# Automatic Underwater Multiple Objects Detection and Tracking Using Sonar Imaging

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CHAPTER 1

# Introduction

Oceans cover approximately 70% of the Earth's surface and contain roughly 97% of the Earth's water supply. Despite the importance of oceanic environment, humans are still unable to explore the full depth of the ocean and discover its resources due to the dangerous, cold and dark underwater environment. However, it is on the seabed in coastal regions where major physical, chemical and biological activities with immediate impact on humans taken place [1]. Furthermore, underwater terrorist threat in harbours and rivers has the potential to destabilise maritime activities [2]. For these reasons, coastal regions are the critical targets for underwater measurement.

As in the exploration of outer space, underwater exploration is more easily and safely performed by robots, because they eliminate the need for humans to be at great depths or in dangerous conditions. Remote Operation Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs) are on the threshold of playing a key role in oceanic exploration. Due to the operating cost, suitably qualified operators and limitation of operation range, and because of safety concerns, the use of conventional ROVs is being overtaken rapidly by a trend toward the use of autonomous underwater vehicles. Recent critical applications of AUVs include mineral mining, pipeline inspection, oceanographic mapping, explosive ordnances hunting, underwater intruder detection and hostile environments sampling (such as for biologically or chemically contaminated waters).

Not withstanding any other form of sensors or sensory applications, it appears that the use of sound and all of its known variants is still the most practical approach to assist AUVs' operations, such as localisation, mapping and obstacle detection. Pin-point positioning and environmental awareness are vital to enable the AUV to navigate and execute a mission effectively and safely. For this purpose, the locations of the AUV are paramount and the need for accurate sensing in unknown environments is critical. Dead reckoning technique integrates the velocity of a vehicle in time to estimate its new position. An AUV's location is determined by previous position and the accuracy of the speed measurements. Nevertheless, all the sensors currently used by AUVs are known to have operational flaws or discrepancies, sometimes referred to as measurement noise. With the accumulation of such errors over time, the vehicle may not localise its position correctly. Building on their success in surface navigation systems, Inertial Navigation Systems (INS) and/or Doppler Velocity Logs (DGPS integrated with inertial sensor measurement) have been introduced into the underwater environment. However, due to the null coverage of the GPS information in the sub sea area, Long Baseline (LBL) or Ultra Short Baseline (USBL) acoustic tracking systems are employed for long term underwater positioning. Examples of such navigation systems can be found in [3-5]. Both systems employ transducers or transducer-arrays to aid AUV navigation. The AUV sends out acoustic signals and receives each returned beacon from the transponder array. AUV's position is determined by the time-of-flight (TOF) measurement from each transponder to the AUV. Figure 1-1 shows such system configurations for AUV localisation.

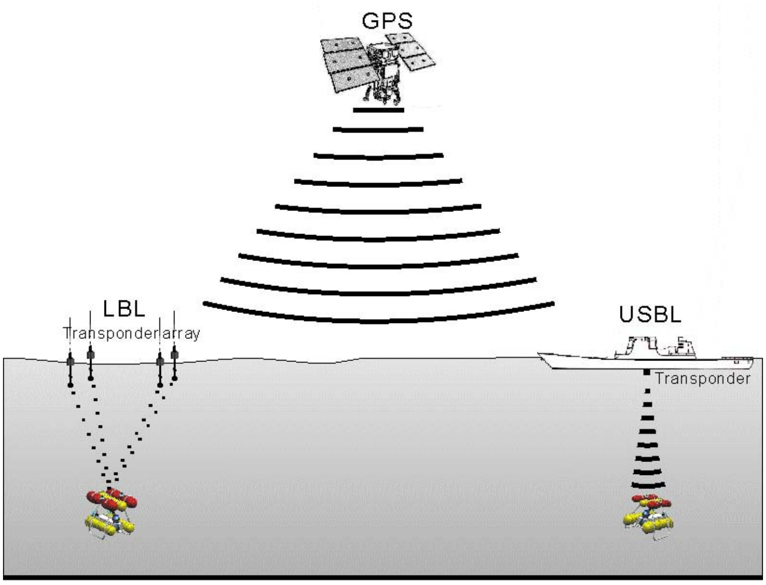


Fig. 1-1 : Typical configurations for AUV localisation using LBL and USBL

As long as the AUV acquires GPS information and measurement from depth sensors, the positions of the AUV will be localised. However, the precision of these systems is compromised by the variation of the sound velocity which accords with the water temperature and density. The need to pre-locate the transducers, the high cost and restriction of the working volume constrain the exploratory capabilities of the vehicle. Furthermore, LBL and USBL systems are essentially prone to accumulating errors which are inherent in the dead-reckoning approaches.

Alternatively, the map matching method is another important technique for AUV localisation. The core of this method is to extract some characteristic features from an image map (local map) and then compare them with the existing map (reference map). As a result, whenever correspondences are found, the AUV position is known. Lucido *et al.* [6] concentrated on bathymetric profiles as measured by side-scan sonar while Sistiaga *et al.* [7] chose reference depth map (RDM) using pencil beam sonar. Map matching localisation, which uses onboard sensors to collect features, successfully guides the AUV in navigating close to the bottom. However, the high resolution bathymetric profiles are difficult to obtain and only an up-to-date map in the operation area can provide reliable localisation of the vehicle.

The goal of simultaneous localisation and mapping (SLAM) or concurrent mapping and localisation (CML) is to enable the AUV to build the map in an unknown environment and concurrently use this map to localize itself. Therefore, SLAM (or CML) has the potential to correct navigation errors for long-term missions. However, SLAM (or CML) suffers from a ‘chicken and egg’ or ‘which came first’ problem. Localising a robot requires a map and to map the environment the robot needs to be localized. Probabilistic algorithms have been introduced to solve the problem by explicitly modelling different sources of the noise and their effects on the measurements. Extended Kalman Filter (EKF) [8] and Particle Filter (PF) [9] are most commonly used to solve the SLAM problems. These two filters rely on Bayesian Theorem to seamlessly integrate imperfect models and imperfect sensing. Underwater targets or obstacles are commonly extracted as points for the estimate procedure. With the applications of probabilistic algorithms in solving system uncertainty, significant achievements in this field have been attained. However, the error produced by recursive EKF and PF schemes, such as employed by dead-reckoning methods that are purely dependent on an unassisted IMU, will grow over the duration of a mission. As additional measurement data from other sensors such as DVL and pose estimates from video and sonar are introduced, the error increment can be constrained and even corrected. Nonetheless, with the benefit of more precise detection methods, there would be less need for reliance on probabilistic algorithms which are used for correcting uncertain measurements caused by the sensor noise.

Besides the commercial values of AUVs to the oceanographic community, many approaches have been proposed in underwater mine or intruder detection and classification using sonar sensors. Chantler *et al.* [10] presented a method which includes a Fast Fourier Transform (FFT) filter to separate dynamic objects (divers) from static objects (pier legs) and the optical flow technique to track moving objects using sector-scan sonar. Reed *et al.* [11] suggested using Markov Random Fields and Statistical Snakes for mine detection form side-scan sonar images. They analysed a sonar image into three regions: highlighted objects, seabed reverberation and acoustic shadow. Bell *et al.* [12] continued to extract the shadow parameters from the image and classify the objects through contours of the shadow. However, due to the strong reverberation noise generated by the bottom sediments in shallow water, acoustic shadows, which are usual in sonar images after the suspending objects inside water, are strengthen by reverberation energy in images. Such analysis becomes difficult due to the large variability in the appearance of the sonar images as well as the high reverberation noise in the images.

Sonar (SOund Navigation and Range), especially active sonar, using underwater sound to detect, locate and classify underwater objects (obstacles) always acts as one of standard obstacle avoidance and target recognition sensors in many of the major AUV fleets around world. The accuracy of the sonar sensor will be partially determined by the prevailing water conditions. The spatial complexity of the ocean induces a variety of notable variables such as turbulence, density, heat and salt differentials which will affect the sensor measurement. This becomes a significant challenge in relation to obtaining up-to-date information of small obstacles for autonomous navigation. Although high resolution sonar sensors are developed to overcome these problems, the high cost and high energy consumption limit their applications in most current AUV studies. To shorten the development cycle and reduce costs, most researchers choose commercial sonar sensors from the market. As mature products, they are designed for skilled human operators instead of computers. Reflected sound pulses are firstly processed by imbedded DSP (Digital Signal Processor) or FPGA (Field Programmable Gate Arrays) circuits. Some useful information may be filtered out before the access of the sensory raw data and eventually increase the difficulties of automatic detection.

With the developers of sea mines availing themselves of modern technology it is probable that their miniaturization is inevitable, the use of shape charges becoming more prevalent it is a likely scenario that a large explosive charge could be hidden on the sea floor with a small detecting unit being placed in the water column. Such mines or explosive ordinance can easily threaten both surface vessels and submarines. The detection of such a small but potentially volatile unit becomes imperative. However, several factors influence the detection of such small objects. For instance, the beam properties, the sonar scan range, the level of noise, reverberation, target strength and scattering cross-section of the object. Moreover, another challenge is the reverberation generated from the boundaries (including water surface and bottom). In most coastal regions, harbours and rivers, the depth of the water is less than 10 meters. Energetic echoes reflected from rocks, coral and mud in such shallow-water environments are often higher than the amplitude of echoes reflected from small objects. Commonly used thresholding techniques or intensive detection algorithms are therefore ineffective because they require the objects' echo to be stronger than bottom reverberation. Further, if both the sonar sensor and small objects are moving, Doppler frequency shifts of the object and bottom reverberation will be similar. Such similarity in frequency domain impedes the ability to distinguish small objects from boundary reverberation using Doppler-based techniques. This study therefore investigated the algorithms for detecting small underwater obstacles (static and dynamic) in confined shallow water environments. The term 'small' here can be understood as follows. The sizes of the obstacles (objects) are much smaller than the vehicle and the ensonification of the obstacles (objects) does not result in specular reflection of the sound waves. For instance, a 14 mm sphere (in radius). The whole system not only provides spatial information in the local surroundings but also provides ancillary estimations about varying surrounding objects, encompassing the sizes and movements. The term ‘shallow water’ in this study is defined as water up to and not exceeding 10 meters in depth.

## 1.1 Project background

This research project presents work carried out by the Robotics Group in the School of Mechanical Engineering, The University of Adelaide and the Maritime Operation Division (MOD), Defence Science and Technology Organisation (DSTO) in Adelaide, Australia. To achieve more flexibility and reliability, an upgrading process is currently being developed. The final goal of the project is to enable the exploration vehicle to operate automatically in shallow waters. As part of the project, an imaging sonar was added to the existing rover, primarily for the purpose of localisation, obstacle detection, tracking and avoidance. Figure 1-2 shows the current rover. For this project, the image sonar was not attached to the vehicle and worked separately to acquire different data-sets for detection and development of tracking algorithms.

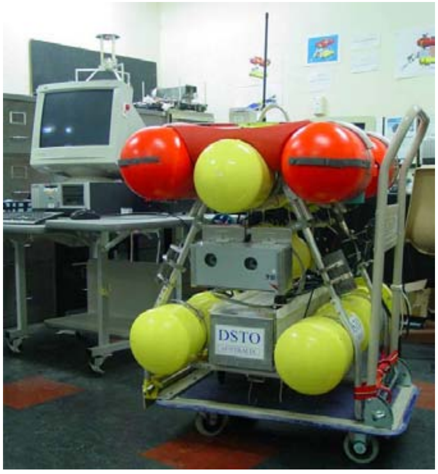


Fig. 1-2: Current AUV on the testing bed

## 1.2 Goal of the study

The primary focus of this research was concerned with small obstacles detection using underwater sonar sensor for the AUV's navigation. Meanwhile, the developed algorithms was able to operate in both confined and naturally occurring shallow water ways with many commercial structures, such as harbours, marinas, ports and canal systems. Future applications for this research may rely on harbour surveillance and port protection missions for an AUV, such as locating underwater intrusion or explosive ordnance. The more specific objectives of this research are listed below.

**Detection and tracking:** Developing an objects-detecting-tracking algorithm with the ability to deal with particularly confined environments. This algorithm should be able to detect the presence of partitions, small objects and other obstructions in the water and track their movement for the purpose of collision avoidance.

**Mapping and localisation:** Designing an efficient approach to localisation of the sonar sensor without other sensory data, and mapping the confined structures. Extracting the features from the acoustic images and building the map according to those features for AUV navigation.

**Experimentation of the sonar sensor:** Evaluating the proposed detection and tracking system in laboratory and natural environments with various situations, including the variation of sensor parameters and sampling environments. Meanwhile, since the final objective of this study is to assist the AUV's navigation, the sensor platform was tested in both static and dynamic circumstances for the obstacle avoidance purpose. The capacity of the developed system will be a direct response to different sonar data acquired under experimental conditions.

## 1.3 Thesis synopsis

The content of this dissertation is divided into four sections. The first section reviews the literature on the use of underwater sonar for obstacles detection and navigation purpose (Chapter 2). The second section introduces the principles of acoustic imaging and the mechanically scanned imaging sonar employed in this research. Some sonar sensing terminologies are also explained (Chapter 3). Algorithms developed for the detecting-tracking system are addressed and are proved by experimental results in different environments in the third section (Chapter 4 and Chapter 5). The last section of this thesis summarizes the contributions and suggests avenues of future research (Chapter 6). A brief description of each chapter is provided below:

**Chapter 2:** *Literature review*. This chapter reviews the obstacle (object) detection algorithms, paying special attention to applications in underwater environments. This chapter also reviews the literature concerning the applications of Mechanically Scanned Image Sonar and Electrically Scanned Image for underwater vehicle navigation.

**Chapter 3:** *Mechanically scanned imaging sonar and preliminary investigation*. This chapter briefly depicts the fundamental theories of underwater sound and operating principles of the sonar sensor. The acoustic imaging process of a mechanically scanned sonar sensor which was chosen for obstacle detection and tracking purposes is also featured in this chapter. Two simple experiments are described to test the ability of the sonar sensor and to decipher the sonar image.

**Chapter 4:** *Objects detection and tracking in structured environments*. This chapter analyses the detection and tracking algorithm developed for enclosed environments. A novel method for mapping the environment and locating the sonar sensor is also detailed. A series of experiments were conducted in an elliptical test tank to demonstrate the effectiveness of the algorithm.

**Chapter 5:** *Objects detection and tracking in natural environments.* This chapter focuses on exploring the use of fuzzy logic algorithms for natural very shallow water (up to 3 meters deep) object detection. A fuzzy logical estimation filter was developed. Underwater obstacles were easily distinguished from the sensory raw data instead of post-acoustics images. The experiments in this chapter replicated a real AUV with the imaging sonar operated in the River Torrens, Adelaide, South Australia.

**Chapter 6:** *Conclusions and future work.* This chapter summarizes what has been discussed in the thesis and considers the focus of future studies.

**Appendices:** These denote the hardware specifications and connections of the sonar sensor.

CHAPTER 2

# Literature Review

An autonomous vehicle must achieve several important capabilities including Self Localization, Self Mapping, Obstacle Avoidance and Path Planning. However, the ability to perceive the surroundings is a fundamental requirement of safe operational procedures that are required for an Autonomous Underwater Vehicle. This is achievable through the use of exteroceptive sensors such as sonar. Therefore, one complex variant must be addressed: object (obstacle) detection. This chapter endeavours to identify the algorithms currently synonymous with Underwater Vehicle Navigation and Object Detection, and then investigate their incompatibilities.

## 2.1 Sonar sensor for object detection

The high attenuation and dispersion of light in water limits the use of high resolution laser and optical sensors for underwater applications. Sonar is the most popular sensorial choice for underwater research. The sound waves can travel through at least many hundreds of meters without losing significant energy. Sophisticated transducer heads and beam forming techniques allow the active sonar to preferentially transmit narrow beams and determine the compass bearing of the reflective object. Various sonar sensors have been developed and applied to different AUVs.

Among these the echo sounder may be the simplest and least expensive for range measurement. The sensor transducer sends a pulse of sound and then waits for the reflected echo. When the pulse from a surface returns to the sensor receiver, the time taken for the round trip can be measured and the distance can then be estimated. Creuze and Jouvencel [13] reported a study regarding the detection and avoidance of cliffs where it was assumed no floating obstacles were above the flat seabed. Three unidirectional echo sounders were mounted on the front of the AUV. The measurement from the horizontal transducer was used to calculate the distance between the vehicle and obstacle. Another two transducers were inclined at an angle of incidence of ±20 degree (angles between horizontal transducer) to measured distances between the sea bottom and sea surface. Based on the orientation of transducers and trajectories of sound waves, the vehicle's dynamic constraints can be calculated. The vehicle's possible activities were judged by the different sensor reading measurements. A relative collision avoidance strategy was then undertaken to control the vehicle's ascent or descent. This method acquired anticipative results. However, this method only helps an autonomous vehicle operating on a vertical plane. Due to the small beam width, the echo sounder cannot cover large water volumes. In terms of reliability and efficiency, an AUV needs to be equipped with appropriate sensing capability when exploring obstacles in an abundant environment.

Another sonar sensor currently used for obtaining bathymetric data or for obstacle avoidance tasks is the mechanically scanned profiler (MSP). The transducer can rotate continuously with a small step angle and produce a series of range measurements. The scan sector can be configured from a few degrees to a complete 360 degrees. The sound beam from the transducer always forms a cylinder shape with small beamwidth. The tapered waveform spectrum penetrates the water and results in a-point-measurement on an object. The profile of the object is therefore acquired through sequential measurements. Barat and Rendas [14] presented a benthic boundary tracking system using a profiler sonar. Sensor returns were classified by probability distributions to extract point features. A mixture distribution model was fitted to the newly arrived measurements. Results from two different types of sea bed demonstrated that the method was adequate for boundary tracking. Similarly, due to the small space coverage and low scan speed, few papers have been published on using MSP for suspended obstacle detection.

Instead of projecting a single sound beam once each time, a multibeam echo sounder (MBES) is composed of an array of transducers. It can concurrently emit adjacent parallel sound beams which illuminate a narrow swath of the across-track direction. This kind of sensor is designed to generate both a bathymetric map and a backscatter image with large areas of the seabed. Hellequin *et al*. [15] involved statistical distributions to characterize the seafloor using a Simrad EM100 (a widely chosen shallow water MBES). Artefacts generated by the sensor system, such as beam pattern effects and uneven array sensitivities, were firstly normalized and cleared. A statistical model for reverberation was introduced for the seafloor's correlation properties, such as roughness and echo sounder geometrical configuration. The correction procedure compensated sensory data coming from each single transducer. Backscatter images generated from rock, gravel and sand were finally distinguished by the *K*-distribution. Although, MBES is an efficient tool for remotely characterizing the seafloor, it is not appropriate for detecting small objects (obstacles) underwater, due to the geometric shape of the sound beam.

Similar to the MSP, mechanical scanning image sonar (MSIS) has a rotatory transducer and emits a fan-shaped beam at different orientations. It is usually mounted at the vertical plane and scans in the horizontal sector around the AUV. Echo intensity values are plotted as a function of range and bearing. The position of reflective objects underwater is shown in an echo graph: a 2D view of the coverage area. Ribas *et al*. [16] have attempted to extract line features from a MSIS in a confined test pool. Due to the low scanning rate, the vehicle's motion resulted in distorted acoustic images. To acquire a more accurate representation of the environment, an Extended Kalman Filter (EKF) was firstly adapted to estimate the state (position and velocity) of the vehicle from the measurements of a compass and a Doppler Velocity Log (DVL). After undistortion, a Hough transform was used to transfer an acoustic image's peak intensity points into a two-dimensional voting space. Since the voting space represents all possible parameterized features' locations, the most voted cells in the Hough space correspond to line features in the environment. Through tracking the most voted cells, line features were detected and extracted from sonar images. MSIS is an effective and efficient tool for underwater object detection. The main drawback of MSIS is the slow refresh rate caused by the low scanning speed.

Electronically scanned image sonar (ESIS), which is also known as multibeam image sonar, can project an array of fan beams and produce a complete acoustic image of an insonified area. Because it commonly detects the area in front of the sensor at a very high speed, it is also referred to as forward looking sonar. It is currently one of the most popular choices for underwater obstacle detection, localization and mapping although it is ten times more costly than a MSIS. Henriksen [17] pre-processed raw data from an ESIS using two levels of threshold to filter out the ambient noise and reverberation. On the assumption that echo strength from the object was significantly higher than the background noise, the highest echo in the single beam was deemed to be the real object. In the meantime, Henriksen successfully reduced the computational burden by dividing the sonar image into a number of partially overlapping regions, which covered the full horizontal view of the AUV. Quidu *et al.* [18] segmented an ESIS image into four areas, each area was associated with a specific value of colour intensity. The strong echo area was firstly separated by a threshold whose value is equal to 75% of the maximum level of the pixels. Then an average filter was applied for smoothing and filtering out noise from the other three areas. Thirdly, the filtered image was thresholded to extract shadow areas. This threshold was determined by the estimation of reverberation mean. Finally, medium echoes detection was performed using the same strong echo area. The left area was grouped into the background and eliminated from the image. A wreck and a school of fish were successfully detected from the image.

A sound beam from side scan sonar (SSS) is still formed like a fan but projected down towards to the sea bed using a perpendicular angle to the direction of the sensor movement. A strip of ensonified area is represented by the echo intensity when the sonar is moved along the horizontal path. Since this sonar is used for imaging large seabeds, the transmission of a longer duration and wide bandwidth pulse results in higher resolution sonar images. Various approaches have been reported as able to detect underwater mines which lie on the bottom or buried under sediment. A paired highlight-shadow region (from the front of the target to acoustic blockage at the rear) is one of the primary features for the detection of mine-like objects. Daniel *et al.* [19] presented a side scan sonar image matching approach based on hypothetical reasoning. Sonar data were firstly normalized to smooth the grey levels and then lowpass filtered. The resultant image was finally segmented by two thresholding schemes on the grey level to label different pixels. Four data classes were obtained after the preprocessing: echo, shadow, reverberation and echo-shadow class. (When an echo bounding box overlaps a shadow bounding box, the echo and the shadow are grouped into a new class called echo-shadow class). Since an object always generates an echo and also causes an acoustic shadow, the matching of the echo-shadow class will constitute a reliable estimate of hypothetical reasoning. Intensity variance, elongation, and surface were chosen as distinctive features for generating a hypothesis and propagation matching strategy. The recursive decision tree of hypothesis propagation ended when no more matches could be found. The best matching solution was extracted from the decision tree. Furthermore, because the side scan sonar is designed for surveying seabed areas, no application was currently reported for detecting objects suspended underwater.

## 2.2 Object detection strategy

According to the above discussions, MSIS and ESIS are the best systems for avoiding oncoming obstacles in water, especially tethered mines. This section provides an overview on current object detecting techniques using MSIS or ESIS.

To obtain identifiable and stable features for navigation, sonar targets were introduced by Williams *et al*. [20] and Newman [21]. The returned echo from a sonar target shows a very good signal to noise rate (SNR) where compared with that from a terrain object. It has a very large magnitude and a small pulse length. Different from sonar targets, terrain objects, such as rocks and the reef walls, have high amplitude but a wide pulse length. Each single returned beam (ping) was firstly thresholded by a predetermined noise value. Then a k-tap FIR (finite impulse response) low pass digital filter is used to filter out large amplitude, high frequency noise. The energetic echoes remaining in the ping history after the FIR filter was applied were classified as 'principle returns'. Those principle returns were finally extracted as point features for an EKF based

SLAM system. The selection of sonar target assists the AUV navigation in a natural environment but simplifies the requirements for the object detection method because both sonar targets and terrain objects show relatively high amplitude echoes. When the size of an object decreases dramatically or the object is in a noisy background, real object echoes and background noise are similar in frequency domain. A low pass filter may not filter out the noise while remaining the objects.

As mentioned above, Ribas *et al*. [16] successfully extracted line features from structured environments. Ribas also reported a better approach to estimating the uncertainty of line features [22]. An undistorted acoustic image was segmented to reduce the computational cost during the Hough voting procedure. A preset threshold was firstly performed from beam to beam and stored the pixels with an intensity value over the threshold value. Secondly, the maxima pixels were selected in each single beam. The selected pixels represented the concrete walls of the environment and finally were put into the Hough voting space for linear feature extraction. Since the distribution of a line feature was approximated to a bivariate Gaussian distribution, the best fit result lies in a probability distribution for a given confidence.

Clark *et al*. [23] demonstrated a GM-PHD (Gaussian Mixure Probability Hypothesis Density) filter-based tracker that successfully tracks obstacles in forwarding-looking sonar images. The detecting procedure in their research involved three steps: an adaptive threshold was applied to identify regions of high reflectivity in the image and another higher threshold was performed to identify the regions with the highest returns. After thresholding, the sonar image was segmented by taking the centroids of high intensity regions. Moreover, Petillot *et al*. [24] designed a two-layers-segmentation algorithm to filter out the backscatter noise from the sonar image. The first layer contained a 7×7 Gaussian filter and an intensity threshold determined by the histogram of the original image. The second layer segmentation also decomposed into two parts: selection of the areas of interest and another two levels of threshold. Once segmented, the different regions representing the obstacles were labelled and geometric features were extracted for the Kalman Filter based tracking system.

Despite the presentation of different techniques or algorithms for automatic detecting purpose in the aforementioned papers, it appears that a constant similarity can be identified: Intensity Thresholding technique. Since objects always generate a higher reflectivity property than the surrounding environment, they are determined by thresholding the acoustic images on intensity. This assumption works well in most operational scenarios but problems may be encounter in confined environments with small obstacles. The main reason is because the walls of a confined environment have a higher reflectivity property than the inside objects. Given a 6 m high, 1 m long and 2 cm thick concrete wall and a 6 cm diametral plastic sphere, the colour intensity of the wall is much higher than that of the sphere. This is mainly because when the acoustic signals encounter an object, part of the energy will reflect back and then be detected by the sensor and part of the energy will refract or diffract. If the vertical beam width is much larger than the cross-section area of an object, more sound energy will pass the object and keep propagating. On the contrary, if the cross-section area of an object is much larger than the vertical beam width, sound waves will reflect back to the source. In fact, echo strength is determined not only by the acoustic signal distance travelled, but also by the material, shape, size and orientation of the object and the cross-sectional area (the object aspect which a sound wave-front reflects). Suspended objects are always deployed at different horizontal planes. If only a small section of an object is scanned by the fan beam, the reduction in reflective area will affect the echo intensity in the image. As a result, small objects or low echo strength objects may be undetectable using intensity threshold.

Reverberation noise is another complex problem in active sonar for automatic target detection. It is mainly caused by the multiple reflections, diffusions and diffractions that occur when sound waves strike the surface and bottom interfaces. In shallow water, if a small target is close to one interface, the reverberation duration is much longer than the target echo. The target object will embed in the reverberation noise and result in a low signal to reverberation ratio. Meanwhile, the presence of boundary reverberation will overlap the acoustic shadow in MSIS and ESIS images, classical detecting methods used the shadow region are inefficient.

Matched field processing (MFP) is a common and useful signal processing tool to localise sources in range, depth and azimuth or to estimate parameters of the ocean waveguide. It refers to array processing algorithms which exploit the full field structure of signals propagating in an ocean waveguide [25]. A block normalized matched filter and a whitening method using AR (autoregressive) modelling are detailed in [26]. However, since the reverberation is strongly corrected with the signal, matching filtering (MF) is inefficient [26]. Ginohac and Jourdain [27] described a deep analysis of Principal Component Inverse (PCI) algorithm to estimate and delete non-stationary reverberation noise. A more deterministic model which considered reverberation as a sum of undesirable echoes was proposed. Assuming that reverberation echoes power was much greater than both signal and white noise power, PCI algorithm estimated the reverberation subspace and then separated the reverberation echoes and target echoes. Generally, a global reverberation model is hard to find because it contains both diffuse and discrete components. Diffuse components can be classified as noises but discrete components look more like signals. Moreover, a non-stationary, coloured noise model leads to computationally intensive detection algorithms due to the complexity of reverberation. Furthermore, the need for prior knowledge about the target strength limits the applications in practical systems.

Instead of directly detecting targets from the strong bottom reverberation, some researchers suppress bottom reverberation before the detection procedure [28]. MTI (Moving Target indicator) techniques operate on the assumption that the target of interest is moving radially to the sonar and reverberation is not. A detection structure which combined an adaptive filter and a fixed notch filter was proposed by Kim *et al* [29].The optimization of the adaptive filter coefficients was based on a stochastic target model in which Doppler frequency is a random uniform distribution. The input signal was then filtered by the fixed filter whose coefficients were copied from the adaptive filter. The essence of MTI techniques is an exploitation of the difference of Doppler frequency shifts between the target and bottom reverberation. However, if both the target and sonar platform is moving slowly, the Doppler frequency shifts of the target and reverberation are similar. Moreover, if the target is small, the reverberation power is much stronger than the target return. In these circumstances, MTI techniques are inefficient because the reverberation can easily mask the target return in frequency domain.

Ren and Bird [30] proposed a detection scheme that provides target sub-clutter visibility in the presence of bottom reverberation. Reverberation produced by the bottom is coherent from ping to ping and this means that the propagation media and waveform are not changed during the transmissions. The signals (except the noise) received from a specific range cell will be similar from ping to ping. Experimental data were collected in a natural lake using a monostatic sonar which was mounted on the bottom of the lake. A target ROV was moved in and out of the sonar beam. Bottom reverberation was modelled as a complex signal composed of a stationary or slowly varying coherent component plus a rapidly varying diffuse component. The target is assumed to be circularly symmetric Gaussian movement. A simple recursive mean estimator was firstly adopted to estimate the coherent component. Received signal in each ping was secondly subtracted by the estimator result to suppress the reverberation. Finally, a globe threshold for circularly symmetrical Gaussian signals was chosen according to a constant false alarm rate (CFAR). Since the bottom reverberation was removed, a moving target needed only to compete with the diffuse component for detection. Therefore, sub-clutter visibility is achieved. However, this is only justifiable because sonar is stationary, and is obviously not a realistic scenario for the AUV in the shallow water scenario.

Reverberation causes a serious problem in many active sonar applications and thus arouses intense research interests. Since the properties of reverberation are strongly correlated with signal, the problem has been studied over a long time in the acoustic signal processing area. However, the detection of a small target with active sonar from the reverberation remains a difficult task and needs to be addressed. So far, in the literature, the chosen methods perform well in most cases but many false alarms have arisen. Those false alarms were mainly inherited from the assumption or constraints of the linear random distribution of the environment. The intensive calculation brought by the non-stationary and coloured reverberation model also impedes the real time application of AUV navigation. Another existing problem is the choice of commercial sonar products. Since they are not specifically designed for scientific research, returned signals will pre-process by imbedding a circuit for display purposes. The energy loss during the pre-processing stage changes the reverberation signal's spectral properties and the above-mentioned signal processing techniques may become inefficient.

## 2.3 Issues motivating this study

Since attenuation of sound as it travels through water is significantly less than that of light and radio waves, sonar sensor becomes a key major factor in underwater exploration and target acquisition. Imaging sonar sensors have proved to be a popular choice in current studies concerning underwater vehicles and harbour protection. Nonetheless, low frequency acoustic signals (compared to optical, radio and laser signals) bring other challenges to underwater research:

***Low resolution***. The hydrophone in the sonar sensor can only record the echo amplitude at each position. Correspondingly, the luminance of each pixel (0-255 grey) in an acoustic image represents the signal intensity. The higher the resolution of the sensor, the higher is the cost of manufacture.

***Object's appearance***. Even regular geometric shaped objects will change significantly in low resolution sonar image. Also, the same object observed by sonar at different times may appear as different geometric shapes. For instance, it may split into several parts or vice versa.

***Reverberation noise***. Shallow water environments in many regions generate much stronger reverberation compared to the returns of small targets. Acoustic shadows after the targets are also overlapped by the bottom reverberation. Since the reverberation mostly arises from the bottom backscattering caused by the roughness of the interface in shallow water, the physical properties are similar to object echoes in the signal history. All this makes it difficult to detect small target echoes in the presence of reverberation.

***Incoherent observations***. Dynamic objects may disappear and reappear from frames as a result of vertical movements, as objects drop in and out from the sonar fan beam.

Although this review is not an exhaustive presentation of all the publications in this field, it indicates that the automatic detection of underwater objects is still a challenging problem. As has been discussed in section 2.2, most approaches have similar features. For instance, among the various applications, MSIS and ESIS are very popular sensorial choices for AUV navigation, because they can search a large area in order to acquire the object information. Depending on the considerations for cost and efficiency, MSIS seems to be the better method for a low cost and light weight AUV. However, using a MSIS in a confined and shallow-water environment generates new problems. A relatively low scanning speed compared to AUV motion distorts the acoustic image and also changes the Doppler shift in the frequency domain. The fan-shaped beam also produces higher reverberation energy compared to small objects' echoes. On the other hand, most signal processing techniques for detecting small underwater objects using sonar sensor introduced a non-stationary coloured model to eliminate the reverberation. However, such a complicated model is hard to obtain and it needs intensive computation. The assumption that the sonar platform is stationary or the object is stationary can not represent the real AUV operational scenario. Therefore, the identified gaps for this study are given as follows:

1. To date, no research has been reported for the detection and tracking of small objects (including centimetre-scale plastic objects) using imaging sonar in confined environments.
2. A simple and reliable method is needed to distinguish the small objects against the reverberation and simultaneously detect highly reflective objects (such as concrete walls and solid river bank) in the AUV operational environment.

The work done throughout this study aims to develop an obstacle detecting and tracking system for AUVs operating in artificially and naturally confined environments. The obstacles introduced in the research are mine-like objects with regular geometric shapes. However, they exhibit poor acoustic reflection properties and their sizes are much smaller than current normal mines. For instance, in a test tank, the introduced obstacles were plastic sphere balls (28 mm in diameter). Meanwhile, since the main aim of this study is to assist AUV navigation in obstacle-abundant environments, the developed algorithms were considered in terms of real time applications.

CHAPTER 3

# Mechanical Scanning Imaging Sonar and Preliminary Investigation

This chapter briefly introduces affiliated imaging sonar sensor and the principles of acoustic imaging. Some important terminology relevant to sonar sensors will also be introduced in this chapter. Firstly, a description of common sonar systems is introduced. Secondly, the acquisition of acoustic imaging is demonstrated by way of explanation of sound behaviour in the water. Thirdly and finally, the ability of the adopted imaging sonar is tested using preliminary experimentation.

## 3.1 The nature of sonar

A number of signals for detecting the presence of underwater objects have been investigated, such as magnetic, optical, thermal (infrared) and acoustic signals. Sonar (sound navigation and ranging) is a device which uses underwater sound to detect and locate objects remotely. Owing to a long radiate range in the water, sound waves are still unsurpassed by other methods, despite the noise pollution which is produced by ambient environments and reverberation. Ambient noise is due to a variety of different sources, such as oceanic turbulence, surface wave, ship traffic and biological noise produced by marine life. The component of the incident sound energy reflected back to the source is known as backscattering. This backscattered energy is reverberation which comprises both the background and echoes from the target itself [31].

Passive sonar detects a target against the background by listening to the sound radiated from the target. In comparison, active sonar uses a projector to generate a pulse of sound, which is called a ping. This ping travels through the water until it collides with an object. Part of the reflected energy is returned as an echo, which is also called a return, and is detected by the hydrophone. Since the time interval between the transmission and the reception of the sound wave can be measured and cooperated with sound velocity in the water, the range of the echoing target can be calculated. Therefore, active sonar has an appropriate sensing capability for AUV exploration in an unknown and turbid-water environment. According to the shape of the sound beam, active sonar can be categorized into two types: pencil-shaped-beam sonar and fan-shaped beam sonar (see Figure 3-1 ).

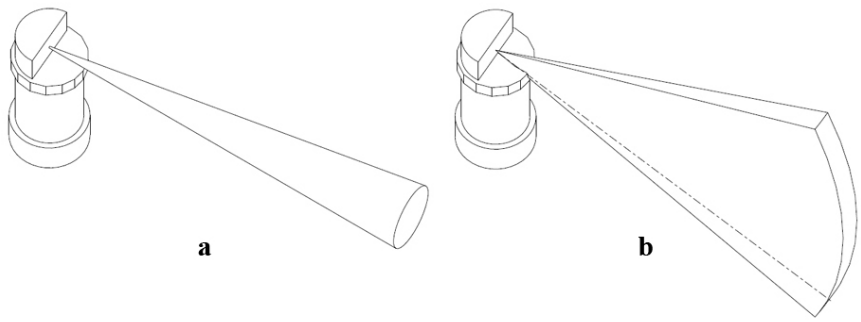


Fig. 3-1 : The shapes of sound beam. (a) the pencil beam; (b) the fan-shaped beam

Sound waves from a pencil-beam sonar is in the form of a narrow cone or cylinder. As a consequence of a low-divergence beam, when sound isonifies a water column and then strikes a target, the intersecting surface of the target and the beam can be extracted as a point. The cross-section of the target area is described by connecting a sequence of points into a profile line. While a fan-shaped beam sweeps across a large area and obtains information about the environment being scanned. Returns are constantly recorded to produce a photo-like image. Sector scan sonar normally looks ahead and rotates the fan-shaped beam by either mechanical or electronic means. In contrast, side scan sonar emits fan-shaped sound waves in a sideways motion and records a series of cross-track slices which are perpendicular to the path of the sensor. A majority of side scan sonar sensors are towed from a surface vessel or mounted on the ship's hull to create images of the seafloor. Figure 3-2 illustrates the different scanning strategies of the sector scan sonar and the side scan sonar. The movements of the sound beam through the water column will result in a series of cross-track slices. An acoustic image is generated by stitching these slices along the direction of motion.

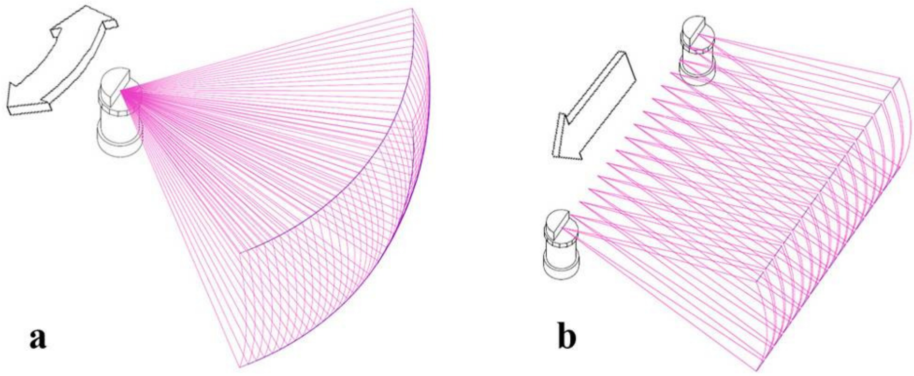


Fig. 3-2: (a) Sector scan sonar: scanning by rotating the beam. (b)Side scan sonar: scanning by moving scanning unit in a straight line with a locked beam direction.

According to the physical characteristics of the sound beam, a majority of pencil-beam-sonar sensors and side-scan-sonar sensors observe the seabed. Typically, pencil beam sonar is employed for cross-sectional profiling in pipeline and trench survey along the seabed. Side scan sonar is applied to accurate mapping of large sections of the seabed or locating seamounts, obstructions and other features on the seabed. Sector scanned sonar is generally mounted vertically to the front of a survey vessel or ROV with the transducer at the top. Common applications for sector scanned sonar include: detecting and locating obstacles along the vehicle moving path, performing searching and rescue missions as well as harbour and port surveillance. Figure 3-3 shows a common configuration of the above mentioned sonar sensors in an underwater vehicle.

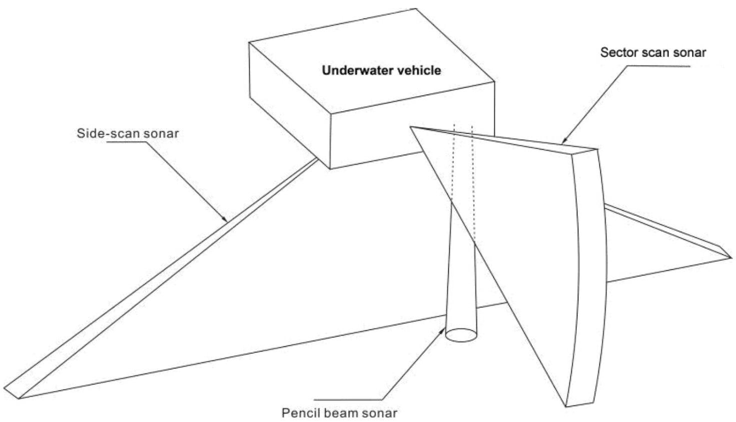


Fig. 3-3: Applications of different sonar sensors underwater

## 3.2 Understanding acoustic images

In many cases, objects in an acoustic image will closely resemble each other in an optical image. However, acoustic images have unique characteristics, which are mainly inherent from the sound behaviours underwater. In this section, the generation of the acoustic image is explained. Two fundamental issues concerning the acoustic image are then followed.

### 3.2.1 Acoustic image generation

Acoustic imaging is a procedure that generates two dimensional images of underwater objects. Figure 3-4 illustrates a single beam from a sector scanned sonar which impinges on the horizontal surface and protruding object. While no objects reflect the sound, no noticeable echo is produced. When the beam strikes the bottom the first distinct echo is detected by the hydrophone. Because the large incident angle and the smooth plane will result in specular reflection, only a small fraction of sound energy is returned. The measured echo strength is low. With the advance of the sound beam, a protruding object reflects acoustic signals back to the sensor. The high echo strength can be observed by the sensor until the sound passes the object. Due to the obstruction of the object, there will be an acoustic shadow immediately behind the object. Following the shadow, bottom reflection will be present again. Imaging sonar will quantize the amplitude of the echo into colour intensity and represent the objects in a digital image.

The water volume being surveyed is illuminated by linking single beams together in a Cartesian plane. Figure 3-5 shows the scanning process of a mechanical scanning sonar and the corresponding acoustic image. There are four objects lying on a flat plane. Different colour zones represent different echo strength measured by the sonar. The grey colour area illustrates the bottom return and it is called bottom reverberation; the white colour regions are caused by the reflections from objects and the dark colour regions include the acoustic shadow and no reflected water column.

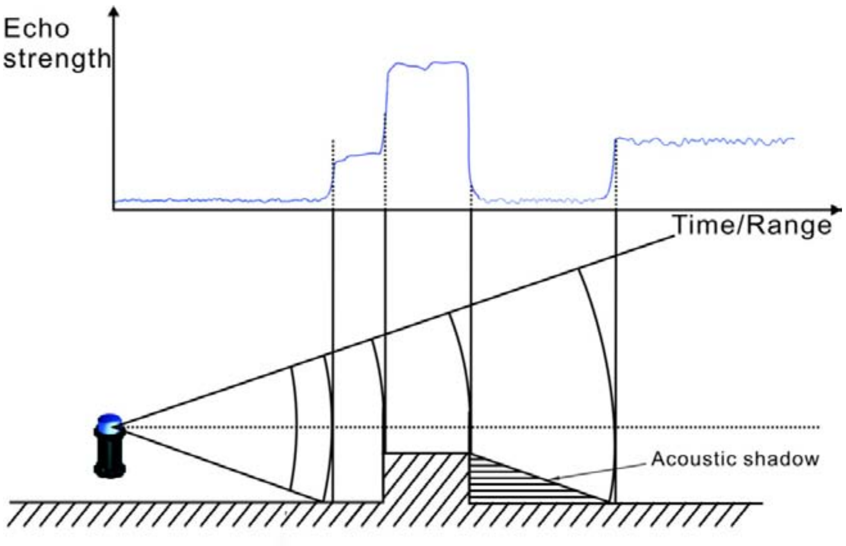


Fig. 3-4: A sound beam intersects with a flat bottom and a protruding object

NOTE:
This figure is included on page 26
of the print copy of the thesis held in
the University of Adelaide Library.

Fig. 3-5: Mechanical scanning sector and an acoustic image. (The original images were obtained from Imagenex Technology Corp., 2002)

### 3.2.2 Multiple reflections

One important issue for two dimensional acoustic images is the simulacrum which is caused by multiple reflected sound waves. If specular reflections arise from the smooth surface, sound waves will rebound back to the source (see Figure 3-6 ). Similar phenomena occur between the object surface and the body of the sonar. A sound beam is reflected with diminishing until its energy is finally absorbed. However, the hydrophone records these multiple reflected echoes as well as the echoes from the real object. When generating the image, there will be several objects which are symmetrically appeared in the image, i.e. the wall acts as a mirror and reflects acoustic waves. The second reflected echoes should have roughly twice the attenuation of the first echo as it has travelled twice the distance. Such multiple reflected phenomena are more common when operating in small confined places (such as a water tank) instead of natural outdoor environments. Figure 3-7 illustrates such simulacrums observed in a small water channel. In this case, the vertical lines at about 0.3 meters in the images are the real boundaries of the water channel. Multiple reflections are also recorded at about 1.5 meters which were mainly caused by the sidewalls of the channel.

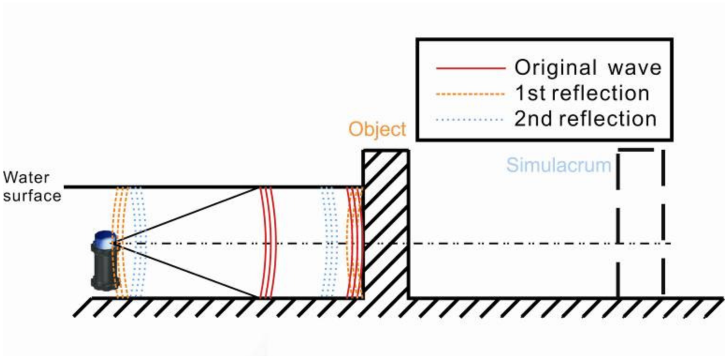


Fig. 3-6: Multiple reflection of sound waves in the water

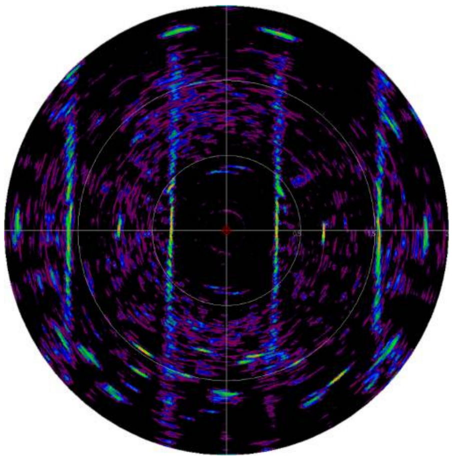

Fig. 3-7: Multiple reflections observed in a small water channel. (The red diamond indicates the sonar centre and grey circles indicate the scan range)

### 3.2.3 Vertical resolution

Another important issue for acoustic images is the vertical resolution. Although the length of the acoustic shadow can be used to infer the height of an insonified object, fan-shaped beam sonar cannot distinguish objects at the same range but having different elevation. This phenomenon originates in the large vertical beamwidth. In Figure 3-8 , two objects are located at the same radiate range of the sound wave. The reflected sound energy will accumulate and contribute to a high-strength-echo to the sensor. In such scenarios, there is no height discrimination even if their actual horizontal distances to the sonar are different.

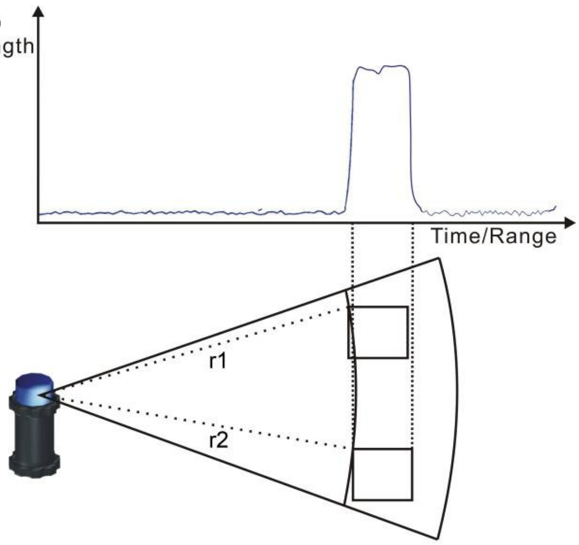


Fig. 3-8: Objects at same range but different elevation (r1=r2)

## 3.3 Imaging sonar for the research

In the previous sections, sonar sensors were classified by the shapes of the sound beam. However, they can also organised by the number of the beam emitted from the sensor projector. Compared to the single beam sonar, multi-beam sonar projects several simultaneous adjacent parallel beams. Multi-beam sonar improves the efficiency and precision of an underwater surveillance system, but it is more complex and expensive than a single-beam sonar. A relatively high energy consumption and greater net weight contributes to the favoured selection of single beam sonar in this research. Since autonomous navigation and obstacle avoidance is the main purpose of this thesis, the focus will be on how to map the front environment instead of the seabed and how to deal with any oncoming obstacles in the vehicle's path. In order to build a relatively low cost and light weight underwater vehicle, a sector scan underwater imaging sonar (Super SeaKing DST Sonar) was used. When the sensor is mounted vertically, the centreline of the sound beam is parallel to the water surface.

### 3.3.1 Super SeaKing DST sonar

Super SeaKing DST Sonar (abbreviated as Super SeaKing), a mechanical scanning sonar from Tritech International, has been adopted as the standard obstacle avoidance and target recognition sonar in many of the major ROV fleets around the world. The CHIRP (Compressed High Intensity Radar Pulse) techniques, used on the Super SeaKing, improve the sonar image resolution five times greater than the image resolution of conventional sonar sensors [32]. There are two mechanically scanned imaging transducers encapsulated within a single housing: one is a 325 kHz CHIRP sonar with operational range up to 300 meters for long range target detection; the other is a 675 kHz CHIRP sonar for ultra-high resolution target detection. Such a high resolution can provide information about the surroundings, including distance and object size. The vertical beamwidth is 20° at 300 kHz and 40° at 670 kHz. The horizontal beamwidth is 3.0° at 300 kHz and 1.5° at 670 kHz. The transducers can continuously or partially scan in either direction mechanically. The stepper motor can step the transducer around the vertical axis with four different steering angles: 0.45°, 0.9°, 1.8° and 3.6°. The power supply to the device is 18-36 Volts at less than 10W. The sonar hydrophone will accept a return signal in the region of 0 - 80dB. Detailed hardware specification can be found in

[32]. Figure 3-9 shows the sonar device and proposed location where it is mounted on the AUV.

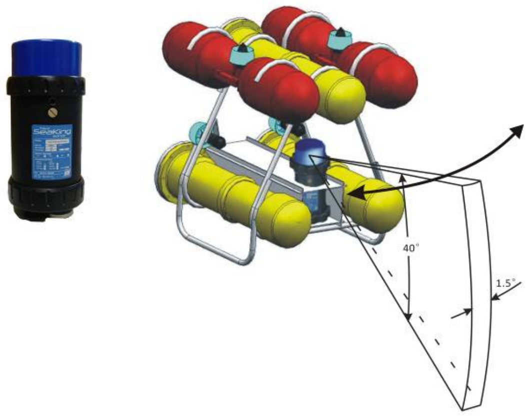


Fig. 3-9: The Super SeaKing sonar and its location when it is mounted on the rover

### 3.3.2 Acoustic imaging process

Super SeaKing is a monostatic sonar, which means that the projector and the hydrophone are co-located in the same transducer. In this context, both the projector and hydrophone are commonly called the transducer. Once a sound pulse is emitted the hydrophone starts to record echoes simultaneously. The return is a sound wave, which is bounced back off objects, thus recording the environment information in the path of the emitted sound pulse. For each single return, the analogue acoustic signal is sampled by the hydrophone in time sequences, which are called Bin. Measuring the time of flight and the speed of sound in water, each Bin can also represent the distance. To produce an acoustic image the amplitude of each return is quantized into discrete bins by two levels of threshold. The amplitude below the low level threshold (Adlow) is plotted as black (grey level 0) and the amplitude beyond the high threshold, is plotted as white (grey level 255). The amplitudes within these two thresholds are assigned to different shades of grey between 0 and 255 (see Figure 3-10 ). The lower threshold controls the sensitivity of the sonar sensor. It also filters out the background and received self noise. The width of these two thresholds is defined as the 'Adspan' or dynamic range which controls the contrast of sonar image. The high level threshold is the sum of the 'Adlow' and 'Adspan'.

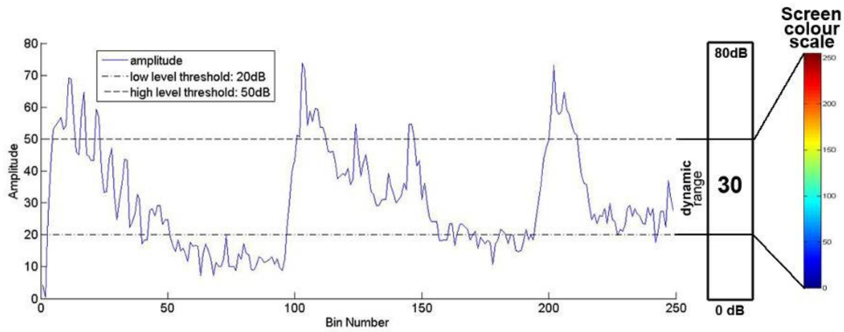


Fig. 3-10: Two level thresholding for a complete return (Dynamic range is 30dB). Sensor scan range is 6m and there are 250 bins obtained in the return. Therefore, each Bin represents 6/250 = 0.024m.

The transducer then rotates in a small steering angle (step size) mechanically after the ping is successfully received. The current heading orientation of the rotating transducer is defined as the bearing. Combining the range and the bearing information, the position and azimuth of the objects along the sound path are then known. The target displays on a polar plot of the bearing versus range. Acoustic image is then generated in a horizontal 2D plane by integrating serial beam sectors together. The scanning period is determined by the combination of step size and scan range. The resolution of the acoustic image is decided by the horizontal beam width and step size. Figure 3-11 shows an example of the 180 degree sector with a step size at 3.6 degrees.

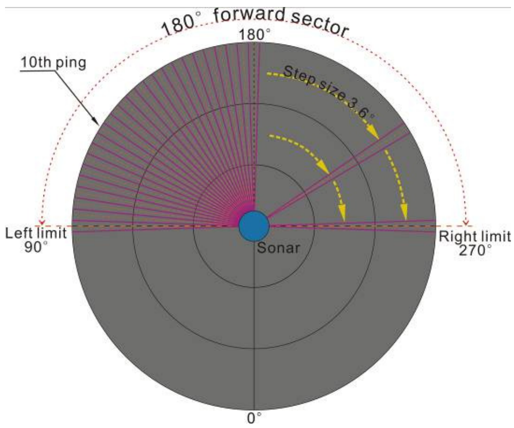


Fig. **3-11**: 180-degree-scan-sector with 3.6 degrees step. 50 (180/3.6) pings will be taken over this sector. The bearing of the 10th return is (90+3.6×10=126°)

SeaNet Pro is the software package for the Super SeaKing. It can be run on Windows Operating Systems (2000 and XP). Through a RS232 COM port, it can control and communicate with a sonar sensor. Using the software interface, operators can easily control the sensor gain, 'Adlow', scan range, scan step, signal frequency and scan sector. In the meantime, data replies from the Super SeaKing are recorded and displayed on the screen in real time. Figure **3-12** shows the SeaNet Pro software GUI.

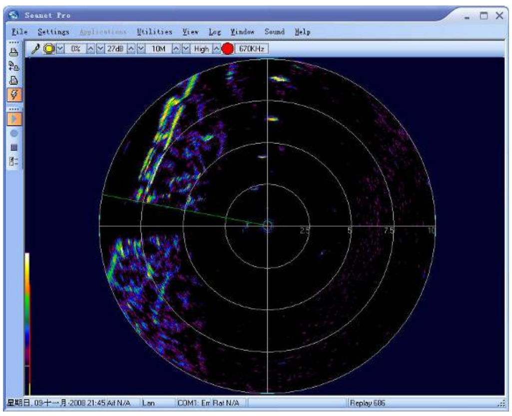

Fig. **3-12**: SeaNet Pro software GUI and displaying

## 3.4 Preliminary experiments and investigation

The main aims of the preliminary experiments were to test the capability of the adopted imaging sonar sensor. A simple automated target detection method was developed and evaluated by the images captured form the SeaNet Pro. The reason of using displayed images is mainly because the raw data was not accessible at that moment.

### 3.4.1 Experimental set-up

The initial experiments were carried out in two different water tanks. One is 0.4m×1.1m×1.0m plastic tank (depth×length×width) and the other one is 0.5m×0.5m×7.0m channel tank. Two 12V batteries connected in series were used to power the imaging sonar. Communication between the computer and sonar was linked via a RS-232 port at 115.2K baud rate. The sonar sensor was set to perform scans in full 360°, while each scan step was set to be 1.8° and frequency was set at 300kHz in both experiments. While operating at high frequency, much noise was observed on the image. The surrounding information can be updated around every 4 seconds in this configuration. Objects introduced for the experiments were: a small cylindrical shaped object with dimensions 6cm×9cm (diameter × length) approximately and a human palm, respectively. The first experimental deployment is shown on the left-hand side in Figure **3-13**, the software, Seanet Pro, coming together with Super SeaKing was used to produce the images shown on the right-hand side in Figure **3-13**. Similarly, the set-up of the second experiment in the water channel is shown in Figure **3-14**.

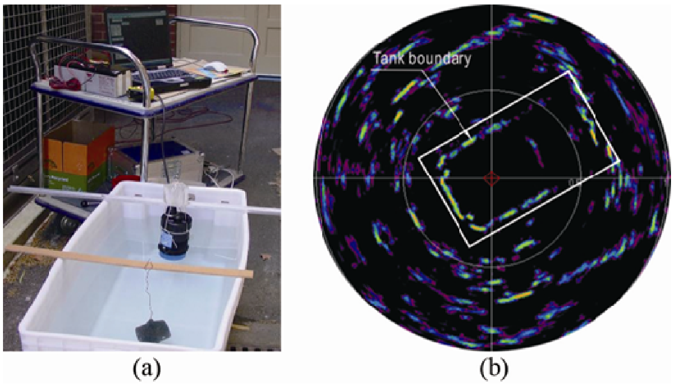


Fig. 3-13: a) Experimental deployment. b) Sonar image generated by the SeaNet Pro. (The red diamond indicates the centre of the sensor and the white rectangle is added afterwards to highlight the tank boundary.)

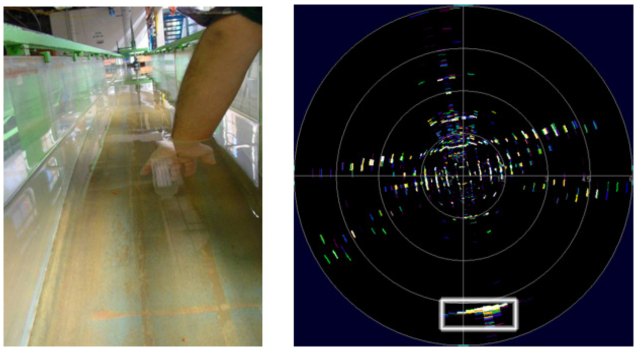

Fig. 3-14: Experimental set-up for human palm detection and sonar image. (The palm is highlighted inside the rectangle.)

### 3.4.2 Automated objects detection

The method for automatic detection presented in this section is relatively simple since the sonar raw data were not accessible at the time of the experiments. Displayed images of the SeaNet Pro were therefore involved. Using the playback function for recorded data provided by the Seanet Pro software, a series of sonar images were captured directly from the screen every 9s, which is the same as the playback period.

In order to identify the moving object in every sonar image, it is necessary to eliminate static objects as well as all unwanted noises that normally appear within real-time data samples. Most static objects, such as the boundary of the water tank, appear to be the same size and shape in the sonar image. However, they had different echo strengths and were displayed different colours in the sonar image. In this situation the mean value image of the image sequences was chosen as the reference image to eliminate static objects and random noise. In addition, the detector will perform within the predetermined tank boundaries only. The method includes the following steps:

1. Reference image Calculation. The reference image is given by Equation **3.1**:

$$\overline{D}(x,y) = \frac{1}{N}\sum_{i=1}^{N} D_i(x,y) \qquad \textbf{3.1}$$

   with $D_i(x,y)$ is the image sequence and $N$ is the total number of images

2. Noise and background elimination. The subtraction image $S_i(x, y)$ is given by Equation **3.2**.

$$S_i(x,y) = |\, D_i(x,y) - \overline{D}(x,y)\,| \qquad \textbf{3.2}$$

3. Binary threshold. Since sound waves are quantized between 0 to 255 (grey colour), the value of binary threshold is simply assigned to 127. The binary image sequence is given by Equation **3.3**.

$$BW_i(x,y) = \begin{Bmatrix} 1 \; if \;\; S_i(x,y) \geq 127 \\ 0 \; if \;\; S_i(x,y) < 127 \end{Bmatrix} \qquad \textbf{3.3}$$

4. Morphological operations. Opening and closing operations were performed by the structuring elements. The purpose of morphological operations was to eliminate the noise from the image and remain the targets. More detailed description for morphological operations can be found in the Chapter 4.

The developed algorithm is shown in Figure **3-15**

```
%% Detector for screen displayed image
function [Targets] = imageDetector(SeaNet_disply)
% 'Target', a binary image contains the targets only
% 'SeaNet_disply' image sequence captured from screen display
% structuring element B
streB1 = square(2);
streB2 = square(3);
streB3 = square(4);
streB4 = square(5);

% read the image into memory
digital = read (SeaNet_disply);

% acquire the number of the captured image
n = getNum(digital);
meanImg = mean(digital); % acquire the mean image
for i = 1 to n
    subImg(i) = abs(digital(i)-meanImg)
    % locate the region for detector
    regionImg(i) = region(subImg(i));
    bwImg(i) = thresholding(regionImg(i))% acquire binary image
    TEMP(i) = close(bwImg, streB1) %morphological close
    TEMP(i) = open(TEMP(i), streB2) %morphological open
    TEMP(i) = close(TEMP(i), streB4) %morphological close
    subFeature(i) = open(TEMP(i), streB3) %morphological open
end
Target = subFeature(i); % output the results
```

Fig. 3-15: Target detector for preliminary experiments

### 3.4.3 Experimental Results

In the plastic tank, ten pictures were recorded for this experiment. Figure 3-16 shows some of the results and Figure 3-17 illustrates the objects' trajectory with a blue line.

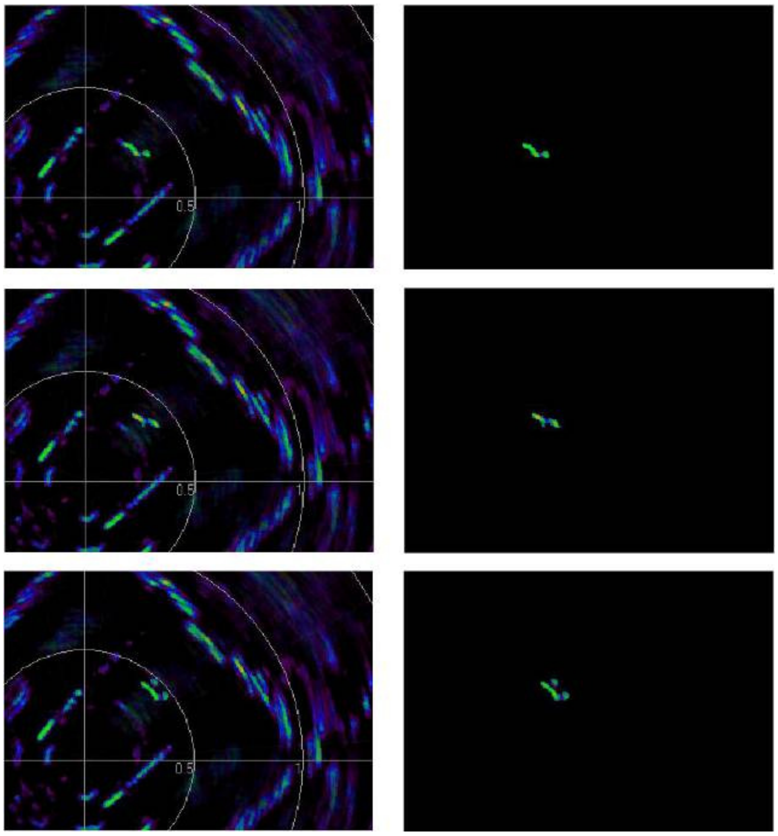


Fig. 3-16: Target detection results. (The left side is the original image and the corresponding result is shown on the right.)

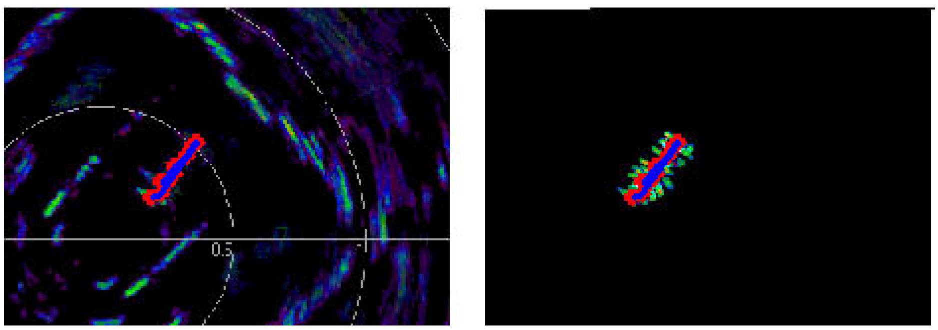


Fig. 3-17: Target trajectory (The blue line is formed by connecting the results together).

In the water channel, 15 pictures were recorded while sonar scanning was in operation. Results are shown in Figure 3-18.

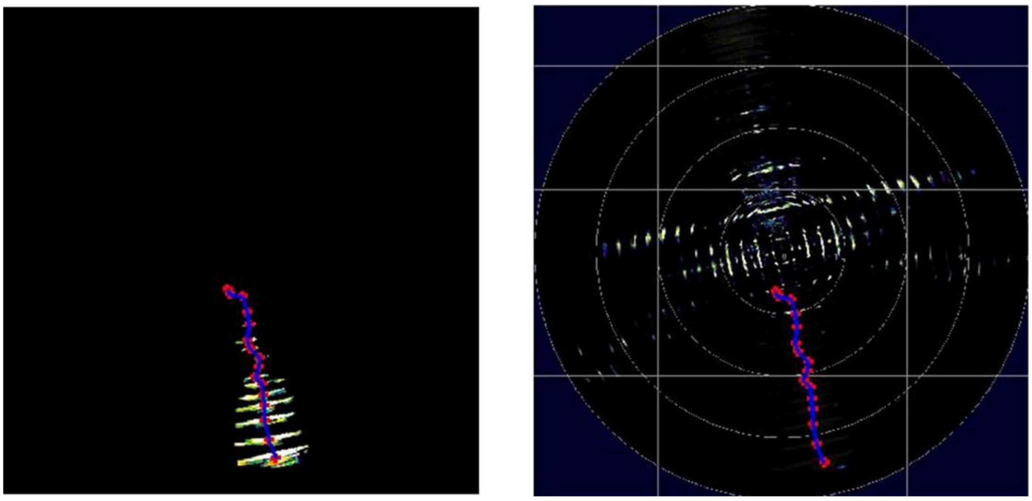

Fig. **3-18**: The identified human palm and its trajectory. (The trajectory was connected by the centre of gravity).

The experimental images demonstrate the satisfied resolution of the adopted sonar sensor. Echoes from small static and dynamic objects were successfully recorded by the Super SeaKing. Acoustic images provide a good reference point for the selection of target objects for future experiments. Moreover, the results indicate that morphological technique for moving object detection is reliable, even without the sonar raw data. It finally formed one basic method for this study.

This experiment and results were presented at Industrial Electronics and Applications, 2008. (ICIEA 2008. 3rd IEEE Conference).