Median M-type K-nearest neighbour (MM-KNN) filter to remove impulse noise from corrupted images

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The median M-type K-nearest neighbour (MM-KNN) filter to remove impulse noise from corrupted images is presented. This filter uses *R* and *M* estimators combined with different influence functions. Simulation results have shown that the restoration performance is better than that of other known filters.

Introduction: Many types of nonlinear filters are based on robust estimation theory and in particular on order statistics theory. Typical applications of robust estimation in image filtering are shown in [1, 2]. In this Letter, we introduce the median M-type K-nearest neighbour (MM-KNN) filter based on combined robust *R* and *M* estimators to calculate the robust point estimate of the pixels within the filtering window. Such a filter processes the value of the central pixel into the filtering window to provide preservation of fine details by use of the KNN algorithm [1] and the redescending *M*-estimators combined with calculation of the median to obtain sufficient impulse noise rejection [3]. We use the simple cut, skipped median, Hampel three-part redescending, Andrews sine, Tukey biweight, and Bernoulli influence functions [1] in the *M*-estimator to provide better impulse noise suppression.

Proposed filter: We propose use of combined RM-estimators [3] that can enhance the robust properties of *M*- and *R*-estimators:

$$\theta_{\mathrm{medM}} = \mathrm{MED}\{X_i \tilde{\psi}(X_i - \mathrm{MED}\{\boldsymbol{X}\}), i = 1, \ldots, N\} \tag{1}$$

where X_i are data samples, $\boldsymbol{X}$ is a data vector, and $\tilde{\psi}$ is the influence function [1]. To increase the quality of filtration via detail preservation into the image we use *K* elements of the sample the values of which are closest to the value of the central pixel of the filter window. This leads to the widely-known KNN image-filtering algorithm [1]. To improve the robustness of the KNN filter, we propose use of the procedure of the RM-estimate from (1). Therefore, the median M-type KNN filter, which we refer to as the MM-KNN algorithm, can be written as:

$$\hat{e}^{(q)}_{\text{MM-KNN}}(i,j) = \mathrm{MED}\left\{g^{(q)}(i+m, j+n)\right\} \tag{2}$$

where $g^{(q)}(i+m,\ j+n)$ is a set of K_c values of pixel weighting in accordance with the $\tilde{\psi}(X)$ influence function within the filter window closest to the estimate obtained at the previous step $\hat{e}^{(q-1)}_{\text{MM-KNN}}(i,j)$. Here, $m, n = -L, \ldots, L$; $\hat{e}^{(0)}_{\text{MM-KNN}}(i,j) = x(i,j)$ is the initial estimate; $x(i,j)$ is the degraded image; q is the index of the current iteration; $K_c(i,j)$ is the number of the nearest neighbour pixels: it reflects the local data activity and spike presence and is determined as [3]

$$K_c(i,j) = [K_{min} + aS(x(i,j))] \le K_{max} \tag{3}$$

Here, a controls the detail preservation; K_{min} is the minimal number of the neighbours for noise removal; K_{max} is the maximal number of the neighbours for edge restriction and detail smoothing; $S(x(i,\ j))$ represents the spike detector:

$$\begin{aligned} S(x(i,j)) = {} & [\mathrm{MED}\{|x(i,j) - x(i+m, j+n)|\}/\mathrm{MAD}] \\ & + [0.5 \cdot \mathrm{MAD}/\mathrm{MED}\{x(i+k, j+l)\}] \end{aligned} \tag{4}$$

and MAD is the median of absolute deviations from the median [1]. The algorithm finishes when $\hat{e}^{(q)}_{\text{MM-KNN}}(i,\ j) = \hat{e}^{(q-1)}_{\text{MM-KNN}}(i,\ j)$. We also propose enhancement of the removal ability of filter (2) to involve the standard median filter. The numerical simulations have shown that for $K_c > 7$ the MM-KNN filter can be substituted by a 3×3 median filter and for $K_c > 350$ we use the 5×5 median filter.

Simulation results: The described MM-KNN filter with different influence functions has been evaluated and their performance has been compared with different nonlinear filters [1, 4, 5]. The criterions used to compare the performance of various filters were the peak signal-to-noise ratio (PSNR) and the mean absolute error (MAE).

The 256×256 'Lena' image was corrupted by 15% of impulse noise (the original 'Lena' image is shown in Fig. 1*a*). Table 1 shows that the PSNR and MAE performances of the proposed MM-KNN filter are often better than in cases when other filters are used. Fig. 1 shows the processed images for test image 'Lena' and demonstrates the impulsive noise suppression. Fig. 1*b* shows the input noisy image the noise probability of which is 15%, and Figs. 1*c*–*d* exhibit the filtered images produced by the 5×5 MM-KNN filter. The restored images appear to have very good subjective quality.

Fig. 1 *Subjective visual qualities of restored image 'Lena' produced by 5×5 MM-KNN filter*

a Original test image 'Lena'
b Input noisy image (with 15% of impulse noise)
c Proposed MM-KNN filtered image (simple cut)
d Proposed MM-KNN filtered image (Tukey)

Table 1: Comparative restoration results for 15% impulse noise for image 'Lena'

Algorithm	PSNR	MAE
5×5 median	23.64	10.16
5×5 weighted median (WM)	25.03	7.53
5×5 lower-upper-middle (LUM)	24.49	9.04
5×5 FIR median hybrid (FIRMH)	23.79	9.03
3×3 rank order mean (ROM)	25.76	8.79
3×3 minimum-maximum exclusive mean (MMEM)	25.67	8.08
5×5 MM-KNN (simple cut)	25.29	8.20
5×5 MM-KNN (skipped median)	26.27	7.09
5×5 MM-KNN (Hampel three-part redescending)	26.14	7.16
5×5 MM-KNN (Andrews sine)	26.10	7.18
5×5 MM-KNN (Tukey)	26.37	7.04
5×5 MM-KNN (Bernoulli)	26.43	7.07

The advantage of our procedure is that the proposed MM-KNN filter does not use training data and the parameters of the proposed filter can be fixed as constants. The optimal values for the parameters of the MM-KNN filter are $a = 4$ and $K_{min} = 5$. The parameters of the influence functions are $r \le 81$ for Andrews sine, $r \le 255$ for Tukey biweight and Bernoulli, $\alpha = 10$, $\beta \le 100$ and $r = 300$ for Hampel three-part redescending.

Conclusions: The designed robust detail-preserving MM-KNN filters are able to remove impulse noise and preserve the edges and fine details. The proposed filtering technique demonstrates better quality of image processing, both in the visual and the analytical sense compared with different known image processing algorithms.

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