MBD-GAN: Model-based image deblurring with a generative adversarial network

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Introduction

1. We propose to establish a framework for inverse imaging with the help of dual theory.
2. We propose a novel model-based GAN which connects the generator and the discriminator with the imaging model.
3. By combining the prior knowledge embedded in the imaging model and deep learning, the proposed network is able to finish the deblurring task with complex blurring kernel.
4. Experimental results demonstrate that our model outperforms other image deblurring methods on quantitative measurements and visual quality.

Problem formulation

A general inverse imaging problem aims at finding the latent image $\mathbf{x}$ from a noisy measurement $\mathbf{y}$

$$\mathbf{y} = A\mathbf{x} + \mathbf{w},$$

Where A is the imaging model and $\mathbf{w}$ is the additive noise.

Dual theory

The problem above is often solved by a constraint optimization problem

$$\begin{aligned} &\text{minimize} && R(\mathbf{x}) \\ &\text{subject to} && A\mathbf{x} = \mathbf{y} \end{aligned}$$

Using the Lagrangian method, we have

$$\min L(\mathbf{x}, \boldsymbol{\lambda}) = \min \{R(\mathbf{x}) + \boldsymbol{\lambda}^T (A\mathbf{x} - \mathbf{y})\},$$

Where $\boldsymbol{\lambda}$ is determined by its dual problem

$$\max g(\boldsymbol{\lambda}) = \max L(\mathbf{x}^*, \boldsymbol{\lambda})$$

and $\mathbf{x}^*$ is the optimized value.

Network

As shown above, $\boldsymbol{\lambda}^*$ is obtained by maximizing $\boldsymbol{\lambda}^T(A\mathbf{x}-\mathbf{y})$ and then $\mathbf{x}^*$ is calculated by minimizing $L(\mathbf{x},\boldsymbol{\lambda}^*)$, and these two parts consist of a min-max problem, which is solved by a GAN architecture.

The whole structure is shown in Fig. 1.

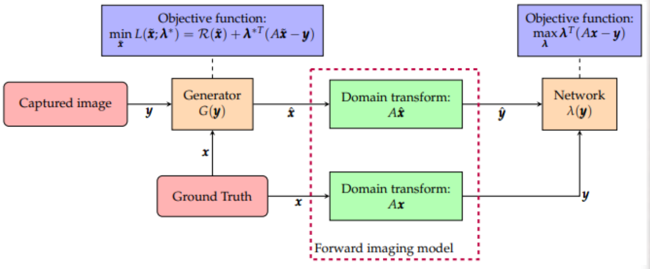

Fig.1 MBD-GAN structure

The generator is used to solve the minimization problem and generates an reconstructed image, then the discriminator is used to solve the maximization problem and gives an evaluation of the generated image.
Since $\boldsymbol{\lambda}$ is only related to $A\mathbf{x}$, an forward imaging model is used between the generator and the network in discriminator.

Network structure

- **Generator** : Resnet-9 (DeblurGAN)
- **Discriminator**: CNN with 6 convolution layer (PatchGAN)
- **Loss**: perceptual loss and WGAN loss with gradient penalty

Results

Table 1. Quantitative evaluation on the same dataset

Methods	PSNR/dB	SSIM
blurred	22.86	0.759
HL [19]	17.90	0.459
IDD-BM3D [21]	21.00	0.647
EPLL [20]	28.70	0.877
FCNN [22]	24.83	0.775
SRN [15]	30.10	0.932
MBD-GAN	**31.74**	**0.953**

Table 2. Quantitative evaluation across different datasets

Methods	PSNR/dB	SSIM
blurred	21.46	0.760
HL [19]	14.60	0.373
IDD-BM3D [21]	17.90	0.473
EPLL [20]	20.19	0.650
FCNN [22]	19.55	0.570
DeblurGAN [16]	26.10	0.816
SRN [15]	26.75	0.837
MBD-GAN	**27.49**	**0.943**

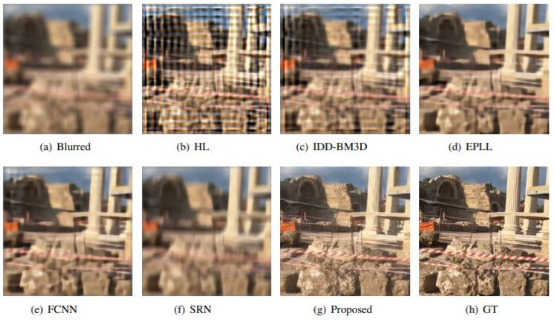

Fig.2 Visual deblurred images

1. We compare the quantitative results with both conventional methods and learning-based methods on 2 public datasets.
2. The proposed model outperforms existing methods on both experiments.
3. The visual results show that our model is able to recover the details with better image fidelity.