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Adaptive parameter selection for preserving edges based on EPLL

Ze, Qin[1,*], Xiulan Sheng[1]
[1] College of education, Jiangsu Open University, Nanjing 210044, China
Email: qinzjsou@163.com
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Abstract: Though image denoising has experienced rapid development, there remain problems to be solved such as preserving the edge and meaningful details in image denoising. In this paper, we focus on this hot issue. Considering the parameter in original method is a constant, we introduce a new adaptive parameter selection based on EPLL (Expected Patch Log Likelihood) by the use of image gradient and the local variance, which varies with different regions of the image. What's more, for solving staircase effect which common in anisotropic diffusion models, we add a gradient fidelity term to release it. The experiment shows that our proposed method proves the effectiveness not only in vision but also on quantitative evaluation.
Keywords: image denoising; adaptive parameter; Expected Patch Log Likelihood; edges

1. Introduction

Images have been a more and more important carrier of plenty information, which can deliver messages intuitively. Unfortunately, images inescapably suffer from noise due to various reasons, such as motion blur and the precision in measurements of sensors. Noise removal has always been a hot issue in the past few decade years, the research that follows is also growing rapidly.

A large number of denoising methods have been proposed during hot discussion. Much work has begun on sparse representation, which regards image patches as the linear combination of some atoms based on a dictionary [1]. After this, low-rank approximation methods also achieve good results [2], [3]. The total variation (TV) has always been a hot topic [4], [5]. Establishing an appropriate prior model directly influences the outcome. So mixture models have raised much concern in image restoration due to its robustness, especially Gaussian Mixture Model [6], [7], [8]. Inspired by this, some further studies have been proposed.

When it comes to noise removal, one sharp problem is always unavoidable. How to preserve as much structural information as possible while removing noise. So preserving edges of the image has become a thorny problem among academic and industry communities. Therefore, a lot of work revolves it. Perona and Malik firstly put forward pioneering model of anisotropic diffusion [9]. This idea was immediately spread due to its powerful effect [10], [11], [12]. Of course, this great approach also has its weakness. The number of iterations has giant influence on results. It always leads to staircase effect after excessive iterations. Inspired by this, Tebini proposed a fast and efficient to speed up the convergence of algorithm [13]. In this paper, we focus on the edge-preserving, and propose a new method of adaptive regularization parameter selection. Moreover, we add a gradient-fidelity term to relieve the staircase effect and preserve more details of image.

2. Proposed method

2.1 Original EPLL Model

Given a noisy image corrupted by noise which can be described as $u_0 = u + v$ Where u represents clean image and v represents noise. We aim at separating the pure image from the noisy one. In some ways one image can be seen as a type of high dimensional data, so making clear of prior knowledge becomes a principal problem. Gaussian mixture model is considered as one of the ideal models to describe statistical characteristics of the gray image. In this paper, the Gaussian mixture model is trained by a set of clean image patches $D = \{a_1, a_2, \cdots, a_N\}$. For each patch a_i , the distribution can be described as the following:

$$p(a_i) = \sum_{i=1}^{K} \pi_k N(a_i \mid \mu_k, \Sigma_k) \tag{1}$$

where

$$N(a_i \mid \mu_k, \Sigma_k) = \frac{1}{(2\pi)^{\frac{d}{2}} \Sigma_k^{\frac{1}{2}}} \exp\left(-\frac{(a_i - \mu_k)\Sigma^{-1}(a_i - \mu_k)}{2}\right) \tag{2}$$

Where π_k is the prior probability for *k-th* component, K is the number of mixing components, μ_k and Σ_k denote the corresponding mean vector and covariance matrix. To simplify notations, using $\Theta = \{\pi_k, \mu_k, \Sigma_k\}$ denote all these parameters. Expectation Maximization algorithm has proven its effect in estimating parameters in various models.

In the E step, estimate the posterior probability for each component

$$p(k \mid a_i, \Theta) = \frac{\pi_k N(a_i \mid \mu_k, \Sigma_k)}{\sum_{k=1}^{K} \pi_k N(a_i \mid \mu_k, \Sigma_k)} \tag{3}$$

Then, we have the likelihood function for all patches as below:

$$LL(D) = \sum_{i=1}^{N} \ln\left(\sum_{i=1}^{K} \pi_k N(a_i \mid \mu_k, \Sigma_k)\right) \tag{4}$$

In the M-step, let so as to estimate parameters, solving it then we get: