Side Scan Sonar Image Resolution and Automatic Object Detection, Classification and Identification

F. Langner[1)], C. Knauer[1)], W. Jans[2)] and A. Ebert[3)]

[1)] Freie Universität Berlin, Institut für Informatik,
Takustraße 9, 14195 Berlin, Germany,
e-mail: Christian.Knauer@inf.fu-berlin.de

[2)] Forschungsanstalt der Bundeswhr für Wasserschall und Geophysik
Federal Armed Forces Underwater Acoustics and Marine Geophysics Research Institute
Klausdorfer Weg 2-24, 24148 Kiel, Germany,
e-mail: WolfgangJans@bwb.org,
fax/phone: +49 431 607-4150/-4278

[3)] FGAN-FOM,
Gutleuthausstraße 1, 76275 Ettlingen, Germany,
e-mail: A.Ebert@fom.fgan.de

***Abstract*-Operational requirements for naval applications have shifted towards the fast, reliable detection and avoidance or elimination of underwater threats (e.g. mines, IEDs (improvised explosive devices), …) over the last decade. For these purposes the ability to reliable separate mines or IEDs from rocks or bottom features is essential. This separation can be much more difficult for IEDs compared to traditional cylindrical or spherical mines.**

Furthermore, automatic target recognition (ATR) approaches are gaining more and more importance for autonomous UUVs. Since no operator is in the loop, these systems are harmed by a limited number of missed detections or a significant number of false targets. In this context the ability to automatically detect and classify objects depends directly on the true resolution of the acoustic imaging system.

All this points towards the need for a high resolution sensor for reliable object detection, classification and identification. Starting with some examples, this paper presents theoretical considerations about the required resolution for the detection, classification and identification process of objects in side scan sonar images. Clues for the required resolution can be directly derived from the Johnson-Criterion for electro-optics systems [1].

Secondly, an image processing software for automatic object detection and classification currently under development at FWG with the assistance of FU-Berlin and FGAN-FOM is presented. This part focuses on an overview of the system and recently developed and tested algorithms. Before applying different detection algorithms, the side scan sonar images are pre-processed including normalization, height estimation plus slant range correction and geo-referencing. Different normalization algorithms can be used. Currently six different screening algorithms for detecting regions of interests (ROIs) with objects of interest are implemented. These screening algorithms base on statistical features within a sliding window, a highlight / shadow analysis after threshold segmentation, a normalized 1d-cross correlation with a template, a modified Maximally Stable Extremal Regions (MSER) approach, a k-means and a higher order statistic based segmentation. Afterwards false detections of ROIs without objects of interest are eliminated by applying a single snake algorithm for the entire highlight and shadow area, a coupled snake algorithms for the highlight area and for the shadow area, a 2d-cross correlation with reference images of MLOs and an iterative segmentation, all combined with robust and fast classifiers. The final processing step is a classifier (Probabilistic Neural Network (PNN)). Also a simple data fusion strategy was tested based on the output of the different screening and reduction of false positives algorithms. Finally, consequences for image processing with improved sensor resolution are discussed.

All algorithms were tested using a data set representing roughly 25 km^2 of the sea floor. This data set was in part collected by the SeaOtter MK I AUV from Atlas Elektronik and gathered in the Baltic Sea and the Mediterranean Sea. Different side scan sonar systems were used.

I. INTRODUCTION

Since many side scan sonar (SSS) systems are capable of imaging large areas of the seafloor with a relatively high resolution in relatively short time, these systems have been often used for mapping the seafloor with a fairly high coverage rate for a wide variety of purposes, including creation of nautical charts, detection and classification of underwater objects and bathymetry features.

Side Scan Sonar (SSS) are the favored imaging sensor for detection and classification of (mine-like) objects sitting on the seafloor from modern UUVs. These systems are rather inexpensive, well understood, and readily available. But, achieving high resolution and high area coverage simultaneously with a conventional SSS is rather difficult and a fundamental limitation of theses systems.

For detection and classification of small and complex objects such as sea mines in SSS images, high resolution (e.g. significantly better than 10x10 cm [1]) would support image interpretation by an operator. Existing high resolution SSS are

1-4244-2523-5/09/$20.00 ©2009 IEEE

barely able to achieve a range of 50m – and not more than 200m as strived for. At the same time high-end automatic image processing approaches such as automatic target recognition (ATR) would profit by an increased resolution. Consequently high resolution signal processing methods such as synthetic aperture sonar (SAS) or tomography methods are currently a very active research area.

In a synthetic aperture sonar, a long antenna is effectively synthesized by coherent combination of pings taken along the line of platform motion. This results in principle in much higher along-track resolution of a SAS compared to a conventional SSS. In addition, the resolution of a SAS can be kept range independent.

Applying e.g. SAS technology will increase the resolution of the shape of an object and / or object shadow under many circumstances and, therefore, will reduce image blurring. This supports and probably improves computer based image analysis such as computer aided detection (CAD), computer aided classification (CAC) and in the end automatic target recognition.

Adding additional information to acoustic imagery by, for example, measuring simultaneously the seafloor bathymetry introduces further improvements for high-end automatic image processing. By using two receiver antennas lying on top of each other interferometric data can be recorded. This allows for producing co-registered bathymetry.

II. Required Resolution

In this first chapter the ability of an observer to perform different tasks in respect to target discrimination will be estimated for a conventional and a high resolution SSS image using Johnson's criteria.

A. Johnson's Criteria

In the late 50s J. Johson was working to develop methods of predicting e.g. target detection, orientation, recognition and identification for night vision systems. Based on studies with volunteer observers, who had to identify scale model targets under various conditions, he got empirical values for the ability of human observers performing visual tasks [2].

Johnson proposed that an observer's utility for target acquisition purposes was proportional to its resolving power for a given target to scene contrast. He used the target's critical dimension to determine this required resolution for a 50% probability of detecting, recognizing, identifying and so forth. This critical dimension corresponds, more or less, to the minimum of the target's height or width as viewed by the sensor. This critical dimension was later substituted by the square root of viewed area by D'Agostino [3].

Johnson's criteria is limited in different respects. For example, Johnson's criteria fails to accurately predict the effect of noise on task performance. The observer appears to require more sensor resolution when the resolution is noise limited as opposed to spatial frequency response limited. Therefore, the Targeting Task Performance (TTP) Metric" has been developed lately [3], that does not have the problems associated with the Johnson metric.

Nevertheless, because of its simplicity many predictive models have been developed that estimate the performance of sensor systems under different environmental and operational conditions using Johnson's Criteria for human observers. In addition, for tasks related to automatic target recognition the underlying assumption is made that well trained / developed image processing algorithms using different approaches achieve similar results as a human observer.

According to Johnson´s Criteria the minimum required resolution (for a 50% probability to discriminate an object to the specified level) is [1]:

- Detection – an object is present
  (2.0 +1.0 / -0.5 pixels)
- Orientation – symmetrical, asymmetric, horizontal or vertical
  (2.8 +0.8 / -0.4 pixels)
- Recognition – the type object can be discerned, e.g. a mine vs. a wheel or stone
  (8.0 +1.6 / -0.4 pixels)
- Identification – a specific object can be discerned, e.g. a G2 vs. a MP80 mine
  (12.8 +3.2 / -2.8 pixels).

B. Applying Johnson's Criteria

In general, the physical along track resolution is the minimum distance between two objects parallel to line of platform movement that are displayed by the sonar as separate objects. For a conventional SSS this is equivalent to the intersection of the horizontal beam width with any point on the seabed and can be calculated by:

$$\Delta y = \sin\Theta\, R \qquad (1)$$

where Θ is the beam width and R the range. The physical across track resolution is the minimum distance between two objects perpendicular to the line of platform movement that are displayed as separate objects. Range resolution is determined by:

$$\Delta x = c\ \tau / (2 \cos\varphi) \approx c\ \tau/2 \qquad (2)$$

where c is the sound speed, τ is the pulse length and φ the grazing angle. This ability to resolve objects on the seafloor by a SSS should not be mixed up with the size of a pixel, which is determined by the number of available pixel in the x and y direction of an acoustic image.

Since across track resolution of a SSS is usually much better than along track resolution, the following considerations will focus on the later. As an example for an conventional SSS the

Klein 3000 system has been chosen [4], which has according to specifications an across track resolution of 0.019 – 0.3 m [τ = 25 – 400 µsec] and an angular resolution (beam width) of 0.70° @ 100 kHz or 0.21° @ 500 kHz (maximum range 600 m @ 100 kHz or 150 m @ 500 kHz). In this context note, that for an conventional SSS system the along track resolution decreases with range while it is constant for a SAS system.

As a reference object an MP80 mine with a size of 533 x 2096 mm [5] has been chosen as a typical object for comparison.

Table I gives the number of independent physical along track resolution cells on the mine for two mine orientations (parallel and perpendicular to the line of platform movement) for the low frequency version of this conventional sonar. These numbers were derived by dividing the dimension of the mine by the physical along track resolution (see eq. 1). Table II gives the same estimates for the high frequency version of this sonar. The different colors stand for an observer's ability to detect (yellow), recognize (green) and identify (blue) the mine according to Johnson's criteria and a 50% probability to discriminate an object to the specified level.

TABLE I
ABILITY OF AN OBSERVATION (SSS - 100KHZ)

No Detection	< 1.5 pixels			
Detection	1.5 – 3 pixels			
Recognition	7.6 – 9.6 pixels			
Identification	10 – 15 pixels			
100 kHz Klein 3000		along track resolution	mine orientation	
			Parallel to track	perpend. to track
PIXELS	20 m	0.24	8.6	2.2
	50 m	0.61	3.4	0.9
	100 m	1.22	1.7	0.4
	150 m	2.44	1.1	0.3

TABLE II
ABILITY OF AN OBSERVATION (SSS - 500KHZ)

No Detection	< 1.5 pixels			
Detection	1.5 – 3 pixels			
Recognition	7.6 – 9.6 pixels			
Identification	10 – 15 pixels			
500 kHz Klein 3000		along track resolution	mine orientation	
			Parallel to track	perpend. to track
PIXELS	20 m	0.073	28.6	7.3
	50 m	0.183	11.4	2.9
	100 m	0.367	5.7	1.5
	150 m	*0.733*	*3.8*	*1.0*

TABLE III
ABILITY OF AN OBSERVATION (SAS - 100KHZ)

No Detection	< 1.5 pixels			
Detection	1.5 – 3 pixels			
Recognition	7.6 – 9.6 pixels			
Identification	10 – 15 pixels			
SENSOTEC [HISAS]		Resolution	mine orientation	
			Parallel to track	Perpend. to track
PIXELS	20 m	0.035	59.9	15.2
	50 m	0.035	59.9	15.2
	100 m	0.035	59.9	15.2
	150 m	*0.035*	*59.9*	*15.2*

As a representative of a SAS system FFI's SONSOTEK sonar has been chosen, which is the experimental version of the HISAS sonar on HUGIN [6, 7]. This 100 kHz SAS system has a 2 x 3.5 cm resolution. Table III gives the number of independent along track resolution cells on the mine for this high resolution system.

These tables clearly indicate that according to Johnson's criteria the ability to detect, recognize and identify a mine is range dependent for conventional systems (see table I). They also show that in case of a conventional 100 kHz system anything other than detection could be difficult due to poor resolution. This situation improves significantly by changing the frequency to 500 kHz (see table II). Further improvements can be achieved by using SAS techniques even for a 100 kHz system (see table III).

It should been pointed out that the given examples for Johnson's criteria applied to a SSS and a SAS sonar images only take into account spatial resolution. It does not take into account, as indicated, the signal to noise situation. Hence, this gives only an indicator of possible problems an automatic detection, recognition and identification algorithm may encounter.

Further on, it should be noted that acoustic imagery can not directly be compared with pictures taken by a vision system because of the imaging situation. In principle, side-scan data represent the convolution of the transmitted sonar pulse with the scattering function of the seafloor for grazing incidence. As a results the sometimes long object shadows appear for example. In actuality, the situation is even somewhat more complex since the final acoustic image also depend on interactions of the transmitted signal with the water column and possibly with the sea surface as well as the transmission, processing and display mechanisms of the SSS. Therefore, the resolution of the final acoustic SSS image is a function of many factors including e.g. pulse specifications, beam spreading, sound speed, seafloor morphology and post-acquisition processes.

Despite these remarks, the presented estimation gives a hint for the usefulness of high resolution SAS systems for image interpretation and automatic image processing.

III. Object Detection and Classification Software

A. Overview

The development of image processing software for automatic object detection and classification purposes was intensified at FWG two years ago [9, 10, 11]. This work started with a Master Thesis and has developed into a PhD Thesis in cooperation with the Free University Berlin, Department of Computer Science and the Research Institute for Optronics and Pattern Recognition (FGAN-FOM). The software developed since then processes acoustic images in four steps (see fig. 1):

At the beginning images are pre-processed. Pre-processing includes normalization, corrections for distortions such as height estimation plus slant range correction and geo-referencing. For normalization different filters can be chosen.

During the second processing step so called Regions of Interests (ROIs) are identified by a single or several combined screening algorithms, which may be caused by a proud object on the seafloor. Currently a set of six screening algorithms is in the system available, which base on statistical features within a sliding window, highlight / shadow analysis after threshold segmentation, normalized 1d-cross correlation with a template, a modified Maximally Stable Extremal Regions (MSER) approach, k-means based segmentation or higher order statistic based segmentation.

Having the ROIs detected in the SSS image, the number of false alarms is reduced by currently applying one out of four or the combination of all four false alarm reduction algorithms. So far a single snake algorithm for the combined highlight and shadow area, a coupled snake algorithm with different coupled polygons for the highlight and the shadow area, a 2d-cross correlation with object templates and a algorithm using an iterative fuzzy segmentation followed by a classification process utilizing the existence of parallel lines for the object shadow contour have been implemented [10, 11]. Two of these algorithms shall be describe a little more in detail, since they have been used for the tests described in Chapter IV:

Segmentation Based Method

This algorithm uses an iterative fuzzy segmentation to extract a more precise shadow contour for a noisy image [11]. This process starts with a segmented image based on threshold segmentation. Then, during an iteration step a membership function for the contour shadow pixels is applied by evaluating two combined fuzzy functions. One function estimates the pixel brightness and one the connectivity depending on a pixel's direct neighborhood.

Determining the shadow contour is followed by a classification process. This process utilizes the shadow area and the existence of parallel shadow edges in the segmented ROI. Normally MLOs have simple geometric shapes, so that

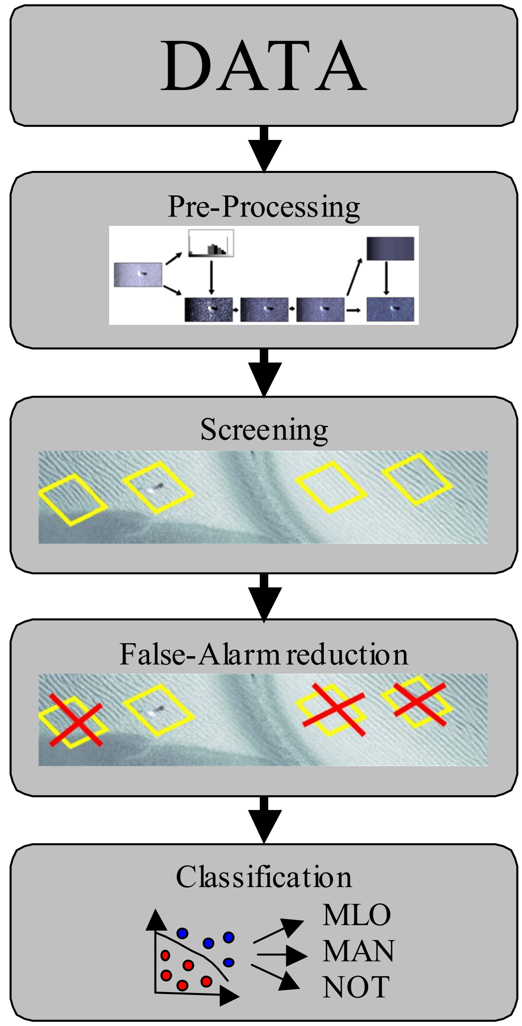

Figure 1. structure of the image processing software
(MLO – mine like object, MAN – man made object, NOT – no target)

the shadow contour shows smooth, straight parallel edges. A Hough Transformation is applied for this purpose. The last used feature is the gray level statistics in the ROI.

Single Snake

The single snake algorithm is a method for outlining the contour of the object highlight plus shadow area in a nosy image [10]. This is done by minimizing an energy function associated with the current contour represented by a polygon. Distinguishing different objects is then done based on the value of this energy function.

In the fourth and last processing step a Probabilistic Neural Network (PNN) is used for the remaining ROIs for final classification. As features for this classification process we use currently primarily some scoring values, which are generated by the false alarm reduction algorithms. These features include the size of highlight plus shadow area in relation to the size for a typical mine image, the ratio of highlight area to shadow area, the difference in the probability density function inside

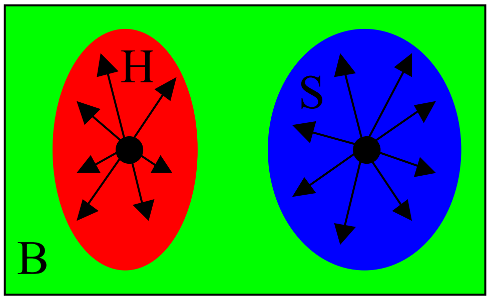

Figure 2. Starting configuration for K-means based segmentation (H = Highlight, S = Shadow, B = Background)

and outside the highlight plus shadow contour, cross-correlation coefficients for object templates and so forth.

B. Recently Added Methods For Screening

Objects in a SSS image normally appear as highlight - shadow pairs. These highlights and shadows can be automatically extracted from acoustic images by segmentation for e.g. screening. Simple approaches use global thresholds for this segmentation into highlight, shadow and background based on image histograms. The main disadvantage of these simple threshold based methods is the poor robustness against speckle and other noise. Since SSS images are typically very noisy, usually more robust methods are required.

We recently added two more sophisticated algorithms to our image processing software: a modified k-means based algorithm and a segmentation algorithm using neighborhood information.

The iterative k-means based screening algorithm divides the acoustic image into small overlapping areas, each with a typical size of an average mine like objects. Within each area the algorithm puts the center of the object highlight in the middle of the left half and the center of the shadow in the middle of the right half of the area as a starting point (see fig. 2). As starting value for the highlight pixel the local maximum, for the shadow pixel the local minimum and for the background the mean value of the local maximum and local minimum are chosen.

The highlight and the shadow cluster variance calculation is based on the difference of pixel values to the mean value and the distance between the pixel position to the center of the highlight or the shadow cluster. In contrast to a traditional k-means algorithm the variance for the background is only determined by the difference of pixel values to the mean value. The following variance functions have been used for the coded algorithm:

Background

$$k_{back.} = (p-v_{b,m.})^2/d^2, \qquad (3)$$

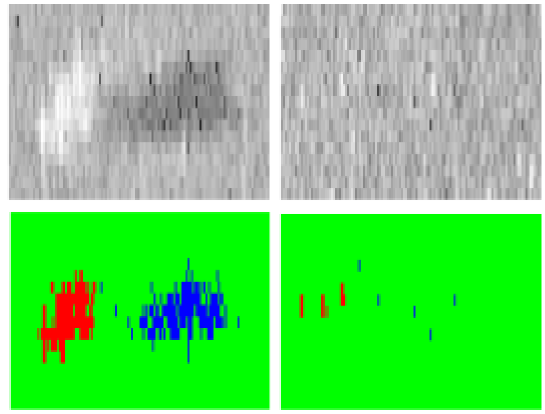

Figure 3. Results from the implemented k-means algorithm (left ROI with MLO, right ROI without MLO)

Highlight

$$k_{high} = (p-v_{h,m.})^2/d^2+(x-x_{h.})^2/x_m{}^2+(y-y_{h..})^2/y_m{}^2, \qquad (4)$$

Shadow

$$k_{shad} = (p-v_{s,m.})^2/d^2+(x-x_{s.})^2/x_m{}^2+(y-y_{s..})^2/y_m{}^2. \qquad (5)$$

p is the pixel value, x and y are the pixel coordinates and the parameters d^2, $x_m{}^2$ and $y_m{}^2$ are scaling parameters for normalization in order to keep the result within [0, 1]. The parameters $v_{b,m.}$, $v_{h,m.}$ and $v_{s,m.}$ represent the mean pixel values for background, highlight and shadow, respectively, and $x_{h.}$, $y_{h.}$ and $x_{s.}$,$y_{s.}$ correspond to coordinates for the center of the highlight cluster and the shadow cluster. These parameters are updated after each iteration step. Afterwards these parameters are assigned to highlight, shadow and background based on the lowest variance.

Fig. 3 shows a typical result for the realized k-means algorithm. The original and segmented images on the left side show an example which includes an object and the two images on the right side an example without an object. After this segmentation the algorithm defines ROIs depending on cluster sizes.

Fig. 3 demonstrates that the relatively simple initialization of the k-mean algorithm used already leads to reasonable results for segmentation. Choosing only one cluster center can for the highlight as well as for the shadow cluster is evidently sufficient.

The existing k-means algorithm may be harmed by he fact that it divides the acoustic image into small piecewise overlapping areas. If the object location is unfavorable in terms of this dividing process, segmentation may fail. A sliding window approach would solve this problem.

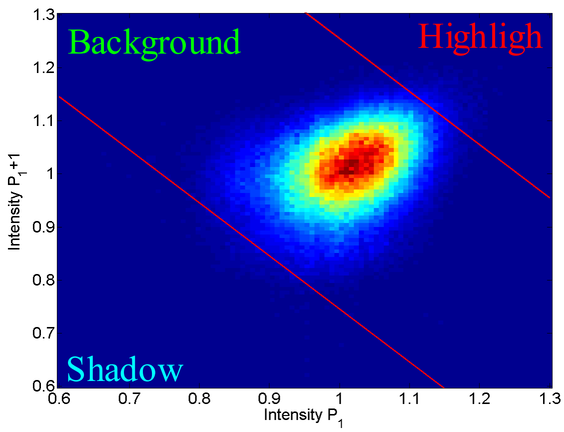

Figure 4. 2D-Histogram

The second lately coded algorithm is a segmentation algorithm using neighborhood information. This is done by performing threshold segmentation based on a higher order histogram. Each neighbor pixel is represented by a new dimension in such a histogram. An example taking only the first, nearest neighbor pixel into account is shown in fig.4. The x–axis represents the normalized pixel value for each viewed pixel and the y-axis the normalized pixel value for the associated neighbor pixel. The color (from blue to red) stands for the frequency that a certain combination of pixel values exists in an acoustic image. The red lines give the limits for segmentation. This technique leads to fast segmentation for acoustic images since, in principle, resolution of the image is reduced by using the neighborhood for segmentation.

In fig. 5 the results for a normal threshold segmentation and neighborhood segmentation are compared. In both images the two MLOs can be identified, but the image generated by the

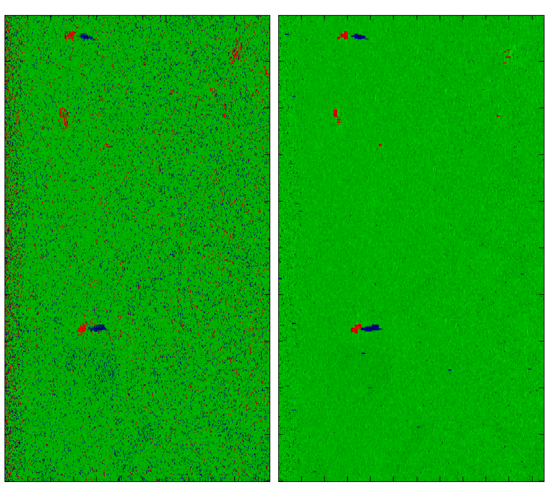

Figure 5. Resultes of the implemented Higher Oder Statistics algorithm (left threshold segmentation without nebourhood, right threshold segmentation with a 14 pixel nebourhood)

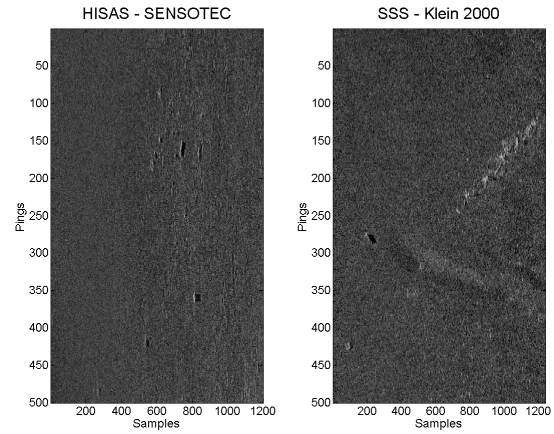

Figure 6. Sonar images for the tests (downscaled for this paper) (left: HISAS SAS; right: Klein SSS, viewed objects are marked with a red square)

segmentation algorithm using neighborhood information contains much less noise. Selecting ROIs after segmentation depends on the existence of highlight – shadow pairs. Using a broader data set for testing, this screening method has shown quite good performance for detecting MLOs.

C. *Planned Activities*

In the near future we plan for improving the algorithms for the reduction of false positives and classification. We are especially interested in using Support Vector Machine (SVM) techniques for the classification process and comparing the results with those gained by a PNN Classifier.

IV. Preliminary Test Results for Conventional and High resolution SSS Images

Two existing algorithms for the reduction of false positives have been used so far by us to get a first clue about the influence of resolution on image processing. These preliminary tests base on a Klein SSS image with a physical resolution given in Chapter II and a pixel size of 3 x 11 cm and a high resolution HISAS image. HISAS has a physical resolution well below 5 x 5 cm and a pixel size which usually reflects this. For the describe first test we have used a somewhat down sampled HISAS example with a pixel size of about 4 x 12 cm and a reduced dynamic range of 8 bits [8]. Fig. 6 shows the two chosen sonar images. The objects viewed was in both cases a typical cylindrical MLO of 2 x 05 m size like a MP80 mine. The position is marked in both images by a red square.

The results for the segmentation based method described in Chapter III are shown in fig. 7. In this example a clear advantage of SAS data (top) compared to the conventional SSS data (bottom) for the used algorithm can not be seen. This is

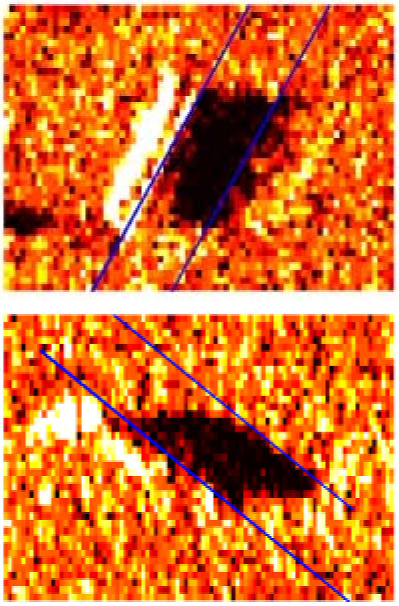

Figure 7. Applied segmentation based algorithm
(Top: HISAS SAS; Bottom: Klein SSS)

related to the fact that the used algorithm makes mainly use of the object shadow for reduction of false positives. Since the object shadow of the cylinder targets in both data sets show a simple geometric shape with parallel edges, results are similar.

But, it should also be noted that the SAS object image is much clearer than the fragmented SSS object image. This commonly observed fragmentation of object images in conventional SSS data is also the reason why our current algorithm mainly uses shadow features. But, the object image (highlight) appears much better in the SAS image and has the expected simple geometric shape for a cylinder. Therefore, high resolution SAS data – and especially with full resolution and dynamic range – offers the possibility to include the object in the classification process for the algorithm. This would make this algorithm probably more reliable and stable.

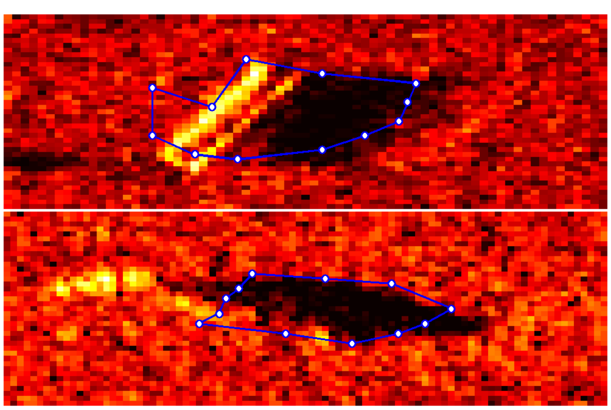

Figure 8. Applied snake algorithm
(Top: HISAS SAS; Bottom: Klein SSS)

Another test was performed with the single snake algorithm also described in Chapter III. The results are shown in fig. 8. This algorithm performs better on the high resolution SAS data than on conventional SSS data. It outlines the contour of the MLO including shadow quite well with the exception of one outlier for SAS data (top) compared to the result for data from a conventional SSS system, where only the shadow is approximately outlined (bottom). Again the much better quality of the SAS object image seems to be the main advantage.

For both data sets our snake algorithm finds the object. Although, this example shows that further improvements for this algorithm should be investigated in order to get a better match of the object including shadow contour and the snake polygon. One option could be the use of nonlinear filters for generating the gradient image.

V. CONCLUSION AND OUTLOOK

Finally, consequences for image processing with improved sensor resolution are discussed.

Resolution is always good is a often heard statement for SSS systems. Goal of the presented short study has been to gain some understanding, which consequences improved resolution has for automatic image processing.

Theoretical estimates for the possibility of recognising, detecting and classifying were derived from Johson's criteria. These theoretically considerations based on the physical resolution of different sonar indicate, that a high resolution sonar systems has a high potential for improving the detection, classification and identification performance – both, for a human operator as well as an automatic target recognition software.

The results of the tests carried out with two algorithms for the reduction of false positives did not give totally different results for high resolution SAS and conventional SSS data. The main reason for this is probably, that these algorithms have been optimised for conventional SSS data. But, these tests also clearly indicate that in case of the SAS data the much clearer object image allows for significant improvements of the used algorithms.

REFERENCES

[1] Fossum, T. and Hagen P.E. , HISAS 1030: The next generation mine hunting sonar for AUVs, UDT EUROPE 2008, Glasgow.

[2] Johnson, J.,: "Analysis of Imaging Forming Systems", in Proceedings of the Image Intensifier Symposium, AD 220|60, pp 244 - 273, Warfare Electrical Engineering Dept., US Army Engineering Research and Development Laboratories, Ft. Belvoir, VA, 1958.
Reprint in:
Johnson, R. B. and Wolf, W. L. (eds.); "Selected Papers on Infrared Design", SPIE Proceedings vol. 513, pp. 761 - 781, 1985.
Or
R. Harney, Combat Systems Vol. I: Sensors, Chapter 4: Imaging and Image-based Predictions, 2005

[3] Vollmerhausen, Richard H., Jacobs, Eddie; “The Targeting Task Performance (TTP) Metric, A New Model for Predicting Target Acquisition Performance”, U.S. Army CERDEC, Fort Belvoir, VA 22060, Technical Report AMSEL-NV-TR-230, 2004.
[4] http://www.1-3klein.com/3000series/3000_Data.pdf.
[5] N. Friedmann, The Naval Institute Guide to the World Naval Weapon Systems.
[6] Hansen, R.E., T.O. Sæbø1, H.J. Callow1 and B. Langli, THE SENSOTEK INTERFEROMETRIC SYNTHETIC APERTURE SONAR: RESULTS FROM HUGIN AUV TRIALS, Proc. 8th ECUA, 2006, Portugal
[7] Sæbø, T.O., H.J. Callow and R.E. Hansen, SYNTHETIC APERTURE SONAR INTERFEROMETRY: EXPERIMENTAL RESULTS FROM SENSOTEK, Proc. 8th ECUA, 2006, Portugal
[8] P.E.Hagen, HISAS 1030, High-Resolution Interferometric SAS, Presentation Eckernförde 28.10.08
and personnel communication
[9] M. Neumann, “Target Detction in Side Scan Sonar Image Data”, FU Berlin, FWG, FGAN-FOM, diploma Thesis, Berlin, 2008.
[10] M. Neumann, C. Knauer, D. Brecht, W. Jans and W. Middelmann, „Computer Aided Detection of MLOs in Side Scan Sonar Images”, UDT EUROPE 2008.
[11] M. Neumann, C. Knauer, B. Nolte, W. Jans and A. Ebert, Target Detection of Man Made Objects in Side scan Sonar Images – Segmentation based False Alarm Reduction -, Acoustics’08, Paris, 2008.