Chapter 11
Adaptive Median Filtering Based on Unsupervised Classification of Pixels

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ABSTRACT

This chapter deals with a novel approach which aims at detection and filtering of impulses in digital images through unsupervised classification of pixels. This approach coagulates directional weighted median filtering with unsupervised pixel classification based adaptive window selection toward detection and filtering of impulses in digital images. K-means based clustering algorithm has been utilized to detect the noisy pixels based adaptive window selection to restore the impulses. Adaptive median filtering approach has been proposed to obtain best possible restoration results. Results demonstrating the effectiveness of the proposed technique are provided for numeric intensity values described in terms of feature vectors. Various benchmark digital images are used to show the restoration results in terms of PSNR (dB) and visual effects which conform better restoration of images through proposed technique.

INTRODUCTION

In various applications like medical, satellite, underwater, robot vision, etc., digital image processing plays a vital role. Image de noising is a primary preprocessing required to almost all image analysts since digital images can deteriorated during acquisition, storage and transmission. Traditional filters are the common for image restoration in digital images (Gonzalez &Woods, 2002). Only smoothing or median filters are not sufficient for removing the impulses, especially

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when the images are highly corrupted. It is also very d*if*ficult to preserve the image details such as edges and dots during image restoration. Median filters (Brownrigg, 1984) perform well but removes thin lines and dots, distorts edges and blurs image fine textures even at very low noise level. The weighted median (WM) filter (Yli-Harja, Astola & Neuvo, 1991), center weighted median (CWM) filter (KO & Lee, 2001) and adaptive center weighted median (ACWM) filter (Chen and Wu, 2001) are improved version of median filters. Two step noise removal operators are the switching median filters (Sun & Neuvo, 1994) use an impulse detector prior to filter the noises. An iterative pixel-wise modification of MAD (PWMAD) (median of the absolute deviations from the median) filter (Crnojevic, Senk and Trpovski, 2004) is a robust estimator of the variance used to efficiently separate noisy pixels from the image details. The tri-state median (TSM) filter (Chen, Ma and Chen, 1999) and multi-state median (MSM) filter (Chen and Wu, 2001) are also available where an appropriate number of center weighted median filters. The progressive switching median filter (PSM) (Wang & Zhang, 1999) performs the noise detection as well as filtering iteratively. The signal-dependent rank ordered mean filter (SD-ROM) (Abreu, Lightstone, Mitra & Arakawa, 1996) is a switching mean filter that uses rank order information for impulse detection and filtering. A directional weighted median filter (Dong and XU, 2007) has been proposed in the literature to remove RVIN in the digital images. This filter performs well but the computational cost is high. The second order d*if*ference based impulse detection (Sa, Dash & Majhi, 2009) developed by Sa, Dash and Majhi, utilizes 3 x 3 window to detect and filter the RVIN in the image. This filter does not work well for the images having high densities of noises. Two switching median filters MWB (Mandal & Sarkar, 2010) and MDWMF (Mandal & Sarkar, 2011) have also been proposed in the literature to remove RVIN. More noise removal operators proposed by Mandal and Mukhopadhyay are EPRRVIN, VMM and GADI and etc., (Mandal & Mukhopadhyay, 2011, 2012). These filters perform excellent when these are applied to images corrupted with RVIN. Several soft computing tools based filters also exist in the literature such as fuzzy filter (Russo & Ramponi, 1996), neuro fuzzy filter (Kong & Guan, 1996). etc to remove impulses in the images.

Among most recent techniques some are: a fast and efficient decision based algorithm for removal of high-density impulse noises (EDBA) (Srinivasan & Ebenezer, 2000), an improved decision based algorithm for impulse noise removal (IDBA) (Nair, Revathy & Tatavarti, 2008), (Nair, Revathy & Tatavarti, 2008), a switching median filter with boundary discriminative noise detection for extremely corrupted images (BDND) (Ng & Ma, 2010), directional switching median filter using boundary discriminative noise detection by elimination (BDNDE) (Nasimudeen, Nair & Tatavarti, 2010) and a fuzzy-based decision algorithm for high-density impulse noise removal (FBDA) (Nair & Raju, 2009). These all methods deal with all four types of noise models, described later. EDBA takes lower processing time and shows good edge preserving quality but a smooth transition between the pixels is lost. For this problem IDBA was proposed, which has also a drawback that it does not work well when the noise density is high in the image. To overcome performance degradation at higher noise density BDND was devised which suffers from high miss detection and false alarm rate at random valued impulse noise with higher time complexity. BDNDE was proposed to overcome the drawbacks of BDND and can eliminate the problems of that filter but not preserves the fine edge details. FBDA was proposed to eliminate all the above problems of the existing filters but still the noise detection rule of FBDA was not strong and subsequently it suffers in sensitivity and specificity issues.

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