LaTeX Author Guidelines for ICCV Proceedings

Anonymous ICCV submission

Paper ID ****

Abstract

Motivated by the weighted Orthogonal Procrustes Problem, we propose a noval weighted Frobenious norm based weighted sparse coding model for non-Gaussian error modeling. We solve this model in an alternative manner. Updating of each variable has closed-form solutions and the overall model converges to a stationary point. The proposed model is applied in real image denoising problem and extensive experiments demonstrate that the proposed model can much better performance (over 1.0dB improvement on PSNR) than state-of-the-art image denoising methods, including some excellant commercial software. The noval weighted Frobeniius norm can perfectly fit the non-Gaussian property of real noise.

1. Introduction

Image denoising is an important problem in computer vision and image processing. The non-local self similarity property of images has been extensively employed in image denoising algorithms.

我们的去噪模型是：

$$\min_{\mathbf{D},\mathbf{C},\mathbf{W}} \frac{1}{2}\|(\mathbf{Y}-\mathbf{D}\mathbf{C})\mathbf{W}\|_F^2 + \lambda\|\mathbf{C}\|_1 \quad \text{s.t.} \quad \mathbf{D}^\top\mathbf{D} = \mathbf{I}. \tag{1}$$

去噪过程如下：

1. 初始化：

我们从原始噪声图得到相似块矩阵$\mathbf{Y}$，我们采用[1]的方法估计彩色带噪图的噪声水平σ_0。初始化权重矩阵$\mathbf{W}^{(0)} = \frac{1}{\sigma_0}\mathbf{I}$, 初始化字典$\mathbf{D}^{(0)} = \mathbf{I}$。

2. 进入内部迭代优化：

对于每一次迭代，模型都需要反复迭代求解$\mathbf{D}$,$\mathbf{C}$直到收敛。For $k = 0, 1, 2, ...$:

a. update $\mathbf{C}$

$$\min_{\mathbf{C}} \frac{1}{2}\|(\mathbf{Y}-\mathbf{D}^{(k)}\mathbf{C})\mathbf{W}^{(k)}\|_F^2 + \lambda\|\mathbf{C}\|_1. \tag{2}$$

有闭合解，每一列单独求解：

$$(\hat{\mathbf{c}}_i)^{(k+1)} = \arg\min_{\mathbf{c}_i} \frac{1}{2}\|(\mathbf{y}_i-\mathbf{D}^{(k)}\mathbf{c}_i)\mathbf{W}_{ii}\|_2^2 + \lambda\|\mathbf{c}_i\|_1. \tag{3}$$

闭合解为：

$$(\hat{\mathbf{c}}_i)^{(k+1)} = \text{sgn}(\mathbf{D}^\top\mathbf{y}) \odot \max(|\mathbf{D}^\top\mathbf{y}| - \frac{\lambda}{(\mathbf{W}_{ii})^2}, 0), \tag{4}$$

b. update $\mathbf{D}$

$$\min_{\mathbf{D}} \frac{1}{2}\|(\mathbf{Y}-\mathbf{D}\mathbf{C}^{(k+1)})\mathbf{W}\|_F^2 \quad \text{s.t.} \quad \mathbf{D}^\top\mathbf{D} = \mathbf{I}. \tag{5}$$

等价于

$$\min_{\mathbf{D}} \|(\mathbf{Y}\mathbf{W}) - \mathbf{D}(\mathbf{C}^{(k+1)}\mathbf{W})\|_F^2 \quad \text{s.t.} \quad \mathbf{D}^\top\mathbf{D} = \mathbf{I}, \tag{6}$$

闭合解为：$\hat{\mathbf{D}}^{(k+1)} = \mathbf{V}\mathbf{U}^\top, \mathbf{C}\mathbf{W}(\mathbf{Y}\mathbf{W})^\top = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\top$.

c. update $\mathbf{W}$ 根据贝叶斯法则，权重矩阵的第i项为

$$\mathbf{W}_{ii} = \frac{\frac{1}{N}\sum_{i=1}^N \|\mathbf{y}_i - \mathbf{D}\mathbf{c}_i\|_2}{\sigma_{\mathbf{y}_i}\|\mathbf{y}_i - \mathbf{D}\mathbf{c}_i\|_2} \tag{7}$$

3. 外部迭代优化：

更新每个块的噪声水平：

$$\sigma_{\mathbf{y}_i} = \sqrt{\sigma_0^2 - \|\mathbf{y}_i - \mathbf{D}\mathbf{c}_i\|_2^2} \tag{8}$$

然后重复步骤2.

References

[1] Guangyong Chen, Fengyuan Zhu, and Pheng Ann Heng. An efficient statistical method for image noise level estimation. In *The IEEE International Conference on Computer Vision (ICCV)*, December 2015. 1