Fuzzy Noble Cluster Based Algorithm for Removal of Mixed Gaussian and Impulse Noises

P.Venkatesan, Dr.G.Nagarajan,

Abstract— Digital images are often corrupted by noise during their acquisition and transmission. A fundamental problem in image processing is to effectively suppress noise while keeping complete the desired image features such as edges, textures, and fine details. In particular, two common sources of noise are the so called additive Gaussian noise and impulse noise which are introduced duringthe acquisitionand transmission processes, respectively. Many methods have been introduced in the literature to remove either Gaussian or impulse noise. However, not all methods are able to deal with images which are simultaneously corrupted with a mixture of Gaussian and impulse noise.The Noble group of an image pixel is a pixel similarity based concept which has been successfully used to devise image denoising methods. However, since it is difficult to define the pixel similarity in a crisp way, propose to represent this similarity in fuzzy terms. Introduce the fuzzy noble cluster concept, which extends the noble cluster concept in the fuzzy setting. A fuzzy noblecluster will be defined as a fuzzy set that takes a noble group as support set and where the membership degree of each noble group member will be given by its fuzzy similarity with respect to the pixel under processing. The proposed filter is able to efficiently suppress Gaussian noise and impulse noise, as well as mixed Gaussian-impulse noise.

Index Terms— *Impulse noise, Gaussian noise, Fuzzy rules, PSMF, Fuzzy Averaging*.

1 Introduction

Most filters for Gaussian noise suppression are designed totake advantage of the zero-mean property of the noise and tryto suppress it by locally averaging pixel channel values. Classicallinear filters, (1) and (2) such as the Arithmetic Mean Filter (2) .To approach this problem, many nonlinear methods have beenrecently proposed, for instance: the bilateral filter, the anisotropic diffusion, the chromatic filter, or the softswitching-methods in (4) and which motivate other fuzzymethods as the fuzzy directional derivative filter, (5) and (6) the fuzzybilateral filter (4), the fuzzy noise reduction method, or thefuzzy-switching filter. The aim of these methods is to detectedges and details by means of local statistics and smooth themless than the rest of the image to better preserve their sharpness.However, these methods commonly identify impulses as detailsor edges to be preserved, and, therefore, they are not able to reducethem It is noted that earlier filters for impulsenoise are based on the theory of robust statistics because impulsesare identified with outlier data, and, therefore, robut to statistics allow appropriately determining noise-free samples and removing outliers. Filters of this family are,the popular median filter, the vector median filter,the vector directional filter, the directional-distance filter,(6) and (7) the HSV vector median filter, among others. These filters are efficient in reducing impulse noisebut their signal-preserving capability is deficient because thefiltering operation is applied to each image pixel regardlesswhether it is noisy or not. To overcome this drawback, several adaptive filters have been recently introduced.

These filters maybe classified into the following categories: switching filters, filters using weighting coefficients, fuzzy filters, and neuro-fuzzy filters. However, many of these techniques select the appropriate noise-free output from the input samples, and therefore, they are notuseful to remove Gaussian noise because in such a case thereare no noise-free samples, (5) and (7).according to the above, the filter design is a challenging taskfor mixed Gaussian-impulse noise removal. A possible solution is to apply two consecutive filters to remove first impulse noise and then Gaussian noise, or vice versa. However, the applicationof two filters could dramatically decrease the computational efficiencyof the method which implies that this solution couldnot be practical for real applications. Therefore, it is more interestingto devise specific filters to remove mixed noise. To date, afew methods in the literature are able to approach this problemefficiently. The *NobleCluster Averaging* (NCA) technique presentedin removes mixed noise by combining a statisticalmethod for impulse noise detection and replacement withan averaging operation to smooth out Gaussian noise. The *TrilateralFilter* (TF) is based on the well-known *BilateralFilter* to (10) and (12) smooth Gaussian noise but including an impulsedetector to be also able to reject impulse noise. The *AdaptiveNearest Neighbor Filter* (ANNF) (8) and its variants, use aweighted averaging where the weights are computed accordingto robust measures so that impulses that receive lower weightsare reduced. The *Fuzzy Vector Median Filter* (FVMF) performsa weighted averaging where the weight of each pixel iscomputed according to its similarity to the robust vector median.Another important family of filters is the partition based filters, which classify each pixel to be processed into severalsignal activity categories which, in turn, are associated toappropriate processing methods. Other filters follow a regularizationapproach based on the minimization of appropriateenergy functions by means of Partial Differential Equations(PDEs).Wavelet theory has also been used to design image filtering methods and the combination of collaborative and wavelet filtering is proposed in addition,other methods based on Principal Component Analysis (PCA) have been studied.

————————————————

- *P.venkatesan is currently pursuing Phd program in digital image processing in **SCSVMV University, Enathur kanchipuram**, Tamil nadu, India. E-mail: pv.ecekanchi@gmail.com*
- *Prof.Dr.G.Nagarajan, HOD/ECE Pondicherry Engineering College Pondicherry Tamil nadu, India.*

The motivation of the method in this paper is the so-called*noblecluster*concept introduced and further studied. The *noble cluster*of a given pixel is a set constitutedby this pixel and those of its neighbors which are *similar* to it.However, the *similarity* between two color pixels is not easilyexpressed in a crisp way, and, therefore, in this work. The Proposeto use a fuzzy representation, this leads us to introduce the *fuzzy noblecluster*concept which use to devise a novel filteringprocedure. This paper uses fuzzy metrics, whichhave been proven to be efficient and effective for noise detection but, in this case, fuzzy metrics are applied to build the *fuzzy nobleclusters*. The proposed method is based onthe consecutive application of a fuzzy rule-based switching impulsenoise filter and a fuzzy average filtering. Both steps use thesame *fuzzy noblecluster*, which leads to computational savings.This filter differs from previous *noblecluster*methodsbecause (i) *fuzzy nobleclusters*are represented as fuzzy sets insteadof crisp sets used. (ii) It employs a novel fuzzymethod first to determine the *fuzzy noblecluster*members and thento assign their corresponding membership degrees, (iii) it usesfuzzy rules to detect impulse noise pixels, (iv) it performsa fuzzy weighted averaging to generate the output. Hence, thecombination of these fuzzy components is the main novelty ofthe proposed method. Experimental results will show that the proposed filtering technique exhibits competitive results withrespect to other state-of-the-art methods.

2. NOBLE CLUSTERS AND FUZZY NOBLE CLUSTERS

Let*F* denote the image to be processed, F_0denote the central pixel of the processing sliding window of size n X n, and let F_i W, i= 1,..,n^2 – 1 denote the pixels in the neighborhood of. Each pixel is represented as a 3-component vector comprising its R, G, and B components. Have chosen the vector approach which is suitable for color image processing since it takes into account the correlation among the color image channels. The peer group of an image pixel, roughly speaking, is defined as the set of its neighbor pixels which are similar to it. There are several ways of determining this set. One of them, introduced in and used in and, is based on the usage of a distance threshold to decide whether a pixel belongs to the peer group or not. This cardinality has been used to decide whether $F_0$is free of impulse noise or not. It is to be noted that because of the usage of a threshold based decision, the peer group is defined in a crisp way. However, since the similarity between two color pixels is an imprecise concept, this approach does not provide a completely satisfactory representation of the peer groups, (7) and (11), therefore, propose to represent this concept using fuzzy theory, from another point of view, the definition fuzzy peer group isbased on the ordering of the pixel neighbors with respect to its similarity to the central pixel, as follows; Let ρ be an appropriate similarity measure between two color vectors. The color vectors in the processing window are sorted in descending order with respect to its similarity to the central pixel. That is, the ordering of the n^2vectors of the processing window results in an ordered set of the elements or the color vectors W'. Then, according to the definition of peer group given in for convenience, the peer group of (m+1) members associated with F_0. This peer group is a set constituted by $F_0$and its 'm'most similar neighbors, i.e.

$$P^{F0}_m = \{F_{(i)}, i = 0, \ldots m\}; \quad (1)$$

The choices of the number of members of the peer group are a main issue within this approach. The works in propose to use the Fisher's linear discriminant (FLD) to solve this task. This method provides the best partition of the input set into two subsets so that it includes neighbors in the *peer group*, and excludes the rest. Unfortunately, this approach does not work properly when the input set contains either only one cluster or more than two clusters of data. In our context, for instance, when processing a homogeneous noise-free area of the image only one cluster of data should be observed and, however, the FLD will always partition the data into two subsets. On the other hand, when three (or more) clusters of data are observed, which may occur for instance in an image area including impulse noise and edges, the partition given by the FLD does not necessarily leads to the desired *noblecluster*, as shown later. According to the previous discussion, it is essential to perform an appropriate construction of the *noble groups*, which involves to accurately determining the number of *noble group* members. This information can be used to decide whether is free of impulse noise. Also, the *noble group* members may be used to smooth the Gaussian noise from. In this paper, propose a more appropriate fuzzy logic-based method to determine the *noble cluster* of an image pixel that will call fuzzy noble cluster, (13) and (14).

3. NEW COLOR IMAGE DENOISING TECHNIQUE

In this section, we investigate the usefulness of *fuzzy nobleclusters* for color imagedenoising. Propose a color image filter for suppression of mixed Gaussian-impulse noise which isbased on the fuzzy noble*cluster* concept and that we name *FuzzyNobleCluster Averaging Filter* (FNCA). As commented in the introductory section, pixel averaging allows removing Gaussian noise because of the zero-mean property of this noise. However, in order to avoid impulse noise perturbing this operation the impulse noise in the image must be reduced first. Therefore, we propose a filter performing in two steps, namely, (i) impulse noise detection and reduction and (ii) Gaussian noise smoothing, so that both steps follow a fuzzy approach that uses the information on the *fuzzy peergroups*, which is the main novelty introduced by the method. To reduce the impulse noise we propose a fuzzy rule based procedure which uses the *fuzzy noble group* concept. For Gaussian noise smoothing, we use a fuzzy averaging among the members of the *fuzzy noblecluster* of the pixel under processing. Fig. 4 shows a diagram of the process applied over each image pixel. The following sections detail the two steps of the proposed filter. The block diagram of the proposed algorithm is given in Fig 1.

3.1 Impulse Noise Detection and Reduction

An impulse noise pixel can be defined as a pixel which is significantly different from its pixels neighbors. Conversely, an impulse noise-free pixel should have some neighbors quite similar to it. According to the above, we can formulate this condition in terms of *fuzzy nobleclusters*as follows: a pixel is F_0free of impulse noise if for *fuzzy noblecluster*$_m^{F0}$it is satisfied that " A^{F0} ($F_{(m)}$) is large" and "$F_{(m)}$is similar to F_0". The following Fuzzy Rule 2 represents this condition:

Fuzzy Rule 2: Determining the certainty of the pixel to be free of impulse noise

IF "is large" and "A^{F0} ($F_{(m)}$) is similar to $F_{(m)}$" THEN "$F_0$is free of impulse noise".

To compute the certainty of the Fuzzy Rule 2 (which is denoted by C_{FR2} (F_0)) we perform analogously that for the Fuzzy Rule 1. That is, the certainty of "A^{F0}($F_{(m)}$) is *large*" is given by L^{F0}, according to (6), and the certainty of "$F_{(m)}$is similar to F_0" is given by the function C^{F0}. Finally, use the product t-norm as the conjunction operator so that

C_{FR2} (F_0) = $C^{F\ 0}$($F_{(m)}$) L^{F0}($F_{(m)}$). Indeed, notice that C_{FR2} (F_0) = C_{FR1} ($_m$). This implies that no additional computation is needed since this certainty is already computed. Now, use C_{FR2} (F_0) to detect and replace impulses according to threshold-based rule shown in (7), at the bottom of the page, where is a threshold parameter with values in [0, 1] whose importance will be discussed later. This procedure constitutes a switching filter between the identity operation andthe VMF operation, which is used for being the most robust and well-known vector filter. However, other robust filtering structures could be applied, as well.

3.2 Gaussian Noise Smoothing Procedure

The second step of the proposed method concerns the Gaussian noise smoothing task. As mentioned above, propose to perform a weighted averaging operation among color vectors. So, to smooth the pixelF_0 use the members of $P^{F0}{}_m$ where the weighting coefficient for each color vector is its membership degree to the *fuzzy noblecluster*as follows:

$$mmF_{out}=\sum_{i=0} FP^{F0}{}_m(F(i))F(i) \;/\; \sum_{i=0} FP^{F0}{}_m(F(i) \qquad (2)$$

It is to be noted that, unlike other smoothing filters based on weighting coefficients, such as those in the set ofNeighbor pixels involved in the proposed smoothing procedure is restricted to the members of the *fuzzy noblecluster*, which implies that only *similar* pixels are used. This approach should perform a better edge and detail preservation than those non restricted approaches since *non similar* color vectors out of the *fuzzy noblecluster*do not perturb the averaging.

4. EXPERIMENTAL RESULTS

The test images Lena (Fig 2) andFlower (Fig 3) have been used to evaluate the performance of the proposed filter. These images have been corrupted with Gaussian and/or impulse noise. For Gaussian noise have used the classical white additive Gaussian model contaminating independently each color image channel where the standard deviation of the Gaussian distribution represents the noise intensity. On the other hand, the two most common impulse noise models assume that the impulse is either an extreme value in the signal range or a random uniformly distributed value within the signal range. These models are known as fixed-value and random-value impulse noise, respectively. Since the removal of fixed-value noise has been extensively studied in the literature and there have been several methods developed and able to suppress this noise effectively, in this paper we focus on the uncorrelated random-value case following the definition in. Mean Absolute Error (MAE), the Peak Signal to Noise Ratio (PSNR), and the Normalized Color Difference (NCD) are the measures used to evaluate the detail preserving capability, the noise suppression capability, and the color preservation ability, respectively for the proposed algorithm.Table 1 gives the comparison of the performance measured in terms of MAE, PSNR, and NCD using the Lena image contaminated with different densities of mixed noise.

5. CONCLUSION

In this paper, are introduced the concept of fuzzy noble cluster for a color image pixel which extends the concept of noble cluster in the fuzzy setting. This noble concept aims to representthe set of all pixel neighbors to a given pixel which are similarto it. Since the similarity between color pixels is an impreciseconcept, we have represented it using fuzzy similarities. Thus, fuzzynobleclusters are built as fuzzy sets where the membershipdegree of the neighbor pixels depends on their fuzzy similarity with respect to the pixel under processing. The proposed method is able to accuratelydetermine the fuzzy noblecluster of any color image pixel overcomingshortcomings of previous noblecluster approaches.Second, have used fuzzy nobleclusters to define a two stepcolor image filter cascading a fuzzy rule-based switching impulsenoise filter by a fuzzy average filtering. Both steps use thesame fuzzy noblecluster, which leads to computational savings.Experimental results have shown that the proposed method isable to reduce mixed Gaussian-impulse noise exhibiting animproved performance with respect to state-of-the-art methodsmainly because of its ability to properly determine the fuzzy nobleclusters. Also, the proposed method is competitive when reducing noise from images which are corrupted only withGaussian noise and only with impulse noise.

REFERENCES

[1] K. N. Plataniotis and A. N.Venetsanopoulos, *Color Image ProcessingandApplications*.Berlin, Germany: Springer, 2000.

[2] R. Lukac, B. Smolka, K. Martin, K. N.Plataniotis, and A. N. Venetsanopoulos, "Vector filtering for color imaging," *IEEE Signal Process.Mag.*, vol. 22, no. 1, pp. 74–86, Jan. 2005.

[3] R. Lukac and K. N. Plataniotis, "A taxonomy of color image filteringand enhancement solutions," in *Advances in Imaging and ElectronPhysics*, P. W. Hawkes, Ed. New York: Elsevier, 2006, vol. 140, pp.187–264.

[4] C. Tomasi and R. Manduchi, "Bilateral filter for gray and color images," in *Proc. IEEE Int. Conf. Computer Vision*, 1998, pp. 839–846.

[5] M. Elad, "On the origin of bilateral filter and ways to improve it," *IEEETrans. Image Process.* vol. 11, no. 10, pp. 1141–1151, Oct. 2002.

[6] R. Garnett, T. Huegerich, C. Chui, and W. He, "A universal noiseremoval algorithm with an impulse detector," *IEEE Trans. Image Process.*, vol. 14, no. 11, pp. 1747–1754, Nov. 2005.

[7] P. Perona and J. Malik, "Scale-space and edge detection usinganisotropic diffusion," I*EEE Trans. Pattern Anal.Mach.Intell.*, vol. 12, no. 7, pp. 629–639, Jul. 1990.

[8] L. Lucchese and S. K. Mitra, "A new class of chromatic filters forcolor image processing: Theory and applications," *IEEE Trans. Image Process.*, vol. 13, no. 4, pp. 534–548, Apr. 2004.

[9] E. Abreu, M. Lighstone, S. K. Mitra, and K. Arakawa, "A new efficientapproach for the removal of impulse noise from highly corrupted images," *IEEE Trans. Image Process.*, vol. 5, no. 6, pp. 1012–1025, Jun.1996.

[10] H. L. Eng and K. K. Ma, "Noise adaptive soft-switching median filter,"*IEEE Trans. Image Process.*, vol. 10, no. 2, pp. 242–251, Feb. 2001.

[11] D. Van de Ville, M. Nachtegael, D. Van der Weken, W. Philips, I.Lemahieu, and E. E. Kerre, "Noise reduction by fuzzy image filtering,"*IEEE Trans. Image Process.*, vol. 11, no. 4, pp. 429–436, Apr. 2001.

[12] S. Morillas, V. Gregori, and A. Sapena, "Fuzzy bilateral filtering forcolor images," in*Proc. Int. Conf. Image Analysis and Recognition*,2006, vol. 4141, pp. 138–145, Lecture Notes in Computer Science.

[13] S. Schulte, V. De Witte, and E. E. Kerre, "A fuzzy noise reductionmethod for colour images," *IEEE Trans. Image Process.*, vol. 16, no.5, pp. 1425–1436, May 2007.

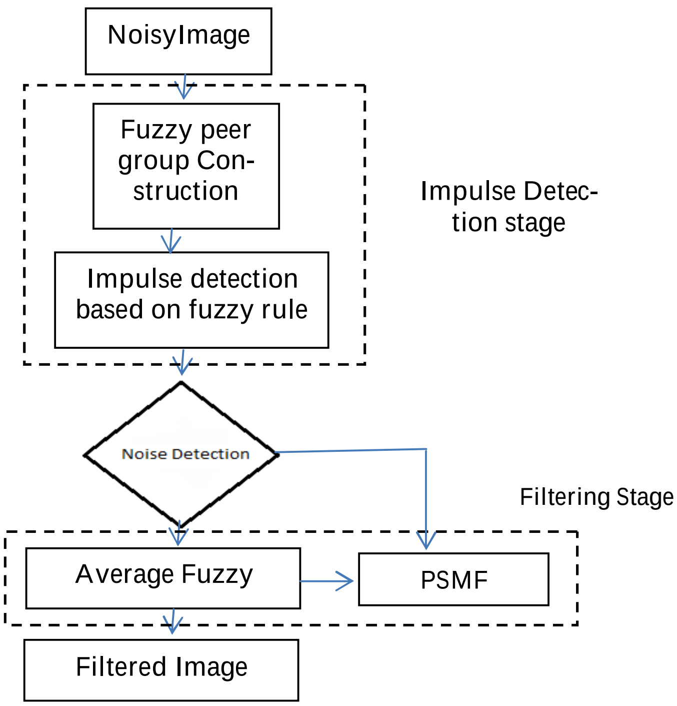

Fig1. Block Diagram of FNCA

Fig 2. Filter outputs for visual comparison: (a) Lena image, (b) image corrupted with (d) GRF, (e) PGA, and (f) FNCA

Table 1.COMPARISON OF THE PERFORMANCE MEASURED IN TERMS OF MAE, PSNR, AND NCD (210) USING THE LENA IMAGE CONTAMINATED WITH DIFFERENT DENSITIES OF MIXED NOISE

Filter	$\sigma = 5$ Gaussian and $p = 0.05$ impulse			$\sigma = 10$ Gaussian and $p = 0.1$ impulse			$\sigma = 20$ Gaussian and $p = 0.2$ impulse			$\sigma = 30$ Gaussian and $p = 0.3$ impulse		
	MAE	PSNR	NCD	MAE	PSNR	NCD	MAE	PSNR	NCD	MAE	PSNR	NCD
None	7.88	20.79	8.24	14.27	18.26	15.23	27.68	14.76	28.24	37.43	13.17	38.40
ANNF	6.81	26.99	4.41	7.42	26.63	5.21	9.38	25.38	7.45	12.29	23.60	10.04
TF	4.82	27.09	5.15	7.18	26.20	6.30	9.92	24.34	8.15	12.12	23.20	10.36
FVMF	6.53	27.04	4.35	7.27	26.64	5.13	9.37	25.04	6.80	11.87	23.75	9.14
PGA	5.20	29.81	4.05	7.26	27.61	6.09	10.14	24.95	8.42	12.91	23.00	10.74
IPGF	4.20	31.57	4.79	7.99	27.35	9.15	14.62	22.37	15.27	18.27	20.33	18.64
FWD	7.62	21.10	7.50	12.16	19.45	12.45	18.12	18.70	17.50	22.40	18.17	20.30
CWF	6.37	24.07	5.60	9.32	25.71	7.61	16.75	21.70	13.97	21.55	19.81	17.82
CRF	7.89	25.06	6.63	10.04	23.45	8.43	15.34	21.15	12.03	19.60	19.70	14.73
GRF	5.46	29.36	3.94	7.88	26.67	5.85	11.70	24.05	9.64	16.60	21.40	13.92
PBF	3.88	32.83	3.90	6.23	29.14	6.48	9.52	25.46	8.34	13.02	22.91	11.73
FNCA	4.22	31.03	3.26	5.76	29.15	4.60	8.11	26.35	6.71	10.68	24.51	8.90