processing and image analysis.

2. For a noisy image, removing the noise and recovering the details are challenging.

3. Deep learning methods show great potential in image denoising.

Main idea

1. Block matching and 3D filtering (BM3D) and the convolutional neural network (CNN) are effective for image denoising.

2. A two-path model is designed which integrates the features from preprocessed images and noisy images.

3. Dual-constraint is used to achieve both noise removal and detail preservation.

4. The frame alignment error is resolved by the block matching technique.

Method

1. A novel CNN framework is proposed which consists mainly of two parallel branches.

2. One of the branch is with the signal constraint, generating the latent signal from the input image. The other is with the noise constraint, generating the noise map from the input image. At the end of the network, different outputs are fused for denoising.

Method

Dual-constraint denoising network

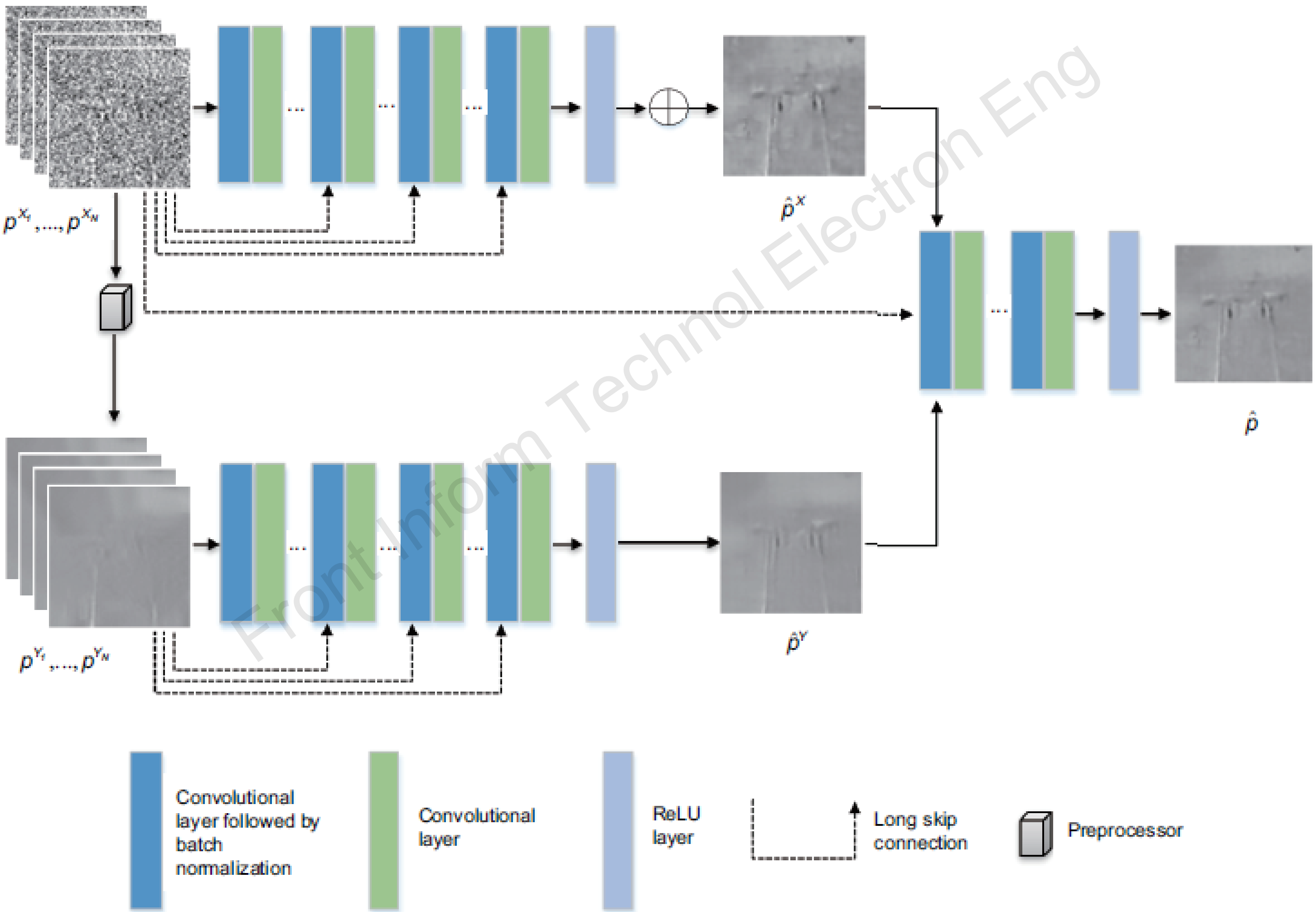


Fig. 1 Network architecture of the proposed method

Major results

Table 2 PSNR (dB) results of different methods on Set12 dataset with the noise level $\sigma = 50$

Image	PSNR (dB)						
	Original	BM3D	VBM3D	DnCNN	DnCNN-AVG	DVDNet	Ours
Cameraman	14.8565	26.1130	26.3541	27.0047	26.3295	26.6340	**29.2958**
House	14.5914	29.6380	30.4681	30.0136	31.2604	30.0157	**32.2391**
Pepper	14.7104	26.6244	27.8517	27.2926	27.6585	27.7167	**29.6813**
Fishstar	14.9202	25.0165	26.0405	25.7012	26.3724	26.5935	**28.7913**
Monarch	14.7085	25.7192	27.1462	26.7648	28.0151	27.7944	**29.6881**
Airplane	15.0593	25.1457	26.4944	25.8656	26.4403	26.6210	**28.5899**
Parrot	15.0288	25.9217	26.2420	26.4830	25.8877	26.3779	**28.7566**
Lena	14.6148	29.0460	30.2706	29.3604	30.2800	29.6825	**31.7309**
Barbara	14.7560	27.2219	27.2955	26.2301	26.9460	27.1064	**29.4681**
Ship	14.5878	26.7175	27.8773	27.1896	27.7527	27.6964	**29.5703**
Man	14.6386	26.8117	27.9689	27.2409	27.9361	27.7163	**29.5781**
Couple	14.5540	26.1038	27.5152	26.8928	27.5083	27.6010	**29.0776**

Best results are in bold

Major results (Cont'd)

Table 3 SSIM results of compared methods on Set12 dataset with the noise level $\sigma = 50$

Image	SSIM						
	Original	BM3D	VBM3D	DnCNN	DnCNN-AVG	DVDNet	Ours
Cameraman	0.1844	0.7689	0.7691	0.7981	0.7758	0.7343	**0.8319**
House	0.1274	0.8153	0.8306	0.8227	0.8416	0.7593	**0.8454**
Pepper	0.1940	0.7928	0.8300	0.8113	0.8323	0.7689	**0.8610**
Fishstar	0.2431	0.7373	0.7824	0.7623	0.7919	0.7886	**0.8476**
Monarch	0.2545	0.8159	0.8585	0.8446	0.8783	0.8211	**0.8946**
Airplane	0.2214	0.7787	0.8245	0.8041	0.8121	0.7986	**0.8533**
Parrot	0.2123	0.7856	0.7931	0.8010	0.7800	0.7376	**0.8458**
Lena	0.1175	0.7995	0.8243	0.8121	0.8283	0.7554	**0.8475**
Barbara	0.2045	0.7935	0.7935	0.7692	0.7800	0.7688	**0.8621**
Ship	0.1605	0.7009	0.7348	0.7172	0.7317	0.7132	**0.7871**
Man	0.1474	0.7034	0.7447	0.7218	0.7390	0.7130	**0.7970**
Couple	0.1694	0.6929	0.7365	0.7234	0.7254	0.7254	**0.7923**

Best results are in bold

Major results (Cont’d)

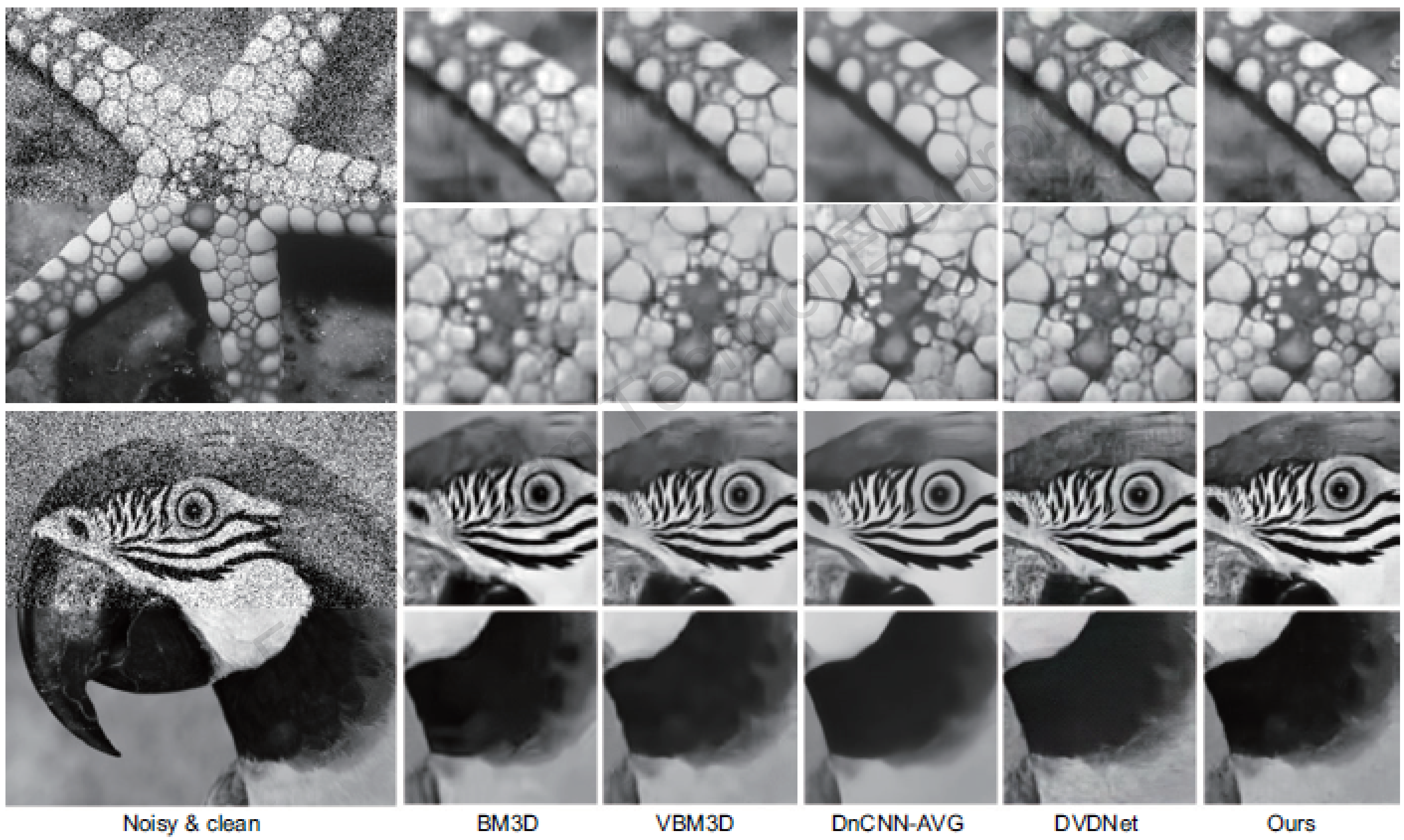


Fig. 4 Visual comparison of examples from Set12 dataset with the noise level $\sigma = 50$. The first column is stitched using the noisy and clean versions; the other columns show the results of BM3D, VBM3D, DnCNN-AVG, DVDNet, and the proposed method

Major results (Cont'd)

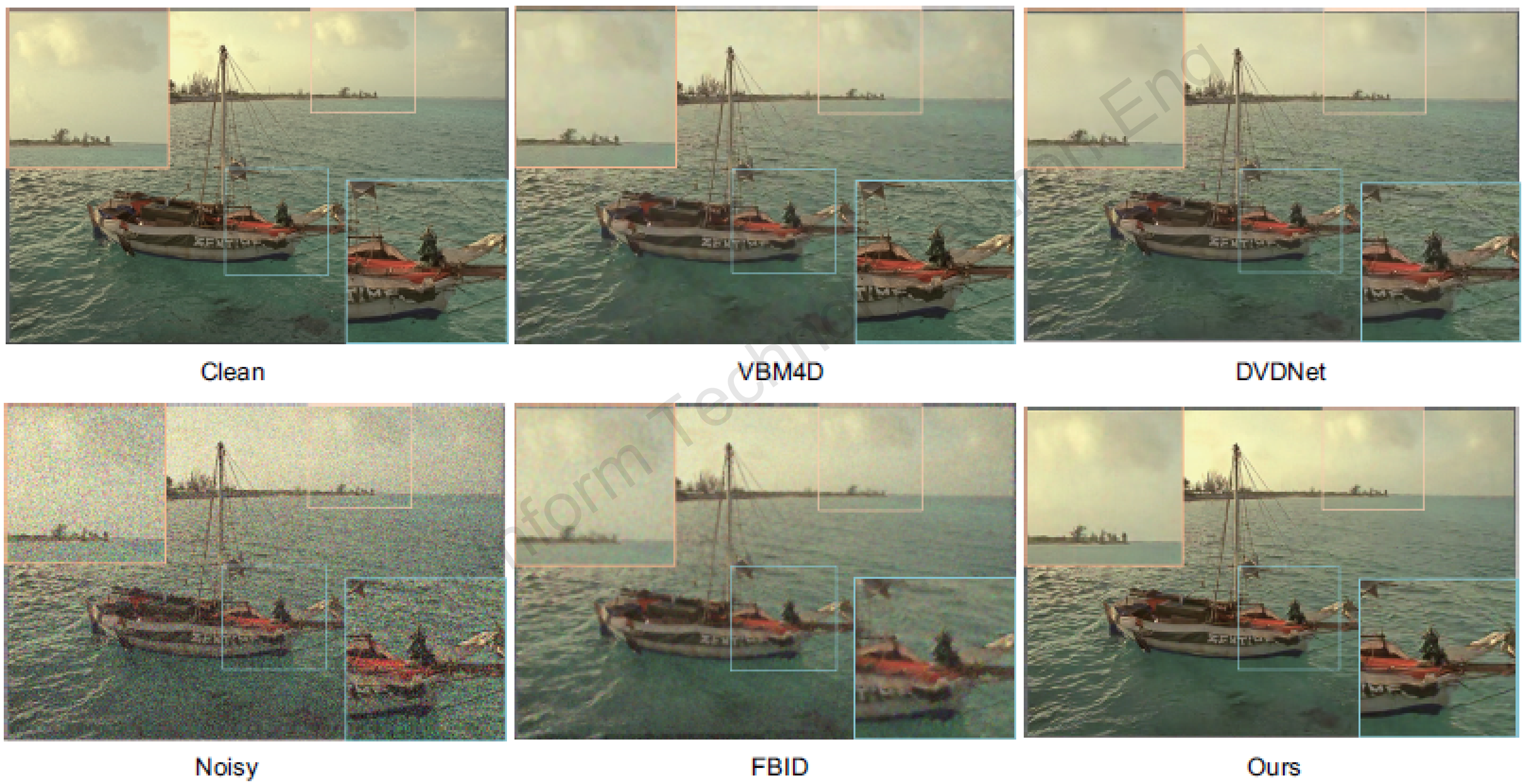


Fig. 7 Visual comparison of color image denoising (one example in the Kodak24 dataset)

Major results (Cont'd)

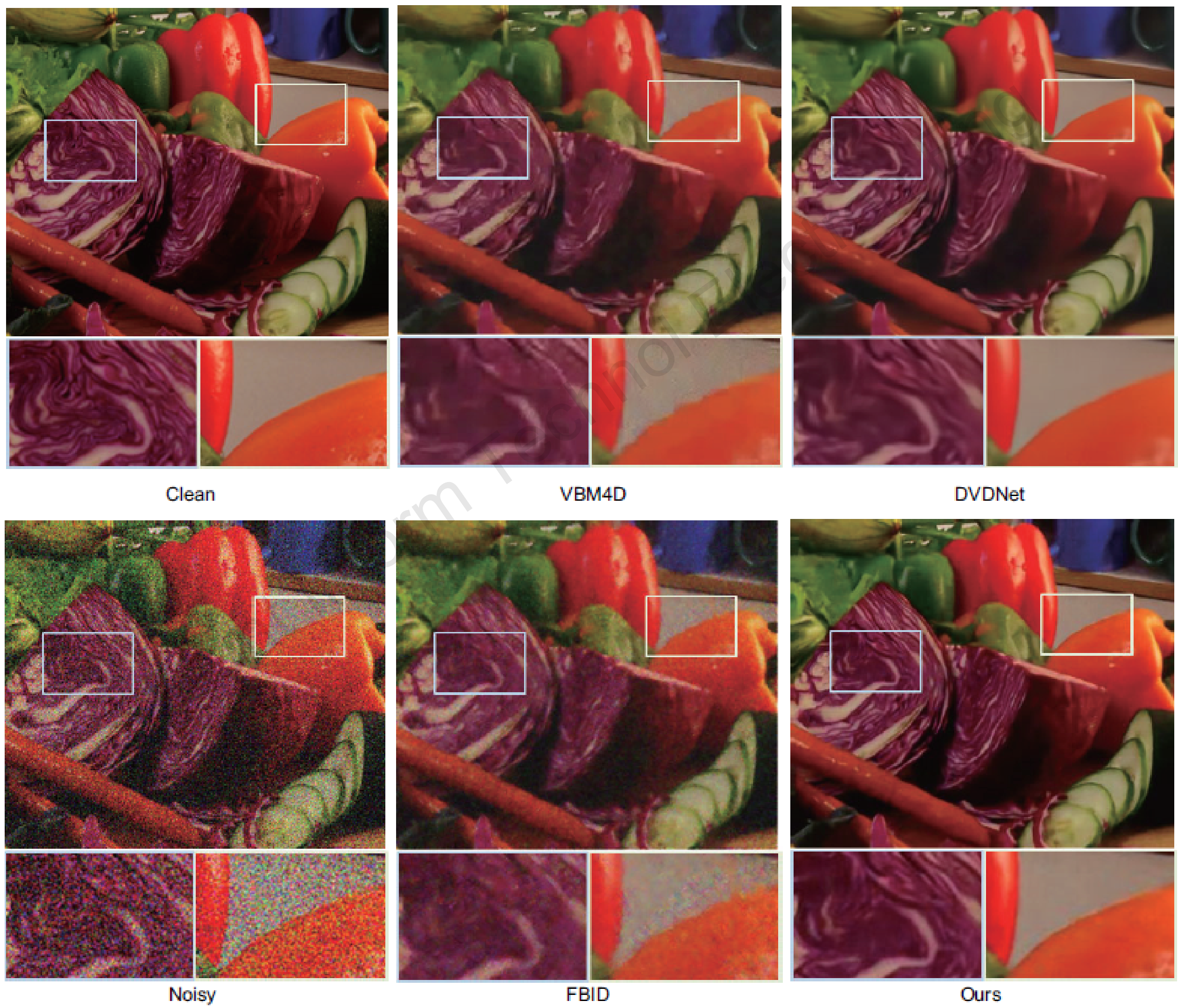


Fig. 8 Comparison of images with frame alignment errors

Conclusions

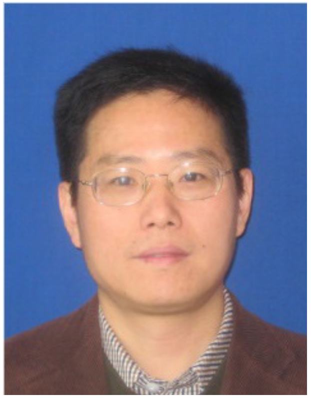
1. A deep neural network for burst image denoising has been proposed which uses a branch to map the noise distribution and a branch to recover the latent signal.

2. The scheme of fusing the noise constraint and signal constraint showed excellent balance on noise removal and texture preservation.

Dan ZHANG received her BE degree from Sichuan University, Chengdu, China, in 2013. She is currently a PhD candidate in the College of Computer Science and Technology, Zhejiang University, Hangzhou, China. Her research interests include computer vision, image processing, and deep learning.

Lei ZHAO, corresponding author of this paper, is an associate professor at Zhejiang University. He received his PhD degree from Zhejiang University in 2009. During 2009–2011, he was a post-doctoral researcher in the College of Computer Science and Technology, Zhejiang University. His research interests include computer graphics, computer vision, image processing, and deep learning.

Duanqing XU received his PhD degree from Zhejiang University. Now he is a professor in the College of Computer Science and Technology, Zhejiang University. His research interests include computer vision, image processing, and deep learning.



Dongming LU is now a professor in the College of Computer Science and Technology, Zhejiang University. He is a vice president of NingboTech University, Ningbo, China. His research interests include computer vision, image processing, and deep learning.