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A mixed noise image filtering method using weighted-linking PCNNs ☆

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Abstract

Image is often degraded by more than one type of noise. In order to design an efficient filter to remove mixed noise from image, this paper proposes a weighted-linking pulse coupled neural network (PCNN) model so as to construct a two-channel parallel noise filter using four PCNNs of this model. This filter detects noise using the pulses generated by neurons, and iteratively removes noise by the pixel signal variation of pulse neurons. The filtering parameters and the iteration stopping conditions are discussed. Experiments show that the proposed PCNN-based filtering method is fast and effective for removing single impulse noise, additional Gaussian noise, as well as the mixed noise of them.

Keywords: Noise image filtering; Weighted-linking PCNN; NMSE; PSNR

1. Introduction

Causing noise is often inevitable at image acquisition, transmission and processing stages. Little noise may often severely damage image quality. Usually, noise may make image understanding and recognizing more difficult. As a result, some serious error may be caused, even a spurious conclusion may be drawn. Thus, noise should be filtered as completely as possible from image. Generally, noise filtering technology consists of two main steps: noise detection and noise removal. Furthermore, during noise filtering, these original image features, such as edges, size and shape, should be kept unchanged.

Generally, two main models are used for characterizing most noise in digital images. They are additive Gaussian noise model and impulse noise model [6]. From the viewpoint of probability, the distribution function of Gaussian noise conforms to

$$g(x) = 1\sigma\sqrt{2\pi}e^{-(x-\mu)^2/2\sigma^2}, \tag{1}$$

where $-\infty \leqslant x \leqslant -\infty$, σ is the standard deviation, and μ is the mean value of noise signal. If the mean value $\mu = 0$, noise signal follows exactly the additive Gaussian noise model [6], which can be formulated as

$$I^{n}_{i,j} = I^{o}_{i,j} + n_{i,j}, \tag{2}$$

where $I^{n}_{i,j}$ indicates the intensity of noise pixel (i,j), $I^{o}_{i,j}$ indicates the original pixel intensity and $n_{i,j}$ is the added noise intensity. Such a type of noise is usually generated during image acquisition. Some classical filters, such as Gaussian filter, recursive two-dimensional (2D) filter [29], adaptive Wiener filter [33], neighbors mean filter, can efficiently remove it, except that they may degrade the sharpness of object edges. To overcome this weakness, some nonlinear methods are developed [31,35,21,15,32,17]. These methods can effectively remove Gaussian noise, however they may bring a new weakness, namely some thin lines and small objects of original image cannot be well preserved.

The other one is impulse noise model. This type of noise may be characterized by replacing the portion of pixel intensity with a random value, while keeping the remainder unchanged [6]. Generally, this impulse noise model can be

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formulated as

$$I^{\mathrm{n}}_{i,j} = \begin{cases} n_{i,j} & \text{with probability } p, \\ I^{\mathrm{o}}_{i,j} & \text{with probability } (1-p). \end{cases} \quad (3)$$

where $I^{\mathrm{n}}_{i,j}$ indicates the total intensity of pixel (i,j), $I^{\mathrm{o}}_{i,j}$ indicates the original pixel intensity and $n_{i,j}$ indicates the added noise intensity. Such a noise is usually caused by transmission error, and it may make pixel intensity abnormally fluctuate. Such a fluctuation is often utilized by many filtering methods.

As we know, linear filtering cannot effectively remove impulse noise because it may mistakenly detect object edge as noise region. Just for overcoming this weakness, some nonlinear technologies [15,2,24,10,3,16] and neural filtering method [37] are specially developed. Like most methods, these also consist of two basic steps, namely noise detection and pixel replacement with an estimated value. However, these methods are only effective for removing impulse noise. For the removal of additional Gaussian noise, they seldom work well.

In addition to these above, wavelet transform (WT) [18] and partial differential equations (PDEs) with partial derivative estimation are also powerful tools for removing noise. The WT-based methods are often categorized into two classes, namely attenuation and selection. Many WT-based ones are developed for removing white Gaussian noise [19,25,26]. Moreover, for PDEs, the classical heat equation [30] and some nonlinear diffusion algorithms [23,36,12,7] are also frequently used for the removal of additional Gaussian noise. However, the two tools have a same application limitation, namely like linear technologies, they are also inefficient for the removal of impulse noise.

Seldom, an image only contains single noise (Gaussian or impulse noise), and it is often contaminated by more than one type of noise, such as mixed noise. The mixed noise is often caused in some complex environment, for example, an image with Gaussian noise is transmitted through a disturbed communication channel. For the existing noise image filtering technologies, most of them are specially proposed for removing single noise [29,31,2,10,3,16,37,17], and some others are presented for the mixed noise removal, such as the local image statistic filtering approach [6], the median-based SD-ROM filter [1], and the fuzzy noise filter [22]. These technologies mentioned above can only remove low-intensity mixed noise, and when they are applied to high-intensity noise, the filtering performances often heavily decline.

This paper gives a study on the removal of mixed noise using pulse coupled neural networks (PCNNs). The initial PCNN model proposed by Echorn originates from the observation of synchronous pulses in cat visual cortex [4]. Lindblad discusses image processing technologies of PCNN [13], and Johnson systematically describes some classical PCNN models and their typical applications in [9]. Moreover, Ranganath and Kuntimad develop several image processing methods [28] using modified PCNNs, such as object detection [27] and image segmentation [11]. In addition, Lindblad also discusses the pinpoint differences as well as similarities between PCNN and wavelet transform in 2D data processing [14]. Recently, various applications of PCNN are proposed, such as the pattern recognition method [20] by Muresan, the image shadow removal approach [8] by Gu, the noise filtering technology [17] by Ma, the image thinning algorithm [34] by Shang, and the intersecting cortical model (ICM) for special image processing [5] by Ekbladа.

However, these traditional PCNNs are only useful for removing single noise [37,17]. To develop the mixed noise removal of PCNN, this paper constructs a two-channel parallel filter by proposing a weighted-linking PCNN model that originates from [9,27,20,8,34]. Like [27,17], this filter also needs to iteratively run, so we design a special stopping condition for determining when the two-channel PCNN filtering finishes. In this filter, each channel consists of two serial PCNNs, and each PCNN iteratively detects and removes noise using neuron pulses and pixel intensity variation, until the given stopping condition is satisfied. In addition to these, to obtain good filtering performance, these channel outputs are fused together using an optimization strategy.

The remainder of this paper is organized as follows. Section 2 introduces the pulse coupled neuron (PCN) model of the proposed network. Section 3 presents how to construct a two-channel filter using four PCNNs, and choose suitable parameters for them. Section 4 exhibits experimental results and comparisons. Finally, some conclusions are drawn in Section 5.

2. Weighted-linking PCNN model

PCNN, a well-known class of neural networks, has many advantages, such as fast parallel processing capability and one-to-one relationship between neurons and image pixels. It can conveniently process image by manipulating its neurons. These advantages make it quite attractive to image processing, as a result, many classical PCNN-based applications have been found. For noise removal, some initial algorithms [28,27,17] have been proposed, but limited by the adopted PCNN models, they are only efficient for removing single type of noise, such as impulse noise or Gaussian noise. How to remove mixed noise using PCNN is a challenging problem that is waiting for being settled. To improve the noise removal ability of PCNN and develop a new method for mixed noise removal, some modifications are introduced into existing PCNNs so as to propose a weighted-linking PCNN model. For explaining this model in a detailed way, the PCN structure of such a model and an eight-neuron linking pattern are illustrated in Fig. 1(a) and (b), respectively.

Before the PCN is introduced, some notations are defined as follows. **N** denotes a PCNN, and $N_{m,n}$ denotes neuron (m,n). $H(N_{m,n})$ denotes the linking-neuron set of