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PROTOTYPE FOR DETECTION OF LANDMINES BY A METALS DISCRIMINATOR USING INTELLIGENT SYSTEMS

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ABSTRACT

The design and implementation of a prototype detector antipersonnel mines using neural networks and fuzzy logic supported by the metal detector Garrett ACE 250 is presented in this paper. This prototype generates a signal source, which is amplified both voltage and current and entered to the primary winding of the sensor. When the emitted signal collides with a metallic object is returned to the sensor and becomes the signal to be processed. The offset angle is used to determine the type of metal and the approximate distance to which the detected object is located. Using a graphical interface in Matlab in real time the signal is shown to the user. As a result, a discriminator prototype metals, programmed in Matlab and the graphical user interface are obtained. The prototype was validated by experimental field testing and a better result was achieved with fuzzy logic achieving the expected discrimination of the types of metal used and the distance at which they are found.

Keywords: metal detector, signal processing, landmines, fuzzy logic, neural networks.

1. INTRODUCTION

The problem of landmines has focused the attention of the world by the social impact caused because they affect not only the population of the armed conflict, but innocent civilians. Large sectors have condemned the use of anti-personnel mines and urged the warring parties to comply with Ottawa Convention and the Law 759 of 2002 (Descontamina, 2019). However, laws have fallen short in removing mines that are buried in many countries and a solution that efficiently enables the removal of these deadly devices is then necessary.

Numerous studies in the field of humanitarian demining have been conducted internationally and nationally aimed at contributing to this problem (Ahmed, 2012; Guzmán, 2004; Mosquera, *et al,* 2007; Pino, 2009). The main problem of humanitarian demining is its inefficiency since the conventional metal detectors fail to distinguish between a mine or a piece of metal buried, generating false alarms, a big waste of time and human losses in many cases. The goal of many countries affected by minefields that threaten the population is the development of intelligent systems that achieve the classification of metals.

This study proposes the development of a prototype detector landmine using intelligent systems, based on the metal detector Garrett ACE 250 (Garrett, 2018). The main contribution is granted to the person making use of the greater device information on the type of material and the depth to which is the metal, in contrast with a conventional metal detector in which a sound is emitted every time the sensor detects a metallic object.

The prototype is then developed to make a detailed analysis of the operation of the Garrett ACE 250, which is used as a sensor. The hardware required to achieve optimum performance of the sensor is implemented. Then the signals are acquired and upgraded to be processed based on pattern recognition techniques (Reynaga and Mayta, 2009). The display data is performed through the graphical environment GUIDE Matlab. Finally, several tests with neural networks and fuzzy logic are performed to determine the efficiency of the implemented methods.

2. MATERIALS AND METHODS

The project is developed in two general phases of implementation of the hardware and the other on programming including graphical interface. Hardware acquisition and signal coupling are made, whereas, with the programming, processing and display are performed as shown in the diagram of Figure-1.

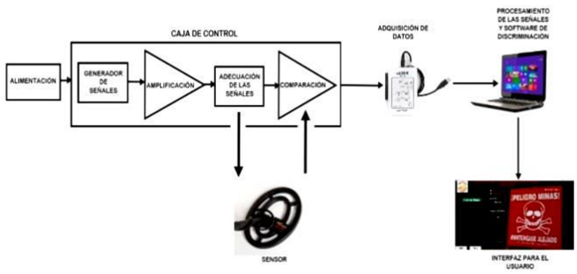

Figure-1. General diagram of the system.

2.1 Hardware Implemented

For this project only used the sensor element metal detector Garrett ACE 250, i.e. the coil. So, they are designed some electronic stages to simulate the operation of the control device; which sends a sinusoidal signal of 32.4 kHz to 6.7 Vpp to the primary winding of the sensor and subsequently received by the secondary winding offset signal whenever a metallic object is detected and then is processed by the software implemented.

2.1.1 Power supply

A fixed dual source that provides 12-volt DC is used to polarize the integrated circuits of the PCB (Printed

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Circuit Board) as are the signal generator and operational amplifiers to ensure proper operation.

2.1.2 Signal generator

XR2206 signal generator is used. To this end, the scheme in its fact sheet with some modifications is performed. The goal is to obtain a bipolar sinusoidal signal at its output because it is the original type of signal generated by the control device of the Garret. Of the same frequency approximate to the working frequency of the Garret is calculated as shown below.

$$f = \frac{1}{RC}$$

Where f is the frequency of the output signal for this case it is assumed 6.8KHz and C 100nF. So, the resistance can be calculated as follows:

$$R = \frac{1}{fC} = \frac{1}{6.8x10^{3} * 100x10^{-9}} = 1.47K\Omega$$

Thus, two resistors of market value, one of 1KΩ and 470K are selected. The sinusoidal signal generated XR2206 of the integrated circuit is shown in the oscilloscope signal of Figure-2.

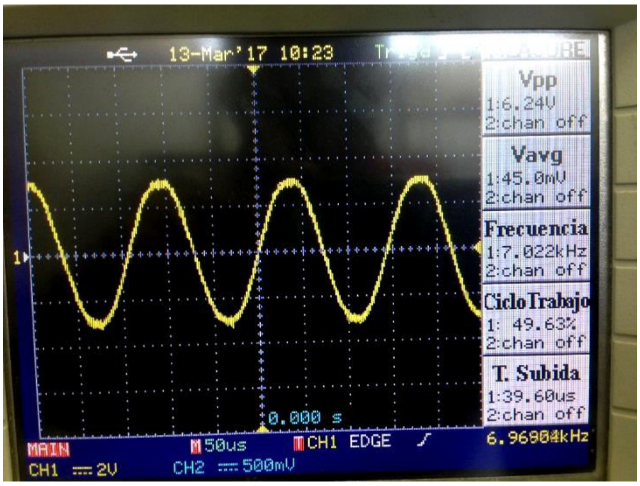

Figure-2. Signal generated by the XR2206.

2.1.3 Amplification

The sinusoidal signal with the desired frequency is amplified with TDA 2030 because the current and voltage generated have low power to drive the primary winding. The TDA2030 is used as a non-inverting amplifier and due to their output type (class AB) and the current generated by the transformer used, the signal current is increased.

2.1.4 Comparator circuits isolation

Because the sensor windings act as a transformer and the land points thereof cannot connect to the same common reference point, it has been designed this stage. These circuits to measure the signal received by the secondary winding indirectly by a TL084 integrated internally contains four operational amplifiers, configured as comparators.

2.1.5 Sensor

The plate of the coils Garret ACE 250 is used as a sensor element. These coils have a number of parameters that were constructed such as impedance, inductance, and resistance which are variables of interest provided by the manufacturer and used for the design stage of the system conditioning.

2.1.6 Design and assembly

Many laboratory tests were performed with the developed system. Then the Proteus ISIS simulation is executed, the tracks are made in ARES PCB Proteus and finally, the card is implemented as shown in Figure-3.

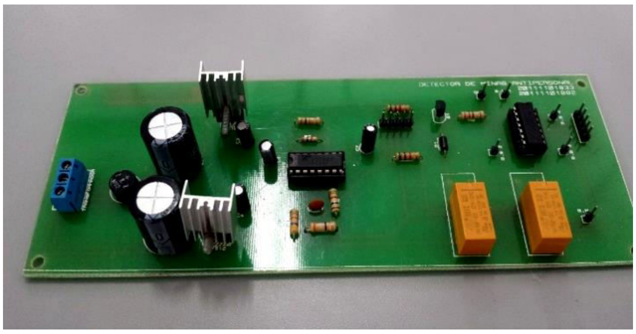

Figure-3. PCB hardware implemented.

The obtained signals from the sensor using the PCB implemented are displayed by the oscilloscope as shown in Figure-4.

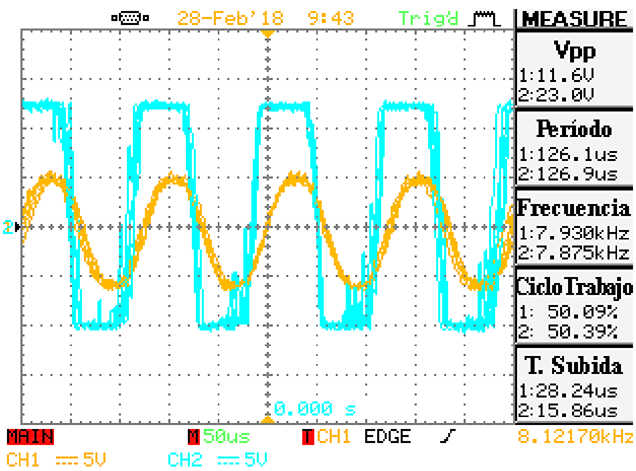

Figure-4. Signals obtained from the sensor with the PCB.

2.2 Software

For data acquisition, The National Instruments NI myDAQ card is selected (National Instruments, 2018). Discrimination algorithms are developed in the Matlab environment (Math Works, 2019). To establish communication between NI myDAQ with Matlab software

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NI-DAQmx is executed, which is a key driver for data acquisition.

2.2.1 Data acquisition

This stage is designed to acquire signals from both windings of the sensor. In this code conditioning at the signals acquired with myDAQ, it is done in order to achieve better signal for processing. The elimination of the initial 10% of the data acquired by both windings was made; these data are not useful since they correspond to the segment in which the oscillator XR2206 has not stabilized. It was also corrected signal symmetry on positive half cycles and negative for proper detection of the zero crossing. Finally, the conditioned signal is shown in Figure-5.

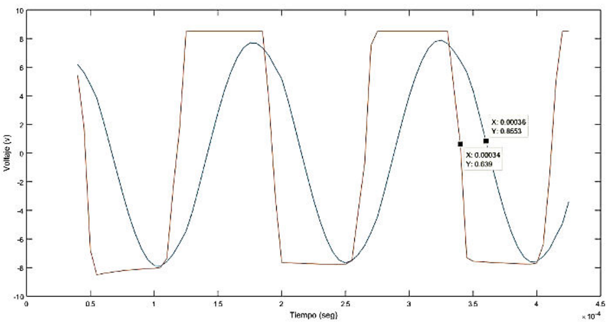

Figure-5. Conditioned signals.

In Figure-5 the signal applied to the primary winding is represented by the blue line sinusoidal signal and the signal read of the secondary winding is represented by square signal in red line.

2.2.2 Resampling

Because the samples obtained by the myDAQ card were not sufficient for the correct detection of zero-crossing, a resampling was performed. The resampling process was performed as follow.

$$\#muestrasDAQ = s.Rate * s.DurationInSgs$$

Where,
s.Rate = 200000 (peak value offered by the myDAQ)
s.DurationInSgs = 1.447 ms, ie:

$$\#muestrasDAQ = 200000\frac{samples}{second} * 1.447ms \cong 290 samples$$

Of these 290 samples, 261 were used due to the cut-out of 10% made to the start signal. After a series of tests, the frequency at which resampling is to be found and corresponds to 10 MHz (f_d). This value and the rat Matlab command are used to obtain the parameters to meet the new number of samples obtained, as shown below:

$$[p, q] = rat\left(\frac{f_d}{f_0}\right)$$

Where $p = 50$ and $q = 1$ are obtained, according to the command "rat" of Matlab. Now, the number of signal samples resampled is given by the equation:

$$\#muestrasresample = 261 * \left(\frac{50}{1}\right) = 1350 samples$$

After this process, a signal with a large number of samples near zero is obtained. These samples are useful for the process of calculating the phase angle between the signals the primary and secondary windings.

2.2.3 Zero crossing and phase shift calculation

The difference in the phase between two points of the signals emitted and received is found. This is accomplished by implementing a zero crossing detector programmatically. The zero crossing detector is done looking for values where the signal amplitude is close to 0V. A matrix where each row refers to a flank and makes each column refers to a value close to 0 is obtained. From this matrix the closest value to 0 from one flank to the other, is extracted, the values obtained for t1 and t2. With that, the gap is between the two signals by the equation below.

$$desfase = \left(\frac{|t1 - t2|}{T} * 360\right)$$

2.2.4 Neural network

Neuronal Network is based on the model multilayer perceptron (Ruiz and Basualdo, 2001). They need to be developed from databases from the samples taken by each capture myDAQ signal from the secondary winding.

For a good workout in the hidden layer network it should be considered, which helps the results generated by the network is more accurate. This layer contains a number of neurons that are calculated roughly following the rule of the geometrical pyramid shown below.

$$h = \sqrt{m * n}$$

Where,
h : initial number of neurons in the hidden layer,
m : number of output neurons.
n : number of input neurons.

The number of neurons of inputs is determined by the amount of signal samples in each catch, this value is 10001. The number of neurons of outputs is given by the number of "bits" that are assigned to the target, then the initial number of neurons is calculated by:

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$h = \sqrt{9 * 10001} \cong 300 neuronas$

To perform network training function, the tool nntraintool (Neuronal Network Training Tool) is used. With this instrument, the network training is observed and monitoring the performance of the network is performed, as shown in Figure-6. A necessary condition for proper training of the network is that the basis vectors input data and output must have the same number of columns.

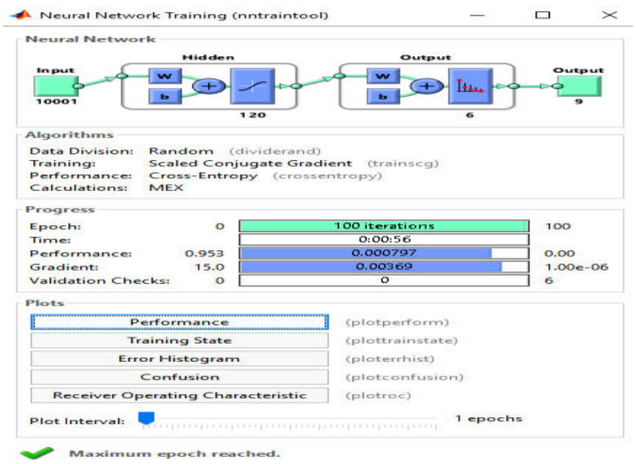

Figure-6. GUI training neural network.

Artificial neural networks must be trained as many times as necessary to obtain a good result when implemented because with few workouts is observed that network performance does not reach considerable value and a number of inconsistencies in response are generated.

2.2.5 Fuzzy logic

In the implementation with Matlab, fuzzy logic is reduced to a set of rules that determine what action is necessary or output for a given input (Gonzales, 2011). The configuration of fuzzy logic for this project is structured by four membership functions input and two output functions as shown in Figure-7. One function is called input offset which is composed of different ranges of angle gap; the other three correspond to the PPV (peak to peak voltage) having the signal depending on the type of material and the distance at which the object is located.

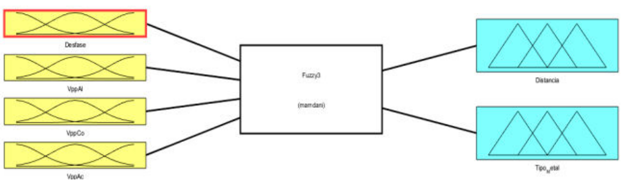

Figure-7. Scheme fuzzy logic implemented.

Output functions are provided by the distance and the type of metal. Each of these functions membership consists of some variables made based on data of tests performed. Subsequently with these values, the rules that logic will work are created.

The rules function as conditionals of type "if" that require two input variables which are phase angle and PPV, as shown in Figure-8. According to these entries is found metal type and distance that finds time to be detected.

1. If (Desfase is dAl) and (VppAl is dAl25) then (Distancia is distancia_25)(Tipo_Metal is Al) (1)
2. If (Desfase is dAl) and (VppAl is dAl0) then (Distancia is Distancia_0)(Tipo_Metal is Al) (1)
3. If (Desfase is dAl) and (VppAl is dAl4) then (Distancia is distancia_4)(Tipo_Metal is Al) (1)
4. If (Desfase is dAl) and (VppAl is dAl5) then (Distancia is distancia_5)(Tipo_Metal is Al) (1)
5. If (Desfase is dAl) and (VppAl is dAl6) then (Distancia is distancia_6)(Tipo_Metal is Al) (1)
6. If (Desfase is dAl) and (VppAl is dAl7) then (Distancia is distancia_7)(Tipo_Metal is Al) (1)
7. If (Desfase is dAl) and (VppAl is dAl8) then (Distancia is distancia_8)(Tipo_Metal is Al) (1)
8. If (Desfase is dAl) and (VppAl is dAl9) then (Distancia is distancia_9)(Tipo_Metal is Al) (1)
9. If (Desfase is dCo) and (VppCo is dCo25) then (Distancia is distancia_25)(Tipo_Metal is Co) (1)
10. If (Desfase is dCo) and (VppCo is dCo4) then (Distancia is distancia_4)(Tipo_Metal is Co) (1)
11. If (Desfase is dCo) and (VppCo is dCo5) then (Distancia is distancia_5)(Tipo_Metal is Co) (1)
12. If (Desfase is dCo) and (VppCo is dCo6) then (Distancia is distancia_6)(Tipo_Metal is Co) (1)
13. If (Desfase is dCo) and (VppCo is dCo7) then (Distancia is distancia_7)(Tipo_Metal is Co) (1)
14. If (Desfase is dCo) and (VppCo is dCo8) then (Distancia is distancia_8)(Tipo_Metal is Co) (1)
15. If (Desfase is dAc) and (VppAc is dAc0) then (Distancia is Distancia_0)(Tipo_Metal is Ac) (1)
16. If (Desfase is dAc) and (VppAc is dAc25) then (Distancia is distancia_25)(Tipo_Metal is Ac) (1)
17. If (Desfase is dAc) and (VppAc is dAc4) then (Distancia is distancia_4)(Tipo_Metal is Ac) (1)

Figure-8. Rules implemented for fuzzy logic.

For programming purposes, the four membership functions are not used simultaneously, for all three contain the values of PPV for each type of metal and in some cases have similar ranges for the same distance; It is why at the beginning of the function are initialized these three variables to zero. Then a series of conditional PPV variable input is associated with the corresponding metal at the entrance.

2.2.6 Graphical interface

Finally, all component software codes are stored as separate functions. These functions are called on one code via a GUI implemented by the GUI (Graphics User Interface) Matlab.

The graphical interface is composed of five main parts as shown in Figure-9. The information supplied by the blocks of the interface is detailed below:

1. Type of detected metal.
2. Image type detected material.
3. Distance which is the object.
4. Phase angle and PPV signals.
5. Graph of the detected signals

Figure-9. Graphical interface designed for the project.

3. RESULTS AND DISCUSSIONS

3.1 Test of the Prototype Field

A small land is defined to perform the actual testing in this area different model of anti-personnel mines

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containing buried metal are planted as shown in Figure-10. The land is located in a dry environment with a level of average vegetation. Plastic materials are used as containers to not interfere with the measurements of the sensor. Each prototype contains the metal plates with which the laboratory tests were conducted, such as aluminum, nails, copper, and steel as shown in Figure-11; but now landmine models are in the middle ground and a certain distance. Once the landmine model installed detection system is tested and measurements using a scanning sensor are performed.

Figure-10. Testing on small land.

Figure-11. Contents of the models of antipersonnel mines.

Although natural obstacles interposed between the sensor and the metal plates, the system designed and implemented performed well yielding the expected results. Field measurements vary little compared to those made in the laboratory, however, it is concluded that the prototype of antipersonnel mines using intelligent systems have good efficiency.

3.2 Result of Neural Networks

Neural networks are trained on the model of pattern recognition and a supervised manner. To accomplish this is used a target composed of 9 bits which help to determine the distance to the metal detection, where the least significant bit (1) determines the farthest distance detection, while the metal is the higher weight (9) determines the nearest distance as shown in Figure-12.

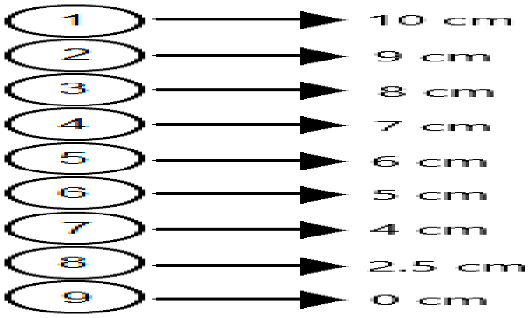

Figure-12. Structure of the target used.

The neural network is trained until achieving good performance, as shown in Figure-13. Then the results are validated by conversion to decimal format for each binary number obtained at the outlet and Table-1 is obtained.

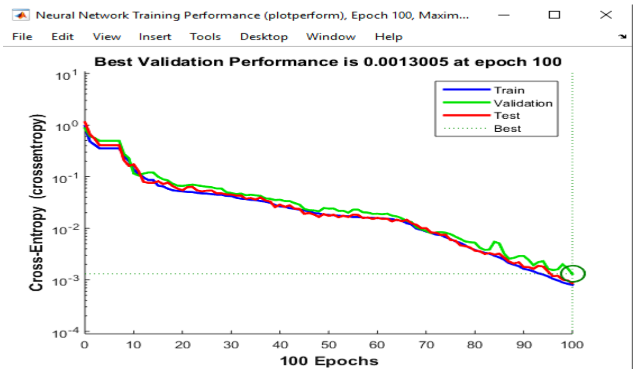

Figure-13. Performance of the neural network.

Table-1. Discrimination obtained with Neural Network.

Salidas Red Neuronal		
# Binario	**# Decimal**	**Distancia (cm)**
100000000	1	10
010000000	2	9
001000000	4	8
000100000	8	7
000010000	16	6
000001000	32	5
000000100	64	4
000000010	128	2.5
000000001	256	0

The data of Table-1 are represented by the graphical interface after making the respective conversion.

3.3 Results of Fuzzy Logic

As it is mentioned earlier, rules work as conditional using two input variables which are phase angle and PPV? As a result, the metal type and distance that it is are estimated as shown in Table-2.

Table-2. Results of fuzzy logic.

Distance		Metal Type	
Rank	**Equivalence (cm)**	**Rank**	**Equivalence (type of material)**
0-2	0	0 to 0.2	Aluminum
2-4	2.3	0.3 - 0.5	Copper
4-6	4	0.55	undetected
6-8	5	0.6 to 0.8	Steel
8-10	6	0.9 - 1.1	other metals
10.5	undetected	Without use	Without use
11-13	7	Without use	Without use
13-15	8	Without use	Without use
15-17	9	Without use	Without use
17-19	10	Without use	Without use

Based on these data and the tool support Fuzzy Logic Designer, the operation of the implemented rules is simulated. Several simulations are performed for each of the rules, in total 22 to see the behavior of outputs and check that the result delivered is indicated. The drawing is saved and then is loaded in the indicated function, fuzzy.

4. CONCLUSIONS

The hardware for the operation of the prototype which captures the different signals obtained by the proposed metal detector was performed. Generating excitation signals of the sensor with power and frequency suitable for the operation were implemented.

During laboratory tests, it was observed that the sensor measurements are affected by changes in the size of the area of the metal object and the position where it is. This causes the peak-to-peak voltages and phase angles vary considerably being the object at the same distance and being of the same type of material.

Through field testing was possible to show that the sensor has a range of optimal detection independent element which is interposed between the object and, for this case was ground and plastic.

After field tests, the best results were achieved with the method of fuzzy logic, because in most of the tests provides evidence the correct information on the type of metal that is already detecting the distance it is.

The results obtained with the artificial neural networks were not the desired due to the training method used which was monitored. This is because it is based on pattern recognition and databases stored there are very similar signals, which creates uncertainty for the network and therefore erroneous results.

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