RESTORATION OF IMAGES CORRUPTED BY MIXED GAUSSIAN IMPULSE NOISE WITH WEIGHTED ENCODING

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Abstract: Data exchange can be achieved with different types of communication. Data can be text, image, audio and video. During the image transmission the images are affected by many types of noise. Mainly Additive White Gaussian Noise (AWGN), Impulse Noise (IN) and combination of both called as "mixed noise". Removal of mixed noise from the original image is critical and challenging work. The noise spreading is not having any predefined model consisting of heavy tail, due to which quality of image reduces. To remove the mixed noise from the image, many methods exist. These are detection based methods. In this method, locations of the noise are detected and then from these locations noise is removed using some algorithms, based on intensity and amount of noise. But these methods will give poor result, if the mixed noise is strong. Hence this paper implements a new effective method to remove the mixed noise. In this method there is no separate step for detection of different types of noise, instead pixel detection via weighted encoding is done which deals with AWGN and IN simultaneously. This proposed method performs better than existing image de-noising methods. It can be applied with multiple types of IN and even in the condition when noise content is more.

Key Words: **AWGN, IN, Mixed noise, weighted encoding.**

I. INTRODUCTION

Image de-noising is one of the important and developing areas in the branch of image processing. Noises are unavoidable during image generation, transmission and reception process, due to which quality of image will be reduced. Unwanted information which are added during acquisition or transmission or reception which destroys the quality of the image is called as "noise".

Image restoration techniques aims at recovering the original images. Images are corrupted by degradation such as linear frequency distortion and noise. This paper is based on image corruption due to noise. Image restoration is defined as the method of elimination of degradation in the image using linear or nonlinear filtering. There are many types of noise exist, out of which mainly two types of noise are considered in real time application. These are AWGN and IN. AWGN is regularly introduced because of the thermal movement of electrons in camera sensors and in other electronic devices. IN is frequently introduced by malfunctioning of the camera sensor pixels, defective memory segments in hardware and transmission error like bit error. In AWGN, each image pixel which is corrupted will be replaced with a value independently sampled from a Gaussian distribution with zero mean, which is going to add with the gray level of the pixel. The image which is corrupted with IN will be having a portion of its pixels exchanged with values of random noise with the remaining pixels unaltered.

There are two types of commonly considered IN, Salt and Pepper Impulse Noise (SPIN) and Random Valued Impulse Noise (RVIN). The image which is degraded by SPIN results in bright pixels in dark regions and dark pixels in bright regions. Image which is degraded by RVIN results in noise in any random pixel locations.

Nonlinear filters such as median filters have been dominantly used to remove IN. However, one shortcoming of median filters is that the image local structures can be destroyed; making the de-noised images looks unnatural. This problem becomes serious when the IN density is high. Various improvements of median filters have been proposed to better preserve the image local structures. Among them, the weighted median filter, the center-weighted median filter and the multistate median filter do not distinguish whether the current pixel is a noise pixel or not, and they tend to over-smooth the fine scale image details.

PCA Dictionary using five quality images will help to extract the PCA dictionary. The dictionary will help to reconstruct the image after removing the noise pixel in the image. Linear Discriminant Analysis (LDA), Independent Component Analysis and PCA are some of the techniques used for feature extraction, among them PCA is one of the feature extraction method in this project, we use that algorithm for its powerful method in image formation, Data patterns, similarities and differences between them are identified efficiently. The other main advantage of PCA is dimension will be reduced by avoiding redundant information, without much loss. Better understanding of principal component analysis is through statistics and some of the mathematical techniques which are Eigen values, Eigen vectors.

WESNR method the proposed noise removing algorithm called as Weighted encoding sparse Nonlocal regularization algorithm. It is newly developed algorithm for removing mixed noise in one process. In this, the process had done by updating the residual value in the image. The residual value initialized by noise image SPIN noise removal image. The SPIN noise is removed by adaptive median filter. Median filtering follows this basic prescription. The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image. The ultimate goal is to bring the corrupted image into original form or to improve the quality of the de-noised image. De-noising process which is also called as "noise removal" is a major difficulty in the branch of image processing. This operation aims at the maximum preservation of fine details, image edges and textures maintaining with respect to noised image in comparison with original image.

II. METHODOLOGY

This paper consist a new algorithm based on the paper proposed by Dong et al. in the year 2013, in which mixed noise is removed by a unified framework algorithm called as weighted encoding with sparse nonlocal regularization. The new method developed will encode the noise corrupted pixel with help of dictionary to remove the AWGN and IN simultaneously. Existing and available mixed noise removal technique, involves two step operations. In first step, impulse noise pixels are detected and then they are removed in second step. This two-step operation is not effective when mixed noise content is more.

In this paper two separate operations are unified into a single frame work called as "sparse nonlocal regularization". This unified frame work method was proposed by Huang et al. in the year 2014. In this method, the reference median value was calculated to resolve whether a current pixel is a noise pixel or not. The method based on, if the absolute value among the reference median with a target pixel is higher, then the target pixel is referred as a noise pixel and consequently the mixed noise is removed by switching the operation between the AWGN removal and IN removal. This regularization procedure is combined with sparse nonlocal self-similarity to improve the noise removal capacity in the algorithm.

Proposed System:

We take a digital image and added two types of noise i.e., AWGN and IN, after that we have applied de-noising process on noise added image.

Weighted Encoding Model:

This paper proposes a new method to remove the mixed noise in which the advanced filter technique is used with respect to other existing filters. The new filters functionality is based on the principle of weighted encoding with sparse nonlocal regularization.

Two types of IN that are used in the real time application are Salt and Pepper Impulse Noise and Random Valued Impulse Noise. The dynamic range of an image is represented within [d-min, d-max]. In the SPIN, the replacement of every image pixel with a given probability takes place having a value d-min or d-max. In the RVIN a pixel value is replaced with any random value in the range [d-min, d-max].

In AWGN, weights are chosen according to shape of Gaussian function. This is very much effective for removing the noise and then to make normal distribution. Amount of noise removal by the filter will be same in all directions. Degree of noise removal is governed by variance. This paper considers two types of mixed noise to analyze the image corrupted with noise. First, AWGN mixed with SPIN and second, AWGN mixed with RVIN and SPIN.

De-noising Model:

In the proposed mixed noise removal method, does not perform removal of AWGN and detection of impulse pixel separately, it combines the two different tasks in a unified framework. This paper proposes a novel weighted encoding model to remove mixed noise, which is not having the separate impulse pixel detection step and it can process the combination of noise AWGN and IN at the same time. The nonlocal self-similarity and sparsity of the natural images are also integrated into the proposed model to make it powerful for mixed noise removal.

Residual Calculation:

Distribution of the noise in the image pixel has heavy tails. Main source for this heavy tail is IN, of the mixed noise. By using normalization technique this heavy tail can be eliminated. Heavy tail generates damages to the original image which is represented in terms loss. The overall heavy tail of complete image is called as residue. Residues are classified separately for AWGN and IN.

Dictionary:

In this paper it is assumed that the dictionary is obtained first and later it is used in the algorithm. The selection of dictionary is an important issue of the sparse coding and reconstruction of an image. In particularly, learning dictionaries from natural image patches is an important process in image restoration. In this paper, a set of local PCA dictionaries are considered, offline from five high quality images with respect to original.

The image patches are divided into many clusters. Each cluster consists of many patches with similar patterns. A complete set of dictionary can be obtained from the each cluster. PCA technique is used to obtain the dictionary. For the image patches to be coded, the dictionary value which is more relevant is considered with the noise pixel patch to replace.

Total number of 2401 200 patches are extracted from the high quality images and then they are divided into 200 clusters with help of *K-means* clustering algorithm. It is simplest method in which clustering is done by iterative procedure. It clusters the data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel in the class with closest mean. Clustering is the technique in which relationship among the patterns of the data set by organizing the patterns into group of clusters such that pattern within a cluster are more similar to each other than patterns belonging to different clusters.

Sparse coding is a class of unsupervised methods for learning sets of over-completes bases to represent data efficiently. The aim of sparse coding is to find a set of basis vectors such that we can represent an input vector as a linear combination of these basis vectors, while techniques such as Principal Component Analysis (PCA) allow us to learn a complete set of basis vectors efficiently.

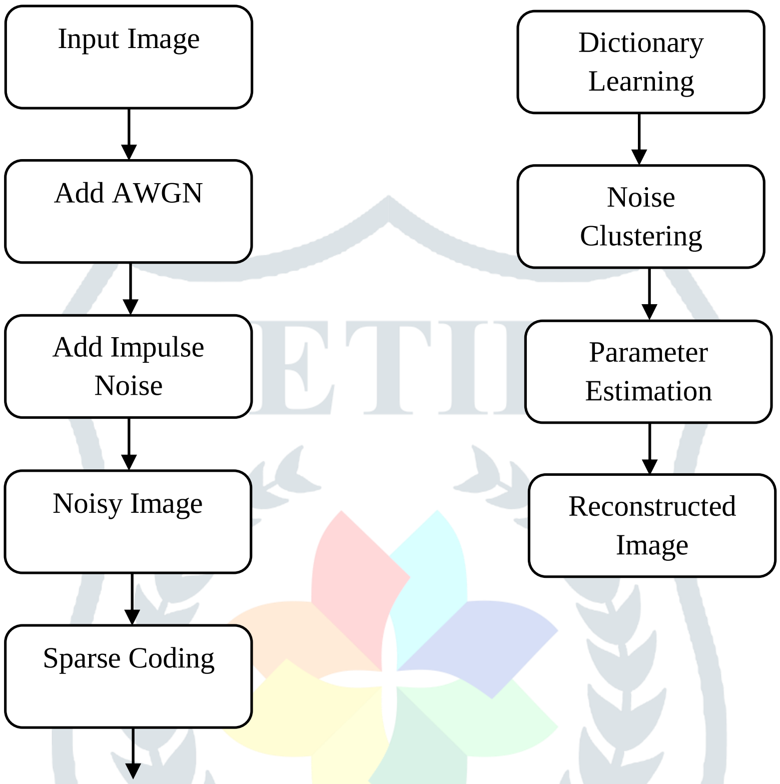

Fig 1: Flow Diagram

- Sparse dictionary learning is a representation learning method which aims at finding a sparse representation of the input data (also known as sparse coding) in the form of a linear combination of basic elements as well as those basic elements themselves. These elements are called atoms and they compose a dictionary. Atoms in the dictionary are not required to be orthogonal, and they may be an over-complete spanning set.
- Depend on the property of noise, it got clustered. How many type of noise are there that many cluster will be formed.
- The operation taking place in AMF is spatial processing, which is to preserve the fine details of the original image and smooth edges of the original images which are corrupted with noise, along with the operation of IN removal. A pixel which is different from majority of neighbors, as well as being not structurally aligned with those pixels to which it is similar is considered as IN. These noise pixels are then replaced by median pixel value of the pixels in the neighborhood which are already done with the noise testing. These processes remove the IN in the initial stages and smooth the other noises.

III. RESULT

Weighted encoding model for mixed noise removal using sparse nonlocal regularization is implemented successfully. The distribution of mixed noise, which is having more irregularity than Gaussian noise alone and normally it, has a heavy tail in its distribution. To overcome from this difficulty, the weighted encoding technique is adopted to remove AWGN and IN together. This paper encodes the image patches over a set of PCA dictionaries which is obtained offline and weighted the coding residuals to eliminate the heavy tail of the distribution. The weights of the noisy image are adaptively updated for deciding whether a pixel is heavily corrupted by IN or not. In this paper along with weighted encoding, image sparsity and nonlocal self-similarity processes are integrated into a single unified framework, which is called as non-local sparse regularization process to improve the stability and efficiency of weighted encoding model over the noisy image.

Fig 2: Original image

Fig 3: Shows the AWGN added image.

Fig 4: Noisy PSNR image.

Fig 5: Final de-noised image after weighted encoding process.

IV. CONCLUSION

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