Vision-Based Underwater Cable/Pipeline Tracking Algorithms in AUVs: A Comparative Study

Alex Raj S.M., Rita Maria Abraham, Supriya M.H.

Abstract— The advancement in the field of communication has led to laying of cables in the seafloor. Pipelines that are used for transporting gas and oil are laid in a similar manner. Due to the dynamic nature of the seabed, these structures may get worn out easily and become useless. In such a situation, regular surveillance of seafloor is unavoidable. As the process is difficult for a human operator, vehicles are used for the same, and are called Autonomous Underwater Vehicles (AUV). AUVs carry out surveys for inspection. Embedding intelligence into AUVs increases the speed of computation and the accuracy is improved. Various sensors associated with AUVs contribute to algorithms for navigational purposes. Various techniques are in use for cable/ pipeline inspection, out of which vision based systems offer cheaper but efficient solutions. This paper provides a review on such vision oriented systems for underwater surveillance.

Index Terms—Autonomous Underwater Vehicles (AUVs), navigation, Underwater image, vision-based

I. INTRODUCTION

Autonomous Underwater Vehicles (AUVs) are unmanned vehicles used to map and monitor marine environments [1].These vehicles can be used to gather high resolution data. This capability of AUVs outperforms the surface vessels as it can fly at low heights aiding in collection of useful data, especially in deep water. AUVs have been used:

i. For seafloor mapping
ii. To detect expelled hydrothermal or cold seep fluids in the water column.
iii. For benthic habitat mapping in shallow waters
iv. For inspection of underwater manmade structures and many more applications.

AUVs can carry sensor payloads including sides can sonar's, cameras, Acoustic Doppler Current Profilers etc. Advances in artificial intelligence will increase reliability and flexibility. If AUVs are given some sort of "intelligence", they can adjust its survey route in accordance with the environmental changes that being monitored by the vehicles.[1]

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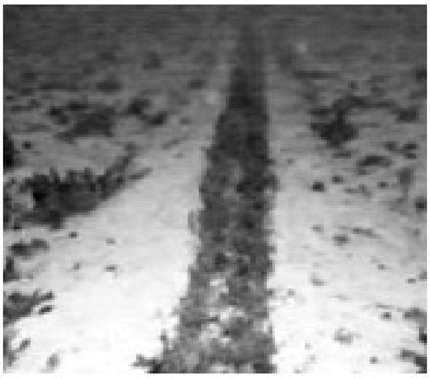

Figure 1: Image of an underwater cable [2]

Cable or pipelines installed in the water bodies require regular inspection and surveillance. AUVs can be used to automate the procedure of inspection. The sufficient feedback of the result of the data collected can be used for determining the navigational route of AUVs. There occurs the need of cable detection algorithms which can be further improved to track the cable under considerations. Shape and uniform colour (to certain extend) can be considered as two main characteristic features of the cable. The colour based detection is not effective since the seafloor is subjected to changes in short or long intervals of time. The cable detection is mainly concerned with the simple two dimensional geometric feature extraction.[3]

The cable recognition methods can be broadly classified into (i) visual methods and (ii) acoustic methods. This survey concerns with the visual approach of cable recognition. Again, the visual approach can be classified into deterministic methods and stochastic methods.[3]

The major steps involved in the deterministic cable detection can be shown as in the following figure. (Figure 2)

Fig. 2: Steps involved in deterministic cable detection

Stochastic cable detection involves the use of probability density functions for estimating the cable position. Example is particle filter (PF) based approach [18],[19].

II. UNDERWATER OBJECT TRACKING METHODS EMPLOYED

Hallset (1991) [4] proposed a model based recognition system for pipeline of moderate depth. CCD camera is used for high resolution images and the rapid imaging. The histogram equalization is performed on image patches of size

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256X256 as an image preprocessing step. 2 Sobel operators (one for each direction) is used for edge extraction and the segmentation process is carried out by the recursive method of region growing. Each segment is then fitted into a rectangle and the minimum enclosing rectangle is computed. Each obtained candidate rectangles are then compared against the data from other sensors ie. compass reading to know the heading and distance to seabed measured using sonar. The disadvantages include the requirement of elaborate sensor integration and occurrence of less sharper edges in real images.

Chen and Nakajima[5] made an attempt in cable parameter prediction using Hough transform. The location of cable is found using inverse Hough transform. The accuracy in cable location is obtained from Hough transform: prediction area and angle of inclination. Edge detection prior to Hough transform is done by a Laplacian of Gaussian filter. The main problems associated with this method include the need of initializing the cable position in the first run and the detection of cable in a curve.

Matsumoto and Ito[6] proposed a software for AUV which can trace the cables in images acquired by a TV camera or recorded using video tape recorder. Brightness adjustment and blurring is done before creating a contrast image using Laplacian filter. Laplacian of Gaussian filter is used to derive a binary image in which the edge pixels are limited to a threshold for controlling the vehicle. The number of edge pixels contained in chosen edge, Hough vote and its weighted sum along with adaptive thresholding decide the candidate for cable position evaluation. Each selected edge is then checked for the nearness to cable edge detected earlier and the candidate edge which secures the maximum score us selected as the cable border. The above mentioned steps are repeated many times so that average deviation alongwith the position of the edge can be found out. The difficulties faced are consumption of time by Hough transform and fixed objects in the images.

Balasuriya et.al (1997) [7] proposed a method in which the sensor fusion is used to estimate the 3D position of the underwater cable. The effects of spatial attenuation in underwater images are minimized by the bandpass filtering based on Laplacian of Gaussian operator. The edge map is generated from the signum of LoG (zero crossings from LoG filtered image). The high concentration of the pixels in a specified direction indicates the presence of underwater images. The cable position is estimated using the parameters obtained using Hough transform. It has real time applications but the problem arises when the amount of data increases; it affects the processing delay. In 1998 Balasuriya and Ura[8] proposed an improved method for cable tracking in which the need of underwater positioning is not at all an essential requirement. The data from CCD camera was fused with other onboard sensors to derive the essential parameters for navigation. The visual data is more used in this method when compared to their previous work.

Grau et. al (1998) [9] proposed a hardware based implementation of texture based cable detection algorithm. Five texture descriptors are defined to characterize the surface parameters in different regions of the image using masks and are learned during learning phase. These are implemented on image which had undergone edge extraction using Prewitt mask and thinning but no transformation. The learned images are then clustered according to the agglomerative hierarchical clustering method. The method is realistic in nature but due to the dynamic nature of the seabed the learning of the descriptors may go in vain. Moreover, the cable position is not at all mentioned.

Zingaretti and Zanoli(1998) [10] described a pipeline as a pair of parallel lines. The image is divided into horizontal strips each of which undergo spatial filtering and vertical edge detection. The dense estimation of edge map creates a horizontal profile which in turn is used in estimating the straight line segments using medfit procedure. The line parameters thus obtained are used along with navigational data and the prediction of cable position is done by Kalman filter.

Ortiz et. al(2000) [11] tries to look for dissimilar regions in the image in a non-supervised way. The captured image is segmented using bidirectional histogram and non supervised clustering algorithm. Line segments are extracted from contours and fitted, filtered and grouped together to form cable parameters. The location, orientation and ROI of the cable in the next image are predicted using a Kalman filter. In the case of a transient failure in ROI analysis, the image is discarded and no new parameters of the cable are computed. Serious errors lead to reset of Kalman filter. The mean success rate of 90% was achieved for a frame rate of more than 25 frames/sec. Complexity increases when the subsea plant growth is excessive.

Balasuriya and Ura in 2000, [12] extended their previous method by incorporating multi-sensors fused together for the cable tracking when it is optically invisible. The rough layout of cable model along with uncertain dead-reckoning data predicts the expected region of location of cable in the image. This reduces area for processing and the processing time.

Gian Luca Foresti(2001) [13] proposed a 3D geometric model of the scene in the image. The edges are extracted using Canny edge detector and improved version of Hough transform is used to extract straight lines. The estimation of the cable position in the next image is done using Extended Kalman filter(EKF). The method is not advantageous to detect and track pipeline partially or fully covered in sand. The presence of obstacles in camera viewfield also affects the algorithm.

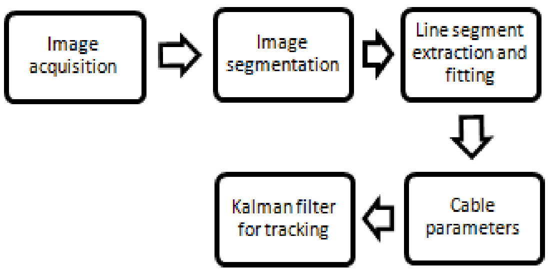

Fig. 3: Steps involved in method proposed in [11]

Conte et.al[14] proposed a visual feedback system for guidance of Remotely Operated Vehicles (ROVs). A PC–based control is used for the initial automation. The data processing is done in two levels: (i) filtering and fusion techniques (ii) symbolic reasoning techniques. This increases the awareness about the environment and increases the reliability of processed data contributing to the purpose of

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navigation. The low level processing in image processor unit helps in the identification of contours of the pipeline. The position of the pipeline contours must be initially provided by the operator, later on, the controller takes the charge of constructing contours in the current image using previous cable location, thus the feedback is implemented.

Lim, in 2004, [15] developed a vision based system for underwater vehicle 'Mako'. The system is developed on the concept that the cable is detected in an image if atleast one set of parallel lines are identified in it. The concept of binary thresholding is also used in this work. Prior to edge detection by a variant of Canny edge detector, smoothing of the image is done using a 5X5 Gaussian filter. The edge detection algorithm involves two step filtering: (i) Convolution with first derivate of Gaussian filter (ii) convolution with Sobel edge kernels. Later on, the minimal set of directions are decided by calculated directions and magnitude of edge points as obtained after filtering steps. The gradient image then undergoes non-maximal suppression, forming edge image containing thinned lines. The edge image formation is followed by the Hough transform for the extraction of lines corresponding to the cable edge. This technique is improved by the method of connected component labeling to reduce line multiplication. Dilation operation further reduces the line multiplicities and it improves the line extraction process. Parallel lines are found from the line- extracted image and the presence of cable is confirmed. The tracking is implemented in the system using the concept of axis of minimum inertia. The centre of mass of cable is calculated with respect to AUV for alignment of cable in the centre of the image. The opening and closing operations lead to the enhancement of this calculation. The axis of minimum inertia is decided and its orientation is calculated for the tracking purpose. The morphological operations can be extended in calculating the axis of minimum inertia for better results.

Asif and Arshad (2006) [16] implemented a method in which the colour image is converted to gray image as a preliminary step. The image filtering is done using Perona - Malik filter, an anisotropic filter which has improved performance over Gaussian filter. The edge detection is done using Sobel operator. The parameter extraction is done using Parameterized Hough Transform. The noise free line can be obtained using Bresenham Algorithm. Prior shape model using B spline curves along with AR model is used estimation using kalman filter.

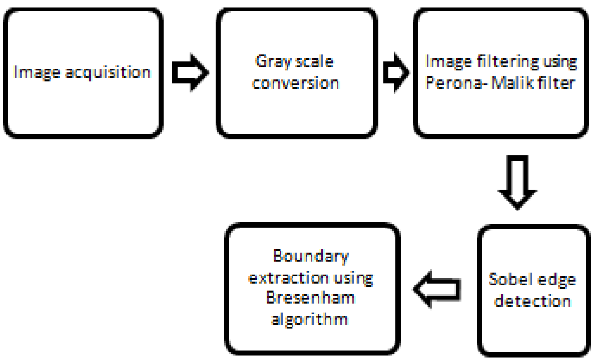

Fig. 4: Steps involved in image processing unit proposed in [16]

Horgan et. al [17] proposed a fast algorithm based on correlation for real time navigation of an AUV. It takes into consideration, the complementary performance of the sensor suite with the vision based motion estimator. The sensor suite includes a compass, depth sensor and altimeter sensors. The object detection section of the algorithm is defined as below: The candidate points in the image are found using high pass filters in both directions which is followed by Harris corner detector. The very next image is searched for the match for the candidate by the translation and rotation of the search window used. The similarity in the two images is measured using correlation. The false matches are removed by the method of Least Median of Squares algorithm. The homographic matrix H is computed using Singular Value Decomposition (SVD). The velocity parameters from matrix H along with camera calibration, altimeter readings from DVL and sampling time is provided to extended Kalman filter for the tracking purposes. The EKF uses a four- degree of freedom constant velocity model. The measurement obtained in regard of velocity, depth as well as heading is used for updating the tracking system. The measurement from DVL and vision system is combined in EKF. The complementary action of the system depends on the location of AUV. DVL readings are relied on when vision is useless in the case when AUV are at a considerable height above the seabed. The accuracy of the navigational system is increased by the motion estimation produced by the vision system when AUV is in deeper water, closer to seafloor.

Wirth et. al [18] adopted a particle filter based approach for cable tracking in 2008. In general, the different models that are involved in cable position estimation using PF are:

i. a state model for representing cables
ii. the movement model that defines the changes of the cable parameters over time
iii. an observation model that evaluates the quality of the different state hypotheses represented by the particle set handled by the PF.[19]

By combining the above mentioned models within the particle filter model, the likelihood of the cable pose can be estimated. For each frame in the video sequence, the previously computed PDF of the cable parameters is used to predict the cable pose in the next frame by the application of motion model. The PDF update is done by means of the observation model. The most appropriate cable pose estimate can then be finally determined from the resulting density.

Due to the confined movement of the vehicle, the cable contours moreover appears to be straight in the images obtained by the camera. In this work, the cable is approximated as two parallel lines separated by a known width. The movement of the cable in consecutive frames is specified by two velocities: drift and diffusion. The observation model, constructed to weight each particle in the cable model, is obtained by projecting the hypothetical cable model into current image. The Derivate of Gaussian filter response in the direction perpendicular to cable borders are added up and this indicate the weight of the particle. The state of the cable in current frame is estimated using particle filter algorithm through the iterative steps of resampling, update, measurement and estimation. The cable can be easily tracked even when the cable is not clearly seen. However, the particle has to initialized using hand labeled ground truth.

Ortiz et. al improved the method described in [19] for tracking fiber optics telecommunication cables of a few cm thickness. The cable is modeled as a single line and it acts as

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the state model. The constant velocity model is considered as the motion model. The observation model required for particle filter is obtained by projection of cable pose over current image. The average filter response of MeX on the image is computed as observational model. Enhanced features for particle reweighing are incorporated into the previous work. The tracking of cable is done using Particle filter algorithm.

Narimani et.al[20] proposed an method for ROV navigation based on adaptive –sliding control for which image processing unit provides the necessary input. At first, the coloured image is converted into grayscale image and edge detection is performed using Sobel operators. The normal parameterized version of Hough transform extracts lines corresponding to cable borders. With respect to Hough peaks, the angle deviation is computed. This method reduces the computation time. The angle deviation obtained is the input to the control unit. The non linear controller method helps in estimation of parameters that are uncertain in nature and aids in input tracking. It also helps in effective removal of disturbances. It doesnot require system model accuracy, which is advantageous.

In 2012, Chen and Jiang [21] proposed a visual servo approach for the pipeline tracking. The underwater environment and features of vehicles have a huge impact on image formation; these lead to irregularities. The irregularities are removed using morphological operations like opening and closing. The unwanted ripples in the resultant image are removed by smoothening by a Gaussian Mask, which is followed by edge detection using Sobel mask. To have an accurate edge location, thresholding based on clustering approach is employed. Before applying Hough transform, a least squared line fitting process is done so that the line segments are preserved in the edge image. Just before this step, thinning operation is done to avoid erroneous fitting. False partial line segments are eliminated using expanding process. The Hough transform is computed so that the most unambiguous line segment is selected as the pipeline edges. The estimation of Region of Interest (ROI) is performed for reduction of search area and computation time. The optical flow approach helps in predicting the location of the pipe. The weighted least squares method provides the solution for optical flow velocities.

Paulo Drews Jr et. al (2012) [22] implemented a method in which captured video is first converted into 320X240 pixel size image. The colour images are converted into gray scale after which the edges in images are detected by Canny edge detection technique. The morphological operations including dilation and erosion are performed on the edge map generated and two parallel lines are extracted using Hough Transform. The main disadvantage of the method is that the width of the target is required to calculate the distance between the two parallel lines.

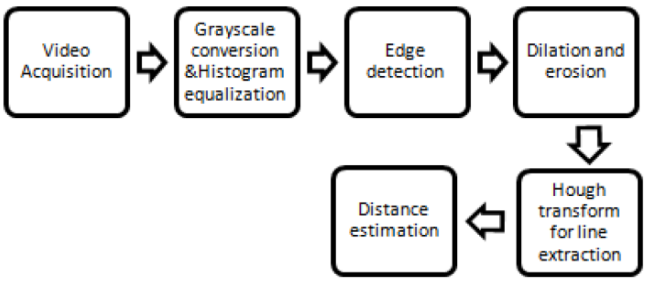

Figure 5: Image processing unit proposed by Paulo Drews Jr. et.al [22]

Devendra Goyal et. al (2012) [23] introduced an improved method for cable detection in which the Canny Edge Detection is done on the gray scale converted image. First of all, Estimated Ground truth is computed. Estimation of Best edge map is done using the computed EGT. The Randomized Hough Transform is used here and two parallel lines are approximated. The method is relatively fast and the storage requirement is less. But the problem is that image quality illumination affects the detection process. The empirical definition of the parameters for RHT is essential. There are irregularities in execution time too.

Yet another method based on particle filter was used by Ortiz and Antich [24] where two different approximations is considered for the cable. For narrow telecommunication cable, the model is a single line with parameter d and alpha α, while for real power undersea cables, it is lines separated by an apparent width. The observation model is built using different filter responses in each case: MeX filter for narrow cables and DoG filter provide accurate results for thicker cables. Horizontal and vertical masks are used for better results. Along with constant velocity model, the cable parameters are updated in current image according to observation based on the previous frame.

In 2015, Chen et. al [25] proposed a method for highly reliable detection of yellow guide rope in images taken in ROV. Target enhancement improves the edge detection. It is done by converting colour image into chrominance component; this process eliminates background noise. Canny edge detector is used for edge pixel extraction. The final step of Canny edge detector involves thresholding. In this proposed method, Otsu's method is used for determining the hysteresis threshold values in an adaptive manner. The probabilistic Hough transform is used for improved line detection. It involves random sampling for selecting set of edge pixels enrolled in voting. This provides an accuracy of about 95 percentage in line detection.

III. CONCLUSION

In this paper, various algorithms used for detection and tracking of cables/pipelines laid in seabed is described. Though there are many methods for undersea cable inspection, vision based systems provide inexpensive solution for navigational purpose. Most of all feature based methods uses edge features for detecting cable borders. Since a cable is better approximated to be a straight line or a pair of straight lines, for extracting out the lines representing cable contours, Hough transform is the ever favourite option. The estimation of cable position and tracking is done in many methods. The methods have varied from time to time. Now it is the time for stochastic approaches like particle filters and its variants in tracking of objects in underwater environment.

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