Neurocomputing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

An image topic model for image denoising

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ARTICLE INFO

Article history:
Received 1 May 2014
Received in revised form
17 November 2014
Accepted 22 November 2014

Keywords:
Topic model
Denoising
Patch clustering
Semantic learning

ABSTRACT

Topic model is a powerful tool for the basic document or image processing tasks. In this study we introduce a novel image topic model, called Latent Patch Model (LPM), which is a generative Bayesian model and assumes that the image and pixels are connected by a latent patch layer. Based on the LPM, we further propose an image denoising algorithm namely multiple estimate LPM (MELPM). Unlike other works, the proposed denoising framework is totally implemented on the latent patch layer, and it is effective for both Gaussian white noises and impulse noises. Experimental results demonstrate that LPM performs well in representing images. And its application in image denoising achieves competitive PSNR and visual quality with conventional algorithms.

1. Introduction

Topic modeling such as the latent Dirchlet allocation (LDA) [1] aims to model collections of discrete data. It simulates the generative process of documents by introducing a latent topic layer and is successfully used in basic document tasks. Recently, topic models infiltrate the domains of image and video processing, such as image segmentation [2–4], categorization [5,6], activity analysis [7], and monitoring [8]. Most works use topic models by seeking equivalent concept between documents and images, or borrowing the idea of latent layer for special tasks.

In this study, we address a latent patch model (LPM), as well as a special kind of topic model, in order to model images. We argue that a quantity of neighborhood pixels is already significant, where the latent patch exists, and image can be considered as a mixture of patches. As a topic model, the goal of LPM is to understand the insight of natural images and to provide a statistical train of thought to complete fundamental image processing tasks. To illustrate the power of LPM, an image denoising algorithm framework is proposed. As a matter of fact, denoising is one of the most conventional and substantial process with respect to images, since an image is usually polluted by noises in the procedure of being captured, digitized, recorded, and transmitted. Hardly can the noised image be performed segmentation, compression, and feature extract tasks. In order to complete this issue, a flood of related algorithms have been proposed. Bilateral filter [9] and Non Local Means (NLM) [10] reach desirable performance, but they fail in the presence of strong noise. Besides, both methods are time consuming. The state-of-art denoising algorithms include BM3D [11] and K-SVD [12]. The BM3D uses 3-D similar patches to perform denoising in the transform domain, while the key of K-SVD is to get an optimal dictionary of image patches adapted for the observed noisy data. Moreover, Gaussian scale mixture (GSM) is studied in [13,14] from the perspective of statistics. Though some of these methods can achieve good results, they tend to behave inefficiently in two aspects. First, many methods cannot get stable enough results in the presence of strong noises. Second, most methods are designed to process a particular kind of noise, such as white Gaussian noise or impulse noise. So far, there have hardly been a method addressed yet that is able to effectively deal with the denoising issue when both strong Gaussian noises and impulse noises are present, including classical methods like median filter (MF), adaptive median filter (AMF) [15], and the methods proposed recently like decision based algorithm (DBA) [16], decision based unsymmetric trimmed median filter (DBUTMF) [17], and modified decision based unsymmetric trimmed median filter (MDBUTMF) [18]. We believe the reason for this phenomenon lies in the fact that these methods are not designed in a unified non-local expression framework.

As mentioned above, we design an image denoising algorithm framework under a proposed generative probabilistic model LPM, called multiple estimation LPM (MELPM). The key of the proposed denoising algorithm framework is that each pixel will be estimated multiple times and reconstructed by the weighted average of estimation expectations. Clustering approach is employed for

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http://dx.doi.org/10.1016/j.neucom.2014.11.094
0925-2312/© 2015 Published by Elsevier B.V.

simplifying the parameter estimation, and then the weight matrix can be obtained depending on the model parameters. When facing with different types of noises like Gaussian and impulse noise, MELPM could choose different denoising strategies. Experimental results demonstrate that MELPM achieves good performance under both Gaussian noises and impulse noises. It is also worth demonstrating that MELPM owns high robustness in complex image contents and high intensity noise conditions.

2. Latent patch model

2.1. Model description

The latent patch model (LPM) is a generative probabilistic model of an image. Similar with LDA [1], the basic idea of LPM is that the images are described by a distribution over latent patches, and patches are influenced by distributions over pixels.

We make an independent assumption with respect to pixels so that the generative process for each image can be described as follows:

1. Choose $N \sim Poisson(\xi)$.
2. For each of $N \times N$ value of pixels k_n:
   (a) Choose a patch $p_n \sim Multinomial(\theta)$.
   (b) Sample the value of pixel $k_n \sim Gauss(k_n|p_n, U)$, conditioned on the patch p_n.

In this model, the dimensionality of patch is defined as M and the number T of categories of patch is a known constant. Pixels attached to different categories and locating diverse coordinates in one category draw from different Gauss distribution parameterized by a $T \times M^2$ matrix U where $u_{ij} = \{u_{ij}, \sigma_{ij}\}$. Here the notations μ and σ denote the expectation and standard deviation, respectively. And following the representation of LDA, the Poisson assumption is significant by no means and more appreciate distributions for the image dimensionality can be utilized as possible.

As a matter of fact, LPM simulates the generative procedure of natural images, as well as modeling, which provides a new approach to understand the insight of images. As a consequence, various fundamental tasks with respect to images should be done under the framework of LPM.

2.2. Patches extraction and clustering

In this section, the procedure of constructing a LPM is introduced. First of all, an image is segmented into a collection of patches. Patch extraction is then carried out in a manner of moving point. During this procedure, we determine the patch size following the rules: smaller size patches are good at describing complex content, while bigger size of patches are good at describing simple texture content.

After patches extraction, we cluster the patches by k-means. The number of clusters increases when the patch contents become complex. Fig. 1 shows a result that image "Lena" is extracted by a size of five pixels and clustered into fifteen clustering centers. It can be seen that patches own similar content in the same cluster.

3. Application of latent patch model

3.1. Overview of MELPM

In this section, we illustrate how to capitalize LPM to explore the resolution for the image denoising task. The image denoising algorithm called Multiple Estimation LPM (MELPM) is a further denoising algorithm framework. MELPM is realized with two successive steps. The result of the first one serves as a patches library for the second one.

In the first step, the target image is modeled using LPM. This step consists of patch division, patch clustering and parameter estimation.

In the second step, each pixel is smoothed, and smooth rule is designed by noise type.

3.2. Multiple estimation latent patch model

Aiming at the image denoising task, there exist two targeted designs for MELPM. First, we introduce a clustering step instead of estimation of θ in order to pursue preferable practicability. Then parameter U can be estimated directly. In other hands, since the nature of denoising is data restoration, we divide the original image into overlapping patches (point-wise segmentation and extension in image edge) to increase redundant information, so that each pixel, attributed to M^2 patches, will be estimated M^2 times. Subsequently, the noises can be smoothed by their weighted average of estimation expectations. That is why we name our algorithm as "ME"LPM. The procedure of MELPM is summarized as follows:

Algorithm 1. Algorithm–MELPM.

Initialization: The number of cluster T and the dimensionality of patch M.
1. Divide patch point-wisely in Fig. 2.
2. Patch clustering.
3. Estimate the parameter matrix U.
4. Smooth each pixel following smooth rules.

Several details are needed to be explained additionally. In step 2, each patch is corresponding to a M^2 dimensional intensity feature vector to support the clustering engine, where we select k-means algorithm due to its straightforward excellence, and it is acclimated to low dimensional feature space. Since clusters with high quality are obtained, we employ Maximize Likelihood to estimate the parameter matrix U according to the independent assumption. Distinguishing from the original LPM, patches here are overlapping so that each pixel corresponds to multiple parameters, as well as distributions, which are used to reconstruct the denoised image. It is obvious that two factors dominate the quality of estimation of single pixel among different distributions: probability of the pixel intensity and the standard deviation. The larger the probability and the lower the standard deviation are, the higher the quality is. As a consequence, we define the weight of j distribution of observed pixel n as follows:

$$\hat{\omega}_{nj} = \frac{1}{e^{|k_n^{(n)} - \mu_{nj}/\sigma_{nj}|} \ln \sigma_{nj}} \tag{1}$$

where $k_n^{(n)}$ and $\{\mu_{nj}, \sigma_{nj}\}$ denote the intensity and j paired-parameter of observed pixel n.

For normalization, formula (1) is rewritten as

$$\omega_{nj} = \frac{\hat{\omega}_{nj}}{\sum_{j=1}^{M^2} \hat{\omega}_{nj}} \tag{2}$$

3.3. Smooth rules

According to different noise types, MELPM provides different smooth rules. For white Gaussian noises, they are needed to be smoothed directly since they distribute in all Gray scale range. The smooth rule adopts

$$k_n = \sum_{j=1}^{M^2} \omega_{nj} \mu_{nj} \tag{3}$$

By contrast, the impulse noises like Salt & Pepper noise usually corrupt the images in a simpler manner. Each corrupted pixel

Please cite this article as: B. Fu, et al., An image topic model for image denoising, Neurocomputing (2015), http://dx.doi.org/10.1016/j.neucom.2014.11.094