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A Novel Patch-Based Denoising Scheme

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Abstract— This paper proposes a denoising scheme which aims at removal of white gaussian noise present in the image. The framework works in spatial domain. We propose a patch-based filter that exploits patch redundancy for image denoising.The system checks for the presence of white gaussian noise in the input image. In the absence of white gaussian noise, it does not undergo denoising scheme. In such case, the image will be displayed as such. If the image contains white gaussian noise, then the framework uses both geometrically and photometricaly similar patches to estimate the different filter parameters. In order to group geometrically similar patches, Fuzzy C-means clustering is employed. Then the implementation uses the estimated parameters to denoise patch wise.

Index Terms— FCM, Filter, Image clustering, Image denoising,Noise identification,White Gaussian noise, Wiener filter

1 Introduction

THERE has been considerable increase in the casual and commercial uses of image and videos recently. Apart from applications in photography, the captured data are often inputs to sophisticated object detection and tracking, and action recognition methods, applications of which permeate different areas. Acquired images are often not of desired quality and need to be enhanced by software. One of the major causes of the performance degradations for most methods is the presence of noise. Noise removal, therefore, forms a critical first step for many applications.

The challenge of any image denoising algorithm is to suppress noise when producing sharp images without compromising finer details and edges in the image.

In order to restrict such loss of detail in the image, it is necessary to make sure that the averaging is performed only over photometrically similar pixels. For example, to denoise the pixel y_i of Fig.1, we should use the intensity information of y_j , but not y_1. However, in the presence of noise, identifying such similar pixels can be challenging. One of the first approaches making use of a data adaptive weight function is attributed to Tomasi et al. (bilateral filter [6]). The weight function here takes into account the local intensity information as well. An additional smoothing parameter h_r is introduced and this intensity bandwidth needs to be tuned based on the corrupting noise level. The added photometric term ensures that similar pixels in the neighbourhood are preferred in the averaging, thus avoiding smoothing across edges. However, as the noise level increases, the filters ability to distinguish between similar and dissimilar pixels degrades quickly.The concept of locality is extended to entire image in [9],[10]

Denoising methods vary widely in their approaches. Based on domain, denoising filters are categorized into two, spatial denoising method and transform denoising method

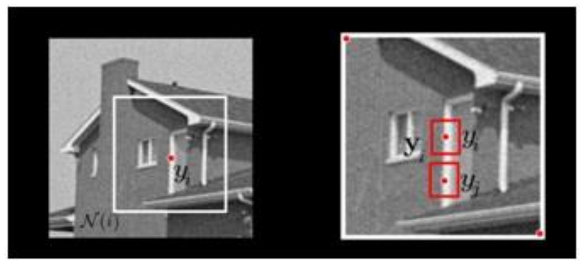

Fig 1: Illustration of the concept of search window N(i), patches and similar patches.

Denoising methods where the pixel intensities are used directly in the denoising process are said to be spatial-domain filters. In general, approaches can be classified as being either a process where denoising is performed by a weighted averaging of pixel intensities, or an explicit model-based approach where parameters of the data model are usually learned from the noisy image itself.

The main motivation of denoising in some transform domain is that in the transform domain it may be possible to separate image and noise components. The basic principle behind most transform-domain denoising methods is shrinkage - truncation (hard thresholding) or scaling (soft thresholding) of the transform coefficients to suppress the effects of noise. For such thresholding, the challenge is to develop a suitable coefficient mapping operation that does not sacrifice the details in the image. The final denoised image is obtained by performing an inverse transform on the shrunk coefficients.

The framework operates in spatial-domain method. Its objective is to handle white gaussian noise present in the image. Initially input image is first checked for the presence of white gaussian noise which is not dealt in [1],where the input should always be noisy. If the image contains white gaussian noise it will undergo denoising operation, else the image will be outputted as such. Denoising scheme involves a filter where the parameters are learned from both geometrically and photo-

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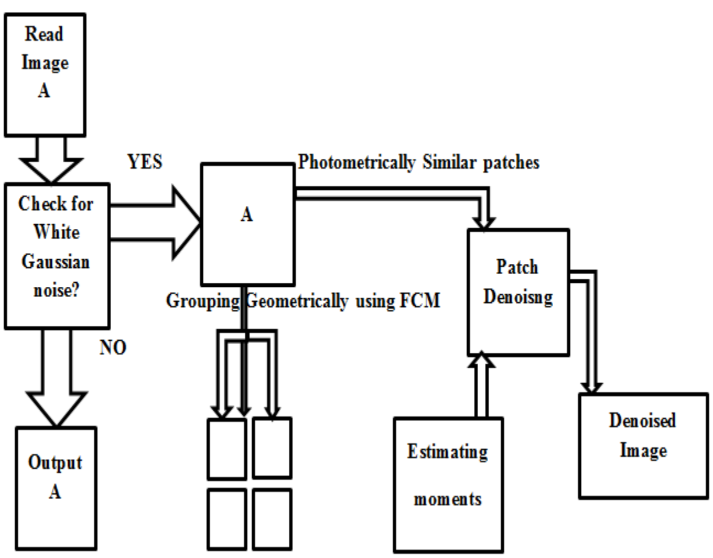
metrically similar patches. For this, the noisy image is first clustered into regions of similar geometric structure. The technique used for grouping geometrically similar patches is FCM(Fuzzy C-means Clustering).The idea of Fuzzy C-means clustering is inspired from [4].In [1] they have used K-means which fail to handle patches which comes at boundary of two clusters. This issue is addressed in the present framework. The mean and the covariance of the patches within each cluster are then estimated. Next, for each patch, photometricaly similar patches are identified and compute weights based on their similarity to the reference patch. These parameters are then used to perform denoising patchwise. To reduce artifacts, image patches are selected to have some degree of overlap (shared pixels) with their neighbours. A final aggregation step is then used to optimally fuse the multiple estimates for pixels lying on the patch overlaps to form the denoised image

2 Proposed Method

The framework operates in spatial domain. The objective is to denoise the image if it contains white gaussian noise. The two main steps include 1) detecting the presence of white gaussian noise (WGN) 2) patch-based denoising.The outline of the proposed system is shown in fig 2.



Block Diagram of Proposed System

2.1 Detection of White Gaussian Noise

An efficient denoising scheme needs to know whether the input image has noise present in it.The work of priyam.et.al [1] does not consider this issue and assumes that input image is always noisy. But in practical this is not the case. Thus detection of white Gaussian noise in an image has relevance.

In [2],[3] training samples of white Gaussian affetcted images have been used.Then filter each sequence through weiner filter[2].Then estimate the Kurtosis of each noisy sample sequence a to yield the reference values of Kurtosis for the White gaussiannoise. An upper threshold value T2 and lower threshold T1, have to set accordingly. Then once the input image is given, extract respective noise samples from the given noisy image. Then estimate its statistical feature Kurtosis .Then this estimated value is compared with the thresholds T1 and T2. If the value falls in the range of T1 and T2 it is assumed that the image contains white gaussian noise. Otherwise it is assumed that image does not have white gaussian noise within it.

Proposed Noise identification method

The basic principle consists of three main steps to identify the noise type.

Step 1: Extract respective noise samples from the given noisy image

Step 2: Estimate statistical feature Kurtosis

Step 3: Use upper threshold and lower threshold to detect white gaussian noise.

The above steps can be summarized as follows:

Assume the original M×N image y(i, j) is contaminated by either additive, ω(i, j). Thus the observed image f (i, j) can be modelled as equation for additive noise, equation. To extract some noise samples, first process the image through wiener filter operator Hk(i,j to obtain estimate,

$gk(i,j) = Hk(i,j) * f(i,j),$ (1)

Next, subtract each processed image, gk(i,j), from f(i,j)to extract respective noise samples, where ω k(i,j), corresponding to white gaussian noise(WGN)

$\omega k(i,j) = f(i,j) - gk(i,j)$ (2)

Next, estimate some simple statistical based features Kurtosis from ωk(i,j). The 4th order moments Kurtosis of a random variable X is defined as

$Kurt(X)= [\![(x-\mu)]\!]^4/\sigma^4$ (3)

where μ and σ are the mean and standard deviation.

Filtering and estimating kurtosis value is done for each training sample.Through experimentation set upper and lower threshold T2 and T1 respectively.So when an image is inputted,the image is filtered to obtain noisy sample and estimate kurtosis.If this value is in the range of T1 and T2,image is identified for noise and patch-based denoising will be performed

Algorithm to Check WGN

Algorithm to Check WGN

INPUT : Image Y

Generate a training sample set of white gaussian affected images
Extract noisy sample from sample images [See(1 2)]
Estimate kurtosis of sample images [See (3 4]
Set Threshold value T1 and T2
Extract noisy sample from input image
Estimate kurtosis of input image
if T1 ≤ Estimate ≤ T2 **then**
  Noisy
else
  Noiseless
end if
end

2. 2 Patch-Based Denoising

Once the image is identified for the presence of noise,it will undergo patch-based denoising otherwise the image is outputted as such.

2. 2.1 Patch-Based Denoising

To alleviate the detrimental effects of noise, the image has to be prefiltered once before the parameters of the framework are learned.The prefiltering is to obtain a "pilot" estimate which is necessary only for strong noise. The necessary filter parameters are then learned from the resultant noise-suppressed image [8]. These parameters are then applied to the original noisy image for denoising. For strong noise, such prefiltering invariably results in noticeably improved denoising performance.

2.2.2 Patch Extraction

Once the pilot estimate is obtained, overlapping patches are ex-tracted so as to perform denoising patch-wise. Denoising the entire image at once will not be able to remove noise effectively.

2.2.3Geometric Clustering using Fuzzy C-mean Clustering

The framework attempts to perform clustering to identify regions of similar structure in the image. To perform clustering it is required to identify firstinformative features from the image. Commonly used low-level features to identify similar pixels or patches are pixel intensity, gradient information or combination of these. The use of such features directly from input image is not advisable for denoising problem due to their instability in the presence of noise. The feature which is used to cluster here is steering kernel weight [5] computed in a neighbourhood are robust to the presence of significant amounts of noise. These weights are roughly representative of the underlying local data structure. Moreover, the normalized weights exhibit invariance to intensitydifference between image patches. Hence, vectorized version of these normalized weights is used as features to perform clustering[7]. At the end of this stage the image has to be divided into not necessarily contiguous regions, each containing patches of similar structure. Hence, the entire noisy image can be thought to be composed of a union of such clusters. Illustration of clustering results is shown below,

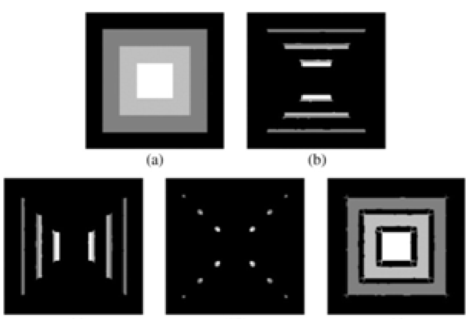


Fig 2: Clustering of simple image based on geometric similarity.

Clustering technique used in proposed system is Fuzzy C-means algorithm(FCM)[4].The motivation of clustering is to segment the image into some prefixed (K) number of clusters such that for each class, the squared distance of any feature (normalized weight) vector to the center of the class is minimized.[7] In [1] they have used K-means clustering algorithm to group geometrically similar patches. If K-means clustering is used it completely neglects those patches which comes in the boundary of two cluster. This can be handled in fuzzy C-means since partial membership to a cluster exists. If a patch has equal probability to belong two clusters, it will be assigned with membership function 0.5.Thus moments will be estimated from both cluster which will then be used in denoising. On the other hand, in K-means algorithm each patch will be assigned to exactly one cluster. Therefore only moments from one cluster will be taken for denoising.

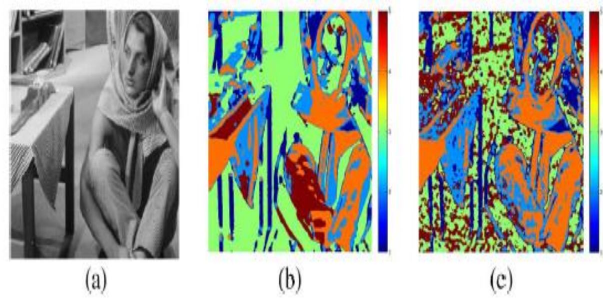


Fig.3. Clustering based on the geometric similarity of patches illustrated onnoise-free and noisy Barbara images with a standard deviation of 15.

2.2.4 Estimation of parameters and patch filtering

Once the image is segmented into structurally similar regions, moments has to be estimated, namely, mean and covariance, from the noisy member patches of each cluster. Next, for each patch, the photometricaly similar patches are identified and compute weights based on their similarity to the reference patch. Weight wij is the contributing factor for patch yj in denoising the reference patch yi. Photometrically similar patches are necessarily geometrically similar as well, and hence, we could limit our search within the cluster of the reference patch. However, errors in clustering can limit the number of similar patches identified. On the other hand, scanning the entire image can be time consuming. Thus restrict the search within the small search window (30 X 30 pixels).Thus means and variance estimated from geometrically similar clusters and weight from photometricaly similar patches form the parameters for denoising.

These parameters are then used to perform denoising each patch. Since we use overlapping patches, multiple estimates are obtained for pixels lying in the overlapping regions. These multiple estimates are then optimally aggregated to obtain the final denoised image.

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Illustration of multiple estimate of single pixel is given below.

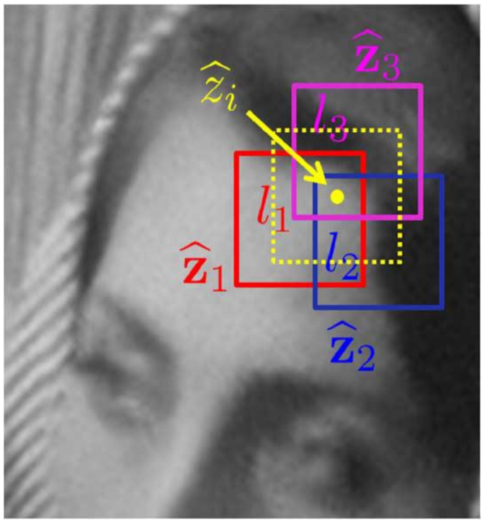

Fig 4: Illustration of how a pixel is estimated multiple times due to overlapping

Since FCM clustering is used it is possible to handle those patches which comes in the boundary of two clusters with mem-bership function 0.5.Unlike K-means in [1] mean and variance are estimated from all clusters with membership function ≥ 0.5.

Algorithm for Novel Patch-Based Denoising Scheme

INPUT Image Y
if Y contains WGN **then**
  Prefilter image to obtain pilot estimate
  Extract Overlapping patches
  L $\leftarrow$ Compute LARK features for each patch
  $\Omega_k \leftarrow$ geometric clustering with Fuzzy C-means(L,K)
  for each Cluster **do**
    Estimate mean
    Estimate cluster covariance
  end for
  for each patch **do**
    $y_j^0 \leftarrow$ identify photometrically similar patches
    $w_{ij} \leftarrow$ compute weights for all y_j^0
    $\hat{Z}_i \leftarrow$ estimate denoised patch
   end
   end
  $\hat{Z} \leftarrow$ aggregate multiple estimates from all $\hat{z}_i$
  end for
else
  Output Y
end if

3 RESULTS

Through experiments we have evaluated the proposed de-noising method on various images at different noise levels. We apply our method to both color images and gray-level images. The results obtained are quite impressive in terms of de-noising achieved with finer details being retained at the same time. The results are shown below.

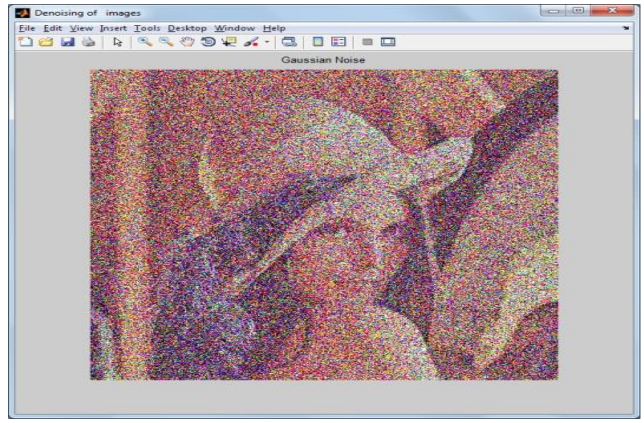

Fig 5: White gaussian noise affected image

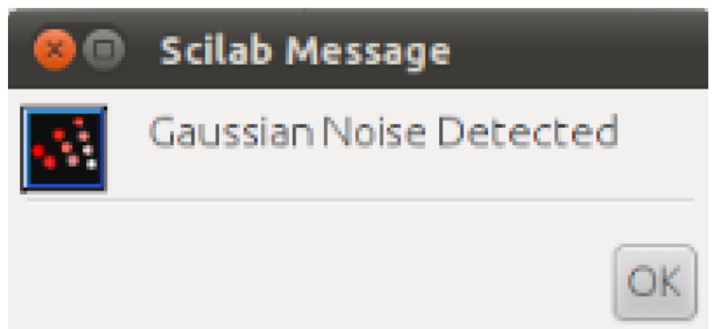

Fig 6: Output of noise detection module.

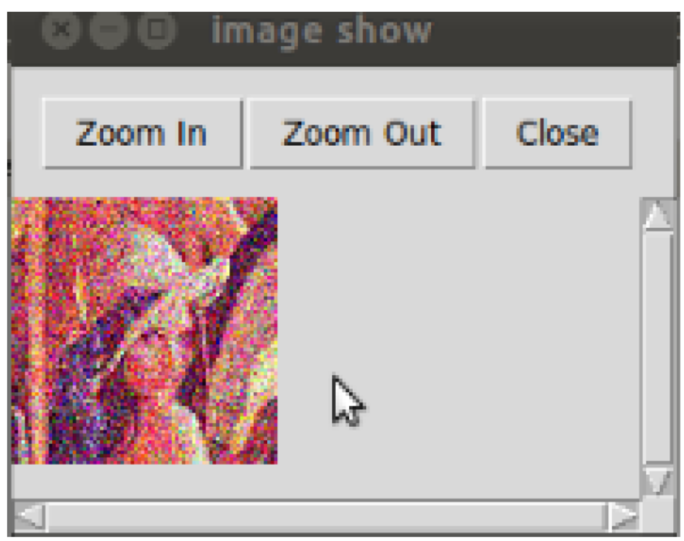

Fig7: Output obtained in prefiltering module.

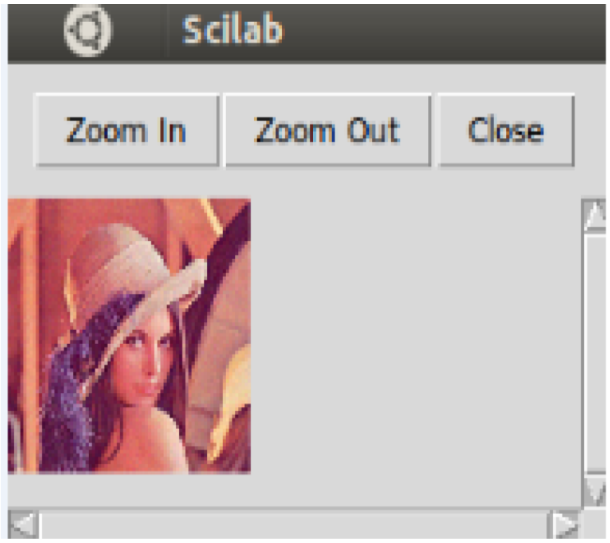

Fig 8: Final output

4 ANALAYSIS AND COMPARISION

These are the MSE and PSNR values obtained for various images.

4.1 Analysis

Image	MSE	PSNR
hounoi	30.28	33.31
flownoi	30.27	33.32
eye2noi	30.34	33.30
eye1nnoi	29.48	33.43
aninoi	32.66	32.99

4.2 Comparision

MSE obtained for existing system (hounoi) =30.28
MSE obtained for proposed system (hounoi) =32.84
PSNR obtained for existing system (Lena) =31.92
PSNR obtained for proposed system (Lena) =33.00

By analysis it is concluded that performance (in terms of denoising) of the proposed system is close to the exiting system.

5 CONCLUSION

In this paper, we have proposed a spatial-domain denoising scheme based on patch-redundancy to remove white gaussian noise. Through experimental validation, we have shown that our method produces results quite comparable with the state of the art. It achieves near state-of-the-art performance in denoising both gray images and color images. The system could detect the presence of white Gaussian noise which made the framework more effective. Thus only White gaussian affected images will undergo patch-based denoising step

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