論文 / 著書情報
Article / Book Information

Title	Landmine Buried Depth Estimation by Curve Characterization of Metal Mine Detector Signals
Author	Alex M. Kaneko, Gen Endo, Edwardo F. Fukushima
Journal/Book name	IEEE/RSJ International Conference on Intelligent Robots and Systems(IROS), , , pp. 5327-5332
Issue date	2013, 11
DOI	http://dx.doi.org/10.1109/IROS.2013.6697127
URL	http://www.ieee.org/index.html
Copyright	(c)2013 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other users, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works for resale or redistribution to servers or lists, or reuse of any copyrighted components of this work in other works.
Note	このファイルは著者（最終）版です。 This file is author (final) version.

Landmine Buried Depth Estimation by Curve Characterization of Metal Mine Detector Signals

Alex M. Kaneko[1], Gen Endo[2] and Edwardo F. Fukushima[3]

***Abstract*— Humanitarian demining aims at clearing landmine affected areas, but the current manual demining techniques are still slow, costly and dangerous. Discrimination methods for distinguishing between real mines and metal fragments would greatly increase efficiency of such demining operations, but none practical solution has been implemented yet. Important information for discrimination are the depth which targets are buried, so estimation methods of this physical property are desired. In this research, a new, accurate and fast method based on Spatially Represented Metal Mine Detector Signals for estimating metallic targets depths using Metal Mine Detectors is presented, which takes advantage of high precision scanning of the minefield using robotic manipulator.**

I. INTRODUCTION

Landmines removal/neutralization is very costly, dangerous and time-consuming. There are many different methods for demining: a) animals [1][2], b) heavy machines [3] and c) metal detectors [4], but all of them are still inefficient and suffer from high false alarm rates (FAR). To support the demining process, Tokyo Institute of Technology developed a semi-autonomous mobile robot, Gryphon (Fig. 1), which can automatically scan with mine sensors over rough terrain, record data and mark suspect spots on the ground, proving to be as good or even better than human operators when using a Metal Mine Detector (MMD) [5]. However, FAR improvements are still desired for making demining operations faster and more efficient.

Several different approaches have been conducted for reducing FAR, such as: [6][7][8][9][10]. Particularly, [11][12] rely on a previously built database for discrimination, but the discrimination is as limited as the number of data in the database. [13][14] utilize a combination of two sensors ("dual-sensor"), a MMD with a Ground Penetrating Radar (GPR). However, a pre-knowledge of buried depths is needed from the operator and FAR arises. [15] uses image processing and MMD signal surface area and volume calculation for estimating size and material of a detected target, followed by depth estimation inclining the MMD in different angles. However, as work [12], it requires information from several depths (layers) for discrimination, considerably slowing down the demining operation. The depth landmines are buried permits quick discrimination of anti-personnel (shallow depths) and Anti-Tank (AT) landmines (deeper). Moreover, depth information permits easier use of GPRs. The material which targets are composed is also a valuable information for discrimination, since landmines are in great part made of steel.

In this work, a new, accurate and fast method for depth estimation of metallic targets using MMDs is presented, which takes advantage of high precision scanning of the minefield using robotic manipulator as shown in Fig. 1.

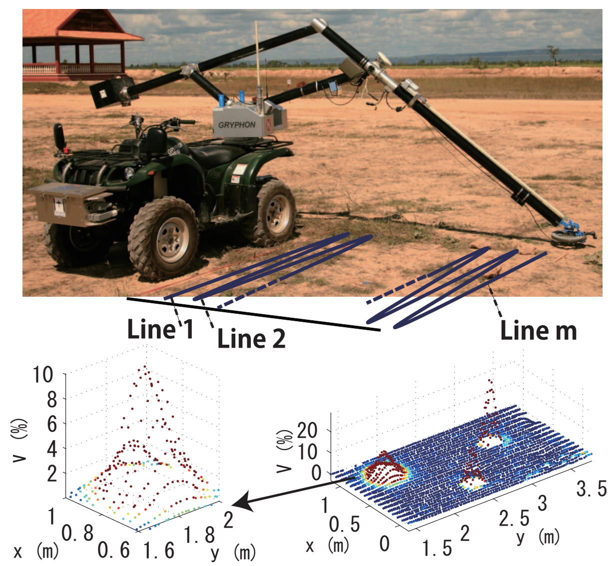

Fig. 1: Demining robot Gryphon and detected signals

II. PROPOSED CURVE CHARACTERIZATION METHOD

A. *Spatially Represented Metal Mine Detector Signals*

Humans usually scan areas swinging the MMD sideways advancing in steps, which the detected signals (called here as V(%)) are transformed into sound and the signals with corresponding positions must be memorized. Robots can also deal with the same task, but with higher precision and repeatability, easily associating signals with the spatial position, processed in real-time and shown to the operator (Fig. 1).

In this research, we define "Spatially Represented Metal Mine Detector Signal" (SRMMDS) as a 3D representation of the MMD signal (Fig. 2). It can be observed the SRMMDS

*This work was supported by JSPS KAKENHI Grant Number 25303012.
[1]Alex M. Kaneko is with Faculty of Science and Engineering, Department of Mechanical and Aerospace Engineering, Tokyo Institute of Technology, Japan. alex@robotics.mes.titech.ac.jp
[2]Gen Endo is with Faculty of Science and Engineering, Department of Mechanical and Aerospace Engineering, Tokyo Institute of Technology, Japan. gendo@mes.titech.ac.jp
[3]Edwardo F. Fukushima is with Faculty of Science and Engineering, Department of Mechanical and Aerospace Engineering, Tokyo Institute of Technology, Japan. fukusima@mes.titech.ac.jp

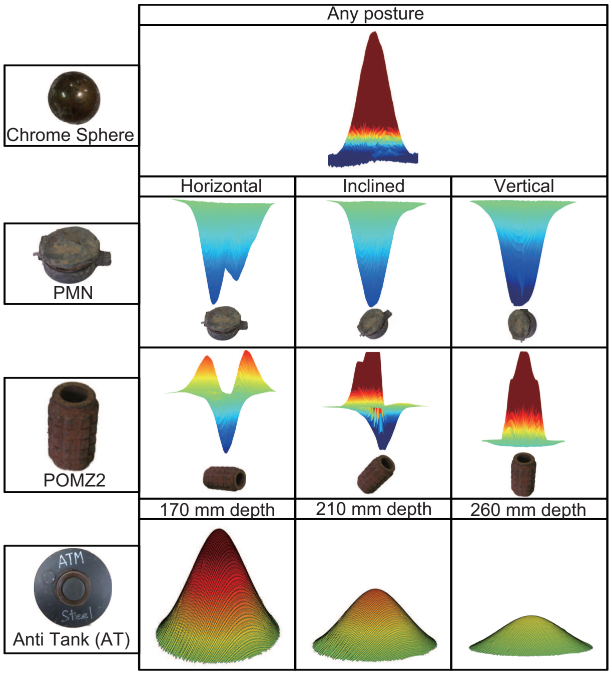

Fig. 2: SRMMDS for different targets and conditions

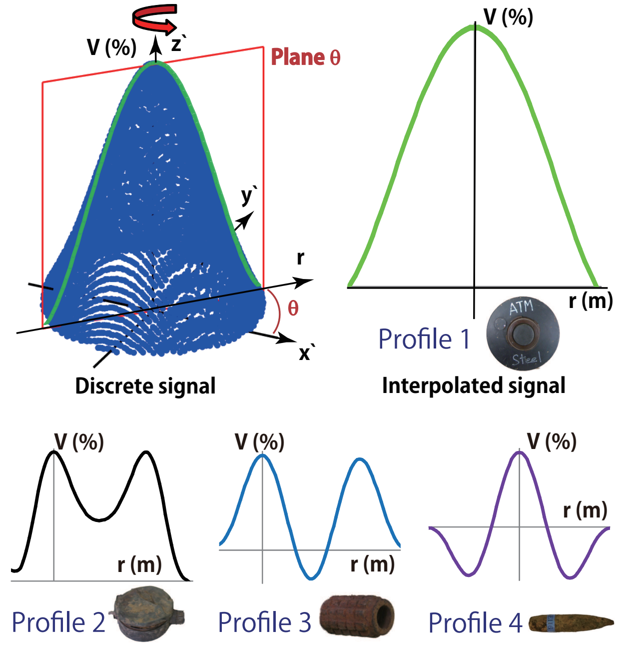

Fig. 3: Cutting plane and main characteristic curves

change according to the target's properties such as size, shape, buried depth and posture, composing very strong characteristics. This suggests that if a database with these characteristics is composed, discrimination could be done by comparing a SRMMDS obtained in the minefield to the closest match in the database.

B. Main Axis and Main Characteristic Curves Definition

For each detected SRMMDs, we set a local coordinate O-xyz', with an x'-y' plane parallel to the MMD scanning plane and z' axis passing through the maximum absolute value of the SRMMDS. Consider an orthogonal plane P_θ to the x'-y' plane that passes through the z' axis and with an angle θ relatively to the x' axis. The characteristic curve defined in this work V(r(θ)) (Fig. 3) refers to the new generated curve, the contour of the intersection of the P_θ with the SRMMDS, with new axis r(θ).

Fig. 3 shows that the characteristic curves for physically symmetric targets as an AT landmine don't change for all θ, and the SRMMDS can be simplified to one characteristic curve. For non-symmetric targets, characteristic curves change drastically according to θ, but simplifications to a set of minimum curves can be done. As shown in Fig. 2, for a particular θ which coincides with the target's longest direction, the curve has many inflections and peaks in relation to other angles. In this work, the characteristic curve with most inflexions and/or peaks is defined as "main characteristic curve" and its axis θ as "main axis", which four main Profiles are possible (Fig.3).

Characteristics curves can be represented by several mathematical relations such as splines and polynomials, in the form of V = f(r(θ)). Since the number of inflections of the characteristic curves is limited, we propose the use of polynomials in the form of eq. 1, keeping the signal characteristic and filtering the noisy raw data. All signals are translated so that the maximum peak is located in r=0 and a_0 has the maximum absolute MMD value of the signal.

$$f(Y) = a_0 r(\theta)^0 + a_1 r(\theta)^1 + a_2 r(\theta)^2 + ... + a_n r(\theta)^n \quad (1)$$

where a_0, a_1, a_2,..., a_n = *polynomial coefficients*

C. Depth Interpolation for Characteristic Curves

In the former sections, we mentioned the possibility of having a pre-built database of different targets with physical properties (depth, posture, size, shape, etc) for permitting easy discrimination. On the other hand, it is not feasible to make a database with all possible combinations, but as shown in Fig 4, characteristics curves for a given target keeps the number of concavity and mainly changes its amplitude according to variations in depth. This fact suggests that inputting an a_0 in one set of target with its different depths the corresponding curve as well as the depth with that a_0 can be generated. For example, in case the input a_0 is 80% the estimated depth is around 160 mm for the AT landmine and 80 mm for the MF21 (a type of MF, further detailed in the next sections), and their corresponding curves are generated in red in Fig. 4. This shows that with a limited number of discrete data, reconstruction of characteristic curves for any depth for that particular target is possible, as shows eq. 2.

$$f^t_{interpolated}(Y) = f(f(Y)^t_1, f(Y)^t_2, ..., f(Y)^t_d) \quad (2)$$

where target = 1, 2, ..., t
depths per target = 1, 2, 3, ..., d

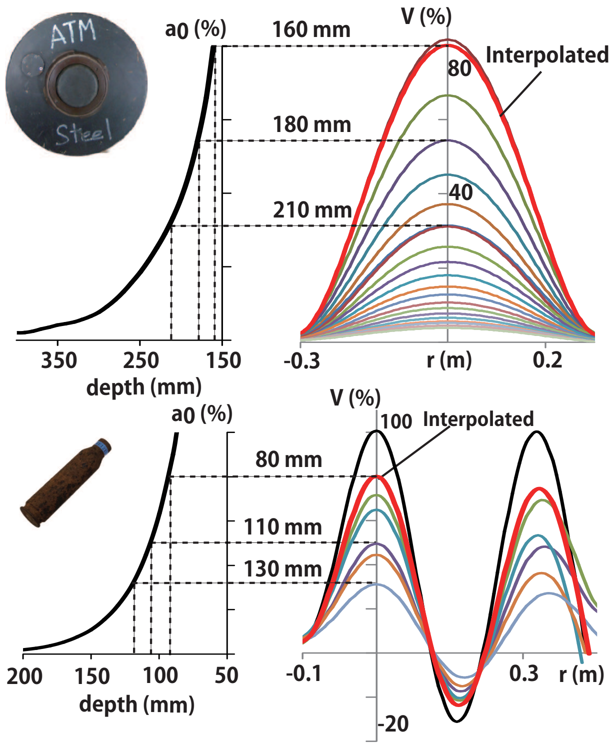

Fig. 4: Example of Depth Interpolation for an AT and MF21 target type Characteristic Curves

D. Searching Criterion

A criterion of similarity (or error) for the searching in the database between two curves is adopted here as the integral of the difference of their polynomials, as shown in eq. 3. A small error indicates good similarity and high possibility of discrimination while higher ones suggest that the target is not part of the database.

$$Error(\%) = \int abs(f-g)/h * 100 \qquad (3)$$

where f and g = polynomials to be compared
$h = max[\int abs(f), \int abs(g)]$

III. Database Building

For verifying the validity of the proposed method we first built a database of characteristic curves in the polynomial form for many targets with different depths and postures using a robotic x-y manipulator. Data with weak ($V(\%)<1\%$) or saturated ($V(\%)=100\%$) signals were removed from the database this time. In total, the database is composed of 34 targets (Fig. 5) in several depths and postures resulting in a total of 340 main characteristic curves.

The targets consist of many shapes (sphere, tube, cylinder, cube) and materials (steel, brass, chrome, aluminum and stainless). The depths vary from 10 to 400 mm and several postures (horizontal, inclined 45^o and vertical) are included. All MFs and AT landmines were taken at linear speed of 50 mm/s, 10 mm line step between scan lines and data density of 0.2 points/mm. Some landmines (PMN, PMN2) are also included, with variable depths, postures and scan steps. Details are as in Table. I.

Fig. 5: Targets used for building the database

TABLE I: Dimensions of the targets used for building the database

Data No	Target	Dimensions	Material
1-222	Bullets and cartridges (MF01 to MF21)	7-27 mm diameter, 27-114 mm height	Steel
223-254	Cube	20 mm edge	Aluminum, stainless, brass
255-274	Cylinder	11 mm diameter, 12.5 mm height	Aluminum, stainless, brass
275-291	Tube	11 mm external diameter, 0.5 mm thickness, 12.5 mm height	Aluminum, brass
292-301	Sphere	25.4 mm diameter	Chrome
302-305	ITOP (I_0)	4.8 mm outer diameter, 0.38 mm wall thickness, 12.5 mm height	Aluminum
306-330	AT	300 mm diameter	Steel
331-335	PMN	112 mm diameter, 56 mm height	Steel
336-340	PMN2	125 mm diameter, 65 mm height	Steel

A. Metal Mine Detector Signal Conditioning

The MinelabF3 Metal Mine Detector [4] was chosen for this experiment. This detector outputs signals in two independent channels (Ch_A and Ch_B), which are combined [16] according to eq. 4, forming a signal with stronger intensity Ch_C used for comparison in eq. 3. However, both Ch_A and Ch_B information are stored in the database and maximum MMD values and depths relation are used for refining and speeding up the search according to eq. 5, which only targets with depth error smaller than a threshold value are used for comparison, while others are directly discarded.

$$Ch_C = Ch_B - Ch_A - median(Ch_B - Ch_A) \quad (4)$$

$$\textit{Depth error(cm)} = abs(depth_B(a_{0B}) - depth_A(a_{0A})) \quad (5)$$

B. Database Integrity

The database was built with a limited number of data taken for discrete depth so that an interpolation method as explained previously should be valid to reconstruct a corresponding curve at a given arbitrary depth. Notice that many minefield conditions exist, but in this work we focus on limited conditions such as targets located in flat grounds, no other metals nearby, scans can be done without obstacles and different types of soils are not accounted. All these parameters are important to be analyzed and will be considered in future work.

In order to verify the "depth interpolation method" and also check the integrity of the database, the following test was conducted: depth interpolation, with search of the closest target. For each data number N, consider it is a detected signal and exclude it from the database, performing the searching in all the remaining data, looking for the target with smallest error. Since no extrapolations are done, data of the shallowest and the deepest depths of each target were used only for interpolation, without being input for estimation. The depth error threshold adopted for eq.5 is 17 mm, which means, if a target has depth error higher than this value than it is discarded as potential candidate for estimation, guaranteeing good estimation levels. The method, then, outputs (estimates) two main information: a) depth (interpolated) and b) target (which is a combination of material, size, shape, etc). Since the method estimates a target, theoretically we could directly discriminate the unknown signal as this target, i.e, as landmine or MF. However, safety issues must be considered for reliable discrimination and for this reason we will deeply discuss this possibility in future work. For now, we only analyze the estimated depth and material.

The estimation results are shown in Table. II and Fig. 6. Comparing to the existing method [15], more targets were analyzed and a greater material estimation rate can be observed: 95 to 100% for Steel, 48 to 74 % for Aluminum and 21 to 79 % for Brass. Even though [15] doesn't mention Stainless and Chrome, in this work the estimation was high, with 65 and 88 %, respectively. The depth estimation resulted in a average error of 4 mm and maximum 39 mm. More than 91% of the data resulted in depth error below 10 mm, while only 1.9% has the error between 30 and 40 mm, what can be considered satisfactory for supporting the use of GPRs. Even though [15] doesn't mention the average depth errors, the time for estimation is hugely smaller for the proposed method (1 s per target) against many minutes per target for the existing method.

TABLE II: Database integrity: material and depth estimation results

	Existing Method [15]	Proposed Method
Average depth error (mm)	-	4
Maximum depth error (mm)	-	39
Estimation time per target (s)	>96	1
Steel (%)	22/23 = 95	197/197 = 100
Aluminum (%)	11/23 = 48	14/19 = 74
Stainless (%)	-	11/17 = 65
Brass (%)	5/23 = 21	15/19 = 79
Chrome (%)	-	7/8 = 88

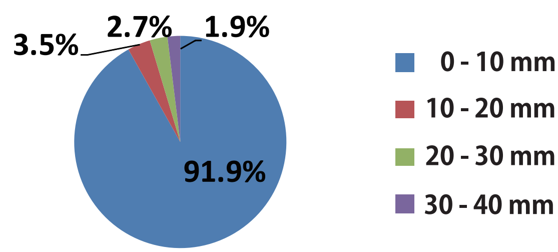

Fig. 6: Database data depth error distribution

All cases which depth error are between 30-40 mm are detailed in Fig. 7. The signals in the database are interpolated very accurately generating curves as expected. However, one can observe that for all cases, the target's profiles are like Profile 1 (Fig. 3), which is the profile with least inflections and peaks, being very poor in characteristics. One can notice that the MF19 is responsible for many high depth error cases. Even though the MF19 is not physically symmetric, its detected SRMMDS for both horizontal and 45^o under certain conditions are nearly symmetric, generating profiles similar to targets such as cubes, tubes and the PMN2 landmined, becoming difficult to estimate.

IV. EXPERIMENTAL RESULTS

The database was built using a x-y manipulator for taking precise data in laboratory. We need to test the behavior and robustness of the method when data taken with Gryphon is input. Some MFs, AT landmine and ITOP simulate target (a standard target for tests, simply called "ITOP" hereon) data were obtained with Gryphon at different depths and compared to the database for depth and material estimation. ITOP is a very important target to be tested for it has the metal content typical of a class of mine [17]. It is also known as "ITOP inserts" since it is conceived for an International Test Operations Procedure project as the metal content of larger simulant mines. There are several types of ITOPs, with different levels of detectability and metal contents. In this work, the used ITOP is the type I_0 with a "hard to detect" level of detectability with dimensions as Tab. I.

In total, 37 data (16 MF data at 70 mm depth, 10 ITOP data at 60 mm depth and 11 AT data from 150

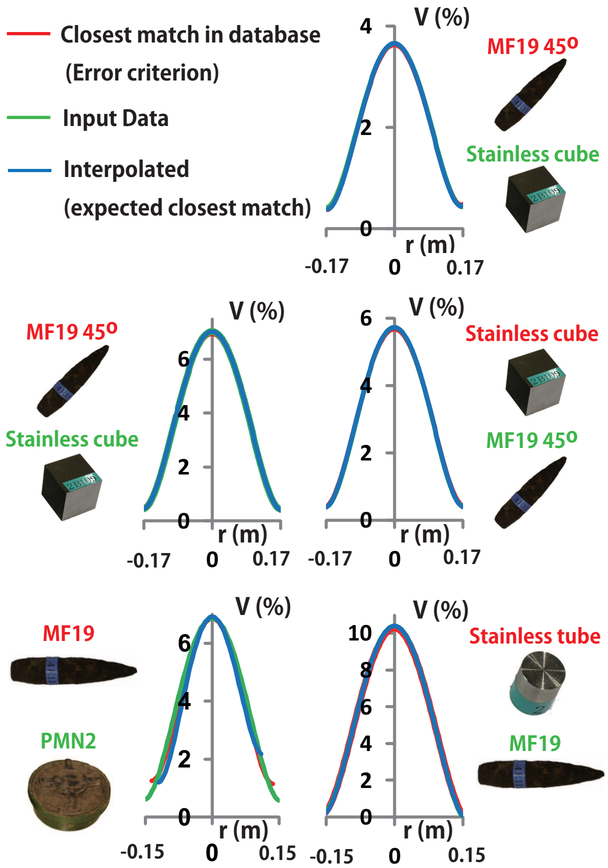

Fig. 7: Targets with 30-40 mm depth errors

TABLE III: Depth and material estimation experiment results

Average depth error (mm)	19
Max depth error (mm)	41
Steel (%)	27/27 = 100%

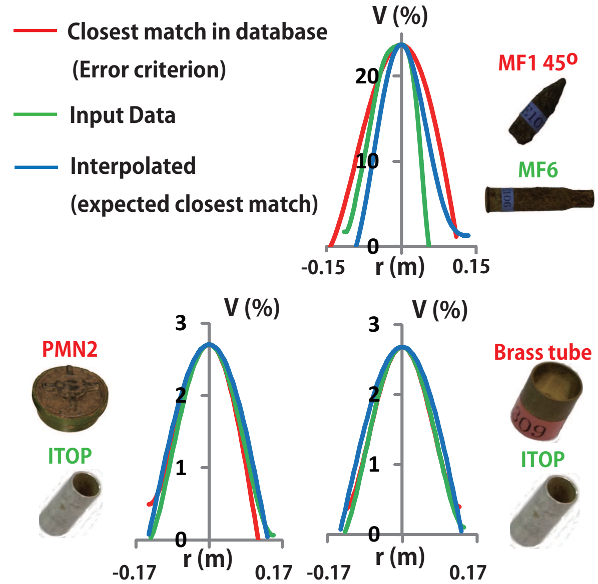

Fig. 8: Target with maximum depth error (top) and examples of ITOP wrong estimation (bottom)

to 250 mm depth) were obtained with Gryphon's default scanning settings: linear speed of 50 mm/s, 40 mm line step between scan lines and data density of 0.2 points/mm. All data is filtered, main axis extracted, translated to the origin according a_0, smoothed and interpolated. The results are shown in Table. III. According to the results, the average depth estimation error increased considerably, when comparing to the database integrity experiment (from 4 to 19 mm). However, 19 mm average error can be still considered a low error and satisfactory for real demining operations, for permitting quick use of GPRs and landmines removal by human operators. The maximum error kept almost unchanged (from 39 to 41 mm). Fig. 8 shows the maximum depth error case, which a MF6 had as closest target a MF1 in 45^o. In this case, the calculated *Error* between the curves is 37%, what is too high, what suggests great chances of wrong estimation, making the *Error* value an important parameter for reliability and must be explored in future work. Deep (AT landmines) and shallow targets (MFs) were correctly estimated according to depth with small errors, i.e, no MF was estimated as deep and no AT was estimated as shallow. It is important to notice that some experienced deminers are able to estimate depths only with a metal detector alone, however, this task is accomplished after several extra swings, slowing down operations in some seconds or minutes. In this work, the same task can be accomplished with less than 1 s for searching and one single scan.

The metal estimation results show that steel could be estimated in 100% of the cases (MFs and AT landmines), while aluminum couldn't be estimated. However, in this experiment, ITOP was used as example of aluminum, but its shape and size are projected to be very difficult to be detected and also to simulate some landmines signals [17] (made of steel), what was a very particular case of aluminum-made target. In fact, 2 of the ITOP data had as closest target the PMN2 landmine, proving the similarity in signal of ITOP and landmines. Some examples of wrongly estimated ITOP are shown in Fig. 8.

The experiments show that steel can be estimated with high accuracy. Even though ITOP is difficult to be directly estimated, the depth for this and other targets can be estimated with small errors. Moreover, observing all cases with highest *Errors*, it is emphasized that targets with characteristic curve as Profile 1 have poor characteristics, leading to difficult estimation.

V. DATABASE SEARCHING TIME

In the previous sections it was shown that the searching for each target could be performed in an average of 1 s/target, considering 340 data in the database and the speeding criteria adopted in this work. However, if we analyze the slowest time (worst case) for different database sizes, we can observe a linear relation, as shown in Fig. 9. This proves that even if very large amount of data is available, the searching in the database can be done parallelly, further decreasing the searching time.

VI. CONCLUSIONS

The authors proposed a new methodology for estimating depth of metallic targets using commercially available Mine Metal Detectors, based on a basic principle of comparison of signals/curves of targets obtained in the mine-field to a pre-build library containing data of many targets at different postures and depths. We introduced the concept of ”Spatially Represented Metal Mine Detector Signal” to the signal obtained from robot manipulator scanning of the mine field and also proposed simplification of the SRMMDS to ”Characteristic Curves” represented by polynomials, which lead to effective signal characterization and estimation in real-time.

With this method, large amount of data can be easily stored in a database and quickly interpolated for representing continuous depth data from limited depth samples with high accuracy. The method can estimate depth with average error of 19 mm and maximum 41 mm, which are accurate enough for supporting the use of GPRs and also for permitting fast discrimination of AT landmines (usually located in deep areas) and anti-personnel landmines (usually buried in shallow areas). As a sub product, the method could also estimate targets materials; steel in 100% of the cases and other types of metals (aluminum, stainless, brass and chrome) in higher rates than the existing method. This is very important for quickly removing objects not made of steel, which is the material usually used in landmines. A major advantage of this method is the time duration for estimation per target. While existing methods take minutes for estimating each target, the proposed method in this work takes only 1 s per target, which can be further reduced if parallel processing is applied.

VII. FUTURE WORK

The proposed method will be expanded for accomplishing discrimination of metal fragments and landmines in demining operations. In this work the calculated value of *Error* was not explored and simply the smallest error was used for estimation, but *Error* can be used as threshold for reliability of the obtained results. Optimizations for the method are desired, such as the necessary scan step and the quantity of data for interpolation for each target for good levels of estimation. Tests in Angola are also planned where more landmines under very realistic conditions (soil, temperature, humidity, etc) will be analyzed for testing the robustness of the method.

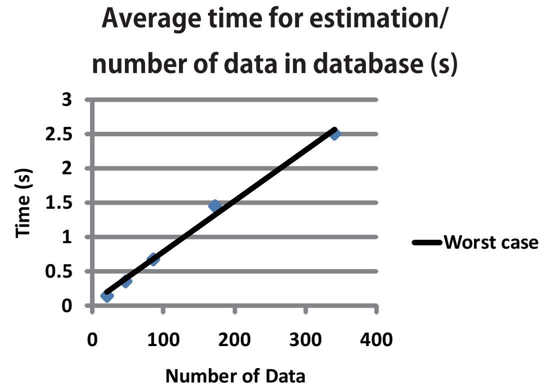

Fig. 9: Average time for estimation of a target per number of data in the database (worst case)

REFERENCES

[1] Hayter D. ”Training Dogs to Detect Tripwires.” Mine Detection Dogs: Training Operations and Odour Detection, June 2003. Geneva International Center for Humanitarian Demining. http://www.gichd.org/fileadmin/pdf/publications/MDD/MDD_ch2_part3.pdf. Accessed in July 3rd, 2013.

[2] Mahoney A. M., Durgin A., Poling A., ”Mine Detection Rats: Effects of Repeated Extinction on Detection Accuracy”, Journal of Mine Action, Vol 16, No 3, pp 61-64, Fall. 2012.

[3] Yamanashi Hitachi Construction Machinery. ”Contributing to the Mechanization of Demining in Colombia's Mountainous Regions”. CSR Report. pp 15-16. 2010. http://www.hitachi-c-m.com/global/pdf/generator/company/csr/report10/09.pdf. Acessed July 3rd, 2013.

[4] Minelab Eletronics. F3 Metal Mine Detector - Instructors Notes and Syllabus. Issue 1.3 March, 2006.

[5] Pavkovic N., Ishikawa J., Furuta K., Takahashi K., Gaal M., Guelle D., ”Test and Evaluation of Japanese GPR-EMI Dual Sensor Systemsat Benkovac Test Site in Croatia”, HCR-CTRO TECH GPR 08-001,March, 2008.

[6] Ho K.C., Collins L. M., Huttel L. G., Gader P. D., Discrimination Mode Processing for EMI and GPR Sensors for Hand-Held Land Mine Detection. IEEE Trans. Geosci. Remote Sensing, vol.42, No.1, pp.249-263, January 2004.

[7] Riggs L. S., Mooney J. E., Lawrence D. E., Identification of Metallic Mine like Objects Using Low Frequency Magnetic Fields, IEEE Trans. Geosci.Remote Sensing, vol.39, No.1, pp.249-263, January 2004.

[8] Gao P., Collins L., Garber P. M., Geng N., Carin L., Classification of Landmine-Like Metal Targets Using Wibeband Electromagnetic Induction.IEEE Trans. Geosci. Remote Sensing, vol.38, No.3, pp.1352-1361, May 2000.

[9] Stanley R. J., Ho K. C., Gader P., Wilson J. N., Devaney J. Landmine and Clutter Object Discrimination Using Wavelet and Time Domain Spatially from Metal Detectors and Their Fusion with GPR Features for Hand-Held Units. Circuits Systems Signal Processing, vol.26, No.2, pp.165-191, 2007.

[10] Collins L., Gao P., Schofield D., Moulton J. P., Makowsky L. C., Reidy D. M., Weaver R. C. A Statistical Approach to Landmine Detection Using BroadBand Electromagnetic Induction Data, IEEE Trans.Geosci. Remote Sensing, vol.40, No.4, pp.950-962, April 2002.

[11] Kruger H., Ewald H., Handheld metal detector with online visualizationand classification for the humanitarian mine clearance. Sensors,2008 IEEE, pp.415-418, 2008.

[12] Freese, M. A. Improved Landmine Discrimination With an Off-the-Shelf Metal Detector, Journal of Mine Action, Vol 2,No 1, pp 93-99, Oct. 2008.

[13] Doheny, R. C. Handheld Standoff Mine Detection System (HSTAMIDS) Field Evaluation in Thailand.

[14] Sato M., Fujiwara J., Feng X., Zhou Z., Kobayashi T. Development of a hand-held GPR MD sensor system (ALIS). Proc.Of SPIE Vol. 5794.Detection and Remediation Technologies for Mines and Minelike Targets X, pp. 1000-1007, 2005.

[15] Narita T., Fukushima E. F., Hirose S. Study of Discrimination Methods for Metal Fragments and Mines in Humanitarian Demining Tasks. The 2010 International Symposium on Intelligent Systems (iFan). Tokyo,Japan. 2010.

[16] Kaneko A. M. and Fukushima E. F. ”Development of an Automatic Landmine Detection and Marking System for the Demining Robot Gryphon”. Journal of Advanced Computational Intelligence and Intelligent Informatics. Vol. 15 No. 6, pages 737-743, 2011.

[17] CEN Workshop Agreement. CWA 14747. ”Humanitarian Mine Action - Test and evaluation - Metal Detectors”. June, 2003.