Simulated evaluation of new switching based median filter for suppressing SPN and RVIN

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ABSTRACT

In the past two decades, the SPN (salt and pepper noise) suppressing method is worldwide interested researches on computer vision and image processing hence many SPN suppressing methods have been proposed. In general, the primary goal of SPN removal method is the suppressing of SPN in digital images thereby one of the recent effective and powerful SPN suppressing methods is a new switching-based median filtering (NSMF), which is innovated for suppressing high density SPN. Consequently, this paper thoroughly examines its efficiency and constrain of a new switching-based median filtering when this filter is used for contaminated image, which is synthesized by SPN and RVIN (random-value impulsive noise). In these simulations, six well-known images (Lena, Mobile, Pepper, Pentagon, Girl, Resolution) with two impulsive noise classes (SPN and RVIN) are used for measuring the its efficiency and constrain. An evaluation of the efficiency is conducted with many previous methods in forms of subjective and objective indicators.

Keywords:
AMF (adaptive median filter)
Digital image processing
NSMF (new switching-based median filtering)
SMF (standard median filtering)

1. INTRODUCTION OF NSMF (NEW SWITCHING-BASED MEDIAN FILTERING)

Digital images [1]-[4] are generally contaminated by impulsive noise [5]-[23] due to communicating unsuccess, improper operating of CCD sensor, ADC synchronized erroneous and memory site erroneous hence noise suppressing method is one of the most vital process for sophisticated digital image process [24]-[26] for instance, face identification, license plate identification, remote sensing, etc. Even through the original Median Filter (SMF) [5]-[7] and Adaptive Median Filter (AMF) [14], [27] are known as the practical noise suppressing method [5]-[23] for SPN, one of the recent effective and powerful SPN suppressing methods is a NSMF (new switching-based median filtering) [28], which is proposed for suppressing only SPN, especially high density. From some results [28], it can conclude that NSMF has good efficiency while the NSMF has low computational complexity however there are no research of the NSMF for SPN at all density and random-value impulsive noise. Consequently, this paper thoroughly examines its efficiency and constrain of a novel modified median filtering based switching technique.

2. STATISTICAL THEORY OF NSMF

The NSMF comprises of four modified processes (Process 1- Process 4) as showing in Figure 1 instead of three processes (for previous proposed method), namely, detection, estimation, and replacement.

a) Process 1: Detecting the processed pixel as noisy pixel or noiseless pixel. If the processed pixel is 0 or 255 then the processed pixel is classified as contaminated noise otherwise the pixel is noiseless.

b) Process 2: Substituting the processed input pixel by using 1st order linear predictor.

c) Process 3: Estimating the expected original image by using a median filtering based on L-estimators.
d) **Process 4:** Replacing contaminated pixels by the estimated pixels.

![Flowchart](image-url)

**Figure 1.** The flowchart of overall method of new switching-based median filtering (NSMF)

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2.1. Statistical Theory of Estimating Process

Let \( X = \{x_1, x_2, x_3, \ldots, x_n\} \) is the original image, which is noiseless, and \( Y = \{y_1, y_2, y_3, \ldots, y_n\} \) is the contaminated image, which is comprised of a set of noiseless pixels \( \{y_{j1}, y_{j2}, \ldots, y_{j_n}\} \) and a set of noisy pixels \( \{y_{j1}, y_{j2}, \ldots, y_{j_n}\} \). Let \( Z = \{x_1, x_2, x_3, \ldots, z_{j1}, z_{j2}, \ldots, z_{j_n}\} \), which is comprised of a set of noiseless pixels \( \{y_{j1}, y_{j2}, \ldots, y_{j_n}\} \) and a set of substituted pixels for the noisy pixels \( \{z_{j1}, z_{j2}, \ldots, z_{j_n}\} \), and \( z_{med} \) be the median of \( Z \).

Let \( x_1[n] \) is the \( i^{th} \) order statistic of the original image and \( \hat{x}[n] \) is the expected original image, which can be defined from set of original noiseless pixels \( \{x_1[n]\} \). By linear prediction, Finite Impulse Response (FIR) linear predictor of order \( p \) can be statistically defined as:

\[
\hat{x}[n+1] = \sum_{k=0}^{p-1} h[n] x[n-k]
\]

where \( h[k] \) are the prediction filter coefficients.

The \( h[k] \) is statistically defined by the Wiener-Hopf [5] equation as

\[
R_k h[k] = r_k
\]

where \( R_k \) is an autocorrelation matrix, \( h[k] \) is predictor coefficient vector, and \( r_k \) is autocorrelation vector. The autocorrelation \( R_k \) can be statistically defined as

\[
E[x[l-k]x[n-k]] = R_k \delta[n-k]
\]

where \( k = 0 \) to \( (p-1) \) and \( l = 0 \) to \( (p-1) \).

By Auto Regressive Moving Average (ARMA) in time domain, the causal Infinite Impulse Response (IIR) predictor is given by

\[
H[z] = z^{-1} [1 - Q[z]^{-1}]
\]

which can be statistically defined as

\[
\hat{x}[n+1] = \sum_{k=0}^{\infty} a_k \hat{x}[n-k] + \sum_{k=0}^{\infty} h_k \hat{x}[n-k]
\]

Let \( \hat{x}[n] \) is an expected original image from one or more noiseless pixels and \( \hat{x}[n] = d[k] \)

\[
E[\hat{x}[n] x[n+1]] = E[d[n] x[n+1]] = \hat{d}[k]
\]

2.2. Statistical Theory of Replacing Process

If the processed input pixel is 0 or 255 then the pixel is defined as a noisy pixel and is replace by the replacing process, which comprises of 10 processing step as following:

1) **Processing Step 1**: Setting the \( 3 \times 3 \) window with center at the processed pixel \( x(i, j) \).

2) **Processing Step 2**: If \( 0 < x(i, j) < 255 \) then the processed input pixel is classified as noiseless pixel and it is left unchanged and, then, the processed pixel \( x(i, j) \) moves to the next position.

3) **Processing Step 3**: If \( x(i, j) = 0 \) or \( x(i, j) = 255 \) then the processed input pixel is classified as noisy pixel and go to Processing Step 4.

4) **Processing Step 4**: Converting the \( 3 \times 3 \) window (2D) to the vector \( Y_x \) (1D)

5) **Processing Step 5**: Sorting to the vector \( Y_x \) (1D) in ascending order

6) **Processing Step 6**: If \( x[n] = 255 \) then replacing \( x[n] \) from left to right by following equation
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\[ x[n] = \alpha \cdot x[n-1] \text{ with } \alpha = (R_{n+1}/R_{n+2}), 0 < \alpha < 1 \] (6)

\[ R_{n+1} = x[n-1] \cdot x[n-2] \] (7)

\[ R_{n+2} = x[n-1] \cdot x[n-1] \] (8)

If \( \alpha = 0 \) then \( x[n] = x[n-1] \)

a) Processing Step 7: If \( x[n] = 0 \) then replacing \( x[n] \) from right to left by following equation

\[ x[n] = \alpha \cdot x[n+1] \text{ with } \alpha = (R_{n+1}/R_{n+2}), 0 < \alpha < 1 \] (9)

\[ R_{n+1} = x[n+1] \cdot x[n+2] \] (10)

\[ R_{n+2} = x[n+1] \cdot x[n+1] \] (11)

If \( \alpha \geq 1 \) then \( x[n] = x[n+1] \)

b) Processing Step 8: Estimating the vector \( Z_{n} (1D) \) by the predicted value, Sort the vector \( Z_{n} (1D) \), and Determine the median value.

c) Processing Step 9: Replace the processed pixel \( x(i, j) \) with its median value.

d) Processing Step 10: Reprocess the Processing Steps 1 to Processing Steps 3 until the entire image is processed completely.

3. ILLUSTRATION OF NSMF

In this NSMF calculation example, the processed pixel intensity is 255 therefore the processed pixel is noisy and the processed pixel is suppressed by NSMF as shown in Figure 2. From the NSMF process, the denoised pixel is suppressed and the output pixel is replaced to be “200”.

4. SIMULATION OUTCOMES

In this simulation section under both SPN and RVIN, six tested images (Lena (256x256), Mobile (704x480), Pepper (256x256), Pentagon (512x512), Girl-Tiffany (256x256) and Resolution (128x128)) are employed to analytically simulate the upper bound of NSMF efficiency. This simulation analyses the noise suppressing efficiency of the NSMF by first applying the SPN and the RVIN on tested images. Subsequently, the NSMF processes for suppressing the noisy images, which are used to compute the PSNR with the known original images. From the simulation outcomes in Table 1 for SPN (salt&pepper noise), the NSMF algorithms have the better quality outcomes than SMF (Standard Median Filter) and GMF (Gaussian Mean Filter) at all cases however the NSMF algorithms have the better quality outcomes than AMF for high noise density.

From the simulation outcomes in Table 2 for RVIN, the NSMF algorithms have the better quality outcomes than SMF (Standard Median Filter), GMF (Gaussian Mean Filter) and AMF at all cases. However, the NSMF algorithms have the worst quality outcomes than AMF for all noise density in Resolution image because this image pixel intensity are “0” or “255”.

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$y(i-L,j+1) = 200$
$y(i,j+1) = 205$
$y(i+L,j+1) = 188$

$y(i-L,j) = 169$
$y(i,j) = 255$
$y(i+L,j) = 255$

$y(i-L,j-1) = 255$
$y(i,j-1) = 255$
$y(i+L,j-1) = 255$

$y(i,j) \text{ is an impulsive noisy image}$

$Y_{old} = \text{Convert } I_{old}(W_{old})$

$Y_{old} = \begin{bmatrix}
200 & 205 & 188 \\
169 & 255 & 255 \\
255 & 255 & 255
\end{bmatrix}$

$Y_{old} = [200 \ 205 \ 188 \ 169 \ 255 \ 255 \ 255 \ 255 \ 255]$

$Y_{old} = \text{Ascending-Sort } (Y_{old})$

$Y_{old} = \text{Ascending-Sort } ([200 \ 205 \ 188 \ 169 \ 255 \ 255 \ 255 \ 255 \ 255])$

$Y_{old} = [169 \ 188 \ 200 \ 205 \ 255 \ 255 \ 255 \ 255 \ 255]$

$Y_{i_{w00}} = 255$

For $i_{w00} = 1, y_{w00}(1) = y_{i0}(1) \rightarrow y_{w00}(1) = 169$

For $i_{w00} = 2, y_{w00}(2) = y_{i0}(2) \rightarrow y_{w00}(2) = 188$

For $i_{w00} = 3, y_{w00}(3) = y_{i0}(3) \rightarrow y_{w00}(3) = 200$

For $i_{w00} = 4, y_{w00}(4) = y_{i0}(4) \rightarrow y_{w00}(4) = 205$

For $i_{w00} = 5, \alpha = y_{i0}(n-2)/y_{i0}(n-1) = 200/205$

For $i_{w00} = 6, \alpha = y_{i0}(n-2)/y_{i0}(n-1) = 205/200$

For $i_{w00} = 7, \alpha = y_{i0}(n-2)/y_{i0}(n-1) = 200/205$

For $i_{w00} = 8, \alpha = y_{i0}(n-2)/y_{i0}(n-1) = 205/200$

For $i_{w00} = 9, \alpha = y_{i0}(n-2)/y_{i0}(n-1) = 200/205$

$Y_{i_{w00}} = [169 \ 188 \ 200 \ 205 \ 200 \ 205 \ 205 \ 205 \ 200]$

$Z_{i_{w00}} = \text{Ascending-Sort } (Y_{i_{w00}})$

$Z_{i_{w00}} = [169 \ 188 \ 200 \ 205 \ 200 \ 205 \ 205 \ 205 \ 200]$

$\hat{y}(i,j) = \text{Median } (Z_{i_{w00}}) = 200$

**Figure 2.** The example of overall calculation of new switching-based median filtering (NSMF)**

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Table 1. Denoising Performance Result of SPN

| SPN     | Tested Images | Noise Density | Observed Image | Denoising Algorithm | PSNR (dB) |
|---------|---------------|---------------|----------------|---------------------|-----------|
|         | Lena (256x256)| 10            | 15.6564        | 0.6146              | SMF       |
|         | Mobile (704x480)| 10           | 15.1637        | 1.9806              | GMF       |
|         | Pepper (256x256)| 10           | 15.3798        | 0.6146              | AMF       |
|         | Pentagon (512x512)| 10          | 15.7999        | 0.6146              | NSMF      |
|         | Girl-Tiffany (256x256)| 10      | 13.6890        | 1.9806              |           |
|         | Resolution (128x128)| 10      | 15.4785        | 0.6146              |           |

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| Tested Images | Noise Density | Observed Image | Denoising Algorithm |
|---------------|---------------|----------------|--------------------|
| Lena (256x256) |               |                |                    |
| 10            | 19.7193       | 31.1555        | 23.2638            |
| 20            | 16.6527       | 29.7106        | 20.1102            |
| 30            | 14.9222       | 27.5271        | 18.2831            |
| 40            | 13.6990       | 24.9693        | 16.9480            |
| 50            | 12.6883       | 22.3406        | 15.8415            |
| 60            | 11.8913       | 19.7498        | 14.9352            |
| 70            | 11.2184       | 17.7591        | 14.1493            |
| 80            | 10.6422       | 16.0345        | 13.4958            |
| 90            | 10.1515       | 14.5534        | 12.9029            |
| Mobile (704x480) |               |                |                    |
| 10            | 18.4574       | 21.4778        | 21.1512            |
| 20            | 15.5151       | 20.8069        | 18.3393            |
| 30            | 13.7727       | 19.7265        | 16.5214            |
| 40            | 12.5299       | 18.5715        | 15.1796            |
| 50            | 11.3304       | 17.1060        | 14.0526            |
| 60            | 10.7497       | 15.5745        | 13.1263            |
| 70            | 10.0875       | 14.2337        | 12.3371            |
| 80            | 9.4794        | 12.9625        | 11.5980            |
| Pepper (256x256) |               |                |                    |
| 10            | 19.1143       | 31.4270        | 22.6205            |
| 20            | 16.0921       | 28.8665        | 19.4820            |
| 30            | 14.3745       | 26.5900        | 17.6137            |
| 40            | 13.1825       | 23.3362        | 16.2549            |
| 50            | 12.0209       | 20.7731        | 15.1438            |
| 60            | 11.3328       | 18.2128        | 14.0998            |
| 70            | 10.7068       | 16.2565        | 13.3352            |
| 80            | 10.1086       | 14.5768        | 12.5873            |
| Pentagon (512x512) |               |                |                    |
| 10            | 20.2113       | 29.5200        | 23.6997            |
| 20            | 17.2386       | 28.0433        | 20.7616            |
| 30            | 15.4355       | 26.6678        | 18.9263            |
| 40            | 14.1860       | 24.9238        | 17.6449            |
| 50            | 13.2544       | 22.9472        | 16.6548            |
| 60            | 12.4342       | 20.9049        | 15.7838            |
| 70            | 11.7829       | 19.0652        | 15.0817            |
| 80            | 11.1849       | 17.3449        | 14.4326            |
| Girl-Tiffany (256x256) |               |                |                    |
| 10            | 16.4414       | 31.6049        | 19.9110            |
| 20            | 13.4343       | 28.1774        | 16.5639            |
| 30            | 11.6674       | 23.8175        | 14.5342            |
| 40            | 10.3946       | 19.8213        | 12.9626            |
| 50            | 9.4483        | 16.7201        | 11.7613            |
| 60            | 8.6273        | 14.0847        | 10.6637            |
| 70            | 7.9734        | 12.1107        | 9.8004             |
| 80            | 7.3939        | 10.4710        | 8.9936             |
| Resolution (128x128) |               |                |                    |
| 10            | 17.7992       | 18.6254        | 20.1134            |
| 20            | 14.6190       | 17.9190        | 17.1729            |
| 30            | 12.7370       | 17.1231        | 15.3050            |
| 40            | 11.3691       | 16.2456        | 13.8148            |
| 50            | 10.5048       | 15.5229        | 12.8678            |
| 60            | 9.7510        | 14.3607        | 11.9178            |
| 70            | 9.9026        | 13.6671        | 11.1682            |
| 80            | 8.4955        | 12.3904        | 10.4038            |
| 90            | 8.0315        | 11.6735        | 9.8152             |

Table 2. Denoising Performance Result of RVIN
5. CONCLUSION

This in-depth research assesses the efficiency of the noise suppressed method based on NSMF under two impulsive noise classes (SPN and RVIN). These simulations employ on six well-known images (Lena, Mobile, Pepper, Pentagon, Girl, Resolution) under two impulsive noise classes for assessing the highest suppressed images in term of PSNR. Many previous noise suppressed methods, such as SMF (Standard Median Filter), GMF (Gaussian Mean Filter) and AMF, are used to assess the analogy efficiency. From simulation outcomes, the NSMF has a good PSNR for high noise density and this filter can work well for RVIN.

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