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Modified BM3D Image De-noising Technique with Shape-Adaptive Principal Component Analysis

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Abstract*— *Image De-noising refers to the recovery of a digital image that has been contaminated by Additive White Gaussian Noise (AWGN). So, there is a need for Image de-noising procedure to reduce the noise level present in the image so as to produce the de-noised image closer to the original image. This paper presents a Modified BM3D-SAPCA Image De-noising technique with Normal Shrink Thresholding. The Image de-noising method that makes use of non-local image modeling, Principal Component Analysis (PCA) and local shape-adaptive anisotropic estimation. Performance of these two thresholding techniques is compared on the basis of PSNR. The Normal Shrink Thresholding technique increases image clarity and image quality as compared to Hard Thresholding Technique.

Keywords*— *SA-PCA, PSNR, SA-DCT, AWGN

I. INTRODUCTION

Research and Technology field requires the application of Image Processing Schemes. Digital images are very important in the areas of geographical information systems. The main challenge in digital image processing in research field is to remove noise from the original image. Thus, De-noising is often a necessary and the first step to be taken before the image data is analyzed. It is necessary to apply an efficient de-noising technique to compensate for such type data corruption.

Thresholding is a simple non-linear technique which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is thresholded by comparing against threshold, if the coefficient is smaller than threshold, set to zero; otherwise it is kept or modified. Soft Thresholding has been used over Hard Thresholding because it gives more visually pleasant images. Because the Hard Thresholding is discontinuous and yields abrupt artifacts in the recovered images.

II. LITERATURE SURVEY

Foi et al. presented a novel approach to image filtering based on the SA-DCT. We use the SA-DCT in conjunction with the anisotropic local polynomial approximation (LPA), Intersection of confidence intervals (ICI) technique, which defines the shape of the transform's support in a point wise adaptive manner. The approach used in this paper is applicable for gray scale as well as color images. The visual quality of the estimate is high, with sharp detail preservation, clean edges and without unpleasant artifacts introduced by the fitted transform.

Dabov et al. proposed a novel image de-noising strategy based on an enhanced sparse representation in transform domain. The enhancement of the sparsity is achieved by grouping similar 2D image fragments (blocks) into 3D data arrays which is known as "groups". Collaborative filtering is a special procedure developed to deal with these 3D groups. Realization is done by using three successive steps: 3D transformation of a group, shrinkage of the transform spectrum, and inverse 3D transformation. The result is a 3D estimate that consists of the jointly filtered grouped image blocks.

Muresan et al. presented this paper presents a novel approach to image de-noising using adaptive principal components. Our assumptions are that the image is corrupted by additive white Gaussian noise. The new de-noising technique performs well in terms of image visual fidelity, and in terms of PSNR values, the new technique compares very well against some of the most recently published de-noising algorithms.

Kaur et al. proposed an adaptive threshold estimation method for image de-noising in the wavelet domain based on the generalized Gaussian distribution (GGD) modeling of sub band coefficients. The proposed method called **Normal Shrink** is computationally more efficient and adaptive because the parameters required for estimating the threshold depend on sub band data.

Buades et al. presented a general mathematical and experimental methodology to compare and classify classical image de-noising algorithms, second, to propose an algorithm (Non Local Means) addressing the preservation of structure in a digital image. The mathematical analysis is based on the analysis of the "method noise", defined as the difference between a digital image and its de-noised version.

Wang et al. proposed the objective methods for assessing perceptual image quality have traditionally attempted to quantify the visibility of errors between a distorted image and a reference image using a variety of known properties of the human visual system. The proposed SSIM index method is motivated from substantially different design principles; we see it as complementary to the traditional approach.

Portilla et al. Proposed a method for removing noise from digital images, based on a statistical model of the coefficients of an over complete multi scale oriented basis. Coefficients neighbourhoods at adjacent positions and scale are modeled as the product of two independent random variables: a Gaussian vector and a hidden positive scalar multiplier.

Dabov et al. (2011) proposed an image de-noising method that exploited non-local image modeling, principal component analysis (PCA) and local shape adaptive anisotropic estimation. The de-noising is performed by shrinkage of the spectrum of a 3-D transform applied on such groups. The non local modeling is exploited by grouping similar image patches in 3-D graphs. The effectiveness of the shrinkage depends on the ability of the transform sparsely represent the true Image data thus separating it from the noise. The sparsity of the true data is further increased by applying a transform along the third dimension of the grouped adaptive- shape neighbourhoods.

III. TECHNIQUE USED

In the proposed work to de-noise the noisy image Modified BM3D-SA-PCA technique is used by Normal Shrink Thresholding and the output is shown by giving the comparison of two thresholding methods based on (PSNR) Peak Signal to Noise. The Input images we load are the standard 512*512 gray scale images. The format of the image we take is of .jpg (Joint Picture Group) and .png (Portable Network Group) type. After that we corrupt the Input Image by Additive White Gaussian Noise. Now we apply the Modified Block Matching 3-Dimensional Shape Adaptive-Principal Component Analysis algorithm to de-noise the image. In this algorithm, shape adaptive-grouping is done by 8-directional LPA-ICI, which defines the shape of the transform's support in a point wise adaptive manner. The fixed-size and non-adaptive square block, are termed as reference block (N_{el}). Find blocks that are similar to the reference one using block-matching. The number of matched blocks is denoted by (N_{gr}).

Determine the transform to be applied on the adaptive-shape neighbourhoods. We have two cases, depending on whether N_{gr}/N_{el} is larger or smaller than a fixed threshold τ.

- If $N_{gr}/N_{el} \geq \tau$, we found a sufficient number of mutually similar neighborhoods to reliably estimate a second-moment matrix. The eigenvectors of this matrix contains the shape-adaptive PCA basis. We retain only those eigenvectors whose corresponding Eigen values are greater than a predefined threshold, thus obtaining a trimmed shape-adaptive PCA transform.
- If $N_{gr}/N_{el} < \tau$, there are not enough similar neighborhoods to use as training data and we resort to the fixed (i.e. non data-adaptive) SA-DCT.

Form a 3-D array (called group) by stacking together the $\min(N_{gr},N_2)$ adaptive-shape neighborhoods with highest similarity to the reference one, where N_2 is a fixed parameter that restricts the number of filtered neighborhoods. Apply the transform on each of the grouped adaptive-shape neighborhoods. Now, apply a 1-D orthogonal transform (e.g. Haar wavelet decomposition) along with third dimension of the 3-D group. Perform shrinkage by Normal Shrink Thresholding adaptive threshold estimation method. This algorithm helps to obtain the de-noised image.

IV. RESULTS

In order to show that the proposed work has good performance for Image De-noising Normal Shrink thresholding technique is used. Performance of this technique is compared by Previous Hard Thresholding on the basis of PSNR.

- The main parameters used in Image De-noising are σ and PSNR, Value of σ =25
- As Input three types of images= BARBARA, BOAT and LENA
- To corrupt the image we use AWGN (Additive White Gaussian Noise).
- To de-noise the image Normal Shrink Thresholding is used.

From the below fig. it is clear that Hard Thresholding and Normal Shrink Thresholding techniques can be used for image de-noising. Normal Shrink Thresholding as a method to de-noise the image provides the best results for de-noising as compare to Previous Hard Thresholding. So, Normal Shrink Thresholding technique in Image De-noising de-noise the image, increases image clarity and image quality.

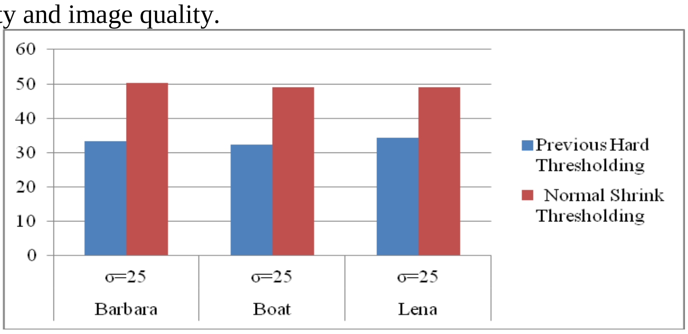

Fig. 1 Comparison of Hard Thresholding and Normal Shrink Thresholding

Table 1. Comparison of Hard Thresholding & Normal Shrink Thresholding Technique with σ=25

Image	**σ(Sigma)**	**Hard Thresholding(PSNR)**	**Normal Shrink Thresholding(PSNR)**
Barbara	σ=25	30.99	50.2922
Boat	σ=25	30.03	49.0965
Lena	σ=25	32.22	49.1165

\Fig. 1 Lena Original Image

Fig. 2 Lena Noisy Image

Fig. 3 Filtered Image Using Hard Thresholding

Fig. 4 Filtered Image using normal shrink Thresholding

V. CONCLUSIONS

In this paper PSNR value is more in Normal Shrink Thresholding as compare to Hard Thresholding for Image de-noising. More value of PSNR shows better image clarity. Normal Shrink Thresholding technique in Image De-noising de-noise the image, increases image clarity and image quality.

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