A Rapid Weighted Median Filter based on Saliency Region for Underwater Image Denoising

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***Abstract*—In this paper, a novel weighted median filter model has been put forward with saliency detection for underwater image denoising. Saliency detection is first taken to only optionally highlight and prominent the salient region in the underwater images. One weighted median filter is further proposed to greatly accelerate the image denoising speed. It has been shown in our simulation experiments that the proposed method not only can provide better performance of suppressing noises and preserving the detailed features in underwater images, but also the running time can be largely shortened.**

Keywords—underwater imaging; denoising; real-time; weighted median filter;

I. INTRODUCTION

The underwater imaging is essentially characterized by its poor visibility because light is exponentially attenuated when travelling in the sea and the underwater scenes tend to be poorly contrasted and hazy. In the ocean investigations, especially those deployed by the remotely operated vehicles (ROVs) and the autonomous underwater vehicles (AUVs), underwater image denoising is hereby one of the most essential and fundamental tasks for the underwater image analysis and understanding the global view of the observations in the sea[1].

In the literature, a variety of image denoising approaches have been developed in the past decades, including the Fourier filter [2], wavelet filter [3], mean filter, wiener filter [4], and the median filter [5], etc. As median filter can reduce image noise and preserve edges, it has become one of the most prevailing approaches. However, in the underwater imaging system, poor visibility is a major limitation， and real-time underwater image processing has also comprehensively taken into consideration for image denoising. Huang [6] proposed a sliding window approach leveraging histograms to compute median in time, which is further accelerated to with the distributed histograms [7]. Constant time median algorithms [8, 9] were also proposed, focusing on reducing histogram update complexity. Kass and Solomon [10] introduced another constant time algorithm based on integral of smoothed local histograms. These proposed median filters uniformly replace the gray-level value of every pixel by the median of its neighbors. Consequently, some desirable details are also removed, especially when the window size is large. In order to improve the median filter, weighted median filter are proposed to effectively filter underwater images while not strongly blurring edges and preserve details. More importantly, it mathematically corresponds to global optimization [11], which produces results with fully explainable connections to global energy minimization. While the key factors in the weighted median filter, i.e., the spatially varying weight and the median properties, make it difficult to accelerate the whole process [12]. In this paper, a rapid weighted median filter based on saliency region has been put forward for the underwater image denoising.

II. GENERAL FRAMNEWORK

A brief flow chart of the underwater image denoising model is shown in Fig.1. Saliency detection is first taken to detect the salient region and prominent the underwater images.

After this, one weighted median filter that based on the saliency region has been proposed in this paper to greatly accelerate the image denoising speed for the underwater vehicles with the following steps:1 ） Decompose the underwater images into local image patches and construct the statistical joint-histogram representation for each image patch, 2) Take the median tracking strategy dynamically by balancing the counting box with respect to the joint-histogram in the neighborhood, 3) Leverage the sparsity of the joint-histogram to get the instant cyclic access to the median tracking for underwater image denoising. It removes noise in the salient region by a rapid weighted median filter so as to ensure the accuracy and stability of the underwater image denoising.

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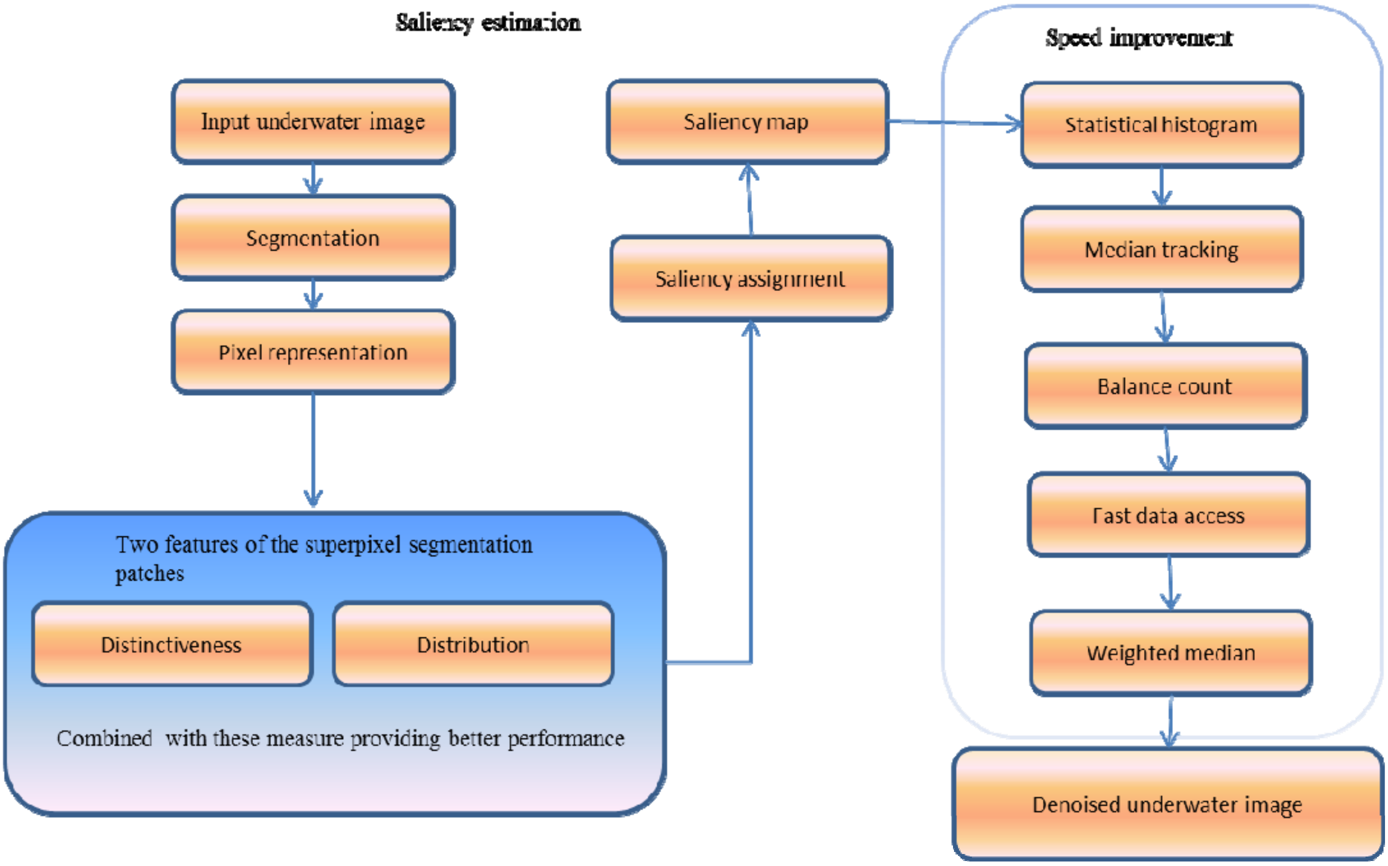


Figure1. the brief flow chart of the rapid median filter model

III. DETECTION OF SALIENT REGION

In this paper we first detect the saliency region of the underwater image. Our algorithm consists of three basic steps.

*A. **Segmentation***

To find the desired target in an given input underwater image $I(x,y)$ with the size $m \times n$, we first decompose it into basic patches that abstracting unnecessary details using SLIC segment toolbox,

$$I(x,y) = \{I_0, I_1, ..., I_i\} \tag{1}$$

where I_i represented the i th patches. Specifically, each decomposed underwater image patch should locally abstract the image by clustering pixels with similar properties (like color) into perceptually homogeneous regions.

*B. **Saliency measure***

Based on this abstraction we then compute the distinctiveness D and the spatial distribution S of these underwater image patches. We first implements the commonly employed assumption that underwater image regions, which stand out from other regions in certain aspects, catch our attention and hence should be labeled more salient. While saliency implies distinctiveness, the opposite might not always be true [13]. Ideally colors belonging to the background will be distributed over the entire underwater image. Then we compute a saliency value V for each patch:

$$V = D \bullet \exp(-k \bullet S),\ k \text{ is a constant.} \tag{2}$$

*C. **Salient value assignment***

Finally, we assign the actual saliency values to the input underwater image to predict patches of interest in underwater image. Then it produces a pixel-accurate saliency map which uniformly covers the objects of interest and consistently separates fore-and background. The saliency maps of the underwater images are shown in experiment section.

IV. A RAPID WEIGHTED MEDIAN FILTER

The weighted median filter (WMF) can replace the current pixel with the weighted median of neighboring pixels within a local window. Formally, in processing pixel p in underwater image I , we consider only pixels within the local window $r(p)$ of radius r centered at p . Different from conventional unweighted median filter, for each pixel $q \in r(p)$, WMF associates it with a weight ω_{pq} based on the affinity of pixel p and q in corresponding feature map f , i.e.,

$$\omega_{pq} = g(f(p), f(q)) \tag{3}$$

where $f(p)$ and $f(q)$ are features at pixels p and q in f, which can be intensity, color, or even high-level features depending on problem definition. g is a typical influence function between neighboring pixels, which can be in Gaussian or other forms. Specifically, each pixel p in the filter is associated with its value $v(p)$ and feature $f(p)$.

A. *Statistical joint-histogram representation*

As mentioned, it is not suitable to use conventional histograms to store weights in the WMF system. In this section, our new constructed statistical joint-histogram H for each local image patch is a two-dimensional count-based histogram which is indexed by pixels values v and features f respectively. Suppose there are n different pixels values, we denote the pixel value index $v=\{v_0, v_1, ..., v_{n-1}\}$ after listing all possible pixel values in an ascending order. Also we denote the total number of different features as m. A feature index f for $f(p)$ can be accordingly resulted in after ordering all features as $f=\{f_0, f_1, ..., f_{m-1}\}$.

In statistical joint-histogram H, pixel p is put into the histogram bin $H(v,f)$ in the f -th row and v -th column. Thus, the whole joint-histogram is constructed as

$$H(v,f)=\sum_{q\in r(p)}\{if((q)=v_v, f(q)=f_f), H_q=1\} \quad (4)$$

where $H(v,f)$ counts the number of pixels with similar features and $q\in r(p)$.

B. *Median tracking strategy*

As one pixel in the underwater image has a very large chance to be similar to some of its neighbors, the median tracking strategy could reduce computation to seek median in the joint-histogram.

Given the center point $c(p)$ and corresponding balance obtained by WMF on the window centered at p, we estimate the new weighted median in the adjacent window at $p+1$. Starting from $c(p)$, if it yields a positive balance in window, we shift the center point to the left by one pixel, i.e. $c(p)-1$. It repeats until the balance becomes negative. Then the point before the last one is set as $c(p+1)$ .Contrarily, if yields a negative balance initially, we right shift it until the balance turns positive. Formally, the balance cell $b(f)$ of the f - th row is constructed as

$$b(f)=\sum_{q\in r(p)}\{if(v(q)\le c, f(q)=f_f), b_q=1\} - \sum_{q\in r(p)}\{if(v(q)>c, f(q)=f_f), b_q=1\} \quad (5)$$

C. *Leverage the sparsity of the joint-histogram*

We also exploit the sparsity of data distributions for WMF in our new structures. We try to present a data structure to get the instant cyclic access to the median tracking for underwater image denoising. Each element can be accessed randomly by index. But when the goal is to traverse all non-empty elements, the new instant cyclic structure that pointing to previous and next non-empty elements can achieve sequential access. The new instant cyclic structure shows in Fig2 where color patches representing non-empty elements and others are empty elements.

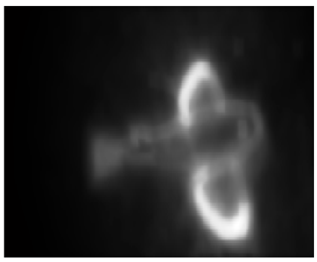
Figure2. Leverage the sparsity of the joint-histogram

V. SIMULATION EXPERIMENT

In our simulation experiments, underwater images were collected by a Myring streamline AUV system with CCD camera with the horizontal resolution 480 TVL/PH and the minimum scene illumination 0.28 lux on board for the underwater visual tasks.. At each observation site, the environmental variables, including the ambient water temperature, current speed at the mooring location, the depth and the direction, as well as the survey-design variables, such as the AUV cruising speed and direction, the navigation and positioning, the altitude above the sea floor, AUV distance from the bottom, were recorded simultaneously. All the simulation experiments have been run on Windows 7 with at least 8 GB of memory and 2 + GHz processor. The execution environment is under MATLAB 7.0.

Fig. 3 (a) and (e) are two examples of underwater images, (b) and (f) list the saliency map from Fig. 3 (a) and (e), Fig. 3 are the original underwater de-noising result, and Fig. 3 (c) and (g) are the Salient image denoising results by both the salient detection and the rapid WMF model together. Table1 lists the performance comparison with the novel rapid salient weighted median filter for underwater image denoising. It has been shown in our simulation experiments that the proposed method not only can provide better performance of suppressing noises and preserving the detailed features in underwater images, but also the running time can be largely shortened from several minutes to less than 1 second.

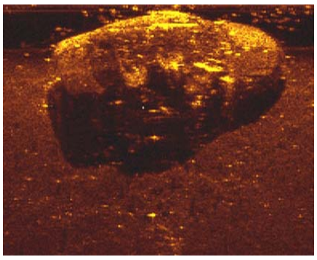
a)Original example image



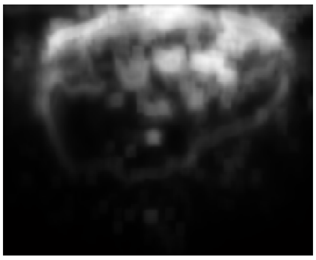
b)Saliency map

c)Salient image denoising

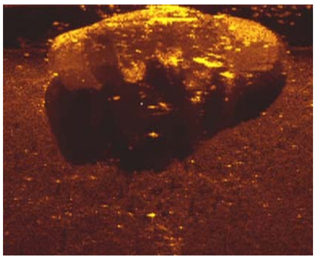
d)Orignal image denoising



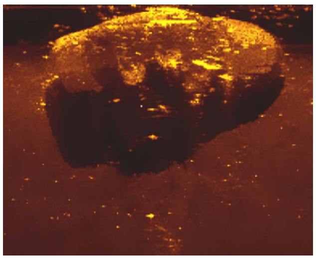
e)The original example image



f)Saliency map



g)Salient image denoising



h) Orignal image denoising

Figure 3 Underwater image denoising result

Table 1 The performance comparison of the weighted median filter

method	Our proposed filter			Weighted median filter		
	Time	Information entropy	SNR	Time	Information entropy	SNR
Sonar images	0.9736	4.9559	18.5668	90.70	4.9550	18.465
Optical images	1.5328	4.9559	18.5668	102.0	4.9550	18.465

VI. CONCLUSION

In this paper, due to the high demand on the real-time underwater image processing, especially for the remotely operated vehicles (ROVs) and the autonomous underwater vehicles (AUVs), one underwater image denoising model has been developed with the help of saliency detection and a rapid weighted median filter so as to pursue an extremely precise and efficient solution. The detection of the region which covers the object of interest has been first implemented by the saliency detection, with the advantages of improvements in result quality, uniformly covering the objects of interest and consistently separates foreground and background. After this, one weighted median filter that could optionally only highlight the saliency detection region has been proposed in this paper to greatly accelerate the image denoising speed for the underwater vehicles. It has been shown in our simulation experiments that the proposed method not only can provide better performance of suppressing noises and preserving the detailed features in underwater images, but also the running time can be largely shortened from several minutes to less than 1 second.

VII. ACKNOWLEDGMENT

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