From Noise Modeling to Blind Image Denoising

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July 10, 2018

Abstract

As we know, traditional image denoising algorithms always consider the noise as white Gaussian noise. However, in the real world, the noise on real images can be more com- plex actually. In this paper, in order to address this problem, the authors proposes a new blind image denoising algorithm. The algorithm can deal with real-world noisy images even when the noise model is not providedI. Using the mixture model of Gauss distribution (MOG) to model the image noise, it can approximate a wide range of continuous distribution. In this paper, the authors use Bayesian nonparametric technique and proposes a novel Low-rank MoG filter (LR-MoG) to recover clean signals (patches) from noisy ones contami- nated by MoG noise.

1. Introduction

In the field of computer vision and image processing, image denoising is always an much important problem. For example, we can process a image to get high-quality image and it is an important pre-processing step for many high-level visual problems such as digital entertainment, object recogniton, image segmentation, remote sensing imaging and so on. The purpose is to recover the clean image $\hat{X}$ from its noisy observation X which is contaminated by noise E as shown in Eq.1.

$$X = \hat{X} + E \tag{1}$$

Estimating $\hat{X}$ from X is an inverse problem. In recent years, many scholars proposed some algorithms [7, 2, 3, 1, 4, 6] to solove the problem. However, most methods consider the noise as the homogeneous white Gaussian distribution. This assumption seems reasonable, because some noise can be converted to Gaussian noise. However, in camera systems, the noise has many sources and can be more complex. So the authors proposes the "blind image denoising" algorithm to estimate the noise model from a noisy observation.

The traditional noise models can fail to solve empirical noise. Fig. 1 demonstrates the performance of [5] on an old photo "Pele". Because of lack of flexibility of the noise model, [5] can only remove some noise but not all noise in some areas and over-smooth details in some other areas. To tackle the problem, the authors of this paper proposed a new non-local blind image denoising algorithm.

2. Background

In this section, the authors introduces the information of Dirichlet process and its construction, which will be used to construct the LR-MoG filter.

2.1. Dirichlet Process

We know that the Dirichlet Process (DP) is a distribution over distribu- tions, *i.e.*, each draw from a DP is itself a distribution. The DP is parameterized by a base distribution H and a concentration parameter α. A good feature favored by DP is that a drawn G from a DP is discrete with probability one and the dimension of G is infinite.

2.2. Stick-breaking Construction

The stick-breaking construction is one of the methods to explicitly represent draws from DP. With a stick-breaking construction, one can directly work with G before drawing θ. Sethuraman proved that a draw G from DP $(, H)$ can be described as Eq.2

$$\begin{aligned} v_i &\sim \textbf{Beta}\left(1, \alpha\right), \qquad & \pi \sim v_i \prod_{j=1}^{i-1}, \\ \theta_i &\sim H, & G = \sum_{i=1}^{\infty} \pi_i \delta_{\theta_i} \end{aligned} \tag{2}$$

Here, **Beta** (a, b) is a **Beta** distribution with parameters a and b. And δ_{θ_i} is the Dirac probability measure concentrated at θ_i. π are the stick lengths, and it is almost sure that $\sum_{i=1}^{\infty} \pi_i = 1$. The stick-breaking construction indicates the discreteness of G as well.

References

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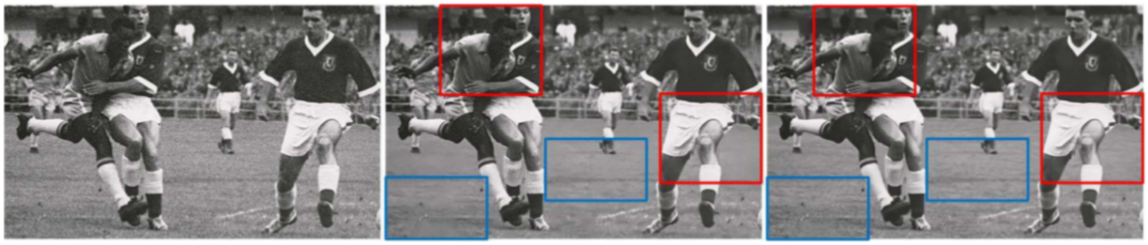

Figure 1. From left to right: an old photo "Pele" with noise; the denoising result of [5] and ours. Zoom in for better visualization.

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