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Paper:

Development of an Automatic Landmine Detection and Marking System for the Demining Robot Gryphon

Alex M. Kaneko and Edwardo F. Fukushima

Tokyo Institute of Technology
2-12-1 Ookayama, Meguro-ku, Tokyo 152-8550, Japan
E-mail: alex@robotics.mes.titech.ac.jp
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Mechanical systems or robots are designed to support human operators during complex and dangerous tasks such as demining operations. Even though the robot Gryphon was created to automate these operations, some of its tasks still rely greatly on the human operator, who has few or no assisting tools to perform efficient decisions. During the landmine detection and marking task in special, the operator is totally responsible for analyzing the scanned data and pointing the potential targets, which makes the system performance unstable and vulnerable to human factors. This article proposes an automatic method for finding potential targets, which the operator has the simple role of accepting or not the decisions taken by the automatic method. Experimental results showed that time duration, POD and FAR were greatly improved compared to the former methods.

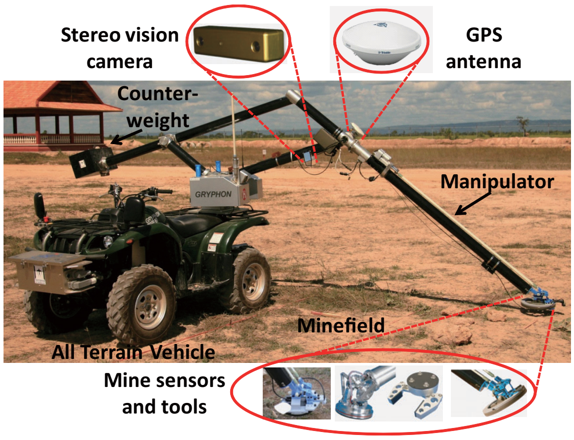


Fig. 1. Demining robot Gryphon overview.

Keywords: demining robots, automatic method, landmine detection, marking task

1. Introduction

Landmines are potential threats that have existed for many decades. While the international community is cooperating in taking preventive actions (such as banning the use and spread of those weapons), efforts in remedial actions (such as neutralization and humanitarian assistance) have also been applied. However, landmine neutralization is dangerous, costly and tedious. Tools are still precarious, and most of the commonly used landmine sensors suffer from high rates of false positives [1].

The Tokyo Institute of Technology developed a semi-autonomous mobile robot called Gryphon-V (**Fig. 1**), to assist the mine detection process. Its manipulator can be equipped with many types of mine detectors and the normally used one being based on Electromagnetic Induction (EMI) sensor, and is able to automatically scan over rough terrains, record data and display the resulting sensor images to the operator, who can then mark suspect spots. The developed robot has been tested in several test fields such as Croatia and Cambodia, showing promising results [2].

Several other attempts have been developed in the world, in automating or assisting human deminers in the scanning process: legged robots [3], wheeled vehicles, tracked vehicles and even suspended inspection tools [4] have been researched. However, research is often focusing on one particular aspect (locomotion or sensing) leading to a weak system integration which results in an ineffective and slow demining operation.

For the Gryphon system in particular, most attention has been paid in the mechanical and electrical design to build a rugged system, and also special consideration in sensing imaging for maximization of Probability Of Detection (POD) and minimization of False Alarm Rate (FAR) for the mine sensing tasks. This proved to be effective, and the latest tests in Croatia (**Fig. 2**) showed that the Gryphon system has the potential to be “as good as humans or even better” considering POD and FAR rated. In this test, all field data was recorded, composed of a total area of 344 m^2 and 228 targets, and during a second evaluation done in laboratory with enhanced visualization methods, the best result (referred as “Gryphon E, 2007” in [2]) was achieved.

Even though Gryphon permits the automation of great part of the demining operation, the task of identifying potential targets is still done by a human operator, and consequently the POD and FAR rates are vulnerable to human factors. In this article, an automatic method for find-

Fig. 2. Gryphon undergoing tests in Benkovac, Croatia.

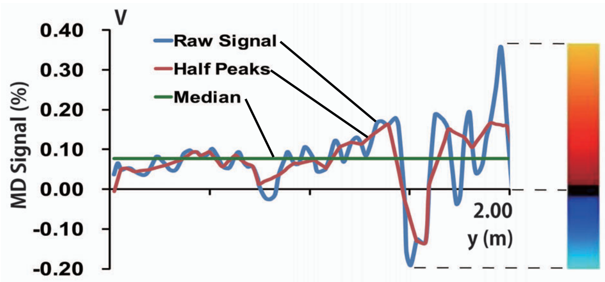


Fig. 3. Example of signal and different filters.

ing potential targets is introduced and its performance is compared to the best result obtained by a human operator (Gryphon E, 2007).

EMI based mine detectors sensors are prone to noises, generated by the soil or metal fragments nearby. **Fig. 3** shows an example of one scan line (**Fig. 4**) of a Minelab F3 metal mine detector (MD) [5] signal obtained in the test field. Even though there are no landmines around, it can be observed that the signal is oscillating around a positive value (offset) of 0.1%. For compensating the offset, before starting the demining operation deminers perform the so called "ground compensation" [6], which the method varies from different makers.

However, from **Fig. 3**, it is possible to see that the noise suffers variable fluctuations, caused by changes in the soil patterns and also by subtle variations in the scan height. The "ground compensation" cannot balance this variable offset, as shows the 2D signals image in **Fig. 5(a)**. The MD has two channels, "A" and "B," which the information is combined to form the final output "V_{out}," which in turn is stored in an array. Even though the normal method adopted with the MD is as Eq. (1) [7], the basic method applied in Gryphon is as Eq. (2), where the output is function of n. It is a parametric variable which is related to an (x, y) position and is sorted according to the data acquisition sequence, the scanning path, as **Fig. 4**.

The 2D image (shown in colors to the operator, but

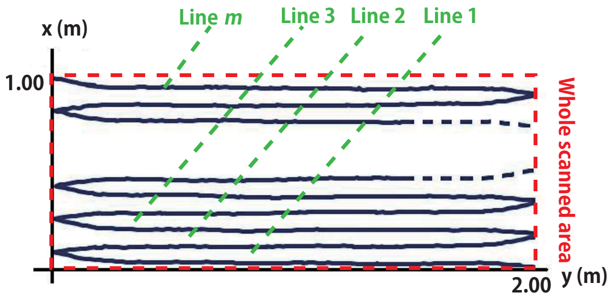


Fig. 4. Lines of a scanned area.

displayed in black and white in this hardcopy) is then composed by attributing colors (shown in the color bar in **Fig. 3**) to the MD signals in the array, where 0 values are represented in black, the maximum value in yellow and the minimum in light blue.

$$V_{out} = \max(|V_A|, |V_B|) \quad \ldots \ldots \ldots \quad (1)$$

$$V_{out_a}(n) = \begin{cases} V_A(n), & \text{if } \max(|V_A(n)|, |V_B(n)|) = |V_A(n)| \\ V_B(n), & \text{if } \max(|V_A(n)|, |V_B(n)|) = |V_B(n)| \end{cases} \quad (2)$$

2. Sensor Pre-Processing and Filtering

In the best result with Gryphon in [2], changes in the data processing led to better visualization of the targets compared to the normal method so far adopted. The signal offset was compensated using the median value of the signals in each scanned area. However, the median value is not the most suitable since the noise along the area is variable as already shown in **Fig. 3**.

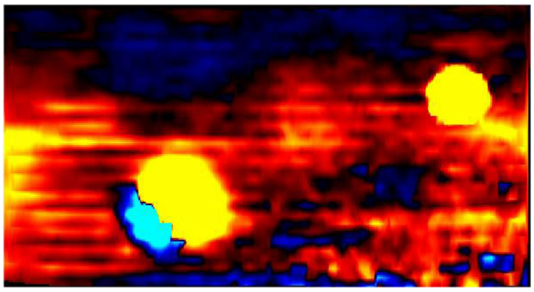
2.1. Proposed Filters

For compensating the variable offset, for instance, a filter through the signal in an average value (middle of two consecutive peaks), following the noise patterns could be applied. In this research, many other approaches for filtering the signals were implemented and analyzed. **Fig. 5** shows the corresponding 2D representation in the user interface of a data filtered with different methods: a) basic method, b) half-peaks offset, c) half-peaks as result d) median of the whole area and e) median of each line of the area.

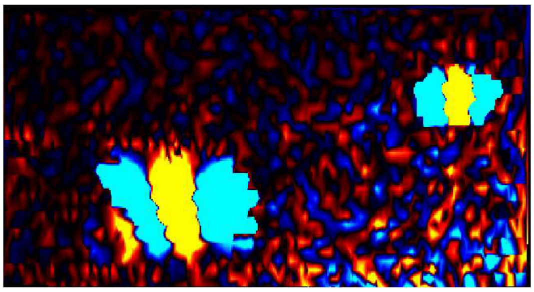
Method "a)" is the one used in the first evaluation during the test field in [2], described in section 1. Method "b)" uses the offset (V_{HP}) calculated in the middle of two peaks (already shown in **Fig. 3** and detailed in the flowchart in **Fig. 6**) and subtracts the values of the raw signal (V_{RS}):

$$V_{out_b}(n) = V_{RS}(n) - V_{HP}(n) \quad \ldots \ldots \ldots \quad (3)$$

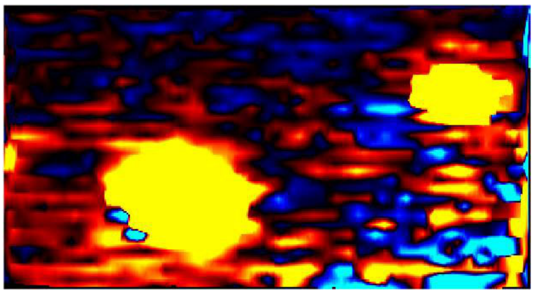
Method "c)" displays the obtained offset line itself:



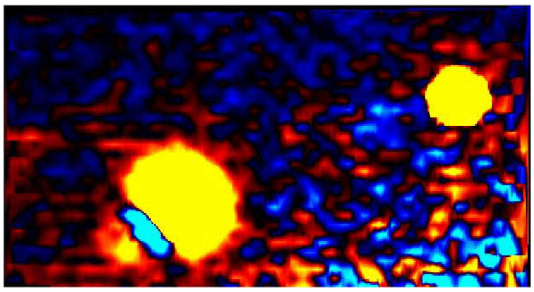
(a) Basic



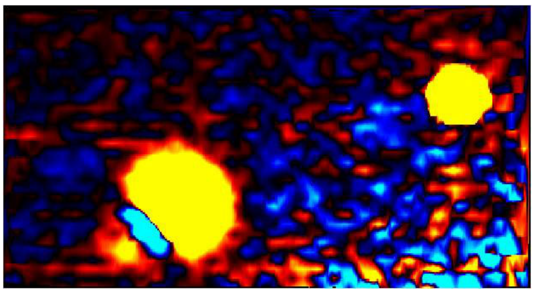
(b) Half-peaks offset



(c) Half-peaks



(d) Median of an entire area



(e) Median of each line in an area

Fig. 5. Resulting images of the filtering methods.

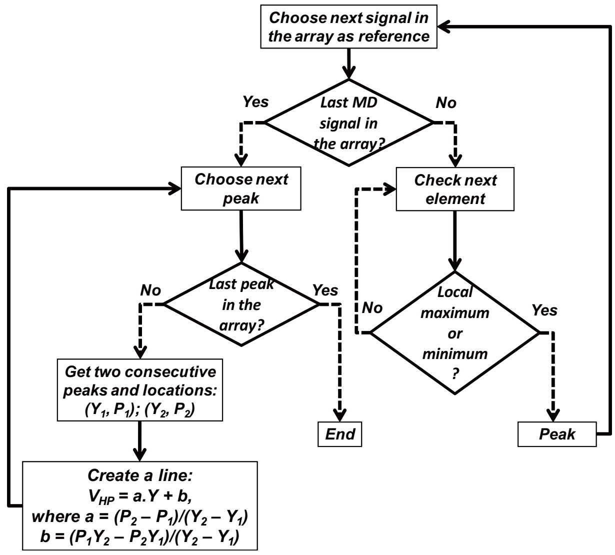


Fig. 6. Half-peaks algorithm.

Table 1. Filters comparative table.

Method	T1	T2	T3	ZC
Basic (a)	○	×	○	83.5
Half-peaks offset (b)	○	×	○	533.5
Half-peaks (c)	○	○	○	147
Area median (d)	○	○	○	222
Each line median (e)	○	○	○	222.5

T1, T2, T3: Size threshold criteria of targets 1, 2 and 3
ZC: Number of Zero Crosses (per m^2)
Size criteria: ○ = Satisfied; × = Not satisfied

$$V_{out_c}(n) = V_{HP}(n) \quad \ldots\ldots\ldots \quad (4)$$

Method "d)" is the one applied during the second evaluation in [2], where the median of the whole scanned area (**Fig. 4**) is used as offset (V_{MA}), as shown in Eq. (5). The algorithm for computing the median is based on the Bubble sort [8] followed by a simple median calculation.

$$V_{out_d}(n) = V_{RS}(n) - V_{MA}(n) \quad \ldots\ldots\ldots \quad (5)$$

Method "e)" is a similar approach, but calculating the median for each line of the whole area (V_{ML}):

$$V_{out_e}(n) = V_{RS}(n) - V_{ML}(n) \quad \ldots\ldots\ldots \quad (6)$$

Table 1 shows a pre-evaluation of the methods. According to the database information (shown in **Fig. 7**), the area contains three targets ("T1," "T2" and "T3"). For a good identification, the first adopted requirement is that the targets have a minimum size so they can be clearly distinguished from noises. In the **Table 1**, "T1," "T2" and "T3" indicate if the resulting sizes are above a determined threshold. Another adopted criteria is the number of zero crosses (variations from positive to negative signals), which a high number indicates that the filter is reaching a good offset level. After computing the sizes

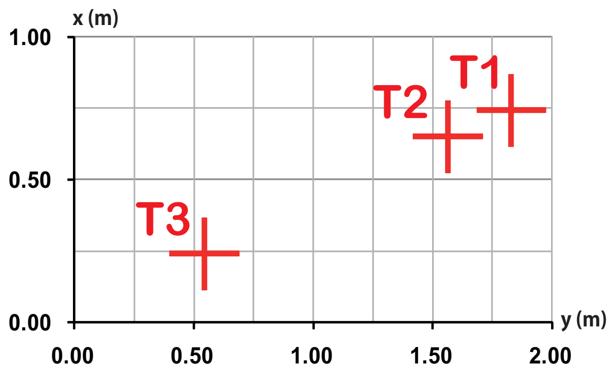


Fig. 7. Database information.

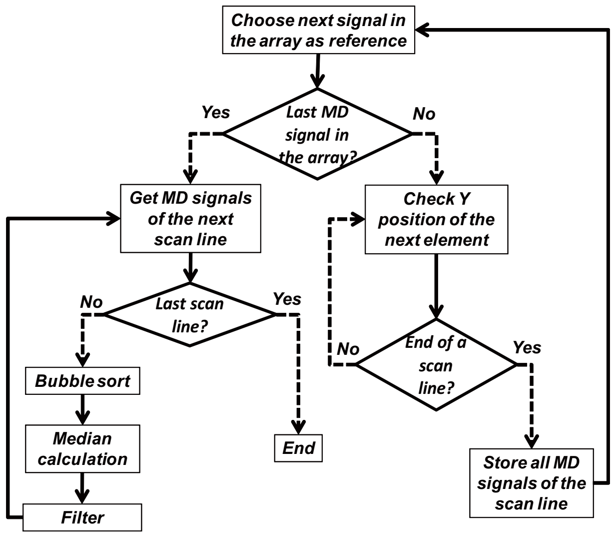


Fig. 8. Algorithm of the best pre-evaluated filter "e)."

and zero crosses, it can be verified that all filters satisfy the size threshold for targets "T1" and "T3," but "T2" was not verified in filters "a)" and "b)." The half-peaks offset showed the best offset level with the highest number of zero crosses (as expected), but finally it distorted "T2" making the visualization unclear. Finally, among the filters that satisfy the threshold level for all targets, the one with highest number of zero crosses is "e)," detailed in the flowchart in **Fig. 8**. Even though targets can be equally seen as in "d)," it is possible to verify more meshes (red and blue alternations in original image) in the upper regions, which helps avoiding false positives.

2.2. Filter Evaluation

The proposed filter "e)" was evaluated and compared with the basic method "a)." Part of the test field data was chosen and 6 subjects non-familiar with demining marked the targets in laboratory. Before the experiment, the subjects received instructions on how to operate the user interface and how to look for potential targets. All

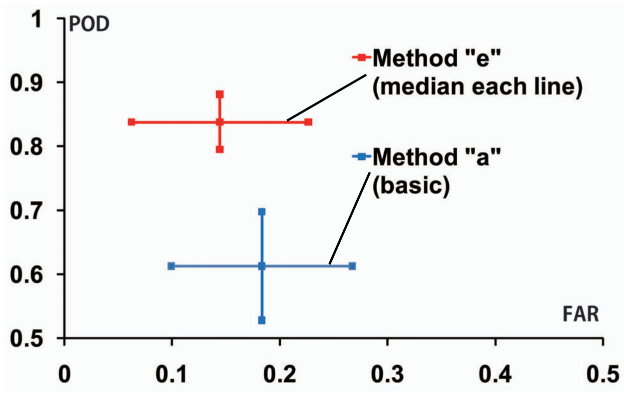


Fig. 9. Experiment results with 95% confidence limits.

Table 2. Average time per m^2.

Method "a)"	Method "e)"	Automatic Method
9.6 s	19.95 s	3.33 s

subjects used the same computer (Windows 7, Intel Core i7, 4 GB RAM), equipped with a Gryphon user interface that was slightly modified for the experiment. Unnecessary command buttons were hidden and all experimental data was pre-loaded in the interface; the subjects had only to shift between one data and another by pressing implemented buttons. Each time these buttons were pressed, all marked targets were automatically stored in a data file. 3 subjects used method "a)" and other 3 method "e)." The experiment was repeated for each group in two different days. The time for completing the whole data of each subject was recorded and an average time for completing each area (m^2) (excluding data loading time) was calculated. The results stored in data files were compared to the database, and POD and FAR of each subject were calculated.

Figure 9 shows the average results for each method [9], which the increase in performance using method "e)" can be clearly noticed. The only disadvantage occurring in method "e)" can be seen in **Table 2**. Since it permits more information visualization, it requires longer decision time from the subjects comparing to method "a)."

3. Automatic Targets Detection and Marking System

The previous section introduced a method that enhances POD and FAR in case a human operator is performing the landmine detection task. Even though the performance was improved, the time duration continued being a drawback, and human factors still persist. This section introduces an automatic method for landmine detection and marking.

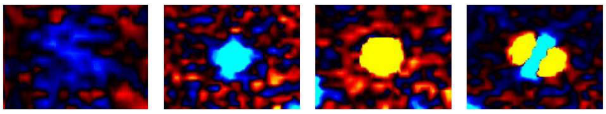


Fig. 10. Examples of target images.

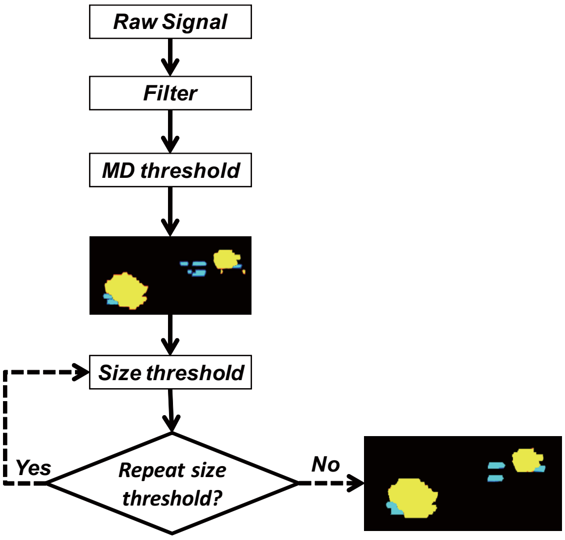


Fig. 11. Targets perimeter searching algorithm.

3.1. Targets Perimeter Searching Algorithm

The implemented algorithm is mainly based on the MD signal amplitude and its represented size in the 2D graph. These two parameters were adopted by analyzing all data, and by previous knowledge of potential targets (**Fig. 10**). The algorithm is shown in the flowchart in **Fig. 11**.

The algorithm was tested with all data from the test field and with different filters. It was verified that using filter "c)" followed by filter "d)" the algorithm performed better, since this filter removes great part of the oscillations and smooths the data, compensating the offset afterwards. For the tests, the right-lower part of the data was not used since it suffers a strong influence of a systematic error existing in the system (which has been removed in the latest system). The result can be seen in **Fig. 12**. According to the information in the database the noise was correctly erased, and the remaining signals represent in fact the perimeter of potential targets.

3.2. Targets Center Searching Algorithm

An algorithm for finding the theoretical location of a target, where the maximum MD signal is located, is proposed.

The algorithm starts with the first element in the MD signals array, used as reference, and looks inside a radius for the surrounding point which has the maximum value. The point with maximum value is the new reference, and the procedure is repeated until no bigger signal is located. These steps are repeated until all MD signals are used as starting point (**Fig. 13**).

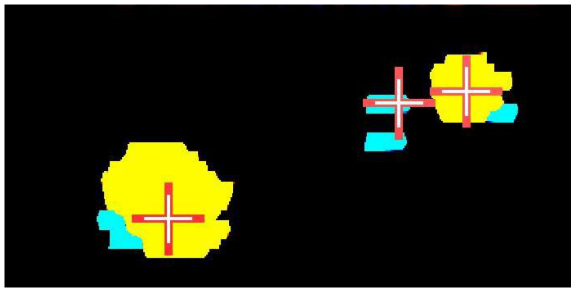


Fig. 12. Resulting image after applying the targets perimeter and targets center searching algorithms.

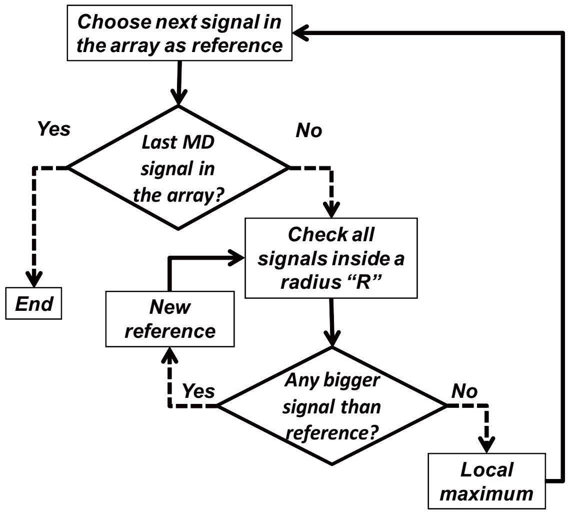


Fig. 13. Targets center searching algorithm.

4. Results

According to the database information, the marks are correctly placed by the above algorithms (**Fig. 12**). Using the developed algorithms, the calculated POD and FAR for all data used is shown in **Fig. 14**. Comparing to the previous best result (Gryphon, E, 2007), there was a slight improvement in the POD (from 93% to 96%) and a negligible increase in FAR (from 0.12 to 0.14).

As indicated in **Table 2**, the average time for each square meter done with the automatic method is about 3.33 s, which greatly reduces the operation time compared to the subjects in the experiment in section 3 (which time varied from 9.6 to 19.95 s for completing each m^2). Another major advantage is the correct location of the input marks, which done manually by the operator could generate errors.

5. Discussion

The use of pre-processing techniques of the data showed to be effective during the landmine detection, increasing the POD and slightly decreasing the FAR of the subjects. The only disadvantage is in the average time that

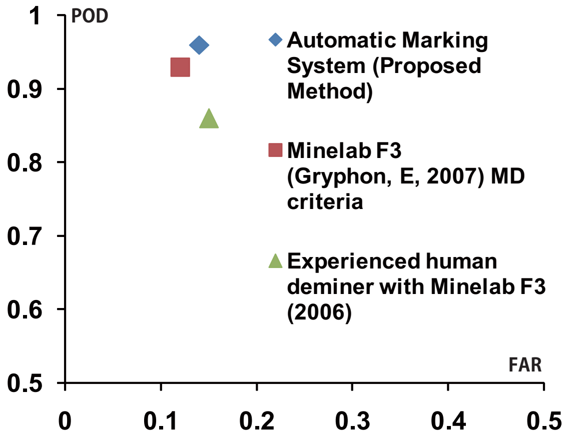


Fig. 14. Comparison between the best result in the test field and automatic marking system [2].

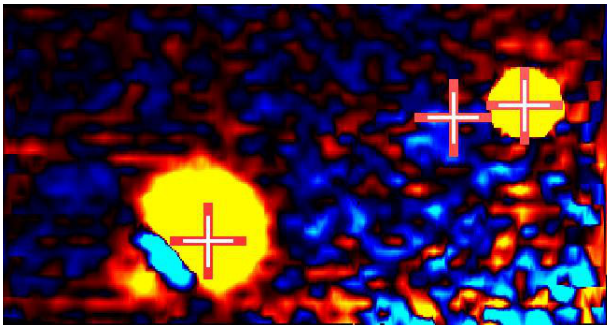


Fig. 15. Final output image displayed to the operator.

subjects took for the new method (almost 2 times more). This is a trade-off due to the increase of information, requiring more attention and decision times.

On the other hand, the automated marking system proved to be very efficient in terms of time, POD and FAR. While human operators have inconstant performances, the automated marking system displays reliable results under any circumstances, excluding great part of the human factors in the system. Moreover, it is much faster than the former manual methods (about 6 times), reaching an average level of “as good as an experienced human deminer” considering the POD and FAR. Another major advantage of the automated method is that it also points the location of the targets center with higher accuracy and precision, compared to a human operator.

Therefore, the landmine detection and marking system proposed in this research implement a fully automatic method, displaying the output image shown in **Fig. 15** to the operator. In this scheme, the operator is provided with: a) pre-processing filters for better visualization of the signals and b) automatic marking system for finding and marking potential targets. After the detection, the robot can start painting the location of the targets on the ground (**Fig. 16**). Nonetheless, it is left to the operator the option of adding or removing marks, if necessary.

Fig. 16. Marking the location of a target.

6. Conclusions

An automatic method for the landmine detection and marking system of the demining robot Gryphon was proposed, and comprises of a) offset filtering, b) perimeter searching algorithm and c) targets center searching algorithm. According to experiments done with data from the real test field, the implemented algorithms and methods proved to be valid, for they reach satisfactory POD and FAR levels, being comparable to experienced human deminers. In addition, with the automatic method, errors caused by human factors are reduced, and time duration is greatly improved. This method was implemented and tested with Gryphon-V equipped with the Minelab F3 metal mine detector. However, the methodology is quite general and can be extended to different types of mine detectors.

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Name:
Alex M. Kaneko

Affiliation:
Department of Mechanical and Aerospace Engineering, Tokyo Institute of Technology

Address:
2-12-1 Ookayama, Meguro-ku, Tokyo 152-8550, Japan

Brief Biographical History:
2008 Bachelor Engineering degree in mechanical engineering (major in automation and systems) from Polytechnic School of the University of Sao Paulo (EPUSP), Brazil
2011 Master Engineering degree in Mechanical and Aerospace Engineering from Tokyo Institute of Technology (TITECH), Japan
2011- Ph.D. Candidate in Mechanical and Aerospace Engineering from Tokyo Institute of Technology (TITECH), Japan

Main Works:
• A. M. Kaneko, M. Marino, and E. F. Fukushima, "Humanitarian Demining Robot Gryphon: New Vision Techniques and Optimization Methods," IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), Taipei, Taiwan, October 2010.
• A. M. Kaneko and E. F. Fukushima, "Basic Studies on Computer-Aided Marking Task Operation for the Humanitarian Demining Robot Gryphon," Int. Symposium on Intelligent Systems (iFAN), Tokyo, Japan, September 2010.

Name:
Edwardo F. Fukushima

Affiliation:
Department of Mechanical and Aerospace Engineering, Tokyo Institute of Technology

Address:
I1-68, 2-12-1 Ookayama, Meguro-ku, Tokyo 152-8550, Japan

Brief Biographical History:
1994- Assistant Professor, Tokyo Institute of Technology
2001- Visiting Researcher, Stanford University
2004- Associate Professor, Tokyo Institute of Technology

Main Works:
• E. F. Fukushima, M. Freese, T. Matsuzawa, T. Aibara, and S. Hirose, "Humanitarian Demining Robot Gryphon: Current Status and an Objective Evaluation," Int. J. on Smart Sensing and Intelligent Systems, Vol.1, No.3, September 2008.

Membership in Academic Societies:
• The Japan Society of Mechanical Engineers (JSME)
• The Robotics Society of Japan (RSJ)
• The Society of Instrument and Control Engineers (SICE)