DIRECTIONAL WEIGHTED MEDIAN BASED FUZZY FILTER FOR RANDOM-VALUED IMPULSE NOISE REMOVAL

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ABSTRACT. Paper presents directional weighted median base fuzzy filter for randomvalued impulse noise removal. In order to detect noise efficiently a fuzzy noise detection process is used whereas noise removal is performed by the directional weighted median based fuzzy filtering process. Proposed technique is compared with existing techniques based on peak-signal-to-noise-ratio (PSNR) and structural similarity index measure (SSIM). Simulations show that the noise removal capability of the proposed technique is much better than the existing techniques.

Keywords: Fuzzy filter, Random-valued impulse noise, Image restoration

1. Introduction. Image restoration is an important branch of image processing, which deals with the reconstruction of images by removing noise and blurriness and making them suitable for human perception [1]. Images can become corrupted during any of the acquisition, pre-processing, compression, transmission, storage and/or reproduction phases of the processing [2]. Liu and Li, in their reviews [3], have divided spatial image restoration techniques into two main categories namely conventional and blind image restoration. In conventional image restoration the information about the degradation process is generally known. This known information can be used to develop a model to restore the corrupted image back to its original form. Such techniques are used to solve motion blur, system distortions, geometrical degradations and additive noise problems. Unfortunately, in most cases, details about the degradation process are either partially or completely unknown, which make the image restoration process much more difficult. In the second category of image restoration [3], the image has to be restored directly from the degraded image without any prior information about the degradation process. Recently more focus has been placed on this category. One of the main tasks in developing such image restoration techniques is noise removal without destroying the image details. Noise smoothing and detail preservation are generally considered as conflicting tasks, because smoothing a region of the degraded image can potentially destroy an edge while sharpening edges may lead to the amplification of noise [4]. In the sequel, we present a directional weighted median base fuzzy filter (DWMFF) to removes random-valued impulse noise while preserving the edges and texture information.

A number of approaches have been proposed for the impulse noise removal. Tukey [5], Astola et al. [6] and Pitas et al. [7] have utilized median filtering to remove impulse noise from the corrupted images. Other filters for removal of impulse noise includes *histogram based fuzzy filter* (HFF) [8], Lee et-al.'s *novel fuzzy filter* (NFF) [9], *genetic*

based fuzzy image filter (GFIF) [10], fuzzy impulse noise detection and reduction method (FIDRM) [11], fuzzy random impulse noise reduction method (FRINR) [12], Nemanja etal.'s universal impulse noise filter based on genetic programming [13], a new directional weighted median filter for removal of random valued impulse noise (DWM) [14] and detail preserving fuzzy filter (DPFF) [4] are the examples of the most recent filters.

In this paper, we present a directional weighted median base fuzzy filter (DWMFF) to restore images corrupted with random-valued impulse noise. DWMFF consist of a fuzzy noise detection process and directional weighted median base filtering process. The fuzzy filtering process utilizes the directional weighted median in such a way that the all of the homogenous pixel values under the considered neighborhood will contribute in removing noise and preserving image details quite efficiently.

The rest of the paper is organized as follows: In Section 2 we explain fuzzy noise detection process to identify the set of noisy pixels present in the corrupted image. Direction based fuzzy filtering process is discussed in Section 3. In Section 4 we present several experimental results. Finally conclusions are drawn from the present work and recommendations for the future work are given in Section 5.

2. Fuzzy Noise Detection Process. Fuzzy noise detection process considers a 5×5 neighborhood around a central pixel at position (i, j) of an image X and calculates the average deviation from the middle pixel using the following equation [12].

$$A_d(i,j) = \frac{\sum_{x=-2}^{x=2} \sum_{y=-2}^{y=2} |X(i+x,j+y) - X(i,j)|}{25}$$
(1)

Average deviations are calculated for the whole image using above equation. Larger average deviation $A_d(i, j)$ means that either the pixel at position (i, j) is noisy or an edge pixel. By simply considering the pixel noisy, the fuzzy filtering process might make the edges blurrier. Therefore, in order to distinguish between the noisy and edge pixel, the following two quantities are calculated.

$$q_{1} = \underbrace{mean}_{x,y \in \{-2\dots+2\}} (A_{d} (i+x, j+y))$$

$$q_{2} = A_{d}(i, j)$$

$$(2)$$

where q_1 is the mean of A_d values under window of size 5×5 . Pixel at position (i, j) will be considered noisy if $|q_1 - q_2|$ is large. This can be implemented with fuzzy set large using the following equation.

$$Degree(i, j) = \eta_{Large} (|q_1 - q_2|, a, b)$$

$$a = \min_{\substack{x, y \in \{-2 \dots +2\}}} A_d(i + x, j + y)$$

$$b = 1.2a$$
(3)

where η_{Large} is the fuzzy set large as shown in the Figure 1.

3. Direction Based Fuzzy Filtering Process. Direction base fuzzy filtering process will be applied to only those pixels which are detected noisy by the fuzzy noise detection process. The output of the fuzzy filtering process for input pixel A(i, j) is denoted as O(i, j) and is calculated as follows:

$$O(i,j) = (1 - w(i,j)) \frac{\sum_{k=-2}^{2} \sum_{l=-2}^{2} X(i+k,j+l)w(i+k,j+l)}{\sum_{k=-2}^{2} \sum_{l=-2}^{2} w(i+k,j+l)} + w(i,j) X(i,j)$$
(4)