Towards Automated HF Sidescan Sonar Performance Estimation

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Abstract: FFI developed the tool “MCM Insite” for Mine Countermeasures (MCM) performance evaluation for Autonomous Underwater Vehicles (AUVs) equipped with side looking sonars. It estimates image quality and image complexity automatically from sonar images. The concept has been successfully applied to different synthetic aperture sonar (SAS) sensor systems taking full advantage of constant spatial resolution and phase information. However, it is more difficult to extract the required image metrics with non-interferometric, high-frequency sidescan sonar (SSS) systems, which are widely used for imaging the seafloor during mine-hunting operations. The main challenge of assessing image quality with SSS is to find a good signal-to-noise ratio (SNR) estimation from its common beamformed amplitude output. Also, for image complexity, the varying along-track resolution over range imposes a challenge when using scale-based image texture techniques. In this paper we aim for a solution for Edgetech SSS at 850 kHz frequency demonstrated on shallow water data.

Keywords: Sidescan sonar, Mine Countermeasures, Performance evaluation
1. INTRODUCTION

Autonomous underwater vehicles (AUVs) equipped with side-looking sonars have become an increasingly important asset for minehunting in Mine Countermeasures (MCM) operations. Sidescan sonar (SSS) systems are commonly used for imaging the seafloor [1] being both more affordable and more widespread in use than high-resolution synthetic aperture sonar (SAS) systems. For running AUV operations autonomously, it is crucial that the vehicle is able to assess its performance automatically in-mission, based on the data collected, in order to adapt to rapidly varying sensor geometry and environmental conditions. The Norwegian Defence Research Establishment (FFI) has developed a tool for MCM performance assessment called “MCM Insite” [2] that couples in-situ estimations of the two parameters image quality and image complexity with a-priori information. Image quality describes the performance of the sonar in providing a proper representation of the seafloor and is affected by e.g. multipath contamination, refractive effects, vehicle stability, navigation accuracy or noise. Image complexity captures the difficulty of recognizing targets in the local image background. It is low for rather featureless seafloors and high in the presence of e.g. clutter, rocks, debris or vegetation.

“MCM Insite” has been successfully applied to both HISAS and MUSCLE SAS data [3]. For SSS it is more challenging to calculate the two parameters, particularly due to a lack of a proper estimation for image quality. If a SSS system is interferometric, it is possible to estimate the SNR from the spatial coherence (i.e., the similarity of the signal on the vertically displaced receiver elements), which is an effective estimate of image quality [4]. Since, however, most operative SSS are not interferometric, it is important to find a way to assess their performance from an amplitude image. In shallow water, image quality can particularly be degraded by multipath returns.

In this paper, we first perform a model-based prediction of the sonar performance in order to divide the image into different range intervals with varying degree of expected performance. This prediction is then followed by an estimation of ping-to-ping coherence and a texture-based technique on the collected sonar data, which estimates the effective sonar range. The image complexity is calculated by applying wavelet variances on the image texture at various scales. We use data of a non-interferometric high frequency (HF) SSS in shallow waters for demonstrating our methods towards performance assessment.

2. DATA

In this study we use a data set of SSS images at 850 kHz that WTD 71 collected in the Eckernförde Bay, Germany, with an Edgetech 2205 SSS system. The entire Eckernförde Bay is a remaining of the last ice age. When the glaciers melted away, the meltwater formed the bay and left a lot of gravel and rocks behind. Over the years the deeper parts of the bay got covered by a thick mud layer. At the edges of the bay the currents washed away the mud and shifted sand from the bluffs into the shallower parts of the bay and formed sandy beaches. The area from which the data were sampled is at the inner part of the bay. It covers the transition area from the deeper parts of the bay towards the shoreline. In this area there are some flat, sandy regions. At some places the underlaying layer of rocks becomes visible. Geologists call this type of sediment “residual sediment”. In combination with the very shallow water (10–15 m) this area is quite challenging due to multipath propagation effects.

Fig. 1 shows data from three parallel survey tracks, where (b) and (c) partly overlap with 20 m difference in line-spacing. The maximum range to each side in the images is 50 m. We clearly see the effects of multipath visible as wavy patterns from as close as 20 m range (e.g. in the last 60 m along-track in Fig. 1(a)), getting stronger with increasing range. Fig. 1(a) shows fairly featureless seafloor, except small scale gravel located between 140 m and 200 m along-
track, while (b) and (c) contain a large area of rocks (port-side), small-scale gravel (in the last 50–60 m along-track) as well as other natural and man-made objects.

At 850 kHz the sonar is specified to have 15 cm along-track resolution at 50 m range, which corresponds to a beamwidth of approximately 0.2°. This is a multi-element system with dynamic focusing to achieve highest resolution at mid to far range, dynamic aperture (or array length) to maintain a fixed limited along-track resolution of 10 cm up to 25 m range, and linear frequency modulation (LFM) pulse forms with pulse compression to obtain better signal power. The maximum range is specified to be 75 m. The pulse bandwidth is 85 kHz giving a theoretical range resolution of 9 mm.

![Sonar images](image)

**Fig. 1:** Sonar images taken with an Edgetech SSS at 850 kHz and 50 m range to each side with 50 dB dynamic range and TVG applied. The vehicle altitude is 4.5 m and the water depth varies between 15 m at the beginning of the tracks and 10 m at the end closer to the shore.

### 3. MODEL-BASED SONAR PERFORMANCE

Model-based sonar performance prediction based on the power budget [5, Eq. (6.62)] can give an initial assessment of the multipath contamination as function of range. It can provide an estimate of the direct backscatter from the seabed and the multipath level (i.e., acoustic signal paths that have been intersecting with the sea surface at least once), together with the additive noise level (either from ambient noise or self noise). This is a common technique used in many sonar applications [6, 7]. The main objection against model-based performance prediction is that the environment must be known a-priori, including the sound speed profile, the sea state (for shallow waters), and the seabed type which often is unknown. We suggest a much simplified model where we assume flat seabed with the same seabed type, known vehicle altitude,
depth, roll and known sonar system parameters. We perform a slight modification to [8] and divide the SSS swath into 5 instead of 4 zones as illustrated in Fig. 2.

1. The water column zone, where no backscattered signal from the seafloor can occur.
2. The backscatter only zone, where multipath cannot be present due to travel time between the seabed and the sea surface.
3. The backscatter likely zone, where multipath theoretically is possible, but the backscatter is dominating based on model predictions.
4. The multipath likely zone, where multipath is likely to affect the image quality.
5. The noise likely zone, where additive noise is likely to affect the image quality.

Fig. 2: Sidescan sonar range zones.

The first and last zone may be used to estimate the noise level if present and visible. Zone 2 provides information for a simple (non-calibrated) model-fit to obtain the general level of backscatter which in return helps to find a good fit for the bottom type [9]. The chosen seabed type, vehicle depth and altitude can then be used to forward calculate the transition between zones 3 and 4.

Fig. 3 shows the relative signal power from measurements for the first and last 60 m along-track in Fig. 1(a), compared with modeled signal, multipath, and additive noise. The calculated transmission loss is removed from the results. There are two major differences between the regions: The 0–60 m region is deeper and has a softer sediment giving less backscatter. The 160–220 m region is shallower and has a harder sediment giving more backscatter. The procedure described in the previous paragraph was followed for choosing the seabed type in the two regions based on the general level of backscatter in zone 2. Then the altitude and depth was used to model the backscatter and multipath levels. The additive noise level was fitted to the starboard side of the first region where noise is clearly visible. We see that the actual shape of backscatter signal and multipath level does not fit perfectly to the measurements. The overall trend, however, fits fairly well, and the five zones capture the different dominating contributions. Zone 1 is characterized by the water column and hence no backscatter. The second zone contains only backscatter signal as there is no multipath possible. Zone 3 can contain multipath, but is dominated by backscatter signal. The fourth zone in Fig. 3 begins when the signal-to-multipath ratio is below 3 dB and for zone 5 the SNR is below 3 dB. The additive noise affects the image quality in the region of low backscatter. The multipath affects the image quality in the shallow region of high backscatter. Note that a constant sound speed was used, and the vertical beam pattern of the sonar was assumed.
Fig. 3: Sonar model for predicted backscatter signal, multipath and assumed noise compared with average measurements (side 1: port, 2: starboard) for the first and last 60 m along-track in Fig. 1(a). Note that the measurements contain information from all three model components. The zones illustrated in Fig. 2 are derived from the model and indicated at the top of each panel.

Fig. 4: Normalized variance plots including texture thresholds for the data from Fig. 1.
4. IMAGE QUALITY

The image quality parameter aims to capture the sensor performance, i.e., the sonar’s ability to “see” the seafloor. Our dataset presented in Section 2 originates from a non-interferometric HF SSS, where the provided data only contained amplitude and no phase information. A natural way to determine sensor performance is the generalized SNR, which can be derived from spatial coherence [10, Ch. 4]. Due to lack of an interferometer, one could instead try to calculate the temporal (ping-to-ping) coherence describing the similarity of the received signals from two consecutive pings. Following the specifications of this sonar system described in Section 2, there is no overlap between consecutive pings in the first 25 m across-track, which linearly increases to 50% overlap for the maximum range of 50 m. This indicates that a ping-to-ping coherence might not be suitable enough for assessing image quality, and is confirmed by our own investigation. It appears that texture is the main driver for high values in our calculation of temporal coherence, which can be caused both by multipath contamination (wavy patterns in the far ranges) or by actual texture on the seafloor, e.g., rocks. This is not ideal as a characterization of image quality. Imaging artifacts, e.g., caused by multipath, speckle or ambient noise, and object shadows should provide a low SNR (hence low image quality), while backscatter from the seafloor and objects on the seafloor provide high SNR (hence high image quality).

A more promising approach to infer image quality is shown in Fig. 4. Here we apply normalized variance as texture measure to the sonar images from Fig. 1 (without water column data), assuming that textures differ between the backscatter and multipath/noise regions. Following [8], we then estimate the effective sonar range as the range threshold that separates the texture measure best into two classes using the maximum between-class variance as optimization criterion. In Fig. 4 there are two range curves, where the magenta curve (local range threshold) results from ping-wise thresholding followed by 25 pings median filtering, and the black curve (global range threshold) is the result after processing the full image as a single data block. Port and starboard side data are handled separately. The magenta curve is more sensitive to variations in local seafloor characteristics, while the black curve is a more robust estimate for the entire image.

In fairly homogeneous regions of good quality (i.e., where there is only one obvious quality class in the texture image), the separation leading to the local thresholds becomes very sensitive to small variations and thus can estimate sonar ranges of less than 10 m and above 40 m within short distance along-track. This can be avoided by adding an along-track smoothness criteria that leads to a high cost for rapid changes of the estimated local sonar range.

We observe that the global threshold appears to provide a reasonable estimate for the effective sonar range at around 40 m on the starboard side of all three examples. This might be due to the fact that the data on the far ranges of the starboard side seem to be more affected by noise than on port side, which is reflected in the low normalized variance values. On the port sides, the global threshold varies between 22 m (Fig. 4(c)) and 31 m (Fig. 4(b)). This is partly due to multipath that according to the model prediction in Fig. 3 can dominate from ranges of around 20 m, but also due to the texture on the seafloor like the rock field. The local thresholds appear to follow the contour of the rock field closest to the sonar. As seen in the model of the last 60 m along-track (Fig. 3(b)), where the water is shallower and the sediment harder, multipath is more likely to contaminate the data, and is particularly visible on the port side images of the last 60 m along-track (see Fig. 1). Our local thresholds capture these strong multipath regions pretty well.

5. IMAGE COMPLEXITY

We see image complexity as a texture-based metric applicable to a variety of sonar data, both SAS and SSS. The metric provides values ranging from 0 (no complexity) to 1 (high com-
plexity). In Fig. 5 we show our results corresponding to the SSS data from Fig. 1 using the wavelet variance method described in [11] for finding mine-size texture in the images. The scales of interest were adjusted to the image pixel resolution with focus on structures in areas of size $0.4\,\text{m} \times 0.4\,\text{m}$ to $1.6\,\text{m} \times 1.6\,\text{m}$. In addition we downsampled the across-track resolution to 10 cm in order to have quadratic pixel resolution. However, please note that, opposed to SAS, in SSS the physical along-track resolution is not fixed with range. As described earlier this resolution varies between 10 cm at 25 m range and 15 cm at 50 m range.

Our complexity metric is driven by objects of mine-size scales, which lead to the highest values. Both single objects of mine-size as well as the large area of rocks in Fig. 5(b) and (c) are clearly captured. The complexity estimates for the overlapping tracks are higher in the rock area in (c) due to the multipath contamination and hence lower contrast between backscatter values and shadows in (b). For the small-scale gravel we obtain fairly homogenous regions of low to medium-low complexity, which is as expected since this is smaller than mine-size (hence less complex), but also not plain seafloor.

![Fig. 5: Image complexity estimates for the SSS data from Fig. 1. The values range from 0 (not complex) to 1 (very complex).](image)

6. DISCUSSION

In this study we investigated methods for evaluating the MCM performance in shallow water with a non-interferometric HF SSS sonar following FFI’s “MCM Insite” performance assessment model. We are using both in-situ measurements and a-priori knowledge. It is more difficult to assess MCM performance for SSS than for SAS. The along-track resolution is not constant across the image and could thus lead to difficulties with a scale-based texture measure for image complexity. This was not observed as a problem with the available data in our case since the image complexity estimates were reasonable compared with the underlying SSS im-
ages, though more thorough research is needed for a proper verification. The main challenge with beamformed non-interferometric SSS amplitude data is the lack of an obvious metric to capture the SNR for estimation of the image quality. We tried ping-to-ping coherence based on the available amplitude information, but the results were more influenced by texture than imaging artifacts. This is due to little or no overlap between consecutive pings.

Our currently best suggestion is to first run a simple model which can help in identifying zones that are dominated by either backscatter, multipath or noise. This is later checked with a texture-based classification of each image that aims to find the effective sonar range to separate the image into two classes of good near range quality (due to backscatter) and poor far range quality (due to multipath or noise). Our results show that this classification works fairly well in the presence of noise and strong multipath. However, the suggested solution is depended on the underlying texture measure, which contains both information on areas of low quality due to multipath or noise, and areas of high variation due to seafloor texture such as rocks, clutter or debris. When there is lots of texture present, it might be possible to use the knowledge provided by the image complexity metric to aid the classification to ignore or damp the influence of mine-size textures. Additionally, when running surveys with tight track spacing, the stability of the image quality estimate can be monitored for overlapping adjacent regions.

REFERENCES


