

Impulsive Noise Resilient Mean Shift Filtering for Effective Color Image Enhancement

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Abstract—The degradation of color images caused by noise significantly diminishes their quality. Consequently, enhancing noisy images becomes a pivotal step in the processing pipeline. In this paper, we present an extension of the widely used Mean Shift (MS) technique. While MS efficiently handles Gaussian noise, it falls short in reducing impulsive noise. Our proposal involves the application of a robust similarity measure between a pixel and the central patch of the processing block. This measure is resilient to the influence of impulsive noise, addressing a limitation of MS. To mitigate the impact of corrupted pixels in the block centered at the pixel being restored, we assign a measure of pixel’s impulsiveness. This ensures that noisy pixels carry significantly less weight in the iterative MS process.

The combination of the robust pixel-to-patch similarity measure with the degree of pixel corruption enables overcoming impulsive disturbances, allowing for the application of the MS technique in suppressing mixed Gaussian and impulsive noise. The proposed technique can serve as a preprocessing step for segmentation, edge detection, and object recognition.

Index Terms—mixed noise, mean shift, image denoising, image segmentation

I. INTRODUCTION

Reducing noise in digital images has been a big focus in image processing for a long time. Recently, with the popularity of devices and apps for taking and sharing color photos online, improving image quality has become even more important. Digital images can suffer from different kinds of noise, causing distortions in their original content. Common sources of noise include issues with camera sensors, heat-related noise, fluctuations in photon flux causing shot noise, errors in analog-to-digital converters, electromagnetic interference, defects in optics and transmission errors.

The resulting problems are often characterized by a combination of two types of noise: additive white Gaussian noise, primarily causing dark and shot currents, and impulsive noise, which appears as pixels with random intensity values across different color channels.

The research primarily centers on investigating two distinct noise models: impulsive and Gaussian noise, each posing unique challenges in image processing. Impulsive noise broadly falls into two categories, the first being *salt-and-pepper* noise which results in damaged pixels having channel values set to either the minimum or maximum intensity. The

second category, Random Valued Impulsive Noise (RVIN), presents a greater challenge due to its unpredictable nature, allowing color pixel channels to assume any random value within the channel’s intensity range [1], [2].

On the other hand, Gaussian noise stands out as the second most common type of image distortion. Additive White Gaussian Noise (AWGN), a specific subtype of Gaussian noise, is uniformly distributed across the image pixels affecting them introducing values from a zero mean Gaussian distribution.

Addressing mixed noise, a blend of impulsive and Gaussian components, poses a challenge in denoising. Existing methods typically focus on individual noise types, causing inefficiencies when confronted with their combination. Techniques designed for Gaussian noise may falter in the presence of impulsive noise, and vice versa.

Common Gaussian noise filters estimate pixel intensity by comparing it with pixels in a local block. The Bilateral Filter (BF) [3] preserves edges while minimizing distortions, however it struggles with impulsive disturbances, resulting in blurring and artifacts in textured areas.

The Non-Local Means (NLM) method [4] adopts a distinct approach by assessing patch similarity rather than individual pixels. It holds promise, especially with extensions such as Block Matching and 3D Filtering (BM3D) [5], which have demonstrated commendable results [6]. However, the presence of impulsive noise significantly affects these methods, necessitating the use of an impulsive noise removal filter as a preprocessing step.

Various image restoration schemes were developed to address the challenges of impulsive and Gaussian noise. These methods first suppress impulsive noise and then use a filter specifically designed for Gaussian noise attenuation [7]. However, this two-stage approach faces limitations, as the masking effect of Gaussian noise hinders accurate impulse detection, leading to unsatisfactory attenuation of remaining noise and visible artifacts.

While individual filters effectively target either impulsive or Gaussian noise, they fall short in managing their combined impact. An alternative approach involves methods that integrate both strategies, addressing mixed noise in a single phase. The Trilateral Filter (TF), a modification of BF, incorporates the Rank-Ordered Absolute Differences (ROAD) statistic, efficiently reducing both impulsive and Gaussian noise [8].

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Other modifications leverage the NLM technique with ROAD-based similarity measures or apply the median of absolute deviations to address the pixel being processed [9]. However, these methods excel with low-intensity noise but encounter challenges with high-intensity, heavy-tailed noise.

To optimize the effectiveness of the Mean Shift (MS) method in scenarios involving impulsive noise, a preliminary impulsive noise removal technique is frequently essential. In our earlier work [10], we introduced an extended version of the MS technique, integrating the notion of pixel-to-patch similarity. Building upon this foundation, our current proposal extends the method fortifying its robustness against impulses that may compromise the MS process.

II. MEAN SHIFT AND ITS FAST MODIFICATIONS

Mean Shift is a popular non-parametric clustering algorithm which is often applied to color image denoising [11]. The basic idea behind the MS method is to iteratively move data points towards the mode of the data distribution.

Let us assume a set of n multivariate observations $\mathcal{X} = \{x_1, \dots, x_n\}$ from the l -dimensional space $\mathbb{R}^l$ with a density estimator $f(x)$ at x calculated using a kernel $K(x)$, satisfying $\int_{\mathbb{R}^l} K(x) dx = 1$, is defined as

$$f(x) = \frac{1}{nh^l} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right), \quad (1)$$

where h is the smoothing parameter or bandwidth. Usually K is a radially symmetric probability density function and usually the Gaussian kernel is used, which gives

$$f(x) = \frac{1}{nh^l} \sum_{i=1}^n G\left(\frac{x - x_i}{h}\right) = c \sum_{i=1}^n \exp\left(-\frac{\|x - x_i\|^2}{2h^2}\right), \quad (2)$$

where c is a normalizing constant and $\|\cdot\|$ denotes the L_2 norm. The gradient of $f(x)$ is then given by

$$f'(x) = \frac{c}{2h^2} \sum_{i=1}^n (x_i - x) G\left(\frac{x - x_i}{h}\right), \quad (3)$$

which can be expressed differently as

$$f'(x) = \frac{c}{2h^2} \left[\sum_{i=1}^n G\left(\frac{x - x_i}{h}\right) \right] \cdot \left[\frac{\sum_{i=1}^n x_i G\left(\frac{x - x_i}{h}\right)}{\sum_{i=1}^n G\left(\frac{x - x_i}{h}\right)} - x \right]. \quad (4)$$

The first term of (4) is a rescaled density estimation and the second one is the *mean shift* vector $m(x) = \hat{x} - x$, where $\hat{x}$ is a weighted mean of $\{x_i\}$. The mean shift $m(x)$ is aligned with the gradient of the density function, indicating its orientation toward the direction of maximum increase. The MS procedure operates iteratively. The observation x is shifted to $\hat{x}$, allowing to formulate the iterative mode-finding scheme as [11]

$$x^{(t+1)} = \frac{\sum_{i=1}^n x_i \exp(-\|x^{(t)} - x_i\|^2/2h^2)}{\sum_{i=1}^n \exp(-\|x^{(t)} - x_i\|^2/2h^2)}, \quad (5)$$

with $t \geq 1$ denoting the iteration number and $x^{(1)}$ the initial point. This technique converges to a local mode and the process concludes when the magnitude of the mean shift vector approaches zero.

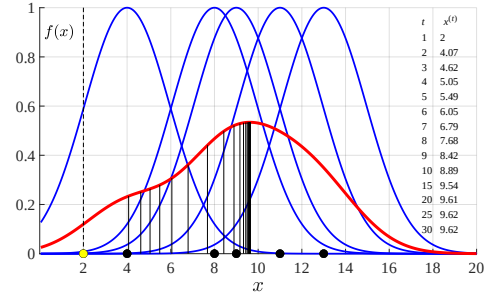


Fig. 1: Successive iterations of the Mean Shift (MS) procedure using Gaussian kernels in the 1D case (blue plots) for $\mathcal{X} = \{4, 8, 9, 11, 13\}$, with bandwidth $h = 2.75$ and initial point $x^{(1)} = 2$, converge at the maximum of the density function, depicted by the red curve.

Figure 2 depicts an exemplary one dimensional Gaussian kernel based density estimation $f(x)$. Starting from $x^{(1)} = 2$, the vertical lines show the values of the successive iteration steps $x^{(t)}$, with approximate values provided on the right side of the plot. The MS procedure converges at the maximum of the density estimation.

The MS in (5) can be also expressed as weighted least squares estimator [12], [13] minimizing a cost function

$$x^{(t+1)} = \arg \min_x \sum_{i=1}^n \|x^{(t)} - x_i\|^2 \cdot G\left\{(x^{(t)} - x_i)/h\right\}. \quad (6)$$

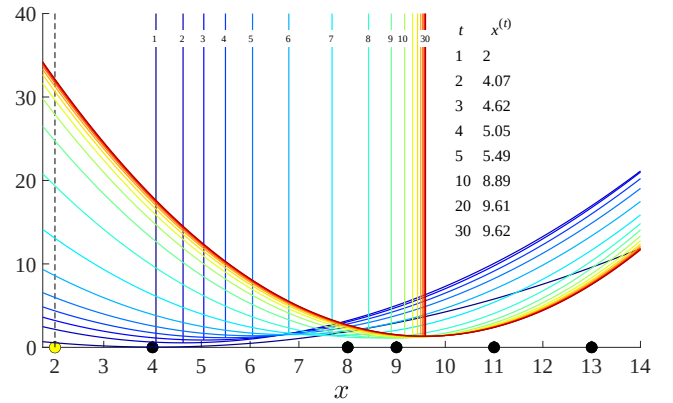


Fig. 2: Plots of the cost function given by (6). The vertical lines depict the successive minima $x^{(t)}$ when the starting point is $x^{(1)} = 2$. The sequence of $x^{(t)}$ is the same as in the MS procedure illustrated in Fig. 1.

Obtaining convergence in the iterative process, which needs to find consecutive points $x^{(t)}$, is laborious as in each iteration, the distances between $x^{(t)}$ and remaining points x_i have to be computed.

To expedite the process of finding local modes, the Medoid Shift (MEDS) algorithm has been proposed. This adaptation relies on the iterative procedure outlined in (6) [13]. Under this modification, only the points $x_i \in \mathcal{X}$, are considered as consecutive observations minimizing the cost function.

An alternative strategy, with the goal of expediting the iterative process for mode localization, was introduced in [12]. The authors proposed a technique called Quick Shift (QS),

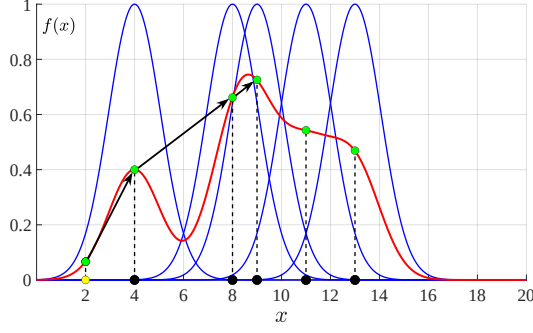


Fig. 3: Using the Quick Shift method and the same set of points as in the examples provided in Figs. 1 and 2, setting $h = 1.5$ and starting from $x^{(1)} = 2$ the iteration process is terminated at $x = 9$ in only three steps. The blue plots depict the Gaussian kernels, while the red curve represents the density estimation derived from (2).

which involves relocating each starting point to its closest neighbor with increased value of the density function and this procedure is iteratively repeated, (see Fig. 3). As evident, if a global mode exists, it becomes the ultimate point of each trajectory originating from $x^{(1)}$.

Concerning color images, the MS procedure works in 5-dimensional space, where 2 dimensions represent pixel position and the remaining are allocated for the RGB color channels. Typically, MS operates with a processing block B of size $(2r+1) \times (2r+1)$, where the value of radius r influences the process of identifying local modes. Thus, the processing block B comprises $N = (2r+1)^2$ pixels indexed as $j = 1, \dots, N$.

The MS algorithm starts at the initial pixel x_i at the center of corresponding block B_i and iteratively calculates the new values of its spatial and radiometric components $x_i^{(t+1)} = (u_i^{(t+1)}, v_i^{(t+1)})$, in each iteration (t)

$$u_i^{(t+1)} = \frac{1}{Z} \sum_{j=1}^N w_{ij}^{(t)} \cdot u_j^{(t)}, \quad v_i^{(t+1)} = \frac{1}{Z} \sum_{j=1}^N w_{ij}^{(t)} \cdot v_j^{(t)}, \quad Z = \sum_{j=1}^N w_{ij}^{(t)},$$

$$w_{ij}^{(t)} = \exp\{-\|u_i^{(t)} - u_j\|^2 / 2\sigma_r^2\} \cdot \exp\{-\|v_i^{(t)} - v_j\|^2 / 2\sigma_s^2\}, \quad (7)$$

where σ_r, σ_s are the color and spatial bandwidths.

The algorithm stops when the magnitude of $\|x^{(t+1)} - x^{(t)}\|$ is smaller than a predefined value ϵ . Then the final RGB values $v_i^{(t)}$ at $u_i^{(t)}$ on the image domain is assigned to the pixel at the starting point u_i and the next image pixel is processed.

The proposed Impulsive Noise Resilient Algorithm (IN-ORA) integrates elements of the MS filter with the ROAD similarity measure [8], incorporating a pixel-to-patch comparison methodology. In the initial step, a block B_i with radius r and a patch W_i of size 3×3 centered at the filtered pixel x_i are created. The filtering outcome is the weighted average of non-impulsive pixels in the processing block. The similarity of a pixel x_j from B_i to the central patch W_i is expressed as

$$S_{ji} = \sum_{v_k \in W_i} \|v_j - v_k\|^2 \cdot \gamma_k / \sum_{v_k \in W_i} \gamma_k, \quad (8)$$

where $\|v_j - v_k\| = d_{jk}$ denotes the Euclidean RGB distance between color components of x_j and x_k and γ_k is the ROAD

based impulsivity measure of pixel x_k . It is defined as

$$\gamma_q = \exp\{-R_q / 2\sigma^2\}, \quad \text{with } R_q = \frac{1}{\alpha} \sum_{l=1}^{\alpha} d_{q(l)}^2, \quad (9)$$

where $d_{q(l)}$ is the l -th smallest Euclidean distance between v_q and the pixels belonging to the local window W_q (whose center is x_q) of size 3×3 and σ is a smoothing parameter. The value of α , where $\alpha \in [1, 9]$, denotes the number of closest pixels from the local window. Note that the similarity measure S_{ji} is not dependent on the number of corrupted pixels in the central patch W_i .

The weight assigned to a pixel x_j from the processing block B_i is calculated as $\omega_{ji} = \exp\{-S_{ji} / 2h^2\}$, where h is a smoothing parameter. The filtering process yields

$$y_i = \sum_{x_j \in B_i} \omega_{ji} \cdot \gamma_j \cdot x_j / \sum_{x_j \in B_i} \omega_{ji} \cdot \gamma_j. \quad (10)$$

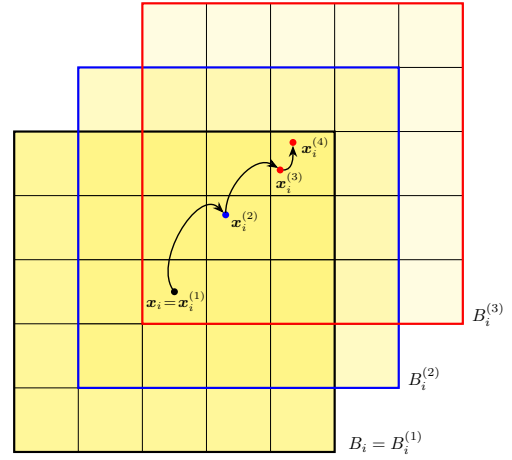


Fig. 4: Trajectory of the central pixel x_i in the MS procedure.

Subsequently, the calculated pixel y_i is integrated into the Mean Shift algorithm. The MS initiates at the pixel x_i at the center of B_i , iteratively computing new values for its spatial and radiometric components in each iteration (t), thus creating a new pixel denoted as $x_i^{(t+1)}$, (see Fig. 4) with

$$u_i^{(t+1)} = \frac{1}{Z} \sum_{x_j \in B} \omega_{ji}^{(t)} \cdot \gamma_j \cdot u_j, \quad v_i^{(t+1)} = \frac{1}{Z} \sum_{x_j \in B_i} \omega_{ji}^{(t)} \cdot \gamma_j \cdot v_j. \quad (11)$$

Here, $Z = \sum_{x_j \in B_i} \omega_{ji}^{(t)} \cdot \gamma_j$, and the weight $\omega_{ji}^{(t)}$ is iteratively updated using the formula (8). In each iteration ($t + 1$), ($t \geq 1$) the central patch of the processing block is extended by incorporating the newly created pixel $x_i^{(t+1)}$, resulting in an extended patch $W_i^{(t+1)}$, ($W_i^{(1)} = W_i$). This extended patch enhances the contextual information, ensuring that the evolving spatial components are progressively included in the analysis. The iterative refinement process dynamically adapts the patch to encompass the updated characteristics throughout the MS iterations. Consequently, the MS algorithm, initiated at the filtered pixel x_i at the center of the corresponding block B_i , incorporates this extended patch $W^{(t+1)}$ in each iteration, contributing to a more comprehensive and adaptive noise

suppression approach for color images. The extension of the patch with the current additional pixel $x_i^{(t+1)}$ is represented as $W_i^{(t+1)} = W_i \cup \{x_i^{(t+1)}\}$. Here, the union operator $\cup$ signifies the extension of the initial central patch with the newly generated pixel $x_i^{(t+1)}$, which originates from x_i .

The impulsivity measure of $x_i^{(t+1)}$ is being calculated accordingly to Eq. (9) with the local window centered at $x_i^{(t+1)}$ or more precisely at the rounded spatial coordinates of $u_i^{(t+1)}$. It is worth noticing that we do not exploit the spatial distances between the pixels in the processing block and its center thus omitting the need to use the spatial kernel presented in (7), which simplifies the algorithm. The flowchart summarizing the proposed method is presented in Fig. 5.

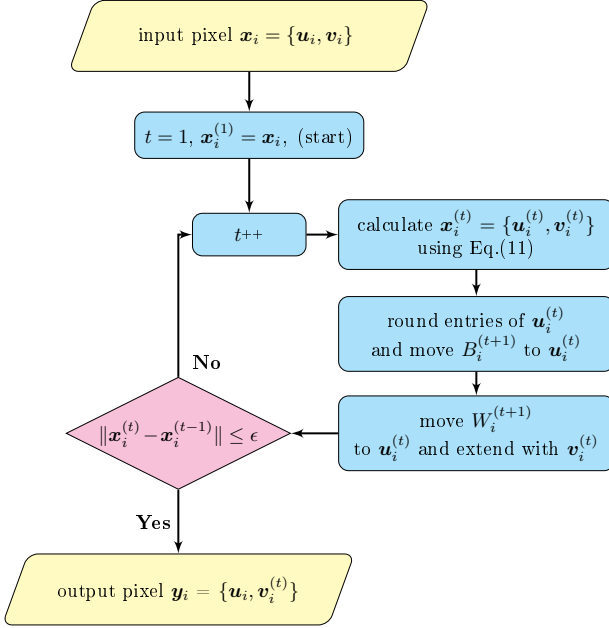


Fig. 5: Flowchart of the proposed robust MS algorithm.

III. INFLUENCE OF PARAMETERS ON THE FILTERING PERFORMANCE

In the experiments a database comprising 100 color images with a resolution of 640×480 was used. These images were subjected to impulsive and Gaussian noise of varying intensities. The dataset can be accessed for download at <http://denoising.net>, as referenced in [14]. For a visual analysis of the impact of parameters on the denoising efficiency, an additional set of test images was prepared. These images include: CLOCK, CAPS, CROSS, BALLOONS and MONARCH, (refer to Fig. 6).

These images underwent contamination with Additive White Gaussian Noise (AWGN) characterized by a standard deviation of $\sigma_n = p$. Subsequently, they were corrupted by Random-Valued Impulse Noise (RVIN) with the percentage of corrupted pixels set to p . Specifically, a noise intensity parameter $p = 30$ implies that the image experienced contamination by Gaussian noise with a standard deviation of 30 and impulsive noise affecting 30% of the pixels. This combination of impulsive and Gaussian noise effectively simulates real

image distortions, as discussed in [10], [15]. The denoising effectiveness of the proposed filter was optimized using the widely employed Peak Signal to Noise Ratio (PSNR).



Fig. 6: Color test images used for experiments.

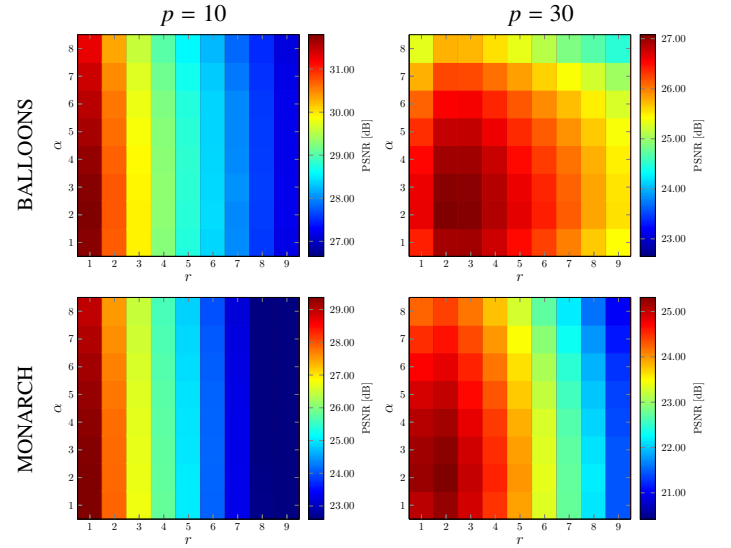


Fig. 7: Dependence of PSNR on α and r for images BALLOONS and MONARCH using best settings of h and σ .

The proposed algorithm, which can be seen as an extension of the MS based robust filter (ROMS) presented in [10], depends on the size r of the processing block B and two smoothing parameters σ and h . As our experiments show, the value of the parameter α which determines whether an analyzed pixel is corrupted or not can be set to a constant value, the same applies to the corresponding smoothing parameter σ .

Figure 7 shows the dependence of the PSNR value on the parameters r and α for contamination levels $p \in \{10, 30\}$ using best possible settings of the smoothing parameters σ and h . The plots show, that the best results are achieved for small block sizes, especially for low contaminated images, where a block of size 3×3 is sufficient. For higher corruption levels, $r = 3$ is sufficient and increasing it leads to oversmoothing and PSNR decrease. For low contamination the parameter α is practically independent on the image structure. We can as-

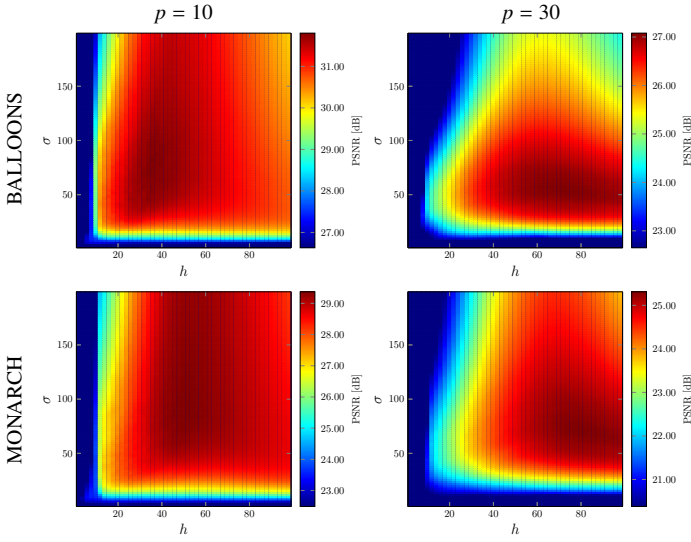


Fig. 8: Dependence of PSNR on h and σ for $\alpha = 3$ and optimal values of r using images BALLOONS and MONARCH.

sume, that $\alpha = 3$ is optimal for all kind of noise contamination.

Another crucial aspect of the INORA algorithm is the selection of smoothing parameters, σ and h . As illustrated in Fig. 8, for low-contaminated images, the σ parameter exhibits minimal dependence on the image, as does the h parameter. Conversely, for higher contamination levels, the optimal σ value converges to $\sigma = 50$. On the other hand, the h parameter demonstrates an almost linear dependence on noise intensity, commencing at $h = 40$ for low-contaminated images and escalating to $h = 100$ for highly contaminated ones. Additionally, this parameter is slightly dependent on the image structure.

To summarize, the optimal settings for the INORA algorithm are: for low contamination levels, a block size of 3×3 and $\alpha = 3$ yield the best results. For high contamination, a block size of 7×7 is sufficient to prevent oversmoothing. The smoothing parameter σ set to 50 should be fine for most applications. The h parameter although should be adjusted linearly, starting at 40 for low contamination and increasing to 100 for high contamination.

IV. COMPARISON WITH COMPETITIVE DENOISING TECHNIQUES

We compared the denoising efficiency of the INORA filter with a set of state-of-the-art techniques using parameter settings recommended in the relevant articles. The convergence of the extended robust MS algorithm is achieved in 10 iterations. However, satisfying denoising is obtained already in the first iteration and subsequent iterations tend to sharpen image edges, which decreases the objective restoration quality measures. Therefore in the analysis of the results we also present the filter performance in the first iteration (INORA₁).

Table I presents a comparative analysis of the new filtering design against a selection of filters designed for color image noise reduction, assessed through performance metrics PSNR and Impulse Removal Index (IRI) [15] on test images depicted in Fig. 6. The chosen filters for comparison are: Robust Mean

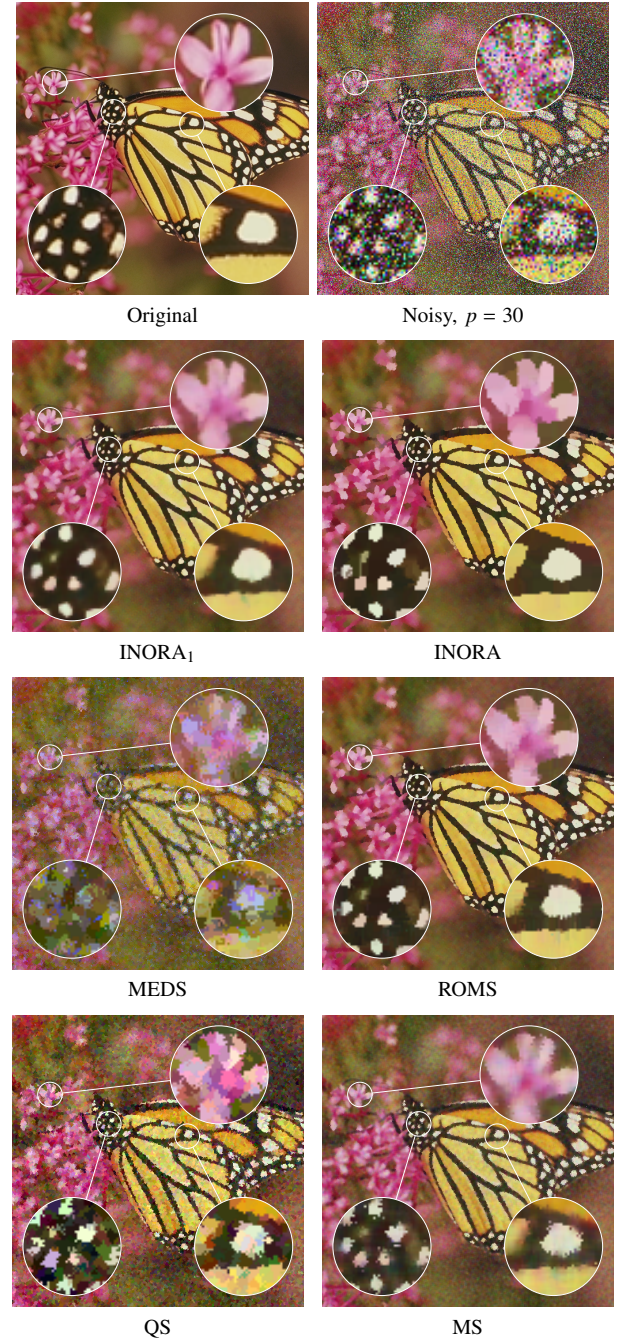


Fig. 9: Filtering results obtained when using image MONARCH contaminated with mixed noise of $p = 30$.

Shift Filter, (ROMS) [10], Mean Shift Filter, (MS) [11], Quick Shift Filter, (QS) [12], Medoid Shift Filter, (MEDS) [13], Bilateral Filter, (BF) [3], Non-Local Means Filter, (NLM) [4], Vector Median Filter, (VMF) [16], Block-Matching and 3D filtering, (BM3D) [5], Patch-based Approach to Remove Impulse-Gaussian Noise, (PARIGI) [17].

The proposed INORA demonstrates satisfying performance compared to competing filters. This is further confirmed through visual analysis of the restored images showcased in Fig. 9. The INORA preserves details, maintains smoothness

TABLE I: Comparison of filters in terms of PSNR and IRI.

p	INORA ₁	INORA	ROMS	MS	QS	MEDS	BF	NLM	VMF	BM3D	PARIGI
PSNR											
WINDOW											
10	31.8	31.1	30.5	29.9	25.4	28.9	28.4	27.7	29.3	28.6	29.7
20	29.5	28.8	28.3	27.0	22.7	25.2	25.2	24.3	25.4	25.4	25.1
30	27.2	26.5	26.3	25.3	20.6	22.9	22.6	22.0	22.7	22.7	22.6
BALLOONS											
10	32.7	31.8	31.2	29.7	26.6	23.9	27.7	27.4	30.0	26.8	28.3
20	30.4	29.3	28.9	27.1	23.6	20.2	23.5	23.0	26.0	22.3	25.5
30	27.9	27.1	26.7	24.9	21.5	17.7	20.3	19.9	22.8	19.3	23.1
MONARCH											
10	30.4	29.4	28.7	28.4	23.3	28.0	27.3	27.0	28.1	27.1	28.2
20	28.2	27.4	26.7	25.1	21.1	24.1	23.6	23.4	23.9	23.4	23.2
30	26.1	25.3	24.8	23.4	19.1	21.9	20.9	20.6	21.4	20.6	20.2
PEPPERS											
10	34.0	33.1	32.7	30.7	26.5	29.5	28.9	27.8	30.6	27.8	29.3
20	31.3	30.3	30.0	28.2	23.5	26.3	24.5	23.7	26.6	23.6	25.5
30	28.8	28.0	27.4	25.8	20.9	23.6	21.3	20.7	23.4	20.5	23.2
CAPS											
10	32.9	32.3	31.7	30.6	28.0	30.0	29.4	29.2	30.1	29.0	29.8
20	31.2	30.1	30.1	28.8	25.2	27.6	25.9	25.6	27.3	25.1	25.5
30	29.4	28.7	28.5	27.5	23.1	25.6	23.0	22.6	24.9	22.2	23.8
IRI											
WINDOW											
10	31.4	30.8	30.1	28.0	23.7	26.9	26.6	25.8	27.5	27.2	26.0
20	28.4	27.6	27.4	25.6	19.9	23.0	22.8	22.0	23.3	23.2	21.3
30	25.6	25.0	24.7	23.2	17.5	20.3	19.9	19.2	20.3	20.1	19.2
BALLOONS											
10	31.4	30.6	29.8	27.5	24.4	20.2	24.8	24.2	28.1	23.5	24.2
20	28.4	27.4	27.1	24.4	20.5	16.3	19.8	19.2	23.4	18.4	21.7
30	25.7	24.9	24.5	21.9	18.0	13.5	16.2	15.8	19.4	15.1	19.6
MONARCH											
10	29.8	29.2	28.5	26.5	22.0	26.2	25.4	24.6	26.6	24.8	25.0
20	27.3	26.5	26.0	23.7	18.7	22.1	20.9	20.5	22.3	20.4	20.2
30	25.0	24.2	23.6	21.3	16.0	19.1	17.7	17.3	18.8	17.2	17.3
PEPPERS											
10	32.9	32.1	31.5	29.2	24.3	27.5	26.3	25.2	29.1	25.0	25.6
20	29.6	28.5	28.3	25.8	20.4	23.7	21.1	20.3	24.3	20.1	21.9
30	26.8	25.8	25.3	23.1	17.4	20.6	17.5	16.9	20.3	16.6	19.8
CAPS											
10	33.4	32.7	32.4	30.4	26.3	29.5	28.2	27.7	29.5	27.2	26.0
20	31.0	29.3	30.0	28.0	22.5	25.8	23.2	22.8	25.8	22.0	21.8
30	28.4	27.8	27.3	25.8	19.9	23.0	19.4	19.1	22.2	18.5	20.2

in homogeneous regions, and ensures sharp, well-preserved edges, distinguishing itself from competitive filters that may distort edges or introduce undesirable artifacts.

In conclusion, this paper introduces an innovative approach to address mixed impulsive and Gaussian noise reduction in color images. Extending the Robust Mean-Shift technique, (ROMS) [10], our novel denoising scheme demonstrates robustness against impulsive noise. The key improvement lies in a refined measure of pixel similarity within the processing block, incorporating a weighted average based on pixel impulsiveness. This ensures reliable similarity evaluation even for heavily corrupted pixels in the block center.

Furthermore, to mitigate the impact of outliers, the impulsiveness of pixels plays a crucial role in the proposed Mean-Shift algorithm, influencing the weighted average calculation. The iterative nature of the impulsive noise resilient Mean-Shift

procedure effectively adapts to varying noise levels, producing denoised images with sharpened edges and preserved details. Our proposed technique excels in handling heavily corrupted images, outperforming existing methods in terms of effectiveness. Beyond noise reduction, the algorithm's edge-enhancing properties position it as an effective preprocessing step for image segmentation and object detection.

Future work will be focused on the adoption of the NLM technique in the construction of the pixel-to-patch measure of similarity, which should further increase the robustness to noise and ability to preserve image details. Additionally, we will conduct experiments on higher-resolution images to integrate the proposed denoising scheme into the image processing pipeline of mobile devices.

The source code of the proposed filter is available at <https://github.com/dkusnik/INORA>.

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