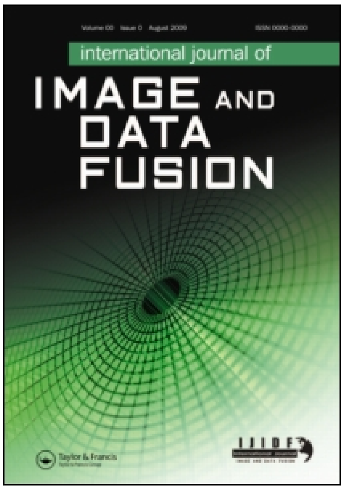

International Journal of Image and Data Fusion
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t911470591

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Online publication date: 18 May 2010

To cite this Article Milisavljević, Nada andBloch, Isabelle(2010) 'How can data fusion help humanitarian mine action?', International Journal of Image and Data Fusion, 1: 2, 177 — 191
To link to this Article: DOI: 10.1080/19479830903562066
URL: http://dx.doi.org/10.1080/19479830903562066

International Journal of Image and Data Fusion
Vol. 1, No. 2, June 2010, 177–191

How can data fusion help humanitarian mine action?

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(*Received 1 September 2009; final version received 14 November 2009*)

In this article, we present our views regarding multi-sensor data fusion potentials to help two types of humanitarian mine action: close-in detection and mined area reduction. Several approaches are discussed, reflecting our thoughts and experience in this extremely sensitive field of application. For close-in detection, our work on modelling and fusion of extracted features is based on two main methods, one related to the belief function theory and the other one to the possibility theory. The approaches are tested using real data coming from three complementary sensors (ground-penetrating radar, infrared sensor, and metal detector), collected within the Dutch HOM-2000 project. These results are obtained within two Belgian humanitarian demining projects, HUmanitarian DEMining (HUDEM) and Belgian Mine Action Technology (BEMAT). In the case of mined area reduction, our multi-sensor data fusion methods are based on the belief function theory and on the fuzzy logic and applied to real data of synthetic-aperture radar and multi-spectral sensors, gathered within the EU project on Space and Airborne Mined Area Reduction Tools (SMART). The importance of including various knowledge sources is discussed too.

Keywords: humanitarian mine action; close-in detection; mined area reduction; multi-sensor data fusion

1. Introduction

Within 10 years of becoming party to the Mine Ban Treaty, mine-affected states are legally required to clear all mined areas on their territory of antipersonnel (AP) mines. Although the first deadlines expire this year, more than 70 states, as well as six areas not internationally recognised, are still believed to be mine affected, according to the latest report of the Landmine Monitor (Landmine Monitor Report 2008). Taking into account other deadly threats (such as antitank mines with antihandling devices as well as cluster bombs) and increasing conflicts around the world, we must continue to seek solutions for detection and removal of these blind killers. In this article, we address this global problem and share our thoughts on how data fusion advances and our community can help humanitarian mine action.

Humanitarian mine action is based on the concept of a mine impact-free world (Acheroy and Milisavljević 2007). Two main humanitarian action types may benefit from data fusion techniques (Acheroy 2007): (1) close-in detection and removal and (2) area reduction. Close-in detection consists in detecting surface or sub-surface anomalies that

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ISSN 1947–9832 print/ISSN 1947–9824 online

DOI: 10.1080/19479830903562066
http://www.informaworld.com

could be related to the presence of mines (e.g. detection of temperature differences using an infrared (IR) camera) and/or detection of explosive materials. Area reduction consists in identifying the mine-free areas out of the mine-suspected areas.

Each of these two types of humanitarian mine action has its own detection difficulties. In the case of close-in detection, the challenge is in obtaining a mine detection rate as high as possible in order to minimise the risk of casualties, while keeping the false alarm rate as low as possible in order to speed up the demining process and make the land usable as soon as possible. In the case of area reduction, the challenge is in reducing the time and resources allocated.

For both the humanitarian mine action types, efficient modelling and fusion of extracted signal features may improve the reliability and quality of single-sensor-based processing. Nevertheless, due to a significant variety of scenarios and conditions that exist between different minefields (related to different types of mines, types of soil and minefield structure) and within a minefield itself (with specific moisture, depth and burial angles), a satisfactory performance of humanitarian mine action tools can only be obtained using multi-sensor and data fusion approaches. The interest of combining several images, for instance, has been highlighted in Maathuis and van Genderen (2004a, b). In addition, since most investigated sensors (such as metal detectors (MDs), ground-penetrating radars (GPRs) and IR cameras) are detectors of different anomalies, combinations of these complementary pieces of information can improve the detection and classification results. Finally, in order to take into account the inter- and intra-minefield variability, uncertainty, ambiguity and partial knowledge, fuzzy sets theory or belief functions within the framework of the evidence theory proved to be useful (Milisavljević and Bloch 2003).

In the following sections, we discuss these two humanitarian mine action types and present approaches which reflect our views of the problem and of a potential solution.

2. Close-in detection

2.1 *Starting remarks*

In case of close-in detection, most of the work done in the field of fusion of dissimilar mine detection sensors is based on statistical approaches (Yägerbro *et al.* 1998, Cremer *et al.* 2001, Yee 2001, Liao *et al.* 2007). Examples of alternative approaches are fuzzy fusion of classifiers (Auephanwiriyakul *et al.* 2002) and neural networks (Stanley *et al.* 2002, Perry and Guan 2004). Typically, statistical approaches lead to good results for a particular scenario, but they often ignore or just briefly mention that several important problems have to be faced in this domain of application (Milisavljević and Acheroy 1999, Gader 2003, Liao *et al.* 2007), once more general solutions are looked for. Namely, the data are highly variable depending on the context and conditions. Then, the data are not numerous enough to allow for a reliable statistical learning (Voles 1998). Furthermore, the data do not give precise information on the type of mine (ambiguity between several types) and it is not possible to model every object (neither mines nor objects that could be confused with them). In this domain of application, some fusion attempts treat every alarm as a mine, and not as an object that could be a mine, but a false alarm as well (den Breejen *et al.* 1999, Perrin 2001). Finally, the issue of statistical correlation among the outputs of demining sensors is not always taken into account in statistical approaches, and usually leads to a reduced performance (Baertlein *et al.* 2001). Further information about the state of the art in land mine detection technology and algorithms can be found in a recent paper (Robledo *et al.* 2009).

2.2 *Our approaches*

In Milisavljević and Bloch (2003, 2008), two main methods have been proposed, one based on belief function theory (Smets and Kennes 1994) and the other based on possibility theory (Dubois and Prade 2006), in order to take advantage of the flexibility in the choice of combination operators (Dubois *et al.* 1999) and to account for different characteristics of the sensors to be combined. In remote sensing applications, these fusion methods have been successfully used (Le Hégarat-Mascle *et al.* 1997, Chanussot *et al.* 2006). Still, to our knowledge, in the domain of AP mine detection, there is no attempt to apply the two fusion theories in parallel and/or to compare them. In other domains, there are some works that compare the two approaches, such as Dubois *et al.* (2001), where belief function theory is opposed to qualitative possibility theory and illustrated on a fictitious example of the assessment of the value of a candidate. Note that on the contrary to that paper, we apply quantitative possibility theory.

Figure 1 illustrates our global close-in detection strategy. From the data gathered by the sensors, a number of measures are extracted (Milisavljević and Bloch 2003, 2008) and modelled using the two approaches. These measures concern:

(1) The area and the shape (elongation and ellipse fitting) of the object observed using the IR sensor.
(2) The size of the metallic area in MD data.
(3) The propagation velocity (thus the type of material), the burial depth of the object observed using ground-penetrating radar, and the ratio between object size and its scattering function.

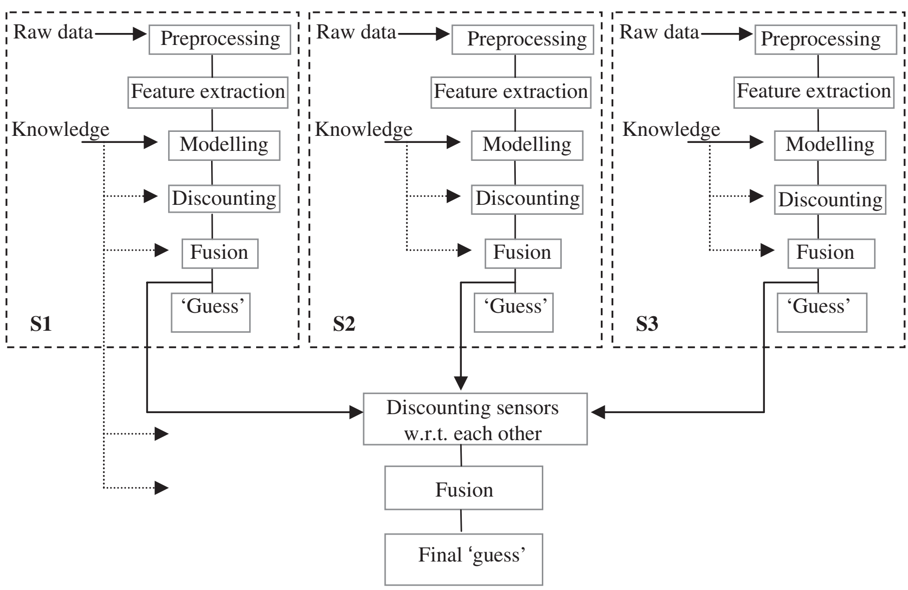

Figure 1. Global close-in detection approach.
Note: S1, S2, and S3 denote sensors.

Although the semantics are different, similar information can be modelled in both possibilistic and belief function models. The decision space contains two hypotheses: mines and friendly objects. Each sensor value is converted into a possibility distribution on this space. In the belief function model, the frame of discernment is the same as the decision space, but the reasoning and decision are actually performed on its power set. Having in mind the comparison between different models, the idea was to design the possibility and mass functions as similarly as possible and to concentrate on the comparison at the combination step. More about the modelling itself as well as about the measures can be found in Milisavljević and Bloch (2008). As a matter of fact, the main difference relies in the modelling of ambiguity. The semantics of possibility leads to model ambiguity between two hypotheses with the same degrees of possibilities for these two hypotheses. On the contrary, the reasoning on the power set of hypotheses in the belief function theory leads to assigning a mass to the union of these two hypotheses.

Another distinction concerns the ignorance that is explicitly modelled in the belief function theory through a mass on the whole set (to guarantee the normalisation of the mass function over the power set), while it is only expressed implicitly in the possibilistic model through the absence of normalisation constraint.

After modelling, the next fusion part is the combination of possibility degrees, as well as of masses, which is performed in two steps. The first one applies to all measures derived from one sensor. The second one combines results obtained in the first step for all three sensors. Details about this part are given in Milisavljević and Bloch (2008).

The final part of our approach is the decision. Since the final decision about the identity of the object should be left to the deminer not only because his life is in danger but also because of his experience, the fusion output is, actually, a suggested decision together with confidence degrees. In case of possibilities, the final decision is obtained by thresholding the fusion result for mines and providing the corresponding possibility degree as the confidence degree. In case of belief functions, as shown in Milisavljević and Bloch (2003), usual decision rules based on beliefs, plausibilities (Shafer 1976) and pignistic probabilities (Smets 1990) do not give useful results because there are no focal elements containing mines alone (Milisavljević and Bloch 2001). As a consequence, these usual decision rules would always favour friendly objects. The underlying reason is that the humanitarian demining sensors are anomaly detectors and not mine detectors. In such a sensitive application, no mistakes are allowed, so in case of any ambiguity, much more importance should be given to mines. Because of that, in Milisavljević and Bloch (2003), guesses are defined, where the guess value of a mine is the sum of masses of all the focal elements containing mines, regardless their shape and the guess of a friendly object is the sum of masses of all the focal elements containing nothing else but friendly objects of any shape. Thus, the guesses are a cautious way to estimate confidence degrees (roughly speaking, the plausibility is considered for mines, i.e. an upper bound of the confidence, while the belief is considered for friendly objects, i.e. a lower bound).

2.3 *Results*

Our approaches have been tested using real data coming from three complementary sensors (MD, GPR, and IR), gathered within the Dutch project HOM-2000 (de Jong *et al.* 1999). These results are obtained within two Belgian humanitarian demining projects, HUmanitarian DEMining (HUDEM) and Belgian Mine Action Technology (BEMAT).

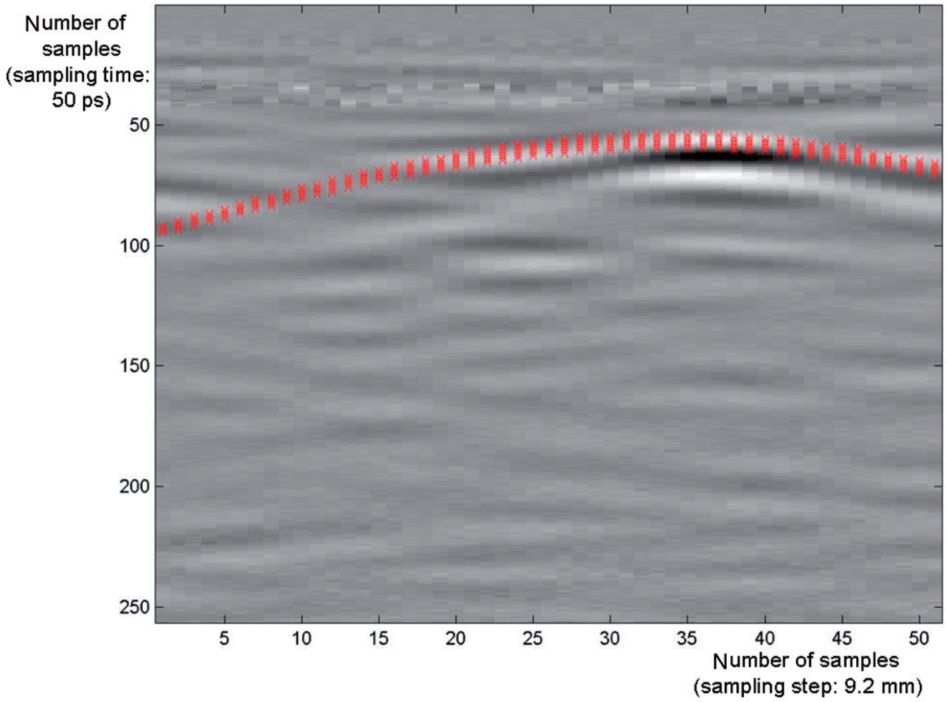

Figure 2. An example of GPR data (B-scan after background removal) together with the extracted hyperbola.

As an illustration, Figure 2 shows a preprocessed B-scan (two-dimensional image representing a vertical slice in the ground, along the scanning direction) of GPR data together with extracted hyperbolic signature of an object, with the hyperbolic shape being a consequence of a poor directivity of the transmitting and the receiving antennas of GPR. An example of IR data is given in Figure 3(a), while Figure 3(b) illustrates MD data, gathered over an X-like metallic shape. The raw MD image is blurred mainly because of a large footprint of the MD coil with respect to the size of metallic objects such as mines.

A set of known objects, buried in sand, has led to 36 alarmed regions in total: 21 mines (M), 7 placed false alarms (PF, friendly objects) and 8 false alarms caused by clutter (FN, with no object). Applying the two proposed approaches to this set of objects resulted in the following. The results of the possibilistic fusion are very promising, since all mines are classified correctly with the proposed approach, as shown in Table 1, where the number on the left side of // shows the result obtained by the belief function fusion, and the right side represents the result obtained by the possibilistic fusion. The number given in the parenthesis in each cell of this table indicates the number of regions selected in the preprocessing step for further analysis, i.e. feature extraction and classification. Regarding correct classification of mines, the results of the possibilistic fusion are slightly better (all mines classified correctly) than those obtained using the belief function method (19 mines detected well). This is due to the increased flexibility at the combination level. False alarms with no objects are correctly identified by the belief function method

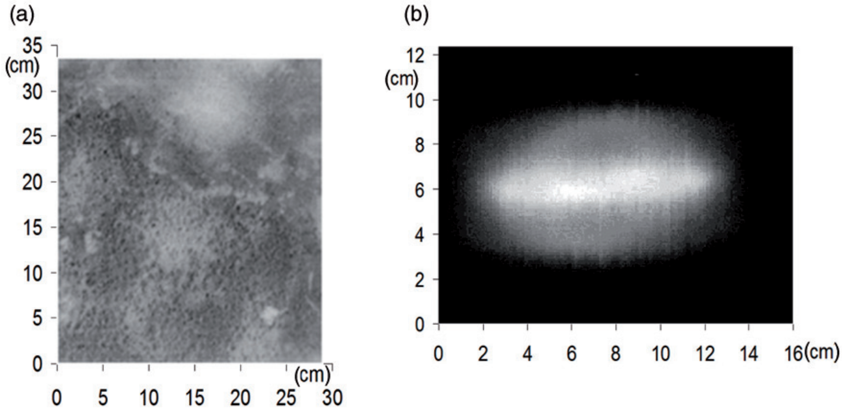

Figure 3. An example of raw IR data (a) and of raw MD data (b).

Table 1. Correct classification results, belief function fusion // possibilistic fusion.

	Sensors			
Classified correctly	IR	MD	GPR	Fusion
M (total: 21)	10 // 18 (18)	9 // 9 (9)	13 // 13 (13)	19 // 21 (21)
PF (total: 7)	3 // 0 (4)	0 // 0 (4)	1 // 2 (6)	2 // 1 (7)
FN (total: 8)	0 // 0 (1)	0 // 0 (0)	6 // 6 (7)	6 // 6 (8)

(six out of eight), and it is the same result as for the possibilistic approach. This result shows that a powerful feature of our methods is in decreasing the number of clutter-caused false alarms without decreasing the result of mine detection, thanks to knowledge inclusion.

Furthermore, analysis regarding the robustness of the choice of the operator has also been performed (within a class corresponding to the type of reasoning we want to achieve). Different operators within the same family have been tested, leading to the maximisation and minimisation of the possibility degrees of mines, thus being the safest and the least safe situations from the point of view of mine detection. The results obtained show that the model is indeed robust, all mines are detected in the second step, for all fusion schemes.

3. Remote sensing mined area reduction

3.1 *Starting remarks*

Thanks to the Mine Ban Treaty, mine clearing operations have been organised in a more controlled and effective way. Still, mine clearance remains a slow and a resource demanding process. It is estimated that, on average, a deminer clears 10 m^2 during a working day using conventional tools such as MDs and prodders. Therefore, humanitarian mine clearance operations must be understood and designed correctly, providing efficient aid to innocent people who may be severely injured by this dreadful pollution. Besides the very long time needed to clear polluted terrain, actual demining campaigns show that the false alarm rate is very large, the threat of plastic mines (which cannot be detected by MDs) is not negligible and the variety of mine clearance scenarios is high, depending on the country, the region, the climate, etc. These facts prove that the humanitarian mine detection is a very complex problem. In addition, the experience shows that it will be a long process to achieve a mine-free world, so the concept of a mine-free world is evolving softly toward the concept of a mine impact-free world, although a mine-free world remains the final goal of the Mine Ban Treaty. By this, the first priority of mine action becomes in allowing affected regions to reach their level of socio-economic standards. This new vision increases the importance of tools that facilitate prioritisation and contribute to a rational and efficient distribution of the available resources.

Several information management systems are developed and used. An example is IMSMA (Information Management System for Mine Action), thanks to the Geneva International Centre for Humanitarian Demining (GICHD) and in use in more than 40 affected countries. Other examples are systems completing IMSMA, such as the EOD IS system (Askelin 1999) developed by Swedish EOD and Demining Centre (SWEDEC) in Sweden and the Prototype for Assisting Rational Activities in Humanitarian Demining Using Images from Satellites (PARADIS) system (Delhay *et al.* 2005) developed by the Royal Military Academy (RMA) in Belgium. Possible entries of such management systems are danger and risk assessment maps provided by the Space and Airborne Mined Area Reduction Tools (SMART) project (SMART Consortium 2004, Acheroy 2005), funded by the European Commission/DG/INFSO. The maps, obtained using data fusion, synthesise the knowledge gathered from the existing data. In the framework of SMART, the fusion module, discussed in the following section, is a very important step, since it allows for taking the best from all available data, and of the large efforts made in the scientific community to design detectors and classifiers adapted to these data. It has proven to be a required step before constructing risk maps. This is an improvement in comparison to existing information management systems in this area. In particular, the proposed approach exploits all available data and knowledge and automatically adapts to the quality of the detectors and classifier outputs.

3.2 *Our approach*

The goal of the SMART project, applied to Croatia, is to provide the human analyst with the SMART system, i.e. a GIS-based system augmented with dedicated tools and methods designed to use multi-spectral and radar data in order to assist in his interpretation of the possibly mined scene during the area reduction process. The usefulness of such image processing tools to help photo-interpretation is, at first place, in the possibility to process automatically a large amount of data and help a visual analysis (Delhay *et al.* 2005). The use of SMART includes a field survey and an archive analysis in order to collect knowledge about the site, a satellite data collection, a flight campaign to record the data and the exploitation of the SMART tools by an operator to detect indicators of the presence or absence of mine-suspected areas. With the help of a data fusion module based on belief functions and fuzzy sets, the operator prepares thematic maps synthesising all the knowledge gathered with these indicators. These maps of indicators can be

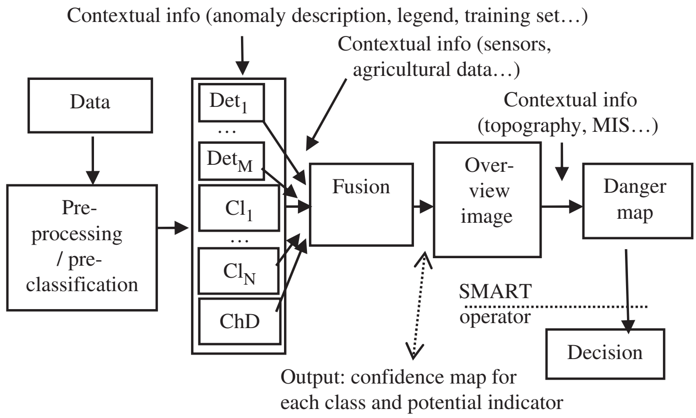

Figure 4. Global SMART approach.
Note: MIS, mine information system; ChD, change detection; Class, classifier; and Det, detector.

transformed into risk maps showing how dangerous an area may be according to the location of known indicators and into priority maps indicating which areas to clear first, based on socio-economic impacts and political priorities. These maps are designed to help the area reduction process.

The global SMART approach is illustrated in Figure 4. More precisely, based on field campaigns and discussions with mine action specialists of the Croatian Mine Action Centre (CROMAC), it was clear that the first task is to set up a list of features (indicators) that need to be looked for in the data, and that could be seen in the data and related to the absence or presence of mines or minefields. Indicators of mine absence are the most important in determining if an area is actually mine safe. These indicators are not numerous, and the key one is the presence of a cultivated field. Most available indicators are the ones that indicate mine presence. Thus, SMART has two applications: (1) area reduction, by detecting indicators of mine absence, and (2) suspicion reinforcement, by detecting indicators of mine presence (Yvinec 2005).

The next step consists in preprocessing, i.e. registering and geocoding the available data as well as restoring the SAR images. This step is followed by the development of methods and tools to detect the indicators based on two approaches: (1) anomaly detection (detecting specific objects in the data) and (2) classification. The final step fuses the information produced by anomaly detectors and classifiers and builds the so-called risk maps.

The fusion step consists of three parts (Bloch *et al.* 2007). First, a pixel-based fusion strategy is applied. Second step is the knowledge inclusion, while the final one is spatial regularisation.

For the first step, several fusion strategies have been developed, either based on the belief function theory or on a fuzzy approach. The results of the classifiers or detectors are used to define the functions to be combined, based on their confidence values and their reliability (including their tendency to potentially make confusions between different classes). The fusion operator is fixed to a conjunctive one in the case of belief functions, since all potential imprecisions are included at the modelling step, while operators with different behaviours can be adaptively designed in the case of fuzzy fusion.

Table 2. Comparison of the normalised sum of diagonal elements of the confusion matrices for two tested methods (i.e. correct classification ratio).

Method	Basic	Knowledge inclusion	Spatial regularisation
Belief functions	0.70	0.81	0.85
Fuzzy	0.79	0.83	0.84

As a matter of fact, knowledge inclusion (second step) is one of the main powers of our algorithms with respect to the commercial ones. This aspect has led to a lot of work in SMART at different levels. Note that knowledge on the classifiers, their behaviours, etc., is already included in the previous steps. At this step, we use only the pieces of knowledge that directly provide information on the land cover classification. Other pieces of knowledge such as mine reports, etc., are not directly related to classes of interest, but rather to the dangerous areas, and are thus included in the danger map construction, which follows the fusion. Several pieces of knowledge proved to be very useful at this step (Bloch *et al.* 2007) and we give here one example, 'sure' detections. Namely, some detectors are available for roads and rivers, which provide areas or lines that surely belong to these classes. There is almost no confusion, but some parts can be missing. Then, these detections can be imposed on the classification results.

The final step, spatial regularisation, is based on the reasoning that it is very unlikely that isolated pixels of one class can appear in another class. Several local filters were tested, performing similarly, such as majority filter, median filter or morphological filters, applied on the decision image. This step allows making spatially consistent decisions, and partially incorporates the spatial integration usually performed during the visual interpretation of the images. Thus, the decision is closer to the one a photo-interpreter would have made.

3.3 *Results*

Results have been obtained on three test sites in Croatia, being representative of southeastern Europe. Note that in order to apply the proposed methodology in another context, a new field campaign would be needed to derive and implement new general rules.

Regarding the fusion module, we have shown in Bloch *et al.* (2007) how the results can be improved by introducing additional knowledge in the fusion process. A spatial regularisation at a regional level further improved the results (Table 2). At the end, the results are at least as good as the ones provided for each class by the best classifier for that class, especially in the case of our fuzzy method (Table 3; note that the most interesting classes for danger map building are the four listed in this table), meaning that the 'best classifier' is not necessarily the same one for all classes. Therefore, the fusion results are globally better than any input classifier or detector. This shows the improvement brought by fusion.

As an illustration, Figure 5 contains the raw image of Glinska Poljana in a visible channel of Daedalus, while results of our fuzzy fusion approach, after knowledge inclusion and spatial regularisation, are shown in Figure 6 for one of the three test sites

Table 3. Correct classification ratios for two methods (after knowledge inclusion and spatial regularisation) and the best classifier for each important class.

Class	Best classifier	Belief function method	Fuzzy method
Abandoned agricultural land	0.84	0.81	0.89
Agricultural land in use	0.87	0.86	0.95
Asphalted roads	0.88	0.96	0.98
Water	0.96	0.97	0.99

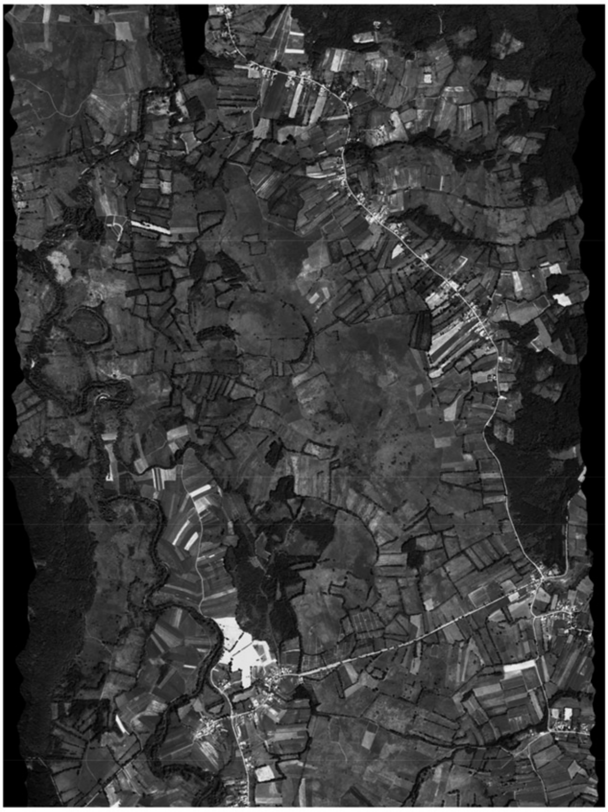

Figure 5. Visible Daedalus channel.

(Glinska Poljana). The colour code for different classes is as follows: abandoned agricultural land – orange; agricultural land in use – yellow; asphalted roads – medium grey; rangeland – light green; residential areas – dark red; trees and shrubs – dark green; shadow – brown and water – blue.

In addition, regarding the whole SMART approach, validation was done by blind tests in all three test sites in Croatia (Yvinec 2005) having 3.9 km^2 in total: Glinska Poljana (0.63 km^2, a fertile valley surrounded by hills), Pristeg (1.5 km^2, rocky,

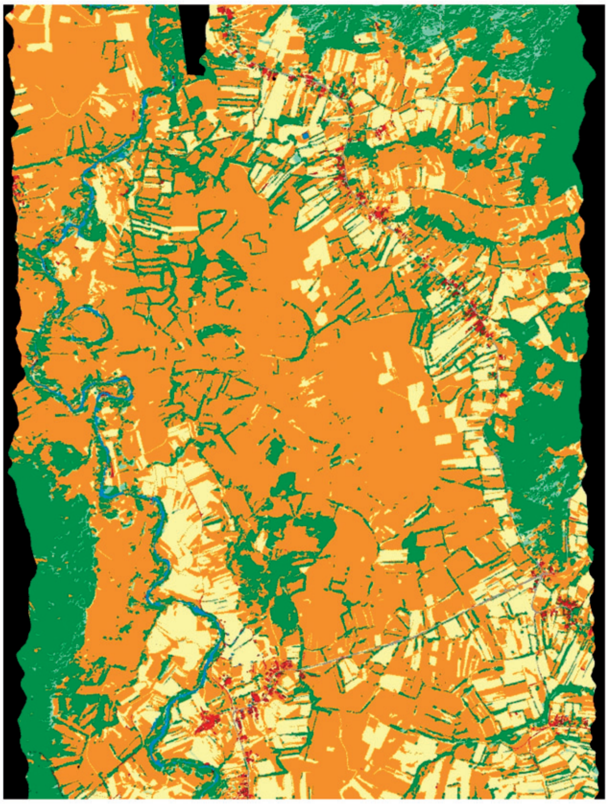

Figure 6. Results with fuzzy approach, after knowledge inclusion and spatial regularisation.
Note: Orange – abandoned agricultural land; yellow – agricultural land in use; medium grey – asphalted roads; light green – rangeland; dark red – residential areas; dark green – trees and shrubs; brown – shadow; blue – water.

Mediterranean area) and Čeretinci (1.7 km^2, flat agricultural area). In each of the sites clearing was performed after the flight campaign in order to have the true status of the mine presence, but this information was not available before the validation of produced danger maps. From the danger maps, a selection of areas proposed for area reduction was done, and areas considered as suspect were selected too. An example of obtained danger maps is shown in Figure 7 (SMART Consortium 2004). Grey areas are outside of the scope of SMART, while no data exists for white areas. Demined areas are light green. Indicators of mine absence are superimposed as parallel white and green lines. The degree of danger is on the scale from green (low) via yellow (intermediate) to red (high).

On average, 25% of the mine-free area has been proposed for reduction: Glinska Poljana – 7.7%, Pristeg – 9.0% and Čeretinci – 47%. The error rate of 0.10% is relatively constant for all three sites. In addition to this technical evaluation, a panel of independent mine action experts working in Croatia has evaluated the SMART method and danger maps, and recognised their contribution to an early stage of area reduction. It has been found that it might be even more suited for risk assessment.

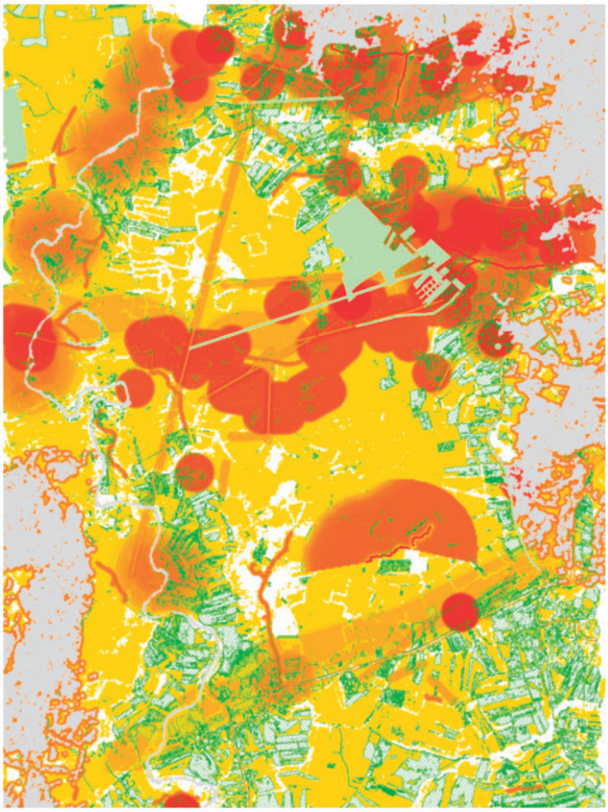

Figure 7. Continuous location map (SMART Consortium 2004).

4. Conclusion

Our experience in working on several fusion methods for close-in humanitarian mine detection and remote sensing mined area reduction is presented. These methods are based on belief functions as well as on fuzzy sets and possibility theory.

Regarding close-in detection, the differences between the two approaches we have developed concern mainly the combination step. The modelling step is performed according to the semantics of each framework, but the designed functions are as similar as possible, so as to enhance the combination step. Different fusion operators have been tested depending on the information and its characteristics. An appropriate modelling of the data along with their combination in a possibilistic framework has led to a better differentiation between mines and friendly objects. The decision rule was designed to detect all mines at the price of a few confusions with friendly objects. This is a requirement of this sensitive application domain, since mines must not be missed. Still, the number of false alarms remained limited in our results. The robustness of the choice of the operator has also been tested, and all mines were detected for all fusion schemes. Note that the proposed modelling is flexible enough to be easily adapted to the introduction of new pieces of information about the types of objects and their characteristics, as well as of new sensors. Furthermore, the proposed approaches give the possibility to the user to interact with the system and thus to influence the whole reasoning process by exploiting his own knowledge.

As far as remote sensing mined area reduction is concerned, we summarised in this article the concept of the whole method, developed within the SMART project, while giving most of the attention to the data fusion task. The proposed fusion approaches are to a large part original and constitute by themselves a result of the project. Results have been obtained on three test sites in Croatia, being representative of the southeastern Europe. In our work, we have shown how the results can be improved by introducing additional knowledge in the fusion process as well as a spatial regularisation step. At the end, the results were better than those obtained with any of the input classifiers or detectors individually, thus demonstrating the interest of the fusion part of the process.

Once again, the user has the possibility to interact by being involved in the choice of the classifiers, in the choice of some of the parameters (in particular for the fuzzy fusion approach, some supervision is still required in the choice of the parameters), and the programmes are flexible enough to allow him to modify them at wish.

All this work constitutes a large set of methods and tools for both research and applicative work, which may be useful for other applications, even in different domains. The developed schemes have a noticeable variety and richness and constitute a real improvement over existing tools.

Acknowledgements

The authors thank the TNO Physics and Electronics Laboratory (The Hague, The Netherlands) for the permission to work on the data gathered on their test facilities within the Dutch HOM-2000 project. This work was also partially supported by the European project SMART. The authors are also thankful to Prof. Marc Acheroy from the Royal Military Academy, Brussels, Belgium, for useful comments.

References

Acheroy, M., 2005. Spaceborne and airborne mined area reduction tools. *In: Workshop on inventory and analysis of operationally validated results related to mine action space- and airborne surveys* (invited paper). Zagreb: Scientific Council of CROMAC.

Acheroy, M., 2007. Mine action: status of sensor technology for close-in and remote detection of antipersonnel mines. *Near Surface Geophysics*, 5, 43–56.

Acheroy, M. and Milisavljević, N., 2007. Signal processing for humanitarian mine action [In the spotlight]. *IEEE Signal Processing Magazine*, 24 (4), 134–136.

Askelin, J.-I., 1999. EOD IS – a Loaded Laptop. *FOA magazine*, *Swedish Defense Research*, 1. Available from http://www.eodis.org/images/stories/articles/foa-tidning.pdf [Accessed 8 November 2009].

Auephanwiriyakul, S., Keller, J.M., and Gader, P.D., 2002. Generalized Choquet fuzzy integral fusion. *Information Fusion*, 3 (1), 69–85.

Baertlein, B.A., Liao, W.-J., and Chen, D.-H., 2001. Predicting sensor fusion performance using theoretical models. *In: Proceedings of SPIE conference: detection and remediation technologies for mines and minelike targets*, 4394, Orlando, 1035–1046.

Bloch, I., Milisavljević, N., and Acheroy, M., 2007. Multisensor data fusion for spaceborne and airborne reduction of mine suspected areas. *International Journal of Advanced Robotic Systems*, 4 (2), 173–186.

Chanussot, J., Benediktsson, J.A., and Fauvel, M., 2006. Classification of remote sensing images from urban areas using a fuzzy possibilistic model. *IEEE Geoscience and Remote Sensing Letters*, 3 (1), 40–44.

Cremer, F., *et al.*, 2001. A comparison of decision-level sensor-fusion methods for anti-personnel landmine detection. *Information Fusion*, 3 (2), 187–208.

de Jong, W., Lensen, H.A., and Janssen, Y.H.L., 1999. Sophisticated test facility to detect landmines. *In: Proceedings of SPIE conference detection and remediation technologies for mines and minelike targets*, 3710, Orlando, 1409–1418.

Delhay, S., Lacroix, V., and Idrissa, M., 2005. PARADIS: GIS tools for humanitarian demining. *In: Proceedings of ISCRAM 2005: Information systems for crisis response and management conference*, Brussels, Belgium. Available from http://www.itep.ws/pdf/MarcAcheroy.pdf [Accessed 8 November 2009].

den Breejen, E., Schutte, K., and Cremer, F., 1999. Sensor fusion for anti personnel landmine detection. *In: Proceedings of SPIE conference detection and remediation technologies for mines and minelike targets*, 3710, Orlando, 1235–1245.

Dubois, D., Prade, H., and Yager, R.R., 1999. Merging fuzzy information. *In*: J.C. Bezdek, D. Dubois and H. Prade, eds. *Handbook of fuzzy sets series, approximate reasoning and information systems*. Boston: Kluwer, 335–401.

Dubois, D., *et al.*, 2001. Using the transferable belief model and a qualitative possibility theory approach on an illustrative example: the assessment of the value of a candidate. *International Journal of Intelligent Systems*, 16 (11), 1245–1272.

Dubois, D. and Prade, H., 2006. Possibility theory and its applications: a retrospective and prospective view. *In*: G. Della Riccia, *et al.*, eds. *Decision theory and multi-agent planning (CISM International Centre for Mechanical Sciences)*. Udine, Italy: Springer, 89–100.

Gader, P., 2003. Signal-processing and sensor fusion methods. *In*: J. Macdonald and J.R. Lockwood, eds. *Alternatives for landmine detection*. Pittsburgh: RAND, 311–326.

Information Management System for Mine Action [online]. Available from: http://www.imsma.org [Accessed 8 November 2009].

Landmine Monitor Report, 2008. *Toward a mine-free world* [online]. Available from: http://www.icbl.org/lm/2008/ [Accessed 8 November 2009].

Le Hégarat-Mascle, S., Bloch, I., and Vidal-Madjar, D., 1997. Application of Dempster-Shafer evidence theory to unsupervised classification in multisource remote sensing. *IEEE Transactions on Geoscience and Remote Sensing*, 35 (4), 1018–1031.

Liao, Y., Nolte, L.W., and Collins, L.M., 2007. Decision fusion of ground-penetrating radar and metal detector algorithms: a robust approach. *IEEE Transactions Geoscience and Remote Sensing*, 45 (2), 398–409.

Maathuis, B.H.P. and van Genderen, J.L., 2004a. Remote sensing based detection of defensive minefields. *International Journal of Remote Sensing*, 25 (23), 5195–5200.

Maathuis, B.H.P. and van Genderen, J.L., 2004b. A review of satellite and airborne sensors for remote sensing based detection of minefields and landmines. *International Journal of Remote Sensing*, 25 (23), 5201–5245.

Milisavljević, N. and Acheroy, M., 1999. An approach to the use of the Bayesian rule in decision level fusion for multisensor mine detection. *Proceedings of physics in signal and image processing*. Paris, 261–266.

Milisavljević, N. and Bloch, I., 2001. A two-level approach for modeling and fusion of humanitarian mine detection sensors within the belief function framework. *In: Proceedings of applied stochastic models and data analysis*, 2, Compiègne, 743–748.

Milisavljević, N. and Bloch, I., 2003. Sensor fusion in anti-personnel mine detection using a two-level belief function model. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 33 (2), 269–283.

Milisavljević, N. and Bloch, I., 2008. Possibilistic vs. belief function fusion for anti-personnel mine detection. *IEEE Transactions on Geoscience and Remote Sensing*, 46 (5), 1488–1498.

Perrin, S., 2001. *Contribution à l'algorithmique multicapteur pour la détection de mines antipersonnel*. Thesis (PhD). Ecole Centrale de Lille, USTL, France.

Perry, S.W. and Guan, L., 2004. Pulse-length-tolerant features and detectors for sector-scan sonar imagery. *IEEE Journal of Oceanic Engineering*, 29 (1), 138–156.

Robledo, L., Carrasco, M., and Mery, D., 2009. A survey of land mine detection technology. *International Journal of Remote Sensing*, 30 (9), 2399–2410.

Shafer, G., 1976. *A mathematical theory of evidence*. Princeton: Princeton University Press.

SMART Consortium, 2004. SMART – final report. Available from http://www.smart.rma.ac.be/ [Accessed 8 November 2009].

Smets, P., 1990. Constructing the pignistic probability function in a context of uncertainty. *In*: L.N. Kanal, *et al*., eds. *Uncertainty in artificial intelligence 5*. New York: Elsevier, 29–39.

Smets, P. and Kennes, R., 1994. The transferable belief model. *Artificial Intelligence*, 66, 191–234.

Stanley, R.J., Gader, P.D., and Ho, K.C., 2002. Feature and decision level sensor fusion of electromagnetic induction and ground penetrating radar sensors for landmine detection with hand-held units. *Information Fusion*, 3 (3), 215–223.

Voles, R., 1998. Confidence in the assessment and use of mine detection systems. *In: Proceedings of IEE second international conference on the detection of abandoned landmines*, Edinburgh, 28–30.

Yägerbro, P., *et al*., 1998. Combination of GPR and metal detector for mine detection. *In: Proceedings of IEE second International Conference on the detection of abandoned landmines*, Edinburgh, 177–181.

Yee, M.L., 2001. Multisensor probabilistic fusion for mine detection. *In: Proceedings of SPIE conference detection and remediation technologies for mines and minelike targets*, 4394, Orlando, 959–969.

Yvinec, Y., 2005. A validated method to help area reduction in mine action with remote sensing data. *In: Proceedings of the 4th international symposium on image and signal processing and analysis*, Zagreb, Croatia.