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Short Communication

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

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ABSTRACT

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.

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 Andreẃs 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 θ_A is given by,

$$\theta_{\mathrm{A}} = \operatorname*{MED}_{i\leqslant j}\left\{\begin{matrix} X_{(i)}, & i\leqslant \frac{N}{2} \\ \frac{1}{2}(X_{(i)}+X_{(j)}), & \frac{N}{2}<i\leqslant N \end{matrix}\right\} \tag{1}$$

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where $X_{(i)}$ and $X_{(j)}$ 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 θ is a location parameter. The robust *M*-estimator solution for θ is determined by imposing certain restrictions on the influence function $\psi(X)$ or the samples $X_i-\theta$, called censorization 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 θ value [8,10]

$$\theta_{\mathbf{M}}=\frac{\sum_{i=1}^{N}X_i\tilde{\psi}(X_i-\mathrm{MED}\{\vec{\mathrm{X}}\})}{\sum_{i=1}^{N}1_{[-r,r]}(X_i-\mathrm{MED}\{\vec{\mathrm{X}}\})} \quad (2)$$

where $\mathrm{MED}\{\vec{\mathrm{X}}\}$ is the median of elements contained in vector $\vec{\mathrm{X}}$ and $\tilde{\psi}$ is the normalized function ψ: $\psi(X)=X\tilde{\psi}(X)$. It is evident that Eq. (2) represents the arithmetic average of $\sum_{i=1}^{N}\psi(X_i-\mathrm{MED}\{\vec{\mathrm{X}}\})$, 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' $\tilde{\psi}_r(X)=\min(r,\max(X,r))=[X]_{-r}^{r}$ [8,10]. Hampel proved different influence functions to derive the function $\tilde{\psi}(X)$ 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],

$$\theta_{\mathbf{MM}}=\mathrm{MED}\{X_i\tilde{\psi}(X_i-\mathrm{MED}\{\vec{\mathrm{X}}\}),i=1,\ldots,N\} \quad (3)$$

$$\theta_{\mathbf{AM}}=\underset{i\leqslant j}{\mathrm{MED}}\left\{\begin{array}{ll} X_i\tilde{\psi}(X_i-\mathrm{MED}\{\vec{\mathrm{X}}\}), & i\leqslant\frac{N}{2}\\ \frac{1}{2}\left[X_i\tilde{\psi}(X_i-\mathrm{MED}\{\vec{\mathrm{X}}\})+X_j\tilde{\psi}(X_j-\mathrm{MED}\{\vec{\mathrm{X}}\})\right], & \frac{N}{2}<j\leqslant N\end{array}\right\} \quad (4)$$

where θ_{MM} and θ_{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 $\tilde{\psi}$ 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 $x\in\mathbf{X}$, 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,

$$\theta_{\mathrm{VL}}=\sum_{k=1}^{N}a_k\cdot Y_{(k)} \quad (5)$$

where $Y_{(k)}$ is an ordered data sample from a digital multichannel image that may be an RGB color image, $a_k=\int_{(k-1)/N}^{k/N}h(\lambda)d\lambda/\int_0^1 h(\lambda)d\lambda$ 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.

Algorithm	PSNR	MAE	MCRE	NCD
VM	21.15	10.73	0.035	0.038
α-TM	20.86	14.97	0.046	0.049
BVD	20.41	12.72	0.043	0.045
GVD	20.67	11.18	0.038	0.040
AGVD	22.01	11.18	0.028	0.036
GVDF_DW	22.59	10.09	0.028	0.039
MAMNFE	22.67	9.64	0.027	0.035
VMMKNN (S)	23.15	10.00	0.033	0.034
VMMKNN (A)	23.07	10.01	0.033	0.035
FASVM	24.80	5.00	0.025	0.017
SWVD	24.30	6.37	0.017	0.022
VMML (S,E,ND)	24.90	7.81	0.032	0.033
VMML (S,L,ND)	25.81	6.49	0.026	0.016
VMML (S,U,ND)	25.88	5.53	0.026	0.026
VMML (S,E,D)	26.13	3.36	0.024	0.027
VMML (S,L,D)	26.46	2.90	0.023	0.027
VMML (S,U,D)	26.47	2.79	0.023	0.025
VMML (A,E,ND)	22.65	12.32	0.034	0.040
VMML (A,L,ND)	25.88	7.00	0.026	0.015
VMML (A,U,ND)	26.52	5.36	0.022	0.015
VMML (A,E,D)	25.25	4.48	0.030	0.023
VMML (A,L,D)	26.59	3.00	0.022	0.029
VMML (A,U,D)	26.73	2.74	0.021	0.025
VAML (S,E,ND)	24.85	7.79	0.032	0.033
VAML (S,L,ND)	26.05	6.32	0.025	0.015
VAML (S,U,ND)	25.99	5.47	0.025	0.024
VAML (S,E,D)	25.86	3.61	0.025	0.027
VAML (S,L,D)	26.54	2.89	0.023	0.026
VAML (S,U,D)	26.68	2.71	0.023	0.025
VAML (A,E,ND)	22.30	12.21	0.035	0.040
VAML (A,L,ND)	25.90	6.91	0.026	0.015
VAML (A,U,ND)	26.56	5.38	0.022	0.015
VAML (A,E,D)	25.01	4.46	0.031	0.024
VAML (A,L,D)	26.27	3.09	0.023	0.029
VAML (A,U,D)	26.52	2.80	0.022	0.026