Int. J. Electron. Commun. (AEÜ) 65 (2011) 132–139

Contents lists available at ScienceDirect

Int. J. Electron. Commun. (AEÜ)

journal homepage: www.elsevier.de/aeue

# Efficient impulse noise detection method with ANFIS for accurate image restoration

Ilke Turkmen *

*Erciyes University, Civil Aviation School, Department of Aircraft Electrical and Electronics, 38039 Kayseri, Turkey*

ARTICLE INFO

*Article history:*
Received 28 July 2007
Accepted 2 February 2010

*Keywords:*
Impulsive noise
Impulse noise detector
ANFIS

ABSTRACT

This paper proposes a novel adaptive neuro-fuzzy inference system (ANFIS) based impulse detection method for the restoration of images corrupted by impulse noise (IN). After the corrupted pixels detected by proposed detector, the Median filtering is performed for only these pixels. The performance of the proposed neuro-fuzzy detector based median filter (NFDMF) is evaluated on different test images and compared with 14 different comparison filters from the literature. Experimental results show that the proposed filter shows better performance than the comparison filters in the cases of being effective in noise suppression and detail preservation, especially when the noise ratio is very high.
© 2010 Elsevier GmbH. All rights reserved.

## 1. Introduction

Images are often corrupted by impulse noise (IN) due to errors generated in noisy sensors or communication channels. IN could degrade the image quality and cause great loss of image details. So it is important effectively to reduce noise from the image to facilitate subsequent image processing operations, such as edge detection, image segmentation, and object recognition. The goal of noise removal is to suppress the noise while preserving image details. To this end, a large number of algorithms [1–28] have been proposed to remove IN.

The median filter is one of the most popular nonlinear filters for removing IN because of its good denoising power [1] and computational efficiency [2]. Median filter utilize the rank order information of the pixels contained in the filtering window. It attempts to remove impulse noise by changing the luminance value of the each pixel in the image by the median value in its neighborhood. However, when the noise level is over 50%, some details and edges of the original image are smeared by the filter [3]. In order to overcome this drawback, different remedies of the median filter have been proposed. In [4] center weighted median filter (CWM) giving more weight only to the center value in the filtering window was presented. A nonlinear filter called tri-state median filter (TSM) combining the standard median filter with the CWM filter was proposed in [5] for suppressing impulse noise. The nonlinear LUM (low–upper–middle) smoothers, which are a subclass of LUM filters [6–8] that take advantage of the computational efficiency of order-statistics based operators, have been shown to be equivalent to the CWM. Methods mentioned above can achieve good results at low noise density, but their denoising performances are unsatisfactory at high noise density. These methods are implemented uniformly across the image and thus tend to modify both noisy and noise-free pixels. Consequently, the effective removal of IN is often accomplished at the expense of blurred and distorted features, thus removing fine details in the image.

To avoid the damage of good pixels, the switching strategy is introduced by some recently published papers [9–14]. The switching scheme consists of the following two parts: the first part is an impulse detector which determines whether a target pixel is contaminated and the second part is a noise reduction filter which modifies only the pixels determined to be IN by the first part. In order to achieve accurate image restoration with the switching scheme, an accurate impulse detector is required, because the impulse detection result is utilized for the noise reduction filter.

Over the last few years, artificial intelligence-based nonlinear techniques such as neural networks and fuzzy systems have been attractive alternatives to classical noise detection and reduction techniques [15–28]. In [16] iterative fuzzy control-based filtering (IFCF) method was presented. The IFCF filter was designed for the removal of both impulse noise and Gaussian noise. This filtering approach is mainly based on the idea of not letting each point in the area of concern being uniformly fired by each of the basic fuzzy rules. The extended iterative fuzzy control-based filter (EIFCF) and the modified iterative fuzzy control-based filter (MIFCF) were also presented in [16]. EIFCF, which is a slightly modified version of the IFCF, was designed to counter the blurring of the image. In IFCF, the image gets more blurred after each iteration. MIFCF was designed to avoid this drawback. Smoothing

* Tel.: +90 352 437 57 44; fax: +90 352 437 57 84.
*E-mail address:* titi@erciyes.edu.tr

1434-8411/$ - see front matter © 2010 Elsevier GmbH. All rights reserved.
doi:10.1016/j.aeue.2010.02.006

www.Matlabi.ir

**Table 5**
Runtimes of the mentioned methods for the *Baboon* image for different IN levels.

| Method | Runtime (s) | |
|---|---|---|
| | % 10 | % 80 |
| CWM | 9.2 | 8.7 |
| TSM | 18.1 | 18.0 |
| LUM | 3.6 | 3.2 |
| FSB | 165.9 | 166.4 |
| IFCF | 783.0 | 850.2 |
| MIFCF | 833.7 | 809.8 |
| EIFCF | 919.6 | 906.2 |
| SFCF | 323.6 | 317.9 |
| FIRE | 277.2 | 274.1 |
| PWLFIRE | 22.8 | 22.3 |
| FMF | 2.0 | 2.12 |
| AWFM | 143.9 | 144.6 |
| ATMAV | 24.9 | 24.6 |
| NNDMF | 2.56 | 2.58 |
| NFDMF | 0.6 | 3.1 |

## 4. Simulation results

The performance of the proposed method is tested under various noise conditions and on several popular images from the literature including *Lena*, *Baboon*, *Boats*, and *Peppers*. These images, which are 8-bit gray level images having the same size of 512 $\times$ 512 pixels, are shown in Fig. 4. The test images used in the experiments are generated by contaminating the original images by IN with an appropriate noise ratios ranging from 10% to 80% with an increment step of 10%.

For comparison, the corrupted test images are also filtered by using several conventional and state-of-the-art IN removal operators including CWM [4], TSM [5], LUM [6], FSB [15] (fuzzy similarity filter), IFCF [16], MIFCF [16], EIFCF [16], SFCF [17], FIRE [18], PWLFIRE [19], FMF [20,21] (fuzzy median filter), AWFM [22,23], and ATMAV [24]. In order to show performance of the ANFIS with respect to the neural network [31], the NFDMF results are also compared with the neural network detector median filter (NNDMF) results. The multilayer perceptron (MLP) network architecture was used in NNDMF. In MLP, the most suitable network configuration was two hidden layer with three neurons. In order to train MLP, the Levenberg–Marquardt learning algorithm [32] was used.

Restoration performances are quantitatively measured by the peak signal-to-noise ratio (PSNR) which is defined as

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right)\text{dB} \tag{11}$$

where mean-squared-error (MSE) is defined as

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[org(i,j) - img(i,j)]^2 \tag{12}$$

where *org* is the original image, *img* is the filtered image of size *MN*. In addition, the mean absolute error (MAE) has also been taken as a quantitative measure to evaluate the levels of the edges and the details preserved, which is defined as

$$MAE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|org(i,j) - img(i,j)| \tag{13}$$

The restoration results for the *Lena* and *Baboon* test images corrupted with 70% IN are illustrated in Figs. 5 and 6, respectively. It is clearly seen from these figures that the proposed filter preserves edge sharpness and reduces many artifacts, even if the noise density is high. The PSNR values of the filters have also been given in Tables 1 and 2 for making quantitative evaluation for *Lena* and *Baboon* test images. It is clearly seen from Tables 1 and 2 that the proposed NFDMF generates the best PSNR values. The MAE values for *Boats* and *Peppers* test images have been given in Tables 3 and 4. It is clear from Tables 3 and 4 that the proposed NFDMF shows better performance than other filters in the sense of being effective in noise suppression and detail preservation, especially when the noise density is very high.

Another important requirement of the modern image enhancement filters is robustness. Tables 1–4 indicate that the proposed NFDMF provides robustness substantially across a wide variation of noise ratios.

In order to evaluate the computational complexities, the runtimes of all the mentioned filters for *Baboon* image for different IN levels were determined and given in Table 5. The runtime analysis of the proposed NFDMF and concerned filters were conducted for test images using a Pentium IV, 3 GHz PC. It is seen from Table 5 that NFDMF is one of the fastest algorithms.

## 5. Conclusion

In this paper, an IN detector based on ANFIS is proposed. It can be seen from Figs. 5 and 6 that proposed NFDMF gives absolutely better restoration results in the restored images when compared with the IN suppression filters mentioned in this paper.

The advantages of the proposed filter may be summarized as follows.

1. The implementation of the method is very easy. It is based on a simple 2-input 1-output NF system.
2. The internal parameters of the NF system are determined by training. Training of the system can easily be realized by using artificial images generated in computer.
3. The NFDMF supplies superior restoration results compared to both median based filters (CWM, TSM, and LUM) and recently introduced fuzzy based filters (FSB, IFCF, MIFCF, EIFCF, SFCF, FIRE, PWLFIRE, FMF, AWFM, and ATMAV). The NFDMF is also better than the NNFMF.
4. The runtime of the proposed filter is less than most of the comparison filters. Finally, proposed method is easy to implement and has a very low execution time.

## Acknowledgment

Author is grateful to Dr. Stefan Schulte for sending her source codes of the comparison filters mentioned in the paper.

## References

[1] Bovik A. Handbook of image and video processing. New York: Academic; 2000.
[2] Huang TS, Yang GJ, Tang GY. Fast two-dimensional median filtering algorithm. IEEE Trans Acoust Speech Signal Process 1979;1(1):13–8.
[3] Nodes TA, Gallagher NCJ. The output distribution of median type filters. IEEE Trans Commun 1984;32(5):532–41.
[4] Ko SJ, Lee YH. Center weighted median filters and their applications to image enhancement. IEEE Trans Circuits Syst 1991;38(9):984–93.
[5] Chen T, Ma KK, Chen LH. Tri-state median filter for image denoising. IEEE Trans Image Process 1999;8(12):1834–8.
[6] Hardie RC, Boncelet CG. Lum filters: a class of rank-order-based filters for smoothing and sharpening. IEEE Trans Signal Process 1993;41(3):1834–8.
[7] Lukac R. Binary lum smoothing. IEEE Signal Process Lett 2002;19:400–3.
[8] Lukac R, Plataniotis KN, Smolka B, Venetsanopoulos AN. Generalized selection weighted vector filters. EURASIP J Appl Signal Process 2004;2004(12): 1870–85.
[9] Eng H, Ma KK. Noise adaptive soft-switching median filter. IEEE Trans Image Process 2001;10(2):242–51.

[10] Paul ME, Bruce K. C language algorithms for digital signal processing. Upper Saddle River, NJ: Prentice-Hall; 1991.
[11] Sun T, Neuvo Y. Detail-preserving median based filters in image processing. Patten Recognition Lett 1994;15(4):341–7.
[12] Lin H, Willson AN. Median filter with adaptive length. IEEE Trans Circuits Syst 1988;35(6):675–90.
[13] Wang Z, Zhang D. Progressive switching median filter for the removal of impulse noise from highly corrupted images. IEEE Trans Circuits Syst 1999;46(1):78–80.
[14] Besdok E, Yuksel ME. Impulsive noise suppression from images with Jarque Bera test based median filter. Int J Electron Commun (AE) 2005;59:105–10.
[15] Kalaykov I, Tolt G. Real-time image noise cancellation based on fuzzy similarity. Fuzzy filters for image processing, 1st ed.. Heidelberg, Germany: Physica Verlag; 2003. p. 54–71.
[16] Farbiz F, Menhaj MB. A fuzzy logic control based approach for image filtering. In: Kerre E, Nachtegael M, editors. Fuzzy techniques in image processing, 1st ed. Heidelberg, Germany: Physica Verlag; 2000. p. 194–221.
[17] Farbiz F, Menhaj MB, Motamedi SA. Edge preserving image filtering based on fuzzy logic. In: 6th EUFIT conference, 1998. p. 1417–21.
[18] Russo F, Ramponi G. A fuzzy filter for images corrupted by impulse noise. IEEE Signal Process Lett 1996;3(6):168–70.
[19] Russo F. Fire operators for image processing. Fuzzy Sets Syst 1999;103(2):265–75.
[20] Arakawa K. Median filter based on fuzzy rules and its application to image restoration. Fuzzy Sets Syst 1999;103:265–75.
[21] Arakawa K. Fuzzy rule-based image processing with optimization. In: Kerre EE, Nachtegael M, editors. Fuzzy techniques in image processing, 1st ed. Heidelberg, Germany: Physica Verlag. 2000. p. 222–47.
[22] Lee CS, Kuo YH, Yu PT. Weighted fuzzy mean filters for image processing. Fuzzy Sets Syst 1997;89:157–80.
[23] Lee CS, Kuo YH. Adaptive fuzzy filter and its application to image enhancement. In: Kerre EE, Nachtegael M, editors. Fuzzy techniques in image processing, 1st ed. Heidelberg, Germany: Physica Verlag; 2000. p. 172–93.
[24] Kwan HK. Fuzzy filters for noise reduction in images. In: Nachtegael M, Van der Weken D, Van De Ville D, Kerre EE, editors. Fuzzy filters for image processing, 1st ed.. Heidelberg, Germany: Physica Verlag; 2003. p. 25–53.
[25] Yuksel ME, Basturk A. Efficient removal of impulse noise from highly corrupted digital images by a simple neuro-fuzzy operator. Int J Electron Commun (AE) 2003;57(3):214–9.
[26] Yuksel ME. A median/anfis filter for efficient restoration of digital images corrupted by impulse noise. Int J Electron Commun (AE) 2006;60:628–37.
[27] Toprak A, Ozerdem MS, Guler I. Suppression of impulse noise in mr images using artificial intelligent based neuro-fuzzy adaptive median filter. Digital Signal Process 2008;18(3):391–405.
[28] Yildirim MT, Basturk A, Yuksel ME. Impulse noise removal from digital images by a detail-preserving filter based on type-2 fuzzy logic. IEEE Trans Fuzzy Syst 2008;16(4):920–8.
[29] Jang JSR. Anfis: Adaptive-network-based fuzzy inference system. IEEE Trans Systems Man Cybernetics 1993;23:665–85.
[30] Jang JSR, Sun CT, Mizutani E. Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence. Upper Saddle River, NJ: Prentice-Hall; 1997.
[31] Haykin S. Neural networks: a comprehensive foundation. New York: Macmillan College Publishing Company; 1994.
[32] Hagan MT, Menjah M. Training feedforward networks with the Marquardt algorithm. IEEE Trans Neural Networks 1994;5(6):989–93.

**Ilke Turkmen** was born in Kayseri, Turkey, on December 26, 1976. She received B.S., M.S., and Ph.D. degrees in electronics engineering from Erciyes University, Kayseri, Turkey, in 1997, 1999, and 2005, respectively. Currently, she is an assistant professor at the Department of Aircraft Electrical and Electronics of Civil Aviation School, Erciyes University. Her current research activities include neural networks, intelligent algorithms, fuzzy inference systems, and their applications to target tracking and image processing.