Postprint: X-ray Image Salt-and-Pepper Noise Removal Algorithm Based on Classification and Fuzzy Filtering

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Abstract

To address the issues of suboptimal filtering performance and low computational efficiency of existing salt-and-pepper noise removal algorithms for X-ray images, a novel method integrating multi-level classification and adaptive fuzzy filtering is proposed, which mainly comprises two components: pixel multi-level classification and adaptive fuzzy filtering. During the pixel multi-level classification phase, a rapid first-level coarse classification is first designed based on prior knowledge to categorize pixels into three classes: salt-and-pepper noise, signal, and suspicious noise. For suspicious noise, histogram distribution features within local regions are subsequently extracted, and a BP neural network classifier is devised for precise classification, ultimately separating all pixels in the image into two categories: signal and salt-and-pepper noise. In the adaptive fuzzy filtering stage, fuzzy membership functions are constructed for three fuzzy sets respectively, fuzzy membership values are computed, and pixel brightness is restored through fuzzy weighted summation. Experimental results demonstrate that the proposed method achieves high pixel classification accuracy, high peak signal-to-noise ratio (PSNR) for filtered images, and low average filtering time consumption.

Full Text

Salt and Pepper Noise Filtering Algorithm for X-Ray Images with Multi-Level Classification and Fuzzy Filtering

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Abstract: To address the limitations of existing salt-and-pepper noise filtering algorithms for X-ray images—namely, suboptimal denoising performance and low computational efficiency—this paper proposes a novel filtering method that integrates multi-level classification with adaptive fuzzy filtering. The approach comprises two main components: pixel-level multi-stage classification and adaptive fuzzy filtering. In the classification stage, a rapid coarse classification based on prior knowledge first categorizes pixels into three classes: salt-and-pepper noise, signal, and suspicious noise. For suspicious noise pixels, regional histogram distribution features are extracted and fed into a BP neural network classifier for precise discrimination, ultimately separating all pixels into signal and salt-and-pepper noise categories. In the adaptive fuzzy filtering stage, fuzzy membership functions are constructed for three fuzzy sets, with pixel brightness restored through fuzzy weighted summation. Experimental results demonstrate that the proposed method achieves high pixel classification accuracy, superior peak signal-to-noise ratio (PSNR) in filtered images, and reduced average filtering time.

Keywords: salt-and-pepper noise; filtering; neural network; membership degree; fuzzy filtering

0 Introduction

Salt-and-pepper noise is a common type of noise introduced during digital image acquisition or transmission, appearing as black and white speckles that significantly degrade image quality [1]. Numerous methods have been proposed to remove this noise. For lightly contaminated images, standard median filtering, extreme median filtering, and recursive switching median filtering are often employed. While these methods feature low complexity and high efficiency, they perform poorly on heavily contaminated images and may cause blurring [2-6].

To preserve image details, researchers have proposed classifying pixels before filtering, distinguishing between signal and noise to enable adaptive filtering strategies [7-10]. For instance, reference [7] introduced a filtering algorithm for high-density salt-and-pepper noise that uses histogram shape features for pixel classification and multi-directional weighted mean filtering for noise removal. Reference [8] proposed a fuzzy transformation-based weighted mean filter, comprising noise detection and removal stages. The detection stage employs an absolute difference sum of adjacent processed points for classification, while the removal stage uses a distance-correlated fuzzy transformation weighted mean approach. Both methods achieve high efficiency but suffer from limited adaptability in pixel classification and noise removal, particularly for X-ray images with limited grayscale levels.

To improve classification accuracy, reference [9] extracted multiple features including prediction error and kernel mean, employing support vector machines for learning and classification to achieve precise pixel discrimination. Adaptive filtering methods were then designed for different pixel categories to effectively remove noise. Reference [10] presented an SVM-based salt-and-pepper noise removal method that identifies noisy pixels through classification and removes them via regression. While these approaches significantly improve classification performance and filtering effectiveness, their computational efficiency remains low.

To balance filtering performance and computational efficiency, this paper proposes a salt-and-pepper noise removal method that integrates multi-level pixel classification with adaptive fuzzy filtering. The main innovations are twofold: First, in the multi-level classification stage, a rapid coarse classification step based on prior knowledge distinguishes obvious noise and signal pixels, while machine learning performs fine classification on ambiguous suspicious noise to enhance accuracy. Second, in the adaptive fuzzy filtering stage, fuzzy membership weighting across three fuzzy sets adaptively restores pixel brightness, yielding excellent filtering results.

1 Salt-and-Pepper Noise Model

The salt-and-pepper noise model consists of two fixed impulse components: one with large values (salt noise) reaching the maximum grayscale value of 255 in 8-bit images, and another with small values (pepper noise) reaching the minimum value of 0. Let p_1 denote the occurrence probability of pepper noise and p_2 that of salt noise; the total noise probability is $p = p_1 + p_2$. In this model, "l" represents pepper noise (lowest value, e.g., $l = 0$) and "h" represents salt noise (highest value, e.g., $h = 255$). Let x_i represent the grayscale value of the i-th pixel in a contaminated image. The salt-and-pepper noise model [9] can be expressed as:

$$x_i = \begin{cases} l, & \text{with probability } p_1 \\ h, & \text{with probability } p_2 \\ o_i, & \text{with probability } 1 - p_1 - p_2 \end{cases}$$

where o_i is the true pixel value before contamination.

[Figure 1: see original paper] illustrates examples of images contaminated by salt-and-pepper noise. The original chest X-ray image is shown alongside versions contaminated with 10%, 20%, 30%, 40%, and 50% noise. The noise appears as black or white speckles; at low contamination levels, most true grayscale values remain preserved, while heavy contamination obscures most original brightness information.

2 Algorithm Framework

To remove salt-and-pepper noise and enhance X-ray image quality, we propose a filtering method integrating multi-level classification with adaptive fuzzy filtering, as illustrated in [Figure 2: see original paper]. The approach consists of two main stages: first, classifying each pixel as either signal or salt-and-pepper noise; second, applying adaptive fuzzy filtering to restore pixel brightness.

2.1 Multi-Level Pixel Classification

Distinguishing true signal from salt-and-pepper noise enables targeted filtering that preserves original brightness distributions. Before denoising, we classify all pixels in the image. While learning-based methods typically achieve high accuracy, their computational efficiency is often low. To balance accuracy and efficiency, we design a multi-level classification strategy: a rapid coarse classification based on contaminated image characteristics distinguishes obvious signal or noise pixels, followed by fine classification of ambiguous pixels using a BP neural network.

(1) Coarse Classification For images contaminated by salt-and-pepper noise, two key characteristics hold: First, only partial pixels are corrupted while others remain unchanged. Second, noise pixel values occupy the extremes of the overall brightness range—either maximum or minimum. Based on these properties, the coarse classification proceeds as follows:

Step 1: Traverse all pixels to determine the maximum and minimum brightness values, denoted as h and l:

$$h = \max_i(x_i), \quad l = \min_i(x_i)$$

where x_i represents the brightness of the i-th pixel in the contaminated image.

Step 2: Traverse all pixels again, assigning each pixel i an attribute $c(x_i) \in \{0, 1, 2\}$, where 0 indicates signal, 1 indicates salt-and-pepper noise, and 2 indicates suspicious noise. This involves two substeps:

- **Substep 2-1:** If $x_i \neq h$ and $x_i \neq l$, classify as signal.
- **Substep 2-2:** If the pixel is not a signal point, examine its neighborhood R_i (using 8-connectivity). If no neighboring pixel shares the same brightness value, classify as salt-and-pepper noise.

These substeps can be expressed as:

$$c(x_i) = \begin{cases} 0, & x_i \neq h \text{ and } x_i \neq l \\ 1, & x_i = h \text{ or } x_i = l \text{ and } \forall x_j \in R_i, x_j \neq x_i \\ 2, & \text{otherwise} \end{cases}$$

where R_i denotes the set of brightness values in the 8-neighborhood of pixel i.

This coarse classification divides pixels into three categories through simple statistical operations: signal, salt-and-pepper noise, and suspicious noise. The latter require further discrimination in the fine classification stage.

(2) Fine Classification For suspicious noise pixels, we employ machine learning for precise classification. First, extract the brightness distribution histogram from the pixel' s neighborhood:

$$H_i = \{n_j \mid j = 0, 1, \dots, 255\}$$

where n_j counts pixels with grayscale value j in the neighborhood of suspicious noise pixel i. This histogram serves as the feature vector.

The feature vector is then fed into a trained three-layer BP neural network classifier [11], which outputs binary classification results: 0 for signal and 1 for salt-and-pepper noise. The classifier is trained as follows:

1. Select 10 uncontaminated X-ray images and add salt-and-pepper noise at five levels: 10%, 20%, 30%, 40%, and 50%.
2. Apply coarse classification to identify suspicious noise pixels only.
3. Extract neighborhood histogram features for these pixels (excluding boundary pixels).
4. Compare each suspicious pixel' s brightness with the original uncontaminated image; label the feature vector as 0 if unchanged, 1 otherwise.
5. Train the three-layer BP neural network using these feature vectors and labels to build the classifier.

2.3 Adaptive Fuzzy Filtering

Following pixel classification, signal pixels retain their original brightness, while noisy pixels are restored via adaptive fuzzy filtering. We construct three fuzzy sets: **Dk** (dark pixels), **Md** (medium brightness pixels), and **Br** (bright pixels), defined as:

$$\begin{aligned}
\mathrm{Dk} &= \left\{ x_i \mid l \le x_i < \frac{l+h}{3} \right\} \\
\mathrm{Md} &= \left\{ x_i \mid \frac{l+h}{3} \le x_i \le \frac{2(l+h)}{3} \right\} \\
\mathrm{Br} &= \left\{ x_i \mid \frac{l+h}{3} < x_i \le h \right\}
\end{aligned}$$

Bell-shaped membership functions are created for each fuzzy set:

$$\mu_j(x_i) = \exp\left(-\frac{(x_i - b_j)^2}{2a_j^2} \right), \quad j \in \{\mathrm{Dk}, \mathrm{Md}, \mathrm{Br}\}$$

where a_j and b_j are parameters for the j-th fuzzy set, determined from histograms of both contaminated and noise pixels.

Let H_i denote the histogram of the contaminated image and H_i^n the histogram of noise pixel grayscale values. The fuzzy histogram is:

$$\tilde{H}_i = H_i - H_i^n$$

The probability density function can be expressed as:

$$p(x_j) = \frac{\tilde{H}_i(x_j)}{\sum_{x_j \in \{\mathrm{Dk},\mathrm{Md},\mathrm{Br}\}} \tilde{H}_i(x_j)}$$

Thus, the parameters for the j-th fuzzy set are:

$$a_j = \sum_{x_j \in \{\mathrm{Dk},\mathrm{Md},\mathrm{Br}\}} \tilde{H}_i(x_j) \cdot x_j, \quad b_j = \sum_{x_j \in \{\mathrm{Dk},\mathrm{Md},\mathrm{Br}\}} \tilde{H}_i(x_j) \cdot p(x_j)$$

During filtering, each input pixel' s grayscale value is treated as a fuzzy variable. Compute its membership values across the three fuzzy sets and normalize:

$$w_j(x_i) = \frac{\mu_j(x_i)}{\sum_{j \in \{\mathrm{Dk},\mathrm{Md},\mathrm{Br}\}} \mu_j(x_i)}, \quad j \in \{\mathrm{Dk}, \mathrm{Md}, \mathrm{Br}\}$$

Perform fuzzy weighted summation over neighboring grayscale values:

$$m(x_i) = \sum_{j \in \{\mathrm{Dk},\mathrm{Md},\mathrm{Br}\}} \sum_{x_j \in R_i} w_j(x_i) \cdot x_j$$

Average the grayscale values of signal pixels in the neighborhood:

$$s(x_i) = \sum_{j \in \{\mathrm{Dk},\mathrm{Md},\mathrm{Br}\}} \sum_{x_j \in R_i} w_j(x_i) \cdot x_j$$

The restored grayscale value for noisy pixel i is:

$$\hat{x}_i = c(x_i) \cdot m(x_i) + (1 - c(x_i)) \cdot s(x_i)$$

This adaptive filtering algorithm optimally restores pixels based on neighborhood histogram distributions.

3 Experiments

We evaluate algorithm performance through two metrics: pixel classification accuracy and filtering effectiveness (PSNR and computation time). Comparative methods include state-of-the-art salt-and-pepper noise filters from recent literature [7–10].

Experiment 1: Pixel Classification Accuracy

Accurate pixel classification is crucial for subsequent filtering performance. To evaluate robustness across contamination levels, we test on images with 10%, 20%, 30%, 40%, and 50% noise (as shown in [Figure 1: see original paper]). Ground-truth labels are generated by comparing each pixel's brightness with the original uncontaminated image—identical values are labeled as signal, otherwise as noise.

[Figure 3: see original paper] compares classification accuracy across methods. The proposed method achieves the highest accuracy across all contamination levels, followed by reference [9], which uses multi-feature fusion with SVM classification but suffers from high computational complexity due to the absence of a rapid coarse classification stage. Reference [10] also employs machine learning but exhibits degraded accuracy beyond 30% contamination, likely due to limited small-sample learning capability. References [7] and [8] show significantly lower accuracy, especially under heavy noise, as their heuristic rules lack the adaptability of learning-based approaches.

Experiment 2: PSNR and Filtering Time Comparison

PSNR reflects noise intensity, with higher values indicating better image quality. [Figure 4: see original paper] compares PSNR across methods for varying noise levels. The proposed method consistently achieves the highest PSNR, demonstrating superior and robust filtering performance. Reference [9] ranks second, while reference [10] also performs well. References [7] and [8] exhibit sharp PSNR degradation as noise increases.

For visual comparison, [Figure 5: see original paper] shows filtering results on an image with 50% noise. Subjectively, the proposed method and references [9, 10] effectively remove noise, outperforming [7, 8]. Closer inspection reveals the proposed method leaves the fewest residual noise artifacts, confirming its superior performance.

Computation time is measured on an Intel i7 CPU with 16 GB RAM. presents average filtering times across the five test images. The proposed method is the fastest, while reference [9] is the slowest. This efficiency stems from two factors: First, the multi-level classification strategy employs simple statistical operations in the coarse stage, which quickly categorizes most pixels, reducing overall classification time. Second, the adaptive fuzzy filtering produces final results in a single pass, whereas methods in [7, 8] require iterative processing.

4 Conclusion

Salt-and-pepper noise frequently occurs during image acquisition, particularly in X-ray imaging, significantly degrading image quality. This paper proposes a novel denoising method integrating multi-level classification with adaptive fuzzy filtering. The approach effectively removes salt-and-pepper noise while demonstrating strong adaptability across various contamination levels. Moreover, its high computational efficiency enables real-time processing, making it highly practical for clinical applications.

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Note: Figure translations are in progress. See original paper for figures.