Possibilistic Multi-Sensor Fusion for Humanitarian Demining

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Abstract—**We propose a method for combining humanitarian mine detection sensors based on possibility theory. Firstly, different features are extracted from the sensor data. Possibility distributions are then derived from the features based on prior information. After that, the combination of possibility degrees is performed in two steps, on separate sensor level and between the sensors. Combination operators are chosen to account for the different characteristics of the sensors. The final decision is obtained by thresholding the fusion result. Promising results have been obtained on a set of real mines and non-dangerous objects. In particular a 100% mine recognition rate was achieved, with a limited number of false alarms.**

Keywords - humanitarian mine detection; information modeling; possibilistic fusion.

I. Introduction

Despite the great efforts and motivation of research teams around the world, there is no single sensor used for humanitarian mine detection that can reach the necessarily high detection rate in all possible scenarios. As a result, a very attractive way towards finding a solution is in taking the best from several complementary sensors. One of the most promising sensor combinations consists in an imaging metal detector (MD), a ground-penetrating radar (GPR) and an infrared camera (IR). We propose here a method based on possibility theory for combining these sensors, which can be easily adapted for other sensors and their combinations.

Most of the efforts made in the field of fusion of dissimilar mine detection sensors are based on statistical approaches [1, 2]. They provide good results for a particular scenario, but they ignore or just briefly mention that, once more general solutions are looked for, several important problems have to be faced in this domain of application [3]. Namely, the data have the following characteristics: (i) they are not numerous enough to allow for a reliable statistical learning; in case of humanitarian demining, it is necessary to have the highest possible detection rate with the highest possible confidence, which asks inevitably for an unrealistic number of samples per mine type for statistical learning; (ii) they are highly variable depending on the context and conditions; (iii) they do not give precise information on the type of mine (ambiguity between several types). In addition, it is not possible to model every object (neither mines nor objects that could be confused with them).

In a previous work [4], a method based on belief function framework has been proposed. Here we propose an alternative approach, based on possibility theory, in order to take advantage of the flexibility in the choice of combination operators [5, 6]. This is exploited here to account for the different characteristics of the sensors to be combined.

According to the general scheme of fusion as described in [7], the main steps of our approach include modeling of the available information and data (Section II), combination, i.e. the actual fusion step (Section III) and a final decision step (Section IV). Preliminary results are reported in Section V.

II. Information Modeling

From the data provided by the three types of sensors, a number of features are extracted, as in [4]. These features concern:

- the shape (elongation and ellipse fitting) as well as the area of the object observed using the IR sensor,
- the size of the metallic area in MD data,
- the burial depth, the ratio between object size and its scattering function as well as the propagation velocity (thus the type of material) of the observed object using the GPR sensor.

As an example, Fig. 1 contains a preprocessed B-scan (vertical slice in the ground, along the scanning direction) of GPR data. Due to the principles of operation of GPR, an object leaves hyperbolic signature in a B-scan. If this hyperbola is correctly detected, as illustrated in Fig. 1, the three GPR features can be directly related to the extracted hyperbola parameters [8].

Possibility distributions are then derived from the features based on prior information, such as the usual size of mines or the typical burial depth.

A. IR features

First two IR features, elongation and ellipse fitting, provide information mainly on regularity. We denote by $\pi_{1I}(MR)$ and $\pi_{2I}(MR)$ the possibility degrees of being a regular-shaped mine (MR), derived from these two features. Similarly, $\pi_{1I}(MI)$ and

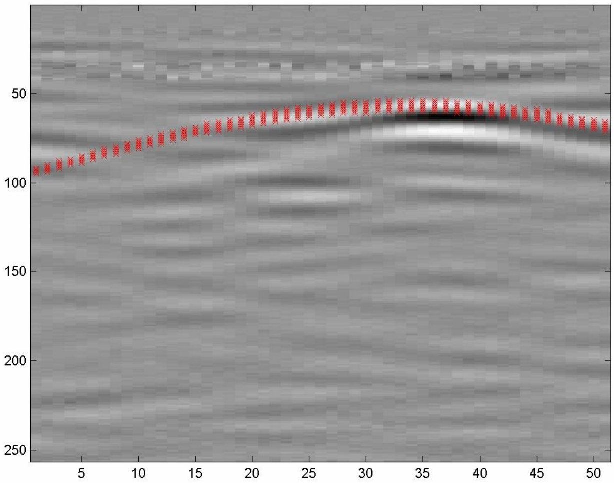

Figure 1. An example of GPR data (B-scan after background removal) and the extracted hyperbola

π_{2I} (MI) denote the possibility degrees of being an irregular-shaped mine (MI). Then, possibility degrees of being a regular-shaped friendly object (FR) and irregularly shaped friendly object (FI) are defined too, and are denoted by π_{1I} (FR) and π_{1I} (FI) for elongation feature and by π_{2I} (FR) and π_{2I} (FI) for ellipse fitting feature.

We calculate r_1 as the ratio between minimum and maximum distance of bordering pixels from the center of gravity (we work on thresholded images) and r_2 as the ratio of minor and major axis obtained from second moment calculation, from which the following possibility degrees are derived:

$$\pi_{1I}(MR) = \pi_{1I}(FR) = \min(r_1, r_2), \tag{1}$$

$$\pi_{1I}(MI) = \pi_{1I}(FI) = 1 - \pi_{1I}(MR). \tag{2}$$

In case of ellipse fitting, let A_{oe} the part of object area that belongs to the fitted ellipse as well, A_o the object area, and A_e the ellipse area. Then we define:

$$\pi_{2I}(MR) = \pi_{2I}(FR) = \max\left(0, \min\left\{\frac{A_{oe}-5}{A_o}, \frac{A_{oe}-5}{A_e}\right\}\right), \tag{3}$$

$$\pi_{2I}(MI) = \pi_{2I}(FI) = 1 - \pi_{2I}(MR). \tag{4}$$

Note that in cases where there is a reliable information that all mines have a regular shape, the possibility degrees of being MR can be reasigned to mines of any shape (M) while the possibility degrees of being MI can be reasigned to friendly objects of any shape (F).

The area directly provides a degree π_{3I} (M) of being a mine. Namely, since the range of possible antipersonnel (AP) mine sizes is approximately known, a degree of possibility of being a mine is derived as a direct function of the measured size:

$$\pi_{3I}(M) = \frac{a_I}{a_I + 0.1 \cdot a_{\mathrm{Im}in}} \cdot \exp\frac{-[a_I - 0.5 \cdot (a_{\mathrm{Im}in} + a_{\mathrm{Im}ax})]^2}{0.5 \cdot (a_{\mathrm{Im}ax} - a_{\mathrm{Im}in})^2}, \tag{5}$$

where a_I is the actual object area on the IR image, while the approximate range of expectable mine areas is between a_{Imin} and a_{Imax} (for AP mines, it is reasonable to set a_{Imin} = 15 cm^2 and a_{Imax} = 225 cm^2). On the contrary, friendly objects can be of any size, so the measured size is uninformative about the possibility of being a friendly object. Hence, the possibility degree is set to one whatever the value of the size:

$$\pi_{3I}(F) = 1. \tag{6}$$

B. *MD features*

In reality, MD data are usually saturated and data gathering resolution in the cross-scanning direction is typically very poor, so the MD information used consists of only one feature, which is the width of the region in the scanning direction, w [cm]. As friendly objects can contain metal of any size, we define:

$$\pi_{MD}(F) = 1. \tag{7}$$

On the contrary, if there is some knowledge on the expected sizes of metal in mines, we can assign possibilities to mines as, e.g.:

$$\pi_{MD}(M) = \frac{w}{20} \cdot [1 - \exp(-0.2 \cdot w)] \cdot \exp\left(1 - \frac{w}{20}\right). \tag{8}$$

C. *GPR features*

All three features of GPR provide information about mines.

In case of burial depth information (D), friendly objects can be found at any depth, while it is known that there is some maximum depth up to which AP mines can be expected. Typically, AP mines can rarely be found buried below 25 cm (D_{max}), sometimes even much shallower, the depth being limited mainly by their activation principles. However, due to soil perturbations, erosions etc., mines can, by time, go deeper or shallower than the depth at which they were initially buried. Thus, for this GPR feature, possibility distributions for mines, $\pi_{1G}(M)$, and friendly objects, $\pi_{1G}(F)$, can be modeled as follows:

$$\pi_{1G}(M) = \frac{1}{\cosh(D / D_{\max})^2}, \tag{9}$$

$$\pi_{1G}(F) = 1. \tag{10}$$

Another GPR feature exploited here is the ratio between object size and its scattering function, d/k. Again, friendly objects can have any value of this feature, while for mines, there is a range of values that mines can have, and outside that range, the object is quite certainly not a mine:

$$\pi_{2G}(M) = \exp\left(-\frac{[(d/k)-m]^2}{2\cdot p^2}\right), \tag{11}$$

$$\pi_{2G}(F) = 1, \tag{12}$$

where m is the d/k value at which the possibility distribution reaches its maximum value (here, m = 700, chosen based on prior information), and p is the width of the exponential function (here, p = 400).

Finally, propagation velocity, v, can provide information about object identity. Here, we extract depth information on a different way than in the case of the burial depth feature [8], and we preserve the sign of the extracted depth. This information indicates whether a potential object is above the surface. If that is the case, the extracted propagation velocity should be close to $c = 3\cdot10^8$ m/s, the propagation velocity in vacuum. Otherwise, if the sign indicates that the object is below the soil surface, the value of v should be around the values for the corresponding medium, e.g., from $5.5\cdot10^7$ m/s to $1.73\cdot10^8$ m/s in case of sand:

$$\pi_{3G}(M) = \exp\left(-\frac{(v-v_{\max})^2}{2\cdot h^2}\right), \tag{13}$$

where $v_{\max}$ is the value of velocity with the highest possibility for mines (here, for sand, it is $0.5\cdot(5.5\cdot10^7 + 1.73\cdot10^8) = 1.14\cdot10^8$ m/s, and for air, it is equal to c), and h is the width of the exponential function (here, $h = 6\cdot10^7$ m/s). If the extracted velocity value differs significantly from expected values for that medium, it can be expected that there is no object (so mine as well) indeed so, again, friendly objects can have any value of the velocity:

$$\pi_{3G}(F) = 1. \tag{14}$$

III. COMBINATION

The combination of possibility degrees is performed in two steps. The first one applies on all features derived from one sensor. The second one combines results obtained in the first step for all three sensors.

Let us first detail the first step for each sensor. For the IR sensor, the proposed combination is:

$$\pi_I(M) = \pi_{3I}(M) + (1-\pi_{3I}(M))\cdot\max(\pi_{1I}(MR), \pi_{1I}(MI))\cdot\max(\pi_{2I}(MR), \pi_{2I}(MR)). \tag{15}$$

Since mines can be regular or irregular, the safest way to combine information about regularity is by using a disjunctive operator (here the max), to be sure not to miss a mine. The two shape constraints (elongation and ellipse fitting) should be both satisfied to have a high degree of possibility of being a mine. Therefore they are combined in a conjunctive way (here using a product). Finally, the object is possibly a mine if it has a size in the expected range, or if it is not in the expected range, but satisfies the shape constraint, hence the final combination.

In case of GPR, it is possible to have a mine if the object is at shallow depths and its dimensions resemble a mine and the extracted propagation velocity is appropriate for the medium. Thus, the combination of the obtained possibilities for mines is performed using a t-norm, expressing the conjunction of all criteria. Here the product t-norm is used:

$$\pi_G(M) = \pi_{1G}(M)\cdot\pi_{2G}(M)\cdot\pi_{3G}(M). \tag{16}$$

For MD, as there is just one feature used, there is no first combination step and the possibility degrees obtained using (7) and (8) are directly used.

The second combination step is performed using the algebraic sum:

$$\pi(M) = \pi_I(M) + \pi_{MD}(M) + \pi_G(M) - \pi_I(M)\cdot\pi_{MD}(M) - \pi_I(M)\cdot\pi_G(M) - \pi_{MD}(M)\cdot\pi_G(M) + \pi_I(M)\cdot\pi_{MD}(M)\cdot\pi_G(M), \tag{17}$$

leading to a strong disjunction [5, 9], since the final possibility should be high if at least one sensor provides a high possibility. This operator is also chosen based on the fact that it is better to assign a friendly object to the mine class than to miss a mine.

IV. DECISION

The final decision is simply obtained by thresholding the fusion result for M. As almost all possibility degrees obtained at the fusion output are either very low or very high, the selected regions having very low values of $\pi(M)$ (below 0.1) are classified as F, and the ones with very high values (above 0.7) are classified as M. There are only a few regions at which the resulting possibility degree for M has an intermediary value. In these cases, as mines must not be missed, the decision is M. In future work, an alternative will be to derive the combination rule for F as well, compare the final values for M and F and derive an adequate decision rule.

V. RESULTS

The proposed approach has been applied to a set of known objects, buried in sand, leading to 36 alarmed regions, corresponding to 21 mines (M), 7 placed false alarms (PF, friendly objects) and 8 false alarms caused by clutter (FN, with no object).

The results are very promising, since all mines are classified correctly with the proposed approach, as can be seen in Table I. In each cell of this table, the number given in

TABLE I. THE CORRECT CLASSIFICATION RESULTS

Classified correctly	Sensors			
	IR	***MD***	***GPR***	***Fusion***
M *(total: 21)*	18 (18)	9 (9)	12 (13)	21 (21)
PF *(total: 7)*	0 (4)	0 (4)	2 (6)	1 (7)
FN *(total: 8)*	0 (1)	0 (0)	6 (7)	6 (8)

preprocessing step for further analysis, i.e. feature extraction and classification. The second fusion step is important, since a decision taken after the first one provides only 18 mines for IR, 9 for MD and 12 for GPR. This illustrates the interest of combining heterogeneous sensors. The results are also slightly better than those obtained previously using the belief function method (19 mines detected). This is due to the increased flexibility at the combination level. False alarms with no objects are correctly identified (6). The placed false alarms are not so well detected (only 2 are correctly recognized as friendly objects). This is not surprising since our model is designed in order to favor the detection of mines. This is also the type of results expected from deminers.

All results have been obtained with the models proposed in Section II, with the same parameters. It should be noted that although the general shapes of the possibility distributions is important and has been designed based on prior knowledge, they do not need to be estimated very precisely, and the results are robust to small changes in these functions. What is important is that the function are not crisp (no thresholding approach is used) and that the rank is preserved (for instance an object with a feature value outside of the usual range should have a lower possibility degree than an object with a typical feature value). There are two main reasons that explain the experienced robustness: (i) these possibility distributions are used to model imprecise information, so they do not have to be precise themselves; (ii) each of them is combined in the fusion process (Section III) with other pieces of information, which diminishes the importance and the influence of each of them.

VI. CONCLUSION

A novel method for fusion of features extracted from heterogeneous sensor data has been proposed, in the framework of a humanitarian demining project. The sensors, based on radar techniques, metal detectors or infrared images, provide complementary information about the nature of the observed object. We have shown that an appropriate modeling of the data they provide, along with their combination in a possibilistic framework allow better decision making, i.e. a better differentiation between mines and friendly objects. The decision rule is designed so as to detect all mines, at the price of a few confusions with friendly objects. This is a requirement of this particular application domain since it is obviously better to ask a deminer to search for an object that is finally friendly than to assure him that an object is friendly while it is a mine. Still the number of false alarms remains limited in our results.

Future work aims at more extensive testing of the proposed approach. It should be noted that the proposed modeling 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.

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