

PATT: A Performance Analysis and Training Tool for the Assessment and Adaptive Planning of Mine Counter Measure (MCM) Operations

P.Y.Mignotte*, J. Vazquez, J. Wood, S.Reed
SeeByte Ltd
30 Queensferry Road, Edinburgh
Scotland, UK, EH4 2HS
(*) pierre-yves.mignotte@seebyte.com

Abstract- Militaries are becoming increasingly aware of the need to quantitatively assess their Mine Counter Measures (MCM) capabilities. Recent developments in mine-hunting technology such as the use of AUV's, automated Computer Aided Detection / Computer Aided Classification (CAD/CAC) models and high resolution sonars must be evaluated to assess their abilities to meet the ever increasing demands of the MCM community. Efficient and cost-effective techniques for training MCM operators are also required.

The Performance Analysis and Training Tool (PATT) module for SeeTrack Military assesses the MCM capabilities of a complete MCM system. The capability of an operator or a CAD/CAC algorithm to effectively clear a survey region is quantitatively measured (e.g. probability of detection) by PATT using an Augmented Reality approach. The key to this approach relies on accurately inserting simulated, ground-truth targets into real sensor data. Automated mission planning, risk analysis and Q-route planning are capabilities which derive the quantitative analysis output from the core PATT module.

MCM capabilities are generally evaluated through sea trials which are both expensive and only use a small number of targets. A statistically robust measure of capability is therefore difficult to obtain. The PATT module deals with this by inserting multiple simulated mine targets into real sidescan sonar data allowing accurate quantitative estimates to be obtained. The topology of the seafloor is estimated through image segmentation algorithms and critical sonar parameters such as the range and resolution are determined during the process to ensure that the simulated targets are accurately integrated into the imagery. Evaluation results can therefore be obtained against a variety of controlled ground truth parameters such as sonar range, mine type and mine orientation.

MCM capabilities are heavily impacted by the environment. The PATT modules uses SeeByte's Seafloor Classification module to provide information on the seabed characteristics within the survey region. A wavelet-based classification system initially classifies each individual sonar image after which a Markov Random Field (MRF) based fusion system merges these results to provide a large scale classification mosaic of the region. The impact of the seafloor on MCM capabilities can therefore also be measured.

The output of the core PATT module is a series of ROC Curves providing a measure of Probability of Detection (PD) versus the Probability of False Alarm (PFA) with respect to the confidence level of the detector for any seafloor type, target type or range of analysis. The statistics can be used to provide a measure of risk of undiscovered mine targets being present in the survey region given the number of targets found using a binomial model. This capability is critical for strategic mission planning. This can later be used for planning Q-routes through the application of Fast Marching methods.

PATT may also be used for AUV re-planning to maximize the use of MCM capabilities. Given the MCM capability evaluation provided by PATT, the system can use this information to provide an optimized mission plan. This mission will consider the survey region being inspected along with the impact this will have on the MCM system to maximize the probability of discovery. Results provided will demonstrate that more sophisticated mission plans are required for complex environments while the typical lawnmower trajectory usually employed in MCM operations is sufficient for benign regions.

This paper will present the core technologies used within the PATT module. First an overview of the augmented reality module will be given. The paper will show how the CAD/CAC performance over different types of seafloor can be used for risk analysis and fast marching based route planning. Results from each of the different components of the tool will be provided. Real and simulated data is presented.

I. INTRODUCTION

Autonomous Underwater Vehicles(AUV's) equipped with high resolution side-looking sonars are now commonplace within Mine Counter Measure (MCM) operations. These vehicles provide the capability to survey large areas of seafloor quickly while the mounted sonars produce high quality images which are able to resolve most proud objects on the seafloor. The navigation solutions aboard the AUV are now accurate enough to allow the collected sidescan data to be mosaiced and geo-referenced providing the AUV operators with a complete situational awareness of the battlespace [1].

AUV's are now becoming increasingly complex with more sophisticated and accurate navigation and sensor configurations being offered. The concept of operations using AUV's is also maturing where the vehicle is slowly transitioning from principally a data collection tool to a core node of an unmanned operation. Increasingly, autonomous mission planning and inspection capabilities are being considered. Throughout this period of development and refinement, it is necessary that militaries are able to quantitatively assess their MCM capabilities. The SeeByte PATT module provides this capability using an augmented reality approach [2]. Simulated mine targets may be added into real sidescan data where both the topology of the seafloor and the sonar parameters are respected during the insertion process. Realistic, ground-truthed images are produced in real-time which an operator or CAD/CAC model may be evaluated against. This data may be presented to the operator as ROC curves relative to important MCM parameters such as mine type and seafloor type or in an intuitive waterfall display. The results from this evaluation may then be used to provide enhanced mission-planning capabilities: based on the PATT output, the risk of encountering another mine may be defined and a risk map for the region defined; using the seafloor classification map [4] provided by SeeTrack Military, an optimized mission plan may be provided which maximizes the probability of detecting mine targets while minimizing the vehicle track and mission time; Later ship route planning capabilities will also be added. Finally, PATT has been made extendable by allowing operators to define and introduce new mine models into the system. This allows users to be quickly trained on new Improved Explosive Devices (IED's) and new mine types.

The paper will first present the basic PATT system and interfaces. Afterwards, the image processing carried out to ensure the imagery produced is accurate is discussed. New features such as the integration of MCM Risk Analysis models and PATT dependant mission planning will also be discussed. The paper is concluded by looking at future proposed enhancements for PATT.

II. THE GENERAL PATT SYSTEM

The PATT module is integrated to SeeByte's SeeTrack Military product and uses some of its core technology blocks such as the Seafloor Classification module. This module allows the mission area to be classified into different regions based on the mine huntability and seafloor complexity. Typical examples of seafloor would be "flat", "sand ripples" and "rocks" where the MCM capability generally falls as the seafloor becomes more complex.

The core PATT system may be seen below in Fig 1. The core modules are described in brief below:

- The user interface allows the operator to launch the analysis, carry out a Post Mission Analysis (PMA) by calling automated CAD/CAC models to do the analysis or by manually selecting targets and select the results interpretation method.
- The Processing Modules section constitutes the core of the PATT module. Once the user has selected the images they wish to use in the analysis, this module carries out the sonar rendering process (discussed later) and ensures that realistic images are created using the simulated mines. The processing modules also create the necessary ground truth data files associated to each image as well as ensuring that the MCM output from the operator and/or CAD/CAC models is compatible with PATT.
- The Performance Analysis Module considers the ground truth position of the targets and the PMA results to produce statistical results against each of the ground truth parameters (mine orientation, range, mine type and seafloor type).
- The PATT Results Interpretation Module provides the user with a set of methods for viewing the results.
- The Mine Model Designer allows the user to specify new mine shapes to insert into the PATT module. Previously PATT was only capable of considering a fixed list of mine types. Users may now introduce new mine shapes into the system.

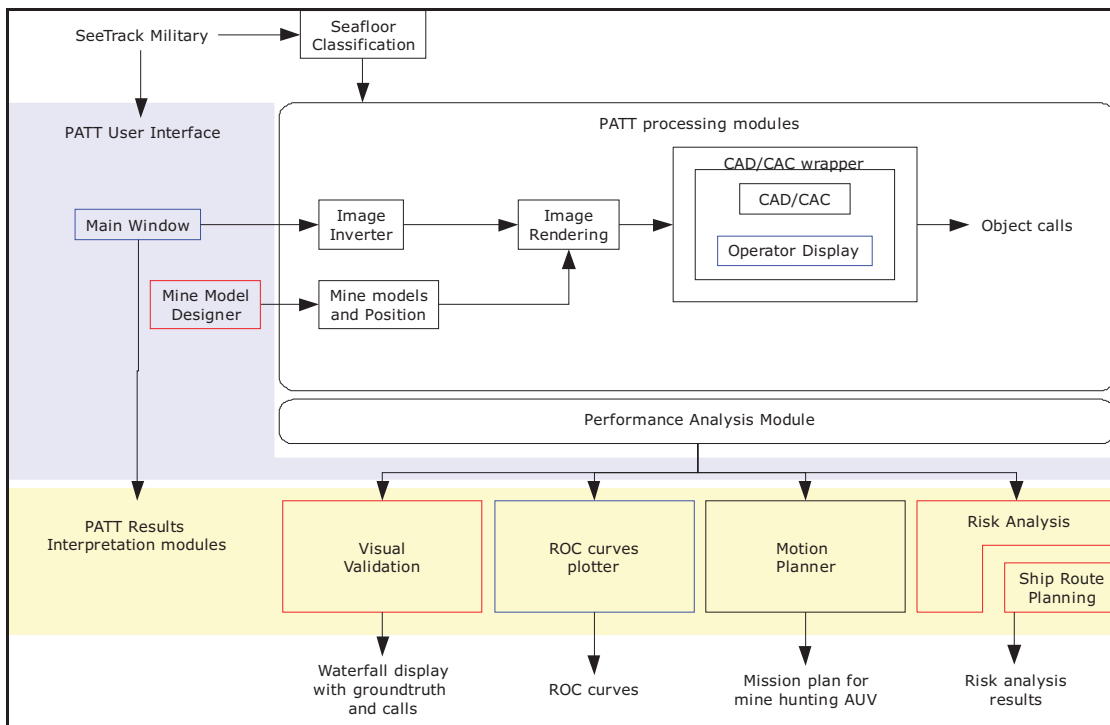


Fig. 1 General Layout of the PATT module describing its key elements and possible manners in which the output may be visualized.

PATT provides two basic modes – “Single Image” (SI) mode or “Mission Mode” (MM). The SI mode allows robust quantitative evaluation results to be obtained for a CAD/CAC model. Multiple targets are added randomly to a specified set of sidescan sonar images where the topology of the seafloor is respected (i.e. a mine sitting behind a large rock will not be seen within the image). The targets are randomly added and each sidescan sonar image is considered as an independent event. In this mode, the user may select the number of targets added to each image which allows many targets to be used in the analysis. This mode allows evaluation ROC curves for the CAD/CAC to be built up in real-time. Typically this type of evaluation data is built up using historical data sets which can have limited similarity or relevance to the mission area that the CAD/CAC is required to evaluate.

MM allows either an operator or CAD/CAC to be tested in a more realistic situation where isolated mine targets may be placed into an entire MCM mission. PATT first provides an interface that allows the operator to place specific mine types at world positions in the mission. PMA is then carried out as normal (using a waterfall display if doing manual detection) after which PATT presents the evaluation results.

It is important to note that manual and automated CAD/CAC PMA are conducted through the interface. The user can therefore evaluate the performance of an automated, manual or mixed PMA analysis. Different PMA strategies can therefore be tested.

The Figure below shows some screenshots of the interface of PATT.

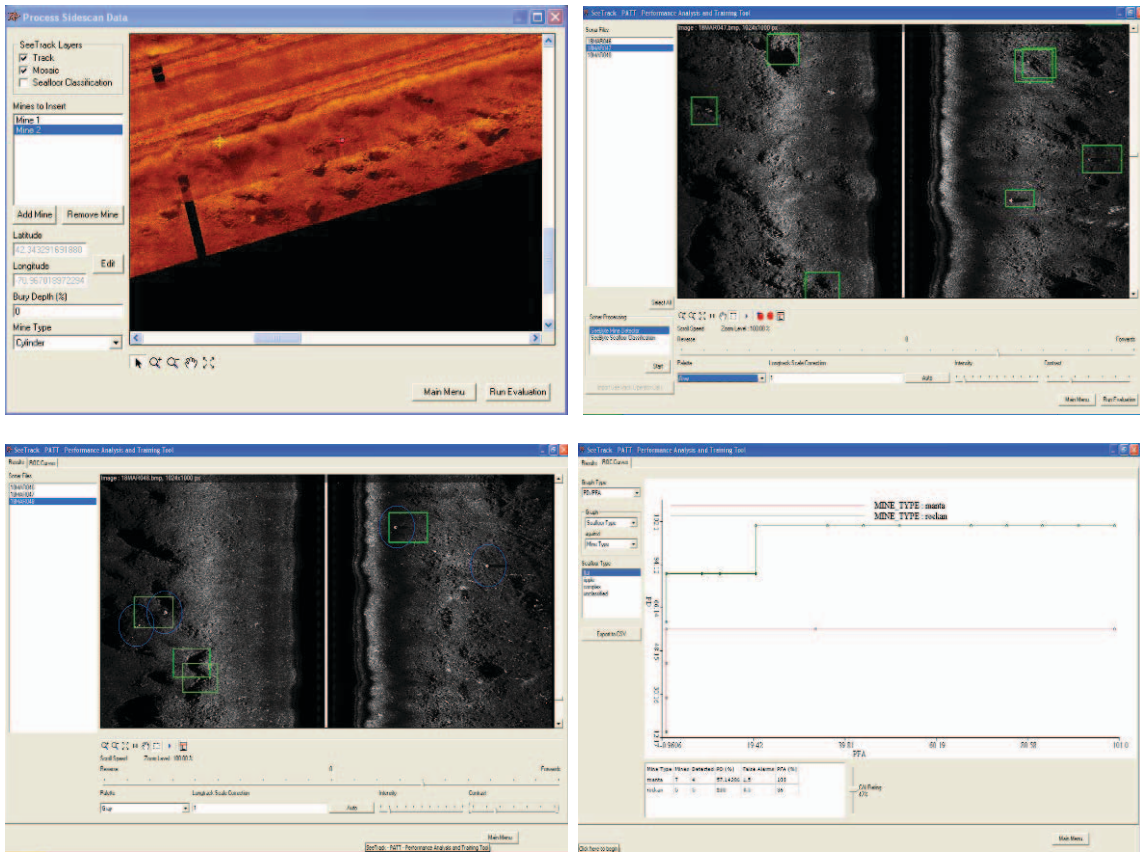


Fig.2 TL – in MM, the user selects where to place targets in the mission. TR - Once targets have been placed into the images, the PMA may be done by manually or using a CAD/CAC. BL – The results may be shown visually, where PMA detection and ground truth results are shown. BR – The PATT evaluation results may be shown as ROC curves and tables for specific parameters.

III. RENDERING THE SONAR IMAGES

The Performance Analysis and Training Tool (PATT) relies on an augmented reality approach where external objects (e.g. mines) are accurately inserted within the test side-scan sonar images. Previous versions of PATT used a computer intensive rendering process which was timely and computationally expensive [2]. This made real-time analysis impossible. Important sonar image artifacts such as the surface returns and beam pattern were also often removed during this process which reduced the realism of the images. These artifacts are problematic for PMA and should ideally remain in the imagery. This section describes a new approach to insert synthetic targets in real images.

The sonar renderer must accurately insert the simulated targets into the images, i.e. respecting occlusions which occur due to clutter while also preserving the sonar image artifacts. The new process now only renders the regions of the image where targets have been added. This ensures that most of the rendered image remains identical to the raw sidescan image and also massively speeds up computation time. In addition, the insertion considers only the seafloor height map computed through the consideration of the shadow regions within the sidescan image which again speeds up computation time so that each image may be rendered in a few seconds. The entire process is described in the figure below:

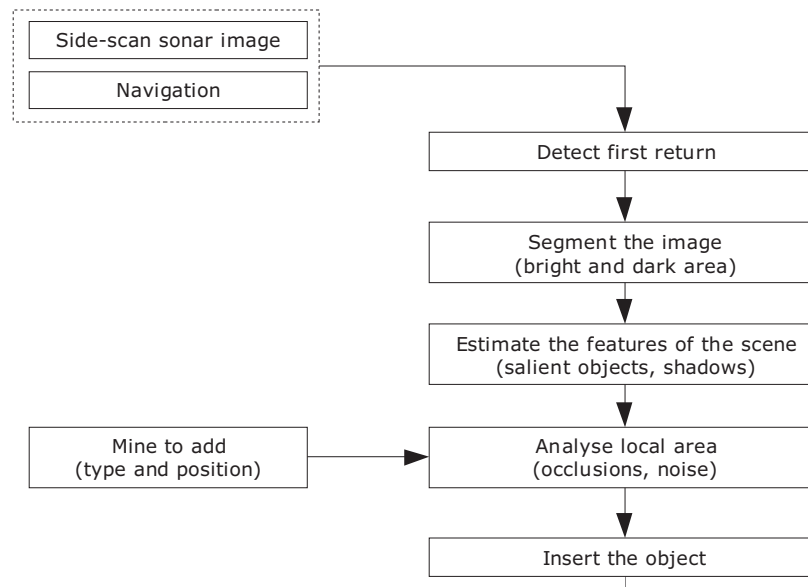


Fig. 3 Data Flow Diagram explaining the Sonar Rendering Process for inserting targets into the sidescan images.

Once an estimate of the seafloor topology has been obtained, the module renders only the areas which are modified due to the addition of synthetic objects. The rendering is performed using a ray tracing model which depends on the following parameters:

- Type of object and insertion parameters (e.g. burial depth): size and shape of the objects are obviously key parameters to rendering.
- Altitude and attitude of the side-scan sonar: this provides the incidence angle of the sonar beam.
- Ratio of reflectivity between the seafloor and the object: the brightness of the inserted object is tuned with respect to the seafloor brightness.
- Presence of occlusions: for a given position and attitude of the side-scan sonar image, objects may be occluded by other objects.

The figure below shows a target being inserted next to and behind a large object. As expected, the target cannot be seen in the imagery when behind the large obstacle.

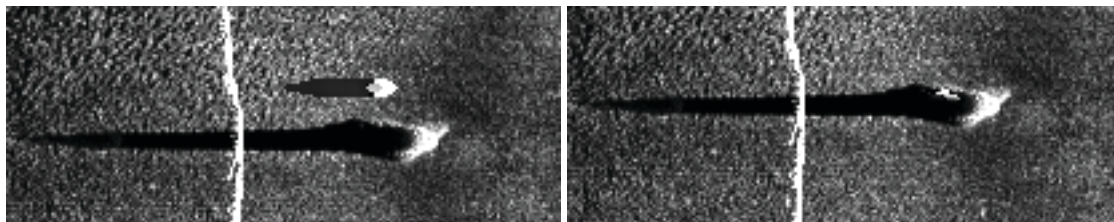


Fig. 4 Rendering of a target next to and behind a large occlusion. When the target is behind the occlusion, it does not appear in the sidescan image.

The figure below shows some rendered results from the new module. These images are produced in 3-4 seconds per image and contain all the original sonar artifacts. The output is a realistic sidescan image which may be used for evaluation and training.

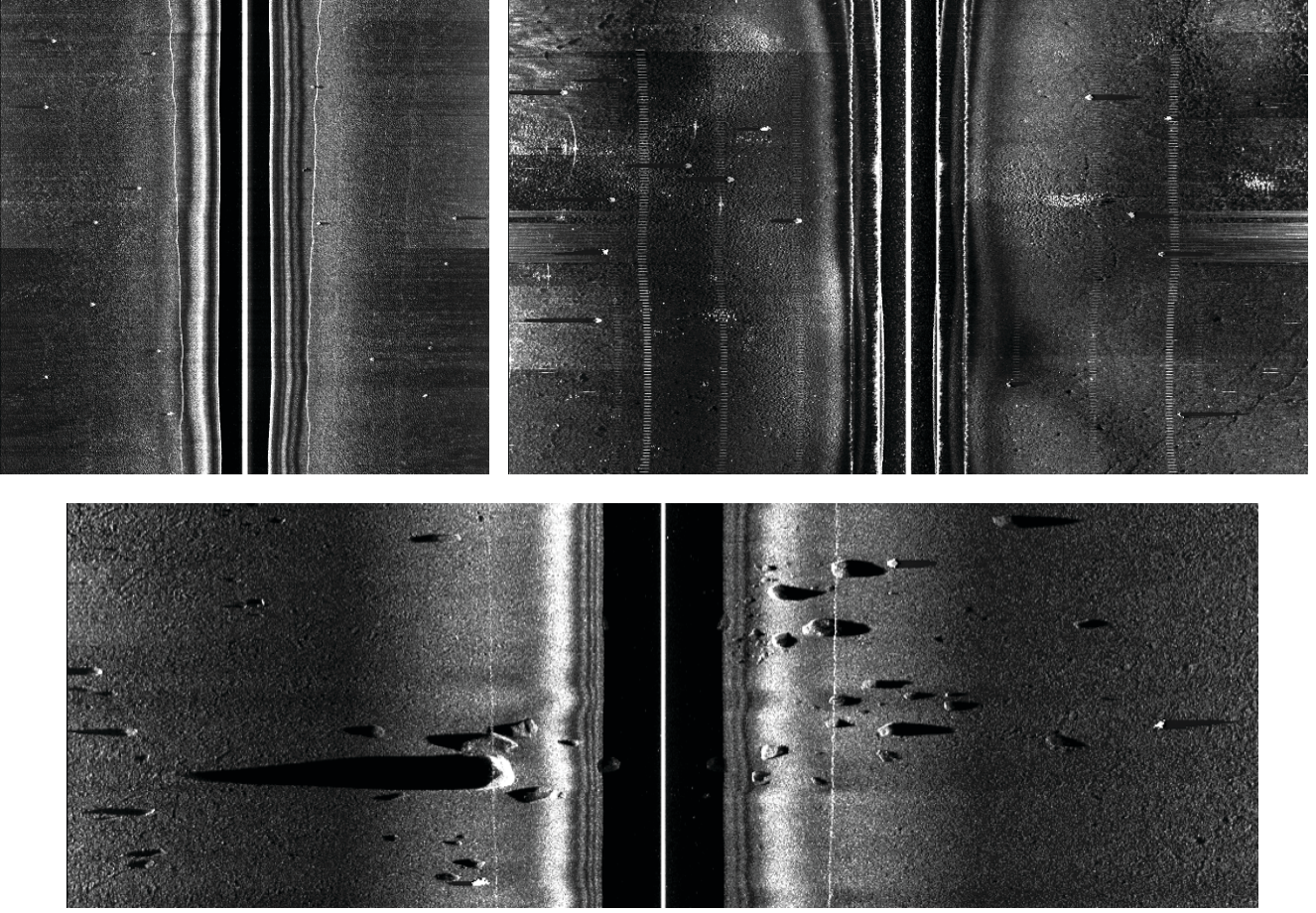


Fig. 5 Examples of the rendering on sidescan sonar imagery.

IV. RISK ANALYSIS

Once the PATT analysis has been complete [2], the user may view the results in a variety of manners. The most common is to view the results as a series of ROC curves or through the waterfall display (see Fig. 2). The results from PATT (principally the probability of detection) may be used to provide an estimate of Risk. This work has been taken from the Centre of Naval Analysis (CNA) [5] who has developed a system for presenting risk in Mine Warfare exercises. The risk can be modeled in two ways. First, the expected number of remaining mines can be estimated based on a probabilistic model. Second, the performance of a risk reduction measure, such as a second run of clearance around the mines found already in the PMA analysis, can be assessed.

The number of residual mines after clearance operations is a key measure of the risk of deploying assets in an area. Let P_c be the probability of detection of the targets and n_c the number of targets that have been effectively detected.

The probability that n_r mines are remaining in the area can be estimated [5] using a Binomial model (1):

$$P(n_r) = P_c^{n_c+1} \cdot (1 - P_c)^{n_r} \frac{(n_c + n_r)!}{n_c! n_r!} \quad (1)$$

This model allows the user to estimate the expected number of remaining mines \hat{n}_r in the area using (2).

$$\hat{n}_r = \sum_{n_r} n_r \cdot P(n_r) \quad (2)$$

This estimation can be refined if some intelligence is available regarding the mining operation or the reliability of the mines (e.g. each mine has a 10% chance of being defective). If prior knowledge is known regarding the probability of a number of mines having been laid, this information can also be represented in (1) using a probability prior.

For each seafloor context (e.g. flat, ripple), the results of the PATT evaluation may be summarized by three values, which give us P_c .

- Number of objects correctly detected
- Number of missed objects
- Number of false alarms in the region

Therefore, once the PMA has been completed and n mines have been found, the operator has access to an estimate of the number of mines which have been missed. The figure below presents a screenshot of the module estimating the number of remaining mines. After running PATT over this mission, the probability of detection over the whole area is estimated to be 87% (18 false alarms). The operator or CAD/CAC has found 14 actual targets. The application of the risk model suggests at least two mines have been missed by the operator or CAD/CAC. This information may be presented as a risk map when different seafloor types are present within the MCM mission area.

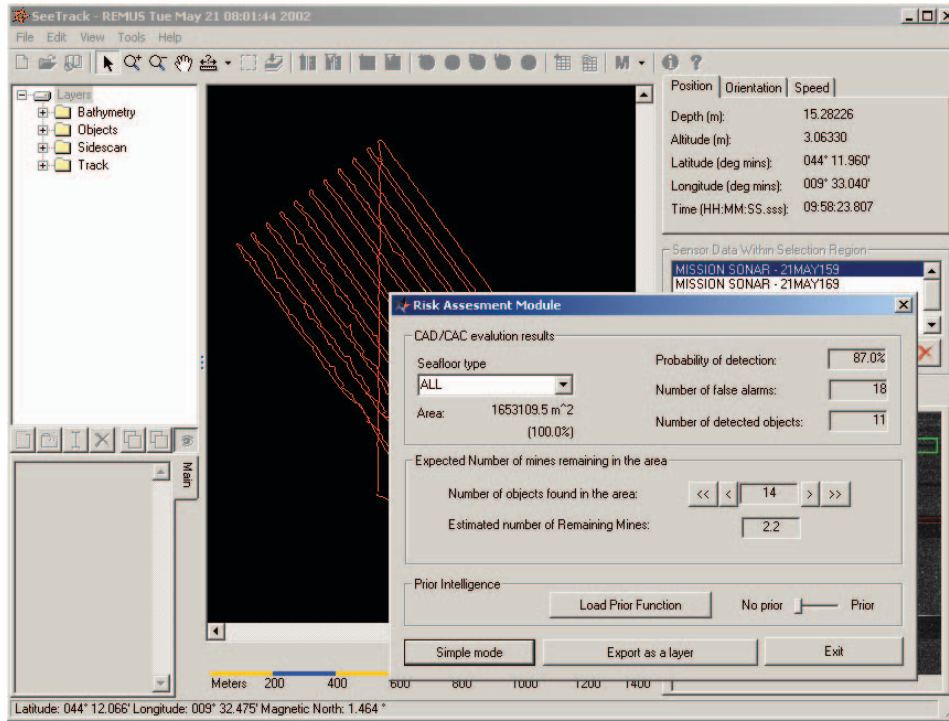


Fig. 6 Risk Analysis GUI showing that based on PATT evaluation results and the PMA analysis, it is likely that there are 2 mine targets remaining.

V. INSERTING NEW TARGETS INTO PATT

The standard PATT module has a small set of standard mine target shapes which may be input into the system. These models are represented in the system by a height map where each value in the map represents the elevation of the target. Once the resolution of the height map is known, the object may be inserted into the imagery at any orientation and attitude at the correct size. SeeByte have recently completed a module which will now allow the operator to input new mine targets into the system. 3D models of mine targets or Improved Explosive Devices (IED's) may be drawn up in a commercial package such as Google SketchUp [4] and then converted into the required PATT format. This will ensure that PATT may be constantly upgraded to

include new targets when evaluating and training new operators and CAD/CAC models. Fig. 7 presents two targets presented, on the left hand side, after design, on the right hand side, after importing them into PATT.

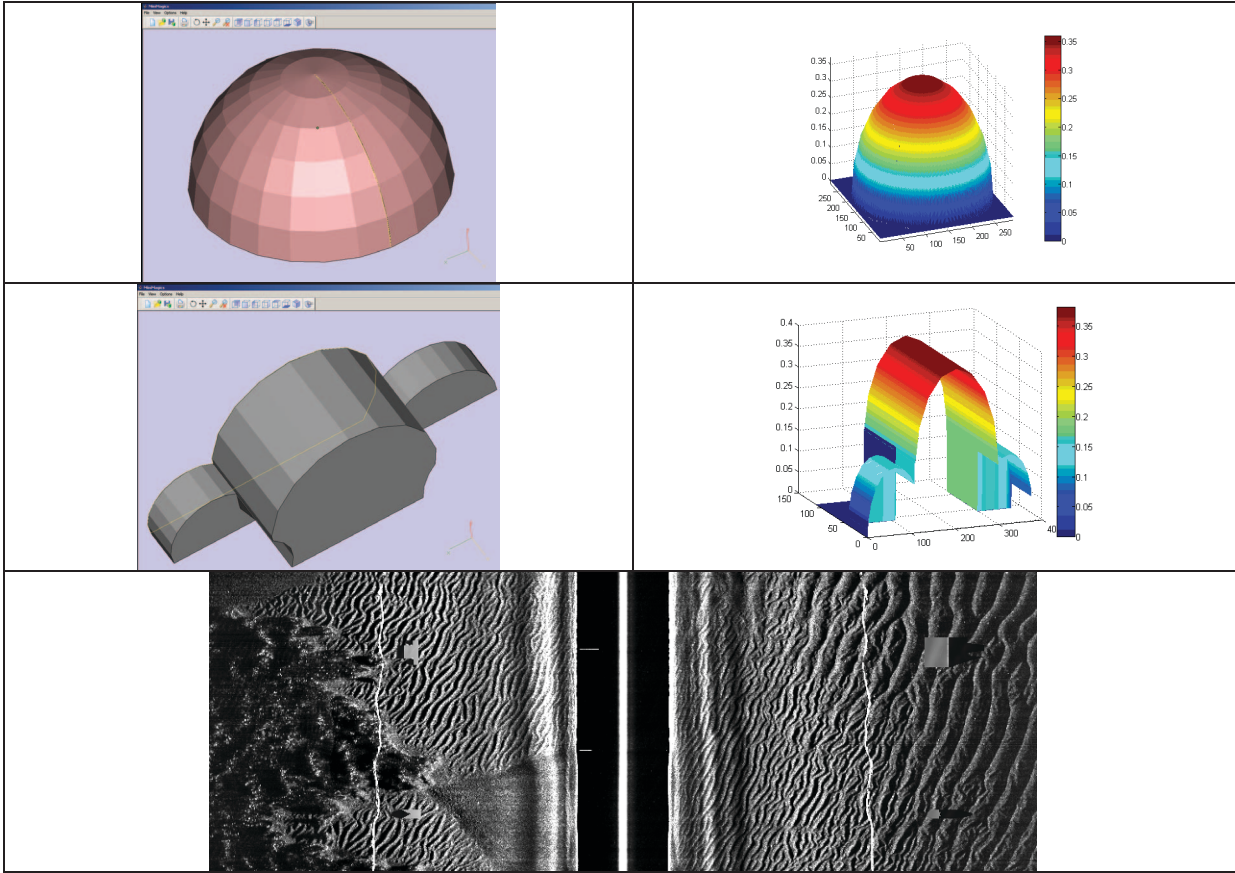


Fig. 7 New targets may be defined in 3D and then input into the PATT system. This will allow new mine target types to be included in the PATT analysis by the operator.
Bottom: a rendered side-scan sonar image with four new mine types.

VI. PATT DRIVEN MISSION PLANNING

A mission trajectory is a sequence of points which an autonomous vehicle visits in a pre-defined order. An optimal trajectory provides a minimization of some global parameters, such as the total distance traveled and the total number of AUV turns while obtaining the mission criteria. In the case of MCM operations, this would be to achieve a desired Probability of Detection of all targets in the area. Standard MCM operations conduct a lawnmower trajectory which does not usually take into account the complexity of the mission area or the expected performance of the operator or CAD/CAC algorithms. With the evaluation results from PATT, it is possible to replace the standard mission plan that is optimized for the capabilities of the MCM system and the mission region under consideration.

The following pieces of information are provided by PATT for the mission planning:

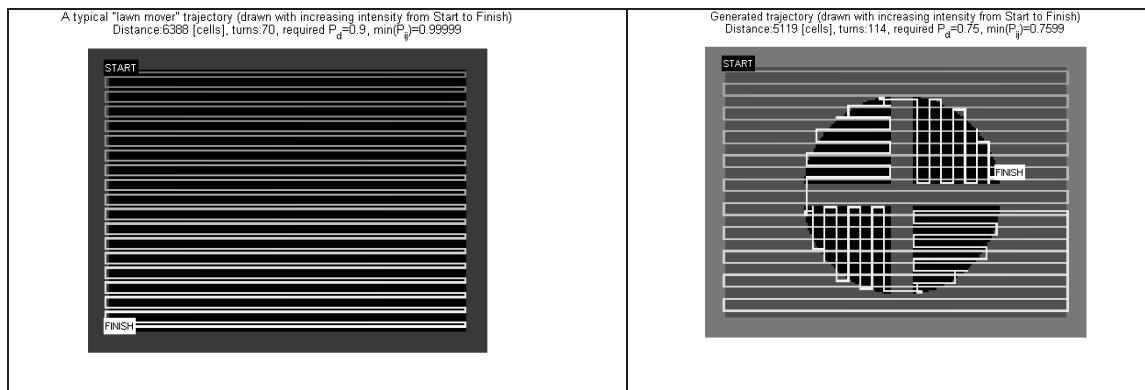
- A seafloor classification map of the region. This functionality is fully integrated into SeeTrack and PATT.
- A lateral range curve describing the probability of detection with sonar range. This describes the Probability of Detection at different ranges and models the fact that there is an optimal sonar range for MCM operations. An example range curve.
- The Probability of Detection values for the different seafloor and range bins as produced by PATT. This information is extracted directly from the ROC curves produced by PATT.

Taking this information, the PATT module should produce a vehicle trajectory plan which is represented by a series of waypoints. The mission planning algorithm uses a grid-based approach where the region is split into non-overlapping cells. Complete coverage can therefore be complete when the vehicle visits each cell the required number of times to meet the pre-defined required Probability of Detection P_d for each cell. A visit is defined by the vehicle passing close enough to the cell such that it falls within the range of the sonar.

The Mission Planning module is tasked with determining how the vehicle should move at any point in time. It does not retain any memory of the vehicles trajectory. The vehicle may be in the middle of a mission where some of the areas have been visited the required number of times to fulfill P_d while others have not. The vehicle may also be surrounded by cells which have already fulfilled the Probability of Detection. Determining a global minima solution to the problem cannot be guaranteed with a reasonable time frame. The aim of this approach is to provide an acceptable local minima solution, defined by the total vehicle distance travelled and the number of turns. The aim of this approach is to provide an acceptable local minima solution, defined by the total vehicle distance travelled and the number of turns.

At each point, the algorithm looks for a suitable trajectory defined by an offset position *offset*, direction θ (N, E, S, W) and length λ . The *offset* is initially searched within a window around the vehicles current position defined by size W . This window is initially kept small to favor offset values ~ 0 but is increased if a suitable trajectory cannot be found. The system is controlled by 3 main parameters. W_{inc} is used when looking for a starting point of a new trajectory. A starting cell is looked for within window W of the current cell. This parameter describes how much this window is increased in size when a suitable start cell cannot be found. Once a starting point has been found, possible trajectories must be determined. These are done using stopping criteria parameter n_{rev} and n_{avg} . These 3 parameters must be optimized to maximize the performance of the system. This is currently done by exhaustively going through the parameter space. Ideally this parameter determination process should be done using an optimization approach such as Simulated Annealing or Genetic Algorithms.

Some Mission Planning results based on the performance evaluation can be seen in the figure below. The first example is a single flat region (the class map underneath is all one color) and the standard lawnmower trajectory is produced as the optimum mission plan. The second example has 4 quarter circle regions where the seafloor is assumed to be more complex and so requires that each cell is visited multiple times to fulfill the required P_d . As the mission plan shows, the rest of the area is visited only once as necessary and the vehicle trajectory length has been minimized. The third example is a real-world example where there are 3 distinct seafloor regions of differing complexity. The produced mission plan clearly shows the areas that need to be visited more often to meet the required Probability of Detection requirements.



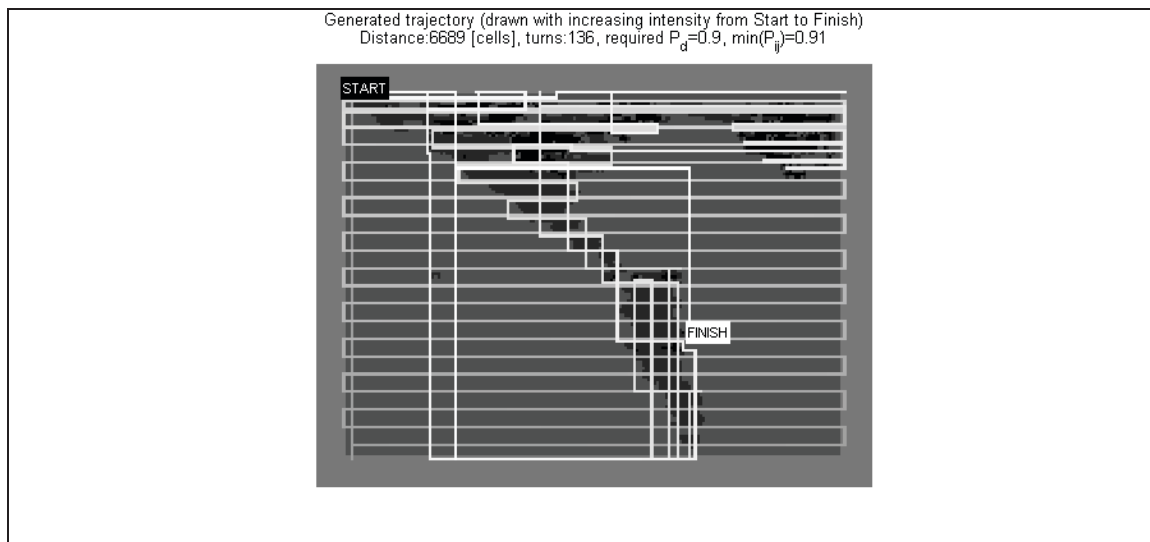


Fig. 8: 3 examples of mission plans built up based on the classification map and PATT information. The first example is a simple, single seafloor example where the standard lawnmower trajectory is provided as the best solution. The other 2 examples are more complex where some areas require multiple passes to obtain the necessary Probability of Detection.

Current work is investigating a used of these risk maps to estimate Q-routes cross these areas. Fast marching methods [7] provide a credible estimate of the safest route between two positions of the surveyed and cleared area.

VII. CONCLUSIONS

This paper has presented SeeByte's PATT module which provides a statistically robust evaluation of MCM capabilities. The module is completely integrated into SeeByte's SeeTrack Military system and allows both CAD/CAC models and human operators to be trained and evaluated. The paper described how it is now also possible for users of PATT to include new mine models into the PATT system. This will allow operators and CAD/CAC's to be trained on new mine threats as required. The evaluation results from PATT may be visualized in several different ways. Standard visualization techniques include the use of ROC curves and viewing the results on a waterfall display. The PATT evaluation results may also be used to provide Risk Analysis results. This may be used after the PMA to assess the risk of undetected mine targets remaining in the field of operations. The results from PATT may also be used to produce a vehicle mission plan which is optimal in terms of the region being inspected and the MCM capabilities of the system. Looking forward, PATT would become an embedded vehicle module which would allow an AUV to alter its mission plan based on the feedback from PATT to ensure the effectiveness of the vehicles MCM assets is maximized.

ACKNOWLEDGMENT

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REFERENCES

- [1] SeeByte. SeeTrack Military, <http://www.seebyte.com/Military>
- [2] S. Reed, Y. Pétillot, A. Cormack, PATT: A Performance Analysis and Training Tool for the assessment and Adaptive Planning of Mine Counter Measure (MCM) operations, in Proceedings of the Institute of Acoustics, vol 29, Part 6, 2007
- [3] S. Reed, Y. Pétillot, A. Cormack, PATT : A Performance Analysis and Training Tool for the assessment and adaptive planning of Mine Counter Measures (MCM) operations, in Proceedings of the Undersea Defense Technologies conference, La Spezia, 2007
- [4] S. Reed, I. Tena Ruiz, C. Capus, Y. R. Pétillot, The fusion of large scale classified side-scan sonar image mosaics, IEEE Trans. on Image Processing, 15(7), July 2006.
- [5] S. Savitz, Psychology and the Mined: overcoming psychological barriers to the use of statistics in Naval Mine Warfare, CNA Technical Report, CRM D0013693.A2, May 2006.
- [6] Google SketchUp, sketchup.google.com, or any other commercial product (e.g. 3DSMax)
- [7] J. Sethian, Level Set Methods and Fast Marching Methods: Evolving Interfaces in Computational Geometry, Fluid Mechanics, Computer Vision and Materials Science, Cambridge University Press, 1999.