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A Denoising Framework with a ROR Mechanism Using FCM Clustering Algorithm and NLM

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***Abstract*--Impulse noise detection is a critical issue when removing impulse noise and impulse/gaussian mixed noise. The framework combines Robust Outlyingness Ratio (ROR) detection mechanism and Fuzzy C Means (FCM) clustering algorithm and Nonlocal Means (NLM) filter. ROR for measuring how impulse like each pixel is and then all pixels are divided into four clusters according to the ROR values. The detection mechanism consists of coarse and fine stage. The output of coarse and fine stage of ROR is passed to FCM in which we use an iterative approach where each data point belongs to one or more centroids. Hence by iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the "right" location within a data set and the image is fine tuned and finally the fine tuned image is passed through NLM filter in which the image is denoised and the output is produced. An overview of a mechanism is to improve image quality in terms of PSNR ratio, through FCM mechanism. Thus it will infer a high quality image compared to other filtering techniques and also increases PSNR ratio. The main objective of this project is to remove noise from input image and improving the efficiency and the visual quality of the image.**

***Keywords*-Image denoising, impulse noise, Gaussian mixed noise, Robust Outlyingness Ratio (ROR), Fuzzy C Means (FCM) clustering algorithm, Nonlocal Means (NLM), Peak Signal to Noise Ratio (PSNR).**

I. INTRODUCTION

Image denoising is an important image processing task, both as a process itself, and as a component in other processes. The removal of noise from the input image is known as image denoising. Image denoising plays a vital role in a wide range of applications such as image restoration, visual tracking, image registration, image segmentation, and image classification. Digital images could be contaminated by noise during image acquisition and transmission due to malfunctioning pixel elements in the camera sensors, transmission errors, faulty memory locations and timing errors in analog to digital conversion [1]. The degraded images severely slow down the following image processing operations such as edge detection and image analysis: ; hence, restoring the original image from the corrupted image is absolutely necessary.

Image denoising is one of the most fundamental, widely studied, and largely unsolved problems in digital image processing, and it has been studied for nearly half a century due to its important role as a preprocessing step in various image applications. Its objective is to recover the original image or the best estimation from noisy data while preserving image details [2]. Image noise may be caused by different intrinsic (i.e., sensor) and extrinsic (i.e., environment) conditions. Data sets collected by image sensors are generally infected by noise. Noise represents unnecessary information which destroys image quality. The most common types of noise models used are: salt and pepper impulse noise, random valued impulse noise and Gaussian mixed noise.

Impulse noise is sometimes called salt and pepper noise or spike noise. An image containing salt and pepper noise will have dark pixels in bright regions and bright pixel in dark region. This type of noise can be caused by analog to digital converter errors, bit errors in transmission etc. Additive Gaussian noise is characterized by adding to each image pixel a value with a zero-mean Gaussian distribution, and it affects all pixels of the image. Such noise is usually introduced during image acquisition. The zero-mean distribution property allows such noise to be removed by average pixel values locally [2].

In section II, the discussion of related work is carried out. In section III, analysis of ROR detection mechanism is performed. In section IV, FCM algorithms are discussed. In section V, the NL-means for impulse noise and mixed noise is described. In section VI, ROR-FCM and NLM are concluded, followed by the references used.

II. RELATEDWORKS

The primary focus of [2] a universal denoising framework is proposed by combining the new detection mechanism with the NL-means (ROR-NLM). Finally, extensive simulation results show that the proposed noise detector is superior to most existing detectors, and the ROR-NLM produces excellent results and outperforms most existing filters for different noise models. Unlike most of the other impulse noise filters, the ROR-NLM also achieves high peak signal-to-noise ratio and great image quality by efficiently removing impulse/Gaussian mixed noise. The author[3] describes an efficient noise reduction approach is proposed by combining Robust Outlyingness Ratio (ROR) which measures how impulse like each pixel is, with noise adaptive fuzzy switching median filter (NAFSM) and fuzzy c-means (FCM) segmentation. Based on the ROR values all the pixels are divided into four levels. Then in the coarse and fine stage introduce the NAFSM filter that optimizes the performance by using fuzzy, median and processing pixel. For further optimization the FCM separates the remaining noisy and noise less pixels for the detection and removal of salt and pepper impulse noise. Finally the NL-means filter is applied to remove Gaussian noise and produce the high quality images. The author [4] describes Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. . With fuzzy *c*-means, the centroid of a cluster is computed as being the mean of all points weighted by their degree of belonging to the cluster. By iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the "right" location within a data set. Performance depends on initial centroids. The primary focus of [5] is to propose an efficient coarse- to fine search technique to reduce the storage and computing time in detecting circles in an image. The accuracy and the rate of convergence of the parameters at different iterations of the algorithm are presented. The results demonstrate that the coarse-to-fine search strategy is very suitable for detecting circles in real-time environments having time constraints.

III. ROR DETECTION MECHANISM

The ROR detection mechanism which is used for measuring how impulse like is a pixel is to its neighbors. When an image is corrupted by salt and pepper impulse noise or random valued impulse noise, the detection of impulse noise is far difficult. The intensity of the noisy pixel will be distinct from its nearest surrounding pixels. The new detection mechanism helps in the detection of such impulse noise. It initially computes the robust outlyingness ratio (ROR) for each and every pixel in the image. ROR measures how much each pixel gets affected by impulse noise. For computing the ROR of a particular pixel, construct a 5*5 window around that pixel. Calculate the difference between the neighboring pixels and median value in the window. Then the median absolute deviation (MAD) is found out. ROR value of a pixel is calculated as follows;

MAD(y) = med(y-m).

MADN(y) = MAD(y)/0.6457

ROR (yi) = (yi-m)/MADN(y).

Where „m‟ is the median value and „y‟ is the Neighboring pixels in the window. Based on the ROR values of each pixel classify all the pixels in the images into four different levels. In each cluster different decision rules are applied to detect the impulse noise based on the absolute deviation. The four levels are the most like level ROR>3, second like level 2<ROR<=3, third like level 1<ROR<=2 and the fourth like level is 0<ROR<=1.

The detection mechanism consists of two stages. The two stages are coarse detection stage and fine detection stage.

Coarse stage:

Step 1: Choose the algorithm parameters, i.e., coarse thresholds $T_1{}^c$, $T_2{}^c$, $T_3{}^c$; window size N(the actual size is(2N+1)*(2N+1); iterations m_c and initial j=1.

Step 2: Initialize the detection flag matrix Map as zeros, where “0s” and “1s” represent good and noisy pixels, respectively.

Step 3: Calculate the ROR of the current pixel. If the ROR is in the fourth level, treat as a good pixel or calculate the absolute deviation d between the current pixel and the median of its local window. Then, compare d with threshold $T_k{}^c$ according to its ROR value. If d is larger than $T_k{}^c$, it is a noisy pixel , or it is a good pixel. Update the flag Map according to the result.

Step 4: Get the median based restored image I according to the detection result. If the flag is 1, represent the pixel with the median of its local window, or do not change.

Step 5: If j<=m_c, j=j+1, then go to step2 or the coarse stage is completed.

Fine stage:

Step 1: Choose the algorithm parameters, i.e., fine thresholds $T_1{}^f$, $T_2{}^f$, $T_3{}^f$, and $T_4{}^f$; window size N(the actual size is(2N+1)*(2N+1); iterations m_f and initial j=1.

Step 2: Initialize the detection flag matrix Map as zeros, where “0s” and “1s” represent good and noisy pixels, respectively.

Step 3: Calculate the ROR of the current pixel and the absolute deviation d between the current pixel and the median of its local window. Then, compare d with threshold $T_k{}^f$ according to its ROR value. If d is larger than $T_k{}^f$, it is a noisy pixel , or it is a good pixel. Update the flag Map according to the result.

Step 4: Get the median based restored image I with detection result. If the flag is 1, represent the pixel with the median of its local window, or do not change.

Step 5: If j<=m_f, j=j+1, then go to step2 or the fine stage is completed.

It is worth noting that the first input image of the fine stage is the final output image of the coarse stage. In the detection mechanism, there are many parameters needing to be pre-given such as window size N; coarse thresholds $T_1{}^c$, $T_2{}^c$, and $T_3{}^c$; coarse iteration m_c; fine thresholds $T_1{}^f$, $T_2{}^f$, $T_3{}^f$, and $T_3{}^f$; fine iteration m_f . Theoretically, the thresholds dominate the performance of the detection algorithm. If the larger thresholds are used, the “false-hit” term is lower and the “miss” term is higher, whereas if the smaller thresholds are used, the results are opposite. In the coarse stage, the purpose is to detect the most impulse like pixels and keep the “false-hit” term as low as possible and then in the fine stage, the purpose is to detect the most impulse like noise while keeping a good tradeoff between the “false-hit” and “miss-term”. Therefore, the thresholds of the coarse stage are relatively larger and the thresholds of the fine stage are smaller.

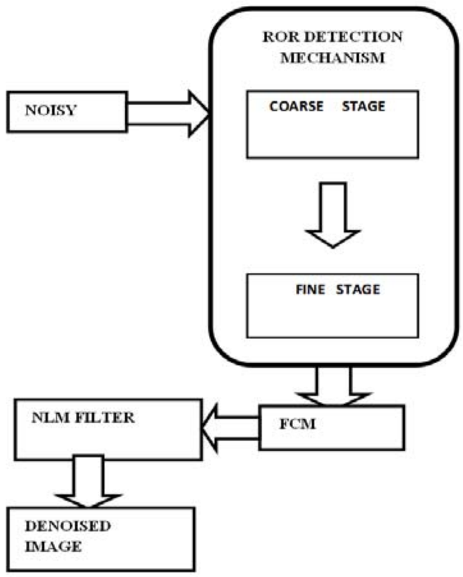


Figure 1: Over all block diagram of Denoising Framework

The output of coarse and fine stage of ROR detection mechanism is passed to FUZZY C MEANS (FCM) clustering algorithm.

IV. FCM

Fuzzy c-means(FCM) clustering algorithm was first introduced by Dunn and later extended by Bezdek. Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. Method is frequently used in pattern recognition. The algorithm is iterative clustering method. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m \left\|x_i - c_j\right\|^2, \quad 1 \le m < \infty$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}}, \quad c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

This iteration will stop when $\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \varepsilon$, where ε is a termination criterion between 0 and 1, whereas k are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m.

The algorithm is composed of the following steps:

Step 1: Initialize U=[u_{ij}] matrix, $U^{(0)}$

Step 2: At k-step: calculate the centers vectors $C^{(k)}$=[c_j] with $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

Step 3: Update $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_k\right\|}\right)^{\frac{2}{m-1}}}$$

Step 4: If || $U^{(k+1)}$ - $U^{(k)}$||< ε then STOP; otherwise repeat step 2.

The image is fine tuned in FCM and this fine tuned image is passed to NON-LOCAL MEANS (NLM) filter.

V. NLM FILTER

Non-Local Means (NLM) is a recent denoising method. It has received a lot of attention from the signal processing community. While standard linear filtering relies on local spatial correlation, the non-local principle exploits the fact that similar neighborhoods can occur anywhere in the image and can contribute for denoising. The standard NLM algorithm is computationally expensive. It proposes to limit the search region within which similar neighborhoods are looked for.

Numerous methods were proposed to accelerate the NLM approach such as a pre-selection of the contributing neighborhoods based on average value and gradient, average and variance or higher-order statistical moments, cluster tree arrangement, and singular value decomposition. Also the computation of the distance measure between different neighborhoods can be optimized using the Discrete Wavelet Transform a moving average filter. Variations of the NLM algorithm have also been proposed to improve the denoising performance, iterative application, combination with kernel regression and spectral analysis, and other similarity measures based on principal component analysis or rotation invariance. The most evolved version of the NLM framework is probably an image, which further processes the selected neighborhoods and gives image visual quality results.

Given a discrete noisy image v = {v(i) | i є I}, the estimated value NL[v](i), for a pixel i, is computed as a weighted average of all the pixels in the image,

$$NL[v](i) = \sum_{j \in I} w(i,j)v(j),$$

where the family of weights {w(i, j)}j depend on the similarity between the pixels i and j, and satisfy the usual conditions 0 ≤ w(i, j) ≤ 1 and Σj w(i, j) = 1. The similarity between two pixels i and j depends on the similarity of the intensity gray level vectors v(Ni) and v(Nj), where Nk denotes a square neighborhood of fixed size and centered at a pixel k. This similarity is measured

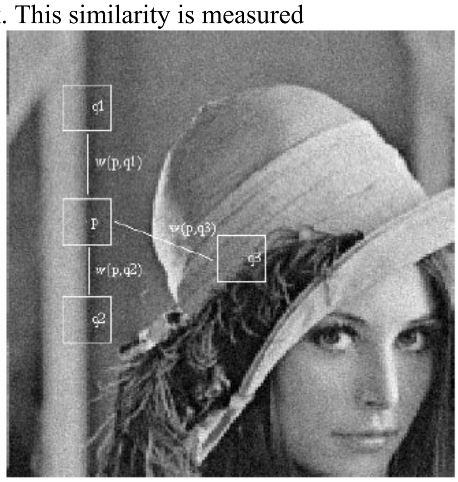


Figure 2. Scheme of NL-means strategy. Similar pixel neighborhoods give a large weight, w(p,q1) and w(p,q2), while much different neighborhoods give a small weight w(p,q3).

as a decreasing function of the weighted Euclidean distance, $\|v(\mathcal{N}_i) - v(\mathcal{N}_j)\|_{2,a}^2$, where a > 0 is the standard deviation of the Gaussian kernel. The application of the Euclidean distance to the noisy neighborhoods raises the following equality

$$E\|v(\mathcal{N}_i) - v(\mathcal{N}_j)\|_{2,a}^2 = \|u(\mathcal{N}_i) - u(\mathcal{N}_j)\|_{2,a}^2 + 2\sigma^2.$$

This equality shows the robustness of the algorithm since in expectation the Euclidean distance conserves the order of similarity between pixels. The pixels with a similar grey level neighborhood to $v(Ni)$ have larger weights in the average, see Figure 2.

These weights are defined as,

$$w(i,j) = \frac{1}{Z(i)} e^{-\frac{\|v(\mathcal{N}_i) - v(\mathcal{N}_j)\|_{2,a}^2}{h^2}},$$

Where $Z(i)$ is the normalizing constant

$$Z(i) = \sum_j e^{-\frac{\|v(\mathcal{N}_i) - v(\mathcal{N}_j)\|_{2,a}^2}{h^2}}$$

and the parameter h acts as a degree of filtering.

It controls the decay of the exponential function and therefore the decay of the weights as a function of the Euclidean distances.

The NL-means not only compares the grey level in a single point but the geometrical configuration in a whole neighborhood. This fact allows a more robust comparison than neighborhood filters. Figure 2 illustrates this fact, the pixel q3 has the same grey level value of pixel p, but the neighborhoods are much different and therefore the weight w (p, q3) is nearly zero.

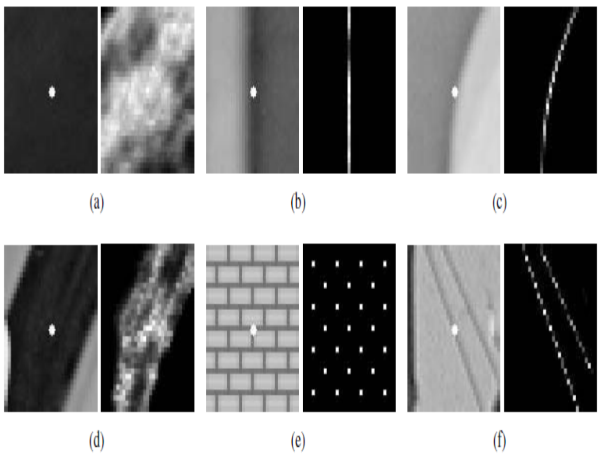


Figure 3. Display of the NL-means weight distribution used to estimate the central pixel of every image. The weights go from 1(white) to zero (black).

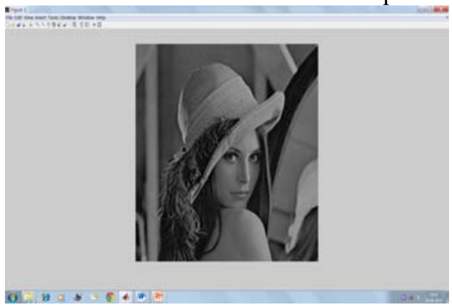
It separates the noised image into a number of patches. It is divided into 8X8 pixels. For every pixel the average of the intensity of the surrounding pixels is calculated.

The most similar pixels to a given pixel have no reason to be close to it. Several existing algorithms scan the vast portion of the image which includes all pixels that are restored. So, NL-means filter computes the weighted average of all the pixels in the image. The weight is based on the similarity between the pixels. Denoised value of a pixel is determined by the pixels with the similar neighborhoods.

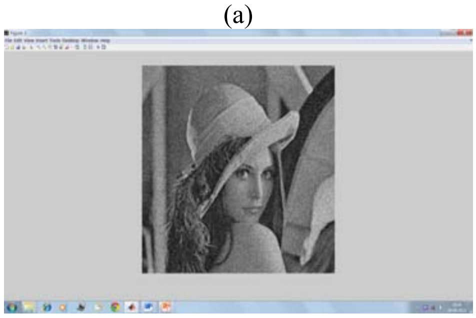
Thus, in the NLM filter the image is denoised and the denoised image is produced.

VI. Experimental Results

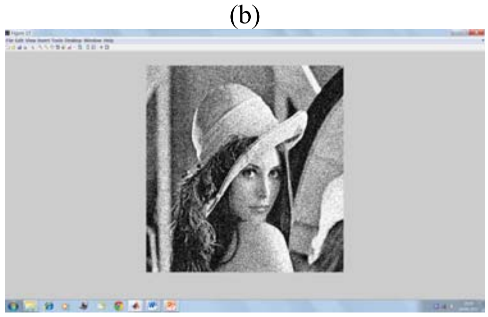
In figure 4, (a) is the input image (b) is the noise added image (c) are the FCM iteration image and (d) are the proposed ROR-FCM-NLM image. This method can be applied to various noise levels images and the experimental results obtained shows that the denoised image is better than earlier denoised techniques



(a)



(b)



(c)

(d)

Fig.4. (a)input image (b)noise added image (c)FCM iteration image (d) ROR-FCM-NLM image

Table 1 shows the PSNR values from the methods for lena image with different noise ratios about random valued impulse noise.

Table 1. Comparison of restoration results in the PSNR values for images with RANDOM VALUED IMPULSE NOISE

METHOD	LENA		
	30%	40%	50%
ROR-NLM	33.1462	31.4046	29.2308
ROR-FCM-NLM	**36.08**	**35.72**	**35.38**

VII. CONCLUSION

In this paper, a denoising framework with a impulse detection mechanism using fuzzy c mean clustering algorithm and nonlocal means has been presented in which the impulse detection mechanism ROR for describing the outlyingness of the pixels and FCM is used to find the arbitrary shape of the image and NL-means to the impulse noise. The proposed approach can be adapted to such models like salt and pepper impulse noise, random-valued impulse noise and mixed noise. Thus, ROR-FCM and NLM increases the efficiency and PSNR and infer a high quality image compared to other filtering techniques.

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