Inclination Angle Effect on Landmine Characteristics Estimation in Sandy Desert using Neural Networks

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***Abstract*— Many places in the world are contaminated with Landmines, normally buried under shallow or deep layers of sand and mud, which causes landmine detection and/or removal to be challenging tasks. To design a reliable landmine sensing system some deep analysis and many test cases are required. In this paper, existence of landmine under the ground surface is examined and its inclination angle effect on detection is analyzed applying finite element method and artificial neural networks. Inverse analyses are used to produce 'forward results'. Applying a contact pressure (lower than the expected landmine activation pressure) on the ground containing a landmine under its surface would produce a pressure distribution that is dependent on the landmine type, depth and inclination. COMSOL Multi-physics is applied to model sandy soil contaminated by two landmines of different types at different depths and surface pressure distribution is obtained applying external pressure load of 1kPa. Three NNs are trained applying the obtained surface pressure distribution data. The first NN is of perceptron type which classifies the introduced objects in sand. The other two NNs are of feed-forward NN type and are developed for estimating depths of two landmines of different types, one for each. The Landmine inclination angles (0^o-30^o) effect on detection rate is studied. The results are tabulated and justified. The results show that the anti-tank landmine is fully detected, while the anti-personnel landmine is only detected with a rate of 75%. It is also shown that landmine characteristics estimation is reliable when its inclination angle is small.**

Keywords*— *Landmine detection; contact sensing; finite element, artificial neural networks; inverse solution.

I. Introduction

Landmines represent a major harmful effect on a number of regions in the world, as it limits the development and increases the personal danger in such regions. There are more than 100 countries affected by Landmines, UneXploded Ordnances (UXO), and Explosive Remnants of War (ERW). Approximately 20 countries are heavily-affected, like that in Egypt from World War II in the period 1939-1945 AC [1]. Landmine detection sensors are the most costive and critical issue in demining process and research [2]. Many sensing technologies and studies are introduced for landmines detection. The most mature technologies are based on the electromagnetic waves [3] (like Electromagnetic induction metal detector (MD), magnometers, and Ground penetration radar (GPR)) [4]. Due to the complexity of the detection, many research works are conducted to gain the best of more than one sensor and consider in the final decision, through their fusion. Sensor fusion methods can be classified to hardware fusion and software fusion [5]. For that, two studies are considered with fuzzy logic principles in order to select suitable sensors for the sand-landmine case [6]. A Study for the elastic-wave interactions with landmines using finite difference method is presented [7]. Eexperimental model and surface-contacting vibrometer for seismic landmine are produced [8], [9]. Active sensing prodder that emits white Gaussian noise vibration is applied to identify the object in front of the pointed tip of the prodder [10]. A separated GPR aperture sensor method is applied to detect buried targets by evaluating and comparing the electromagnetic coupling between the transmitting and receiving antennas [11]. Almost all presented sensors are contactless sensors. However, it is expected that, through the advance in MEMS technology, light-weight ground-contact sensors will be introduced to detect landmines. In this work, an analysis based on contact sensor concept will be presented.

A finite element modelling tool, COMSOL Multi-physics is software that has suitable user interface and capabilities to couple many physics with facilities. Contact pressure modelling with COMSOL is verified analytically in [12]. The structural mechanics module supports contact boundary conditions using contact pairs. The contact boundary pair comprises a flat boundary and a curved boundary. A comparison with theoretical and experimental results is tabulated in [13]. In this work, 2D modelling for the sand-landmine is presented using COMSOL Multi-physics.

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Artificial intelligent techniques such as Fuzzy Logic (FL), Particle Swarm Optimization (PSO) and Neural Networks (NN) can be used to extract nonlinear relations. The PSO algorithm is coupled to Finite Elements analysis to identify a buried object from its ElectroMagnetic Induction (EMI) signature [14]. Fuzzy logic is applied for automatic landmine detection based on the GPR volumetric data [15]. In this work, three NNs are trained and applied to detect landmines.

Most of the presented research works in landmine detection is carried out while the landmine is in normal configuration, (without inclination). However, in a real situation, landmine position and inclination may be changed because of environmental conditions. Few works are available in the literature for examining landmines inclination angles effect on their detection rate. Authors of [16] has presented the effects of ground surface roughness, soil inhomogeneity and target inclination on the classification performance of landmines. However, the deteriorated results of inclined targets assure the need for more analysis. In this paper, the effect of the landmine inclination angles on its detection rate is presented.

This paper is organized as follows: Problem definition is presented in section II. Material and methods including landmine activation pressure calculations, finite element model and NN training are presented in section III. Forward and inverse approaches results are presented in section IV. Conclusions are presented in section VI.

II. PROBLEM DEFINITION

The presence of landmine inside sand causes certain effects. Some effects can be utilized for landmine detection at ground surface with corresponding sensors. In this study, the considered effect is the contact pressure. By applying loading pressure (less than the activation pressure of any landmine) to the sand surface, a pressure distribution is generated on the sand surface due to the difference between the Young's modulus of the sand and landmines. By measuring this pressure distribution by contact pressure sensor (which is proposed to be applied in the future), landmine type and depth may be detected. For NN training purpose, pressure measurement is replaced by finite element model output which is presented in 2D using COMSOL. The 2D model of a landmine inside sand (2m x 2m x0.5m) is shown in Fig.1.

The finite element work is done for free sand, and sand with an object at different depths (5 mm to 205 mm). The

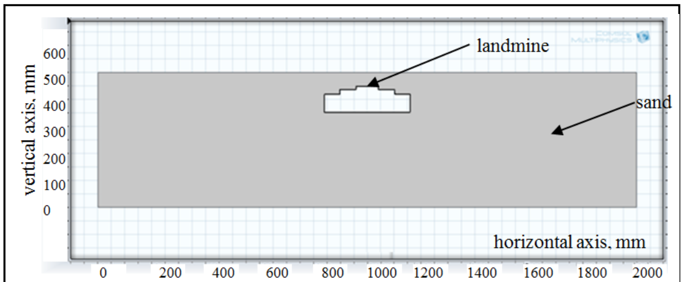


Fig.1 2D model with COMSOL Multiphysics

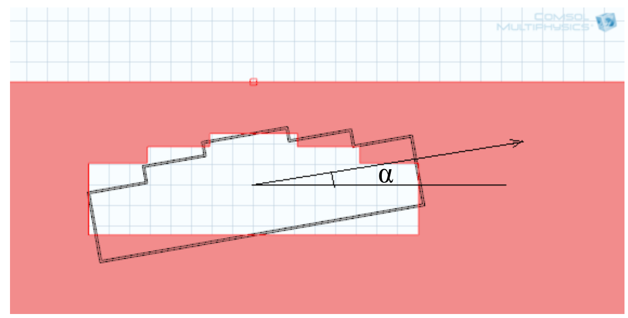


Fig.2. inclined Landmine

objects studied are as follows: Antitank (AT) 'LM01' landmine, Antipersonnel (AP) 'LM02' landmine, food can 'CAN200' with a diameter and a height of 200mm and finally a rocky sphere 'ROCK200' with a diameter of 200 mm.

Due to the differences in the pressure distributions profile with different landmines at different depths, the landmine type and depth can be determined by artificial intelligent techniques as it will be introduced in the next section. Also we study the effect of inclined landmine with a certain angle, fig.2, where the pressure distribution is different from that when the landmine is horizontal.

For different types of landmines, the detectability is measured by the detection rates (true alarm, false alarm, and multiple detections).

III. MATERIAL AND METHODS

In this section two landmine types are used for this study the 1st is noted as 'LM01' which is an anti-tank landmine MK7 and the 2nd is noted as 'LM02' which is an anti-personnel landmine, Fig.3. Two different objects (not landmines) of an intermediate size (200mm) comparing to the aforementioned landmines are considered. 'CAN200' is a food can with diameter and height of 200mm, 'ROCK200' is Rocky sphere with diameter of 200mm, and also 'SandOnly' is object free.

A. Landmine Activation Pressure

The activation pressure is one of the most important considerations in the demining studies. It is the loading pressure which causes the landmine detonation. Based on the,

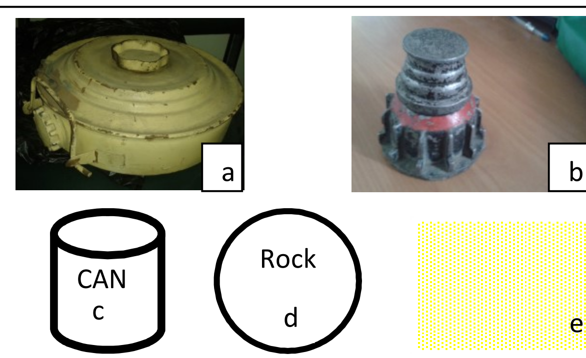


Fig.3. a. Anti-tank MK7 'LM01' b. Anti-Personnel 'LM02' c. CAN200 d. ROCK 200 e. SandOnly

available online, information portals [17], [18] dimensions and activation load of a set of landmines are shown in Table I. The activation pressure is calculated for each landmine, and the safe contact pressure threshold can be selected as 1.9 kPa. In this study, the applied boundary pressure load is 1 kPa.

TABLE I. LANDMINES ACTIVATION PRESSURE CALCULATIONS.

Land-mine Type	**Dimensions (cm)**	**Activation load (kg)**	**Activation pressure = Force/Area**
MK5 (AT)	Diam: 20.3	114.45	34.6 kPa
MK7 (AT) [a]	Diam: 32.5	150 to 275	17.7 kPa
Rieglmine43 (AT)	Length: 80 Width: 9.5	180 to 360	23.2 kPa
S mines (AP)	Diam: 10.2	3 - 5.5	3.5 kPa
Tellermine 35,42,43(AT)	Diam: 31.8	90- 180	11.1 kPa
B-2(AT),V-3, (like)TMB2	Diam: 27.3	115/9.8	1.9 kPa
M71 copy of TM46	Diam: 30.5	120–400	16 kPa
T79 copy of TS50	Diam: 9	12.5	19.2 kPa

a. MK7 is the Anti-Tank landmine noted with 'LM01' in this paper

B. *Finite Element Model*

The forward and inverse approaches are utilized here to generate an artificial data using: the finite element models and then, the NN to detect the landmine characteristics: (type and depth) as shown in Fig.4. In this subsection, the sand–landmine in 2D finite element model using COMSOL Multiphysics is simulated, as shown in Fig.1. The work is carried out for each one of the two landmines at different depths 50,100,150,200 mm and at each depth with landmine inclination angles 5^o, 10^o, 15^o, 20^o, 25^o, 30^o. The materials are assumed to be homogeneous, isotropic, and linearly elastic: for the can and the mine casing (steel: E = 210 GPa, ν=0.3), the sand (sandstone: E = 10 GPa, ν=0.295) and adhered to a rigid rock from bottom. The dimensions are 2m x2m x0.5 m. The meshing is of triangular type, extremely fine size, (maximum: 20mm, minimum: 0.04mm) and regular refinement number is 3. Fig. 5 and Fig.6 show the ground surface contact pressure when the external applied load from top is 1kPa, for the above mentioned case. These pressure distribution cases are exported to text file then MATLAB programs are coded in order to unify the spline interpolation in the range (500 to 1500 mm) in order to be used in the next step, the neural network simulation.

C. *Neural Networks*

The used NNs here are three. For classification, perceptron neural network (PNN) is used, Fig.7, and for depth detection, two feed forward neural network (FFNN), are used, Fig.8. It would appear that NN are promising in providing better solutions for determining landmine characteristics (type, depth) under the ground. The three NNs are trained to determine the landmine characteristics. The ground surface contact pressure graphs were the inputs to the network and the landmine characteristics were the desired outputs. The distinct features of the NN make this approach very useful in situations where the

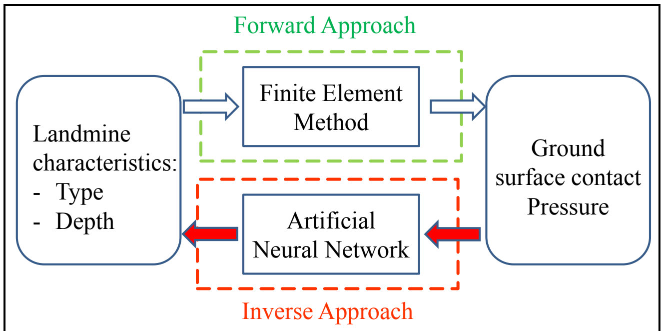


Fig.4. Flowchart of forward and inverse approaches

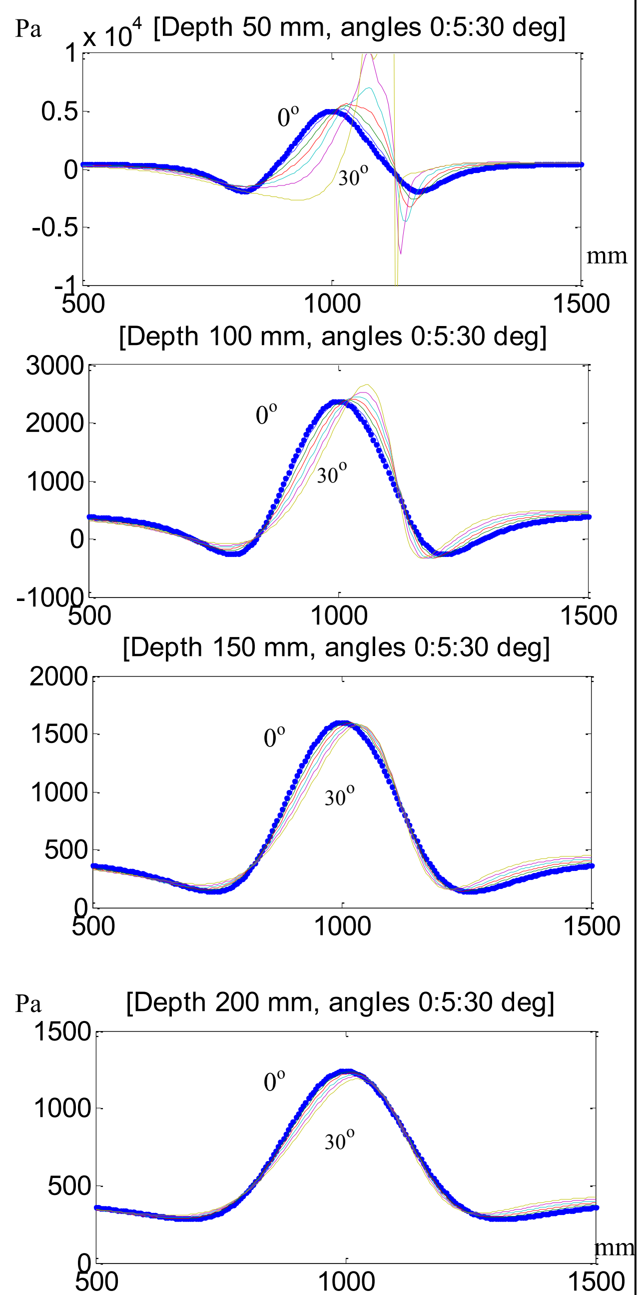


Fig.5. LM01, inclination effect on surface contact pressure at depth 50, 100, 150, 200 mm

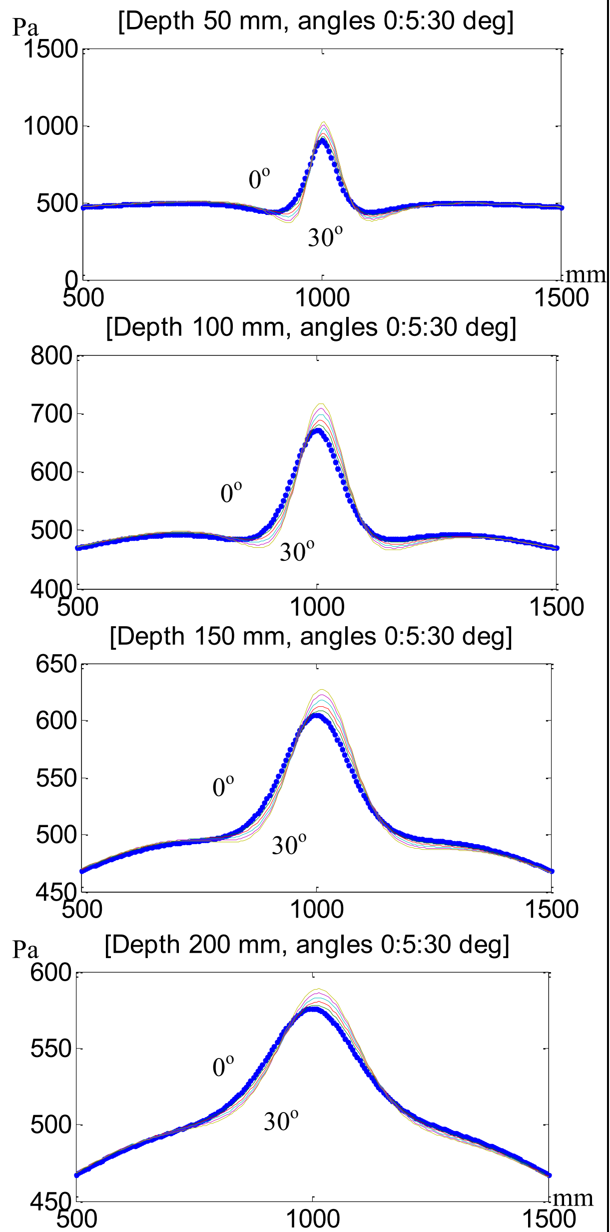


Fig.6. LM02, inclination effect on surface contact pressure at depth 50, 100, 150, 200 mm

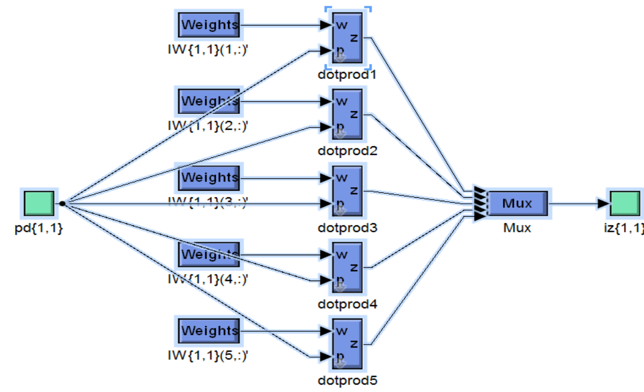
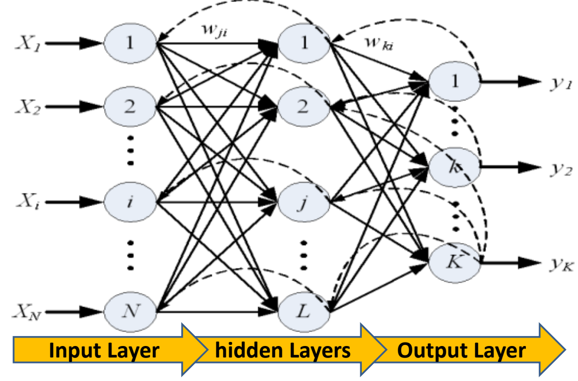


Fig.7. Perceptron NN using MATLAB, with hard limit function

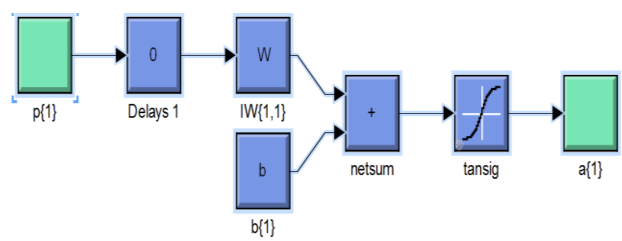
Levenberg-Marquardt Algorithm

dw = - (jw*jw + I*mu) \ jw*E

Where:- dw: weight change, jw: Jacobean of performance, E: all errors, I: the identity matrix, and mu: adaptive value.



(a) Back-propagation training algorithm



(b) FFNN structure using MATLAB

Fig.8. Feed forward NN, with non-linear function tansig

functional dependence between the inputs and outputs is not clear. Some characteristics of the NN approach which were beneficial for complex cases (like landmine detection in this study) are as follows: The NN approach is effective in modelling non-linear relationships between the dependent and independent variables, using an approach similar to a 'black box'. The NN approach has prediction and optimization capabilities and can be updated with new data. Also it can be used to predict the response for new experimental conditions after the models are trained [19].

The PNN is trained to classify between 5 cases ('LM01', 'LM02', 'CAN200', 'ROCK200' and 'SandOnly') so number of neurons is 5 as shown in fig.7.

The PNN learning rule:

$$dw = e * p' \qquad (1)$$

Where: the weight change dw for a given neuron from the neuron's input p (where p' is the transpose) and error e [20]. This algorithm is named 'learnp'. Also, for the FFNN training; the back-propagation algorithm is used. In the learning process, to reduce the inaccuracy of FFNN, it uses the gradient-decent search method to adjust the connection weights [21]. The back-propagation training is shown in Fig.8.

The data is divided between training and validation, to check if the NN well leant the relation or not. In table II, the training and validation errors are listed for PNN, which indicate that the bigger landmine (LM01) has higher true alarm rate, lower not detected rate and lower false alarm rate.

TABLE II. PERCEPTRON NN (CLASSIFICATION) TRAINING AND VALIDATION

\ Detect Data from	LM01	LM02	CAN200	Rock200	Only Sand
Training results					
True alarm	100%	61.90%	100%	100%	100%
Not Detected	0%	28.10%	0%	0%	0%
False alarm	0%	0%	0%	61.82%	0%
Validation results					
True alarm	95%	60%	100%	100%	100%
Not Detected	5%	40%	0%	0%	0%
False alarm	0%	3.20%	0%	56.50%	0%

True alarm rate = number of correct detections / total number of the data pair for certain object
True alarm rate + Not Detected = 100%
False alarm rate = number of detections which are not correct / total number of the data pair for object

Two FFNNs are trained to detect the depth of LM01 and LM02. In table III, the training and validation root mean square of errors for different NN sizes (1: 4 neurons) are listed for FFNN, which indicate that the best performance is acquired when the NN of size 2 neurons.

TABLE III. FEED FORWARD NN TRAINING AND VALIDATION, ROOT MEAN SQUARE OF ERROR (RMSE)

Number of neurons	LM01		LM02	
	Training	Validation	Training	Validation
1	0	0.057	0	0.214
2	**0**	**0.013**	**0**	**0.131 select**
3	0	0.020	0	0.139
4	0	0.032	0	0.180

IV. SIMULATIONS AND RESULTS

The forward and inverse approaches are utilized here to generate an artificial data using the finite element models and the NN to detect the landmine characteristics: (type and depth) as shown in Fig.4. For the two landmines LM01 and LM02 at depths 50, 100, 150, 200 mm in sand and with certain inclination angles 5^o, 10^o, 15^o, 20^o, 25^o, 30^o, Finite element models are built and the surface pressure distribution curves are generated of each case as shown for LM01 in Fig.5 and for LM02 in Fig.6. The target of this simulation is the to apply these surface pressure curves to the PNN (which was trained using data with no inclination) and find the effect of inclination on the detection rates for the landmine type. Also, to apply the same surface pressure curves to FFNNs designed for each of the LM01 and LM02, (which were trained using data with no inclination) in order to detect the depths. The results are tabulated in Table IV, which show that LM01 is fully detected but multiple detections are found, while LM02 is detected only with 75% with false detection with 25%. Table V and Table VI show the depth detections for LM01 and LM02 which indicate the exact depths are detected when the inclination angle is zero, while error increases when the inclination increase, which is logically true.

TABLE IV. INCLINATION EFFECT ON ALARM RATE

Object Type	Data of LM01	Remarks	Data of LM02	Remarks
LM01	100%	All detected	--	--
LM02	--	--	75%	Only 75%
CAN200	11%	Multiple detections	0%	--
ROCK200	32%	Multiple detections	25%	False detection
Sand	4%	Multiple detections	0%	--

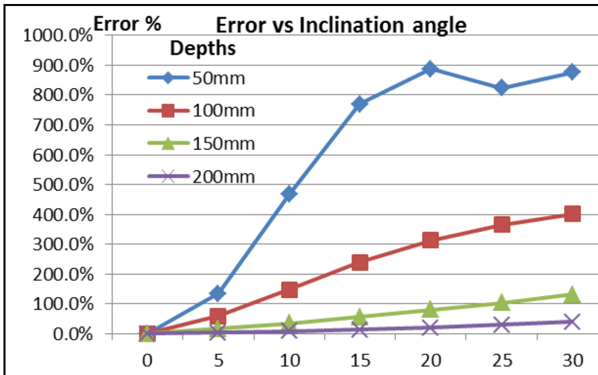


Fig.9. LM01 inclination angle effect on the depth detection error

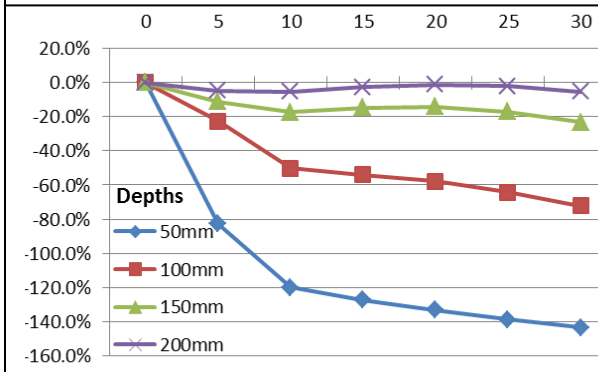


Fig.10. LM02 inclination angle effect on the depth detection error

TABLE V. LM01 INCLINATION EFFECT ON DEPTH DETECTION

Actual Depth	50 (mm)		100 (mm)		150 (mm)		200 (mm)	
Angle^O		Error%		Error%		Error%		Error%
0	50	0	100	0	150	0	200	0
5	117	134	160	60	174	16	207	3.5
10	283	466	247	147	203	35.3	216	8.0
15	435	770	339	239	235	56.7	227	13.5
20	494	888	413	313	270	80	241	20.5
25	462	824	466	366	306	104	259	29.5
30	488	876	502	402	346	130.7	280	40.0
Error average:	565.4		218.1		60.4		16.4	

TABLE VI. LM02 INCLINATION EFFECT ON DEPTH DETECTION

Actual Depth	50 (mm)		100 (mm)		150 (mm)		200 (mm)	
angle^O		Err%		Err%		Err%		Err%
0	50.0	0	100.0	0	150.0	0	200.0	0
5	8.7	-82.7	77.4	-22.6	133.1	-11.2	190.8	-4.6
10	-10.1	-120.1	49.8	-50.2	124.0	-17.4	189.6	-5.2
15	-13.7	-127.4	46.2	-53.9	128.0	-14.7	194.7	-2.7
20	-16.7	-133.3	42.3	-57.7	129	-14.0	197.5	-1.3
25	-19.4	-138.9	35.9	-64.1	124.6	-16.9	195.9	-2.0
30	-21.8	-143.5	27.8	-72.2	115.1	-23.3	189.7	-5.2
Error average:	-106.6		-45.8		-13.9		-3.0	

When the object gets deeper, the absolute error in depth detection decreases. Which is also logical, as the closer the object to ground surface the greater the effect of the inclination angle. At inclination angle 0^o there is no error in the NN detecting the depth. The error increases as the inclination angle increases, and the error effect of the inclination angle is dominant as the landmine is closer to the ground surface.

$$Error= (depth\ estimation\ by\ NN) – (Actual\ depth) \quad (2)$$

In Fig.9 for LM01, the error in depth detection increases as the inclination angle increases and at all depths which is logical. Also Fig.9 indicates the error decrease as the landmine depth increase. The reason is that the closer the inclined object to ground surface makes greater deformation to the pressure curve at inclination angle zero. The positive error indicates that the increase of the NN estimation than the actual depth of the landmine.

In Fig.10 for LM02, the absolute error in depth detection increases as the inclination angle increases and at all depths which is logical. Also Fig.10 indicates that the absolute error decrease as the landmine depth increase. The negative error indicates that the decrease of the NN estimation than the actual depth of the landmine (means that the NN in this situation see the object closer than it is really exist).

V. CONCLUSIONS

Buried objects under the ground surface give different pressure distribution when exposed to pressure loading, which can be distinguished at the ground surface. A 2D finite element models are done and executed for different objects in sand, which give these pressure curves with different objects and at different depths.

The proposed inverse approach based on neural networks is a reliable and efficient tool for landmine detection in order to accurately estimate the basic parameters of the landmine (type, depth) in sandy desert. There is a non-linear correlation between the landmine characteristics and their effects on the extracted features. Neural network is used to extract from these curves information about the object type and depth. These curves are divided into two groups, group for training and group for validation. The true alarm rate for training LM01: 100%, LM02: 61.90%, average: 80.95%. While, the true alarm rate for validation LM01: 95%, LM02: 60%, average: 77.5%.

The Landmine inclination angles (0^o-30^o) effects are studied. The results are tabulated and analyzed, which show that anti-tank (LM01) is fully detected, while anti-personnel (LM02) is detected with 75% and false detection with 25%. At inclination angle 0^o, there is no error in the NN detecting the depth. The error increases as the inclination angle increases, and the error effect of the inclination angle is dominant as the landmine is closer to the ground surface.

The future work would be enhancing the training NNs, introducing a contact sensor and verifying its applicability in landmine detection.

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