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INVESTIGATING THE BENEFITS OF INFORMATION MANAGEMENT SYSTEMS FOR HAZARD MANAGEMENT

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Abstract: With increasing concern of hazardous materials being maliciously released to cause mass casualties and panic, there is a growing interest in the use of Information Management (IM) systems for incident support. These IM systems facilitate collaborative planning, aid decision support and provide an accurate and up-to-date picture of the evolving hazard. However, little has been done to investigate the benefits and effectiveness of these systems, particularly when used prior to an event or while the immediate hazard is still present; this work aims to address this. We have developed the Prototype Response and Information Management Engine (PRIME) which enables us to investigate the effectiveness and potential benefits of IM systems for incident support. PRIME integrates optimised sensor placement, sensor management, sensor data fusion, data assimilation, rapid hazard modelling, recommended mitigation, and links to scientific reachback. Using metrics and measures of effectiveness, combined with a chemical and biological (CB) synthetic environment to produce realistic simulated challenge data, we are evaluating the effectiveness of each component or combination of components. We present the results of the study to date, including what benefits CB information systems can provide over current procedures, and whether an increasing level of automation and sophistication can provide real benefits. The study has shown that computer optimisation of CB sensor placement and assimilation of CB sensor data can increase the utility of CB defence assets and improve situational awareness thereby aiding decision making.

Key words: *chemical, biological, CB, information management, hazard modelling, sensor placement, data assimilation*

INTRODUCTION

In hazard release incidents it is particularly important to have good situational awareness in order to make the most effective decisions and save lives. CB and other sensors can be deployed to measure the presence of toxic airborne contaminants; however it is necessary, and a significant challenge, to make best use of the information provided to determine how a hazard will evolve in order to warn people appropriately. This has particular relevance to military and homeland security applications. The aim of these IM systems is to provide the best possible picture of the evolving hazard and a range of decision aids to support commanders in choosing the most effective responses. Capabilities may include sensor data fusion, hazard prediction and effects models, and auxiliary tools such as sensor placement optimisation. These benefits need to be evaluated against the aim of the system, i.e. to minimise the number of casualties and level of damage and disruption caused.

In order to investigate the potential benefits, we have developed a prototype called PRIME. It integrates a range of decision aids and support capabilities within an information management system, including: automated sensor placement; a sensor management system, including sensor models; real-time sensor data fusion; rapid dispersion modelling; casualty and effects modelling; mitigation modelling; and information display. It has been designed so components can be reconfigured and different components can be switched in and out to facilitate investigation and evaluation. In this study we have focused on the benefits of automated sensor placement and also sensor data fusion.

EVALUATION APPROACH

Evaluation system

Two different methods have been used for producing the challenge: a simple modelling approach that allows large numbers of Monte Carlo sampled scenario variations to be carried out, and a more advanced computationally intensive approach that allows a more detailed analysis. Both are part of our evaluation system for conducting studies.

The high level approach uses rapid modelling of each scenario and providing results data that allows the calculation of evaluation metrics, in this study the number of casualties. The modelling uses simplified representations that capture the main aspects of the physics and processes involved, including Gaussian dispersion modelling for the transport and diffusion, response and effects, and the statistics of the results.

The highly detailed modelling uses an advanced synthetic environment (SE) that has been used to produce challenge data (Bull, 2009). The core component is a physics-based concentration fluctuation model that produces realistic time series correlated in space and time. The SE includes models for sensors, human effects and performance, and mitigation response. Figure 1 provides an example simulated concentration realisation field. By integrating these instantaneous concentration fields a challenge dosage can be calculated and then casualty estimates produced. Effective dosages can be calculated for each mitigation approach proposed, for example, and results compared with the base challenge dosage.

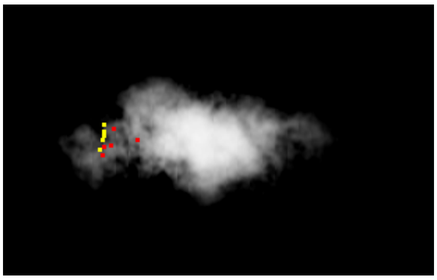

Figure 1. An example concentration realisation field with modelled sensor alarm status (red – alarming, yellow – not).

Scenarios

Two sets of scenarios were used: one for a military base in Afghanistan and the other for a city in the UK. Throughout the study, care was taken to ensure it was completely unclassified and no classified information was used. Populations were estimated from openly available imagery, meteorological data was obtained from unclassified sources or from created distributions, and sensor and agent properties were also taken from unclassified sources or plausible values were used.

The first set of scenarios focused on Bagram air force base, Afghanistan (Figure 2). A 5 km domain was used and permitted sensor locations were within the base perimeter. The timescales for threat were defined as:

1. Indefinite – there is no specific information on the threat so a uniform distribution is used (A). Annual climatology is used as the weather input.
2. Long term – there is a belief that the base may be targeted so the threat distribution is focused on this (B). The climatology data for the winter months was used for the meteorology.
3. Medium term – there is intelligence that the entrance to the base may be targeted in the following month, July (C). The climatology weather for July is used.
4. Short term – there are reports that insurgents may attack using mortars or from hand held devices from the north east and so a possible threat profile is produced (D). The 5 day weather forecast is used as the meteorological input.

Figure 2 shows the threat distributions used in the threat evaluation.

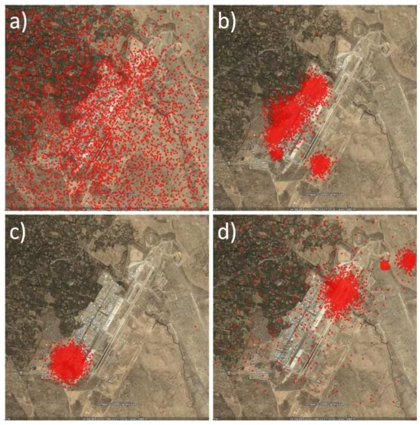

Figure 2. Bagram air force base with release locations (in red) giving threat distributions: A – uniform, B – Gaussians over key areas of the base, C – Gaussian centred on base entrance, and D – distributions representing release capacity of insurgents.

The second set of scenarios is based in Bristol, UK (Figure 3). It consists of a 5 km square domain that includes most of the central area of the city. Here the scenarios considered were based on protecting against combinations of threats and timescales, which affected the meteorological conditions. The challenge scenarios for Bristol were defined by:

- Four threat location distributions – one focused on an open space in front of the local government headquarters (A), another in a square in a commercial area (B), a third widely dispersed but centred on the city centre (C) and the fourth along the river route into the city (D).
- Five meteorological distributions represented by wind roses of the annual meteorology for Bristol, two climatology data sets for two separate months, a three day weather forecast and a totally uniform meteorological distribution.

This resulted in 20 different combinations, and for each of these both chemical and biological releases were considered. Figure 3 shows the threat distributions used in the challenge evaluation.

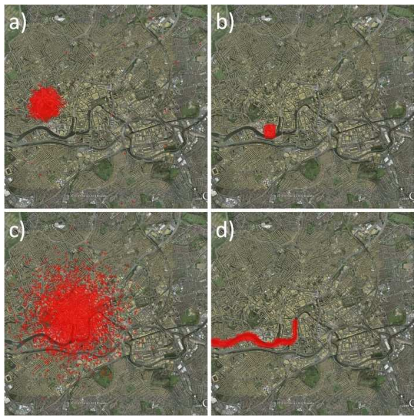

Figure 3. Bristol with release locations (in red) showing threat areas: A – College Green, B – Queen's Square, C – dispersed threat area, and D – River Avon.

Capabilities evaluated

The study has focused on the following two sets of capabilities:

- Automated sensor placement.

  Sensors for detecting toxic airborne materials are important assets that can be expensive and often limited in availability. CB sensors need to be positioned with care to provide the maximum information to allow timely identification of an accidental or intentional release of dangerous materials. The aim is to minimise the casualties and effects, and this should be the key goal of any placement strategy.

  There are two main approaches to sensor placement: (1) Rules-based sensor placement in which sensors are placed according to heuristic rules. This approach is particularly appealing to the military as it provides set of rules that can be followed consistently and which can be described by doctrine. (2) Computational optimisation, which involves running multiple dispersion simulations and then using an optimiser to determine the best placement. We have implemented a computer optimisation approach called SPARTA (Sensor Placement Algorithm for Rapid Theatre Assessment), which we have used in this evaluation study (Griffiths, 2010a). The main challenge to the sensor placement development is computation time. To be robust, the optimisation requires many simulations (in fact several thousand are typically required) because of the range of possible event scenarios and conditions and the need to ensure sufficient coverage of these using Monte Carlo sampling. Much of the development has focused on methods for handling the large numbers of simulations efficiently when optimising. SPARTA has been designed to reduce runtimes compared to other approaches without compromising the integrity of the optimisation. It can produce an optimised sensor placement within 10 minutes on a standard personal computer. Figure 4 shows an example output.

  For the evaluation, we implemented a number of rules-based methods that place sensors using prescribed rules. These include some commonly used rules and some more sophisticated ones developed based on the results of sample test cases carried out using the automated optimisation techniques. The rules we have considered are:

1. Place the sensors evenly around the perimeter of protection area.
2. Spread the sensors evenly throughout the protection area.
3. If the threat and protection areas do not overlap, place the sensors evenly around perimeter of the protection area; otherwise spread them evenly throughout protection area.
4. For chemical, if the threat area and protection area do not overlap, place evenly around the part of the protection area perimeter that faces the threat area; otherwise spread them throughout the overlap area. For biological, always place on perimeter of the protection area.

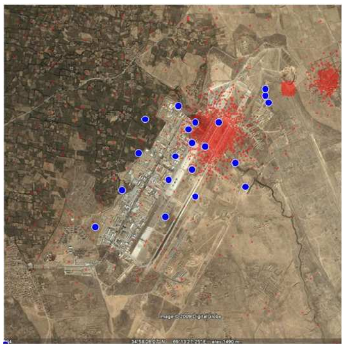

Figure 4. Example SPARTA optimised placement of 20 chemical sensors (blue) – short term deployment case.

- Sensor data fusion.
  In the absence of any other information, the current military approach is to interpret the observation point as being the source location. In fact this is very unlikely to be the case and hence the assumption will lead to error in the hazard prediction. An additional issue is the lack of local meteorological observations or up-to-date accurate weather prediction data necessary for hazard modelling. There has been a significant research to investigate whether computational techniques can be used to fuse sensor data and provide better hazard prediction. There are several approaches to the problem. These include fusing data to determine a source term that best matches the observations and data assimilation that uses observations to refine a modelled representation of hazard. The output of a source estimation algorithm can be used to make a hazard prediction using a standard dispersion model.

  We have developed a simple data assimilation approach that fuses real-time sensor observations to provide a CB hazard "now-cast" (Griffiths, 2010b). Our Nowcast approach represents the hazard as a collection of Gaussian puffs, which it optimally fits to current observations using the expectation-maximisation (E-M) algorithm (Dempster, 1977). Because it requires no dispersion or other complex modelling, it is extremely fast providing a nowcast hazard estimate in real time. Figure 5 shows input concentration data and resulting concentration fields based on the Nowcast puff fits. In this example run, a large number of sensors have been simulated, although in the actual evaluation cases we use much lower (typically 10), more operationally realistic numbers.

  An important benefit of the E-M approach adopted is that it produces a set of Gaussians that are compatible with many hazard dispersion models. Nowcast has been interfaced to a simple rapid Gaussian puff model, which uses its output to automatically produce a hazard prediction. An issue for operational hazard prediction is that available meteorology may be older forecast data or observations taken at a significant distance from the release, which results in inaccurate meteorological inputs for the hazard prediction model. The Nowcast algorithm developed does not require a meteorological input, and as it provides an estimate for the evolving hazard it is able to estimate the underlying local wind speed and direction, which can then be used by the dispersion model.

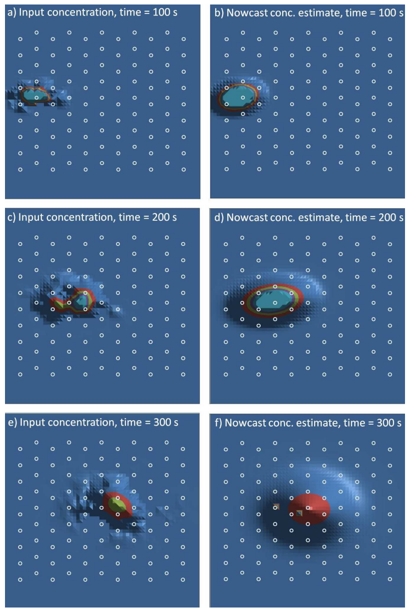

Figure 5. Comparisons of challenge concentration fields (input) shown on the left (a, c and e) and Nowcast concentration estimates (output) shown on the right (b, d and f) at times 100s (top – a and b), 200 s (middle – c and d) and 300 s (bottom – e and f) from true release time. Circles show sensor locations.

Evaluation metrics

The metrics calculated for the two parts of the study were:

- For sensor placement, the total casualty reduction for each of the approaches (Rules 1-4 and SPARTA computer optimisation). The casualties are calculated based on mitigation actions being taken based on sensor warnings.
- For sensor data fusion, the Measure of Effectiveness (MOE) approach, described by Warner (2004):

$$MOE = \left(\frac{A_{OV}}{A_{OB}}, \frac{A_{OV}}{A_{PR}} \right) \tag{1}$$

where AOB is the area of challenge dosage (i.e. observation) above a threshold, A_{PR} is the area of predicted dosage above the threshold and A_{OV} is the area where both dosages are above the threshold. We also consider the distance of MOE coordinate to (1, 1) – the perfect match – to facilitate comparisons between approaches.

RESULTS

Sensor placement

For the high-level analysis runs, 5,000 individual challenge scenarios were sampled for each of the 48 main test scenarios (4 for each of chemical and biological for Bagram, 20 for both agents for Bristol). SPARTA and the four rules-based placements were evaluated using these challenges. For each scenario the average reduction in casualties was calculated based on available mitigation in response to modelled sensor response for the placements. The results shown in Figure 6 and Table

1 reveal that SPARTA outperforms all the rules-based approaches in over 95% of the scenarios (in those cases where it does not the results are near identical) and provides overall best casualty reduction.

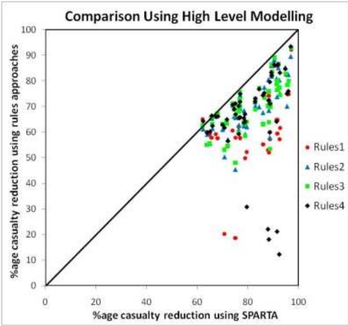

Figure 6: Results of the high-level analysis. Points in the area below the diagonal line indicate cases where SPARTA performed better.

Table 1: High-level analysis rankings and average percentage casualty reductions for SPARTA (SP) and Rules 1 to 4 (R1-R4).

Rank	SP	R1	R2	R3	R4
1	46	1	0	0	1
2	0	5	13	14	16
3	1	8	12	17	10
4	1	16	11	10	10
5	0	13	11	7	9
Average rank	1.1	3.4	3.5	3.2	3.1
Average casualty reduction	81.3%	65.0%	69.3% 69.5%	64.8%	

For the detailed evaluation, 160 challenges for Bagram (20 samples from each of the 8 scenarios) and 400 challenges for Bristol (10 samples from the 40 scenarios) were performed against each sensor placement produced by SPARTA and the four rules. The casualties for each were calculated with no defensive measures, and then where mitigation action was taken if a sensor alarmed, with results averaged for each. Figure 7 and Table 2 show SPARTA performs best, providing the best placement in nearly two-thirds of cases and substantially greater overall casualty reduction.

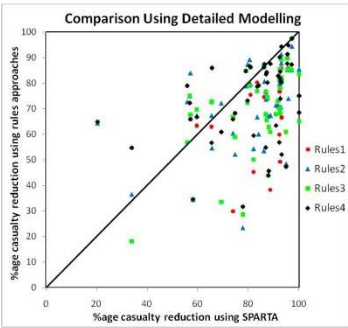

Figure 7: Results of the detailed analysis. Points in the area below the diagonal line indicate cases where SPARTA performed better.

Table 2: Detailed analysis rankings and average percentage casualty reductions for SPARTA (SP) and Rules 1 to 4 (R1-R4).

Rank	SP	R1	R2	R3	R4
1	31	0	4	3	10
2	3	5	12	10	18
3	4	10	9	16	9
4	4	19	9	12	4
5	6	14	14	7	7
Average rank	2.0	3.9	3.4	3.2	2.6
Average casualty reduction	86.7%	72.2%	76.2%	75.7%	76.5%

Sensor data fusion

For each of the 200 different challenge scenarios, the following runs were made for the comparison:

- A release from the true source location and time – the True Release approach.
- A release from the point of the first sensor to raise its alarm status – the current military Doctrine approach.
- The Nowcast assimilation method. As this provides updated estimates over time, a hazard dosage prediction was selected for a time between the first and last sensor observation.

In each case the models were provided with the actual meteorological conditions used in the challenge simulation.

The MOE results for each of these runs are shown in Figure 8. This shows all three approaches are clustered near to the (1, 1) perfect match. Considering the average distance from the ideal (1, 1) coordinate, we find that the distance is 0.196 for the True Release approach, 0.216 for the Doctrinal approach and 0.166 for the Nowcast method. In fact in 144 of the 200 cases Nowcast provides the best estimate in terms of closeness of match to the challenge. This suggests Nowcast is performing the best, even better than the True Release approach, which is somewhat surprising. It is likely that the Nowcast algorithm is refining the prediction based on the sensor data realisation so that it is able to outperform the True Release ensemble prediction modelling.

Of particular interest in this work was whether the Nowcast data assimilation approach could compensate for errors in meteorological input, which is a significant operational issue. The scenarios were rerun but this time with a random error of 10^o to 30^o introduced into the meteorological input. The results in Figure 9 show that the performance deteriorates substantially when we provide erroneous meteorological, however we see Nowcast is significantly better than the other methods.

The poor True Release and Doctrine results reflect the error in the input wind direction. The average distance to the (1, 1) ideal coordinate is 0.831 for True Release, 0.771 for Doctrine, and 0.278 for Nowcast, which is by far the best. In fact Nowcast provides the best estimate in 193 of the 200 cases in terms of closeness to matching the Challenge dosage. This demonstrates Nowcast is assimilating the sensor data and providing an improved meteorological estimate as this is used by the coupled dispersion model.

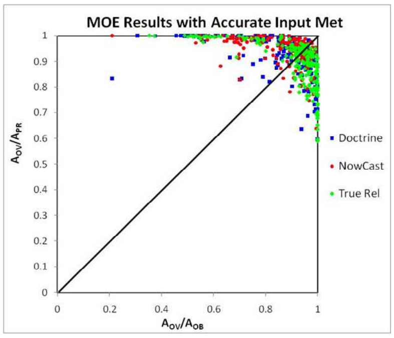

Figure 8: MOE results for Doctrine, Nowcast and True Release dosage predictions compared to Challenge Dosage, and with accurate input meteorology.

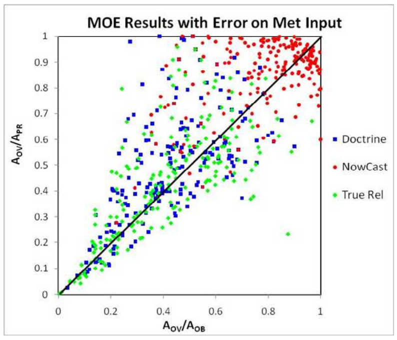

Figure 9: MOE results for Doctrine, Nowcast and True Release dosage predictions compared to Challenge Dosage, and with random error (10^o - 30^o) in the meteorological input.

CONCLUSIONS

The study has investigated two key aspects of CB hazard modelling:

- Sensor placement. The comparison of the SPARTA computer optimisation with four rules-based approaches using both high level and detailed modelling approaches shows that in both cases SPARTA performed the best overall. One perceived drawback of computer optimisation for operational sensor placement is computation time. However, SPARTA demonstrates it is possible to provide robust results rapidly, in less than 10 minutes. Although rules based approaches show some utility and have some benefits it is likely computer optimisation will outperform them on the key measure of performance – placing sensors to best protect people and assets.

- Sensor data fusion. Comparisons between a data assimilation method (Nowcast) and two other methods – the current standard doctrinal approach used by the military and using the true release location – have demonstrated that the Nowcast approach provides improved hazard predictions. Particularly in the situation where the meteorology is uncertain, Nowcast is seen to provide significant benefits; it is able to estimate the local meteorological conditions. In these more operationally realistic circumstances, it provides hazard estimates that are much closer to the true hazard, indicating that the Nowcast is capable of improving situational awareness.

The study has shown that computer-based decision aids and CB IM systems do have the potential to provide real benefits to decision makers. The investigation has shown that sensor placement can be optimised to provide better information to the IM system, and sensor data fusion techniques can provide improved situation awareness over current methods. Work is ongoing to evaluate the benefits of other components within the PRIME system.

REFERENCES

Bull, M.D. and I.H. Griffiths, 2009: A Flexible CB Evaluation System. Presented at *13th Annual George Mason University Conference on Atmospheric Transport and Dispersion Modelling*, 14-16 July 2009.

Dempster, A.P., N.M. Laird and D.B. Rubin, 1977: Maximum Likelihood from Incomplete Data via the EM Algorithm. *J. of Royal Statistical Society*, Series B (Methodological), **39** (1), 1–38.

Griffiths, I.H., M.D. Bull and I. Bush, 2010a: Evaluation of Sensor Placement Techniques. Presented at *90th AMS Annual Conference*, Atlanta, Georgia, 17-21 Jan 2010.

Griffiths, I.H., M.D. Bull and and L. Carrivick, 2010b: Real-Time Fusion of Sensor Data to Achieve Improved Situational Awareness. Presented at *90th AMS Annual Conference*, Atlanta, Georgia, 17-21 Jan 2010.

Warner, S., N. Platt and J.F. Heagy, 2004: User-Oriented Two-Dimensional Measure of Effectiveness for the Evaluation of Transport and Dispersion Models. *J. Appl. Meteor.*, **43**, 58-73.