International Journal of Engineering & Technology, 7 (3) (2018) 1751-1756

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET
doi: 10.14419/ijet.v7i3.13159
Research paper

A novel method to detect foreground region using morphological operations with block based enhancement for underwater images

M. Sudhakar [1] *, M. Janaki Meena [1]

[1] SCSE, VITCC, Chennai, India
**Corresponding author E-mail: malla.sudhakara2015@vit.ac.in*

Abstract

Automation of detecting the Foreground Region (FR) or Shape of the object is essential in several computer vision, object recognition applications and poses several challenges in case of underwater images. Although Synthetic Sonar Images produce better quality images scattering of light, color distortion and poor lighting conditions are the few characteristics that effects the natural scene of the captured image. A novel technique for extracting the foreground region from a low quality underwater image is presented in this paper. We have decomposed the image in to multiple levels based on discrete wavelet transforms (DWT) for improving the sharpness or to reduce the fogginess in the image in order to get the clear image. Subsequently, to determine the sharpness of the local patches in the image a block based SSI algorithm is presented. Finally, the segmentation is performed by computing the binary gradient mask with the Sobel edge detection algorithm along with morphological operations. The proposed method is fast, extracting the accurate foreground regions and also detect the smallest particles present in the image. The results are qualitatively compared with the improved fuzzy c-means clustering (FCM), Otsu's Threshold and FCM thresholding by considering the static background images.

Keywords: *Block-Based SSI; Foreground Extraction; Morphological Operations; Fuzzy Segmentation.*

1. Introduction

Oceans cover almost 33% surface of the earth. In spite of the truth is that ocean plays a foundational part of human life, exploring the research in the underwater world is very little from a long period in the history. The technologies and the methods developed in the recent years allowed us to explore, monitor and analyze the underwater world constantly. It helps in marine biology, archaeology, observing species behavior, analysis of coastal biodiversity [1], fishing and developing statistics for various underwater living creatures [2]. Dim lighting conditions and undesirable noise in the input image poses numerous challenges in underwater image and video analytics. (1) Interest point detection is difficult since the poor lighting conditions gives relatively poor contrast images (2) The dynamic change in the positions of diver or AUV system and the target results the object detection to be complex in the captured image. (3) Since the image is captured in poor light conditions the information present in the image also very limited and recognition of these objects still challenging. Most importantly, several image analytics methods suffering with poor results with this kind of issues.
Numerous innovations have been developed to monitor and track the marine environment. For example, Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUV) and Systems Targeting Objects (STO) etc. will captured the images or videos in the deep sea. Although the advanced technology in Side Scan Sonar systems yields the underwater images are high in resolution, the detection of FR and shape of the objects are critical since there is a speckle noise in the underwater environment. The noise may be introduced in the image because of either light scattering or color distortion in the background. For the smallest objects it is almost incredible to detect the accurate shape of the living or non-living creatures in the underwater world [3]. Detection of such kind of objects in underwater area is crucial in applications such as marine geology, commercial fishing etc. In the literature, there are two kinds of approaches for object detection in sonar images by considering the background disturbance. First, parametric methods, compute the probability density function (PDF) of the sea floor to detect the object. Constant False Alarm Rate (CFAR), Greatest CFAR, Smallest CFAR and fuzzy CFAR [4] are the techniques that comes under these methods. Second, non-parametric methods don't consider the statistical background disturbance. To detect the man-made objects Chew et.al considered improvement in the contrast of the image by combining self-adaptive technique, thresholding techniques [5]. Texture based detection proposed by Liu et.al [6], and Tsallis entropy based method proposed by Rajeshwari et.al. [7], are the examples for non-parametric methods.
Detection of foreground region has wide range applications in computer vision, image and video analytics. For example in Image retrieval, content based image resizing, image compression identifying the foreground region part is helpful. For example, it is useful to quickly acquire the valuable information as well as to manage the storage space and transmission resources productively. There exists numerous methods for background modeling in video processing with the help of moving background/frames but very little work has done for still images especially in the underwater images [9]. Keeping in mind we have proposed a method to extract the accurate foreground regions of the image. To achieve this goal we have divided the work into three steps. First, to reduce the dominant colors in the input image, we have used a color correction algorithm proposed by us. Second the DWT is used to decompose the image in to multiple levels and for each level we increased the sharpness

by taking the global perception. We also considered the local perception of the image in each sub band and updated the pixel values in the image. Finally, to get the accurate regions of the foreground we took the concepts of mathematical morphology. The proposed work is compared with the conventional techniques such as FCM, Otsu's method, FCM Thresholding. The remainder of the paper is explained as follows: In section II, the related works in aspects such as Otsu's thresholding, FCM and few notation of mathematical morphology are covered. Section III describes the work proposed in this paper. Section IV describes the results and discussions of the proposed work along with the qualitative comparison. Section V concludes the paper with future work.

2. Related theory

Otsu's Strategy was a standout amongst other thresholding methods for real world images with respect to consistency and shape measures. The fundamental principle of Otsu's method is to minimize the weighted with-in class variance and to maximize the between-class variance. The first step in Otsu's method is construction of the histogram, Later it directly works on the gray level histogram, which contains 0 to 256 levels. The weighted within-class variance is calculated as:

$$\sigma_w^2(t) = q_1(t)\sigma_1^2(t) + q_2(t)\sigma_2^2(t) \tag{1}$$

For a particular class the probabilities q1 and q2 are estimated as:

$$q_1(t) = \sum_{i=1}^{t} P(i) \tag{2}$$

$$q_2(t) = \sum_{i=t+1}^{I} P(i) \tag{3}$$

The Otsu's algorithm works for bimodal images and uniform illumination. It uses the mechanism of exhaustive search to evaluate the criterial to maximize the between-class variance. If the quantity of the classes increased, then this method take more time to select the multilevel threshold.

2.1. Fuzzy C-means segmentation

FCM is an iterative clustering technique, which provides optimal 'c' number of partitions by minimizing the weighted function with in total sum of squared error objective function shown in (4). It allows a single piece of data to belong to two or more number of groups i.e. C≥2. It is unlike to the traditional clustering methods, in which it assigns each data pattern to each cluster with some degree of probability. In other words, the data item may belongs to multiple clusters instead of a single cluster. This kind of techniques are more appropriate for the real time applications in which there exists some overlaps between the groups within a dataset [8]

$$\text{FCM} = \sum_{k=1}^{n}\sum_{i=1}^{c} m_{ik}^{q}\, d^2(x_k, u_i) \tag{4}$$

In equation (4), x_k is the k^{th} data item in 'X' in a 'S' dimensional space i.e. X= $\{x_1, x_2 \ldots x_n \in R^S\}$, 'n' denotes the quantity of data items, 'c' denotes the quantity of the clusters i.e. $2 \le c < n$, 'm_{ik}' is the membership degree of 'x_k' in the cluster 'i', 'q' denotes the weighted component in each fuzzy membership, 'u_i' is the cluster i^{th} center. $d^2(x_k, u_i)$ is the distance between 'x_k' and the center 'u_i'. The FCM is computed in an iterative manner and it should be minimized. Let us go in detail about the FCM segmentation, Assume X is a set of data contains $\{x_1, x_2 \ldots x_n\}$. The goal is to divide this data set 'X' in to 'c' number of fuzzy partitions or subsets as P = $\{\mu_1, \mu_2 \ldots \mu_n\}$ by satisfying the following conditions:

$$\sum_{i=1}^{c} \mu_i(x_k) = 1 \;\forall\; k \in N_n$$

$$0 < \sum_{k=1}^{n} \mu_i(xk) < n \;\forall\; i \in N_c \tag{5}$$

Here 'c' = positive Integer. We compute the centers for the clusters (v1, v2….vn} to the partitions P = {µ1, µ2... µn} respectively by:

$$v_i = \frac{\sum_{k=1}^{n}[\mu_i(x_k)]^m}{\sum_{k=1}^{n}[\mu_i(x_i)]^m}\, x_k \text{ for i belongs to} N_c,\ m > 1 \tag{6}$$

Now we can define the cluster centers by:

$$J_m(P) = \sum_{k=1}^{n} \cdot \sum_{i=1}^{c}[\mu_i(x_i)]^m \, \|x_k - v_i\|^2 \tag{7}$$

Here ‖.‖ is inner product in space R_p and the distance between two values computed by $\|x_k - v_i\|^2$. The task is to minimize the value getting from the equation (7) to get a better performance index.

2.2. Mathematical morphology

This section covers the notations of mathematical morphological operations on a binary image which are used for background subtraction from the original image. These operations are also helpful to remove the noise or the holes present in the foreground or background in the image. Dilation and Erosion are the two fundamental operations, in which the structuring element or kernel will be moved in a specific way (i.e. similar to the convolution operation) over the input image to get the noise free image. Consider an image denoted as 'I', and structuring element as 'S'.

The dilation of an image 'I' with 'S' is denoted as a set operations as shown below:

$$I \oplus S = \{(x + y) \mid x \in I, y \in S\} \tag{8}$$

We can also define the dilation as the union of the structuring element centered at the pixel 'x':

$$I \oplus S = \bigcup_{x \in I} S_x \tag{9}$$

Similarly the Erosion also can be computed with the following set operations:

$$I \ominus S = \{x \in Z^2 \mid p + y \in I \;\forall\; y \in S\} \tag{10}$$

Alternatively, erosion can also computed with the help of dilation as follows:

$$I \ominus S = \sim(\sim I \oplus S^*) \tag{11}$$

Here ~I denotes the negation of Image 'I' and S^* is the reflected structuring element of 'S'. The dilation and erosion of two images 'I' and 'S' are shown in Figure 1 and the corresponding algorithms are shown in Figure 2.

$$\underset{I}{\begin{matrix}0&0&0&0\\0&1&1&0\\0&0&0&0\end{matrix}} \qquad \underset{S}{\begin{matrix}&1\\1&1\end{matrix}} \qquad = \qquad \underset{I \oplus S}{\begin{matrix}0&1&1&0\\0&1&1&1\\0&0&0&0\end{matrix}}$$

(A)

$$\underset{I}{\begin{matrix}0&0&1&1&0\\0&0&1&1&0\\0&0&1&1&0\\1&1&1&1&1\end{matrix}} \qquad \underset{S}{\begin{matrix}1\\1\\1\end{matrix}} \qquad = \qquad \underset{I \ominus S}{\begin{matrix}0&0&0&0&0\\0&0&1&1&0\\0&0&1&1&0\\0&0&0&0&0\end{matrix}}$$

(B)

Fig. 1: Dilation and Erosion for Small Image A. Dilation, B. Erosion.

Algorithm 1: Dilation
Input: Image I, Structuring element or kernel S
Output: Dilated Image of I (D^I) = I ⊕ S.
Step 1: Start with all- zero image D^I
Step 2: for each y ∈ S
Step 3: Compute Shifted Image I_y
Step 4: Update $D^I = D^I \vee I_y$
Step 5: end for

Algorithm 2: Erosion
Input: Image I, Structuring element or kernel S

Output: Erosion of Image I (E^I) = I ⊖ S
Step 1: Compute E^I = ~(I)
Step 2: Dilate E^I with S^* i.e. $E^I \oplus S^*$
Step 3: Invert E^I

Fig. 2: Algorithms for Dilation and Erosion.

3. Proposed methodology

The main goal of extracting the foreground region from the image is that to isolate the frontal objects that are potentially confusing with the background region of the same image.

3.1 Block based enhancement

There exists some sharpness estimators, in which sharpness or blurriness can be predicted automatically [14-15]. These algorithms are helpful in object detection, increasing the image quality and image restoration and several works done earlier in this regard [10-11]. These methods assume that the edges are affected by the blur and the level of blurriness is estimated accordingly to remove it. In this paper, we have used the dynamic wavelet-based technique to estimate the sharpness or blurriness globally as well as locally. As a first step, noise will be removed i.e. denoising, Secondly the input image is decomposed in to multiple level separable DWT. The four decomposed sub bands are shown in Figure 3.

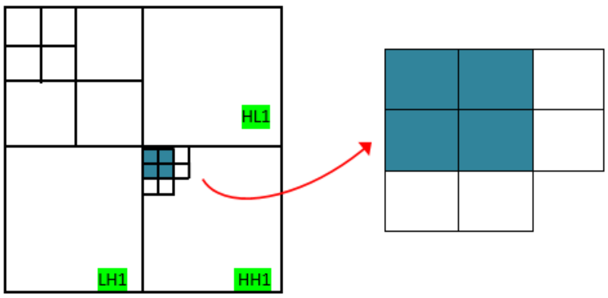


Fig. 3: Composition of Image in to Sub Bands.

Later Log energies of the DWT were computed for each sub level.

$$LE_{LH_n} = \log_{10}\left(\frac{1}{C_n}\sum_{i,j} LH_n\ (i,j)\right) \tag{12}$$

$$LE_{HL_n} = \log_{10}\left(\frac{1}{C_n}\sum_{i,j} HL_n\ (i,j)\right) \tag{13}$$

$$LE_{HH_n} = \log_{10}\left(\frac{1}{C_n}\sum_{i,j} HH_n\ (i,j)\right) \tag{14}$$

The log energies were computed separately for each sub band from the (12), (13) and (14). Here 'C_n' denotes the number of DWT Coefficients at level 'n'. These number of sub bands may be taken from 2 to 4. In this work we have taken '3' levels, i.e. LL Level is omitted. Scalar Index is computed as weighted average of the log energies which are computed in the earlier step. The Values of (12), (13) and (14) are stored in LH, HL and HH respectively. The total Log energy at each level is computed as

$$TLE_n = ((1-W)*((LH+HL)/2)) + (W*HH) \tag{15}$$

Here the 'W' is the weight and is considered as 0.8 in our work. We have considered several underwater images and computed the Scalar Sharpness Index (SSI) measure as to get the sharpened image. The SSI can be computed as:

$$SSI = \sum_{n=1}^{3} 2^{L-1} * TLEn \tag{16}$$

Along with the global sharpness of the input image, local sharpness is estimated using block based technique. The Block Based SSI (BBSSI) is computed by:

$$P = \sum_{i=1}^{SB} SSI_i^2 \tag{17}$$

$$BSSI = \sqrt{\frac{S}{SB}} \tag{18}$$

This technique is most aggressive and straightforward technique and giving the better results at present to estimate the sharpness [12]. This method also gives the result in less time compared to the state-of-the art methods. The combination of these two techniques are used as preprocessing or filtering to enhance the quality of the low quality underwater image. All the images in these continuous intervals can be processed with this technique and all the sharpened images are combined together. The result of the enhancement of this method depends upon the size of the block. For example in Figure a. we have taken a hazy underwater image and computed the result with different block sizes. We have done experiments on various block sizes and the optimal block size for an image should be greater than 120 and Less than 150 and moreover it depends upon the haze present in the image [13].

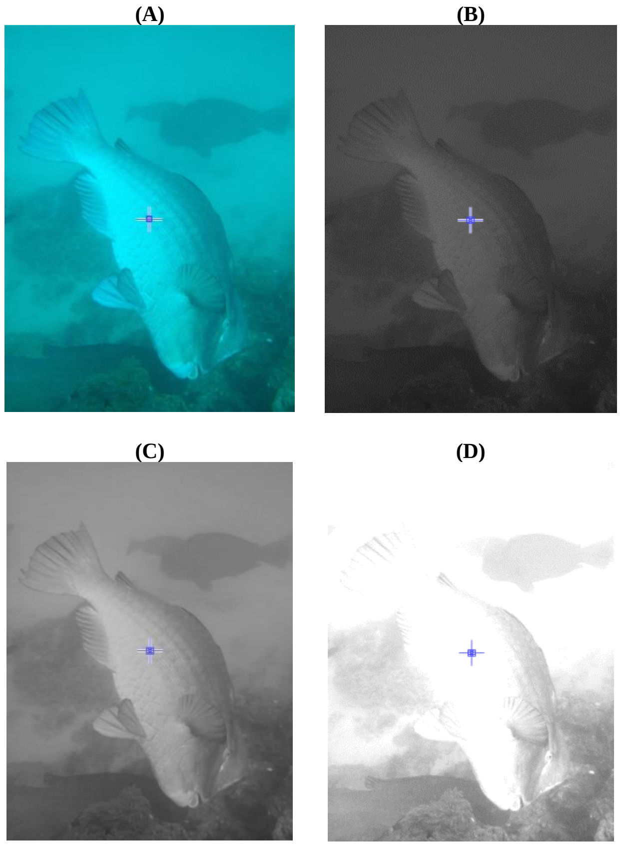


Fig. 4: Block Based Enhancement. Block Size(RXC) A. Input Image B. 64X64 C. 128X128 D. 256X256.

3.2. Mathematical morphology

Morphology has expansive set of digital image processing operations that process the images according to its shape. These operations uses a structuring element or kernel over the input image and produced the output image with same size. The output pixels are obtained by comparing the corresponding pixels of the input image along with its neighborhoods. Selecting the size and shape of these neighborhood will affect the result of the morphological operation. In this work, a thresholding operation has been applied, subsequently Sobel edge detection algorithm is applied to the input image. Later the dilation, erosion and region filling operations are applied to the binary gradient mask for getting the foreground region. We also used the outline morphological operation for getting the border around the segmented region after extracting the foreground region. The gray level image of the original input image is shown in Figure 5.a. The Sobel edge detection result is shown in Figure 5.b, The Dilation of the binary gradient will enhance the borders in the binary gradient mask and then the filling region with holes is shown in Figure 5.d.The step by step flow of this work is shown in Algorithm 3.

Algorithm 3: Foreground Extraction
Input: Underwater Image (UI)
Output: Segmented Foreground Image (FI)
Step 1: Read the Underwater Input Image (UI)
Step 2: Convert the Color Image (UI) to Gray Scale Image (GI)
Step 3: Threshold the Image and apply the Sobel edge detection.
Step 4: Store the Binary Image in BW and initialize FF =0.5
Step 5: Take the 3X1 and 2 Dimensional Structuring elements as S1, S2.
Step 6: BWD=Dilation (BW, S1 S2)
//Apply the dilation with S1, S2 over BW and Store it in BWD
Step 7: Apply the filling operation on the current result and store It in BWF
Step 8: Clear the boards and store the result in BW_Boarder
Step 9: Take the structuring element for erosion in S3
Step 10: BWE= Erosion (BW_Boarder, S3)
Step 11: Store the segmented result FI= BWE

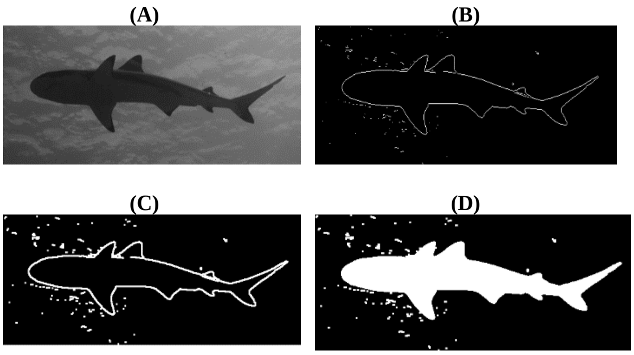
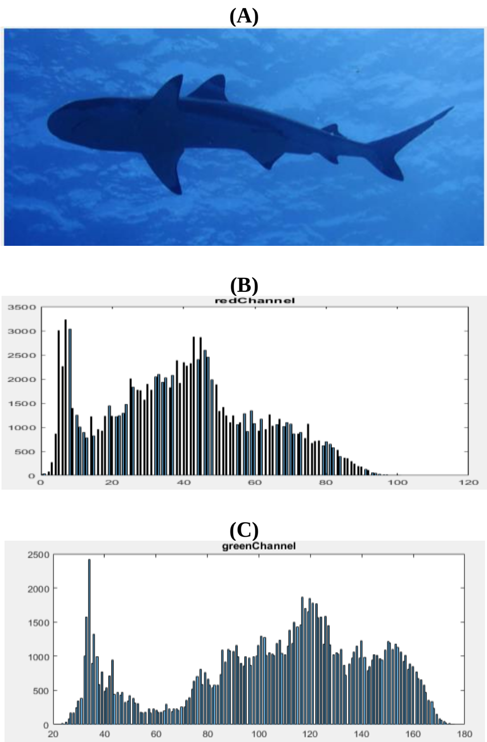


Fig. 5: Morphological Operations A. Input Image. B. Binary Gradient Mask C. Dilation D. Filling Holes.

4. Results & discussion

We have considered an underwater color image as input. Mostly, the dominant colors present in the image will be either blue or green because of its wavelength. We can clearly observe domination of blue pixels for the corresponding input image compared to the red pixels of the same image in Figure 6.



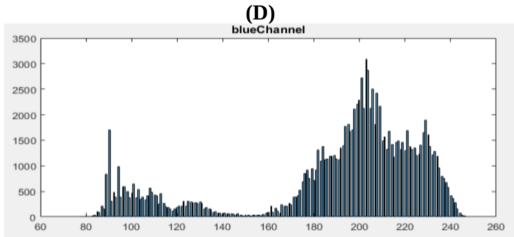


Fig. 6: Histograms of RGB Image.

In our previous work, to decrease the dominant colors in the input image we have used a color correction algorithm based on Dark Channel Prior, but for most of the SAS images, the color correction did not play a key role, since the captured image itself appears like an outdoor image. Later, the image is decomposed using DWT and then Block based enhancement algorithm is applied on a set of continuous images and finally merged back as a single one. The resultant image is much clearer than the original image, since the sharpness is increased through the applied method. Consider a dim contrast image, and we applied the block based enhancement in which the block size is given as 128 and the results are shown in Figure 7. Figure 7.b and Figure 7.c are the first and second level decompositions respectively and Figure 7.d is the gray level result of Block Based Enhancement.

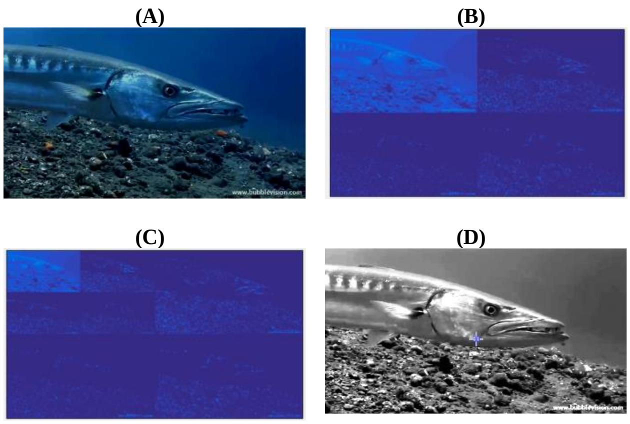


Fig. 7: Decomposition of Input Using DWT A. Poor Contrast Image. B. First Level of Decomposition C. Second Level of Decomposition D. Sharpened Image.

With the help of thresholding and Sobel edge detection algorithm initially we have found the binary gradient mask on the resultant enhanced image. Finally, the morphological operations are applied to the enhanced image to extract the foreground region. For example, dilation operation is applied on the binary gradient image to get the solid edges and subsequently region filling and erosion operations are applied in this case. Figure shows the results of this step. Our Subjective comparison with the conventional segmentation techniques shows that this method is giving the better results. Here Fuzzy C-means Clustering (FCM) for segmentation, Otsu’s Thresholding, FCM Thresholding are considered to compare our result. Three underwater images have taken in Figure 8 and foreground extraction results of various methods are shown in Figure 8.d to Figure 8.o.
The qualitative comparison shows that our work is giving better result than the rest of the methods discussed. This method is also used to find the smallest objects and many other suspended particles present in the underwater [17]. Figure 9.a shows that image is completely dominated with blue color and detecting the smallest objects will become tricky in this case. The pixel values of the object region is slightly different compared to the pixels with no object i.e. blue. We have selected a particular region of the image i.e. Figure 9.b in which the object is present (highlighted in red color rectangular box) and those pixels are shown in Figure 9.c and the detection of these smallest objects shown in Figure 9.d.

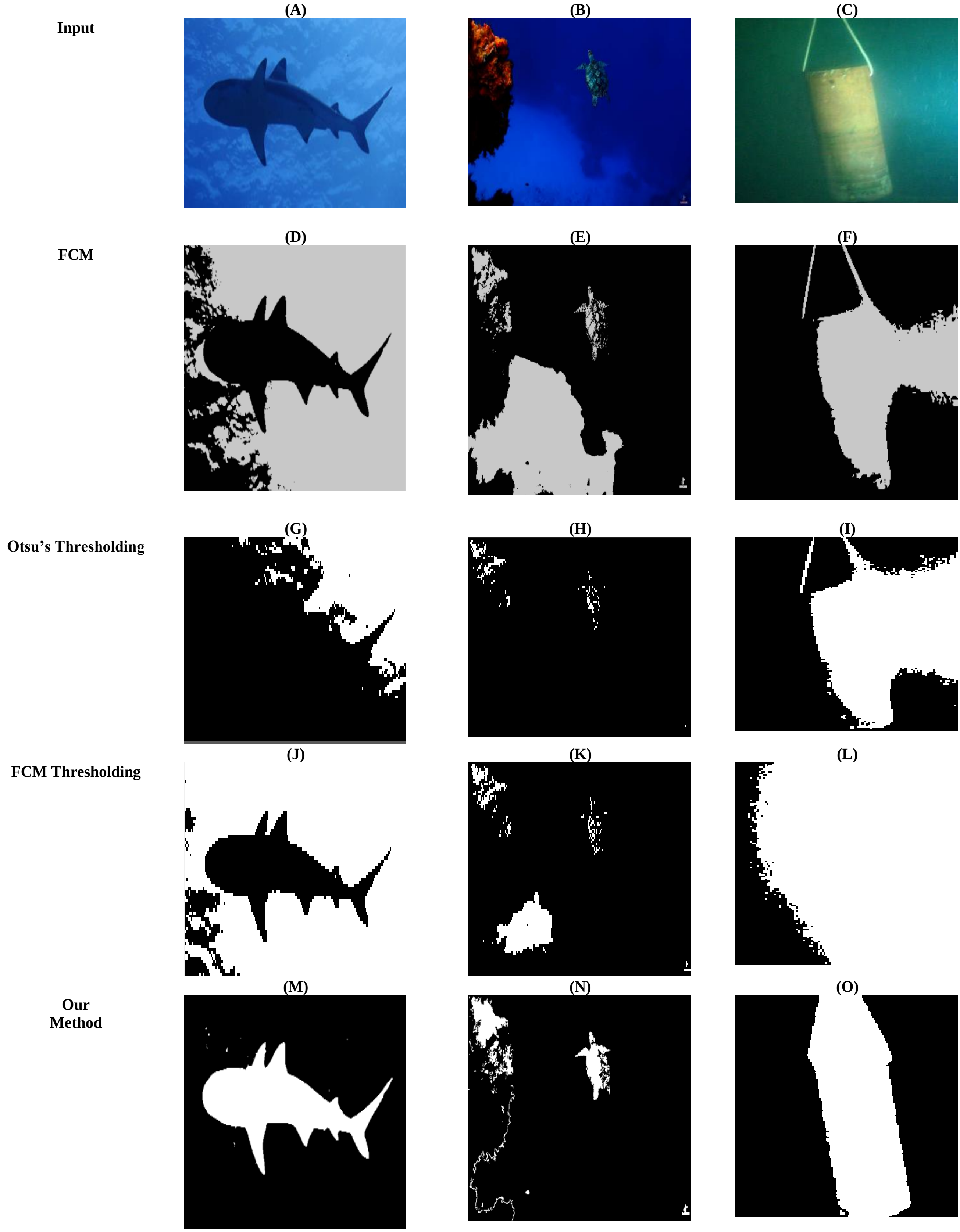


Fig. 8: Qualitative Comparison of our Work.

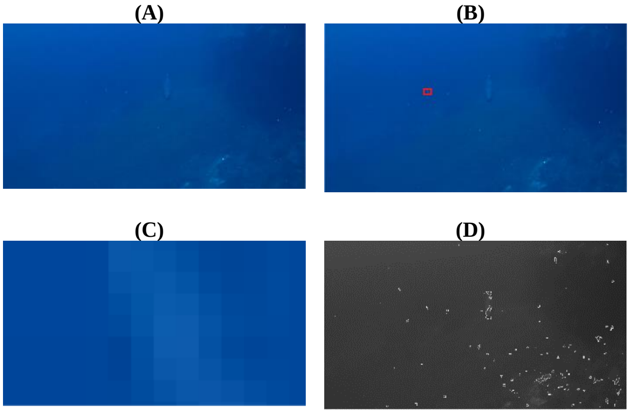


Fig. 9: Detection of Small Objects Using Proposed Method.

5. Conclusion

Detection of foreground region has wide range of applications in computer vision, image and video analytics. For example in Image retrieval, content based image resizing; image compression identifying the foreground region part is helpful. To extract the FG, First we have applied a color correction algorithm to reduce the dominant colors present in the captured image. Once the image is color corrected the noise will be removed, with the help of DWT the image is decomposed in to four sub bands. The logarithmic value of energies were computed for each sub band and total log energy is computed with the weighted average of the each sub band and with the global perception SSI is computed. The images were also enhanced by considering the local perception using block based enhancement technique. Subsequently thresholding and edge detection algorithms were applied to find the binary gradient mask and mathematical morphological operations were performed on the resultant image to get the foreground region of the image. In this research, morphological operations were performed on binary images and this technique is effective ng for images with less background noise. The research may be extended to identify the accurate shape of the smallest objects in the underwater image using gray level morphological operations.

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