PATT: A PERFORMANCE ANALYSIS AND TRAINING TOOL FOR THE ASSESSMENT AND ADAPTIVE PLANNING OF MINE COUNTER MEASURES (MCM) OPERATIONS

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1 INTRODUCTION

SeeByte's SeeTrack Military provides a situation awareness (MCM) solution that helps EOD personnel get a single picture of their battlespace by processing data across all assets.

Militaries are becoming increasingly aware of the need to quantitatively assess their Mine Counter Measures (MCM) capabilities. MCM operations are currently carried out by skilled human operators who require constant training to remain effective. Traditional methods such as sea trials are expensive to organise and limited in their capability to provide a robust evaluation. Conversely, simulator models are slow and often not realistic enough to provide credible results. Recent developments in mine-hunting technology such as AUV's, CAD/CAC models and high resolution sonars also need to be evaluated to assess their abilities to meet the ever increasing demands of the MCM community [1].

This paper presents a methodology to quantitatively evaluate human operator performances and validate ATR systems. The PATT module operates from SeeTrack Military which provides a situation awareness solution to the MCM problem, by providing a single interface for viewing data from multiple assets. The PATT module utilizes the advanced data visualization, classification and mosaicing capabilities of SeeTrack when evaluating the ATR system. The framework of the PATT module is based on Augmented Reality (AR) where real sonar images taken from the survey region are modified using mine simulator models to generate a ground-truthed theatre of operation. The MCM abilities of an ATR system or a human operator may then be quantitatively evaluated [2].

The PATT module will enable the user to assess the capabilities of a complete MCM system. The system encompasses the survey region being considered, the sonar being used as well as the ATR system under evaluation. Evaluation results may be presented relative to a range of parameters such as the seafloor type and mine type. Using the performance information provided by PATT will allow optimal mission plans, specific to the MCM system under use, to be produced. The PATT module may also be used to evaluate any MCM system.

The remainder of the paper is organised as follows. Section 2 provides a high level overview of the PATT module and describes the different running modes available to the user. Section 3 provides a brief summary of the key technologies used within the PATT module. Section 4 provides results from the various modes of PATT while Section 5 concludes the paper and discusses future developments.

2 PATT OVERVIEW

2.1 Factors which impact MCM Performance

The ability of an ATR system or a human operator to detect and identify mine-like objects on the seafloor will be dependant on a number of system features. In this context, the 'system' under evaluation is considered to encompass the survey region, the sonar being used, the ATR system and the mission plan.

- The clarity of an object within the sensor data will depend on the across and along track resolution of the sonar. This will be directly dependant on the frequency of the sonar and the length of the aperture. Improving the resolution, and so increasing the number of pings on the object, enables man-made objects to be distinguished from natural object.
- The height of the AUV above the seafloor will impact the grazing angle of the sonar with respect to the object. ATR systems often use the shadow of the object to detect possible mine targets, which becomes more apparent as the AUV altitude is reduced.
- The type of seabed within the survey region will impact the ability of an ATR system to detect objects. The 3D variation of the seabed with respect to the object height will impact how easily the highlight and shadow regions of an object may be discerned.
- The mission plan used will impact the success of the MCM mission. Lawnmower trajectories are used to ensure that any object present on the seafloor will appear in multiple sonar images, maximising the possibility of detection. Even when appearing in multiple images, the range and orientation of the object with regard to the sonar will impact how visible the object appears.

2.2 PATT Methodology

Finding a methodology to consistently assess AUV performances is complex. The performance will depend on all the parameters described in section 2.1. Identifying the influence of each of them is critical to the future development of new systems. Two approaches have been used in the past:

- NURC and the US Navy have performed extensive experiments using real targets and real vehicles [1] (GOATS, BP02/03, various AUV Fests). However, these experiments are expensive to run contain only a limited number of targets and situations can be covered. Extracting meaningful statistics and quantifying as opposed to qualifying the performance of a particular system is difficult. It is also unlikely that performance in one environment will extrapolate easily to another given the strong dependence of the side scan sonar imagery to environmental conditions and sonar systems.
- Sonar simulators are available to various degrees of realism [2]. However, they are in general prohibitively computer intensive and sometime lack the realism of real systems as simplifying assumptions are made to render the models tractable [3].

The PATT module uses an augmented reality to combine the advantages of both approaches. Using real data, the evaluation remains a true representation of the system which will be used in terms of both the sonar and the survey region. The simulation aspect of PATT allows very realistic targets to be added to the data. Ground truth data is also available to evaluate the ATR (computer or human) performances in various scenarios.
The proposed solution is best described in Figure 1. The idea behind the proposed framework is to evaluate a system rather than its components.

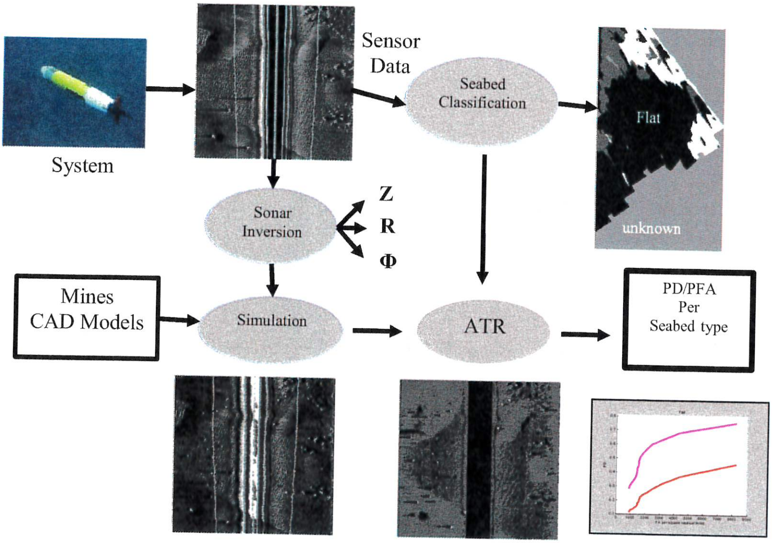

Figure 1 The proposed approach of PATT for evaluating MCM systems.

2.3 PATT Modes of Operation

The PATT module integrated into SeeTrack Military has 3 different running modes. These modes allow the user to obtain detailed results according to their specific needs. The different modes may be described as:

- Single Image Analysis Mode: This mode is used to provide statistically robust results regarding the performance of the ATR system under evaluation. In this mode, images are considered as isolated events. Multiple mines (of different type, orientation and range) may be added to each image which may then processed by the ATR system.
- Multi-image Analysis Mode: In this mode, the user is first provided with a mosaic of the survey region. Seafloor classification information is also provided. Mines may be placed anywhere in the mission. The geometry of the mission is respected in this mode ensuring that any mine placed into the survey appears within all relevant images at the correct range and orientation. The mode allows the ATR to be tested under more realistic scenarios and will also allow future technologies such as fusion modules and mission planning modules to be tested.
- Training Mode: This mode has been created to allow operators to be trained and evaluated on realistic data sets. Similar to the Multi-image analysis mode, a supervisor may place mines anywhere within the survey region. The operator is then able to view the mission data through a waterfall display, highlighting possible mine threats. After the operator has finished his analysis, evaluation results are provided detailing the number of correctly detected mines and the number of false alarms.

3 PATT TECHNOLOGIES

This section provides a brief overview of some of the key technologies used within the SeeByte PATT module. Further details may be found in [2].

3.1 Seafloor Classification and Mosaicing

Extensive research has been carried out in seabed segmentation and classification using side scan sonar [4][5] but never in the specific context of MCM. For MCM purposes, the 'huntability' of a region will depend on both the texture (flat, ripples, complex) and the clutter density (the density of mine-like objects on the seafloor).

The Seafloor classification module within SeeTrack Military uses both the texture and the clutter density to segment the survey region into different regions according to huntability. Individual images are first classified using physical features (such as the height of the seafloor) after which the result is smoothed using a Markovian model [6]. To improve the overall accuracy of the classification result and to enable the large scale characteristics of the survey region to be seen, the individual classification results are fused together to produce a classified mosaic. It has been shown that this type of fusion can dramatically increase the accuracy of the classification [5]. An example of a fused mosaic (containing the information from over 200 individual classified images) may be seen below in Figure 2.

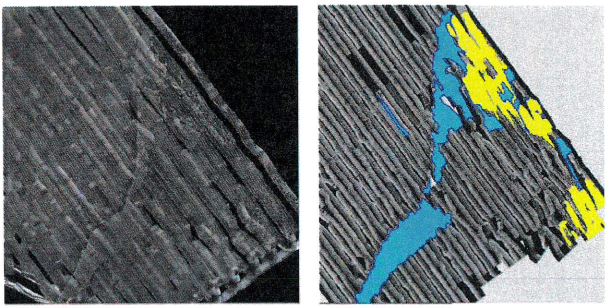

Figure 2 Classified Mosaic of a region of seafloor containing flat, rippled and complex areas. The classification accuracy is very accurate due to the fusion process.

3.2 Sonar Inversion Process

To be able to accurately place simulated mines into the data collected from a real (and unknown) scene, it is necessary to obtain an estimate of the seafloor topology. The topology of the scene must be respected before meaningful evaluation results may be obtained.

Efforts towards the use of side-scan sonar for the indirect determination of seabed topography have been scarce [7][8]. The main reasons are the complexity of the full mathematical projection model and the high number of procedures required for preprocessing the original source data. In most cases where acquisition of seabed topography is important, attention is driven to more straightforward solutions such as multi-beam bathymetric systems. The idea behind the sonar inversion process [9] is to recover the main parameters involved in the sonar image formation. These are bathymetry, reflectivity and sonar parameters. The sonar parameters are here reduced to the beam pattern. The navigation effects, such as pitch and roll are ignored.

The sonar scattering process is modelled using a traditional Lambertian model. This allows the returned intensity to be derived from the observed scene parameters. This simple model for diffuse scattering assumes that the returned intensity depends only on the angle of incidence of the illuminating sound pulse, and not on the angle of observation or on the frequency of the pulse. Under these assumptions the intensity I returned from a seabed point p can be represented by the following expression:

$$I(\vec{p}) = K\,\Phi(\vec{p})\,R(\vec{p})\cos(\theta(\vec{p})) \qquad (1)$$

where Φ represents the intensity of the illuminating sound wave at point *p*, *R* is the reflectivity of the seafloor, θ is the incidence angle of the wave front and *K* is a normalization constant. The viewed intensity can be related to the Reflectivity (R), Topology (Z) by

$$I(x,y) = K\,\Phi(x,y)\,R(x,y)\cdot \frac{Z(x,y) - x\cdot\frac{\partial Z}{\partial x}(x,y)}{\sqrt{x^2+Z^2(x,y)}\cdot\sqrt{\left(\frac{\partial Z}{\partial x}(x,y)\right)^2+\left(\frac{\partial Z}{\partial y}(x,y)\right)^2+1}} \qquad (2)$$

Obtaining the model parameters from the observed intensities is an under-determined problem since there is only one observation at each point for determining the beam-pattern, height map and reflectivity. An expectation-maximization [10] approach is used to solve this problem. Further details of the sonar rendering process may be found in [2].

An example of the recovered beam-pattern, height map and reflectivity estimates may be seen in Figure 3 . As can be seen from the figure, the reconstructed image is very similar in appearance to the original image.

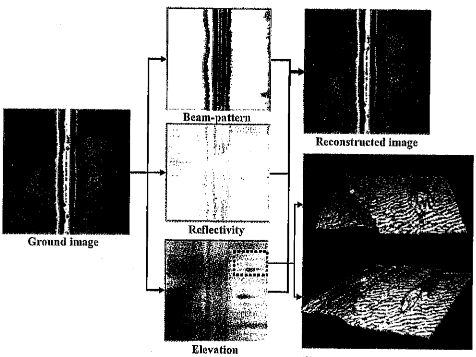

Figure 3 Estimates of the reflectivity, beam pattern and height map are obtained from the sidescan image. The reconstructed image can be seen to be similar in appearance to the original image.

3.3 Mine Simulation and Generation of Ground Truth Data

Targets to be added to the sidescan images are represented by a height map and a reflectivity map. Insertion of a new mine type is therefore simple and to do and requires only a new set of maps to describe the object. The mines are added to the images by locally altering the reflectivity and height maps. The resolution of the sonar is respected during this process. The elevation and orientation for each object are described within a ground truth file. Other relevant mine parameters such as range, seafloor class, latitude and longitude are also stored to ensure that the PATT results may be provided with respect to a rich variety of parameters.

3.4 CAD/CAC Algorithms

The PATT module is capable of evaluating any CAD/CAC system that provides output compliant with the module. Currently, the Seebyte CAD/CAC system has been integrated into the PATT system. The NSWC Panama City CAD/CAC will be integrated soon. Militaries will therefore be able to use PATT to evaluate new ATR technology.

4 PATT RESULTS

Results are shown below for the different PATT modes. Results may be viewed in the PATT module as a Probability of Detection/Probability of False Alarm (PD/PFA) curve or as a PD curve. The PD is defined as the percentage of correct mine targets detected for a given CAD/CAC threshold value. The PFA is the defined as the percentage of the total number of false alarms detected at the same threshold value. This PFA measurement can provide confusing results (aPFA of 1.0 does not inform you on whether 1 or 1000 false alarms were wrongly detected). To counteract this, the PATT module also provides a table providing numerical results.

4.1 Single Image Analysis Mode

The single image analysis mode is used to provide robust statistics on the expected performance of the MCM system. The first example shows a benign flat seafloor mission containing several hundred sidescan images. 10 simulated mines were added to each image, providing enough mine results to provide robust statistics on the expected performance of the ATR system under observation. Figures 4 contains a mosaic of the region (produced using SeeTrack Military), and a few examples of the rendered images. 2 screen shots from the PATT module can be seen in Figure 5. The information produced by PATT immediately shows the difference in expected performance obtained for different mine types and at different sonar ranges.

Figure 6 contains a SeeTrack screen shot from another mission containing flat, rippled and complex seafloor regions. Some results from the PATT module for this data set may be seen below in Figure 7. The results clearly show the expected degradation in results as the seafloor becomes more complex. The graphs show that for an equivalent PD performance to be obtained on sand ripples as on the flat areas, a higher false alarm rate must be accepted.

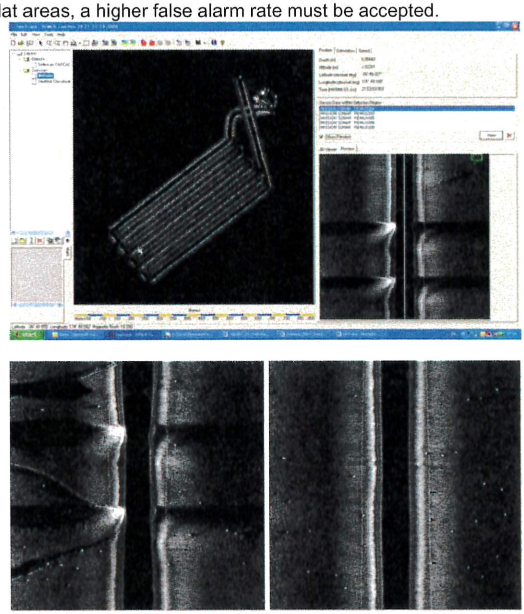

Figure 4 Mosaic of a sidescan survey as seen in SeeTrack along with 2 examples of the sonar images produced by the PATT module for evaluation. There are a large number of simulated mines in each image.

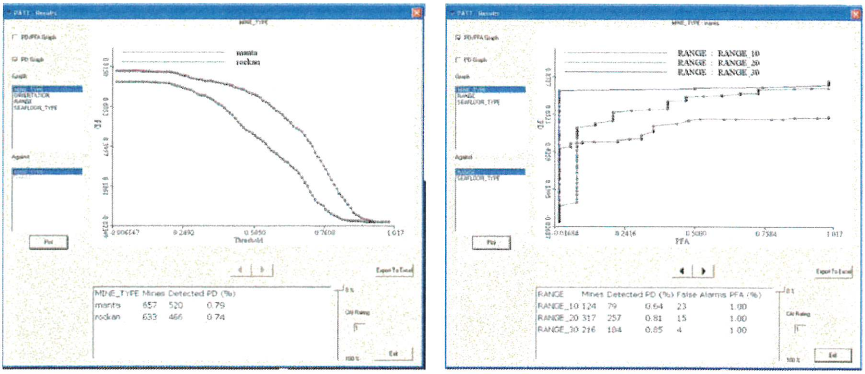

Figure 5 A set of sample PATT results from the mission shown in Figure 6. A PD graph is shown on the left showing how well the CAD/CAC is able to detect manta and rockan class mines within the data. The right graph shows how the range of the objects impact the PD/PFA graphs.

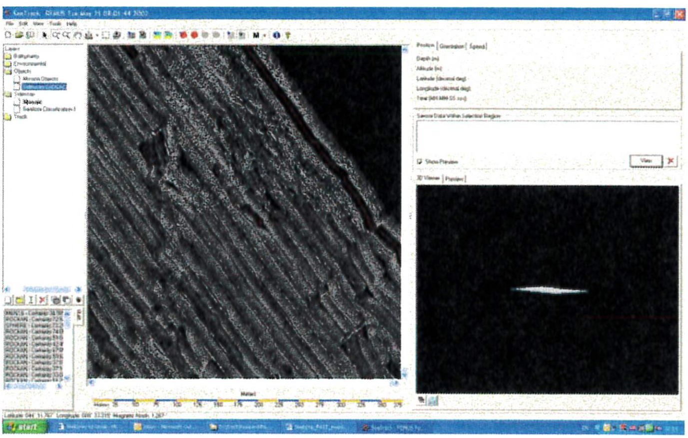

Figure 6 Screenshot from another mission containing regions of flat sand, ripples and complex regions. The performance of the ATR system on this survey will be dependant on the particular seafloor types present.

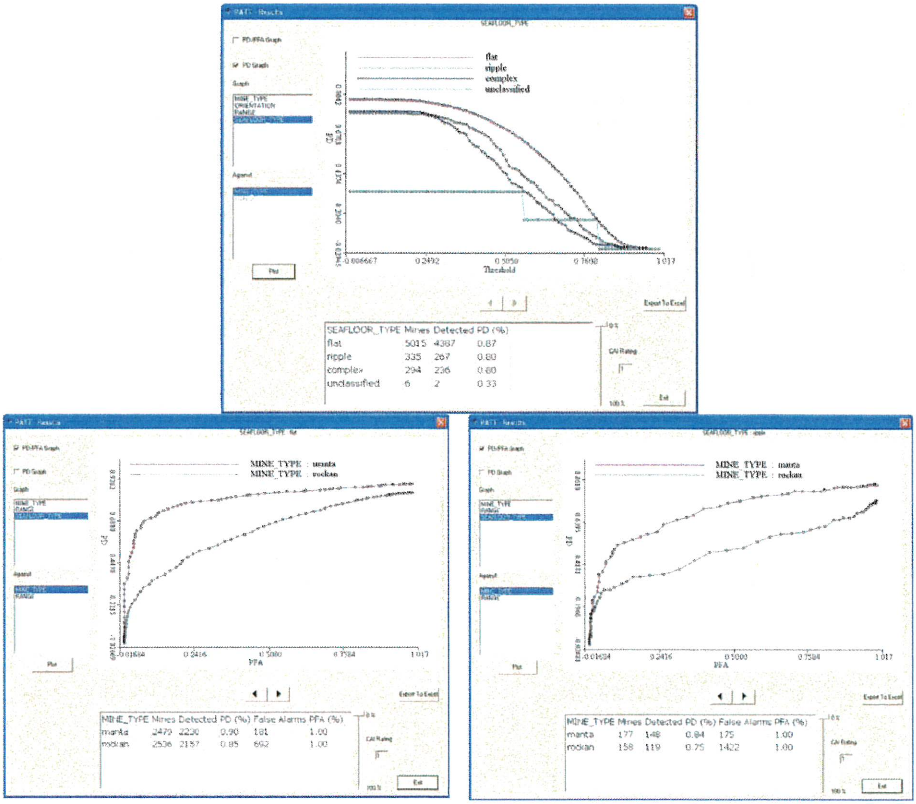

Figure 7 Selected results from the PATT module for the mission shown in Figure 8. The top graph is a PD graph for the different seafloor types present. The PATT module immediately shows that a higher PD can be expected from the ATR system on a flat seafloor. The bottom graphs show PD/PFA for the flat and ripple regions.

This information may be used to produce a mission plan based on the specific system evaluation. An optimal MCM performance may therefore be obtained by considering the specific attributes of the region being surveyed, the sonar, the specific ATR being used and the types of objects being looked for.

4.2 Multi-image Analysis and Training Mode

The multi-image analysis model allows an ATR system to be evaluated under realistic mission conditions. The single-image mode considers each image in isolation, using large numbers of simulated mines to produce a robust quantitative evaluation of the expected performance of the ATR system. In multi-image analysis mode, mines are added to specific position in the survey region. Using the navigation information from the AUV the PATT module then adds the mine, at the correct range and orientation, to all relevant images from the mission. This mode therefore allows the user to evaluate specific mission plans. In this mode, the evaluated 'system' therefore includes the survey region, the sonar, the ATR system and the mission plan.

In training mode, simulated mines are also placed in specific locations in the survey region. The navigation of the mission is again respected, ensuring that each mine appears in every image that contains the mine position. An operator may then view the survey data through a waterfall display, selecting regions believed to be mine-like. The PATT module can then provide an evaluation result for the operator, provide results in relation to the different mine and seafloor types present in the survey region.

Figure 10 contains the Graphical User Interface (GUI) which allows the user to add simulated mines to specific locations in the survey region. The user is supplied with a mosaic and seafloor classification result when placing the mines. The figure also contains an example of the waterfall display the user would use in the Training Mode to identify possible mine-like targets.

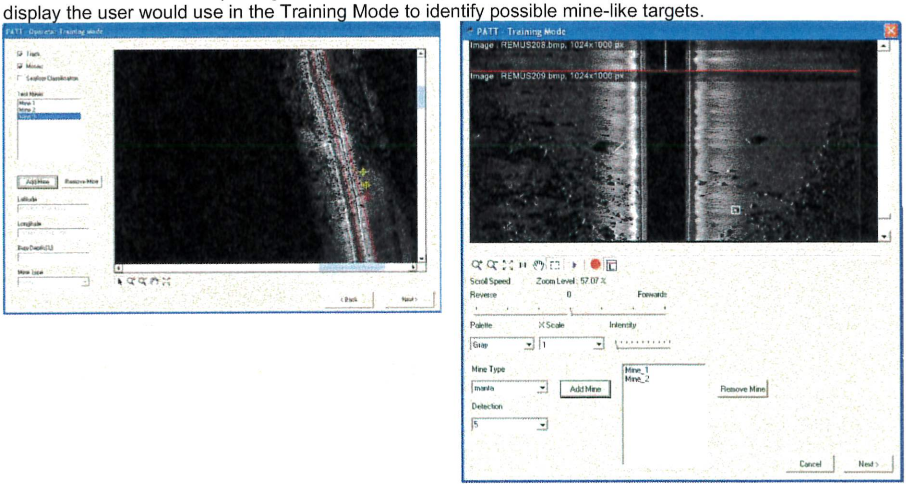

Figure 8 In Multi-image analysis mode or in Training mode, the operator can add mines to specific locations in the mission as seen on the left. When in training mode, the user is able to select possible mine targets. After the user has finished his evaluation, the PATT provides the operator with performance results.

5 CONCLUSIONS AND FUTURE WORK

This paper has presented a PATT module for evaluating MCM systems. The MCM 'system' is defined to include parameters such as the specific survey region, the sonar and the selected mission plan. Both ATR and human operators may be evaluated. The PATT module uses an augmented reality approach which mixes the real data from the survey region with simulated mine shapes. This allows accurate ground truth data to be built up and ensures that robust statistics with regard to a side range of parameters may be obtained. Future work will include developing an automated mission-planning module which will provide the user with an optimized mission plan based on the PATT output results.

6 REFERENCES

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