Bayesian Sensor Fusion for Land-mine Detection Using a Dual-sensor Hand-held Device

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Abstract—This work presents a methodology and practical implementation of sensor fusion for land-mine detection using a novel multi-sensor hand-held device composed by a triple coil metal detector and a gas sensor. The proposed approach consists on merging data from both sensors in order to reduce the false alarm rate, particularly by using odor information. A Bayesian approach is proposed for the sensor fusion. Results show a false alarm rate of 1.4 to 1, a mine detection rate of 100% and a mine localization mean absolute error of 3 cm. Furthermore the resulting mine presence probability distribution maps represent an important visualization tool for mine clearance hand-held device users.

I. INTRODUCTION

The UN estimates that there are currently more than 100 million active mines scattered over 70 countries. It would take over 1000 years to clear the entire world of mines provided that no additional mines are planted, however for every mine cleared, 20 are laid. Every year over 24000 people are killed or maimed by landmines. Humanitarian de-mining is a dangerous task which usually leads to victims among the men and women that devote their lives to this cause. Therefore, big efforts are being made by the scientific community towards developing systems that are able to detect land-mines efficiently while keeping the users safe [1]. One of the emerging technologies are systems that combine two devices, a Metal Detectors (MD) and a Ground Penetration Radar (GPR). Recently Sato et al developed the ALIS [2], a compact hand-held GPR and MD device, allowing the visualization of the output of the system in real time. Other examples of similar systems include the MINEHOUND proposed by Daniels et al [3]. Huang et al presented a six-legged robot for humanitarian de-mining that makes use of this hybrid technology [4].

Land-mines can be divided into three groups. Anti-tank mines react to ground pressures of over 1653 kg/m², what corresponds to approximately 150 kg of weight pressing the mine pressure plate, usually with a diameter near to 34 cm for this type of mine; moreover these mines can also be triggered by induction. These mines do not concern humanitarian mine clearance as they are normally not triggered by the weight of humans. Anti-personnel mines bounce up before exploding or explode in a certain direction and can also be divided in at least two subgroups: trip-wire mines (usually located above the soil and triggered by wire) and pressure mines (buried near the soil surface). These are lethal within a radius of about 30 m. Blast anti-personnel mines include less than 100 g of explosive. These are the most common type of mine due to the fact that they have a very simple construction and as a consequence are very cheap (down to one US dollar [5]). When dug or surrounded by grass they can be very hard to spot, making them very hard to locate. Blast mines are triggered by a ground pressure of about 10 kg/dm². These mines are not designed to kill, but to badly maim [5]. The problem of determining which characteristics can be used to locate a mine is extremely complex [6], most mines encapsulation are made of plastic and usually contain a low metal portion. However, mines differ from each other in construction materials, shape and size. When an operator uses only the metal detector to locate mines, a high false alarm rate (up to 1000 false alarms per mine found) are commonly triggered. Among the reasons for such a problem are high mineralized soils, harmless metallic objects, and also the low metal content in newer anti-personnel mines [7]. There is however one component a land-mine cannot be built without, something that is not otherwise found buried underneath the surface: explosives.

Using the odor of explosives for locating mines is not a novel idea. In fact the use of dogs for mine detection has increased dramatically [8][9] since the first humanitarian mine clearance programme was initiated in Afghanistan in 1989. In 2002, an estimated 750 dogs were at work in 23 countries [10]. The African Giant Pouched rat has also been successfully employed for odor-based mine detection [11]. On the downside using trained animals for mine clearance presents many challenges and problems [12]. Animals get tired and can be unpredictable. Furthermore they must be trained before they are able to locate mines. Recent developments in the artificial detection of explosive vapours [13] and also portable systems like “fido” from Flir systems [14], encourage the exploration of mine-clearance systems equipped with gas sensors. Therefore the focus of this paper is sensor fusion.

In this article we propose to use odor information to decrease the false alarm rate during land-mine clearance with a metal detector. The data provided by both sensors was fused using the proposed Bayesian methods. Additionally, a visual feedback system is also presented, which provides an important tool to avoid gaps on the covered area [15]. Visual feedback is obtained by processing position referenced measurements. The proposed system was validated on a real-like environment using a surrogate blast land-mine. In section II we introduce
the assemblage of our dual-sensor hand-held device.

II. DUAL-SENSOR HAND-HELD DEVICE

Our dual-sensor hand-held device was designed to detect safe versions of mines in the sense that they do not contain actual explosives. Surrogate mines containing alcohol were used (more on this in section IV-A), the motivation behind this is twofold, first the people involved in this project will not be exposed to real explosives, second MOX sensors are very cheap, reliable and also applicable for the detection of explosive vapors [16].

A. Metal Detector

The metal detector used in this work is Vallon VMP3 (figure 1), a pulse induction, three-coil metal detector. Pulse induction detectors do not excel at type of metal discrimination because the reflected pulse length of various metals are not easily separated. On the other hand they are useful in many situations in which other metal detector technologies would have difficulty, such as in areas that have highly mineralized soils. Furthermore pulse induction systems can detect metal objects at greater depths when compared to other metal detector technologies.

B. Gas Sensor

The gas sensor used in this work is a e2v MiCS 5521 metal-oxide (MOX) sensor. These solid-state sensors have the advantage of being small, having low power consumption, low in cost, and can be easily batch fabricated. The e2v MiCS 5521 targets the detection of reducing gases such as carbon monoxide (CO), hydrocarbons (HC), and volatile organic compounds (VOC).

An artificial nose was designed around the e2v MiCS 5521 having sensor compatibility in mind. The metal detector should have as little metal around its coils as possible system-wise, however the gas sensor should be placed close to the middle coil of the metal detector. The solution was to design an artificial nose with as little metal as possible. The nose itself is divided in two parts. Close to the coils of the metal detector is a small circuit board containing the e2v MiCS 5521 sensor and an 16-bit ADC coupled with a 3D printed plastic sampling chamber. A small Teflon tube connects a filter placed underneath the center coil of the metal detector to the entrance of the sampling chamber (see figures 2(a) and 1(b)). Underneath the metal detector, around the filter there is a funnel. The goal is to help blocking the wind in the area of the current scan. Moreover, an Arduino micro-controller is used, positioned near the handle of the metal detector, to interface with the i2c ADC and control the pump which aspires the air that passes through a Teflon tube and than the sampling chamber (figure 2(b)). Both sensors are able to operate properly in simultaneous, the artificial nose does not interfere with the metal detector readings while the pulses generated by the coils do not interfere with the gas sensor circuit.

C. Sensor Tracking

The sensors described previously are integrated into a single hand-held device. Estimating the pose of these sensors in a global reference frame is required to properly estimate the location of buried mines hence several different approaches were studied. The use of accelerometers and an optical position tracking system was investigated in the HOPE-Project [17]. Accelerometers are unable to completely solve this issue on
their own mainly due to the problem of position drift caused by the effects of noise during the double integration (to estimate velocity and position). In [18] an optical tracking method was studied and an average position error of 1.3 cm was achieved using a stereo camera setup.

Henceforth, we propose a two-stage approach regarding localization. A visual-marker is placed right on top of the metal detector antenna (see figure 1(a)), and optical tracking is then performed by a stereo pair of cameras. The cameras are fixed to a backpack carried by the user holding the dual-sensor hand-held device, thus the referential frame of the sensors can move in relation to the referential frame of the backpack. The transformation between both referentials is estimated by the optical tracking algorithm. The backpack is equipped with an GPS RTK (u-blox NEO-6) and an IMU (Xsens MTi). These sensors are fused using an Extended Kalman (EKF). The result is an estimation of the location of the backpack in the world referential with an error of about 1 cm. The transformation tree is thus hand-held device \( \rightarrow \) backpack \( \rightarrow \) world. Figure 4 shows a picture of the complete setup. Figure 3 contains a diagram of the system described. The block Sensor Fusion is further discussed in the next section.

III. SENSOR FUSION

A. Modelling

Let the data from the metal detector be \( LC \) for left coil, \( CC \) for center coil and \( RC \) for right coil; and the data acquired from the gas sensor be \( OD \). The sample acquisition is 10 Hz for all four variables, and the movement performed by the human arm had an approximated speed of 4 seconds per pass, a 0.75 m pass width was defined. Since the movement of the arm is continuous, and the tracking of the sensor is guaranteed, it is possible to assume that time increment is directly influencing spatial variations.

A dynamic Bayesian network is a tool of probabilistic inference along time, furthermore, the Bayesian posterior probability reflects the belief in the classified result (the probability of presence of a mine on the current time/location), based on the prior information (past acquired values) and on the current observations. Feature-level sensor fusion was also studied in [19] and [20], where preliminary results of fusion for pulsed and continuous metal detectors were presented.

The input variables \( (LC, CC, RC, OD) \) were modelled on a two-level dynamic Bayesian network structure, this network is represented in figure 5. The tree represents the causality order, since Bayesian theory is based on events, this tree can be interpreted as: the probability of a mine to “occur” along time/space is dependent of the probability of each one of the four leaf variables \( P(Mine|LC, CC, RC, OD) \) and also is dependent of the previous instant result. Moreover, conditional independence between the four leaf variables is assumed, this assertion is possible due to the fact that a data variation from one of the sensors does not directly affect any of the others.

The overall result is predicted at the belief variable \( Mine \), among the scope \( \{Mine_{yes}, Mine_{no}\} \). The resultant fusion map is the probability of \( Mine_{yes} \), which vary between 0% and 100% for each point of the scanned area.

B. Learning

For the inference to be possible, learning data needs to be provided. That means that a set of samples values of \( (LC, CC, RC, OD) \) need to be collected in the assured presence of a mine. The learning data was then collected via supervised learning. For several training datasets (explained in more detailed on section IV-B), the known positions of the mines were manually designated, and the data of our four leaf variables was collected and associated with a high probability of mine presence. The same process was repeated for clean areas, and areas with metal clutter to teach the system what is and what is not a mine.

C. Inference

The inference stage is where the posterior is generated, data \( D \) is obtained from the sensors, leading us to equation (1). Consider that \( y_1 \) to \( y_2 \) are the two possible mine states \( \{Mine_{yes}, Mine_{no}\} \), and each dimension of \( x \) corresponds to one of the previously described random variables, namely: \( LC, CC, RC \) and \( OD \). Since the learning data for \( Mine_{yes} \)
is unimodal per each sensor, assume that \((X_1, ..., X_n)\) are independent given \( Mine \) and \( X_i \) is determined according to (2).

\[
D = ((x_1, y_1) ... (x_n, y_n)), x_i \in \mathbb{R}^d, y_i \in \mathbb{R}
\]  

(1)

\[
X_i \sim N(prior^T x_i, \sigma^2)
\]  

(2)

At first, \( prior \sim U(1/n) \), however throughout the iterations, the posterior of \( t-1 \) becomes the prior on \( t \). Finally, by using the Bayes’s rule, we have the posterior equation (3) where \( x_m \) is the most recent sensory data acquired.

\[
P(Mine|x_m) = \frac{\prod_{i=1}^{n} P(x_i|Mine) \ast P(Mine)}{P(x_m)}
\]  

(3)

The output of the Bayesian estimation is then scattered in space. The last step of the sensor fusion is to fill in the gaps by interpolating the available data. This is accomplished using Kriging, an interpolation method commonly used in geostatistics. Kriging is based on the notion that the value at an unknown point in space should be the average of the known values at its neighbors weighted by the variogram of the distance to the unknown point [21]. The output of the sensor fusion described in this work is a mine presence probability distribution map.

IV. EXPERIMENTAL VALIDATION

A. Surrogate Mines

Surrogate mines contain all the relevant characteristics of a real mine, are designed to realistically model the physical shape, size, fuse principles and trigger force characteristics of real land-mines. Surrogates provide an important tool for evaluating the effectiveness of equipment used in mine clearance operations and for training de-miners under safe conditions. Recently surrogate mines that also mimic the response of explosives to GPRs have been developed, allowing for systems containing these sensors to be tested without the actual presence of explosives. However there are currently no manufacturers producing surrogate mines that mimic real mines as far as odor is concerned. In this work we are not interested in reproducing the vapours released by the explosives in land-mines, but to mimic the release process, in fact we want to augment and speed up the process in order to focus on the aspect of sensor fusion. To achieve this goal we propose to fill the surrogate mine with a textile immersed in alcohol. The top cover is then drilled in several places to allow the quick evaporation of the alcohol. The mine is then buried close to the surface. The alcohol will quickly evaporate and will be easily detectable at the surface by the artificial nose presented in section II-B.

(a) The M114 anti-personel blast mine closed.

(b) The mine opened exposing the alcohol embedded textile used as a surrogate for the vapours released by the explosives found in mines.

Fig. 6. The surrogate M114 anti-personal blast mine used in this work.

B. Experiments

A dataset for training and validation was extracted outdoors using the setup presented in section II. Three scenarios were designed for the dataset extraction. All three scenarios consist of a \( a = 0.75 \times 0.85 \) area of dirt containing one or more buried objects. Scenario 1 (figure 7(a)) contains a M114 surrogate mine, a small metal pin similar to the one found inside the M114, a can of soda and three metal screws. Scenario 2 (figure 8(a)) contains the M114 surrogate mine and the previously mentioned metal pin. Scenario 3 (figure 9(a)) contains the soda can, the small pin and the three metal screws. The objects used for the three scenarios can be seen in figure 6(a). A user performed a sweep for each scenario by...
moving the hand-held device from $x = 0$ m to $x = 0.75$ m and making small increments along the y-axis after each passing (allowing for the scans to overlap), this sweep movement is represented by a red arrow in figure 7(a). The goal was to perform a coverage of the area. A set of 10 scans were performed for each scenario on a total of 30 scans. The dataset was randomly divided in three parts and cross validation was performed, the first part of the dataset was used for training and the second part for validation followed by the opposite. After validating the learning in both directions, we proceed testing the third part. Samples of the results can be found in the following section.

V. RESULTS AND DISCUSSION

The maps in figures 7, 8 and 9 show the results for the covered area scanned with our dual sensor hand-held device. The minimum and maximum values of the presented results were adjusted independently for each sensor and the metal detector maps were constructed with the center coil only. Since the scans were manually executed (human arm) it is normal to notice some imprecision around the edge of the covered area, visible as black margins. Table I, contains the values of the false alarm rates for each sensor independently from each other, and the same measurement for the resulting fusion; the error indicated in this table is the respective mine localization absolute error, for each scenario, computed for metal detector only and for the fusion map.

For scenario 1 (figure 7(b)) it is possible to see that the mine and the small metal pin were detected as low metal structures, represented by the dark blue color; in 7(d) we can verify that although the odor plume has spread with the wind, as shown in figure 7(c), the results of the proposed Bayesian fusion still kept a peak of probability at the correct mine’s location, reducing the false alarm rate in comparison to only using the
metal detector. For scenario 2, and due to the fact that we only had 2 low metal objects on the scene, the metal detector did not provide enough information to distinguish them, the odor plume was probably spread by the wind, however, since the fusion probability of mine depends on the combination of both sensors, in this case the fusion still holds a low localization error. The third scenario represents an area with no mines, so although the metal detector alone would give false alarms, since the odor sensor did not perceived any sign of "explosives" during this scan, the probability distribution map was influenced and did not pass on more than 12% of probability, thus resulting in a zero false alarm rate for this scenario. Results show a small increment in the error of the position, when comparing the Bayesian fusion with the metal detector generated map; this is due to the fact that the gas takes a small amount of time to travel along the tube from the inlet to the sampling chamber. This small period of time generates a dislocation of the odor position on the consolidated map.

VI. CONCLUSIONS

The proposed Bayesian fusion significantly reduced the usual high false alarm rate generated by the mine-detector alone to 1.4 to 1, a mine detection rate of 100% and a mine localization mean absolute error of 3 cm were also achieved. The proposed system also presents a significant advantage in comparison to the existing MD/GPR hand-held systems as it allows both sensors to run in simultaneous, speeding up the coverage process. The resulting mine presence probability distribution maps provide a good visual feedback to the user by indicating the location of the mines in realtime. The same technology will also allow to verify if the user is performing the scan at the speed recommended by the mine-detector manufacturer and if the ground is being completely covered by the scan. Future work will see the integration of a gas sensor that reacts to explosive vapors. Furthermore the system will also be integrated into a mobile robot for autonomous mine clearance.

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