

# MULTISTAGE DENOISING BASED ON LINEAR AND NONLINEAR METHODS

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**ABSTRACT**-Single stage based image denoising suffers due to insufficient data collection within noisy image. In this paper we propose a multistage denoising based on linear and nonlinear methods. We build internal and external data cube for each noisy patch by finding similar patch from the correlated images. We then reduce noise by two stage filtering approach. Since noisy patch will affect the results we propose graph cut based optimization for external data cubes method to improve patch matching accuracy. The internal denoising is frequency truncation on data cubes. After combining internal and external denoising results we obtain a preliminary result. This completes the first stage. The preliminary denoising result improves the patch matching accuracy and provides more matching points for second stage. In the second stage adaptive filtering is used for external denoising and weiner filtering is used for internal denoising. The final denoising result is obtained by combining the results obtained from second stage internal and external denoising. Experimental results shows that our denoising scheme outperforms other denoising approaches in both subjective and objective quality measurements.

**Index terms**-Imagedenoising, datacubes, linearmethod, nonlinear method.

## I. INTRODUCTION

Removing the noise present in an image seems to be an important problem in many applications. Many intelligent methods have been proposed for denoising. when the noise level is low it is desirable to proceed with single image denoising. Because the patch matching accuracy is less when the noise level is high. so there is a necessity for multistage denoising. so we propose multistage denoising by exploring both internal and external correlations [1].

To improve the patch matching accuracy we use graph cut based optimization method. There are two

significant advantages in this paper. The first thing is that the first stage denoising result provides more matching points and improves patch matching accuracy. The second thing is that it provides filtering parameters for the second stage.

## II. METHODOLOGY

The input image is added with additive white gaussian noise to produce the noisy image. The noisy image is given as

$$I_n = I_0 + n \quad (1)$$

where,

$I_n$  is a noisy image,

$I_0$  is a input image,

$n$  is a additive white gaussian noise.

Our intention is to recover  $I_0$  from  $I_n$ . For that we are going for two stage denoising as shown in . The steps involved are Preprocessing, retrieval of correlated images, first stage denoising and second stage denoising.

## PREPROCESSING AND RETRIEVAL OF CORRELATED IMAGES

Preprocessing involves registration of noisy images with the correlated images. Retrieval of correlated images is the process of extracting the images. SIFT [2] based method is used to retrieve the correlated images.

**FIRST STAGE DENOISING**

It includes two steps. one is external denoising and another one is internal denoising.

**A. EXTERNAL DENOISING**

The noisy image is divided into patches. Each patch is compared with the patches of the correlated images[3]. L2-distance metric is used as a comparison parameter. It is given as,

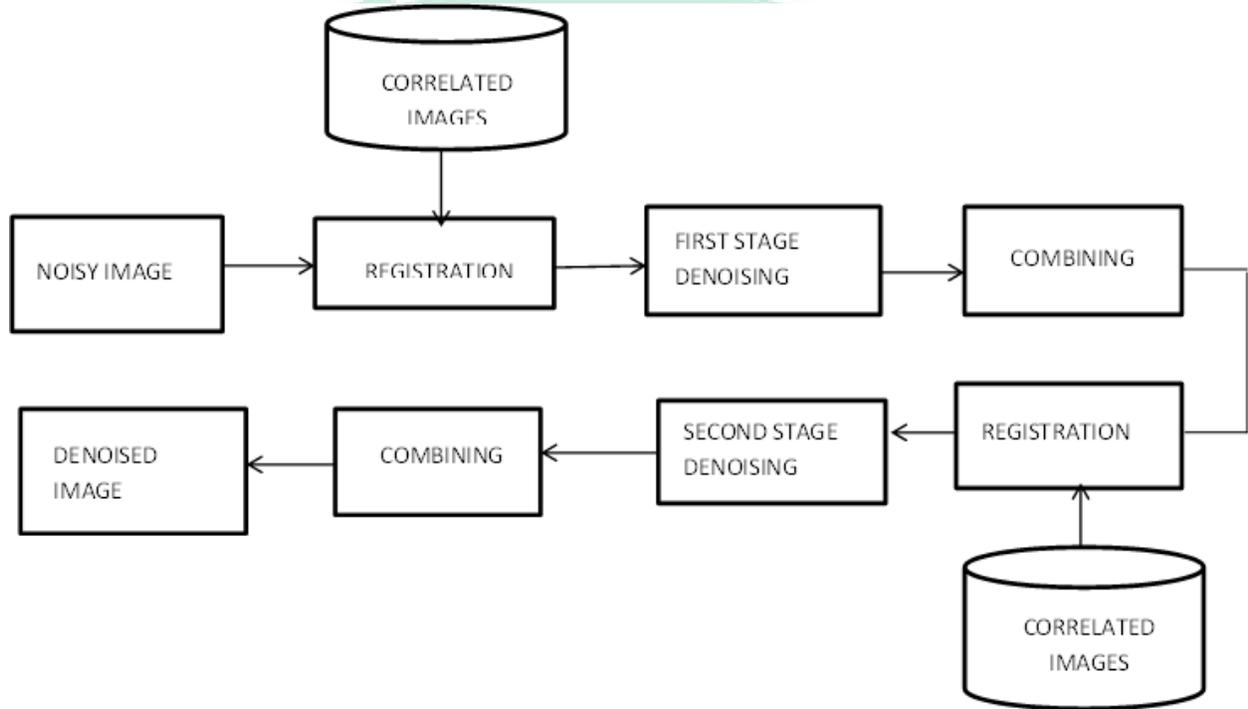


Fig.1 Block Diagram of Denoising System.

$$E(t) = \sum_i D(p_i, Q(t_i)) + \beta \sum_{(i,j) \in N} s(t_i, t_j) \quad (2)$$

where,

$(D(p_i, Q(t_i)))$  is  $l_2$  distance between patches of noisy image and the correlated images.

$s(t_i t_j)$  is the smoothness term,

$\beta$  is a weighting parameter for smooth constrain compensation.

**B. INTERNAL DENOISING**

The first step in internal denoising is to build a 3D cube by finding the k-nearest neighbour for each patch. The filtering is done by performing hard thresholding on the transformed coefficients of 3D

cubes. Transformation involves 2D wavelet and 1D Hadamard. It is given as,

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

where,

$\lambda_{3D} \sigma$  is a threshold value,

$T_{3D}, T^{-1}_{3D}$  are forward and inverse 2D wavelet and 1D Hadamard transform,

$H(.)$  is a hard thresholding.

**C. COMBINED DENOISING**

The external denoising preserves the high frequency information. The internal denoising preserves the low frequency information. so these two results are combined to preserve both the low and high frequency information. It is described as,

$$\tilde{p}^{1st} = T_{2D}^{-1} \frac{T_{2D}(\tilde{p}^i) \odot \omega^i + T_{2D}(\tilde{p}^e) \odot \omega^e}{\omega^i + \omega^e} \quad (4)$$

Where  $T_{2D}$  and  $T_{2D}^{-1}$  are the forward 2D DCT and inverse 2D DCT,

$\odot$  denotes the point wise multiplication.

$\omega^i$  and  $\omega^e$  are the weighting matrices which is used to combine the frequency coefficients of internal and external patches.

### SECOND STAGE DENOISING

It also includes an internal and external denoising.

#### A. EXTERNAL DENOISING

The first stage output is matched against the correlated image. This completes the second stage registration. After registration the images will be sent to external denoising. Adaptive filtering is used as an external denoising. The first step is to retrieve k2-NN patches from the data set by comparing with the input. The correlation matrix is computed as,

$$R_W = \sum_{i=1}^{k_2} \omega_i q_i q_i^T \\ = q_{2D} W q_{2D}^T \quad (5)$$

where  $\omega_i$  is a Gaussian kernel function which is given as,

$$\omega_i = \exp\left(-\frac{\|q_i - p\|_2^2}{2\sigma^2}\right) \quad (6)$$

#### B. INTERNAL DENOISING

Here the first step is to build 3D cubes [4]. one ( $\tilde{p}_{3D}^{i2nd}$ ) is built by finding similar patches for first stage denoising result. Another ( $p_{3D}^{i2nd}$ ) is built from noisy image using the similar location patches as matched in  $\tilde{I}^{1st}$ . The denoising is done by applying weiner shrinkage coefficient to 3D cubes. It is given as,

$$\hat{p}_{3D}^{i2nd} = T_{3D}^{wie^{-1}} (W^{wie} \odot (T_{3D}^{wie} (p_{3D}^{i2nd}))) \quad (7)$$

where  $W^{wie}$  is a shrinkage coefficient described as below,

$$W^{wie} = \frac{|T_{3D}^{wie}(\tilde{p}_{3D}^{i2nd})|^2}{|T_{3D}^{wie}(\tilde{p}_{3D}^{i2nd})|^2 + \sigma^2} \quad (8)$$

After internal denoising the combining will be done similar to that of the first stage.

### III. EXPERIMENTAL RESULTS



Fig2. image with keypoints

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



TABLE I.

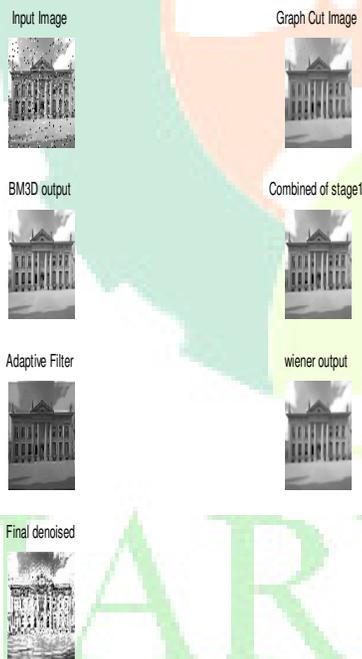
METHODS	PSNR	MSE
BEFORE DENOISING	28.173083	49.763037
AFTER DENOISING	34.301233	98.675262

The above tabulation shows the psnr and mse before and after denoising.

## REFERENCES

Fig3.set of correlated images

Set of correlated images that are retrieved by using SIFT features were shown in fig 3



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Fig 4. Combined output of all the stages