Combining Median Filtering and Adaptive Switching Weight Mean Filter for Enhanced Salt-and-Pepper Noise Removal

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# **INTRODUCTION**

Digital images are often susceptible to noise during acquisition or transmission. Salt-and-pepper noise is a common type of impulsive noise that manifests as pixels with extreme intensity values, appearing as either black (salt) or white (pepper) speckles within an image. This noise can significantly degrade image quality and hinder further image processing tasks. This project proposes a two-stage denoising approach to address salt-and-pepper noise effectively. We combine two techniques:

**Median Filter:** A robust and efficient non-linear filter, the median filter excels at removing impulse noise like salt-and-pepper. It operates by replacing a pixel's value with the median value of its local neighbourhood, effectively suppressing outliers caused by noise.

**Adaptive Switching Weight Mean Filter (ASWMF):** This method is designed to refine the denoising process and preserve image details. ASWMF utilizes an adaptive window centred on each pixel. It first identifies and removes potential noise pixels within the window. Then, it assigns weights to the remaining pixels, prioritizing those outside the diagonals for detail preservation. Finally, it calculates a weighted mean, called the switching weight mean, and replaces the centre pixel's value with this value.

**Combining Techniques:**

**Median Filter as Pre-processing:** The median filter effectively handles high-density salt-and-pepper noise in the initial stage. It suppresses extreme noise pixels without relying on complex calculations.

**ASWMF for Detail Refinement:** The ASWMF takes over after the median filter's pre-processing. It focuses on refining noise removal and preserving image details by leveraging its adaptive weighting mechanism.

This two-stage approach aims to achieve a balance between robust noise removal and detail preservation. The median filter tackles the bulk of the noise, while the ASWMF refines the results, potentially leading to superior denoised images compared to using either technique alone.

**Project Objectives:**

* Implement both the median filter and the ASWMF algorithms.
* Combine these techniques into a two-stage denoising pipeline.
* Evaluate the performance of the combined approach on test images with varying salt-and-pepper noise densities.
* Compare the results with those obtained from using the median filter or the ASWMF individually.

**Proposed Method**

**Stage 1: Median Filtering**

1. **Input:** The input to this stage is the noisy image corrupted by salt-and-pepper noise.
2. **Local Window:** For each pixel in the noisy image, a fixed-size square window centred on that pixel is considered. This local neighbourhood represents the pixels used in the filtering process.
3. **Sorting and Ranking:** The intensity values of all pixels within the window, including the center pixel, are sorted in ascending order.
4. **Median Selection:** The median value from the sorted list is selected.
5. **Output Replacement:** The center pixel's intensity value in the noisy image is replaced with the selected median value.
6. **Iteration:** This process of applying the median filter is repeated for each pixel in the noisy image, effectively creating a denoised image.

**Stage 2: Adaptive Switching Weight Mean Filter (ASWMF)**

1. **Input:** The input to this stage is the image denoised in Stage 1 using the median filter.
2. **Adaptive Window:** Similar to Stage 1, a fixed-size square window is centered on each pixel in the denoised image.
3. **Noise Pixels:** The pixels that were identified as noise while applying the median filter are still considered to be the noise pixels and ASWMP is applied on those
4. **Weight Assignment:** Weights are assigned to the pixels in the window. Here, pixels on the diagonals of the window (i.e., top-left to bottom-right and top-right to bottom-left) receive lower weights, while pixels outside the diagonals receive higher weights. This prioritizes the influence of non-diagonally neighboring pixels, aiming to preserve image edges and details.
5. **Switching Weight Mean Calculation:** A weighted mean of pixels' intensity values is calculated, considering the assigned weights. This weighted mean is termed the "switching weight mean."
6. **Output Replacement:** The center pixel's intensity value in the denoised image from Stage 1 is replaced with the calculated switching weight mean.
7. **Iteration:** Steps 2-7 are repeated for each pixel in the Stage 1 denoised image, generating the final denoised output.

**Combining the stages:**

The median filter in Stage 1 effectively addresses the bulk of the salt-and-pepper noise, particularly in areas with high noise density. The ASWMF in Stage 2 refines the denoising process, focusing on preserving image details and suppressing any remaining noise. It uses the same median filter to decide whether an image is noisy or not. This two-stage approach is expected to achieve a more comprehensive and effective denoising outcome compared to using either technique alone.

**Literature reviews:**

**Adaptive Impulse Detection Using Center-Weighted Median Filters**

**Tao Chen and Hong Ren Wu**

In this work, the authors address the challenge of impulse detection in image processing. Previous median-based impulse detection methods tend to perform well for fixed-valued impulses but struggle with random-valued impulse noise, or vice versa. To overcome this limitation, the authors propose a novel adaptive operator that leverages center-weighted median (CWM) filters with varying center weights.

The primary goal is to design an impulse detection scheme that works effectively for both fixed-valued and random-valued impulses, regardless of the noise ratio.

**Methodology:**

The proposed adaptive operator computes estimates based on the differences between the current pixel and the outputs of CWM filters.

The CWM filters are designed with different center weights, allowing them to adapt to various impulse scenarios.

Extensive simulations demonstrate that the proposed scheme consistently suppresses both types of impulses, even when noise ratios differ.

**Results:**

The adaptive impulse detection method outperforms existing approaches by providing robustness across different impulse noise scenarios.

By incorporating the switching scheme based on impulse detection, the proposed filter effectively removes both fixed-valued and random-valued impulses.

**A Speckle Noise Removal Method**

**Ayesha Saadiya and Adnan Rashdi**

This paper focuses on the challenge of speckle noise in echocardiographic images. Speckle noise diminishes important information in an image and affects a physician’s ability to interpret the image correctly.

**Proposed Method:**

The authors propose an intelligent denoising algorithm for echocardiographic images. The input image is divided into different regions: smooth, texture, and edge, using the coefficient of variation. Fuzzy logic is used to draw boundaries between these image regions. Average filter and fractional integral filters are deployed to denoise pixels of various regions.

**Conclusion:**

The proposed technique significantly improves the quality of the denoised image by suppressing maximum noise and producing no artifacts. It outperforms existing state-of-the-art techniques, both visually and quantitatively.

**An Improved BPDF Filter for High Density Salt and Pepper Denoising**

**Dang N. H. Thanh, Le Thi Thanh, V. B. Surya Prasath, Ugur Erkan**

The BPDF (based on pixel density filter) is an effective filter designed to remove salt-and-pepper noise. However, its effectiveness is limited to low and medium noise levels. In this paper, the authors propose an improved version of the BPDF specifically tailored to handle high-density salt-and-pepper noise.

Their method demonstrates efficacy even at very high noise levels (above 90%). The denoising quality is assessed using peak signal-to-noise ratio and structure similarity metrics. The proposed approach outperforms both the original BPDF filter and the DAMF filter in denoising experiments.

**Methodology:**

The authors enhance the BPDF filter by introducing a new procedure. This modification enables the improved BPDF to effectively handle high-density noise, making it suitable for challenging denoising scenarios.

**Results:** The denoising performance of the proposed method is compared against the original BPDF filter and the DAMF filter. The evaluation metrics include peak signal-to-noise ratio (PSNR) and structure similarity. The results demonstrate the superiority of the improved BPDF in handling high-density salt-and-pepper noise.

**Spatially Adaptive Total Variation Image Denoising Under Salt and Pepper Noise**

**P. Rojas and P. Rodriguez**

A novel algorithm for ℓ1-TV denoising of grayscale and color images. The authors focus on images corrupted with salt-and-pepper noise, a less explored area compared to the widely studied ℓ2-TV case (images corrupted with Gaussian noise).

Total Variation (TV) denoising is a well-known technique for image noise removal. It’s designed to preserve edges while smoothing other regions. However, the selection of an appropriate regularization parameter is critical for optimal denoising results. Existing methods struggle with salt-and-pepper noise, where individual pixels are either completely black or white.

**Methodology:**

The authors propose an adaptive approach for ℓ1-TV denoising under salt-and-pepper noise. The key components of their algorithm are:

* Outlier Estimation: An adaptive median filter is used to estimate the outliers (corrupted pixels) in the noisy image. This initial step helps identify the regions affected by salt-and-pepper noise.
* Spatially Adaptive Regularization Parameter: The ℓ1-TV problem is solved only for the noisy pixels (outliers). The regularization parameter is spatially adapted based on local statistics. This adaptability ensures effective denoising even in highly corrupted regions.

**Results:**

Experimental results demonstrate the effectiveness of the proposed method. Even when a significant portion (90%) of the image is corrupted, the algorithm produces accurate denoised images.

**Total Variation L1 Fidelity Salt-and-Pepper Denoising with Adaptive Regularization Parameter**

**Dang N. H. Thanh , V. B. Surya Prasath, Le Thi Thanh**

The Total Variation (TV) regularization is a powerful tool for image denoising and other image processing tasks. While most existing methods focus on TV denoising using the L2 norm, this paper introduces an improved approach based on the L1 norm.

Specifically, the proposed method adapts to the characteristics of salt-and-pepper noise, making it effective even for images with moderate contrast and high noise levels.

The authors compare their adaptive TV-L1 denoising model with other salt-and-pepper denoising methods, including TV-L1 and the BPDF method, demonstrating its efficacy in handling challenging noise scenarios.

**Methodology:**

The authors enhance the TV denoising model by incorporating an adaptive regularization parameter based on the L1 fidelity.

The focus is on effectively handling salt-and-pepper noise, which is particularly challenging due to its impulsive nature.

**Results:**

The proposed method is evaluated against other denoising techniques, including TV-L1 and BPDF.

The effectiveness of the adaptive TV-L1 denoising model is demonstrated, especially for images with high noise levels and without extreme contrast.

**Adaptive Median Filters: New Algorithms and Results**

**H. Hwang and R. A. Haddad**

In their research, Hwang and Haddad propose two new algorithms for adaptive median filters. These algorithms are designed to handle images corrupted by impulse noise while preserving image sharpness.

**Ranked-Order Based Adaptive Median Filter (RAMF):**

* + The RAMF algorithm is based on a **two-level test**.
  + At the first level, it checks for the presence of residual impulses in the median filter output.
  + The second level determines whether the center pixel itself is corrupted by an impulse or not.
  + RAMF outperforms the nonlinear mean filter in removing both positive and negative impulses while maintaining image sharpness.

**Impulse Size Based Adaptive Median Filter (SAMF):**

* + SAMF focuses on detecting the **size of the impulse noise**.
  + It is simpler and performs better than Lin’s adaptive scheme.
  + SAMF effectively removes high-density impulsive noise and nonimpulsive noise while preserving fine image details.

The authors conducted simulations on standard images, confirming that these algorithms are superior to standard median filters. Their work contributes to enhancing image quality in the presence of impulse noise.

**Dataset Description:**

The dataset is taken from the same source that the base paper has used (i.e from www.eecs.berkeley.edu/Research/) we have taken 20 plus grey scale images later to which salt and pepper noise is added gradually.The proposed denoising filter is applied on the images to restore them.

The dataset images are no different from the images of any other denoising algorithms or methods

**Dataset link:**

<https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/BSDS300>