Characterization of Mine Detection Sensors in Terms of Belief Functions and their Fusion, First Results

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Abstract - ***In this paper, characterization of mine detection sensors in terms of belief functions and their fusion are presented. Need for fusion of mine detection sensors is discussed, and reasons for choosing Dempster-Shafer framework are pointed out, taking into account specificity and sensitivity of the problem. This work is done in the scope of the HUDEM[1] project, where three promising and complementary sensors are under analysis. These sensors are presented, and detail analysis is performed in case of fusing the data from them. A way for including in the model influence of various factors on sensors and their results is discussed as well and will be further analyzed in the future. The application of the approach proposed in this paper is illustrated on the frequent case of detecting metallic objects, but the possibility for modifying it to some other situations exists.***

Keywords: humanitarian mine detection, sensor fusion, Dempster-Shafer method, mass assignment, discounting factors.

1 Introduction

Humanitarian mine detection is a very sensitive and, unfortunately, still unsolved problem. There are several reasons for that, and among them the following three are the main ones [14]:

- nature is very imaginative and creative, placing an endless number of obstacles, i.e. environmental factors, on a deminer's way, such as rocks, ferrous soils, moisture, etc.; that causes a lot of problems in predicting possible factors and their influence on mine detector performance;
- mine manufacturers do not lack imagination and creativity either, producing an almost endless variety of features of mines [5], e.g. size, composition, shape, activation principle etc.; as a result, mine detectors always go at least one step behind the mine producers, and, furthermore, the solutions for detection are often too big, expensive or slow to be useful in real situations;
- there is a lack of funding for (humanitarian) mine detection projects.

The first two points given above explain also why it is not possible to use just one sensor while trying to solve the problem: there is no single sensor that can reach necessarily high detection rate in all possible scenarios. A sensor that works well in one scenario, for one type of soil, moisture, temperature, burial depth, mine material, size, shape, fails to detect mines in a different scenario. Therefore, a lot of effort has been made in order to take the best from several complementary sensors. One of the most promising combinations in that sense is: an imaging metal detector (MD), a ground penetrating radar (GPR) and an infrared camera (IR).

Furthermore, since reliability and detection capabilities of any sensor are strongly scenario dependent, it is very important to characterize each of the sensors that are combined. In other words, ways for modeling influence of various factors on sensors and their results, as well as on results of combination have to be investigated in detail, with the aim of obtaining fusion results that would be as good as possible for some concrete scenario.

At this point, another question arises: which method to use in order to obtain such good results? It is well-known that there is no universal approach for information fusion and that its choice should strongly depend on the problem itself [1], [2], [10], [13]. It should be pointed out that in this domain of application, we have to deal with following information:

- the data are basically numerical (images, sensor measurements);
- they are not numerous enough to allow reliable statistical learning (as shown through our previous work [6]);
- they are highly variable depending on the context and conditions;

[1]HUDEM (HUmanitarian DEMining) is a technology exploration project on humanitarian demining launched by the Belgian Minister of Defense with funding provided by his Department, the Ministry of Foreign Affairs and the State Secretariat for Development Aid.

- they do not give precise information on the type of mine (ambiguity between several types);
- not every possible object can be modeled (neither mines nor objects that could be confused with them).

That is why we propose an approach based on belief functions in the framework of Dempster-Shafer (DS) theory [9], [12], since in this framework, ignorance, partial knowledge, uncertainty and ambiguity can be appropriately modeled. The main motivation for exploring possibilities of modeling mine detection system in this framework is to be easily able to include and model existing knowledge regarding:

- the three mine detection sensors under analysis (e.g. detection of IR is limited to several centimeters below the soil surface in the best case, standard GPR cannot detect surface-laid and shallowly buried objects, MD can detect just objects containing metal, etc.),
- well-known mine laying principles (e.g. antipersonnel (AP) landmines[2] are usually buried on the depths up to 25-30 cm, not deeper),
- mines themselves (e.g. around 90% of laid mines are highly metallic, majority of currently laid mines around the world are with circular top surface, appearing elliptical in images of these three sensors in the general case because of some burial angle, etc.),
- objects that each of these sensors can easily confuse with mines (e.g. stones of adequate size and shape for IR and GPR sensor, metallic cans for MD, etc.).

There is another aspect of our ideas that has to be mentioned. It is known that in humanitarian mine detection mistakes are not allowed, i.e. the detection rate has to be as high as possible. We believe that the approach of combining sensors should surely improve detection results, but that it is not possible to reach the highest possible level of detection, simply because it is not possible to predict all the real situations where mines can be found. Because of that, our idea is to give to a deminer as much information as possible, starting from processed data of separate sensors up to a final conclusion on the basis of that, but the final decision has to be left to the deminer. Therefore, the result of this DS model should be an ordered list of guesses what a currently observed object could be, together with confidence in these results.

It should be also pointed out that there is no criterion by which it is possible to say that if it is fulfilled, the object is a mine[3], it can be just the opposite, i.e. to have a criterion that can tell us when an object is (most probably) not a mine. Consequently, our results tell how expectable is that an object is not a mine, or that it is either a mine or something else. Although it may sound as a drawback of the method, it should not be forgotten that mines should not be missed, so detecting that something is not a mine and that it is a mine or something else seems to be the safest approach in this complex problem.

In the following, some characteristics of MD, GPR and IR sensors from the mine detection point of view will be presented. On the basis of that as well as general ideas for applying the DS approach, explained above, the appropriate choice of criteria and of respective mass assignment for each of the sensors will be discussed, in the case that an object under observation is metallic. Also, preliminary ideas for including in the model confidence of sensors in their assessments, importance of each criterion as well as deminer's confidence in each of the sensors will be presented, based on the idea of introducing discounting factors [3], [9], [11].

2 Characteristics of imaging MD, GPR and IR sensors

As a general remark, it should be noted that all these three sensors are assumed to be co-registered (as it is the case in the practice) in sense that they all refer to the same area on the ground, so a good information about location exists in 2D, while the information about the third dimension, i.e. depth position of the object is missing and can be extracted only from information given by MD and GPR, leading to potential problems when these two sensors disagree, i.e. either (at least) one of them is not reliable or they do not refer to the same object (since they do not sense the same phenomenon).

2.1 An imaging MD

Metal detectors are one of the oldest and most efficient sensors used in mine detection. As their name says, they detect all metallic objects, and not mines in particular, as long as metal content of that object is larger than a sensitivity threshold of the MD. Different metal detection technologies exist, but the basic concept is the same and simple: while the detector head moves above metal, the detector senses a change in the magnetic field below it. As long as a mine has enough metal, a MD can be used alone. Of course, mine manufacturers are aware of this fact, so more and more mines with less and less metallic content are produced. On their behalf, producers of MDs are trying to cope with that: currently MDs can track less than 1/10 of a gram of metal at a depth of 10 cm [4], but in that case their threshold of sensitivity has to be very low, and that will cause a lot of false alarms as well. Therefore, the other

[2]AP landmines are the problem of humanitarian demining, so that is what is understood under the term "mines" mainly used in this paper.

[3]This is the truth for our three sensors, but, apparently, not in general, e.g. in case of some newer sensors of explosive, such as NQR. These sensor technologies are not mature yet, so their usefulness is still to be seen. Possibilities and implications of including such type of sensors in our model will be analyzed in the future.

two sensors are sometimes aimed not to detect mines, but to lower the number of false alarms. On the other hand, nowadays, mines even completely without metal are produced as well, so that case should be analyzed as well if a detection method should be longer-lasting one.

Main advantage of this sensor is that it is not influenced by soil moisture and other weather-dependent factors. The factors that influence quality of mine detection by MDs are:

- metallic objects (debris, cans etc.)- cause a lot of false alarms;
- ferrous or magnetic soils - cause false alarms;
- metal content of a mine - the higher, the better.

A traditional MD has just a sonar signal indicating the presence of metal on or in the ground. In the last years, an improvement has been made by converting this signal to an image. This type of MD, so-called imaging MD, is under our analysis [15].

2.2 A GPR

This type of sensor includes two antennae, a transmitting one and a receiving one. The first antenna emits an active signal through the ground, and the second one receives the signal reflected from any buried object of which dielectric constant differs from the one of the soil. The main problem of this sensor is soil moisture, that drastically weakens the signal and limits the burial depth on which mines could be detected. Also, other buried objects cause increase in number of false alarms. Standard GPRs have problems in detecting surface laid mines because of strong surface reflection. Some solutions exist (e.g. ultra-wideband GPR or using more than one receiving antenna), but still are not mature and operable enough to be taken for sure. Therefore, we could say that factors of influence on GPR mine detection performances are:

- buried non-dangerous objects - the more resembling to mines in size and shape, the worse;
- burial angle - affects the appearance (size and the shape) of an object in the image[4] ;
- moisture - wetter the soil, weaker the signal;
- difference in the permittivity between an object (a mine) and the soil;
- burial depth - the larger, the worse - if the soil is wet, otherwise not (for burial depths of AP mines); once again, surface laid and shallow buried mines are problematic for most GPRs, i.e. dependence of performance of GPR on burial depth is not monotonic.

[4]We restrict our analysis on imaging GPRs [8].

2.3 An IR

The principle behind the IR mine detection is that a metallic mine conducts and radiates heat at a different rate than a plastic mine or the soil and vegetation and that they all have different heat capacity. Main limitations of this sensor arise from the fact that it needs solar loading for developing passive heat signature. It means that trees, buildings, clouds limit possibilities of mine detection because they lower solar loading; rain or snow even completely eliminate solar loading. Furthermore, any other object that resembles to a mine (cans, rocks etc.) with its own thermal signature easily causes false alarms. Also, IR sensor cannot "see" mines that are below solid objects such as foliage. Finally, if all the problems mentioned above are avoided, the daily evolution of thermal signatures [6] cannot be skipped, i.e. the fact that because a mine and its surroundings receive solar loading at different rates, there are periods in a day when thermal contrast between a mine and its environment reaches maximum, and other periods when a mine and its surroundings are on the same temperature (so the mine is "IR invisible"). Precise times when these events occur depend on the time of the year, place on the Earth, i.e. the inclination of the sun etc.

To summarize, following factors influence the detectability (either improving it or lowering it) of IR sensors [6]:

- non-dangerous objects - the more resembling to mines in size and shape, the worse;
- burial angle - affects the appearance (size and the shape) of an object in the image;
- moisture - wetter the soil, weaker the signal;
- time of the day - daily evolution of the thermal contrast;
- burial depth - the deeper, the worse;
- precipitation - the stronger and longer, the worse;
- difference in thermal emissivity, conduction and heat capacity between a mine and the soil;
- obscuring objects - above a mine, on the surface or close to it (a very often example is vegetation - the higher and denser, the worse).

3 Choice of criteria and resulting mass assignments

The most usual case in mine detection reality is when an observed object has a high metallic content, causing a strong response of a MD. Therefore, that is the first case we decide to analyze and model in this framework, hoping that it could be a good basis for further modifications and generalization to other cases.

If all three sensors are (equally) reliable and if a MD claims that the object is highly metallic, the following classes of objects can exist:

- MR (metallic mine of regular, i.e. circular or more generally - elliptical, shape),
- MI (metallic mine of irregular shape),
- FR (friendly, i.e. non-dangerous object of regular shape) and
- FI (friendly object of irregular shape).

They create the frame of discernment Θ. Furthermore, the criteria that can give the most information about the real identity of the object in this case, for our knowledge, are the following:

- for each of the three sensors:
  1. ellipse fitting, that is, how well the shape of the object fits in an ellipse, assigning masses to subsets {MR, FR}, {MI, FI}, Θ;
  2. shape elongation, again giving masses to {MR, FR}, {MI, FI}, Θ;
  3. area/size, by which information about expectable size range of mines is included, assigning mass mainly to Θ within that range, and to {FR, FI} elsewhere;
- for MD: burial depth, including the knowledge about the depths where mines can be expected, so, again, assigning masses to Θ and {FR, FI};
- for GPR:
  1. depth dimension of the object, that gives, similarly as information about area, masses to {FR, FI} and to Θ;
  2. comparison of the depth position of metal detected by MD and the object depth interval sensed by GPR; if they are in accordance, masses are assigned mainly to Θ, if they are not, a largest part of masses should go to subset {FR, FI}.

The masses are defined as functions depending on measure of ellipticity, elongation factor, area, depth, respectively. They are detailed in [7]; see also example in Figure 1.
The measures that can be extracted from the sensors do not provide, in general, information about classes of interest individually. For instance, elongation provides information about shape, but not about the nature of the object, so it cannot disambiguate between mines and friendly objects. Similar observations can be made for the other measures. Because of this, the focal elements of the proposed model are generally disjunctions of hypotheses, and not singletons of the set of discernment. This is possible in the context of belief function theory, which is another advantage of this choice.

4 Discounting factors

As previously pointed out, behavior of each of the three sensors is strongly scenario-dependent, referring to:

- quality of the acquired data, that influences assessment of sensors when judging about some criterion, importance of each criterion and confidence in that sensor;
- reliability/detection ability of each of the sensors under particular weather conditions, type of soil etc, that affects again confidence in that sensor;
- types of objects under analysis, influencing importance of each of the criteria, etc.

That means that there should be a way to include influence of various factors (environmental conditions, data quality etc.) on the obtained results; since it would be very difficult to model individually each environmental factor and its influence, we propose to include them in one discounting factor. Furthermore, we should allow a deminer to have a possibility to give his own opinion about reliability of each of the sensors within a concrete scenario, i.e. his confidence in each of them. Finally, depending on a concrete situation, some criteria could become more important (and reliable), others less. These are main reasons for including discounting factors [3], [9], [11] in our model.

Discounting factors, d_{ij}, consist of three types of parameters:

- g_{ij} - confidence level of sensor j in its assessment when judging criterion i (0 - not confident at all, 1 - completely confident);
- b_i - level of importance of criterion i (1 - very low, 3 - very high);
- s_j - deminer's confidence into sensor j's opinion,

where $i \in \{a, c, d, e, f, h\}$, $j \in \{G, I, M\}$, with: a - area, c - comparison of depth information from MD and GPR, d - depth, e - elongation, f - ellipse fitting, h - depth dimension of an object, G - GPR, I - IR, M - MD.

4.1 First ideas for estimating g_{ij}

4.1.1 Area/size for IR and GPR, i.e. g_{aI} and g_{aG}

Level g_{aI}, i.e. confidence of IR sensor in its assessment when judging the area criterion, we define as a function of agreement in area between this sensor and area extracted by MD. Namely, in one of the starting steps, we decide on the basis of the strength of signal of MD (or/and the area detected by it) which case we analyze. That means that before this moment, we already decided, on the basis of this MD signal, that we analyze the case of high metal content (i.e. metallic) object. What is also done before this moment is that, since IR does not give information about distance from it and the observed object, the area extracted by this sensor is estimated on the basis of the depth information extracted by MD. At this point, we can have two cases:

- (area detected by MD) $\approx$ (area detected by IR); in ideal case of a high metal content object these two areas would be equal, but this equality is understood here with some allowed estimated tolerance because of two reasons:
  1. measurements are imprecise, and therefore we cannot expect a strict equality;
  2. IR and MD do not measure the same objects (the same phenomenon): if a metallic mine is composed of two different parts, A and B, where A is metallic, B is not, but is seen by IR (e.g.: it is a metallic mine with plastic handles, where, IR would see a slightly larger area than MD, in ideal case), then IR will measure size(A)+size(B) while MD just gives information about size(A);

  in this case, we propose to calculate g_{aI} as:

  $$g_{aI} = \frac{\min(MD\,area, IR\,area)}{\max(MD\,area, IR\,area)};$$

  (so that maximum value of this factor does not exceed 1 in case that area of IR is slightly smaller than the one of MD);
- otherwise, i.e. areas detected by MD and IR are (quite) different (in either sense); the possibility that it is a low-metal content object should not exist at this level since this should have been checked before, i.e. at this point, this possibility is excluded; what remains is that these two sensors do not refer to the same object[5]; therefore, in the next step, these two areas are compared with area information extracted by the third sensor, GPR; if GPR area is similar to one of the previous two, then that sensor and GPR are clustered together, and the third one separately, and our analysis "switches" to the case where GPR and that sensor with similar area refer to the same object, while the third one refers to another; if there is no similarity in areas between these three sensors, the case when they all refer to different objects has to be further analyzed.

The same reasoning as above can be applied for the calculation of g_{aG}, that is, confidence level of GPR in its assessment when judging area criterion: it can be again compared with MD area, etc.

4.1.2 Ellipse fitting for all three sensors (g_{fI}, g_{fG}, g_{fM})

Confidence of IR sensor in its estimation of masses regarding ellipse fitting criterion is a function of the shape itself (and of ellipse fitting criterion and mass assignments as well), that is, the larger the separation (mass difference) between regular and irregular set, the larger the confidence in the assessment; for example:

$$g_{fI} = (m_{fI}\{MR, FR\} - m_{fI}\{MI, FI\})^2.$$

[5] This possibility can still exist in the previous case as well, but it is not analyzed for that case since it will be further checked in the future work, through conflicts between sensors.

Estimation of the confidence levels for this criterion for the other two sensors is defined similarly, i.e.:

$$g_{fG} = (m_{fG}\{MR, FR\} - m_{fG}\{MI, FI\})^2,$$

$$g_{fM} = (m_{fM}\{MR, FR\} - m_{fM}\{MI, FI\})^2.$$

4.1.3 Elongation (g_{eI}, g_{eG}, g_{eM})

Similarly to the previous criterion, we define the confidence level in estimation of elongation as function of how well regular and irregular subsets are distinguished by the chosen criterion:

$$g_{eI} = (m_{eI}\{MR, FR\} - m_{eI}\{MI, FI\})^2,$$

$$g_{eG} = (m_{eG}\{MR, FR\} - m_{eG}\{MI, FI\})^2,$$

$$g_{eM} = (m_{eM}\{MR, FR\} - m_{eM}\{MI, FI\})^2.$$

4.1.4 Comparison of depth information of GPR and MD (g_{cG}) and burial depth by MD (g_{dM})

At this point, results of two sensors are compared, and it is not known for sure which one is more reliable (we have deminer's belief about that, but this information is already directly included in calculation of discounting factors).

As already mentioned, this criterion assigns masses to the subset of friendly objects {FR, FI} and to the full set in function of agreement in depth location extracted by these two sensors, in sense that if they agree well, mass is given mainly to the full set (such an object can be anything) and if not, it is assigned to friendly objects (i.e. such an object is quite surely not a mine or at least one of the two sensors is not reliable). These mass assignments are illustrated in the right side of Fig. 1, where x is the depth position detected by MD, measured from the top level detected by GPR, and d is the depth dimension sensed by GPR.

Consequently, confidence level of GPR in its assessment regarding this criterion is a function of the mass given to a full set, i.e. to how well these two sensors agree - if they are in agreement, we can believe that both sensors are quite reliable and vice versa. Additionally, this confidence depends on the depth information as well; namely, a stronger confidence to this comparison is put if the depth is within the range that is detectable by GPR - we should not give too high confidence in this assessment if the depth is very shallow (since standard GPR does not work well in that range), or if it is too large. Therefore, this confidence level is defined as:

$$g_{cG} = m_{cG}\{\Theta\} \cdot f(depth),$$

where function $f(depth)$ has a shape given in the left side of Fig. 1.

Accordingly, since it is not known which sensor is more reliable, depth estimation of MD has to be the function of its agreement with GPR, i.e.:

$$g_{dM} = m_{cG}\{\Theta\}.$$

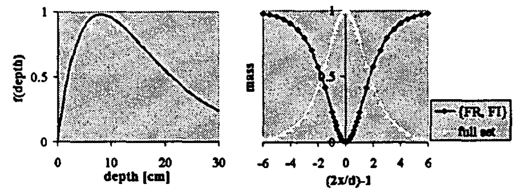

Figure 1: Confidence in GPR in function of depth estimated by MD (left), mass assignments for the depth comparison criterion (right)

4.1.5 Depth dimension by GPR, g_{hG}

We propose to define this confidence level also as a function of the depth information (again as in Fig. 1), since GPR is not reliable neither for surface-laid or shallowly buried object nor for very deeply buried ones (how deep it can go, strongly depends on moisture level, so it could be later modified to include this information, if we will be able to measure this information). Accordingly, it is calculated as:

$$g_{hG} = f(depth).$$

4.1.6 Area/size by MD (g_{aM})

The confidence of MD in its assessment when judging about area of the object is defined as a function of the strength of the signal, or, of the maximum value of pixels in its image response in comparison to the image scale:

$$g_{aM} = \frac{\max response}{image\ scale}.$$

4.2 What about s_j ?

These coefficients, in general, depend on factors that influence on reliability of sensors, such as environmental conditions, i.e. time of the day, moisture etc. Since we do not know whether we will have collateral data and which of them, at this moment we give full confidence to a deminer's opinion about reliability of sensors. We should be aware that this confidence will be probably biased by a deminer's trust in each of the sensors, either because he is more familiar with some of them than with some others, or because of his personal opinion about reliability of a particular sensor in the current scenario (especially for parameters that are difficult to quantify, e.g. how dense and high the vegetation is, how good the weather is, etc.).

By this idea, a deminer will give us, for each of the sensors, numbers describing his belief in reliability of that sensor, where the higher the number, the larger the confidence in that sensor. Therefore, if two sensors have the same confidence number, that means that the deminer's belief is that they are approximately equally reliable in that scenario. Deminer, of course, does not have to use the full range, i.e. the full scale, if there is no completely reliable or unreliable sensor. Also, since people do not think necessarily on the same way, some deminers probably prefer rough scales (e.g. from 1 to 3), and others more subtle ones (from 1 to 10, for example). Because of that, the minimum of his scale is restricted to 1, for the sake of simplicity, but the deminer is allowed to choose the maximum himself. Of course, the values he gives have to be rescaled. Therefore, besides his numbers about trust in each of the sensors, he will give his scale as well. Including this possibility to the model means that we have to be careful while comparing results obtained by different scales (e.g. if two deminers with different choices of scale observe the same scenario), especially if we want to compare resulting masses after combination. On the other hand, the relationship between masses obtained by one scale should not be disturbed by choosing another one; it can be expected that indeed this will be preserved, and that is the most important thing for further analysis of results, i.e. creating an ordered list of guesses about the true identity of an observed object.

4.3 How to estimate b_i ?

For these coefficients, that represent importance of criteria, there are several open possibilities, that will be further investigated in the future work:

- their choice can be again left to a deminer (how important for him is each of the criteria), and this solution is applied in the paper;
- their values can be preset for each of the predictable cases, i.e. they can depend only on the currently explored case (e.g. metallic object, low-metal content object etc.);
- they can be at the beginning chosen all the same, and after combination of masses, these coefficients can be tuned depending on which subset has the highest mass (e.g. if the first guess is that it is a regularly shaped metallic mine, coefficients will be adjusted so that the criteria that give more information about this type of object become more important); then, combination with these modifications can be performed, and if the results are consistent, we can be more confident in them; if not, we can decrease the confidence in the first subset, and perform the same analysis for the subset with the second highest mass, etc.; possibility that this way induces some bias should be investigated as well.

4.4 Finally - how to calculate d_{ij} ?

For the moment, we choose a very simple function of the three types of coefficients discussed above, where each factor could be used in successive discounting, and then the global factor would be a product, such as:

$$d_{ij} = 1 - g_{ij} \cdot (k_1 \cdot s_j + l_1)(k_2 \cdot b_i + l_2),$$

where k_m and l_m, $m = 1, 2$, are coefficients that, obviously, have to be tuned. That is a serious task that will be done in the future work, through a careful study of their influence, if they are all necessary or not. This will be done not only by comparing resulting discounting factors, but also the influence on resulting masses and decisions. For the beginning, the simplest is to take:

$$l_1 = l_2 = 0,$$

$$k_1 = \frac{1}{s_{scale}},$$

$$k_2 = \frac{1}{b_{scale}},$$

i.e. to calculate the global discounting as:

$$d_{ij} = 1 - g_{ij} \cdot \frac{s_j}{s_{scale}} \cdot \frac{b_i}{b_{scale}},$$

where s_{scale} and b_{scale} are scales for s and b parameters, respectively.
We expect that after having gathered the data from all three sensors it will be possible to finally adjust all these parameters, as well as previously explained mass assignments per criterion. Using these coefficients, masses assigned for each of the sensors and for each criterion are modified in the following way:

- for some subset $A \neq \Theta$, new masses, $m_{ijNEW}(A)$, are computed from the initial ones, $m_{ij}(A)$, as:

$$m_{ijNEW}(A) = (1 - d_{ij}) \cdot m_{ij}(A);$$

- for full set:

$$m_{ijNEW}(\Theta) = (1 - d_{ij}) \cdot m_{ij}(\Theta) + d_{ij}.$$

5 First results

Once the masses are calculated and discounted for each criterion and for each sensor, we can combine them using the well-known DS conjunctive rule [9] in unnormalized form, in order to preserve mass of empty set (i.e. strength of conflict, as will be explained soon):

$$m(A) = \sum_{\substack{i,\, j \\ A_i \cap B_j = A}} m_1(A_i) \cdot m_2(B_j),$$

where m_1 and m_2 are basic mass assignments, and their focal elements are A_1, A_2, ... A_k and B_1, B_2, ... B_l, respectively.

Figure 2: Test images

We can imagine four cases; for each of them, obtained (unnormalized) masses are given in Table 1:

- case 1 - an elliptical metallic object given in Fig. 2 is seen approximately equally by all three sensors and it is buried on a depth where mines can be expected, its area is similar to mines, its depth dimension is again as for mines, and MD and GPR agree about its depth position; discounting is not included;
- case 2 - it is similar to the first one, but with discounting factors, where just factors for confidence levels are included, i.e. it is assumed that all sensors are highly reliable and that all criteria are equally important;
- case 3 - MD and GPR behave as in the previous two cases, i.e. detect some moderately buried object, but performance of IR sensor is drastically influenced by some factors; because of that, its detection is limited to the surface (e.g. if vegetation is high and dense), where it registers some object of the similar area as the object that other two sensors detect, but of the X-shape (as in the right side of Fig.2); there is no discounting, i.e. a deminer cannot express his doubts about reliability of IR;
- case 4 - discounting is included in the previous case, and a deminer claims that the scale of reliability of sensors is 5, where he gives the highest level of confidence for GPR and MD, but the lowest for IR; importance of all criteria remains equal.

Table 1: Resulting masses after combination for four analyzed cases

	Cases			
Masses	case 1	case 2	case 3	case 4
m{FR}	0.0585	0.0558	0.0127	0.042
m{FI}	1.6e-07	9.6e-05	8.8e-06	3.9e-04
m{FR,FI}	1.8e-12	9.5e-05	6.9e-13	5.9e-04
m{MR,FR}	0.9279	0.9015	0.2021	0.899
m{MI,FI}	2.5e-06	0.0017	1.5e-04	0.087
m{Θ}	2.8e-11	0.0015	1.1e-11	0.0096
m{∅}	0.0135	0.0393	**0.785**	0.0394

As can be seen, there is no important change in the results for the cases 1 and 2, indicating that under almost ideal conditions, discounting factors do not influence results to a great extent. On the other hand, the case 3 (i.e. without discounting) has a high degree of conflict between sensors (high value of mass of empty set before normalization), indicating that something is wrong with some of the sensors[6]; this information would have been lost if DS rule in normalized form were applied (i.e. masses were divided by (1-m{∅})). After discounting (case 4), the value of conflict is suppressed to a great extent, thanks to the fact that influence of the sensor that is not reliable is heavily discounted.

[6] "Open-world assumption" (something outside the frame of discernment happened) is justification for keeping masses unnormalized.

Therefore, even if in some of previous steps it is not noticed that these sensors do not refer to the same object, i.e. they are not clustered in two groups, behavior of the system and, most importantly, final result can be significantly improved by introducing confidence factors and allowing to a deminer a possibility to express his opinion about reliability of each of the sensors.

Several possibilities for interpreting these results exist, depending mainly on the way the subsets containing mines (and something else) are treated. We choose the cautious approach, where such subsets are treated as a potential danger. Indeed, in all these examples the object under observation is likely to be a mine (or something that resembles to it), and the results show the same, giving a high mass to a subset of regular shapes, containing mines.
These are just a few examples of obtained results, showing that our model behaves in accordance with what can be expected in reality, i.e. these results are promising.

6 Conclusion

In this paper, reasons and ideas for modeling fusion of mine detection sensors within the DS framework are given. The main advantage of this approach is its possibility of including existing knowledge about the problem. On the basis of this knowledge, the choice of criteria for the very frequent problem of detection of large metallic objects is presented. Furthermore, a way is shown for including discounting factors that can model influence of environmental conditions, i.e. of a concrete scenario through deminer's confidence in reliability of each of the sensors, relative importance of criteria, as well as confidence of sensors in their assessment when judging about some criterion. Finally, first results of fusion with included discounting are obtained, that seem to be very promising. We expect that these masses will become even more realistic and results even more useful once the trials are done, from which it should be possible to pool these preliminary mass assignments and discounting factors.
In the future work, possibilities of generalizing this model to other cases will be investigated, ways to add discounting factors will be further tested, and ideas to modify the model by allowing the possibility that sensors do not refer to the same object will be analyzed.

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