Sensor Network Performance Modelling for Weapon Locating

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ABSTRACT

This paper describes the development of a tool that predicts the coverage and performance of sensor networks. Specifically it examines weapon locating radars and acoustic sensors in different terrain and weather conditions. The computer environment and multiple sensor models are presented. Fusion of sensors takes multiple predicted accuracy metrics from the single sensor performance models and combines them to show networked performance. Calculations include Cramer-Rao lower bound computation of the sensors and the fused sensors source location error. Results are presented showing the outputs of the models in the form of sensor accuracy maps superimposed onto terrain maps.

1.0 INTRODUCTION

Detection of and reaction to indirect fire events (artillery and rockets) is becoming a topic higher on the military agenda as force protection becomes a key factor in operations.

In general, two forms of weapon locating systems are used. Weapon locating radars have been in service for many years, they are large and vulnerable as the power and antenna size needs to be significant to detect small targets at long range. Acoustic sound ranging systems have been used for many years, current systems are composed of a network of microphone arrays spread over a large base line, to achieve accuracy and coverage. However, more recently concepts of unattended acoustic sensors have been proposed, reducing cost, vulnerability and possibly increasing accuracy. The interaction of these sensors with the environment and the targets of interest are complex, and deploying such assets for near optimum performance is a very difficult task.

The UK currently hold the MAMBA weapon locating radar and the ASP acoustic weapon location systems. In addition a number of COBRA radars are currently being procured. Furthermore the ADDER requirement is currently being formulated to acquire a weapon locating capability for rapid effect forces. It is likely that no single sensor system will meet the ADDER requirement and therefore a network of sensors may need to be considered.

This paper describes models that predict coverage and performance of weapon locating sensors that are being assessed by QinetiQ. Additional publications on this subject are given in reference [1] and [2].

The aim for this research is to aid the user to assess their current assets, evaluate possible improvements and determine the merits of networking for Network Centric Warfare (NCW) or Network Enabled Capability (NEC) in the UK. In addition the tool facilitates research of concepts into the future sensors and topologies, to enable low cost solutions by optimising performance and netted sensor distribution and densities.

Paper presented at the RTO SET Symposium on "Capabilities of Acoustics in Air-Ground and Maritime Reconnaissance, Target Classification and Identification", held in Lerici, Italy, 26-28 April 2004, and published in RTO-MP-SET-079.

This computer-modelling tool has a final aim for rapid assessment of performance to aid field based deployment, which requires simplified models for fast computation.

The radar sensor assessment models the transmitter and receiver, target characteristics, radar management properties, radar detection and source prediction algorithms. Acoustic sensor assessment is divided into models for the source, propagation, sensor and assessment of the source-locating algorithms. The propagation model predicts both the sound pressure level and propagation delay, so that directional accuracy of processing algorithm can be fully assessed.

Due to the deployment objective and that the sensor performances are linked to the surrounding terrain, the tool's development environment is graphical on a map background. This is expanded in the sensor performance model sections (3 and 4). The next section describes the tool's environment in greater detail and its fundamentals of operation.

2.0 ENVIRONMENT AND CONCEPTS OF OPERATION

The deployment tool allows the user to lay objects onto a map, with objects being:

- sensors or sensor systems;
- Artillery systems OR areas in which artillery systems may be operating (*gun areas*);
- *point targets* OR areas in which artillery systems may be firing into (*target areas*).

These terms are used in the results Section 6.

This allows focused and informed sensor system performance to be evaluated. This is contrary to the location of artillery systems anywhere, firing on anywhere which requires too many elements for calculation or that are useful once results are integrated and averaged for presentation.

When placing a radar sensor it can be configured by loading previously saved parameter sets, or up to 40 operational parameters can be defined. Parameters include basic radar performance parameters such as mean power and antenna gain, or specific parameters that describe the radar resource management, and signal and data processing techniques. This allows the definition of any in-service weapon locating radar system to be modelled by the deployment tool.

When placing an acoustic sensor system, it is assumed to be a linear network of 12 triangular arrays each with three microphones in a fixed configuration. This configuration can be edited to change the number and relative position of microphones and arrays. Microphone sensitivity is definable whilst other acoustic system parameters are defined when a location performance simulation is executed.

The meteorological factors can be globally defined, in which wind speed, wind direction and wet or dry conditions can be specified.

Sensors in the environment may be enabled or disabled. When multiple sensors are enabled the displayed location results are from fused data. Fusion methods are discussed in section 5.

The artillery systems are modelled using databases that are loaded in once a system is placed onto the map. The data base contains: firing tables used for selection of charge weights and projectile types; acoustic specific data, for example the Sound Pressure Levels (SPL); Radar specific data, for example RCS; and trajectory specific data for example the drag.

The result values calculated using the models are presented in the *gun areas* or *target area* as colour patches, scaled so that results can be graphically assessed, in addition exact values can be interrogated using the mouse pointer. Sensor model simulations and fusion give multiple results, including accuracy, parameters expressing the shape of the accuracy distribution and different sensor combinatorial results. These results can be individually displayed so that sensor, algorithm and fusion performance can be assessed, in addition the shape parameters allows assessment of resolution in the case of multiple weapon firings.

The following sections detail the methods for simulating the radar and acoustic sensor performance, the method used for fusion of performance results from multiple sensor data is then discussed.

3.0 RADAR PERFORMANCE ASSESSMENT MODEL

Weapon locating radars are usually large phased arrays, which is driven by the low observability of their targets, high accuracy requirement and the agility required to intercept and track their targets.

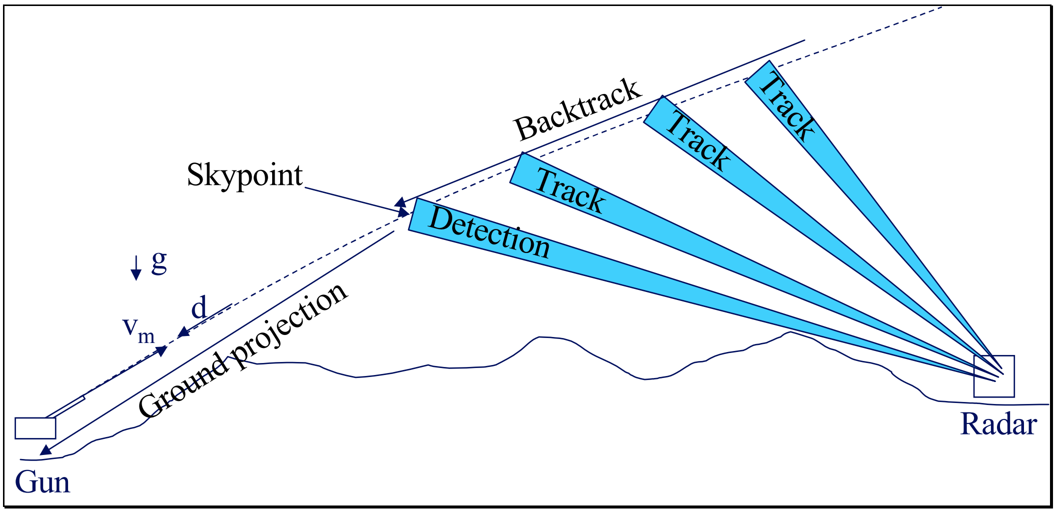

Figure 1 The radar process of locating and artillery system ground position

Figure 1 illustrates a typical sequence carried out by a weapon locating radar for location of an artillery shell. The process involves detection, tracking and backtracking, or model fitting to a ground intercept.

The factors that determine the location accuracy of an artillery system (on the ground) are:

- The location of first detection of the shell or rocket (the skypoint), a function of the radars surveillance strategy and the geography.
- The variance of radar measurements of the projectiles position, a function of the radar resolution and SNR of the measurement.
- The ability for a sequence of measurements to calculate the parameters of the projectile’s trajectory.

To simulate the first factor, the radar surveillance strategy needs to be emulated over the digital terrain database with height data information. The point at which the radar has line of sight is calculated for the given trajectory, scenario and set of radar beam scan position, determined by the search strategy. The skypoint is predicted based on the average scan time and the probability of detection. To obtain a sequence of measurements the projectile tracking is modelled which is dependent on the radar management function, probability of detection and field of view.

The measurement accuracy is then evaluated and location performance is assessed which is explained in further detail in the following subsections. The techniques and algorithms introduced in this section give the ability to define many levels of complexity for computation of the location accuracy, especially in definition of mixtures of techniques and models.

3.1. Radar measurement models

The radar measurement accuracy of each measurement point is based upon the radar resolution, predicted SNR and processing performed by the radar.

Three processing techniques are considered for weapon locating radar performance measurement accuracy improvement

- No processing, where the standard deviation is typically half the resolution
- Centroid processing, This typically entails polynomial curve fitting over returns in neighbouring resolution cells. The standard deviation can be improved by up to factor 3 over the No processing case, depending on the SNR.
- Monopulse processing. In phased arrays this typically entails processing of two formed beams with different phase centres, the angular accuracy is improved by phase comparison. The Standard deviation can be improved by a factor 10 over the No processing case, depending on the SNR[3].

These models cover most variants of the processing algorithms available for weapon locating radar, incorporating a degree of generalisation to limit the number of parameters required to define a radar system in the deployment tool.

These accuracy measures typically require transformation into Cartesian covariance estimate for use by the trajectory models[4][5].

3.3. Trajectory fitting performance modelling

The simplest model for an artillery shell's trajectory is the vacuum drag model, this model considers a constant velocity vector throughout the trajectory in addition to an opposing gravity vector that opposes the constant velocity. The Cartesian projectile position is given by:

$$\underline{p} = \underline{p_1} + \underline{v}t + \underline{G}t^2 \qquad (1)$$

where p_1 is the skypoint vector position
v = the constant velocity vector
t = the time elapsed from the time vector
G= the gravity acceleration vector, ie [0,0,-g/2]
g = the gravity acceleration coefficient.

Using maximum likelihood theory the skypoint's Cartesian position and vector velocity accuracy can be calculated from the series of measurements biased by their covariance estimates to a greater degree of accuracy than the skypoint measurement. Furthermore the ground location position can be calculated by predicting the point on the ground surface by backtracking the skypoint vector using the same trajectory model.

In addition, maximum likelihood can also be used to estimate the covariance matrix for the skypoint vector and then the location position (if the location positions height does not vary significantly within the accuracy ellipse) using:

$$S_x = \left(\sum_{n=1}^{N} m_x{}^T S_{y_n}{}^{-1} m_x \right)^{-1} \tag{2}$$

Where S_y is the covariance matrix of the initial measurements/parameters
y_n is the vector of measurement parameters, e.g. [x,y,z] position
m_x is the matrix of gradients of the transformation function (the Jacobian matrix) as is used in the maximum likelihood process (in determination of the maxima)
x is the vector of transformed parameters e.g. $[x_1, y_1, z_1, \dot{x}_1, \dot{y}_1, \dot{z}_1]$
N is the number of measurements being fused (e.g. measurements in time)

More sophisticated trajectory models are required to fully represent the behaviour of artillery shell trajectories or to represent rocket trajectories, these models have additional components that account for:

- Additional acceleration components due to drag, wind, coriolis force, centripetal forces, lift, magnus and cross magnus.
- transformations between inertial and non-inertial co-ordinate schemes
- non-linear function derivations for gravity[6] and drag[7][8]

Although these models inevitably result in iterative numeric solutions to calculate the location position from the measurements, equation (2) holds for computation of the covariance (using different Jacobian matrices for the different trajectory functions). However in [9], Hall presents equations for covariance that consider the effect of parameter variances separately to measurement variances, such that:

$$S_x = \left(\sum_{n=1}^{N} \left(\begin{array}{c} \left(m_x{}^T S_{y_n}^{-1} m_x \right)^{-1} \\ \left(m_x^T S_{y_n}^{-1} m_x + m_x^T S_{y_n}^{-1} m_z S_z m_z^T S_{y_n}^{-1} m_x \right) \\ \left(\left(m_x{}^T S_{y_n}^{-1} m_x \right)^{-1} \right)^T \end{array} \right) \right)^{-1} \tag{3}$$

where S_z is the assumed covariance matrix of the parameter vector z (containing estimates for drag, gravity etc.) and m_z is the Jacobian matrix with partial derivatives with respect to vector z.

The covariance matrix representing accuracy of the ground position is two-dimensional signifying a multivariate Gaussian probability density function. In the military environment, a single parameter is used to represent accuracy, the Circular Error Probability (CEP)

The CEP is defined here as: the circle radius about the true location that encompasses 50% of the probability density function. Although obtaining values of the CEP from the covariance matrix is not directly solvable an empirical formula has been derived by the authors, to reduce computation, given below:

$$CEP = E_1 \left(c_0 + c_1 \frac{E_2}{E_1} + c_2 \left(\frac{E_2}{E_1} \right)^2 + c_3 \left(\frac{E_2}{E_1} \right)^3 + c_4 \left(\frac{E_2}{E_1} \right)^4 \right) + \varepsilon \quad , \quad E_1 > E_2 \tag{4}$$

where $E_1$and E_2 are the largest and smallest eigen-vectors of the covariance matrix, the parameters c_0 to c_4 are [0.675, -0.13488, 1.7079, -1.6043, 0.53343] and $\varepsilon < 0.01CEP$ when $E_1 < 10E_2$.

4.0 ACOUSTIC PERFORMANCE ASSESSMENT MODEL

For an artillery gun firing, acoustic sensors are cued by the firing event itself. Acoustic sensor systems require multiple sensors to obtain positions based on time delay and angle of arrival, and to give adequate accuracy.

The location accuracy performance of an acoustic sensor system is determined by the signal-to-noise ratio, the acoustic signature, relative positions of sensors in the network, the effects of propagation between the gun and the sensor and the algorithm used to fuse the data from multiple sensors.

Although QinetiQ have demonstrated acoustic location of rockets the accuracy is not for consideration in this paper, therefore the acoustic sensors considered are optimised for impulse signals expected from artillery events.

The modelling process generates the gun signature and sound pressure level (SPL), the degradation of the signal due to propagation effects between the gun and each sensor, the detector characteristics and finally, the performance of the location algorithm. These processes are discussed individually below.

4.1. Source models

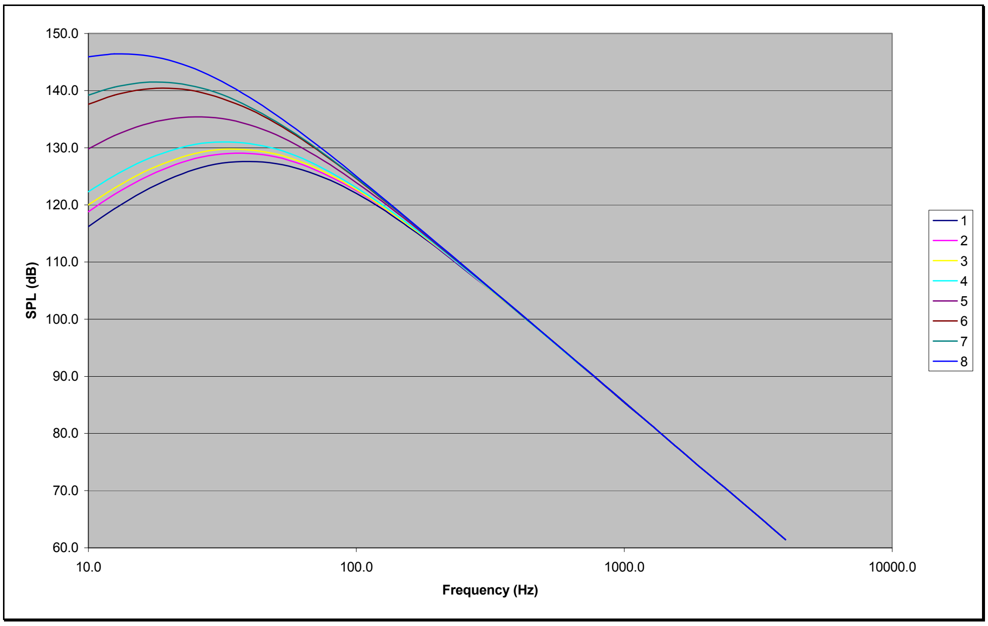

Figure 2 Example source frequency response using the Weber radius method for a gun firing eight different charge weights

The gun-firing event has previously been modelled as a spherical source with an SPL calculated from weapon characteristics and the charge used. This model has been further developed to include the one-third octave band spectrum of the blast, which is calculated from the Weber-radius[10]. The artillery database contains SPL values and one-third octave band spectra (10Hz to 4kHz) for each weapon system, charge weight and projectile type. Example SPL spectrums for different charge weights are given in Figure 2.

4.2. Propagation models

4.2.1 Introduction

Environmental conditions can limit the capabilities of acoustic sensors on the battlefield. Acoustic propagation is very dependent upon atmospheric conditions and terrain, which have a significant effect upon the path that the acoustic energy takes from the source to the receiver. This influences the level and coherence of the received signal and hence the performance of acoustic sensors.

The amplitude of the acoustic signal decreases with increasing distance from the source and the high frequencies are further attenuated due to atmospheric absorption. Meteorological conditions, such as wind, temperature gradients and turbulence, cause fluctuations in signal level due to refraction and scattering effects. Wind and turbulence also degrade the coherence of the wavefront, which may cause errors in direction finding arrays.

The wind direction has a significant effect on the received signal level and hence the detection range of a sensor. The signal level is enhanced when the sensor is located downwind of the source and reduced when it is upwind. From acoustic propagation trials[11] QinetiQ have observed the signal level at a receiver 112m from a constant source varying by up to 25dB as the wind direction changed.

Topographical features, such as hills, can cause non-line-of-sight shadow zones where the acoustic signal is reduced and detection by acoustic sensors is less likely. Diffraction occurs around objects, which has two effects: it attenuates the signal strength, and it alters the apparent angle of arrival of the sound. These two effects are much less significant at low frequencies. The type of ground and the ground cover also influence the level and frequency content of the received signal.

An acoustic sensor’s ability to detect an event or target of interest is dependent upon the signal-to-noise ratio (SNR) at the sensor, that is the difference between the signal level at the receiver and the local background noise. A high SNR will lead to a better probability of detection and higher quality classification and bearing accuracy.

The background noise can be due to many things such as nearby machinery, vehicles, streams or rustling leaves. However, wind noise is often the most significant source of background noise, particularly in rural areas. The noise level increases with wind speed as it is caused by the turbulence generated as the air moves around the microphone. Foam windshields are used to reduce wind noise with minimal degradation of the wanted signal; however, wind noise can still be significant at low frequencies and can cause false detections in blustery conditions.

These external factors have such a significant effect on the received signal that it is essential that they be accounted for when predicting the performance of acoustic sensors. An acoustic propagation model has been incorporated into the sensor network performance tool. The model accounts for the effects of meteorology and terrain and enables the prediction of the likely performance of acoustic sensors in a particular situation.

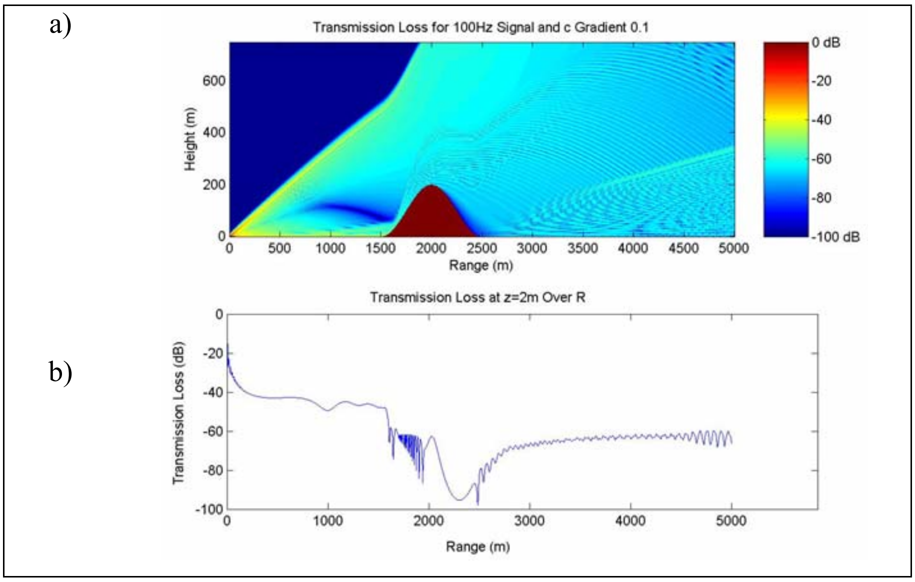

Figure 3 Attenuation of SPL when a hill is positioned between a source and sensor (a) height vs. range, (b) at 2 m above the ground level.

4.2.2 Implementation

Two comprehensive propagation-modelling tools have been developed that show how acoustic signatures propagate in different meteorological and terrain scenarios. The first is a hybrid Boundary Integral Equation/Fast Field Program (BIE/FFP) model, which has been validated for ranges of up to 1km [12]. The second uses Parabolic Equation (PE) techniques for SPL and channel filter characteristic calculations. Figure 3 shows the output of the PE model for a 100Hz signal propagating downwind over hilly terrain. These models are complex and computationally intensive, especially at high frequencies. These models provide reliable results, but are too slow for the network performance tool. They also require a comprehensive set of input parameters including ground impedance and vertical sound speed profiles. This data is not always readily available, so a number of simplifications and approximation are necessary.

A simplified acoustic propagation model has been developed that is able to provide rapid predictions. The propagation model predicts the SPL at the receiver in one-third octave bands from 10Hz to 4kHz. The model has a modular structure where each propagation effect is assumed to be independent and the attenuation due to each effect is calculated separately. The total attenuation in each frequency band is the sum of the attenuation due to each effect. The required source signature is obtained from the artillery database and the respective attenuation is applied to each one-third octave band. The Log SPL at the receiver is the sum of the Logs of the contributions from each frequency band. The propagation effects considered are:

- spherical divergence of the sound energy;
- air absorption;
- terrain (due to ground effect or barriers);
- diffraction;
- wind speed and direction;
- temperature gradients;
- turbulence.

The propagation effect of air absorption is modelled according to ISO 9613-1:1993 [13]. The ground effect is modelled using the Delay and Bazely ground impedance model [14]. Because of the numerical complexity of these models a number of scenarios have been pre-calculated to improve the deployment tool's execution speed. Seven types of ground are considered, including sand, grass and concrete, and several source and receiver geometries have been modelled for each ground type.

Terrain features, such as hills, are modelled as thin barriers of infinite width perpendicular to the direction of the propagation. The calculation of the insertion loss due to a barrier is based upon Maekawe's method [15], which uses the difference in the path length between the direct source to receiver path and the minimum path over the top of the barrier. This method has been extended to include multiple barriers, where the path difference between the source to receiver direct path and the minimum path over the top of all of the barriers is used to calculate the loss in each frequency band.

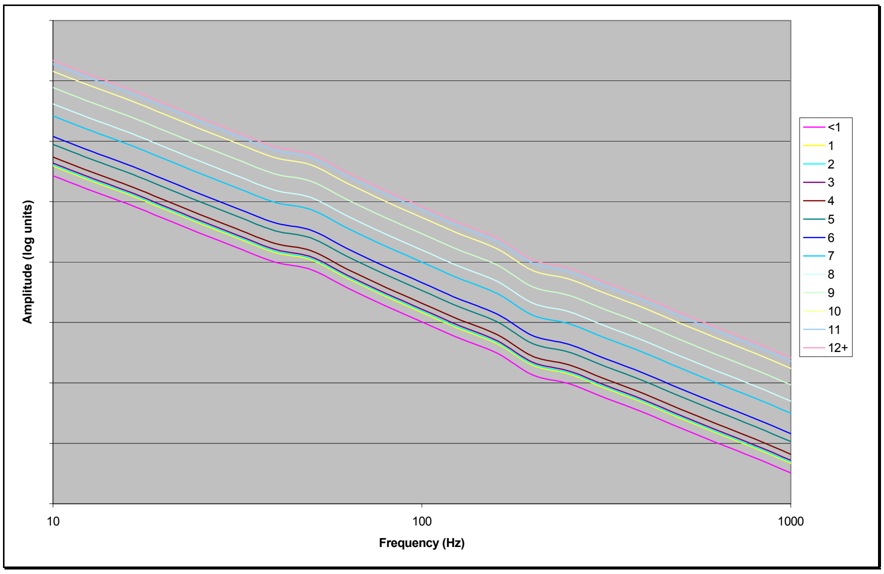

Figure 4 Background noise spectrum in a rural area for different wind speeds (legend gives wind speed in m/s)

Empirical models are used for the wind, temperature and turbulence effects. An example of wind noise spectrums are given in Figure 4, the data was obtained from a database of simultaneously recorded meteorological and acoustic data collected during a number of trails. Mean and standard deviation values of attenuation under various meteorological conditions have been calculated and these values form a look-up table that can be called upon as required. Experience has shown that the signal level at the receiver varies significantly over a short time period. Therefore, a mean and variance figure is tabulated to express the relative signal level at each sensor and indicate the expected variation in signal level over time.

The propagation model is also used to estimate the wavefront deformation, both in terms of the deviation from the expected time of arrival of the signal at each sensor and impact on the coherence of the signal. The effective speed of sound in a particular direction will be altered by the component of the wind vector in the direction of propagation. This has the effect of altering the propagation time of the signal to each sensor, which causes errors in time of arrival calculations across the network. Turbulence causes local fluctuations in the sound speed and the apparent direction of arrival of the acoustic signal. This introduces timing errors between the microphones in a network. The combination of these two effects is used to assess the bearing accuracy of a network of sensors due to the timing errors introduced.

4.3 Detection characteristic

The detector characteristic could be just a simple threshold, after which absolute time is recorded for calculation of time difference between microphones. Alternatively the maximum likelihood time difference is calculated by cross correlation of signal recordings between sensors, in which the peak correlation corresponds with time difference.

The time difference error is a function of the received acoustic signature, which is converted into signal to noise ratio. The noise is modelled as ambient noise appropriate to the local area and a wind noise component that increases with wind speed. The one-third octave band data for this model has been taken from numerous acoustic propagation trials.

Valid detections are declared in the model providing the SNR is greater than a threshold, which is definable in the deployment tool for applicability to different acoustic weapon locating systems.

The best fit to simulated data for the standard deviation of the error in the timing for the cross correlation performance is given by the author's empirical formula:

$$\sigma_{td} = \max\left[\frac{0.00273}{\left(f\,SNR\right)^{0.94} T^{0.25}}\ ,\ \frac{1}{2SR}\right] \tag{5}$$

where SR is the sample rate SNR is the peak signal to noise ratio T is the signal correlation length and f is the acoustic signatures maximum significant frequency (the highest frequency component in the signature with at least half the maximum power).

This maximum likelihood value is used for further analysis of algorithm accuracy.

4.4. Location algorithm models

There are three classes of algorithms used solely or together for calculation of location position. These three are discussed below.

4.4.1. Time difference of arrival (TDOA), spherical solution

This algorithm depends on sensors being distributed in a manner that records the spherical spread of the wavefront. Using a simple time reference discussed above, the gun position is calculated by solving the following equation:-

$$\tau_{ij} = \frac{\sqrt{(x_i - x_s)^2 + (y_i - y_s)^2}}{c} - \frac{\sqrt{(x_j - x_s)^2 + (y_j - y_s)^2}}{c} \tag{6}$$

where τ_{ij} is the TDOA between sensors i and j, (x_i, y_i) is the position of the i^{th} sensor post, c is the speed of sound and (x_s, y_s) is the position of the gun, numerical techniques are required to calculate the location, however equation (2) can be used to calculate the accuracy of the solution (x_s, y_s). Solutions to this equation include Taylor's Method for the general case, Fang's and Chang's methods as closed form solutions to the three sensor post case. Here the uncertainty in the sensor post positions, the measurement of the TDOA and the fluctuations in the speed of sound result in uncertainty of the solution (x_s, y_s). It is this uncertainty that is calculated using equation (2).

4.4.2. TDOA planar solution

A wavefront propagating from a point source will appear to be planar to a small array of acoustic sensors. With this assumption the propagating wave can be described from the following formula:

$$\tau_{ij} = \frac{\Delta x_{ij} \cos(\theta_s) + \Delta y_{ij} \sin(\theta_s)}{c} \tag{7}$$

where $\tau_{i,j}$ is the time difference between sensors *i* and *j* in a small array of sensors. Δx_{ij} and Δy_{ij} are the distances between sensors. As $\tau_{i,j}$ is measured and Δx_{ij} and Δy_{ij} are known, the equation can be inverted to reveal the bearing to the gun. In this case errors in sensor positions, TDOA measurement and errors in the speed of sound approximations are accounted for in equation (2) to predict the overall error on the gun bearing.

4.43. Triangulation algorithms

Triangulation algorithms can be used in tandem with the TDOA planar solutions. From the bearings calculated at two or more nodes, triangulation can be used to generate the Cartesian position of the gun. (x_s, y_s) are given by solving the following simultaneous equations:

$$y_s = x_s \tan(\theta_i) + (y_i - x_i \tan(\theta_i)) \quad , \quad y_s = x_s \tan(\theta_j) + (y_j - x_j \tan(\theta_j)) \tag{8}$$

where (x_i, y_i) is the position of the i^{th} node and θ_i is the bearing from the i^{th} node to the gun. Here the errors on the bearing and on the measured node positions result in a an error on the calculated gun position. The error on (x_s, y_s) is calculated, once again, using equation (2).

In the above three cases there are many sources of error that propagate through the solution to give an error on the calculated gun location. One such error is due to the uncertainty in the speed of sound. It is, however, possible to characterise the variation on the speed of sound from a simple wind flow model. In this way a variable that would once have been a random variable with unknown characteristics and hence accounted for in equation 3, becomes a measurable error and accounted for in equation (2). The speed of sound model derived from first principles is given by:

$$c(\theta) = u\cos(\alpha - \theta) + \sqrt{{c_0}^2 - u^2 \sin(\alpha - \theta)^2} \tag{9}$$

where c_0 is the speed of sound and standard temperature and pressure in a windless environment, θ is the bearing to the gun from a particular position, α is the wind direction, and *u* is the wind speed.

5.0 FUSION

The combination of the results from multiple sensors or sensor systems for this application can only be performed at the location stage as both acoustic and radar sensors use different cues for their operation.

For this tool, the biases and registration errors (with respect to the true map position) that are not accounted for in the sensor algorithms above are not modelled, any significant errors are symptoms of incorrectly configured systems. In addition, the deployment tool assumes that association of events is perfect, as the simulation defines the scenarios. Therefore, it can be assumed that the fusion of a number of declared locations come from probability density functions with the same mean. The distribution about the mean is given by their covariance matrixes, which can be combined by a simplified version of equation (2) such that the fused covariance is given by:

$$S_F = \left(\sum_{n=1}^{N} S_{p_n}{}^{-1} \right)^{-1} \tag{10}$$

where S_{p_n} is the covariance matrix of the location from the *n*th sensor

However in practice this 'full' fusion may not be possible when netting sensors because the covariance matrix may not available at the fusion centre. There are three levels of fusion are possible:

- 'full' fusion;
- averaging longitude and latitude locations from different sensors;
- using the results from the sensor with highest accuracy.

Naturally full fusion results in higher accuracy which raises a second important use of these models, that is by predicting location covariance matrices of the individual sensors, fused location accuracy can be improved, even if sensors do not relay anything other than the location to the fusion centre.

Results from the current stage of the deployment tool's development are presented in the next section, from which conclusions are drawn.

6.0 RESULTS

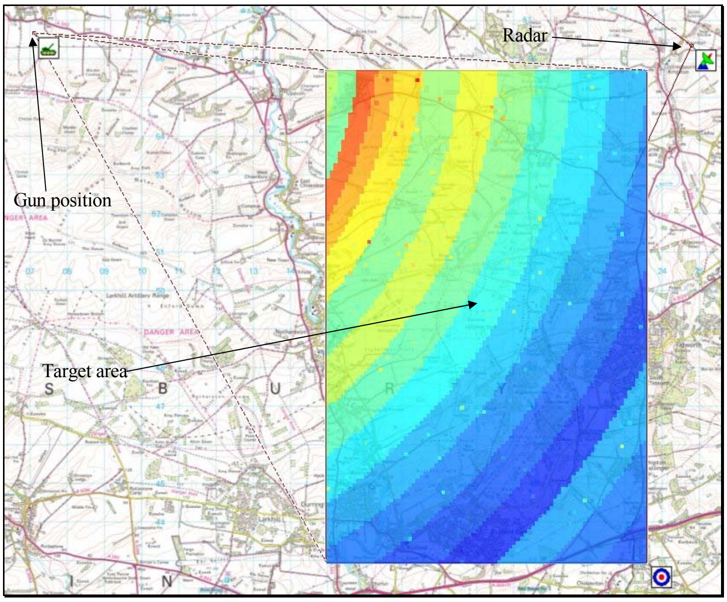

Figure 5 CEP mask calculated from weapon locating radar, where gun position is known position, firing towards a *target area*.

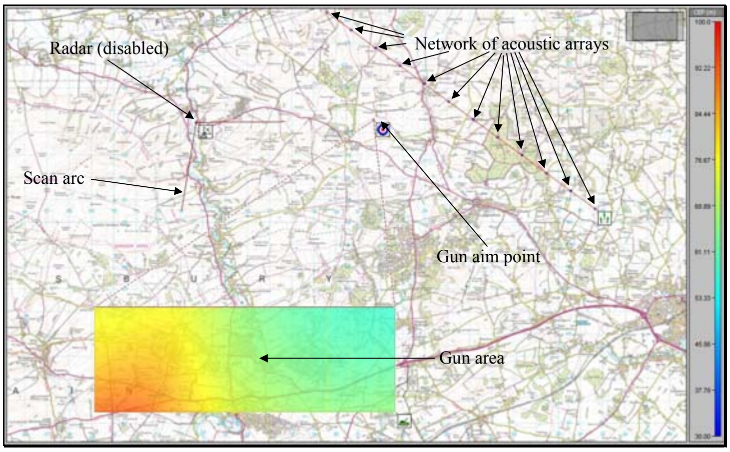

Figure 6 CEP mask calculated from a network of acoustic sensors, where a potential *gun area* is firing towards a *point target*.

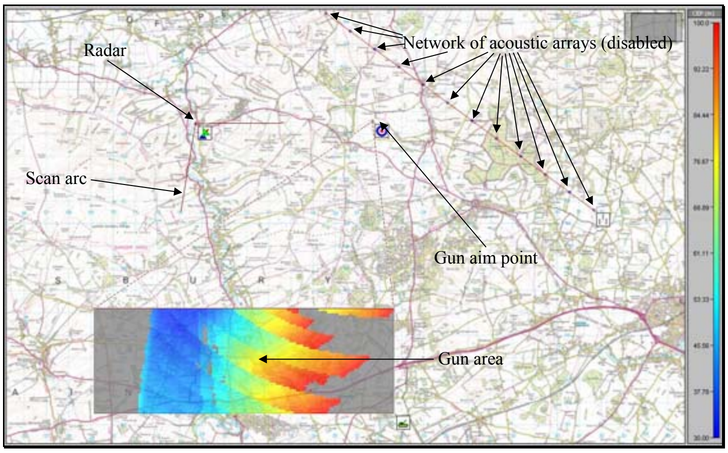

Figure 7 CEP mask calculated from weapon locating radar, where a *gun area* is highlighted as a square, firing towards a *point target*.

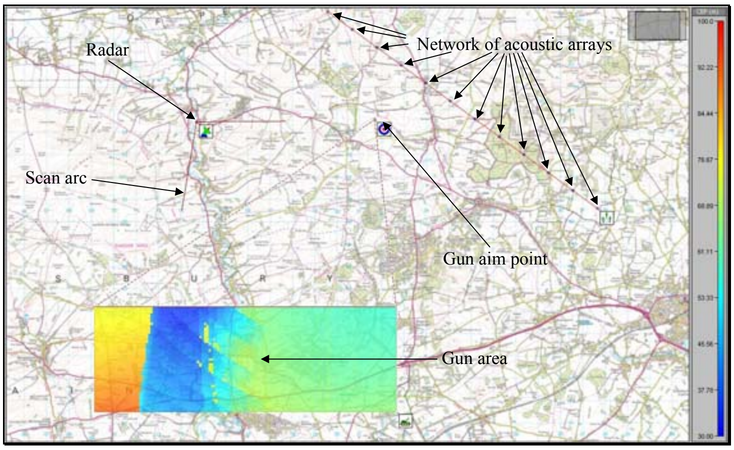

Figure 8 CEP mask calculated from the fusion of covariance matrices from a radar and an array of acoustic sensors.

The results given in Figure 5 to Figure 8 show the CEP values calculated from the covariance matrices for various scenarios detailed in the figure captions. The acoustic results use the simple propagation models and assume that planar TDOA techniques are used on each 3-microphone node, triangulation algorithms are then assumed to obtain a location. The radar performance results are based upon the vacuum drag trajectory model, with centroid processing assumed in range calculation, and monopulse processing implemented in calculation of the angular position of up to 20 tracked artillery shell positions. Figure 6, Figure 7 and Figure 8 show identical geometries, however different sensors are enabled to show the effect of fusion.

The result values are given as colour, scaled so that they can be graphically assessed. In Figure 5 the gun could be firing to any position in a *target area*. In the case where a *gun area* is calculated, the results are displayed over the map (Figure 6, Figure 7 and Figure 8). The colour mask properties are shown in the colour bar on the right of the screen, however a grey colour indicates that the value is out of the currently selected colour range.

7.0 CONCLUSIONS

The objective of producing a high accuracy model of radar and acoustic sensors for weapon location has been achieved. However the results that are given only represent the current development level of the tool which is currently limited to vacuum drag radar model. The tool is structured so that the sensor model can implement many sensor algorithms for performance comparison. The performance calculated is related to modelled systems algorithmic and measurement errors, however algorithms implemented give answers derived from the Jacobian matrix so tend to give the Cramer-Rao lower bound performance. Given this proviso, sensor algorithms and deployment configurations can be conceived, compared and validated. This is especially useful in the implementation of new concepts such as in the use of unattended ground sensors and multistatic sensors.

Also, an additional important use is apparent, in the improvement in location accuracy of fused sensor locations.

Although not shown in this paper, specific results have been verified by Monte-Carlo simulation of the selected scenarios, in which numeric solutions to the location positions are calculated.

Further development of this work to satisfy rapid assessment of the full array of future sensors and sensor systems is required. This involves integration of new algorithms and development of rule of thumb performance with representative performance when compared to the rigorous models presented in this paper.

ACKNOWLEDGEMENTS

This paper was produced under funding from MOD ARP 04.

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