IMPLEMENTATION OF IMAGE DENOISING METHOD WITH AN IMPROVED CLUSTERING

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Abstract : Image denoising has been a well studied problem in the field of image processing. This paper address the implementation of effective image denoising method using fuzzy c-mean clustering, where zero mean additive white Gaussian noise is to be removed from a given image. A patch- based wiener filter (PLOW) is introduced that exploits patch redundancy for image denoising. The method uses both geometrically and photometrically similar patches to estimate the different filter parameters. For this, fuzzy c-means clustering algorithm is used. Fuzzy c-mean results faster and reliably good clustering when compare to k-mean in image denoising. Patch denoising using fuzzy c-mean results in high signal to noise ratio and Structural Similarity Index (SSIM). Visually good images can be obtained by the proposed method. This denoising approach designed for optimal performance and is experimentally verified on a variety of images and noise levels.

Keywords : Additive White Gaussian Noise, Image Denoising, fuzzy c-mean clustering, PLOW.

Introduction : With the recent advances in imaging technology, image denoising has found renewed interest among both researches and camera manufacturers. Applications now range from the casual documentation of events and visual communication to the more serious surveillance and medical fields. This has led to increasing demand for accurate and visually pleasing images. All digital images contain some degree of noise. Often times this noise is introduced by the camera when a picture is taken. Image denoising algorithms attempt to remove this noise from the image. Ideally, the resulting denoised image will not contain any noise or added artifacts. Image denoising has been studied for decades in computer vision, image processing and statistical signal processing. This problem not only provides a good platform to examine natural image models and signal separation algorithms, but also becomes an important part to digital image acquiring systems to enhance image qualities. The influence and impact of digital images on modern society is tremendous and image processing is now a critical component in science and technology. This paper addresses the classical problem of removing Additive White Gaussian Noise (AWGN) from a corrupted image. PLOW algorithm can strongly restrain Gaussian noise compared to other filters [6].Additive White Gaussian Noise is the common type of noise that is present in natural images in large quantity and its removal is therefore necessary.

Clustering is the process of dividing the data elements into classes or clusters so that items in the same class are similar as possible, and items in different classes are dissimilar as possible. Fuzzy current state-of-the-art denoising methods with this bound. P.Chatterjee and P.Milanfar proposed a way to bound how well an image can be denoised [7]. In this work they extend the formulation to more practical case where no ground truth is available. A clustering is a class of algorithms for cluster analysis in which allocation of data points to clusters is fuzzy. In fuzzy clustering, data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of association between that data element and a particular cluster. Fuzzy C-Means (FCM) is an unsupervised clustering algorithm that has been applied to wide range of problems involving feature analysis, clustering and classifier design. FCM attempts to find the most characteristic point in each cluster, which can be considered as the center of the cluster and then the grade of membership for each object in the cluster.

The challenge of any denoising algorithm is to suppress the noise while producing sharp images without loss of fine details. In this paper, we propose a new denoising filter motivated by our statistical analysis of the performance bounds for patch based methods [5], [7]. The framework uses photometrically and geometrically similar patches for the filtering process.

This paper is organized as follows: Section II includes the related work. Section III describes the PLOW filtering method. Section IV presents the system model for the proposed work. Section V gives the experimental results and discussions. The paper is concluded in Section VI.

Related Work : The researches continue to focus attention on it to better the current state-of -the-art. The performance bounds for the image denoising problem studied in [5] and this work estimates a lower bound on mean squared error of the denoised result and compares the performance of novel adaptive patch based approach [1] is proposed for image denoising and this method is based on a point wise selection of small image patches of fixed size in the variable neighborhood of each pixel. Development and generalization of tools that make contact with the field of non parametric statistics and results for use in image processing and reconstruction[2].They adapt and expand Kernel regression ideas for use in image denoising, up scaling, interpolation, fusion and more. In [3], they described a method for removing noise from digital images, based on statistical model of the coefficients of an over complete multiscale oriented basis neighborhood of coefficients at adjacent positions and scales are modeled as the product of two independent random variables, a Gaussian vector and a hidden positive scalar multiplier.

Plow Filtering Method : : Additive white Gaussian noise is the most common type of noise found in natural images. Here the denoising is performed on a patch by patch basis. This denoising approach works in the spatial domain motivated by the statistical analysis of performance bounds [5], [7]. The patch based denoising exploits the patch redundancy, where the parameters are learned from both geometrically and photometrically similar patches. The noisy image is first segmented into regions of similar geometric structure. The segmentation is performed by Fuzzy C-Means clustering. The clustering process is much effective and also takes less time for clustering compared to that of k-means clustering [8],[9]. The mean and the covariance of the patches within each cluster are then estimated. Photometrically similar patches for each patch are then identified and compute the weights based on the similarity to the reference patch. These parameters are used to perform denoising patch wise. Image patches are selected to have some degree of overlap with each other. The multiple estimates for the pixels lying on the overlapping patches are then aggregated to form the denoised image.

a) PLOW Denoising Method

PLOW is an LMMSE filter [4] that exploits both geometric and photometric redundancies. Filter designed to (asymptotically) achieve performance. Performance comparable or exceeding state-of-the-art in terms of MSE/PSNR and visual quality is performed. PLOW with fuzzy c-mean clustering based filtering is much better than k-mean clustering based filtering for image denoising [8],[9]. The data model for the observed image is assumed by:

$$y_i = z_i + \eta_i , i = 1,....., M \qquad (1)$$

Where M is the number of pixels in the image. Here z_i is assumed to be the actual pixel intensity which is corrupted by the noise η_i. The photometric similarity between the noisy patches as

$$\left\| \tilde{\varepsilon}_{ij} \right\|^2 \le \gamma_n^2 = \gamma^2 + 2\sigma^2 n \quad \text{Where}$$

$$\tilde{\varepsilon}_{ij} = y_j - y_i \qquad (2)$$

In (2), γ is chosen as a small threshold dependent on the number (n) of pixels in the patch. In PLOW denoising method, initially set the parameters patch size and number of clusters. Then noise standard deviation σ is estimated. After the estimation, set the parameter $h^2 = 1.75\sigma^2 n$. The LARK feature is computed in order to perform Geometric Clustering and the geometric clustering is performed by fuzzy c-means clustering. For each cluster estimate the mean patch size and cluster covariance. Photometrically similar patches are identified for each patch and weights are computed. The denoised patch is then estimated and the error covariance. Finally multiple pixel estimates are aggregated to obtain the denoised image.

b) Geometric Clustering : To perform geometric clustering, it needs to identify that capture the underlying geometric structure of each patch from its noisy observations. Such features need to be robust to the presence of noise, as well as to differences in contrast and intensity among patches exhibiting similar structural characteristics. Using the LARK features [2], run the fuzzy c-means to cluster the noisy image into regions containing geometrically similar patches.

c) Fuzzy C-Means Clustering Algorithm

FCM clustering techniques are based on fuzzy behavior and provide a natural technique for producing a clustering where membership weights have a natural interpretation. Clusters are formed based on the distance between two data points. In this algorithm data are bound to each cluster by means of a membership function, which represents the fuzzy behavior of the algorithm. To do this algorithm have to build an appropriate matrix whose factors are numbers between 0 and 1, and represent the degree of membership between data and centers of clusters. FCM is a method of cluster, which allows one piece of data to belong to two or more clusters. It is based on the minimization of objective function:

$$J_m = \sum_{i-1}^{N} \sum_{j-1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2 , 1 \le m < \infty \qquad (3)$$

Where m is any real number greater than u_{ij} is the degree of membership of x_i in the cluster j,x_i is the i^{th} of d-dimensional measured data, c_j is the d-dimension centre of the cluster, and $\|*\|$is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function with the update of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left[\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right]^{\frac{2}{m-1}}}, c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m} \qquad (4)$$

This iteration will stop when $\max_{ij}\{ |u_{ij}^{(k+1)} - u_{ij}^{(k)}| \} < \xi$, where ξ is a termination criterion 0 and 1, whereas K is the iteration steps. This procedure converges to a local minimum or saddle point of J_m.The algorithm is composed of following steps:

Step 1: Initialize U=u_{ij} matrix, $U^{(0)}$

Step 2: At k-step calculate the centers vectors $C^{(K)}$ = $[c_j]$ with $U^{(K)}$

Step 3: Update $U^{(K)}$, $U^{(K+1)}$

Step 4: If $\| U^{(K+1)} - U^{(K)} \| < \xi$ then STOP; otherwise return to step 2.

In this algorithm, data are bound to each cluster by means of a Membership function, which represents the fuzzy behavior of the algorithm. FCM clustering techniques are based on fuzzy behavior and provide a natural technique for producing a clustering where membership weights have a natural (but not probabilistic) interpretation. This algorithm is similar in structure to the K-Means algorithm and also behaves in a similar way [10], [11].

d) Estimating Cluster Moments

Vec (.) denotes the vectorization operation and the convolution (*) implies the addition of forward gradients in the horizontal and vertical directions. The parameters estimated from each cluster of the image can be directly used for denoising

e) Calculating Weights for Similar Patches

The patches within the noisy image that are photometrically similar to given reference patch are first identified. Once the similar patches are identified for a given reference patch, denoising with the more similar patches exerting greater influence in the denoising process are performed. This is ensured by the analytically derived weight w_{ij} which determines the contributing factor for patch in denoising the reference patch. Weight is related to the inverse of the expected squared distance between the underlying noise-free patches and a noise term .The weight is calculated by

$$w_{ij} \approx \frac{1}{\sigma^2} \exp\left\{ -\frac{\|y_i - y_j\|^2}{h^2} \right\} \qquad (9)$$

The smoothing parameter h^2 is a positive parameter that controls the rate at which the contributing factor is driven to zero as the patches become less similar.

Once the image is segmented into structurally similar regions, the moments are estimated namely, mean and covariance, from the noisy member patches of each Cluster. Since the noise patches are assumed to be zero mean i.i.d., the mean of the underlying noise-free image can be approximated by the expectation of the noisy patches within each cluster as

$$\hat{\bar{z}} = E[y_i \in \Omega_k] \approx \frac{1}{M_k} \sum_{y_i \in \Omega_k} y_i$$

(5)

Where $\boldsymbol{\Omega_k}$ denotes the k^{th} cluster with cluster cardinality M_K. Working with the sample covariance $\widehat{C}_Y$,we estimates the covariance of the underlying noise-free patches as

$$\hat{C}_z = [\hat{C}_y - \sigma^2 I]_+ \qquad (6)$$

Where σ^2 is the noise covariance and $[X]_+$ denotes denotes matrix X with its negative Eigen values replaced by zero and the noise standard deviation is given by

$$\hat{\sigma} = 1.482 \,\text{median}(|\nabla Y \text{-median}(\nabla Y)|) \qquad (7)$$

Where ∇Y is the vectorized form of the gradient of the input image Y.The gradient image ∇Y is calculated as

$$\nabla Y = \frac{1}{\sqrt{6}} vec\left(Y * \begin{bmatrix} 2 & -1 \\ -1 & 0 \end{bmatrix} \right). \qquad (8)$$

In the algorithm the parameter is kept fixed at $h^2 = 1.75\boldsymbol{\sigma}^2 n$. This was empirically found to be close to the optimal h^2 value for a wide range of images and across different noise levels.

f) Aggregating Multiple Pixel Estimates

The filter is run on a patch basis yielding denoised estimates for each patch of the noisy input. To avoid block artifacts at the patch boundaries, the patches are chosen to overlap each other. As a result, the multiple estimates for the pixels lying in the overlapping regions are obtained. These multiple estimates need to be aggregated to form a final denoised image. The covariance of the proposed estimator given by $C_e \approx \left(\hat{C}_z^{-1} + \sum_{j=1}^{N_i} w_{ij} I \right)^{-1}$

(10)

The necessary parameters of the proposed filter can be estimated from a given noisy image. The accuracy of estimating such parameters is dependent on the strength of the noise corrupting the image. Noise affects different parameter estimation steps differently.

System Model :
Since image denoising to be done by PLOW using k-mean and fuzzy c-mean, the standard images available from MatLab 2008 is used as samples. For experimentation, MatLab 2008 is used.

The parameters considered for evaluation are as follows:

Image name (.jpg)	K-Mean PLOW denoising			Fuzzy C- Mean PLOW denoising		
	Time(ms)	PSNR	SSIM	Time (ms)	PSNR	SSIM
House	0.38266	74.643	0.50531	0.03315	74.7772	0.51259
Cameraman	0.26355	73.2565	0.50354	0.022209	73.3869	0.514
Lena	0.25696	75.6263	0.70692	0.019599	75.7281	0.71086
Peppers	0.64097	70.5488	0.64534	0.05253	70.6974	0.65811
Greens	0.36143	72.0421	0.5213	0.039271	72.0726	0.5510
Autumn	0.36945	76.9491	0.94547	0.071878	78.4801	0.8453
Football	0.37377	73.7339	0.17056	0.018329	73.7931	0.17298
Boat	0.36814	72.0412	0.5211	0.032971	72.0716	0.5401
Stream	0.37621	73.7329	0.1706	0.017392	73.7642	0.1792
Monalisa	0.38813	72.0283	0.55278	0.035972	72.1316	0.56004

Table 1: Result Of K-Mean And Fuzzy C-Mean Based Plow Denoising

1) Total time taken for clustering: It is the time taken for cluster the input image for denoising.
2) PSNR: PSNR stands for Peak Signal to Noise Ratio and it is calculated using the following equation:

$$s(x,y) = \frac{\sigma_{xy}+C}{\sigma_x \sigma_y + C}$$

Where σ_{xy} indicate multiplication of pixel value of filtered and noisy image and C is the constant value.When PSNR is bigger, it is considered that

Experimental Results :
The experimental results show that PLOW with fuzzy c-mean clustering is much better than k-mean clustering based denoising [8], [9]. The noisy image is given as the input and the denoised image is obtained as the output by passing through the PLOW filter. This noisy image is allowed to pass through PLOW filter with both k-mean and fuzzy c-mean clustering method. Total time, PSNR and SSIM are noted for both the cases. PLOW with fuzzy c-mean clustering based denoising has obtained better results i.e. which take low processing time, higher PSNR and SSIM value when compared to the k-mean clustering based PLOW. The experimental results prove that the proposed fuzzy c-mean clustering based PLOW filter is showing high performance in image denoising when compared to k-mean clustering based PLOW. While considering the measurement values from the table 1, it is obviously clear that PLOW with fuzzy c-mean clustering based denoising method is better than k-mean clustering based method in terms of

$$\text{PSNR}=20\log_{10}\ (255/\sqrt{MSE})$$

3) SSIM value between input image and denoised image: SSIM is calculated using following equation:

noise level is lower. Also SSIM index can be viewed as a quality measure of the image with respect to another image of higher quality. Higher the SSIM value, the image is of better quality [12].

time taken, PSNR and SSIM values for different images. Since fuzzy c-mean based PLOW has less time consuming and showing high performance in image denoising.

Conclusion : In this paper, we have proposed a fuzzy c-mean based PLOW filtering method for an image to perform image denoising and compared with k-mean based PLOW filtering. The parameters considered are time taken for image clustering, PSNR and SSIM, for both the methods such as fuzzy c-mean using PLOW and k-mean using PLOW. The performance evaluation of image denoising using PLOWS with k-mean and fuzzy c-mean is done for the standard and the result arrived which showed that PLOW with fuzzy c-mean clustering based denoising is better when compared to k-mean clustering based denoising method. The proposed algorithm had a computationally inexpensive convergence process. It gives best result for image denoising.

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