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Multistage Denoising Based On DWT Thresholding

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Abstract: In this paper we proposed multistage denoising based on dwt.single stage denoising performance is dropped seriously due to high noise level.whenthe noise level is high, there will be significant loss. In order to avoid this we proposed multistage dwt based denoising.In each stage we proposed an internal and external denoising process.we have used different filtering schemes for each stage.since graphcut based denoising is used as an external filtering,the patch matching accuracy will be more. It will also provide more matching points.The combining process in each stage is based on dwtthresholding. The noise is equally spreaded throughout the coefficients in wavelet domain.Therefore by using this method we can achieve better psnr and mse values.

Key words: Imagedenoising · External filtering · Internal filtering · Datacubes · Linear method · Nonlinear method

INTRODUCTION

Images taken with bothconventional film cameras and digital cameras will pick up noise from various sources. In addition to this the use of these images require that the noise should be removed to certain extentforaesthetic purposes as in artistic work or marketing, or for practical purposes such as computer vision. The main aim of an image denoising algorithm is to achieve both noise reduction and feature preservation. The Single image denoising methods are used to recoverimage details by finding the similarity inside the noisy image itself. Certain approaches concentrates on pixel-level denoising methods, which only consider the similarity between a noisy pixel and its neighboring one. Other methods such as BM3D [1], non-local means, low-rank regularization and high order singular value decomposition learned simultaneous sparse coding (LSSC) group patches which are similar in the noisy image and then retrieve theircommon structures. our proposed method] comprises of five sections as proposed in [2]. Section II explains about proposed methodology. Section III and section IV explains about image registration and correlated image retrieval.sectionV explains about first stage denoising and section VI explains about second stage denoising.

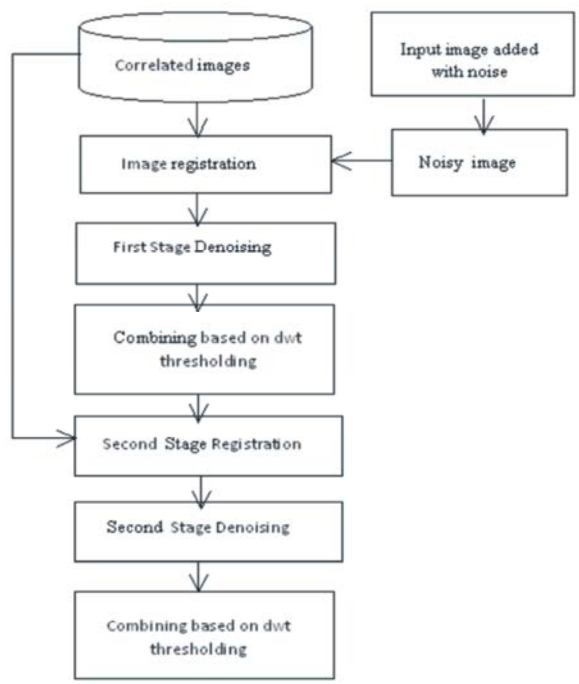

Fig. 1: Flow Diagram Of Denoising System III.

Proposed Methodology: The intention of our proposed method is to recover the original image from the noisy image as shown in Fig 1. It is mathematicslly described as follows,

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$$l_n = l_0 + n \quad (1)$$

where, l_n is a noisy image, l_0 is a input image, n is additive white gaussian noise.

Each stage of denoising includes an external denoising system and an internal denoising system. In the first stage, graph cut based method and frequency truncation on internal cubes are used as an external and internal denoising.In the second stage, adaptive filtering and weiner filtering is used as an internal and external denoising.

Image Registration: It is the process of aligning the images with respect to geometric correlations. This process involves designating one image as the reference and applying geometric transformations to the other images so that they align with the reference. Even though the correlated images are similar, normally captured in different views, illuminations and focal lengths. Finding similar patches from these images will not only involves computational burdens, but also reduce the matching accuracy.

Although the existing matching algorithm for patches could find patches across rotations and scales, it will not produce good results. To overcome this problem, we proposed an approximate alignment through geometric registration to improve the correlation between the noisy image and retrieved images. First, we estimate the correspondences of feature points between the each of the correlated images and noisy image I. We adopt the matching criterion proposed in [3] and obtain a set of matching points.we can obtain more matching points in the second stage since the noise has been greatly reduced in the first stage. It helps us to obtain a better registration result.

Correlated Image Retrieval: Image retrieval is the process of extracting similar images by comparing the original image with that of the external dataset images. SIFT method [4] is used for this purpose. SIFT based method involves scale-space extrema detection, keypoint localization, keypoint description and orientation assignment.

Scale-Space Extrema Detection: It involves the process of detecting locations which are invariant to scale change of the image. It can be implemented by searching stable features among all possible scales, using a continuous scale function known as scale space. It is described as below,

$$L(x, y,\sigma) = G(x, y, \sigma) * I(x, y) \quad (2)$$

Where * is the convolution operation and gaussian function is given as,

$$G(x, y,\sigma) = \frac{1}{2\pi\sigma^2} \exp(-(\frac{x^2+y^2}{2\sigma^2})) \quad (3)$$

For the efficient detection of stable keypoint locations in scale space, a scale space extrema based on the difference-of-Gaussian function is used.It is given as,

$$D(x, y,\sigma)= (G(x, y, k\sigma) - G(x, y,\sigma)) - I(x, y)$$
$$= L(x, y, k\sigma) - L(x, y,\sigma) \quad (4)$$

Local Extrema Detection: To find the local minima and maxima of D(x, y,σ), each sample is compared to its eight neighbours in the test image and nine neighbors which lies above and below. If it is larger than all of these neighbors or smaller than all of them,then it will be selected.

Orientation Assignment: For each image sample, the orientation and gradient magnitude is precomputed using pixel differences. Locations with multiple peaks of similar magnitude,will have multiple keypoints.

Feature Vector Formation: Based on local image properties, a consistent orientation is assigned to each keypoint.Feature vector can be represented with respect to this orientation and therefore attain invariance [5] to image rotation.

First Stage Denoising

External Denoising: The external denoising involves the process of making image patches and comparing each patch with the correlated images to get the patch that is equivalent to that of the original image.Graph cut method is used to perform this filtering.It is described as,

$$E(t) =\sum_i D(p_i, Q(t_i)))+\beta\sum_{(i,j)\epsilon N} s(t_i, t_j) \quad (5)$$

where,

$(D(p_i, Q(t_i)))$ is l_z distance between p_i and $Q(t_i)$

β is a weighting parameter

Internal Denoising: It involves the process of building 3D cubes and then applying filter to the cubes. Filtering is perfomed by applying hard thresholding to the transformed coefficients of 3D cubes as proposed in.

It is described as,

$$\widetilde{P_{3D}} = T^{-1}_{3D}(H(T_{3D}(P_{3D}), \lambda_{3D}\ \sigma)) \quad (6)$$

where,
$\lambda_{3D}\sigma$ is a threshold value,
T_{3D} is a forward 2D wavelet and 1D Hadamard transform,
$T^{-1}{}_{3D}$ is a inverse 2D wavelet and 1D Hadamard transform,
H(.) denotes hard thresholding.

Combining: It is the process of combining external and internal denoising results by using dwtthresholding. This completes the first stage denoising.we proposed bayes thresholdingfor this purpose.dwt transform is taken for both the denoising result and by fixing a threshold the required coefficients will be retrieved.

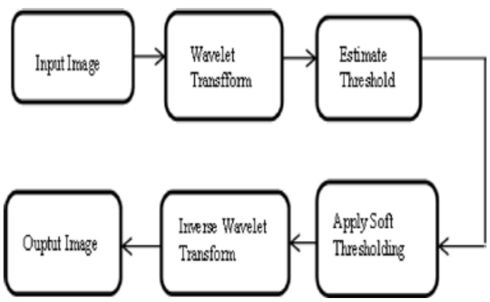

Fig. 2: Dwt Thresholding Based Combining

This completes the combining stage. The threshold value will be selected as,

$$t = \sigma^2/\sigma_3 \quad (7)$$

where
σ^2-noise variance
σ_3 -signal variance without noise

Second Stage Denoising: The first stage denoising result will be taken as the input for the second stage. The second stage registration is performed with the help of first stage output and the correlated images.

External Denoising: Filtering is done with the first stage output by using adaptive filtering. Adaptive filtering is performed by applying kernel to the patches. It is described as,

$$R_W = \sum_{i=1}^{k_2} \omega_i q_i q_i^T$$

$$= q_{2D} W q_{2D}^T \quad (8)$$

kernel function is described as below,

$$\omega_i = \exp\left(-\frac{\|q_i - p\|_2^2}{\|\sigma^2\|_2^2}\right) \quad (9)$$

Internal Denoising: Two 3D cubes are built here. one is based on searching similar patches for first stage denoised result. Another is built by searching patches for noisy image matched against first stage output. Weiner shrinkage coefficient is applied to 3D cubes to get the denoised image. It is given as,

$$\hat{p}_{3D}{}^{i2nd} = T_{3D}^{wie\ -1}(w^{wie}?(T_{3D}^{wie}(p_{3D}{}^{i2nd}) \quad (10)$$

Whereas the shrinkage coefficient is described as below,

$$w^{wie} = \frac{|T_{3D}^{wie}(\hat{p}_{3D}^{i2nd})|^2}{|T_{3D}^{wie}(\hat{p}_{3D}^{i2nd})|^2 + \sigma^2} \quad (11)$$

Finally the two denoising results are combined similar to the first stage to produce the final denoised result.

RESULTS AND DISCUSSION

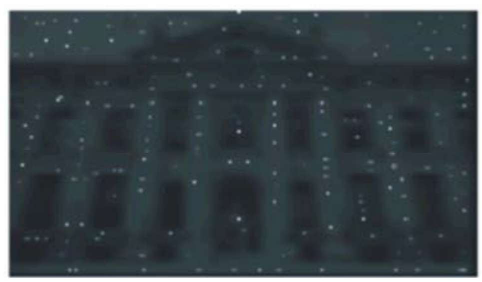

Fig. 3: Image With Keypoints

The above figure demonstrates the image with keypoints which were obtained by using SIFT method.

Fig. 4: Image Added With Salt And Pepper Noise

Fig. 5: Output Of Graphcut Denoising

Fig. 6: Output Of Adaptive Filtering

Table I.

METHODS	PSNR	MSE
DCT BASED DENOISING	23.87384	166471.139187
DWT BASED DENOISING	30.301233	1124.523615

CONCLUSION

The proposed DWT thresholding based denoising is implemented using Matlab by taking different oxford building images.Based on the mathematical analysis it is clear that the DWT thresholding based denoising will produce better psnr value when compared to DCT based denoising as proposed in.So by using this type of denoising we can obtain a better denoised image.

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