FROM SIGNAL EXCESS TO TRACK CLASSIFICATION USING THE MULTISTATIC TACTICAL PLANNING AID (MSTPA)

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1 INTRODUCTION

The Multistatic Tactical Planning Aid (MSTPA) is a model, currently in development at the NATO Undersea Research Centre (NURC), with an aim towards becoming a decision support tool for planners and operators of Multistatic sonar systems[1]. The premise of the tool is to model the acoustics in the most efficient way such that an initial decibel value of signal to noise ratio may be quickly translated into more operational metrics. The tool may be used in two modes – a simulation mode in which scripted targets are driven through a Multistatic network in order to determine various performance metrics – an optimization mode in which optimum sensor positions or waypoints are generated.

The desire to transition MSTPA from an acoustic tool to a decision support tool stems from the current interest within nations to procure and develop sonar systems with multistatic capability. The well known advantages of these systems, such as increased area coverage and track holding, come at the cost of increased operational complexity. Consequently, there is a requirement for a tool that, in addition to providing a purely acoustic solution, can enhance the understanding of operators, and assist their decisions when planning a multistatic mission. The MSTPA tool has been integrated within the OpenSea simulation environment also developed at NURC. This will allow both submarine operators, and Anti Submarine Warfare (ASW) planners to play in real time against each other while MSTPA determines their relative performance.

The transition towards decision support requires the use of optimization routines and Monte Carlo simulations in order to account for the stochastic nature of many of the input and output parameters associated with sonar performance assessment. Consequently, the acoustic routine must determine a signal to noise ratio value as quickly as possible, while maintaining sufficient fidelity, to allow for the calculation of subsequent operational metrics in a timely manner. MSTPA therefore employs an acoustic engine based on many of the principals of mode theory developed by D Weston and expanded by C Harrison at NURC [1,3,4].

This paper describes the current status of the tool, the proposed path towards decision support, and presents output based scenario A2 as defined for the David Weston Sonar Performance Assessment Workshop.

2 CURRENT MODEL STATUS

The MSTPA tool provides operational metrics by considering the entire chain of events from an initial detection to the eventual classification of a track. The model begins with the determination of signal excess and associated probability of detection. Contacts are generated taking into account the localisation error of the sensors involved. All contacts, from targets, clutter and additional false returns are then sent to a tracker. The resulting tracks are then sent to a classifier in order to determine the point at which an operator would raise an alert and initiate an engagement. The following sections describe each step in more detail.

2.1 Signal Excess

Any metric for a sonar system most of course begin with the determination of signal to noise ratio and signal excess (assuming some value for detection threshold). The MSTPA tool employs the ARTEMIS model (Adiabatic Reverberation and Target Echo Mode Incoherent Sum) to determine the target echo

(TE) and reverberation level (R) from which the signal excess (SE) may be determined according to the basic sonar equations below.

$$SE = TE - (BN \oplus (R - G)) - DT \quad (1) \quad \text{where} \quad BN = (AN \oplus SN) - DI - 10\log(T) \quad (2)$$

BN	= background noise (dB)	AN	= ambient noise (spectrum level dB)
SN	= self noise (dB)	DI	= directivity index (dB)
T	= pulse length (s)	G	= gain against reverberation (dB)
DT	= detection threshold (dB)		

ARTEMIS was developed at NURC and employs the principals of mode theory introduced by the late David Weston whereby a continuum of modes is equivalent to a continuum of ray angles or flux. The principals have been further developed by C Harrison at NURC such that fast acoustic solutions may be obtained for environments with fully range dependent bathymetry and sound velocity profile through interpolations of wave number and ray angles[2,3,4]. The acoustic module also accounts for a fully bistatic target strength and determines the gain against reverberation (G) as a function of target Doppler by means of a Q function [5,6].

The signal excess value determined by the equations above is assumed to be the mean value of a normal distribution with user defined standard deviation (σSE). The fluctuation in signal excess from variations in the underwater environment is accounted for by a simulated lambda-sigma process [7]. This process produces a modified signal excess by sampling from the assumed normal distribution and applying the same offset to subsequent pings taking into account the probability of correlation (Pc) determined form the user defined 50% correlation time in seconds (t_{50}).

$$Pc = e^{-\lambda t} \quad (3) \quad \text{where} \quad \lambda = \frac{-\ln(0.5)}{t_{50}} \quad (4) \quad \text{and } t = \text{transmission interval in seconds}$$

2.2 Contact formation

Once a value of signal excess has been determined following the application of the lambda-sigma process, a corresponding value for instantaneous probability of detection (Pd) may be calculated. The equation below uses the error function (erf(x)) to determine the fraction of the signal excess distribution with positive values resulting in detections – this makes a simplifying assumption that signal excess is a normal distribution about the mean value (SE) with standard deviation σSE to account for uncertainties in the environment, propagation, and target strength. This allows for a stochastic approach to detection when applied within Monte Carlo routines.

$$Pd = \frac{1}{2}\left[1 + erf\left(\frac{SE}{\sqrt{2}\,\sigma SE_{\square}}\right)\right] \quad (5) \quad \text{where} \quad \operatorname{erf}(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}\,dt \quad (6)$$

Having determined Pd, the model generates a random number between 0 and 1 from a uniform distribution and generates a contact if it is less than or equal to the value of Pd. When the instantaneous probability of detection is combined with the simulated lambda sigma process over a number of Monte Carlo runs, a realistic cumulative probability of detection is observed. Further statistical distributions of signal excess will be investigated in future iterations of the tool. These may include the Swerling function as described in [8].

When an object is deemed to have been detected the model generates a contact according to the localization error associated with the given sonar system [9,10]. A receiver within a multistatic system receives both the direct blast from the source followed by, at some time τ later, a reflected return from a target object. Applying the geometry of Figure 1, the receiver determines the range of the target object according to the equation below

$$R_{RT} = \frac{c^2\tau^2 - R_{SR}^2}{2(c\tau - R_{SR}\cos[(\alpha)])} \quad (7)$$

All parameters of the equation are sampled according to an assumed normal distribution centered on the actual value with a user defined standard deviation. Contacts then appear somewhere within an approximate ellipse centered on the actual target object location. All localization errors are assumed to be independent. However, subsequent iterations of the tool will investigate correlation of these errors by employing the lambda sigma process as used in the determination of signal excess and described in Section 2.1.

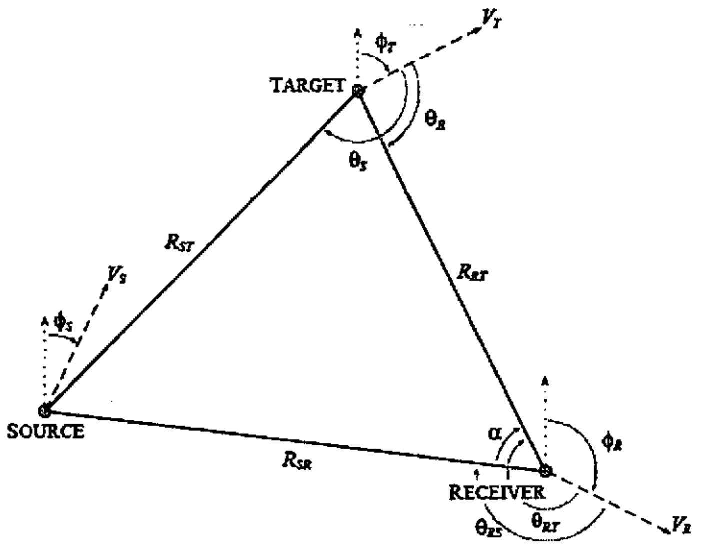

Figure 1 - Bistatic geometry

The reverberation determined by the acoustic engine, together with the background noise level is assumed to be the mean power level of a Rayleigh distribution of intensities. In the absence of a true signal a false contact will be generated if the actual noise or reverberation level at a particular moment exceeds the mean level (due to normalisation). Therefore the probability distribution of this intensity ratio is simply a Rayleigh distribution with a mean of one (7). Consequently, for a given signal to noise intensity ratio threshold DT_i, the probability that it is exceeded (probability of false alarm *Pfa*) may be analytically determined from the area under the Rayleigh distribution. This results in the following equations.

$$P(x) = \frac{\pi x}{2} e^{\frac{-\pi x^2}{4}} \quad (8) \qquad Pfa = e^{\frac{-\pi}{4} DT_i^2} \quad (9) \qquad \text{where} \quad DT_i = \sqrt{10^{\frac{DT}{10}}} \quad (10)$$

False contacts are generated in time-bearing space relative to the receiver with each beam divided into a number of time bins with a resolution equal to 60/c seconds. This agrees with current sonar processing in which the time extent of the normalizing window is set such that a 60 meter target can just be resolved.

The model then samples from the binomial distribution using the *Pfa* value together with the number of time bins for each beam to determine the number of false contacts to be generated. The number of time bins is determined between the calculated time of arrival of the direct blast and the acquisition time of the receiver. This prevents any contacts forming within the blanking region or beyond the maximum acquisition range of the receiver. Contacts are then randomly distributed in time along each beam. The time and bearing of each contact is converted to a position using Equation 6 taking into account the appropriate measurement errors as described in Section 3.4. Note that the measurement error in the calculation of arrival time is not required since the contacts are already randomly distributed in time.

The model then generates a simulated signal to noise intensity ratio for each contact which must be greater than *DTi* and be drawn from the Rayleigh distribution. This requires the cumulative Rayleigh distribution *D(x)* (with a mean of one) such that *D(DTi)* may be determined. A uniformly distributed random number D_{rand} is then drawn between *D(DTi)* and 1. The sampled signal to noise intensity ratio *snr* is then determined from the inverse of the cumulative distribution.

$$D(x) = 1 - e^{\frac{-\pi x^2}{4}} \quad (11) \qquad snr = \sqrt{\frac{-4\ln(1 - D_{rand})}{\pi}} \quad (12)$$

Additional statistical distributions may be implemented so long as the inverse of the cumulative distribution can be determined.

Further contacts from clutter objects are generated. A clutter object within MSTPA is essentially a stationary target object with some value of target strength such that the above processes for contact generation may be applied to it.

The end result of the contact generation processes described above may be seen in Figure 2 in which a collapsed beam plot is shown for a target submarine moving past a stationary source and receiver with additional clutter objects and a background of false returns. The parabolic feature is the moving target object whereas the horizontal striations arise from the application of the lambda sigma process to stationary clutter objects. Note that the localization error is apparent in the jitter of clutter and target contacts in time.

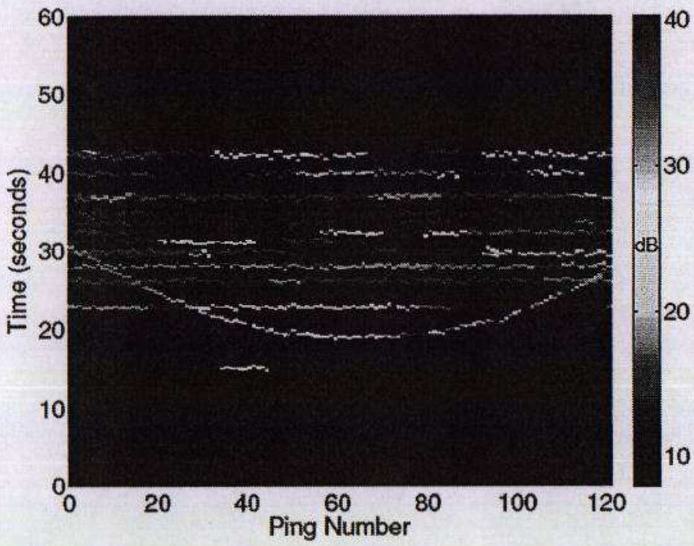

Figure 2 - Simulated collapsed beam plot

2.3 Tracking

All contacts, whether from targets, clutter, or false returns, for all combinations of source and receiver are sent to a central tracker. Tracking is used to obtain contact histories (tracks) and better estimates of the target position and velocity than can be gleaned from raw contact data. Tracking also reduces the amount of irrelevant information that an operator has to deal with and therefore enhances the ability of the whole system in detecting and localising a threat submarine from amongst clutter and noise. The implemented tracker uses simple but standard, logic based criteria for track initiation and termination. This entails M detections out of N pings to initiate a track and L consecutive missed detections for track termination. All tracks are then processed using a discrete Kalman filter [11]. Contacts are associated to tracks using the global nearest neighbor scheme [12] to be updated to the multi-hypothesis scheme at a later time.

The ability of the model to generate track output is an important step towards more operational metrics, since, from an operator point of view, a positive signal excess alone does not allow for tactical decisions to be taken. A positive signal excess results only in a small 'blip' on the sonar screen amongst many others. It is not until a track has been generated that a sonar operator is alerted to the possibility of a threat, and then, following classification, can make tactical decisions.

2.4 Track classification

The track classification process implemented within MSTPA is used to determine the point at which an operator would raise an alarm and thereafter initiate the prosecution of a threat. The tool does not consider any actions after this point (e.g. fire control solution or weapon deployment) and so a simulation may be stopped once a target has been classified as such. This can save time when a large number of runs are required within a Monte Carlo simulation.

The classification module uses the machine learning technique of sequential probability ratio testing (SPRT) to determine a target likelihood score between 0 and 1 based on the distribution of headings and displacement within a particular track history[13]. Sequential analysis consists of summing the likelihood ratios at each ping to accumulate evidence for hypothesis testing. For convenience we use the log-likelihood ratio, such that

$$\mathcal{L}(n) = \sum_{i=1}^{n} \ln\left(\frac{P(t_i|\theta_0)}{P(t_i|\theta_1)}\right) \qquad (13)$$

where the function $P(t_i|\theta_0)$ represents the probability distribution of the observation vector t_i for a target track, and $P(t_i|\theta_1)$ for a non-target track.

The SPRT compares the log-likelihood ratio to two boundaries, A and B, such that

- accept the hypothesis $H_0 : \theta = \theta_0 \Rightarrow target$ if $\mathcal{L}(n) \geq A$
- accept the hypothesis $H_1 : \theta = \theta_1 \Rightarrow non-target$ if $\mathcal{L}(n) \leq B$
- wait for more data if $B < \mathcal{L}(n) < A$

This final step in the modeling process allows for investigations into the effect of false classifications from clutter and noise on mission success. The results extend the concept of false alarm, traditionally considering only contacts, to the problem of false classification and the costly deployment of assets to prosecute a non-existent threat.

2.5 Example output

The end result of the processes described above is shown in Figure 3 in which both experimental and simulated tracker output is shown for a bistatic scenario including a source (SA) and receiver (RD). The tracks are colour coded according to the following classifications - non-target = Green - target = Red - unclassified = Blue. The actual target track is shown in pink and we see similar tracker output for both real and simulated data.

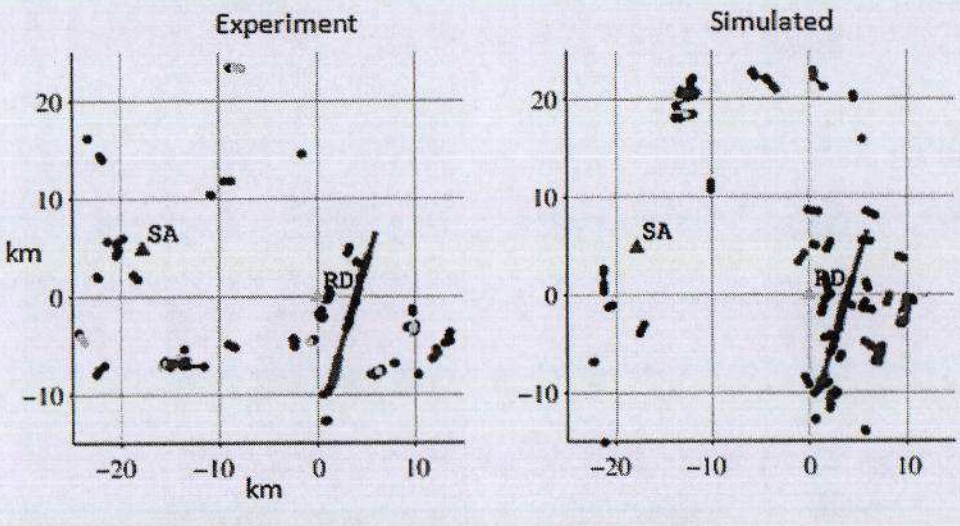

Figure 3 - Experimental and simulated track and classification output

3 THE TRANSITION TO DECISION SUPPORT

The final stage of MSTPA development is the transition from a model into a true operational decision support tool. The decision support process for a typical operational mission must begin with an automated ingestion of real time environmental data. Data mining techniques will be developed to extract information using rule based fuzzy logic systems. This approach has been used at NURC to determine whether an amphibious landing should be conducted according to such factors as currents, wave height and surf zone index using an expert system [14]. Once the relevant environmental information is extracted it will be passed to the MSTPA tool in order to generate the acoustic solution and thereafter some operational metric. In this sense the MSTPA tool becomes a central calculation engine within a greater chain of decision support processes. These will include optimisation techniques combined with decision and game theory to account for realistic target behaviour. The final stage of this process will be the eventual display of decisions to an operator. It is here that human factor concerns may be raised as to whether an operator requires his decision to be made, or rather, relevant information and options presented to him in such a way as to assist his decision.

3.1 Modelling an intelligent threat

Any operational metric relating to the ability of a network to detect, track and classify a threat submarine must carefully consider the behaviour of that threat. The MSTPA tool has been used to determine a number of performance metrics for a given sensor network operating against many straight running submarine threats as shown in Figure 5. However, this type of target behaviour represents a least intelligent, and perhaps least realistic, threat. There is then a scale of threat intelligence that a decision support tool must consider when presenting results to the operator. Work has been conducted using the A* path planning algorithm to model a worst case threat which has complete knowledge of both sensors and environment and can determine its own least cost path through the network [15]. Figure 4 shows three such paths through a multistatic network consisting of one source and three receivers in which the cost function may be either,1) number of detections, 2) number of (3 from 5) track initiations, or 3) a combination of both (⊗ represents a detection). It can be seen that the targets are able to minimise the cost function through course alterations affecting their bistatic target strength and hence probability of detection. Figure 6 shows undetected targets transiting through the multistatic network of Figure 5. The performance of the network is vastly reduced when attempting to counter an intelligent threat.

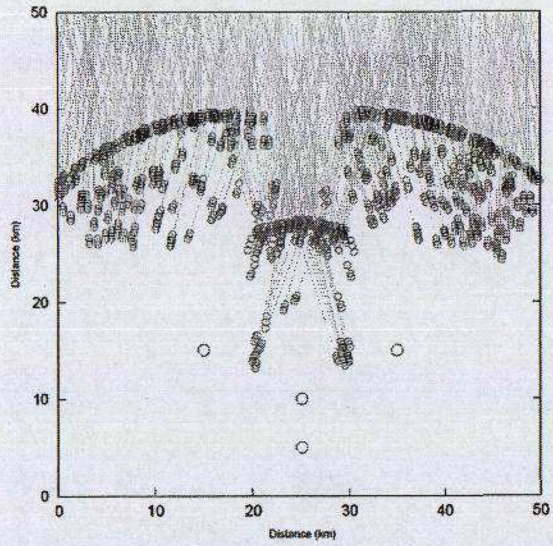

Figure 5 - Simple behaviour

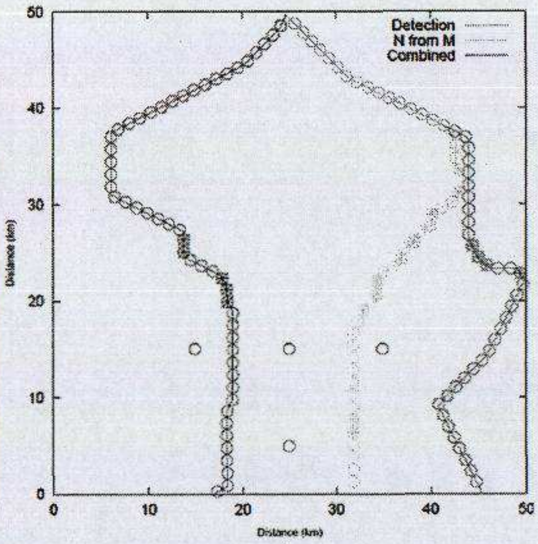

Figure 4 - A* Examples

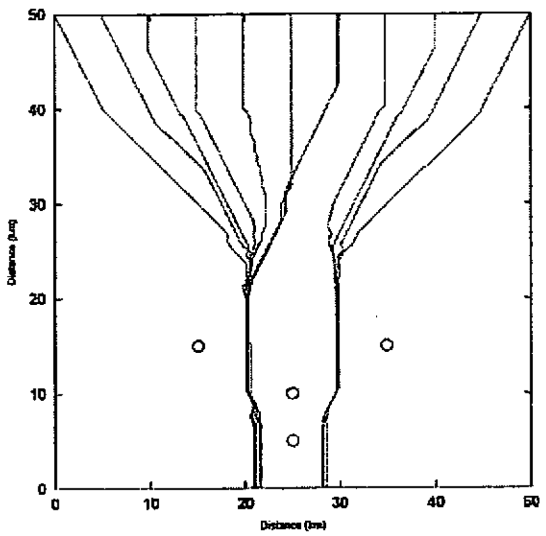

Figure 6 - Barrier penetration

The results shown above represent least intelligent (no network knowledge, straight trajectories) and most intelligent threats (full network knowledge and optimised trajectories) implemented within MSTPA. A realistic threat will probably lie somewhere between these two extremes of intelligence. Current work is focussing on additional intelligence routines that seek to model a target with incomplete knowledge of the network (assuming that receivers are covert for example). One approach is to develop a set of reactive logic instructions for a target that will determine its course of action, in terms of modified heading, depth, and speed, based on the counter detection of the source transmission and its knowledge of the environment. A second approach considers game theory in order to determine the target strategy that will maximise its utility by minimising the number of times it is detected. Game theory allows us to consider the ability of a threat to plan its strategy based on its knowledge of a how a planner will react (he knows that we know that he knows ...). A two player, zero sum game may be envisaged in which the planner seeks to maximise the number of detections while the target seeks to minimise. Such a game may be solved by various techniques (linear programming, mini-max equilibrium) to determine the best strategy (or mix of strategies) to be employed by the target and network planner.

3.2 Optimisation

A genetic algorithm (GA) has been implemented in MSTPA in order to generate optimum sensor positions for a static network, and waypoints for a mobile network, according to a number of performance metrics [128]. It is at this point that the need for a fast acoustic solution becomes apparent. The GA approach tries many thousands of potential network geometries as it fine tunes the solution. The cost metric for each 'try' may be a coverage map requiring many signal excess calculations. Figure 7 shows intermediate sensor positions generated by the genetic algorithm (labled 1-3) on its way toward the optimal solution (4). The performance metric in this case is the area of the scenario with a signal excess value greater than 0 (shaded blue). The scenario includes a monostatic sensor (Tx+Rx) with an additional multistatic receiver (Rx) which may be placed anywhere in the scenario area. The environment is characterised by an iso-velocity sound speed profile over the continental shelf bathymetry shown in the figure.

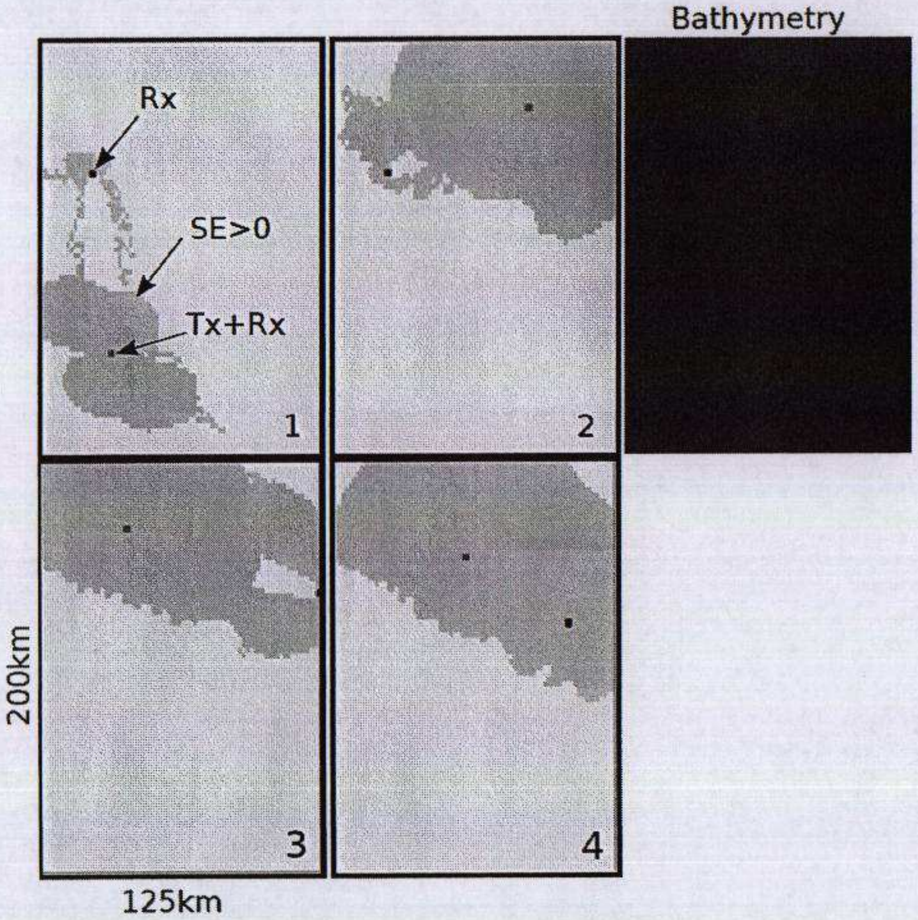

Figure 7 - Sequential output from the genetic optimisation routine

4 CONCLUSION

This paper serves as an introduction to the main elements of the MSTPA tool with which operational metrics may be determined from an initial value of signal to noise ratio. The need for a fast acoustic solution to allow for subsequent tracking, classification, and optimisation routines has been addressed using the mode theory approach developed by D Weston and expanded by C Harrison.

Current work seeks to transition the model towards becoming a decision support tool such that optimised sensor networks may be generated taking into account realistic threat behaviours and fully range dependent environments.

5 REFERENCES

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