A Review of Sensor Data Fusion for Explosives and Weapons Detection

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ABSTRACT

The combination or fusion of data from multiple complementary sensors can potentially improve system performance in many explosives and weapons detection applications. The motivations for fusion can include improved probability of detection; reduced false alarms; detection of an increased range of threats; higher throughput and better resilience to adversary countermeasures. This paper presents the conclusions of a study which surveyed a wide range of data fusion techniques and examples of the research, development and practical use of fusion in explosives detection. Different applications types such as aviation checkpoint, checked baggage and stand-off detection are compared and contrasted, and the degree to which sensors can be regarded as 'orthogonal' is explored. Whilst data fusion is frequently cited as an opportunity, there are fewer examples of its operational deployment. Blockers to the wider use of data fusion include the difficulty of predicting the performance gains that are likely to be achieved in practice, as well as a number of cost, commercial, integration, test and evaluation issues. The paper makes a number of recommendations for future research work.

Keywords: sensor fusion, data fusion, explosives, explosives detection, weapons, aviation, security, stand-off

1. INTRODUCTION

There is an extensive literature on sensor, data and information fusion across a wide range of application areas dating back some 40-50 years. This work is summarised in a number of textbooks[1-4] and references therein. There have, however, been few general studies and reviews of sensor data fusion applied to explosive and weapons detection in the open literature. In 1997, Currie and colleagues gave an overview of image and sensor fusion for concealed weapons detection[5] and in 2007 the US National Academy of Sciences published a review[6] entitled 'Fusion of Security System Data to Improve Airport Security'. Textbooks and reviews of explosives detection techniques and equipment[7-8] cover the topic briefly, if at all.

This paper is based on a study which reviews data fusion theory; identifies and describes commercially available products, implementations and research into applications of data fusion in explosives and weapons detection. Relevant work from other fields is also discussed. The gap between state-of-the-art and required technical capabilities is analysed and the future potential of the technology is estimated. The study concludes with some tentative ways forward and recommendations for further research.

2. MOTIVATION FOR SENSOR DATA FUSION

There are a number of reasons to consider data fusion in explosives detection in order to meet a number of different applications requirements:

1. **Improve detection performance** – it may be desirable to increase P_D and/or reduce P_{FA} of a system for one, or across a number of, specific threat classes.

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2. **Increase the number of threat classes detected** – the use of different sensor types may increase the number of threat classes detected by a system. Examples include the use of x-ray diffraction in addition to x-ray CT to improve the detection of specific threat types; and, the use of metal detectors and millimetre-wave imagers to detect both (small) metallic and (larger) non-metallic threats.

3. **Improve non-functional aspects of the security process e.g. increase throughput, reduce intrusiveness, reduce cost** – for example, the use of a high throughput (or minimally intrusive, or low cost) front-end system with, say, high P_D and high P_{FA} as a pre-selector for slower, more intrusive or more costly technologies, which are only used for alarm resolution. Clearly, the case for this depends on the 'business case' in any particular situation, taking into account throughput, individual sensor performance and costs.

4. **Increase resilience to adversary countermeasures** – a fused or layered system is harder for an adversary to probe and be able to predict its performance and weaknesses. The so called 'Swiss cheese' analogy is an effective way to think about this. All systems have weaknesses or holes, but in a well designed layered system not only do the holes not line up, but also it is not possible to see where the holes in subsequent layers are until the earlier layers have been passed. In addition a fused system enables more complex variations to be introduced into a screening process to thwart a potential attacker by making it more unpredictable.

5. **Increase deterrence value** – since it is harder for an adversary to predict the performance and weaknesses, the actual and the perceived risk to them of being detected and failing in their mission is higher. This risk of failure is believed to be a key deterrent – both to individuals and their organizations.

6. **Increase ability to vary or tune the security process** – fusion may provide more control over a security system to tune it to detect specific threats; accommodate new threats; tune for specific functional or non-functional performance requirements; introduce random changes for deterrence purposes; and so on.

3. APPROACHES TO DATA FUSION

The most widely used data fusion model is the Joint Directors of Laboratories (JDL) model[9]. This is a functional model which identifies fusion activities at a number of different levels (0-5). All the levels are used in complex, 'big-picture' fusion applications such as battle scene analysis which may involve the identification and tracking of multiple objects and reasoning about their nature and intent. Explosives detection is mainly concerned with level 1 of the model, where sensor outputs are combined to identify the threat state of individual objects.

Level 1 fusion can combine the data from sensors in three different ways:

- Data level fusion (pixel or image level fusion) – combines raw data from different sensors into a more meaningful representation of an object.

- Feature level fusion – identifies features of an object (such as edges) from individual sensors, which are then fused with features from other sensors.

- Decision level fusion (classifier combination) – detection decisions (and confidence) of sensors are fused to form a joint decision.

Receiver operating characteristic (ROC) curves which describe the trade-off between detection rate (P_D) and false alarm rate (P_{FA}) as system sensitivity is altered are an important way of characterising detection systems with a binary (threat/no threat) output.

The performance of multiple sensors in a fused system depends on the degree of independence of the sensors. If sensors measure different characteristics of a threat, or if they are sensitive to different threat classes, they are loosely said to be complementary or 'orthogonal'. Formally, sensors are orthogonal if they are conditionally independent. Depending on the distribution of threat characteristics/classes, fusing a small number of orthogonal sensors can give a significant increase in system performance. Fusion does not always lead to large gains, however, and sensors are not always as orthogonal as they appear at first sight. Correlations between sensors are important and can significantly reduce performance gains[10-11].

3.1 Decision fusion techniques

Decision fusion provides a way of combining the output from disparate sensors. There are a number of decision fusion approaches, using either probabilistic or heuristic methods.

The most common approaches used today in explosives detection are the heuristic methods based on AND- or OR-logic. AND-logic, widely used in aviation security search combs, only declares a threat if all sensors alarm – this reduces the detection rate, but decreases false alarms. OR-logic declares a threat if any of the sensors gives an alarm – this tends to increase detection probability at the cost of increased false alarms. AND/OR logic can be used when the only output from a sensor is its alarm/clear state. It gives operational performance advantages since it is not necessary to screen every object with all of the sensors.

When there are only two sensors and the outputs are binary, the AND/OR logic approaches are all that can be done. As the number of sensors increases, the number of ways the outputs can be combined increases rapidly and a large number of voting strategies become possible. These include simple majority voting and more complex sensor dominance strategies. Sensor dominance is an interesting strategy to adopt when sensors are very unequal in performance: if a particular (strong) sensor alarms, then a threat is declared; otherwise several (weaker) sensors have to agree before a threat is declared. Optimised approaches have been developed both for uncorrelated and correlated sensors[12-13].

When sensors give a quantitative output which can be taken as a measure of the confidence level in the sensor output or probability that a threat has been detected, then a range of parametric[6] or probability-based fusion approaches become possible[1].

Bayesian fusion takes Bayes' theorem[14] as a starting point. Bayesian fusion updates the probabilities of different hypotheses based on observational evidence and prior probabilities. It has the advantages that only the individual probabilities need to be calculated; the computation is relatively straightforward; and that probabilities can be chained such that evidence from new sensors can be simply be added. Its disadvantages are that: prior probabilities need to be known or estimated; sensors need to be conditionally independent or 'orthogonal'; and indeterminate sensor outputs can present a problem.

Bayesian Network Data Fusion uses a modified probability model using conditional probabilities to allow for the dependencies between sensors. It has been applied applied in recent years to a number of problem areas including mine detection[15], road traffic monitoring[16] and climate control in livestock production buildings[17].

Dempster-Shafer theory[18-20] extends the Bayesian approach so as to better handle uncertainty such as that given by indeterminate sensor outputs. Dempster-Shafer theory models the way humans assign measures of belief to combinations of hypotheses (called propositions) rather than individual hypotheses. Whereas Bayesian methods assign probabilities to individual hypotheses (and require a complete set of hypotheses so that the total probability adds up to one), Dempster-Shafer assigns evidence, called probability mass, both to individual and combinations of hypotheses. *A priori* knowledge can be incorporated by assigning initial probability masses to propositions. When the propositions are all mutually exclusive, Dempster-Shafer becomes equivalent to the Bayesian approach.

In terms of fusion performance, studies have often found Dempster-Shafer to be somewhat more effective as a data fusion strategy, although generally the performance difference is not large. Furthermore, in cases where fusion is found to improve detection or decision performance, both techniques are effective. In cases where fusion fails, both techniques tend to fail[21-23].

Classifier combination is another approach to decision level fusion for the case of binary sensors, where the decision threshold of each sensor can be changed. These use linear or non-linear algorithms, to optimise some measure of the ROC curve of the combination[24-31].

3.2 Image fusion

Image fusion is a data-level fusion technique which provides a heuristic way of presenting complex information, e.g. from sensors operating at different wavelengths, to an operator[32-34]. It involves careful registration of images to correct for differences in alignment (translation and rotation), scale, perspective distortion and camera aberrations. The image combination or image fusion proper combines features of each registered image based on some measure of relevance or saliency. Techniques such as so called 'image pyramid' and wavelet transform methods are used to combine images which have different spatial resolution. The techniques are relatively mature, with both hardware and software image fusion products available[35]. Whilst mainly used for remote sensing, image fusion has been used to combine millimetre-wave and visible wavelength images to assist operator interpretation of the data in PBIED and concealed weapons detection systems[36-38].

3.3 Performance of fused systems

The gain or improvement in P_D and/or P_{FA} from sensor fusion is often difficult to estimate in practice. Whilst the performance of simple AND and OR combinations of independent (conditionally independent or 'orthogonal') sensors can be calculated by simply multiplying probabilities, in more complex situations and with more sophisticated fusion algorithms, the fusion gain is harder to calculate. This is mainly because sensors are not usually completely independent. Dependencies between sensors tend to reduce the benefit of sensor fusion as discussed above. Most of the work on the assessment of different fusion methods has been based on modelling (which is dependent on the assumptions made) or on test and evaluation programmes (which are often costly). The performance of different fusion approaches is also very dependent of the specific application, so it is not possible to make detailed predictions about the merits of specific fusion algorithms based on the results of testing in a different application.

Hall and Steinberg[39] identified a number of issues and limitations of data fusion. These were distilled into a list of so called 'dirty secrets' as follows:

- There is no substitute for a good sensor. No amount of data fusion can substitute for a single accurate sensor which measures the desired phenomenon. Whilst inferences can be made from sensors and combinations of sensors which measure various properties of an object, this will never be as robust and accurate as a sensor which measures the specific property of interest.

- Downstream processing cannot make up for errors in upstream processing. Data fusion cannot correct for calibration errors or failure to extract the correct signatures from a sensor, prior to input into the fusion process

- Sensor fusion can result in poor performance if incorrect information about individual sensors is used. For example, if sensor accuracy is not well characterized, then a fusion system will probably assign incorrect weighting to the results from individual sensors. Incorrectly designed, it is certainly possible for a fused system to perform worse than the best sensor in it.

- There is no such thing as a magic data fusion algorithm. There is no perfect algorithm that is optimal in all situations. As we have discussed, each algorithm has its own underlying assumptions and if these are not met then it will not be the optimal approach.

- There will never be enough training data. Characterising a multivariate distribution in order to train or derive the parameters of a fusion algorithm requires a large amount of training data. Problems need to be analysed and modelled in order to exploit simplifying assumptions such as the independence of sensors.

- It is difficult to quantify the value of a data fusion system. Whilst it may be possible to make predictions about the performance improvements in an idealized system or to carry out laboratory tests, it is difficult to identify and understand the effect of all the variables which affect performance when the system is put into an operational environment.

4. EXPLOSIVES DETECTION DATA FUSION IMPLEMENTATIONS, PRODUCTS AND RESEARCH

There are examples of operational implementations of sensor fusion and a number of commercially available products in applications such as aviation security, vehicle screening and mine detection, but overall, there are fewer than might be expected, given the technical challenges of detection systems and the potential gains that fusion could provide.

Aviation checked baggage screening[40] and search combs for checkpoint passenger screening is one example of operationally implemented sensor fusion. The fusion algorithms used are simple: generally comprising a high detection probability sensor (x-ray or archway metal detector) with a relatively high false alarm rate followed by a series of AND logic steps to resolve alarms, but all the essential features of a data-fused system are present.

Likewise, there are relatively few commercial products which incorporate significant degrees of sensor fusion. Those that exist fall into three main categories:

- Fused systems for checked baggage screening, aimed at reducing false alarm rates and increasing detection probabilities on specific threat types. Several of the larger security system vendors have developed systems which fuse x-ray diffraction (XRD)[41-42] or nuclear quadrupole resonance (NQR)[43] with multi-view or x-ray computed tomography (CT) explosives detection systems.

- Systems for vehicle and container screening which combine high energy x-ray and Thermal Neutron Activation (TNA) techniques[44]. The x-ray is used to scan the whole vehicle or container to identify potential threat locations. These locations are then interrogated using TNA which can identify threat materials but which are too slow to use on the whole vehicle.

- Combined detection technologies such as X-ray, trace detection and others for automatic screening of bags at sporting events and venues[45].

- Enhancements to millimetre-wave imaging systems, combining visible and/or IR images to improve segmentation and automatic threat detection.

Safran's Morpho Division (formerly GE Security) has developed an open protocol called Detection Systems Fusion Protocol (DSFP)[46] for the interconnection of systems and fusion of detection data. DSFP implements a Bayesian approach and transmits detection probabilities for a defined set of threat classes from detection system to detection system in a chain. The interface between systems is designed to protect proprietary vendor information, issues with which have held back previous data fusion initiatives. DSFP was initially developed for checked-baggage screening.

Over the last 20 or so years, a number of programmes have developed mine detection equipment which combines different sensors, particularly metal detectors and ground-penetrating radar (GPR)[47-49]. Mine detection continues to be the subject of data fusion research in several university groups with a number of very sophisticated techniques being developed[50-56,10] as well as both theoretical work and experiments on the performance of fusion algorithms[10,11,57]. Deployed systems, however, tend to use much simpler fusion approaches.

Unexploded ordnance (UXO) detection is quite closely related to mine detection in terms of the techniques employed. The US Naval Research Laboratory has compared fusion techniques and developed a Dempster-Shafer based approach with some success[58-61].

The detection of buried IEDs has become very important in recent years. Again, many of the detection techniques from mine detection can be used, and much of the research work in laser spectroscopy for explosives detection is aimed at this problem.

4.1 Research projects

There are a number of ongoing research projects investigating fusion in concealed explosives and weapons detection. Projects break down into three main areas:

- Laser spectroscopy
- Imaging systems
- Architecture development, test and evaluation

A number of groups are working on the fusion of laser induced breakdown spectroscopy (LIBS) and Raman spectroscopy, especially for stand-off detection. LIBS is sensitive and provides information on elemental composition but not molecular structure. Raman spectroscopy has good specificity to molecular structure, but is less sensitive[62-69]. IR spectroscopy has also been included as an additional sensor type for fusion[70]. For point detection of explosives vapour traces, the XSense project is exploring the fusion of a range of MEMS sensors: Surface Enhanced Raman Spectroscopy (SERS); colorimetric; calorimetric and micro-cantilever sensors[71-72].

Fusion of millimetre-wave, IR and visible wavelength sensors for concealed weapons and explosives detection has been considered since the early days of millimetre-wave imaging[73] and continues with today's more sophisticated technologies[37,74-75].

A number of end-user agencies and research organisations have investigated sensor fusion concepts and architectures for security applications. TSA has explored a future checkpoint or 'tunnel of truth' concept combining a number of technologies for aviation checkpoint security. The US National Academy of Sciences report[6] on data fusion for aviation security describes simulations of AND/OR logic and parametric fusion based on the analogue output of the sensors. The EU FP7 XP-DITE project is developing approaches for the evaluation of the detection performance of combinations of detection systems for aviation security, including multi-sensor systems combining x-ray with trace vapour and trace particle detection[76].

The US Department of Homeland Security ran a programme to test and evaluate integrated-system architectures for stand-off explosives detection in applications such as large public events. The programme, called Standoff Technology Integration and Demonstration Program (STIDP), carried out a series of field trials of multi-sensor systems[77-78] .

The EU FP7 Integrated Mobile Security Kit (IMSK) project[79] developed a number of sensors and fusion techniques that could be used to protect venues from explosives and other attacks. The NATO STANDEX (Standoff Detection of Explosives) project for indoor screening at railway termini and other mass transport applications[80].

5. RELEVANT WORK IN OTHER FIELDS

Work in adjacent fields such as chemical sensing has applied similar fusion of complementary sensors and fusion techniques to those used in explosives detection[81-82]. Fusion is also important in a large number of different fields including military target tracking and recognition; IED detection; medical imaging and diagnostic testing; non destructive testing and industrial process control; computer security; and remote sensing[83-87]. Techniques developed in many of these fields may be relevant and applicable to explosives and weapons detection.

For example, relevant material from the medical area includes work on diagnostic decision-making and operator-interpreted sensors, and work on classifier and ROC curve combination. Another area of interest is the increasing use of multiple imaging technologies, or modalities, in medical diagnostics. Human operator interpretation of multiple medical imaging modalities is similar to the interpretation of images from different concealed weapons and explosives systems. Both security and medicine share a need for the development of techniques for automatic threat recognition.

6. SYSTEMS INTEGRATION

System integration has to be carried out in order to do data fusion and is one of its enabling technologies. The key aspect from a sensor fusion perspective is that an individual sensor can no longer be regarded as the complete system. This has several implications:

- sensors need interfaces and interface standards;
- sensors may need to accept pointing or other commands from external systems;
- sensors may no longer 'own' the system's user interface;
- sensor products for use in fused systems may have less overall functionality than stand-alone sensors, with marketing and commercial implications for the companies which make them;
- there are potential IP and commercial issues between manufacturers when information about the internal workings of a system needs to be exposed in order for it to fit into a fused system;
- test methods are needed both for individual sensors and fused systems.

These issues are likely to impede the development in the short term as end-users and equipment manufacturers need to adapt to a more system-oriented paradigm. Interface standards initiatives such as the NEMA Digital Imaging and Communication in Security (DICOS) standard[88], which parallels a similar standard (DICOM) in medical imaging should facilitate sensor fusion initiatives.

7. STATE OF THE ART SUMMARY

The state-of-the-art in sensor data fusion applied to explosives and weapons detection may be summarized as follows:

- Some well established applications, such as checked baggage screening in aviation security use a simple form of sensor fusion – mainly employing AND logic. These exploit the existence of a 'strong' sensor (i.e. one which can be operated at high P_D) as a first line sensor, with subsequent alarm resolution steps. They also take advantage of the strong situational control and accurate tracking of the bags being screened.

- There are some examples of automated fusion being developed to broaden the range of threat classes that can be detected. The operational deployment of these is, however, quite limited.

- There are only a small number of examples of the operational deployment of more advanced probabilistic fusion techniques in explosives and concealed weapons detection, e.g. GE's DSFP to combine x-ray CT and diffraction.

- The fused systems in aviation security generally still have human operators in the loop (at least for the secondary alarm resolution steps). There is little deployment of automated multi-sensor systems.

- Stand-off people screening is at a relatively early stage of development. Experiments and tests carried out in the STIDP programme and elsewhere have helped elicit requirements for ongoing work in developing architectures and infrastructure for an eventual sensor fusion system.

- Considerable work has been carried out in sensor fusion, particularly for decision-level fusion in mine detection. The conclusions of this work are that most fusion techniques can improve performance, but that none is consistently the best. Hand-held dual sensor mine detectors still rely heavily on the human operator to fuse the output of the two sensors.

- There has been little work in the counter-terrorism explosives and weapons detection research community comparable to that in mine detection on the evaluation of different data fusion approaches.

- Development in emerging technologies such as laser spectroscopy for explosives detection are (in some cases at least) embracing sensor fusion at an earlier stage of the development lifecycle.

- Millimetre-wave imaging uses additional technologies (such as IR and visible wavelength cameras) to supplement the relatively low intrinsic quality of the images that can be produced.

- There is little in the way of toolkits that can be used for sensor fusion in explosives detection. The GE DSFP approach may provide the basis of a tool which can be used more generally, but this needs to be evaluated.

- There has been little analysis or understanding built up as to what constitutes an orthogonal set of sensors for particular applications. The same applies to the quantitative benefit that can be expected from sensor fusion.

- There are also a number of 'blockers', for both the user and developer communities, which can hold back the deployment of sensor fusion. These include the costs of multiple sensors; commercial issues arising since solutions may require components from multiple vendors; IP issues arising from the need for vendors to expose information about their systems and algorithms; and, testing and certification issues of complex systems.

8. CONCLUSIONS AND RESEARCH NEEDS

Whilst progress has been made, there are a number of potential opportunities for the further use of sensor data fusion within established explosives detection applications such as aviation security, as well as in emerging areas such as stand-off detection and crowded place scenarios. We believe that this development would be facilitated by research into a number of data fusion topics, focused on explosives detection as an application. These areas include:

- **Predicting sensor fusion performance** – It is costly to build and test multiple sensor systems. As has been done in few areas, such as mine detection, research should be carried out into ways of modelling systems to predict their performance.

- **Determining the degree of orthogonality of sensors -** Many fusion approaches rely on an assumed orthogonality or conditional independence of sensors. Lack of orthogonality causes fusion algorithms to perform less well than predicted. Research should be carried out into methods of defining and establishing the correlations between sensors, with respect to a given set of threat classes, operational contexts, background and clutter, modes of threat concealment, etc.

- **Partitioning performance requirements -** This is the inverse problem to that of predicting fusion performance. Designers of systems need to know that, given an overall detection performance requirement (P_D, P_{FA}), how can these requirements be partitioned between the individual sensors that would be combined in a fused system?

- **Methods of testing and certifying sensor-fused systems -** A fused system can be viewed and tested as a single system. This does not, however, facilitate 'plug and play' systems strategies or the deployment of systems from different vendors. Methods for testing at the component level, perhaps against different criteria from those used in single system testing, are required.

- **Designing fusion algorithms with cost functions -** Techniques need to be developed for building cost functions into fusion algorithms, for example, identifying the cost/benefit in terms of detection performance, operating cost and throughput, of introducing a new sensor into a system.

- **Adaptive, cued and 'opportunistic' screening strategies -** Different persons/objects may be viewed as having different *a priori* threat probabilities. Techniques need to be developed and evaluated for adaptive screening strategies where the sensitivity/discrimination settings on systems are varied according to these threat probabilities.

- **Improved tracking algorithms** - Tracking is a key enabling technology for crowded places applications in order to associate the results of different sensor scans with the individual being screened. Improved multi-camera tracking algorithms are needed, capable of tracking tens or hundreds of people in- or outdoors and in a range of lighting conditions. Tracking systems have errors and uncertainties just like detection systems. Methods need to be developed to combine the effects of tracking and sensor errors.

- **Operator-interpreted systems -** Many fusion algorithms use a parametric output from each sensor, such as a numerical detection 'score'. In operator-interpreted systems, it is difficult to place consistent quantitative scores on these outputs. Work is needed in this area to identify ways that operator-interpreted data can best be incorporated into data fusion schemes.

- **Cross-fertilisation with different fields -** There are relatively few practical examples of data fusion in explosives detection and not many case studies. Work on data fusion in other fields such as medical diagnostics; machine learning; non destructive testing; should be studied further for applicability. There is also the potential for increased cross-fertilisation within the different explosives detection disciplines.

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