Short Communication

Multichannel image processing by using the Rank M-type L-filter

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Robustness

A B S T R A C T

In this paper, we introduce the Vector Rank M-type L (VRML)-filter to remove impulsive noise from color images and video sequences. The proposed filter uses the Median M-type (MM) and Ansari–Bradley–Siegel–Tukey M-type (AM) estimators into L-filter to provide robustness to proposed filtering scheme. We also introduce the use of impulsive noise detectors to improve the properties of noise suppression and detail preservation in the proposed filtering scheme in the case of low and high densities of impulsive noise. Simulation results indicate that the proposed filter consistently outperforms other color image filters by balancing the trade-off between noise suppression, detail preservation, and color retention.

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1. Introduction

Have been investigated different algorithms to noise suppression in multichannel images during the last decade. Particularly, nonlinear filters applied to color images have been designed to preserve edges, details and chromaticity properties, while suppresses impulsive noise [1,2]. Nonlinear filtering techniques apply robust order statistics theory that is the basis for design of the different novel approaches in digital multichannel processing [3]. These algorithms have demonstrated good ability in removing of impulsive noise, preserving the fine image details, as well in chromatic properties of the filtered color image [4–7].

In this paper, we introduce the Vector Rank M-type L (VRML)-filter to remove impulsive noise from color images and video color sequences. This filter utilizes vector approach and the Median M-type (MM) and Ansari–Bradley–Siegel–Tukey M-type (AM) estimators [8,9] with simple cut and Andrews sine influence functions [8] in the filtering scheme of L-filter to obtain sufficient noise suppression for each channel of RGB color image. We also introduce the use of impulsive noise detectors to improve the properties of noise suppression and detail preservation in the proposed filtering scheme in the case of low and high densities of impulsive noise. To demonstrate the performance of the proposed filtering scheme in real applications, we applied it for filtering of Ku and UHF band SAR (Synthetic Aperture Radar) images, which naturally have speckle noise. Simulation results in impulsive degradation indicate that the proposed filter consistently outperforms other color image filters used as comparative by balancing the trade-off between noise suppression, detail preservation, and color retention.

2. Rank M-type estimators

The Rank M-type estimators are based on the R-estimators and M-estimators. The R-estimators form a class of nonparametric robust estimators based on rank calculations [8,10]. In the case of absence of any a priori information about a probability distribution and data moments the most powerful rank test is the median. If the probability density function is a symmetrical one, the Wilcoxon test of signed ranks is asymptotically the most powerful one and it determines the Wilcoxon order statistics estimator [8,10,11]. These order statistics tests could be used to construct different robust order statistics estimators too.

The Ansari–Bradley–Siegel–Tukey estimator $\theta_A$ is given by,

$$\theta_A = \text{MED}_{i,j} \left\{ \begin{array}{ll}
X_{(i)}, & i \leq \frac{N}{2} \\
\frac{1}{2} (X_{(i)} + X_{(j)}), & \frac{N}{2} < i \leq N
\end{array} \right. $$

(1)
where $X_{i0}$ and $X_{j0}$ are elements with rank $i$ and $j$, respectively, and $N$ is the size of sample. This estimator is constructed using the median (upper form in the right side in Eq. (1)) and Wilcoxon (lower form in the right side in Eq. (1)) estimators and it combines the properties of these order statistics tests providing more robustness [9].

Huber proposed the $M$-estimators as a generalization of Maximum Likelihood Estimators (MLE) [8,10]. $M$-filters are simply $M$-estimators of the location parameter needed in filtering applications. The estimation of the location parameter can be found by using $\sum_{i=1}^{N} \psi(X_i - \theta) = 0$, where $\theta$ is a location parameter. The robust $M$-estimator solution for $\theta$ is determined by imposing certain restrictions on the influence function $\psi(X)$ or the samples $X_i - \theta$, called censoring or trimming. The standard technique for the $M$-estimator assumes the use of Newton's iterative method that can be simplified by a single-step algorithm to calculate the lowered $M$-estimate of the average $\theta$ value [8,10]

$$\hat{\theta}_{M} = \frac{\sum_{i=1}^{N} X_i \psi(X_i - MED(\bar{X}))}{\sum_{i=1}^{N} 1_{-r_i}(X_i - MED(\bar{X}))}$$ (2)

where $MED(\bar{X})$ is the median of elements contained in vector $\bar{X}$ and $\psi$ is the normalized function $\psi(X) = X \psi(X)$. It is evident that Eq. (2) represents the arithmetic average of $\sum_{i=1}^{N} \psi(X_i - MED(\bar{X}))$, which is evaluated on the interval $[-r, r]$. The parameter $r$ is connected with restrictions on the range of $\psi(X)$, for example, in the case of the simplest Huber’s limiter type $M$-estimator for the normal distribution having heavy ‘tails’ $\psi(X) = \min(r, \max(X, r)) = |X|^r_1$ [8,10]. Hampel proved different influence functions to derive the function $\psi(X)$ by cutting the outliers off the primary sample [10].

The proposal to enhance the robust properties of $M$-estimators and $R$-estimators by using the $R$-estimates consists of the procedure similar to the median average [8,9],

$$\hat{\theta}_{RM} = MED\{X_i \psi(X_i - MED(\bar{X})), i = 1, \ldots, N\}$$ (3)

$$\hat{\theta}_{AM} = MED\left\{X_i \psi(X_i - MED(\bar{X})), \frac{1}{2}[X_i \psi(X_i - MED(\bar{X})), + X_j \psi(X_j - MED(\bar{X}))], \frac{N}{2} \leq j \leq N\right\}$$ (4)

where $\hat{\theta}_{RM}$ and $\hat{\theta}_{AM}$ are the Median M-type (MM) and Ansari-Bradley–Siegel–Tukey M-type (AM) estimators, respectively. The Median M-type (MM) estimator (3) is the usual median when the function $\psi$ is represented by the simplest Huber's limiter type M-estimator. Eqs. (3) and (4) can be also applied for 2D signals (images).

The $R$- and $M$-estimators are well-known robust estimators of location and they have already been used in image processing applications resulting in the so-called $R$- and $M$-filters. We can mention some properties of these filters [10,11]:

The median filter is preferred when the observation data have long-tailed distributions. It is very suitable for the removal of impulsive noise, a median having window dimension $N = 2v + 1$ can reject up to $v$ impulses proving a correct reconstruction. The median filter has good edge preservation properties; it can be easy proven that, if the filter window is symmetric about the origin and includes the origin, the corresponding median filter preserves any step edge. A special case of $R$-filters is called Wilcoxon filter, it has been proven effective in the filtering of white additive Gaussian noise. However, it does not preserve edges as well median filter does. The reason for this is that every possible pair is averaged.

The properties of $M$-filters depend on the choice of the function $\psi(x)$. The influence function of an $M$-estimator shows the influence of an additional observation on the estimate. The influence function gives information about the effect of an infinitesimal contamination (outlier) at point $x \in X$, i.e., it offers local information. For example, the Huber estimator, and the corresponding $M$-filter can reject up to 50% of outliers. The Huber estimator tends to the median when $r$ tends to zero, because in this case the estimator tends to the sign($x$) function. It also tends to the arithmetic mean when $r$ tends to infinity. Therefore the $M$-filter is a compromise between the median and the average filters. Impulsive noise can be effectively filtered because the $M$-filter is a robust estimator of location and it limits the influence of very large or very small observations.

Finally, according to the properties described above, in Eqs. (3) and (4) the $R$-median estimator provides good properties of impulsive noise suppression and detail preservation, and the Wilcoxon estimator suppresses the white additive Gaussian noise; and the $M$-estimator uses different influence functions according to the scheme proposed by Huber to provide better robustness in the case of impulsive noise suppression, for these reasons it can be expected that the robust properties of MM- and AM-estimators can exceed the robust properties of the base $R$- and $M$-estimators. In recent works we demonstrated the robust properties of these RM (MM and AM)-estimators in comparison with $R$- and $M$-estimators [8,9,12].

### 3. Proposed Vector Rank M-type L-filter

The proposed Vector Rank M-type L (VRML)-filter combines the use of $L$ algorithm and the robust Rank M-type (RM) estimators [13].

The following representation of Vector L-filter is often used,

$$\hat{\theta}_L = \sum_{k=1}^{N} a_k \cdot Y_{(k)}$$ (5)

where $Y_{(k)}$ is an ordered data sample from a digital multichannel image that may be an RGB color image, $a_k = \int_{h_{(k-1)+}}^{h_{(k)}} h(\lambda) d\lambda$, $d_{(k)}$ are the weighted coefficients, and $h(\lambda)$ is the probability density function.

**Table 1** Comparative restoration results for 20% impulsive noise for “Lena” color image.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>PSNR</th>
<th>MAE</th>
<th>MCRE</th>
<th>NCD</th>
</tr>
</thead>
<tbody>
<tr>
<td>VM</td>
<td>21.15</td>
<td>10.73</td>
<td>0.035</td>
<td>0.038</td>
</tr>
<tr>
<td>x•TM</td>
<td>20.86</td>
<td>14.97</td>
<td>0.046</td>
<td>0.049</td>
</tr>
<tr>
<td>BVD</td>
<td>20.41</td>
<td>12.72</td>
<td>0.043</td>
<td>0.045</td>
</tr>
<tr>
<td>GVD</td>
<td>20.67</td>
<td>11.18</td>
<td>0.038</td>
<td>0.040</td>
</tr>
<tr>
<td>AGVD</td>
<td>22.01</td>
<td>11.18</td>
<td>0.028</td>
<td>0.036</td>
</tr>
<tr>
<td>GVD_DW</td>
<td>22.59</td>
<td>10.09</td>
<td>0.028</td>
<td>0.039</td>
</tr>
<tr>
<td>MAVFNE</td>
<td>22.67</td>
<td>9.64</td>
<td>0.027</td>
<td>0.035</td>
</tr>
<tr>
<td>VMML (S,L,D)</td>
<td>23.15</td>
<td>10.00</td>
<td>0.033</td>
<td>0.040</td>
</tr>
<tr>
<td>VMML (A,L,D)</td>
<td>23.07</td>
<td>10.01</td>
<td>0.033</td>
<td>0.035</td>
</tr>
<tr>
<td>VMML (S,E,D)</td>
<td>24.80</td>
<td>5.00</td>
<td>0.025</td>
<td>0.017</td>
</tr>
<tr>
<td>SWVD</td>
<td>24.30</td>
<td>6.37</td>
<td>0.017</td>
<td>0.022</td>
</tr>
<tr>
<td>VMML (S,E,ND)</td>
<td>24.90</td>
<td>7.81</td>
<td>0.032</td>
<td>0.033</td>
</tr>
<tr>
<td>VMML (S,L,ND)</td>
<td>25.81</td>
<td>6.49</td>
<td>0.026</td>
<td>0.016</td>
</tr>
<tr>
<td>VMML (S,U,ND)</td>
<td>25.88</td>
<td>5.53</td>
<td>0.026</td>
<td>0.026</td>
</tr>
<tr>
<td>VMML (S,E,D)</td>
<td>26.13</td>
<td>3.36</td>
<td>0.024</td>
<td>0.027</td>
</tr>
<tr>
<td>VMML (S,L,D)</td>
<td>26.46</td>
<td>2.90</td>
<td>0.023</td>
<td>0.027</td>
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<tr>
<td>VMML (S,U,D)</td>
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<td>0.025</td>
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<td>0.034</td>
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<tr>
<td>VMML (A,L,D)</td>
<td>25.88</td>
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<td>0.022</td>
<td>0.015</td>
</tr>
<tr>
<td>VMML (A,E,ND)</td>
<td>25.25</td>
<td>4.48</td>
<td>0.030</td>
<td>0.023</td>
</tr>
<tr>
<td>VMML (A,L,ND)</td>
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<td>3.00</td>
<td>0.022</td>
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</tbody>
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The VL (Vector L) filter can be written by means of use of an influence function as,

\[ h_{VL} = \sum_{m=1}^{N} a_m \cdot \psi(y_m) \cdot y_m \]  

where \( y_m \) are the noisy image vectors in sliding filtering window, which includes \( m = 1, \ldots, N \) vectors \( y_1, y_2, \ldots, y_N \) located at spatial coordinates in the filtering window, and \( \psi(y_m) = \begin{cases} 1 & m \leq N_l \\ 0 & \text{otherwise} \end{cases} \)

is the influence function [8,10].

We propose to improve the robustness of the VL filter by using the Rank M-type estimators adapted to process 2D signals (multichannel images). For convenience the Median M-type (MM) estimator (3) is written as [8],

\[ h_{DMM}^{MM} = \text{MED}_{w}(y_m - \text{MED}(Y_N^m)), \quad k = 1, \ldots, N \]  

where \( y_m \) is a data sample of the multichannel image, \( \psi \) is the normalized influence function \( \psi(Y) = Y \psi(Y) \), and \( Y_N^m \) is the primary data sample.

The Ansari–Bradley–Siegel–Tukey M-type (AM) estimator [9],

\[ \begin{align*} 
\theta_{DMM}^{AM} &= \text{MED}_{w} \left\{ Y_m \psi(Y_m - \text{MED}(Y_N^{m})), \right\} \\
&= \left\{ \begin{array}{ll} 
Y_m \psi(Y_m - \text{MED}(Y_N^{m})), & m \leq \frac{N}{2} \\
\frac{1}{2} [Y_m \psi(Y_m - \text{MED}(Y_N^{m})) + Y_N \psi(Y_N - \text{MED}(Y_N^{m}))], & \frac{N}{2} < m < N 
\end{array} \right. 
\end{align*} \]  

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\end{align*} \]  

is the influence function [8,10].
Fig. 2. Subjective visual quantities of restored “Lena” color image, (a) input noisy image corrupted by 30% impulsive noise in each a channel, (b) FASVM filtered image of (a), (c) VAML filtered image of (a), Eq. (11), (d) VAML filtered image of (a), Eq. (12), (e) input noisy image corrupted by 50% impulsive noise in each a channel, (f) FASVM filtered image of (e), (g) VMML filtered image of (e), Eq. (11), (h) VMML filtered image of (e), Eq. (12).

\[
\theta_{VAML} = \text{MED}_{m,n} \left\{ \frac{\text{MED} \left\{ a_m \cdot \left[ Y_m \hat{\psi}(Y_m - \text{MED}(Y_n)) \right] \right\}}{a_{\text{MED}}}, \quad m, n \leq \frac{2}{3} \right\} + \text{MED} \left\{ a_n \cdot \left[ Y_n \hat{\psi}(Y_n - \text{MED}(Y_m)) \right] \right\}, \quad \frac{3}{4} < m \right\}.
\]
where $Y_m\psi(Y_m - \text{MED} \{Y_N\})$ is set of values of vectors $y_m$ which are weighted by value in accordance with the influence function $\psi(y_m)$ in a sliding filtering window, the simple cut $\psi_{\text{cut}}(y_m) = y_m$,

$$1 - r, r(y_m) = \begin{cases} y_m, & |y_m| \leq r \\ 0, & \text{otherwise} \end{cases}$$

and Andrew's sine $\psi_{\text{sin}}(y_m)$ =

$$\begin{cases} \sin(y_m/r), & |y_m| \leq r \\ 0, & \text{otherwise} \end{cases}$$

influence functions are used in the filtering scheme [8], where $r$ is connected with restrictions on the range of $\psi(y_m)$, $y_m$ are the noisy image vectors in a sliding filtering window, which includes vectors $y_1, y_2, \ldots, y_N$ located at spatial coordinates $(i,j)$ in the sample to be processed, $a_m$ are the weighted coefficients used into the proposed filtering scheme, and $a_{\text{MED}}$ is a constant scale defined as the median of the coefficients $a_m$. The same reasoning is done for the sub-index $n$ in Eq. (10).
We also propose to enhance the impulsive removal ability of VRML filters to involve an impulsive noise detector. For this reason we implement two versions of the proposed impulsive noise detector. The first impulsive noise detector incorporates the edge preservation property (left side of Eq. (11)) and power in noise detection (right side of Eq. (11)) when the impulsive noise percentage is low (up to 20% of impulsive noise), it is defined as [14],

$$\frac{\text{rank}(y_c) \leq T_1 \lor \text{rank}(y_c) \geq N - T_1 \land |y_c - \text{MED}(y_N)| \geq T_2}{(11)}$$

where $y_c$ is the vector of interest (the central vector in the filtering window), $T_1 > 0$ and $T_2 > 0$ are thresholds, and $N$ is the length of the data. The second one is used when the levels of impulsive noise are high, this detector checks the difference between the value of the median and pixel of interest. It is written as,

$$|y_c - \text{MED}(y_N)| \geq T_3$$

(12)

where $T_3 > 0$ is a threshold.

The parameters for proposed VRML filters were found after numerous simulations in different test images degraded by impulsive noise. The idea was to find the parameters values when the values of the criteria PSNR and MAE would be optimum. In our experiments, a $3 \times 3$ sliding window was applied. The parameter of Andrew’s sine influence function is $r \leq 35$, and for the impulsive noise detector $T_1 = 3$ and $T_2 = T_3 = 0.3 \text{MED}(y_N)$. To compute the weighted coefficients $a_m$ we use the exponential, Laplacian and uniform distribution functions indistinctly. To understand better the algorithm of proposed VRML filter, it is realized as follows:

1. Read the RGB image input.
2. Choose one of the impulsive noise detectors and one of the proposed filters.
3. From the initial $3 \times 3$ sliding filtering window, compute the next steps.
4. Compute the impulsive noise detector in the current sliding window. If the central pixel in the filtering window is noisy then the next step is realized. Otherwise, the central pixel is noise free and the output’s filtered value is the central pixel value and the step 8 is done.
5. Compute \( Y'_m \in \{ Y_m - MED \{ Y_k \} \} \) using the simple cut or Andrew's sine influence function to find those pixels in the current sliding window will be used in the filtering scheme.

6. Compute the coefficients \( \alpha_m \) according to the number of pixels found in step 5 and with them compute the constant scale \( \alpha_{MED} \). For convenience this step can be computed previously.

7. Compute the proposed filter \( \psi_{VRML} (\psi_{VMML} OR \psi_{VAML}) \). This value is considered as the output filtered value.

8. Move the 3x3 sliding filtering window and continue with the step 4 up to process the rest of the image.

To determine the computational complexity of proposed VRML filter, the metric adopted to evaluate distance was the L-norm (with \( L = 1 \)). For example, given an \( r \times r \) window, containing \( N = r^2 \) samples \( Y = \{ y_1, y_2, \ldots, y_n \} \in \mathbb{R}^n \) the number of elementary operations required to evaluate a vector distance based on L-norm is \( 2p \) algebraic sums and \( p \) comparisons and absolute values, and the overall complexity of vector median is given by \( O(2p^2) \) algebraic sums and \( O(p^2) \) comparisons and absolute values [15]. The computational complexity of proposed filters is similar to vector median complexity during several steps of the algorithm because it computes the MED\{Yk\} but in these steps the complexity increases as follows:

The step 4 increases the complexity with 3 comparisons, 2 algebraic sums, 1 absolute value, and 2 logic operations with Eq.(11).

The step 5 requires 8 algebraic sums, 8 comparisons, and 8 multiplications to find those pixels will be used in the filtering scheme. The variable \( \alpha_{MED} \) is computed as \( O(a) \) where \( a < N \) is the number of the weighted coefficients \( \alpha_m \) used in the step 6, these coefficients can be computed previously.

Step 7 requires 8 multiplications and 1 division in the case of VMML filter, and for the VAML filter increases with 1 algebraic sum and 1 division.

4. Overall filtering performance

The VMML filter [13] and the proposed VAML filter with the simple cut (S) and Andrew's sine (A) influence functions, the exponential (E), Laplacian (L), and uniform (U) distribution functions and, the impulsive noise detector (D) and without it (ND) have been evaluated, and their performance have been compared with vector median (VM), trimmed mean (-TM), basic vector directional (BVD), generalized vector directional (GVD), adaptive GVD (AGVD), double window GVD (GVD_DW), multiple non-parametric (MAMNF), vector median M-type K-nearest neighbour (VMMKNN), fast adaptive similarity VM (FASVM) and selection weighted vector directional (SWVD) filters [6,7,16–18].

The criteria used to compare the restoration performance of various filters were the peak signal-to-noise ratio (PSNR) for evaluation of noise suppression, the mean absolute error (MAE) for quantification of edges and details preservation, the mean chromaticity error (MCRE) for evaluation of chromaticity retention, and the normalized color difference (NCD) for quantification of color perceptual error [1–3].

The 320 × 320 color image “Lena” was corrupted by 20% of impulsive noise for each RGB color channel. Table 1 shows that the performance criteria are often better for the proposed VRML filters in comparison with other filters in the most of cases. By other hand, one can see that the proposed VMML filter provides better results in terms of detail preservation (MAE) in comparison with VMML in the most of cases but in some cases the VMML improves VAML in terms of noise suppression. To choose the type of influence function is not critical but it depends of the complexity of influence function. From Table 1 we observe that the use of Andrew’s sine influence function in the VMML and the simple cut influence function in the VAML provide the better results in the most of cases. In the case of distribution functions, the uniform function improves the results of proposed filters in comparison with the Laplacian and exponential functions. Fig. 1 shows the subjective visual quantities of restored zoom part of color image “Lena” according with Table 1. From this Figure we observe that the proposed VMML and VAML filters with and without impulsive noise detector appear to have better visual qualities in comparison with the reference filters.

When impulsive noise levels are high, we can use the impulsive noise detector described in Eq. (12). In this case, we degraded the image “Lena” with different percentages of impulsive noise. The performance results in terms of PSNR and MAE are given in Table 2, in the case of proposed VRML filters with the use of no detector (ND), and the impulsive noise detectors (D) defined in Eqs. (11) and (12) and FASVM filter used as comparative. From this Table, we can see that the use of impulsive noise detectors depend of the density of impulsive noise. In the case of use of impulsive noise detector given by Eq. (12), it has the better performance when the noise levels are high (>25%) in comparison with (11). We also observe that the proposed VRML filters have better performance than FASVM in the most of cases, the performance of proposed VAML is better than VMML when the noise levels are high providing more noise suppression and detail preservation. Fig. 2 presents the subjective visual quantities of restored color image “Lena” by use of the proposed VMML and VAML filters. From these figures, one can see that the noise detector in Eq. (12) shows better performance when the noise level is high in comparison with the performance of detector used in Eq. (11).

Fig. 3 shows comparative restoration results between the proposed VMML and VAML in the case of 40% of impulsive noise, where we observe that the VAML provides better noise suppression and detail preservation in comparison with VMML with the use of noise detector (12). It is due that the proposed VAML combines the robustness of median and Wilcoxon estimators with the M-estimator.

In the case of impulsive noise suppression in video sequences, we use one frame of the 176x144 video color sequence “Miss America”, which was corrupted by 15% of impulsive noise. Fig. 4 exhibit the processed frames for test frame “Miss America” explaining the impulsive noise suppression. The restored frames with proposed VRML filters have better objective and subjective quality in comparison with MAMNF and VMMKNN filters. Also, the proposed VAML filter outperforms the proposed VMML in the case of use of impulsive noise detector (11).

Finally, to demonstrate the performance of the proposed filtering scheme we applied it for filtering of SAR images, which naturally have speckle noise. The filtering results are presented in Fig. 5 for the “Manzano” image (forest near Manzano State Park, New Mexico). It is possible to see analyzing the filtered images that speckle noise can be efficiently suppressed, while the sharpness and fine feature are preserved using the proposed VRML filters with noise detector (11).

From the experimental results we conclude that the proposed VAML filter provides better detail preservation and noise suppression in comparison with the VMML filter when the noise levels are high but when the noise levels are low the best results are for VMML filter in the most of cases. The use of uniform distribution function permits to obtain better results in comparison with other distribution functions. Finally, we recommend the use of simple influence function because it is easy to implement and requires less computational complexity.
5. Conclusions

The VMML filter [13] and the proposed VAML filter are able to remove efficiently impulsive and speckle noise and preserve the edges and details in color imaging. These filters use the robust MM and AM-estimators with different influence functions in the L-algorithm. We use impulsive noise detectors in the proposed filtering scheme to provide better noise suppression, detail preservation, and color retention. The VRML filters have demonstrated better quality of image processing, both in visual and analytical sense in comparison with different well known color image processing algorithms.

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