ASSESSMENT OF CLASSIFICATION BASED ON SIMULATED SYNTHETIC APERTURE SONAR IMAGES

A Cederholm Swedish Defence Research Agency (FOI), Stockholm, Sweden
M Jönsson Swedish Defence Research Agency (FOI), Stockholm, Sweden
E Parastates Swedish Defence Research Agency (FOI), Stockholm, Sweden
I Karasalo Swedish Defence Research Agency (FOI), Stockholm, Sweden

1 INTRODUCTION

At the Swedish Defence Research Agency (FOI) synthetic aperture sonar (SAS) used for mine hunting in shallow water has been a research topic since the mid 90's. Recently we have reported about work concerning unmanned underwater vehicles (UUVs) and the importance of proper navigation systems to produce enhanced SAS images[1]. In this study, methods were presented which handle correction of navigation data obtained from an inertial navigation system (INS) on an UUV. Developments of UUV-based SAS-systems have come far, and today there are systems used in military operations[2]. However some significant challenges remain in the development towards increasingly autonomous underwater vehicles (AUV).

One particular research area of interest is detection and classification of underwater objects from SAS images. Since synthetic aperture processing offers high resolution images it is an obvious choice for a high quality classifier. In this context, image processing is a vital ingredient in a successful system. By computer aided detection and computer aided classification (CAD/CAC) the autonomous capability will eventually be reached. Still, computer constraints remain connected to the possibility of processing data onboard a vehicle, and there are decisions which have to be made regarding the methods for CAD/CAC. A CAD/CAC system could start with a database containing information of mines, where the information range from characteristic length scales to complete SAS images. With a SAS system on an UUV an image spanning a larger part of a sea bottom is obtained and possible mine like objects (MLOs) can be detected. Here edge detection algorithms[3] could play a part, that correlate to the characteristic length scales of the mines. CAD/CAC could end here, however the classification can be carried out further. After a mine has been detected the image is extracted from the overall SAS image. If the database is composed of SAS images a correlation of the possible mine is performed. The SAS image could be more idealized by segmentation algorithms[3,4].

This paper will sketch two multistage model-based CAC systems, which use SAS images of generic targets obtained from circular sonar trajectories. The first method is based a neural networks algorithm, while the second method addresses correlation.

2 SONAR DATA

For the simulated data set the SAFIX software is used, where echoes from the targets are modeled using ray-path approximations. In SAFIX, each target is modeled as an acoustically impenetrable object with a smooth surface. The acoustic intensity of the echo contribution from target to receiver is computed in two steps. The reflection point at the target $\mathbf{r}_{tar}$, for the ray traveling between the source to the target and back to the receiver is computed by minimizing the raylength with respect to all points $\mathbf{r}$ on the target surface. Then the acoustic intensity I_{tar} of the echo contribution at the receiver can be written as

$$I_{tar} = \frac{I}{\left[1+2g_t R_t(\mathbf{r}_{tar})\right]\left[1+2g_r R_r(\mathbf{r}_{tar})\right]}, \quad (1)$$

where I is the acoustic intensity of the transmitted signal at $\mathbf{r}_{tar}$, and where g_t and g_r denote the principal radii of curvature of the target surface at $\mathbf{r}_{tar}$. The quantities $R_t(\mathbf{r})$ and $R_r(\mathbf{r})$ in equation (1), are the lengths of the transmitted and the reflected ray segments.

For the present CAC study we have chosen a sonar system composed of a uniform half-wavelength receiver array with 20 elements with the transmitter placed in the middle of it. As a source signal a linearly frequency modulated pulse with center frequency 30 kHz and bandwidth 50 kHz was selected. A homogeneous water column was assumed and the sonar system was moved along a circular track with a radius of 30 m and at a depth of 30 m above the objects. During each simulated trial 792 pings were registered at a sampling frequency of 500 kHz. Sketches of typical generic objects used in SAFIX are found in Figure 1, as well as the corresponding SAS images. The SAS images have been produced using the sonar parameters specified above.

3 CAC

For classification of underwater mines we here propose two approaches based on neural networks and image correlation respectively and present some results of numerical simulations. Measured sonar data, input to both methods, are assumed to be obtained by a sidescan sonar, mounted on an UUV. The UUV moves along a circle, with its centre coinciding with the position of a priory detected object on the seabottom. Both methods also require that a data base is available, containing SAS images of modelled MLOs. Such images could be obtained by SAS processing of noise free synthetic sonar data, produced by SAFIX simulating the same environmental conditions and setup as in the measurements, see section 2. Note that the database should contain several images of the same MLO, where its orientation with respect to the simulated SAS trajectory is varied in a systematic way.

The neural networks based method requires preprocessing of SAS images from measurements in terms of segmentation. The image is segmented into regions of background and target, represented by black and white pixels respectively. A classifier is then utilized, based on a binary Hopfield neural network [5], in order to investigate the similarity between the segmented image and images in the database. The Hopfield model is an associative memory and tries to mimic the human brain capacity to think thru associated paths. For example a certain smell or song can bring back memories from a long forgotten event. The neuron network contains the same number of neurons as the number of pixels in the image and each neuron is assigned to a specific pixel. In this way any image can be represented by setting the values of the individual neurons in the network equal to the image pixel values. For every iteration step the output of each neuron is given as a weighted sum of the outputs of the other neurons, as shown in equation (2).

$$x_j(n+1) = \mathrm{sgn}\left[\sum_{i=1}^{K} w_{ji} x_i(n)\right], j = 1,2,\ldots,K. \tag{2}$$

This means that if the network is given an image the network will change the image until a local minimum is reached and a stable image is produced. The idea is that the simulated SAS images of all mines in the database should be stable network states, and when the network is presented to a noisy SAS image it will converge to the simulated image that is closest to the measured image. If the network should memorize N images for the images $M_{n,j}$ with $n=1..N$, the weights w_{ji} in (2) are chosen as in equation (3)

$$w_{ji} = \frac{1}{N}\sum_{n=1}^{N} M_{n,j} M_{n,i}. \tag{3}$$

In (3) the indices i and j denote pixel or neuron number and (3) can be seen as finding the mean pixel value dependency on other pixel values over the training set.

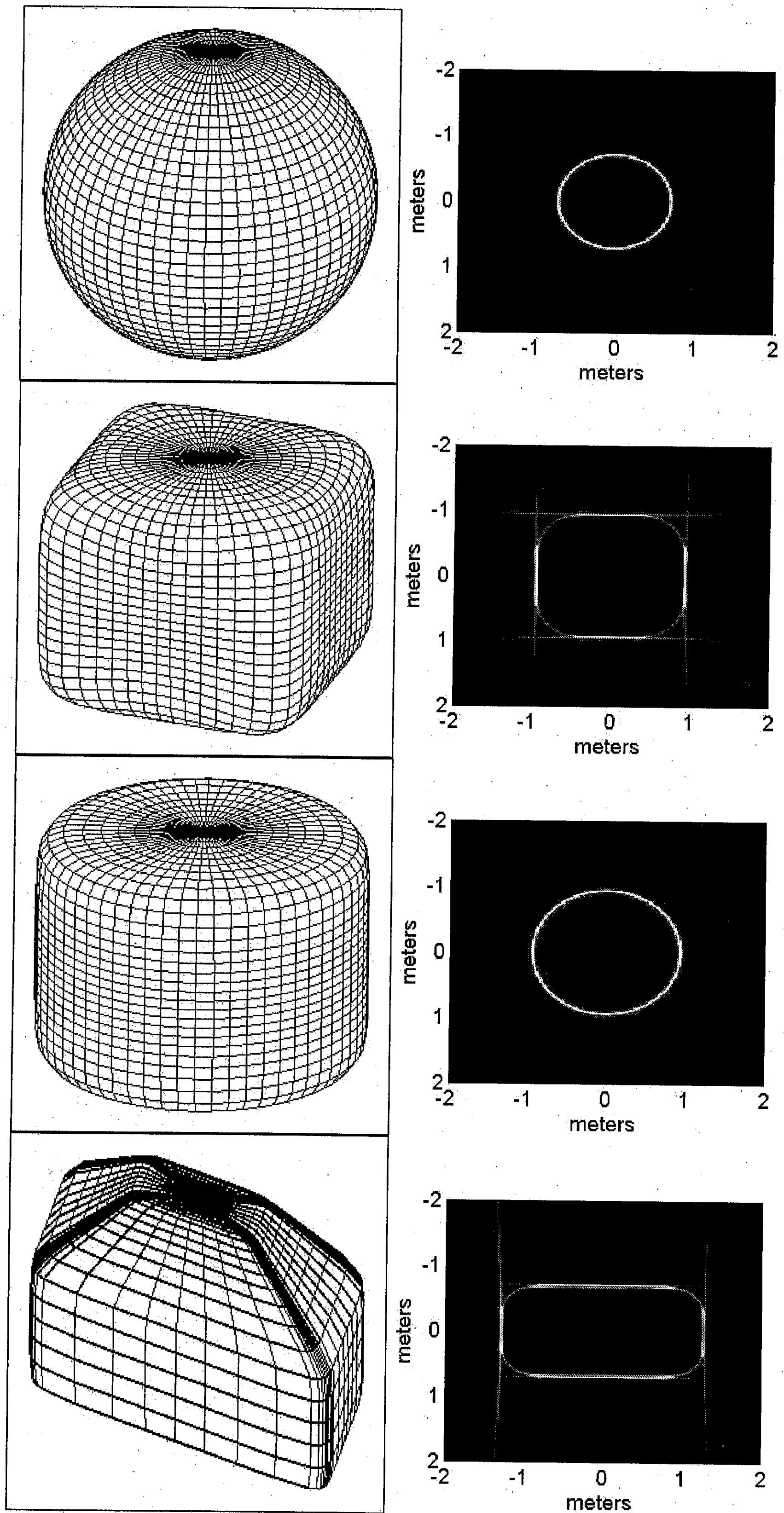

Figure 1: Left - Sketches of generic objects modeled by the SAFIX SAS-simulator, i.e. sphere, box, cylinder and coffin. Right – Corresponding SAS image using a circular track.

To test the algorithm four different targets where selected, see Figure 1, i.e. a sphere, a box, a coffin and a coffin rotated clockwise by 45 degrees. Simulated SAS images of each target were produced using a circular path and the target in the circle centre, as specified in section 2. A threshold was applied that transformed the multicolour SAS images to binary images where each pixel has the value 1 or -1. The threshold was chosen so that pixels containing the target were given the value 1 and pixels not containing the target were given the value -1. The network was then trained on the simulated binary SAS images according to equation (3). To simulate a measured image, Weibull-distributed noise was added to each simulated multicolour SAS image. Weibull-noise produce typical background speckle [6]. The noisy image was then segmented into target and background using a threshold. The segmented image was then passed to the neural network. The process was repeated for each target and in every case the network successfully converged to the right image. Results for the rotated coffin will follow. Figure 2-3 shows the binary simulated SAS image of the rotated coffin, the simulated multicolour SAS image of the rotated coffin with added Weibull noise, the segmented SAS image of the rotated coffin with added Weibull noise and finally the stable image produced by the network when given the segmented SAS image of the rotated coffin. Note that Figure 2 left and Figure 3 right are equal showing that the network classified the image correctly.

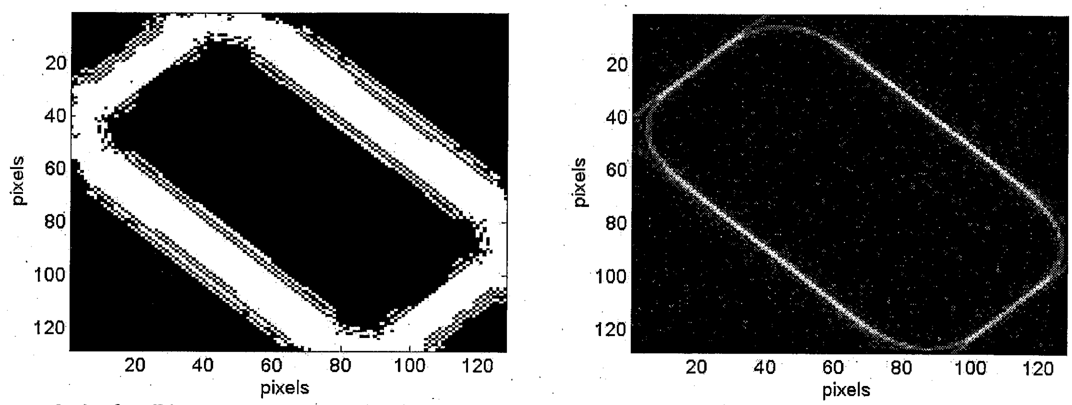

Figure 2: Left - Binary simulated SAS image of the rotated coffin. Right - Simulated multicolour SAS image of the rotated coffin with added Weibull-distributed noise.

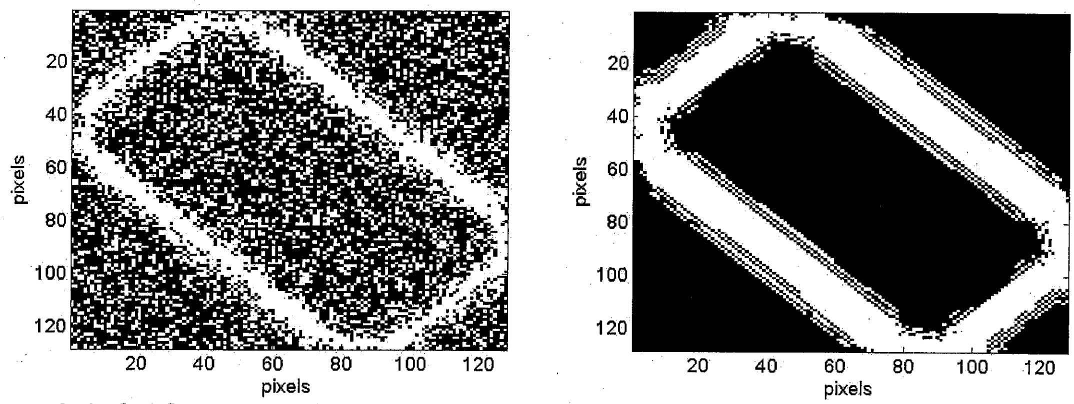

Figure 3: Left - Segmented SAS image of the rotated coffin with added Weibull-distributed noise. Right - Resulting image produced by the neural network when given the segmented SAS image of the rotated coffin, Figure 2 left.

For the second method the similarity between observed and simulated SAS images is measured by correlation. Every simulated image in the database is correlated with the observed. The maximum correlation value in each one of the resulting ambiguity surfaces is regarded as the measure of the similarity. Figure 4 exemplifies this method with some simulated results. The left column shows SAS processing of synthetic data with Weibull-distributed noise superimposed. In the right column ambiguity surfaces are found when correlating with a noise free image of the coffin. Among the three noisy images, the algorithm did successfully recognize the one containing the coffin in the correlation kernel for SNR levels down to 0.2 dB. The same performance was observed when correlating the observed images with the other two simulated images.

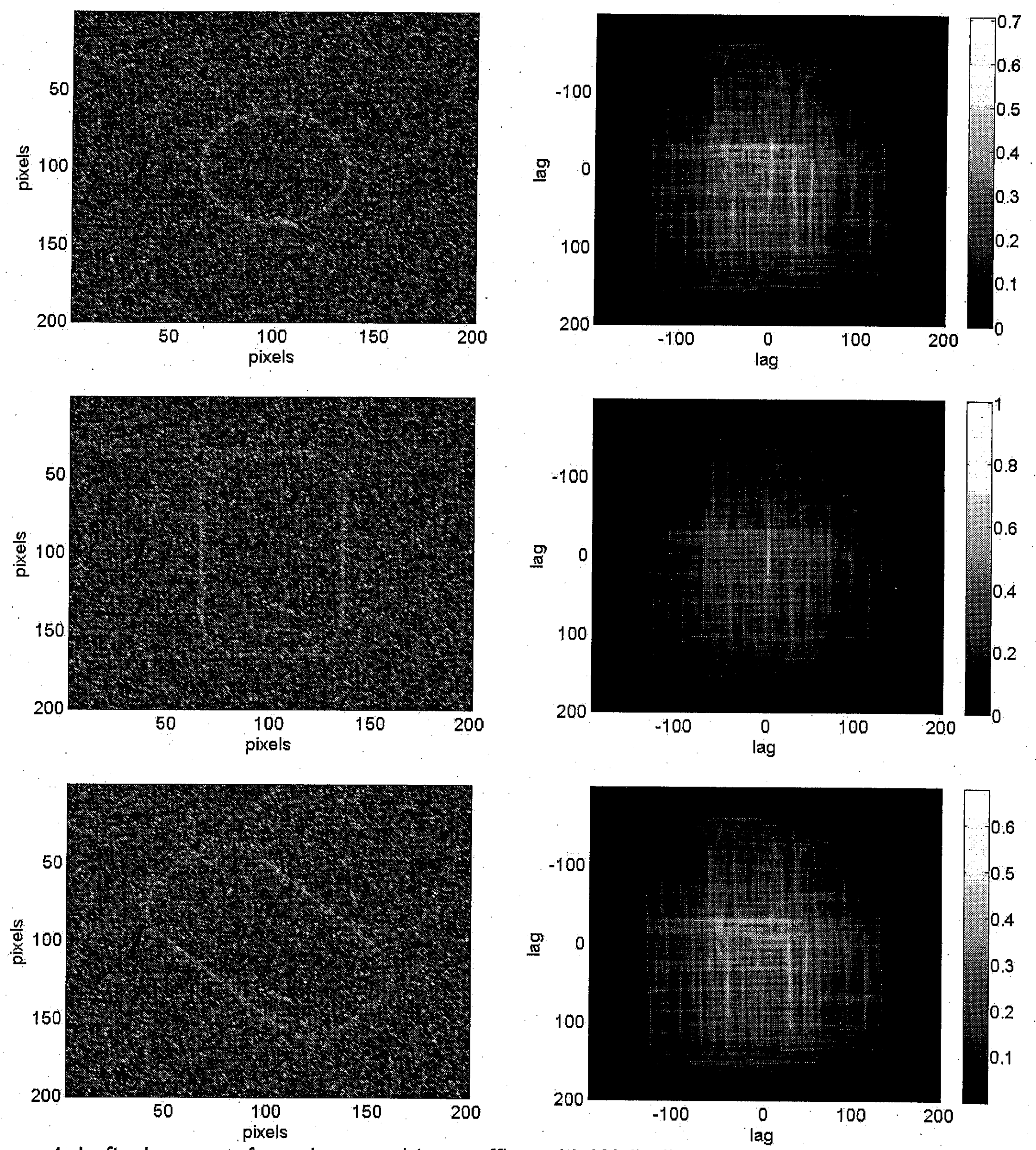

Figure 4: Left - Images of a sphere and two coffins with Weibull-distributed noise, obtained by SAS processing along a circular track. The bottommost coffin was rotated counter clockwise by 45 degrees. Right - Ambiguity surfaces, obtained by correlation of the images in the left column with a noise free image of the rotated coffin.

4 CONCLUSIONS

CAD/CAC is important for enhancing the autonomous capabilities of mine-hunting UUVs equipped with SAS. Echo modeling tools are in this context an essential ingredient for the development of

CAD/CAC and constitute a valuable complement to real data. As shown in the paper, the SAFIX software can describe almost any target within the limits of acoustic ray theory and the computations are less time consuming in comparison to full-field computations. The discrepancies that still exist in comparison to full-field computations are however not critical for the assessment of CAC.

We have evaluated two CAC methods for mine-hunting applications. Starting from a SAS image containing a MLO both methods are based on comparing this image with a database of SAS images of mines. The comparison requires the SAS images to be processed by e.g. edge detection and segmentation algorithms, but for the assessment of CAC at this stage this is not vital. The neural network method successfully classified all tested objects. However in this case only four different targets were studied. An investigation of a larger image database is needed before its performance can be fully evaluated. In this study synthetic data were used instead of real data, which simplifies the problem. Furthermore SNR dependency was not investigated in detail. An increased noise level would certainly reduce performance. For a low SNR a more sophisticated segmentation algorithm is probably needed. The correlation method is promising in the sense that it works well, at a reasonably low SNR. The method could be further improved by use of smoothing kernels prior to correlation. We plan a more thorough investigation using a larger image database, experimental data and different SNR levels.

5 ACKNOWLEDGMENTS

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6 REFERENCES

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