A Global-Local Noise Removal Approach to Remove High Density Impulse Noise

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Abstract

Impulse noise removal from images is one of the most important concerns in digital image processing. Noise must be removed in a way that the main and important information of image is kept. Traditionally, the median filter has been the best way to deal with impulse noise; however, the image quality obtained in high noise density is not desirable. The aim of this paper is to propose an algorithm in order to improve the performance of adaptive median filter to remove high density impulse noise from digital images. The proposed method consists of two main stages of noise detection and noise removal. In the first stage, noise detection includes two global and local phases and in the second stage, noise removal is also done based on a two-phase algorithm. Global noise detection is done by a pixel classification approach in each block of the image and local noise detection is performed by automatically determining two threshold values in each block. In the noise removal stage only noise pixels detected from the first stage of the algorithm are processed by estimating noise density and applying adaptive median filter on noise-free pixels in the neighborhood. Comparing experimental results obtained on standard images with other proposed methods proves the success of the proposed algorithm.

Keywords: Impulse Noise; Noise Detection; Noise Removal; Adaptive Median Filter.

1. Introduction

Digital images are normally corrupted by many types of noise, including impulse noise. Impulse noise, even with a low noise percentage, can change the appearance of the image significantly. This is because, the impulse noise, normally has a very high contrast to its surroundings. Malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission of the image in a noisy channel, are some of the common causes for impulse noise in digital images. The amplitude of the corruption is relatively very large compared with the strength of the original signal. As a consequence, when the signal is quantized into L intensity levels, the corrupted pixels are generally digitized into either two extreme values, which are the minimum or maximum values in the dynamic range (i.e. 0 or L-1). For this reason, impulse noise normally appears as white or black dots in the image, thus also referred as salt-and-pepper noise [1]. Median filtering, because of its nonlinear behavior, is suitable to remove the impulse noise in image. This is because of their simplicity and capability to preserve edges. The filter mechanism is to replace each pixel value with the median of neighboring pixel values in the window. Standard median filtering is a good choice to achieve reasonable results, but, the problem arises when the ratio of the noise is higher than 50%, in which there is a good chance that median is a corrupted pixel rather than a clean one [2]. Many variations of median filter have been proposed. In the adaptive median filter, window size will change according to the noise level [3]. At higher noise densities a larger window size is used and at lower noise densities a smaller window size is used. This method is very time-consuming due to increasing the window size and has poor results in high density noises because it replaces a pixel with another pixel which is in a far distance from it and so less correlation with it [4]. Replacing a far pixel with a noisy one mainly results in edge loss and blurring [2]. Weighted median (WM) filter selectively give some weights to pixels in the filtering window usually with the central pixel contributing the most [5]. Although the detail-preserving abilities of WM filters are better than median filters, their noise removing abilities are not as effective [6]. Topological median filter (TMF) operates based on a computed connectivity map and therefore is relatively unaffected by disconnected features in the neighborhood of the center pixel [7]. TMF and WM result in better preserving of edges and details, however, the resulting image quality is not desirable since uncorrupted or noise free pixels are also processed and it causes loss of great details from image, such as thin lines. Most of the past median filters were designed on the basis of detection of noise pixels before image filtering, also known as decision

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based or switching algorithms. Impulse detector of [6] is based on absolute difference of pixel value and median or weighted median value in a neighborhood of pixel. A progressive switching median filter, where impulse detector is applied progressively in iterative manner, has been proposed in [8]. Impulse noise detection technique of [9] is based on the minimum absolute value of four convolutions obtained using one-dimensional Laplacian operators. In [10] noise detection is performed at two stages: noise candidates are first selected using the homogeneity level, and then a refining process follows to eliminate false detections. The algorithm of [11] is based on a fuzzy impulse detection technique. In [12] a global-local noise detector is proposed and removing noise is performed based on adaptive median filtering. In [1] based on only the intensity values, the pixels are roughly divided into two classes, which are “noise-free pixel” and “noise pixel”. Then, adaptively changes the size of the median filter based on the number of the “noise-free pixels” in the neighborhood. For the filtering, only “noise-free pixels” are considered for the finding of the median value. In [13] in the first stage, the positions of noise pixels are detected by thresholding the absolute difference between the noisy image and its sparse representation. In the next stage, the pixels that are detected as noisy ones are replaced using image in-painting through sparse representation. In [14] a new impulse detection algorithm based on combination of Luo-statistic and k-means clustering has been presented. In [15] the difference between the central pixel and its neighbors aligned in four directions in a local window is used to detect noise. Then the noisy pixel is replaced by a histogram weighted mean filtering value. In [16] the concept of two threshold values for detection of impulse noise is introduced. Proposed method in [17] employs an artificial neural network to decide whether a pixel is corrupted or not. In [19] the proposed technique consists of two stages: noisy pixel identification and restoration. In the first stage absolute directional difference of the neighborhood pixels is used to identify the noise pixels. In the second stage an edge preserving contextual model based on a Gaussian kernel is proposed to restore these pixels. In [20] a combination of adaptive vector median filter (VMF) and weighted mean filter is proposed for removal of high-density impulse noise from color images. In the proposed filtering scheme, the noisy and non-noisy pixels are classified based on the non-causal linear prediction error. For a noisy pixel, the adaptive VMF is processed over the pixel. Whereas, a non-noisy pixel is substituted with the weighted mean of the good pixels of the processing window.

In this paper, it has been attempted to achieve more desirable results by presenting an algorithm to detect and remove noise. The proposed method combines the advantages of the methods in [1] and [12] in order to achieve better results in terms of visual quality.

Rest of the paper is organized as follows. In section 2 the proposed algorithm including noise detection and noise removal stages is discussed. Section 3 reports the experimental results of proposed algorithm, and the paper ends with concluding remarks in Section 4.

2. Proposed algorithm

Noise detection and noise removal are the main steps to eliminate noise from natural digital images which in this paper each one contains multi implementation levels. The figure below shows a block diagram of the proposed algorithm.

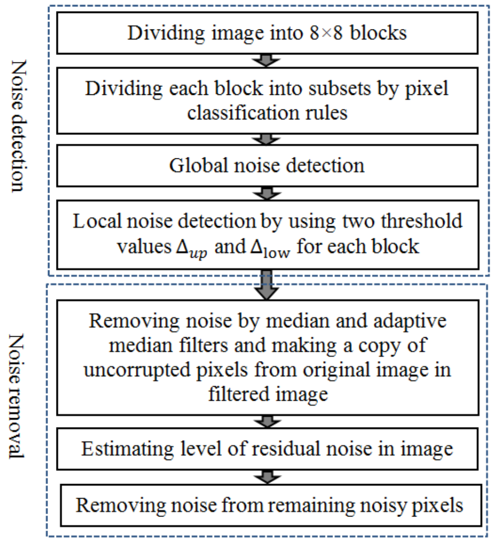

Fig.1. Block diagram of the proposed algorithm

We will explain more about different parts of the block diagram in the rest of the paper.

2.1 Global - Local Noise Detection

Noise detection process is a combination of global and local noise detectors [12]. For this process, the noisy image is divided into M×M blocks which are neighbors together but not overlapping each other, while uncorrupted pixels in each block should be homogeneous. According to [18] if the block size is chosen 8×8, uncorrupted pixels in each block can be assumed homogeneous. Also, it is assumed that the maximum and minimum values in the dynamic range represent the impulse noise.

2.1.1 Pixel Classification in Each Block

After that the image was divided into 8×8 blocks, assume that $Q_{8\times8} = \{p_{1,1}, p_{1,2}, \dots, p_{1,8}, \dots, p_{8,1}, \dots, p_{8,8}\}$ shows a set of all pixels in a 8×8 block. $p_{i,j}$ represents the pixel in row i and column j of this block. $q_1, q_2, \dots, q_{64}$ are the pixel intensity values of the $Q_{8\times8}$ set in ascending order. $q_1, \dots q_i, q_{64}$ will be classified as follow [12]:

If $\varphi_1, \dots, \varphi_l$ are subsets of $Q_{8\times8}$ and include $q_1, \dots q_i, q_{i+1}$ where: $\varphi_l = \{q_j, \dots, q_i, q_{i+1}\}$ and $1 \le l, 1 \le j \le i+1$. and if φ_{l+1} is an empty set and $q_{i+2}, q_{i+3}, \dots q_{64}$ are not classified, three rules of pixel classification for classification of q_{i+2} are as follow:

1. If $\frac{q_{i+2}-q_{i+1}}{q_{i+3}-q_{i+2}} \le 2$, q_{i+2} belongs to φ_l, otherwise q_{i+2} is added to φ_{l+1} subset, note that if $q_{i+2} - q_{i+1} = q_{i+3} - q_{i+2} = 0$, let $\frac{q_{i+2} - q_{i+1}}{q_{i+3} - q_{i+2}} = 1$.

2. If $\frac{q_{i+2} - q_{i+1}}{q_{i+3} - q_{i+2}} < \frac{1}{2}$, $q_{i+3} \in \varphi_{l+1}$.
3. If $\varphi_{l+1} = \{q_{i+2}\}$ or $\{q_{i+3}\}$, a new empty subset φ_{l+2} is initialized and pixel classification for φ_l is finished.

Based on these three rules, $q_1, \ldots q_{64}$ will be classified. Finally, $Q_{8\times8}$ set is divided into L subsets, so that $Q_{8\times8} = \bigcup_{l=1}^{L} \varphi_l$.

Since with the selection of 8×8 block size, free-noise or uncorrupted pixels can be assumed homogeneous in all block, the difference between these pixels are too small and noisy pixel values are significantly different from noise-free pixel values. So the noise-free and noise pixels are two obviously different types of pixels. Thus, in general, each subset of $Q_{8\times8}$ could only include one type of pixels: noise-free or noisy ones.

2.1.2 Global Noise Detection

Before the noise pixels are identified, we give a definition of the degree of similarity between two subsets. Let $\tilde{Q}$8×8 and $\bar{Q}$8×8 be any two 8×8 blocks of a noisy image. Let $\gamma(\tilde{\varphi}l, \bar{\varphi}m)$ denote the degree of similarity, where $\tilde{\varphi}$l and $\bar{\varphi}$m are any two classified subsets of $\tilde{Q}_{8\times8}$ and $\bar{Q}$ 8×8, respectively. Let $\tilde{\varphi}_l = \{\tilde{q}_{l,1}, \tilde{q}_{l,2}, \ldots, \tilde{q}_{l,k}\}$ and $\bar{\varphi}_l = \{\bar{q}_{m,1}, \bar{q}_{m,2}, \ldots, \bar{q}_{m,n}\}$, where $\tilde{q}_{l,1} \leq \tilde{q}_{l,2} \leq \cdots \leq \tilde{q}_{l,k}$ and $\bar{q}_{m,1} \leq \bar{q}_{m,2} \leq \cdots \leq \bar{q}_{m,n}$. For $\gamma(\tilde{\varphi}l, \bar{\varphi}m)$, two cases are listed as follows:

1. If $\tilde{q}_{l,1} \leq \bar{q}_{m,1} \leq \bar{q}_{m,n} \leq \tilde{q}_{l,k}$, let

$\lambda_{h_1,h_2} = \sqrt{\frac{1}{n_\lambda}\sum_{i=1}^{n_\lambda}\left(\bar{q}_{m,h_1+i} - \tilde{q}_{l,h_2+i}\right)^2}$ and

$\mu_{h_1,h_2} = \min\left(\left|\frac{\bar{q}_{m,h_1+n_\lambda} - \bar{q}_{m,h_1+1}}{2(n_\lambda - 1)}\right|, \left|\frac{\tilde{q}_{1,h_2+n_\lambda} - \tilde{q}_{l,h_2+1}}{2(n_\lambda - 1)}\right|\right)$,

where:

$n_\lambda = \min(n, k)$, $0 \leq h_1 \leq n - n_\lambda$, and $0 \leq h_2 \leq k - n_\lambda$. Then

$\gamma(\tilde{\varphi}l, \bar{\varphi}m) = 1 - \min_{h1,h2}\left(\frac{\lambda_{h_1,h_2}}{\mu_{h_1,h_2}}\right)$,

if $\lambda_{h_1,h_2} = 0$ and $\mu_{h_1,h_2} = 0$, let $\left(\frac{\lambda_{h_1,h_2}}{\mu_{h_1,h_2}}\right) = 0$.

2. If $\tilde{q}_{l,1} \leq \bar{q}_{m,1} \leq \tilde{q}_{l,k} \leq \bar{q}_{m,n}$, suppose:

$\hat{\tilde{\varphi}}_l = \{\tilde{q}_{l,j-1}, \tilde{q}_{l,j}, \ldots, \tilde{q}_{l,k} \in \tilde{\varphi}_l | \tilde{q}_{l,j-1} \leq \bar{q}_{m,1} \leq \tilde{q}_{l,j}\}$

And $\hat{\bar{\varphi}}_m = \{\bar{q}_{m,i} \in \bar{\varphi} | \bar{q}_{m,i} \leq \tilde{q}_{l,k}\}$, where: $1 \leq i \leq n$ and $1 \leq j \leq k$.

Let $\eta(\varphi)$ denote the number of elements in set φ.

If $\max\left(\frac{\eta(\hat{\tilde{\varphi}}_l)}{\eta(\tilde{\varphi}l)}, \frac{\eta(\hat{\bar{\varphi}}_m)}{\eta(\bar{\varphi}m)}\right) < \frac{2}{3}$, $\gamma(\tilde{\varphi}l, \bar{\varphi}m) = 0$,

Otherwise: $\gamma(\tilde{\varphi}l, \bar{\varphi}m) = \gamma(\hat{\tilde{\varphi}}l, \hat{\bar{\varphi}}m)$. Then, according to the first case, $\gamma(\hat{\tilde{\varphi}}l, \hat{\bar{\varphi}}m)$ is educed.

According to the two cases, we consider $\tilde{\varphi}$l is similar to $\bar{\varphi}$m if $\gamma(\tilde{\varphi}l, \bar{\varphi}m) \geq \frac{1}{2}$ otherwise not similar.

If there exists a certain kind of subsets in 95% or more of 8×8 blocks of a noisy image and these subsets are similar to each other, all elements of these subsets are regarded as corrupted pixels. Other noise pixels will be identified in next section.

2.1.3 Local Noise Detection

After the global noise detection, there are corrupted pixels that have not been identified. These corrupted pixels are as the remaining noise pixels among the uncorrupted one. Therefore, the local noise detection phase is used as follows.

An estimate of the original image from the noisy image is obtained by an adaptive median filter. The number of noise-free pixels in the filtering window for each pixel must be at least three. If the number is less than three, the window width should be increased by one pixel in each of the four sides and it repeats until the number reaches to three. P_{nos} and P_{med} denotes two pixel matrices of a noisy image and the estimated image respectively and $\Delta P = P_{med} - P_{nos}$ represents difference between these two images.

If ΔP_{sub} is an 8×8 matrix of ΔP and $\Delta P_{sub}(x, y)$ is an element of ΔP_{sub}, the threshold values can be defined as follows:

$$\Delta_{up} = \sqrt{\frac{1}{n_{sub}}\sum_{i=1}^{n_{sub}}(\Delta P_{sub}(x_i, y_i))^2}, \Delta P_{sub}(x_i, y_i) \geq 0 \quad (1)$$

$$\Delta_{low} = -\sqrt{\frac{1}{m_{sub}}\sum_{j=1}^{m_{sub}}(\Delta P_{sub}(x_j, y_j))^2}, \Delta P_{sub}(x_j, y_j) \leq 0 \quad (2)$$

Where n_{sub} represents elements number of $\{\Delta P_{sub}(x_i, y_i) | \Delta P_{sub}(x_i, y_i) \geq 0\}$ and m_{sub} represents elements number $\{\Delta P_{sub}(x_i, y_i) | \Delta P_{sub}(x_i, y_i) \leq 0\}$ .To detect noise pixels, the two proposed threshold values are used as follows:

If $\Delta P_{sub}(x, y) > \Delta_{up}$ and $\Delta P_{sub}(x, y) < \Delta_{low}$, pixel (x, y) is detected as a noise pixel.

2.2 Noise Removal

The phase of image filtering according to [1] is presented as follows:

In the first step, the initial filtering window size for each noisy pixel is selected 3×3. If the number of noise-free pixels in the filtering window is less than three, the window width should be increased by one pixel in each of the four sides and it repeats until the number reaches to three. In sequential iterations, each noisy pixel is replaced by the median of all pixels in the window. At the end of the first stage, noise pixels remaining in this step are replaced by median values resulting from applying a median filter with a 3×3 window width on the initial noisy image.

In the second step of image filtering noise mask Z(x,y) is defined in such a way that one and zero are applied to noise and noise-free pixels, respectively. Now, we can obtain the total number of residual noise pixels:

$$T = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} Z(x, y) \quad (3)$$

By achieving this value, an accurate estimate of impulse noise level in the image can be obtained. So the ratio of noise pixels to total pixels of the image, which is a value between zero and one, is calculated from the following equation:

$$\partial = T/MN \quad (4)$$

By applying a filter on the input image I, the filtered image g is achieved.

$$g(x,y) = [1 - Z(x,y)]I(x,y) + Z(x,y)m(x,y) \qquad (5)$$

Where Z is noise mask introduced in the previous stage and m is the median value obtained by the adaptive method for noise pixel. According to the algorithm presented in [1], to find m, for each pixel location (x,y) where Z(x,y) is equal to one, the following steps are performed.

- initializing the window width (W):

$$W = 2Rmin + 1,\ R_{\min} = \frac{1}{2}\left[\sqrt{\frac{7}{1-\partial}}\right] \qquad (6)$$

Computing the number of noise-free pixels located in the mask

- If the number of noise-free pixels in the window is less than 8, the window size is increased by 2 and return to previous step.
- Calculation of the m(x,y) value based on the noise-free pixels in the window.
- Computing the $g(x,y)$ based on Eq. 5.

After applying this algorithm finally, at the end of the second stage, the residual noise pixels is replaced by median values using a median filter, once with 5×5 and once with 7×7 window width, on initial noisy image.

3. Experimental Results

In this paper the size of the evaluated images is 512×512 and their intensity is 8 bit in gray scale. The results presented here indicate that the new filter is able to remove impulse noise specially more effective in high noise density and further details of the original image is preserved. In contrast to other methods that require repeating the algorithm at least twice to get the desired result, in proposed method the algorithm is applied just once, to get the desired result. Some standard criteria to evaluate the system performance in this field are defined for an M×N image as follow:

$$PSNR = 20\log_{10}\left(\frac{MAX_O}{\sqrt{MSE}}\right) \qquad (7)$$

$$MSE = \frac{1}{M\times N}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}[O(i,j) - g(i,j)]^2 \qquad (8)$$

Where MAX_O represents the maximum value of the original signal. $O(i,j)$ And $g(i,j)$ indicate the original image pixels and the filtered image pixels respectively. Table (1) indicates the results of implementation of the proposed algorithm on standard images Elaine, Lena and Boat with different noise density. In Table 2 the success of the algorithm compared to standard median filter, TMF [7], improved switching median filter (ISM) [9] and global–local noise detection-based adaptive median filter (GLAM) method presented in [12], is shown. Also in Table 3 comparing the performance of the proposed method with the results of the methods proposed in [16], [17] and [19] on Lena image in two different %40 and %60 noise density corroborate that the proposed algorithm provides better performance than the existing state-of-art impulse de-noising methods. Figures 1, 2 and 3 show the noisy images and filtered images for different noise densities. By increasing the noise density in images, error reduction and thus the success of the proposed method is more visible.

Also, the result of the proposed method in [17] and the result of our proposed method on Boats image with noise density of %60 are shown in Figure 4.

Table 1. Results of proposed algorithm on standard images Elaine, Lena and Boat with different noise density

	Elaine		**Lena**		**Boat**	
Noise Density	**PSNR**	**MSE**	**PSNR**	**MSE**	**PSNR**	**MSE**
10%	47.70	1.10	45.39	1.87	43.81	2.70
20%	44.58	2.26	42.21	3.90	40.74	5.47
30%	42.56	3.60	40.32	6.03	38.97	8.23
40%	41.11	5.02	38.99	8.20	37.66	11.12
50%	40.01	6.48	37.94	10.44	36.55	14.38
60%	38.88	8.40	36.95	13.09	35.71	17.44
70%	37.83	10.70	36.03	16.21	34.80	21.52
80%	36.90	13.25	35.22	19.53	33.97	26.05
90%	35.20	19.62	33.94	26.33	32.94	33.03
95%	32.89	33.39	32.32	38.08	31.53	45.69

Table 2. Comparison between the proposed method and other methods on the Elaine image with noise density of 80%.

		MSE	**PSNR**
Standard Median filter	5×5	1415.5	16.62
	7×7	409.55	22.00
	9×9	240.33	24.32
TMF [7]		402.61	22.08
ISM [9]		231.54	24.48
H.IBRAHIM [1]		214.62	24.81
GLAM [12]		59.68	30.37
OUR METHOD		13.25	36.90

Table 3. Comparison between the proposed method and other methods on the Lena image

Noise Density	**[16]**	**[17]**	**[19]**	**Proposed method**
%40	31.45	31.79	34.91	38.99
%60	27.02	28.80	31.81	36.95

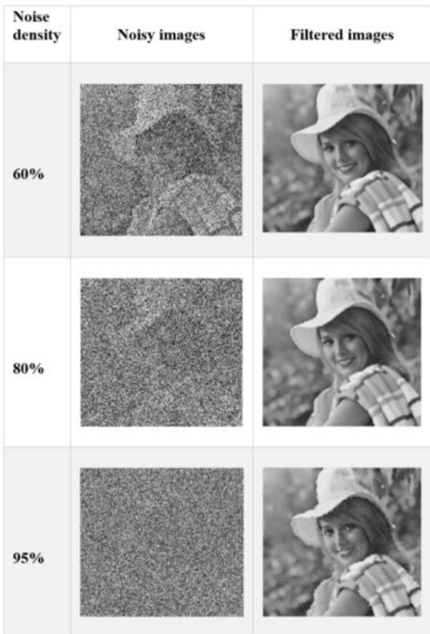

Fig. 2. Results of proposed algorithm on corrupted images of Elaine

Fig. 3. Results of proposed algorithm on corrupted images of Lena

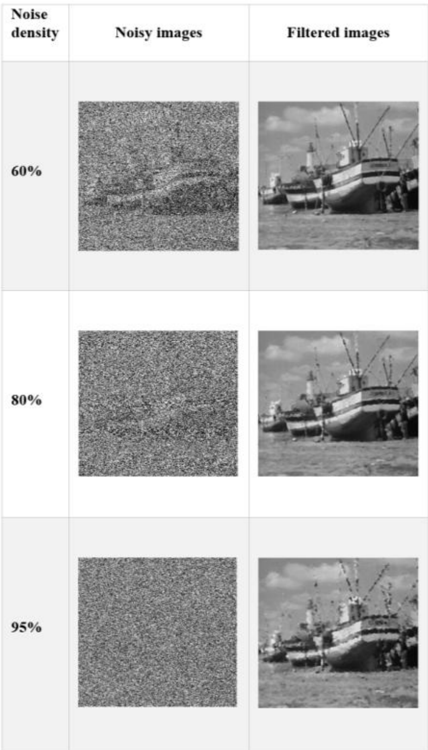

Fig. 4. Results of proposed algorithm on corrupted images of Boat

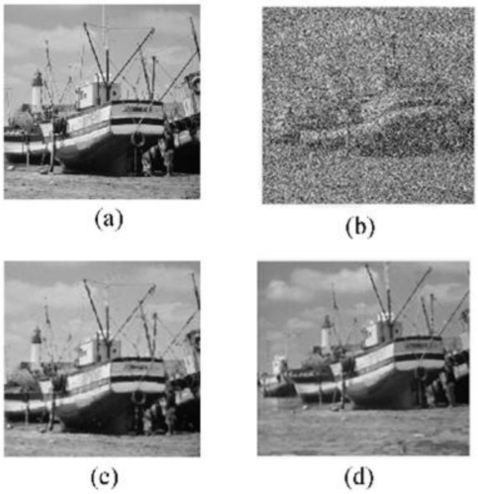

Fig. 5. comparing results on Boats image, (a) original image, (b) 60%noisy image, (c) result of [17], (d) result of proposed method

4. Conclusion

In this paper, a new algorithm for impulse noise removal from digital images is proposed. The algorithm uses a logical combination of previous proposed global-local noise detectors and adaptive median filters to achieve better results. The implementation results on different standard images show the success of proposed algorithm in comparison to other proposed methods.

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