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EPITOME BASED IMAGE DENOISING AND COMPARISION WITH TRANSFORMED DOMAIN

Sinchana B S[1], Reshma Verma[2]

[1]*ECE, M S Ramaiah Institute of Technology, (India)*

[2]*ECE, M S Ramaiah Institute of Technology, (India)*

ABSTRACT

The concept of epitome of an image was given by Brendan J Frey and NebjsaJojic in 2002. Epitomes are condensed version of the image which represents the most constituent elements of corresponding image. It finds application in areas of image segmentation, image in-painting, and image denoising. The paper compares the state of the art denoising using epitomes and by using epitomes to obtain basis using PCA. Denoising is done in the transformed domain after obtaining the basis. Denoised levels of epitome based approach is compared with the PCA approach.

Keywords : Basis, Denoising, Epitome, PCA, Transformed Domain

I INTRODUCTION

The most important problem in the field of computer vision and image processing is image denoising where the primary goal being estimating the original image by suppressing noise from a noise-contaminated version of the image. Image noise may be caused by different intrinsic (i.e., sensor) and extrinsic (i.e., environment) conditions which are often not possible to avoid in most situations. Hence, image denoising plays an important role. While many algorithms have been proposed for the purpose of image denoising, the problem of image noise suppression remains an open challenge, especially in situations where the images are acquired under poor conditions where the noise level is very high. There is a vast improvement in the methods of image restoration of late especially in the field of image denoising. The state-of-the-art techniques rely on two major hypotheses that hold true for natural images: (1) image patches from distant locations are often structurally similar and (2) image patches can be accurately expressed as a sparse linear combination of vectors from a dictionary. This dictionary could be a well-known universal basis, such as Fourier, discrete cosine transform (DCT), or wavelet (or overcomplete extensions of the same),or it could be trained offline on a set of representative images.

In the present work Epitome based image denoising is being done. The image denoising is also done in transformed domain by method of Principal Component Analysis. The denoising results in terms of PSNR is found for both methods and comparision is done. The paper by Shah et al. [1] gives a technique that generates epitome [2] of a given image, and performs denoising in transformed domain.

An image modeling scheme named “Epitome” was proposed by Brendan J. Frey and NebjsaJojic in

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2002 [2]. The epitome of an image is its miniature, condensed version containing the textural and shape components of the image. The epitome still contains most constitutive elements needed to reconstruct the image. It is a patch based, probabilistic model. The epitomes are generated using Expectation Maximization (EM) algorithm. Patches are used as training data to the EM algorithm. Epitome consists of two components: 1) Parameter image and 2) Set of mappings, which maps the patches of the epitome to the corresponding patches of the input image. The E-step of the algorithm calculates the expectations of mappings and M-step maximizes the log likelihood which is the log probability that the training patches are generated from the epitome. Epitome generation tries to group together similar patches and generates a representative patch by taking weighted average of these similar patches. The EM algorithm for the epitome does the weighted average of similar patches to generate the representative patches in the epitome. So, while generating the epitome of the noisy image, due to the weighted average of similar patches, the epitome patches are expected to be noise-reduced patches. Now, since the patches in the epitome are noise-reduced patches, reconstructing the image from the epitome gives the image with reduced noise. Thus, image denoising is also an application of epitome.

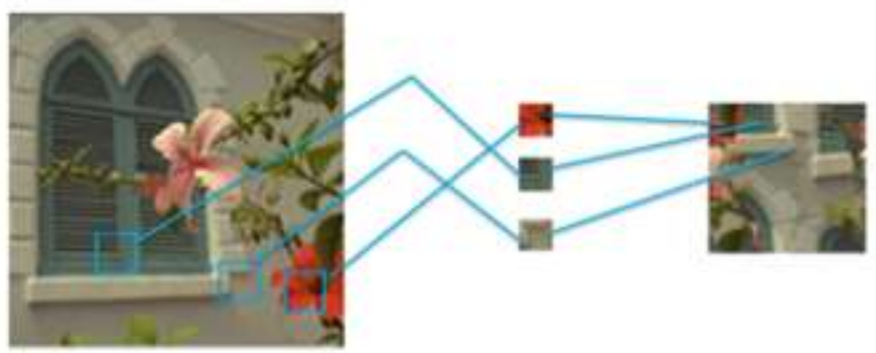

Figure 1 : Relation between image and its epitome

The epitomes are used to obtain basis using Principal Component Analysis. The denoising is done in the transformed domain by thresholding. Weiner filtering can also be used for the purpose of denoising.

The paper is organized in the following manner. Section 2 describes theories of Epitome and PCA. Epitome based image denoising and the proposed approaches are discussed in Section 3. Experimental results are presented in Section 4 followed by conclusions.

II THEORY

2.1 Theory of Image Epitome

*Epitome Generation :*As proposed in [2] Epitome is an image of parameters that gives a generative model of patches taken from the input image. A set of random patches from input image are taken which is used as training sequence to generate the epitome. Expectation Maximization(EM) algorithm is used to generate the epitome. The epitome can be of any size. For sake of convenience usually a square is taken. Epitome has two components – parameter image and set of mappings. Take X to be a 2D input image on an underlying domain K. For parameter image E and set of mappings M, let patch beX_n. A mapping $m \in M$ with probability $p(m)$ is selected where $\sum_{m \in M} p(m)=1$. Each value in $Xn(k)$ is obtained independently using parameters in epitome pertaining to selected mapping i.e$E(m[k])$. The probability density of function of the patch conditioned on $m$and E is given by :

$$p(Xn|m, E) = \prod_{k \in K} f(Xn(k) ; E(m[k])) \quad (1)$$

where$f$ (.; .) is the probability density function for each value in the patch. Let $X_1, X_2, \ldots, X_n$be patches of original image. Assuming the patches to be i.i.dsamples the likelihood of epitome is :

$$l(E ; X) = \sum_{n=1}^{N} p(Xn \mid E) \quad (2)$$

Marginal likelihood is :

$$p(Xn ; E) = \sum_m p(Xn, m ; E) \quad (3)$$

$$= \sum_m p(Xn \mid m; E)\, p(m) \quad (4)$$

Log likelihood of the epitome becomes :

$$L(E \mid X) = \sum_{n=1}^{N} \log \left(\sum_{m \in M} p(m)\, p(Xn|m, E)\right) \quad (5)$$

This is the log probability that the training patches are generated from the epitome. Now the task is to find E and M. E must be maximized. Done with the help of EM algorithm. This works in two steps :

- E step : Here probabilities of all possible mappings $m \in M$ are calculated using Bayes rule :

$$p(m \mid Xn, E) = \frac{p(Xn|m,E)p(m)}{\sum_m p(Xn \mid m,E)\, p(m)} \quad (6)$$

- M step :Parameters in E are updated with the goal of maximizing log likelihood

Gaussian distribution is added to the log likelihood equation and the expression becomes equivalent to Gaussian Mixture Model. With this new expression we get the mean $\mu(j)$ and variance $\sigma^2(j)$ at the jth position of the epitome:

$$\mu(j) = \frac{\sum_{n=1}^{N} \sum_{m:j-m \in K} p(m|Xn, E)Xn(j-m)}{\sum_{n=1}^{N} \sum_{m:j-m \in K} p(m|Xn, E)} \quad (7)$$

Variance is :

$$\sigma^2(j) = \frac{\sum_{n=1}^{N} \sum_{m:j-m \in K} p(m|Xn,E)(Xn(j-m)-\mu(j))^2}{\sum_{n=1}^{N} \sum_{m:j-m \in K} p(m|Xn,E)} \quad (8)$$

2.2 Principal Component Analysis : As proposed in [4]

Denote the image x as x = $[x_1, x_2, \ldots, x_m]^T$ be m component vector variable denoted as by

$$\mathbf{X} = \begin{bmatrix} x_1^1 & \cdots & x_1^n \\ \vdots & \ddots & \vdots \\ x_m^1 & \cdots & x_m^n \end{bmatrix} \quad (9)$$

the sample matrix of x, where x_i^j, j = 1,2,…,n, are the discrete samples of variable x_i, i = 1,2,…,m. The i^{th}row of sample matrix **X**, denoted by

$$X_i = [x_i^1 \; x_i^2 \ldots\ldots x_i^n] \quad (10)$$

is called the sample vector of x_i. The mean value of X_i iscalcaulated as :

$$\mu_i = \frac{1}{n}\sum_{j=1}^{n} X_i(j) \quad (11)$$

and then the sample vector X_i is centralized as

$$\overline{X_i} = X_i - \mu_i = [\overline{x_i^1 x_i^2} \ldots\ldots \overline{x_i^n}] \quad (12)$$

Accordingly, the centralized matrix of X is

$$\overline{X} = [\, \overline{X_1^T\, X_2^T\, X_m^T} \,]^T \quad (13)$$

Covariance matrix is calculated as :

$$\Omega = \frac{1}{n}\overline{X}\overline{X}^T \quad (14)$$

The goal of PCA is to find an orthonormal transformation matrix P to de-correlate X, i.e. $\overline{Y} = P\overline{X}$ so that the co-variance matrix of Y is diagonal. The covariance matrix $\Omega$is symmetrical. PCA completely decorrelates the original dataset $\overline{X}$. Generally speaking, the energy of a signal will concentrate on a small subset of the PCA transformed dataset, while the energy of noise will evenly spread over the whole dataset. Therefore, the signal and noise can be better distinguished in PCA domain.

III DENOISING

3.1 Epitome based denoising :

For a given noisy image X, its epitome is generated. The epitome is used to reconstruct original image by overlapping the patches $X_1, X_2, \ldots, X_n$. The corresponding matching probabilities are calculated using (6). The mapping with the highest probability is selected, and the epitome corresponding to this mapping is chosen. On the whole, one transforms an image to its epitome, and reconstructs it back. This leads to reduction of noise.

3.2 Epitome based transform domain denoising

Most state of the art denoising techniques involve using a transformation to take an image from spatial domain to a different domain, where noise is then removed. Shah et al. [1] have taken the assumption that using such a transform domain based image denoising can bring about improvements in the performance of epitome based noise removal techniques.The epitomes generated are used to obtain basis using PCA. Denoising is performed in the transformed domain using hard thresholding. The steps used are as follows

- Generate the epitomes of noisy image X
- Use these epitomes to generate basis vectors using PCA
- Denoise the noisy image in the transformed domain using hard thresholding
- Inverse transform is applied to get denoised version of the image

IV EXPERIMENTS

The experiments are conducted on a set of natural grayscale images of size 256x256. The noisy images are generated by adding additive white Gaussian noise (AWGN). Noise levels of (noise variance) σ= 10, 20, 40 are considered. Epitomes of size 8x8 was taken and denoising was done using the two methods. The PSNR is calculated to find the denoising.

V RESULTS

The PSNR values given in the table indicates that the epitome based denoising gives better noise removal when compared to using the PCA method.

VI CONCLUSION

Epitomes are miniature condensed version of the image. It works by the concept of grouping together similar patches. The reconstruction of the image is done by taking the weighted average of similar patches which causes noise to be reduced. The paper gives method of using epitomes to find the PCA basis and denoising is done in the transformed domain. The results indicate that the use of epitome based method (without performing transformed domain) gives significant noise reductions.

σ = 10

Image	Epiotme based approach	Transform domain based approach
Barbara	68.18	30.43
Lena	71.80	32.75
Hill	60.28	29.95
Couple	61.46	29.95
Cameraman	60.16	30.72

Table 1 : PSNR (dB) values obtained in the two methods for noise variance σ = 10

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σ = 20

Image	Epiotme based approach	Transform domain based approach
Barbara	68.10	28.40
Lena	69.98	29.92
Hill	59.98	27.07
Couple	61.37	27.69
Cameraman	59.46	28.43

Table 2 : PSNR (dB) values obtained in the two methods for noise variance σ = 20

σ = 40

Image	Epiotme based approach	Transform domain based approach
Barbara	68.15	25.89
Lena	69.78	26.74
Hill	68.67	25.05
Couple	62.21	26.49
Cameraman	60.54	25.48S

Table 3 : PSNR (dB) values obtained in the two methods for noise variance σ = 40

(a)



(b) (c) (d)

Figure 2 : (a) is the input image (b) is noisy image of σ = 10 (c) is denoised image with epitome reconstruction (d) is PCA based denoising

(a)

(b) (c) (d)

Figure 3 : (a) is the input image (b) is noisy image of σ = 10 (c) is denoised image with epitome reconstruction (d) is PCA based denoising

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