A Shadow-Removal based Saliency Map for Point Feature Detection of Underwater Objects

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***Abstract*---The point feature detection is one of the most essential and fundamental tasks for underwater objects in ocean investigations. In this paper, a streamline AUV system that adopts the side scan sonar on board has been set up to explore our underwater visual tasks. Before attempting to detect the point features, the raw underwater sonar images must be preprocessed by shadow removal. The saliency map will be further explored with the contrast determination filter at various scales and then the point feature detection model can be completed on the basis of the saliency map. It is shown from the simulation experiments that the proposed model could achieve great performances in the point feature detection with both robustness and effectiveness.**

Keywords---Underwater sonar images; Point feature detection; Shadow removal; Saliency map; SURF

I. INTRODUCTION

In ocean investigations, the reliable feature detection is one of the most essential and fundamental tasks for underwater objects. There has already been more and more concern on the precise detection of the point features, line features, circle features, etc, in the complex underwater environment [1, 2]. Among them, the point features are widely and commonly exist in both structured and unstructured underwater objects [3].

A variety of point feature detection researches in the literature have been developed in the past decades, including the Harris corner detector, Smallest Univalue Segment Assimilating Nucleus (SUSAN) algorithm, Scale-Invariant Feature Transform (SIFT) algorithm and Speeded Up Robust Features (SURF) algorithm, etc.. Harris corner detector proposed in 1988 has been widely used, while it is not scale-invariant [4]. Smallest Univalue Segment Assimilating Nucleus (SUSAN) is an approach to low level image processing, which has been traditonally used for object recognition [6, 7]. Lowe introduced the SIFT algorithm in 1999. This allows to detect scale-invariant point features [8]. SURF is a scale and rotation invariant detector and descriptor presented by Bay et al. As it outperforms existing methods with respect to repeatability, distinctiveness, and robustness, yet be computed and compared much faster, it has become one of the most prevailing approaches. However, in practice, the stability of the point feature detection in the sea is not always accurate and maintained due to the poor visibility of the underwater environment. Hereby, saliency map is then made full use of to undertake the underwater point feature detection.

In this paper, we try to explore a robust and stable point feature detection scheme with the help of saliency map for the underwater objects [5, 9, 13-19]. We make use of the SURF algorithm to perform the point feature extraction and the AC method created by Achanta et al in 2008 to identify the saliency of the underwater sonar image region. The paper is organized as follows: Section II describes the general framework of the point feature detection in our system. Section III introduces the underwater sonar images preprocessing, especially the shadow detection and removal [10-12]. Section IV is about generating the saliency map of the underwater sonar images and Section V describes the point feature extraction on the basis of saliency map. Section VI shows the simulation experiments. Finally, in Section VII conclusions are presented.

II. GENERAL FRAMEWORK

Here a brief flow chart of our proposed point feature detection framework is shown in Fig.1. A streamline AUV system is first set up with the side scan sonar on board for our underwater visual tasks, which emits the sound pulses by the transducer down toward the seafloor to fulfill the bathymetry and physiognomy detection. Since the side scan sonar could simultaneously introduce an accompanying acoustic shadow in the collected images during its exploration, we try to develop a shadow detection and removal strategy at first. After this, one high quality saliency map of the underwater

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sonar images will be generated by combining the individual salient regions at various scales with a center-surround contrast determination filter with respect to low-level features of luminance and color, and evaluated by a distance metric between the center and its surrounding regions in the underwater sonar images, via the approximation of the luminance and color-opponent dimensions in the Lab color space. On the basis of saliency map, SURF is at last taken to perform the point feature extraction by steps of the underwater sonar image integral acquirement, the point feature calculation with Hessian matrix, the scale space representation and the point feature localization. In our work, we concentrate only on the detected points and we discard the descriptors.

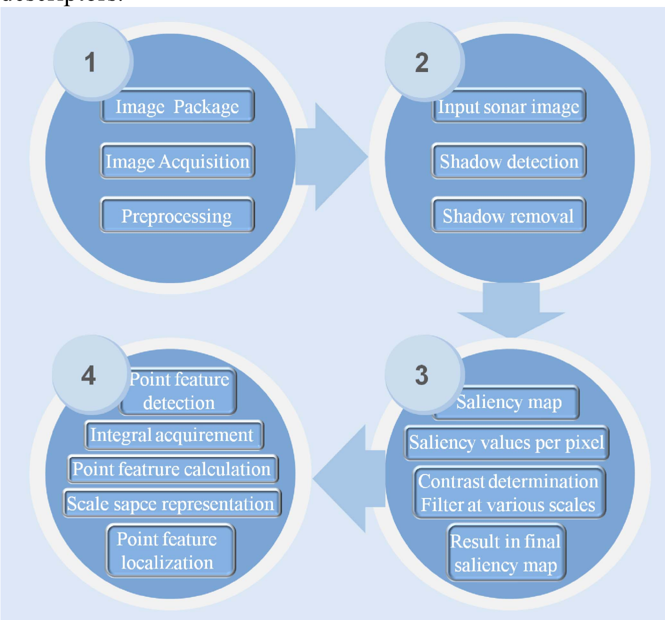

Fig. 1. The flow chart of the point feature detection in our proposed model

III. SHADOW DETECTION AND REMOVAL

Since the acoustic shadows in an underwater sonar image can cause point feature extraction algorithm to fail, we try to perform a shadow removal image at first. Acoustic shadows are formed behind the objects in the underwater environment because the sound waves travel generally along straight line over short distances. Therefore, the principles of acoustic shadow formation are essentially the same as in optics.

The prospective shadow region of the underwater sonar images could be defined from an occluding edge characterized by a sharp drop till a sign of the slope of the signal turns from negative to positive with a certain threshold. With the location of shadow region recorded the gradient of the shadow edge in the differentiated underwater sonar images are further set to zero so as to perform a reintegration process by formulating the shadow removal as a 2D Poisson equation and deliver the underwater images without shadows.

IV. SALIENCY MAP

In this work, we identify the saliency as the local contrast of an underwater sonar image with respect to its surroundings using the low-level features of luminance and color at various scales. At a given scale, the contrast based saliency value $s_{x,y}$ for a pixel at position (x, y) in the underwater sonar image is determined as the distance D between the average vectors of pixel features of the inner region R_1 and that of the outer region R_2 (Fig.2.) as:

$$s_{x,y} = D\left[\left(\frac{1}{N_1}\sum_{p=1}^{N_1}\vec{v}_p\right),\left(\frac{1}{N_2}\sum_{q=1}^{N_2}\vec{v}_q\right)\right] \tag{1}$$

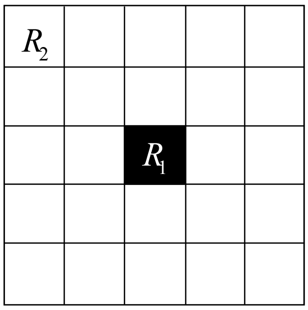

Fig. 2. Inner square region R_1 and outer region R_2

where $\vec{v}$ is the feature vector corresponding to a pixel and N_1 and N_2 are the number of pixels in R_1 and R_2 respectively. To generate the feature vectors for color and luminance, we make use of the CIELab color space [13] concentrated on the perceptual differences in it are approximately Euclidian, D in Equation 1 is:

$$s_{x,y} = \left\|\vec{v}_1 - \vec{v}_2\right\| \tag{2}$$

where $\vec{v}_1 = [L_1, a_1, b_1]^T$ and $\vec{v}_2 = [L_2, a_2, b_2]^T$ are the average feature vectors for regions R_1 and R_2 respectively.

At various scales, the change in scale is affected by scaling the region R_2 instead of scaling the image (Fig.3.). Region R_1 is usually chosen to be one pixel. For an image of width w pixels and height h pixels, the width of region R_2, namely w_{R_2} is varied as:

$$\frac{w}{8} \leq \left(w_{R_2}\right) \leq \frac{w}{2} \tag{3}$$

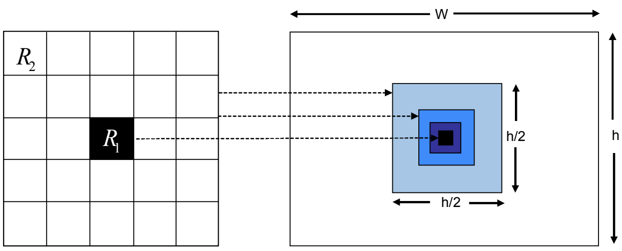

Fig. 3. The width of R_1 remains constant while that of R_2 ranges according to Equation 3 by halving it for each new scale.

assuming w to be smaller than h (else we choose h to decide the dimensions of R_2). This is based on the observation that the largest size of R_2 and the smaller ones (smaller than $\frac{w}{8}$) are of less use in finding salient regions.

The former might highlight non-salient regions as salient, while the latter are basically edge detectors. So for each image, filtering is performed at three different scales (according to Eq.3) and the final saliency map is determined as a sum of saliency values across the scales $\vec{S}$:

$$m_{x,y} = \sum_{\vec{S}} s_{x,y} \tag{4}$$

$\forall x \in [1,w], y \in [1,h]$ where $m_{x,y}$ is an element of the combined saliency map $\vec{M}$ obtained by point-wise summation of saliency values across the scales.

V. POINT FEATURE DETECTION

The SURF algorithm is further taken to search for the stable features from the underwater sonar images on the basic of saliency map. SURF approximates or even outperforms previously proposed schemes with respect to repeatability, distinctiveness, and robustness, yet can be computed and compared much faster.

A. Integral acquirement

SURF makes use of the underwater sonar integral image to reduce the computation time drastically. Rectangle features can be computed very rapidly using an intermediate representation for the underwater sonar image which we call the underwater sonar integral image. The underwater sonar integral image at location (x, y) contains the sum of the pixels above and to the left of (x, y) inclusive：

$$ii(x,y) = \sum_{x' \le x, y' \le y} i(x', y') \tag{5}$$

where $ii(x, y)$ is the underwater sonar integral image and $i(x, y)$ is the original saliency map image. Using the following pair of recurrences:

$$p(x,y) = p(x,y-1) + i(x,y) \tag{6}$$

$$ii(x,y) = ii(x-1,y) + p(x,y) \tag{7}$$

where $p(x, y)$ is the cumulative row sum, $p(x,-1) = 0$, $ii(-1, y) = 0$.

Once the underwater sonar integral image has been computed, it takes three additions to calculate the sum of the intensities over any upright, rectangle features (see Fig.4.). Hence, the calculation time is independent of its size as Eq.8.

$$\sum = ii(x_4, y_4) - ii(x_2, y_2) - ii(x_3, y_3) + ii(x_1, y_1) \tag{8}$$

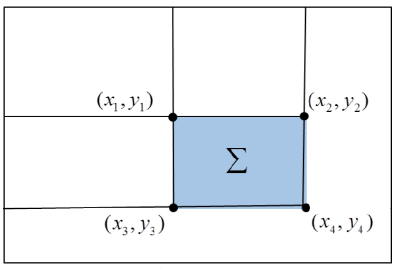

Fig. 4. Calculate the sum of intensities inside a rectangular region of any size.

B. Point feature calculation with Hessian matrix

The detector is based on the Hessian matrix, but uses a very basic approximation. More precisely, we detect blob-like structures at locations where the determinant is maximum. In contrast to the Hessian-Laplace detector by Mikolajczyk and Schmid [16], we rely on the determinant of the Hessian. Given a point $X = (x, y)$ in an underwater sonar image, the Hessian matrix $H(X, \sigma)$ in X at scale σ is defined as follows

$$H(X,\sigma) = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \tag{9}$$

where $L_{xx}(X,\sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the point X , and similarly for $L_{xy}(X,\sigma)$ and $L_{yy}(X,\sigma)$.

As Gaussian filters are non-ideal in any case, the approximation with box filters is pushed to take place of second-order Gaussian filter. These approximate second order Gaussian derivatives and can be evaluated at a very low computational cost using integral images. The calculation time therefore is independent of the filter size.

The approximation are denoted by D_{xx}, D_{xy}, and D_{yy}.

$$Det(H_{approx}) = D_{xx} D_{yy} - (0.9 D_{xy})^2 \tag{10}$$

C. Scale space representation

Interest points need to be found at different scales. Scale spaces are usually implemented as an image pyramid. Due to the use of box filters and underwater sonar integral images, we do not have to iteratively apply the same filter to the output of a previously filtered layer, but instead can apply box filters of any size at exactly the same speed directly on the original image and even in parallel. Therefore, the scale space is analyzed by up-scaling the filter size rather than iteratively reducing the image size.

D. Point feature localization

In order to localize interest points in the underwater sonar image and over scales, a non-maximum suppression in the neighbourhood is applied. Specifically, we use a fast variant introduced by Neubeck and Van Gool [17]. The maxima of the determinant of the Hessian matrix are then interpolated in scale and image space with the method proposed by Brown and Lowe [18].

VI. SIMULATION EXPERIMENT

In our simulation experiments, we set up a Myring streamline AUV system with one side scan sonar on broad to collect the benthic images for the underwater visual tasks, with the frequency band 100kHz-600kHz, the expd operating ranges (per side) 120m-500m, the pulse length 5ms-20ms, the across track resolution 1.4cm-6.3cm, the along track resolution 0.45m-1.9m per 100m, the horizontal beam width 0.26o-1.28o, the Vertical beam width 50°. All the simulation experiments were run on Windows 7 with at least 8 GB of memory and 2+GHz processor. The execution environment is under MATLAB 7.0. Fig.5. and Fig.6. are respectively one example image and its corresponding shadow removal image. Here the saliency map generation with and without shadow removal step for the example underwater sonar image are listed in Fig.7. in comparison. Fig.8. shows one point feature matching result between the original image as well as its saliency map with the shadow removal. We could see that the proposed approach remains the most characteristic point features and removes those redundant ones, and hereby undertakes a quite stable point feature extraction process. It has been shown from the simulation experiments that the proposed model could achieve great performances in the point feature detection with both robustness and effectiveness.

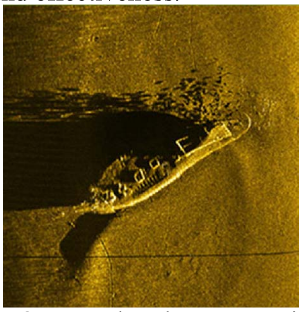

Fig. 5. One example underwater sonar image

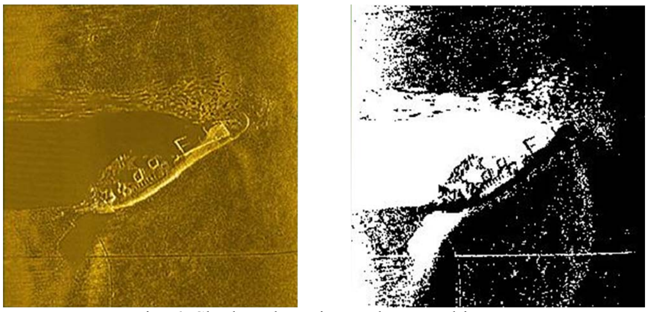

Fig. 6. Shadow detection and removal image

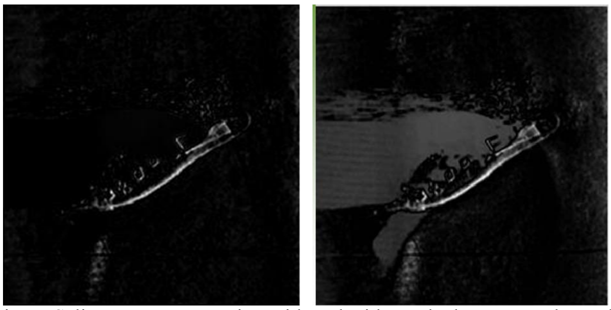

Fig. 7. Saliency map generation with and without shadow removal step for the example underwater sonar image

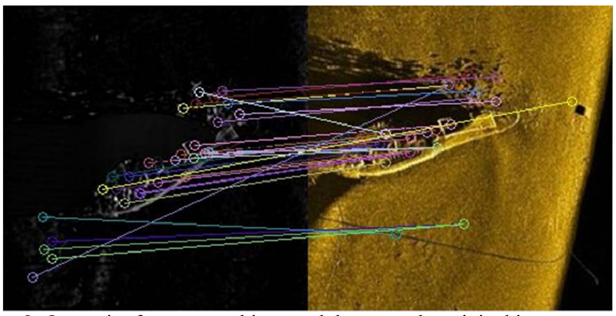

Fig. 8. One point feature matching result between the original image as well as its saliency map with the shadow removal

VII. CONCLUSIONS

In this paper, we have proposed one point feature detection scheme with the help of saliency map to purse a quite stable point feature extraction process with both robustness and effectiveness for the underwater objects. Acoustic shadows in a sonar image, poor visibility of the underwater environment and the variations in the illumination, viewpoints, etc., have been comprehensively taken into consideration. We tried to develop a shadow detection and removal strategy at first to reduce the influence of the shadows in an underwater sonar image. After this, one high quality saliency map of the same size and resolution as the input shadow-removal underwater sonar images has been generated using low-level features of luminance and color. At last, on the basis of saliency map, the point feature extraction has been implemented by the SURF algorithm by steps of the underwater sonar image integral acquirement, the point feature calculation with Hessian matrix, the scale space representation, the point feature localization and orientation assignment. Simulation experiments have shown that the proposed model remained the most characteristic point features and removed those redundant ones, and hereby undertook a quite stable point feature extraction process with both robustness and effectiveness.

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