Research on Obstacle Recognition for UUV Based on Multi-beam Forward Looking Sonar

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Abstract

Obstacle recognition is one of the key technologies for Unmanned Undersea Vehicle (UUV). In this paper, the design of obstacle recognition based on multi-beam forward looking sonar is presented. First of all, Gaussian mixed model operator is adopted in adaptive threshold segmentation to segment the sonar image into regions of interest and background. Secondly, we use morphological operation to remove noise and pseudo-target in the image. At last, obstacle contour is fitted into an ellipse using least squares method and then we calculate minimum and maximum distance, maximum and minimum azimuth angle between obstacle and multi-beam forward looking sonar. Results obtained on real sonar data are shown and discussed. Our experimental results show that the way can obtain accurate obstacle distance and azimuth angle information.

Keywords: obstacle avoidance, segmentation, unmanned undersea vehicle (UUV), multi-beam forward looking sonar

1. Introduction

With the rapid development of the national economies and population growing, land-based resources face depletion, while oceans which cover over 71% of the Earth's surface area bears extremely rich in biological resources and mineral resources, the ocean has become an important national strategic objectives. As one of the most important means to explore ocean, Unmanned Undersea Vehicle (UUV) technology has been concerned by marine countries in the world. UUV which do not need human intervention can complete tasks such as autonomous navigation, obstacle avoidance, autonomous operation and so on. Autonomous obstacle avoidance is one of the key technologies for UUV, and obstacle recognition is a prerequisite and core of the autonomous obstacle avoidance.

Currently, the most UUV obstacle avoidance systems use low-resolution sonar as data collection device which produces poor image of the obstacle. It is suitable for Remotely operated vehicles (ROV) and is not suitable for UUV [1], [2]. With the development of multi-beam forward looking sonar technology in recent years, it is a good choice for UUV obstacle avoidance system [3].

Based on the above discussions, this paper proposes a method based on Gaussian mixed model and least squares method to identify obstacles. The method uses multi-beam forward looking sonar to acquire images. Firstly, Gaussian mixed model operator is used in adaptive threshold segmentation to segment the image into regions of interest and background. Secondly, morphological operation is used to remove the noise and pseudo-target in the image. Lastly, obstacle contour is fitted into an ellipse using least squares method and we compute minimum and maximum distance, maximum and minimum azimuth angle between obstacle and multi-beam forward looking sonar. The experimental results show that the way can obtain accurate obstacle information.

This paper discusses an efficient design of obstacle recognition based on multi-beam forward looking sonar. The rest of this paper is organized as follows. In Section II, we introduce the multi-beam forward looking sonar used in this paper. Section III details the segmentation technique we have developed. Section IV demonstrates in detail the design of feature extraction. Results are also shown using real sonar data. Finally, a conclusion is drawn in Section V.

2. Sonar Introduction

The sonar used for collecting the data used throughout this paper is multi-beam sonar 837B of Imagenex Technology Corporation. This sonar was mounted on UUV looking forward as depicted in Figure 1.
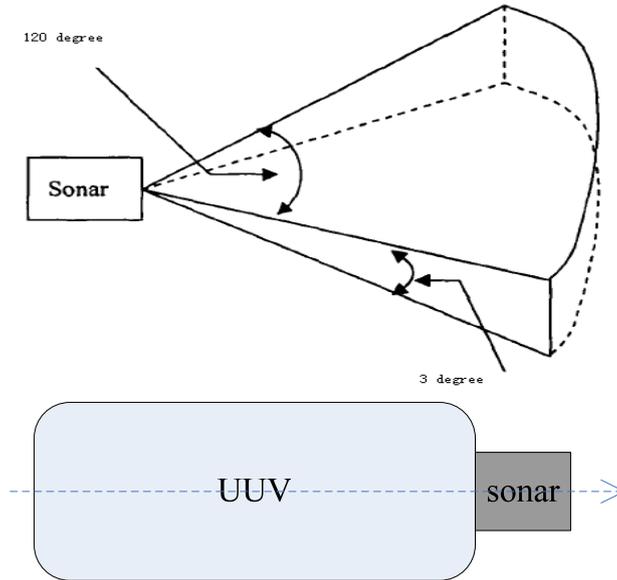
Figure 1. 837B sonar characteristics and mounting configuration

Table 1 shows characteristics of 837B sonar.

Table 1. Characteristics of 837B Sonar

Parameter	Value
FREQUENCY	120KHz
TRANSDUCER BEAM WIDTH (nominal)	Receive: 120° x 3° Transmit: 120° x 3°
MAX. OPERATING DEPTH	300m
FRAME RATE	Up to 20 fps
INTERFACE TO PC	Standard: 10 Mbps Ethernet (10 BASE-T) using TCP/IP
POWER SUPPLY	22 – 32 VDC at less than 5 Watts
WEIGHT	21kg(in Air)

2. Segmentation

Much work has been done on the segmentation of side-scan sonar images, but not so much on forward-looking sonar images. On the whole, segmentation is performed on still images, or separates the moving and static parts of the images using fast Fourier transform (FFT) techniques [4], [5], [6]. Multi-beam sonar images are noisy and need to be filtered. The noise is mainly due to backscatter from either the sea surface or the sea bottom. Taking into account the characteristics of the multi-beam forward looking sonar, we do not use the grid method used more often in optical image processing and use Gaussian mixed model to segment the images.

2.1. Gaussian Mixed Model

The segmentation approach based on Gaussian mixed model is usually under the Bayesian framework [7], [8]. Notations used throughout this paper are as follows. Let

$x_i(i=1,2,\cdots,N)$ denote the observation at the ith pixel of an image, and x_i has characteristics of independent distribution. Here, it is assumed that an image consists of K classes. Every class obeys known probability distribution $\phi_j(x\,|\,\theta_j)$ which is determined by a set of parameters θ_j. According to the set of parameters, the posterior probability distribution is

$$P(x_i\,|\,\Theta)=\sum_{j=1}^{K}\pi_j\phi_j(x_i\,|\,\theta_j)\tag{1}$$

The parameter π_j is the prior distribution of the pixel x_i belonging to the class θ_j, which satisfies the constraints

$$0\le\pi_j\le 1\,and\sum_{j=1}^{K}\pi_j=1\tag{2}$$

In general, $\phi_j(x\,|\,\theta_j)$ is Gaussian distribution which has its own mean μ_j and covariance $\sum_j$. The Gaussian distribution $\phi_j(x\,|\,\theta_j)$ is given by

$$\phi_j(x\,|\,\theta_j)=\phi_j(x\,|\,\mu_j,\sum_j)=$$
$$\frac{1}{\sqrt{|\,2\pi\sum_j\,|}}\exp\{-(x-\mu_j)^T\sum_j{}^{-1}(x-\mu_j)\}\tag{3}$$

(1) is called to be Gaussian mixed model.

2.2. Adaptive Threshold Segmentation
A single, fixed threshold generally generates results which are highly dependent on the background level. We have used an adaptive threshold technique based on Gaussian mixed model. Given the distribution from (1), the adaptive threshold segmentation model [9] is given by

$$g(x,y)=\sum_{s=-\frac{n-1}{2}}^{\frac{n-1}{2}}\sum_{,t=-\frac{n-1}{2}}^{\frac{n-1}{2}}w(s,t)f(x+s,y+t)\tag{4}$$

Where n is odd number($n=1,3,5,7,\cdots$), $w(s,t)$ is operator kernel, $f(x+s,y+t)$ is sonar image and $g(x,y)$ is threshold value. Different operator kernel generates different threshold value which is used to segment sonar image and therefore different segmentation results are obtained as showed in Figure 2.

From Figure 2 we can see the following results: (1) Segmentation result preserves the dam contour information well but contains more noise which will increase the whole system computation load when using dimension parameter $n=5$. (2) Segmentation result contains less noise but removes some useful dam contour information which will increase the whole system complexity load when using dimension parameter $n=9$. (3) Better segmentation result is obtained when using dimension parameter $n=7$.

Through a large number of experiments, we find the following results: (1) The smaller the dimension parameter n is chosen, the more noise and useful information segmentation result contains. That will increase the whole system computation load. (2) The greater the dimension parameter n is chosen, the less noise and useful information segmentation result contains. That will increase the whole system complexity load. Through statistical analysis of

experiment results, it is found that a good compromise is achieved between complexity load and computation load when dimension parameter $n = 7$ is chosen.

sonar original image of dam

$n = 5$

$n = 7$

$n = 9$
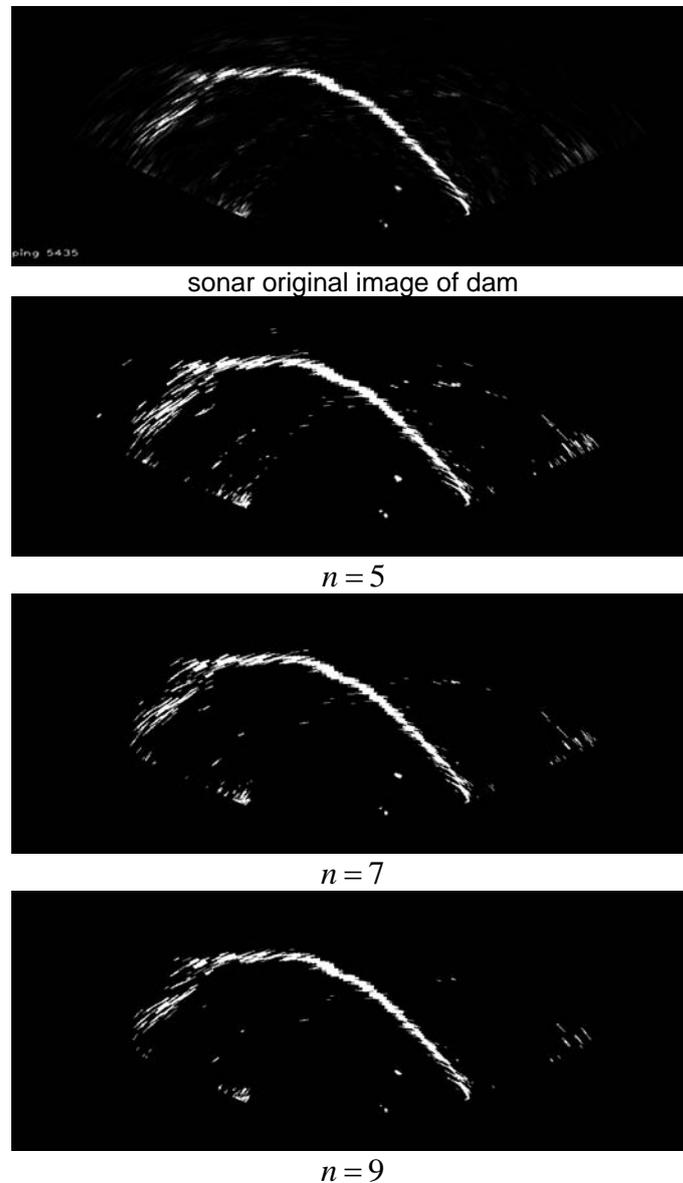
Figure 2. Dam sonar image segmentation results
of using different operator kernel dimension parameters

3. Feature extraction

Obstacle recognition based on multi-beam forward looking sonar has the following characteristics: (1) In order to ensure the accuracy and validity of the identification, the sonar of high resolution is needed to collect information. (2) Characteristics of the underwater acoustic channel and ocean noise make noisy sonar images. (3) Faster computation speed is required to ensure real-time requirements in the image processing.

The basic features of the obstacle such as position, azimuth and size are useful information for UUV navigation system. Feature extraction of an object is a very complex issue [10]. As for two-dimensional image, feature is usually divided into two categories: (1) The contour of the target region. (2) Description operator of the target region. Currently, the widely

used features include area, perimeter, ellipse, circle, line, curve and so on. Ellipse feature is often more appropriate in multi-beam forward looking sonar image processing. Elliptic equation is the following:

$$Ax^2 + Bxy + Cy^2 + Dx + Ey + F = 0 \tag{5}$$

sonar original image of dam

$(c = 0.9, d = 0.9)$

$(c = 0.9, d = 1.3)$

$(c = 1.3, d = 0.9)$

$(c = 1.3, d = 1.3)$
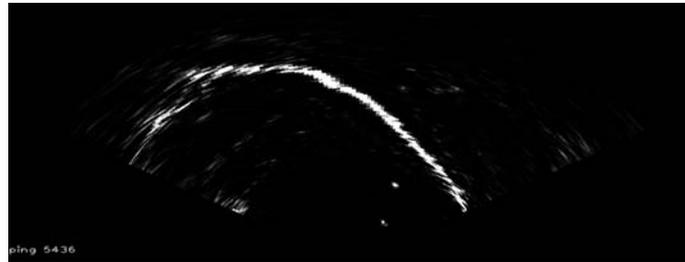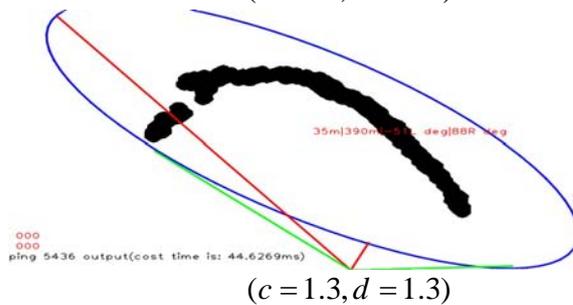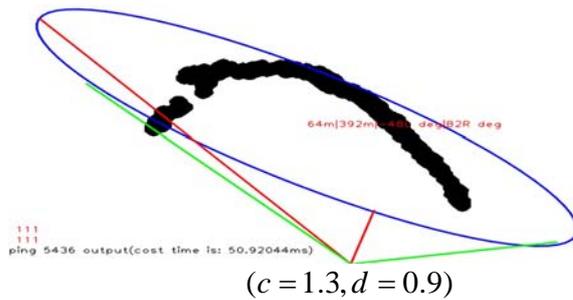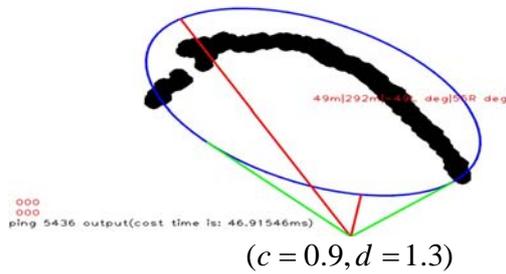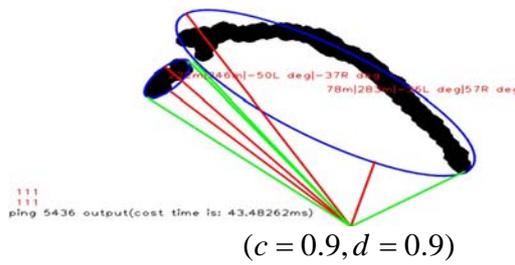
Figure 3. Dam sonar image recognition results of using different fit coefficients

Ellipse can be uniquely determined by the six parameters (A,B,C,D,E,F). Our proposed algorithm is the following. First, Obstacle contour is fitted into an ellipse using least squares method. Second, the elliptic curve is divided into 45 equal arcs. Third, the 45 equal arcs are fitted into 45 lines and vertex coordinates of these lines are computed. Four, minimum and maximum distance, maximum and minimum azimuth angle between vertex coordinates of these lines and multi-beam forward looking sonar are calculated by using search algorithm, and then we get minimum and maximum distance, maximum and minimum azimuth angle between obstacle and multi-beam forward looking sonar. The accuracy of ellipse fitting results determine the accuracy of obstacle recognition. Obstacle recognition results are showed in Figure 3 using different long axis fit coefficients "c" and short axis fit coefficients "d" of ellipse.

From Figure 3 we have the following results: (1) When $(c = 0.9, d = 0.9)$ is used, ellipse fitting result contains good trunk contour of dam and gets accurate distance and azimuth angle information, but some contour of dam is out of the ellipse. (2) When $(c = 0.9, d = 1.3)$ is used, ellipse fitting result contains well trunk contour of dam, but distance is not accurate. (3) When $(c = 1.3, d = 0.9)$ is used, ellipse fitting result contains well trunk contour of dam and has accurate distance and azimuth angle information. (4) When $(c = 1.3, d = 1.3)$ is used, ellipse fitting result contains wholly trunk contour of dam, but gets worse distance information. Through a large number of experiments, we find the result that a good compromise is achieved between the accuracy of ellipse fitting result and distance and azimuth angle information when $(c = 1.3, d = 0.9)$ is chosen.

4. Conclusion

We have presented here a design of obstacle recognition based on multi-beam forward looking sonar. The effect of the design has been demonstrated on real sonar images. We get accurate distance and azimuth angle information of obstacle by using Gaussian mixed model, morphological operation and least squares method. Experimental results demonstrate that the way we proposed in this paper can obtain accurate obstacle distance and azimuth angle information.

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