Pattern Recognition Based on Multimodular Neural Networks

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Abstract: The purpose of the research is to develop a method that can make minesweeping safer by no longer demanding human assistance for the localization of landmines. The objective is to create a robot that can find specific landmine types by their geometric features. For this, the required knowledge is acquired by methods based on artificial neural networks. The final result is the demonstration of the algorithm of an intelligent robot's pattern recognition module that can achieve the first step of demining an area, which is localizing mines without risking human life.

Keywords: soft computing, artificial neural network, demining

1 Introduction

One of the main imperfections of landmines is that the target can not be chosen, so the resident population, workers of humanitarian associations and the natural wildlife are also in great danger just like soldiers. There are only estimations about the number of accidents, since most of them take place in developing countries, but approximately 20.000 tragedies happen each and every year, which means two per hour (for example, between 1979. and 2005. in Cambodia more than 45.000 people were injured, 75% of them was civilian [1]).

There are more than 80 countries all over the world known as minefields, and no one knows the exact number and position of mines about a certain area. The most dangerous places are Afghanistan, Angola, Burundi, Bosnia and Herzegovina, Cambodia, Chechnya, Colombia, Iraq, Nepal and Sri Lanka. In addition to this, some of the countries do not provide official and precise report concerning the problem, like Burma, India and Pakistan.

This paper is organized as follows: in Section 2 related works are examined. It is followed by the presentation of the proposed method and explanation in detail. The last two sections of the paper show some of the latest experimental results and conclusions drawn from them.

2 Related Work

Several demining methods have been developed, of which the most important are manual search with metal detector, trained dogs, bees [2], rodents [3], plants [4], bacteria [5], nuclear and acoustic techniques [6] and even pattern recognition on infra-red images [7].

Every method has its own advantages, but also disadvantages: there are always types of landmines that can not be detected with the given technique, like plastic mines when using metal detector [8]. Another aspect is when we use animals in order to acquire information, we place another living being in great danger, which is highly morally questionable, not to mention that the biology of animals can hugely affect the indication result.

Regarding the fact that landmines have well-defined geometry, we can assume that a novel technique based on geometric features can be very successful in the process of demining. Although, since the orientation vary in great range and the environment is rather noisy, a hard computing pattern recognition method would not be flexible and robust enough, so we suggest a novel soft computing based approach (like in [9]), that is based on artificial neural networks (as in [10]).

3 Proposed Method

In this section the proposed method is discussed in detail. Firstly, the suggested detector is presented, which is followed by defining patterns and complexity reduction. After that, input space transformation and network architecture are introduced. Finally, the created Graphical User Interface is demonstrated which is followed by the review of learning and the essential early stopping.

3.1 The Detector

The very first problem to solve is how to acquire information of the landmine. We introduce a new, pressure-based detector (Figure 1). Placing 20 of these simple indicators in a line with a distance of five centimeters, we can obtain information of a one meter long line, so if we execute 20 measurements, we know the required data of one square meter. It is noticeable that the data acquisition is very simple, fast and does not require human assistance, which is a great advantage of the suggested method. Another feature is that on different land types there is only one parameter to be set: the pressure of the piston. In this way, the method can be easily used in a Cambodian forest as well as in an Iraq desert.

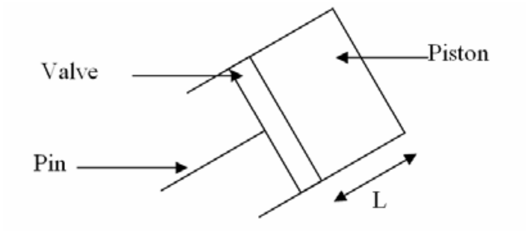

Figure 1
The pressure-based detector

3.2 Patterns

Observing the landmine types that are used in the last decades we can notice a typical feature: they are rather circular in a horizontal segment. To demonstrate that the suggested method is flexible and can be easily used for different types of landmines, we will search for two different landmines that are from this kind. Both of them are of 20-25 cm diameter, one of them is a simple disc, the other one has a knob in the center (Figure 2). Using a data acquisition grid with 5 cm segments, the observed landmine types can be seen as a round in a 5×5 square and can be characterized with 13 measured inputs (the other 12 inputs are indifferent). In this way, our „virtual landmines” can be seen as vectors containing 13 elements, where the measured value (deepness) can be from the set of {0;1;2}.

		2		
	2	**2**	**2**	
2	**2**	**2**	**2**	**2**
	2	**2**	**2**	
		2		

		2		
	2	**1**	**2**	
2	**1**	**2**	**1**	**2**
	2	**1**	**2**	
		2		

Figure 2
Basic patterns

In practice, landmines are positioned by airplanes or artillery, so their lay is not perfectly horizontal. In addition to this, we are not aware of which side is in front of us, so we have to pay attention to these invariances (skewness and orientation). As a result, we have eight other patterns for each type in addition to the mentioned ones (k×45° rotation, k=1,2,…,8).

3.3 Complexity Reduction

Simply using these vectors as the input of the neural network, its size would be huge and the learning speed would be very small. Instead of this, we should decompose the basic patterns to smaller ones, so that the dimension of the input space decreases. With this simplification, the learning speed can be hugely increased.

	2			
2	**2**			
	2			

		2		
		1	**2**	
			1	**2**

Figure 3
Partial patterns

Concerning the basic patterns, we can divide them into smaller groups, the so-called partial patterns (two of them can be seen in Figure 3). With this simplification we can reduce the input dimension to 3-5 from 13, but increase the number of patterns from 18 to 46, which is a beneficial trade-off.

3.4 Input Space Transformation

We only discussed the noise-free case so far, but in reality there is always a great amount of disturbing noise, so pattern recognition is definitely not such easy. We presented the basic and the partial patterns, but only with discrete numbers (from the set of {0;1;2}). In practical use, the measured input is from the continuous range of [0,2]. If we simply use the raw values, the learning takes too long and the distinction is not contenting enough. The other extremity is naively rounding them, but this is not robust enough, because it is very sensitive to noise. The suggested preprocessing method is somewhere in the middle.

We divide the range to discrete domains that are continuous, so we gain the advantages of the two approaches, but throw away their drawbacks (Equation 1). With the discrete domains we can roughly characterize the deepness to „LOW", „MEDIUM" and „HIGH", so the separation is satisfying and the learning is fast, and with the continuity of the domains we can distinguish the fine features, consequently the method is tolerant to noise.

$$\hat{x}_{preproc} = \begin{cases} c \cdot x^2 & , \quad if \quad x \in [0;0.5) \\ 1 + \mathrm{sgn}(x-1) \cdot c \cdot (x-1)^2 & , \quad if \quad x \in [0.5;1.5) \\ 2 - c \cdot (x-2)^2 & , \quad if \quad x \in [1.5;2] \end{cases} \tag{1}$$

Since the activation function of the used neurons is steep in the neighborhood of zero, we should shift and narrow the region (Equation 2).

$$x_{preproc} = \frac{\hat{x}_{preproc} - 1.5}{2} \tag{2}$$

3.5 Network Architecture

Regarding theoretical results, we used Multi Layer Perceptrons [11] to fulfill the classifications. In order to decrease the number of neurons and the learning time, we took advantage of our a priori knowledge: we created subnets to learn specific subproblems, so we constructed a hierarchical structure (Figure 4).

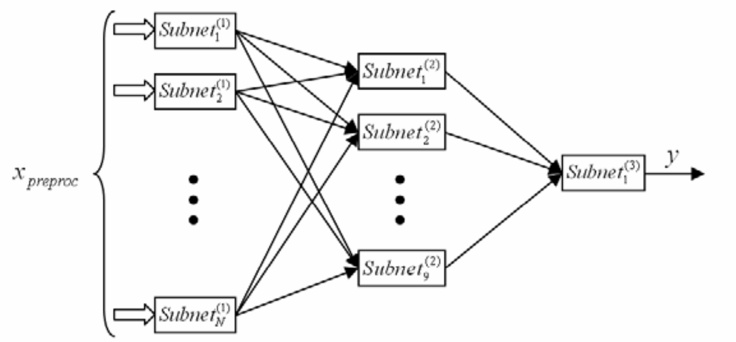

Figure 4
Multimodular structure

There are three layers of subnets: in the first one we can find 22 or 24 subnets depending on the landmine type: their objectives are identifying the partial patterns. The second layer executes the composition: it learns the appropriate coexistence of the specific partial patterns, so it detects the main patterns. The task of the third layer is to summarize the knowledge, whether the input vector is from a landmine or not.

Since the required knowledge for us is a „yes or no", we need a stepfunction at the end of the third layer, whose comparation level is noise-dependant (the greater the noise the lower the level).

3.6 Graphical User Interface

A special Graphical User Interface (Figure 5) is very helpful, because we can easily set and modify the most important parameters, like landmine type, teaching and network parameters, set sizes, number of landmines and the amount of noise.

Usually we divide our data to three disjunct set: learning, validation and test set. The first one is for teaching the network, the second is to check the performance during the teaching (and early stopping), the last one is for the ultimate test after teaching.

Since in our case the precision and the knowledge of precision are essential, we separate a test set before the learning phase, so we can only define the ratio of the learning and validation set sizes.

To get relevant and objective information about the performance, we place „almost mines” on the minefield when we test our system, so we can decide whether we can identify real mines and neglect everything else or not. Modeling human errors, defined amount of incorrect train data is allowed while teaching.

Another very useful application is the Result Window that provides numerical and graphical information as well: we gain knowledge on the performance and see the observed minefield with the found and the missed landmines.

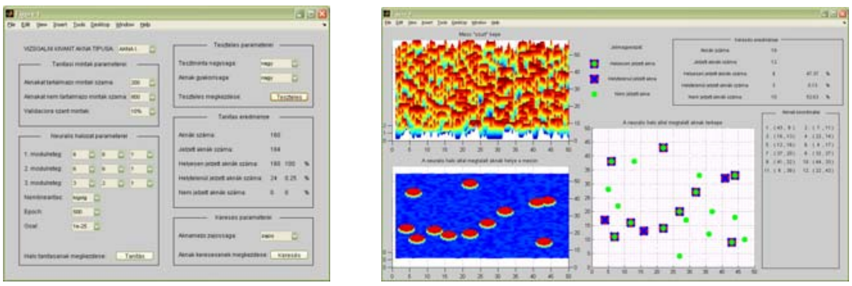

Figure 5
Graphical User Interface and Result Window

3.7 Learning

We can see the typical teaching phase on Figure 6: performance is getting better rapidly for a few dozens of epochs, after that we notice stagnation, so it is practical to stop teaching (early stopping) to avoid overfitting. Applied training method is one of Levenberg-Marquardt’s.

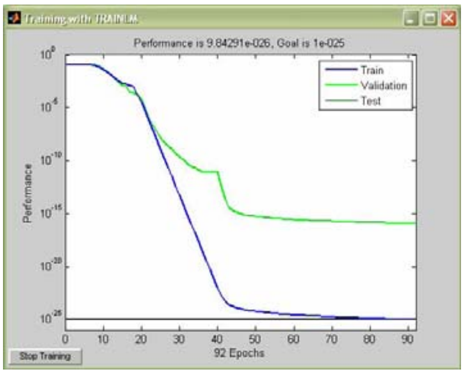

Figure 6
Typical error curves

4 Experimental Results

We examine three different network size (“small”, “appropriate” and “too large”):

1) [3-3-1]-[3-3-1]-[3-3-1] neurons per layer (224 and 238 total),
2) [6-6-1]-[6-6-1]-[3-2-1] neurons per layer (409 and 503 total),
3) [10-10-1]-[10-10-1]-[5-5-1] neurons per layer (611 and 704 total).

In the final test phase, we created a completely new environment: there are not only mines on the observed minefield, but „almost mines” as well. Without this complication we could not be sure about the performance of the system, because on a real minefield there are branches, bones and rocks that have to be separated from searched mines.

One of the most important characteristics of the results is the performance on the train (Figure 7 and Figure 9) and test set (Figure 8 and Figure 10) are quite similar, so the networks learned the problem, not only the train data. According to the results, we can claim that with early stopping we could avoid overfitting, which is a very frequent problem when using artificial neural networks.

With the „small networks” the number of correct identifications and false negative signals are almost equal, so it can not be used, since only half of the mines can be localized. Increasing the complexity (means adding new neurons to the network) a great development can be seen with the networks of „appropriate size”: the ratio of correct identifications is very high (little lower than 100%) while there are hardly any false negative signals. It means that approximately all of the mines are properly indicated and none of them is missed, which is a quite impressive achievement. Further increasment on the complexity decreases the number of false positive identifications, which means the network is getting more robust to noise (branches, rocks and bones).

We have to mention that the ratio of false positive identifications is about 10-20% but this is not a great problem since indicating a branch is much more preferable than missing a mine.

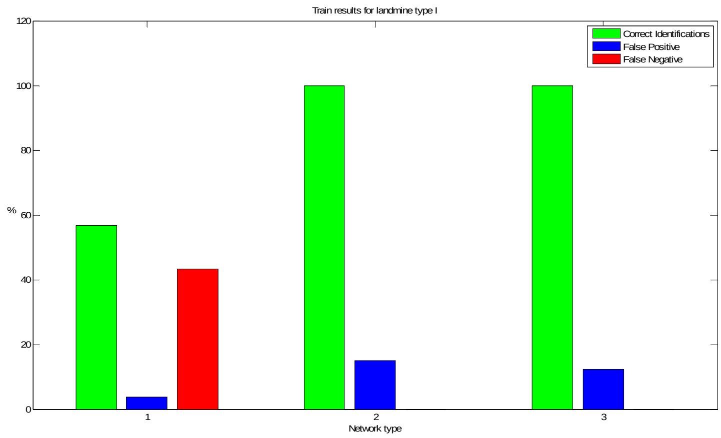

Figure 7
Train results for landmine type I

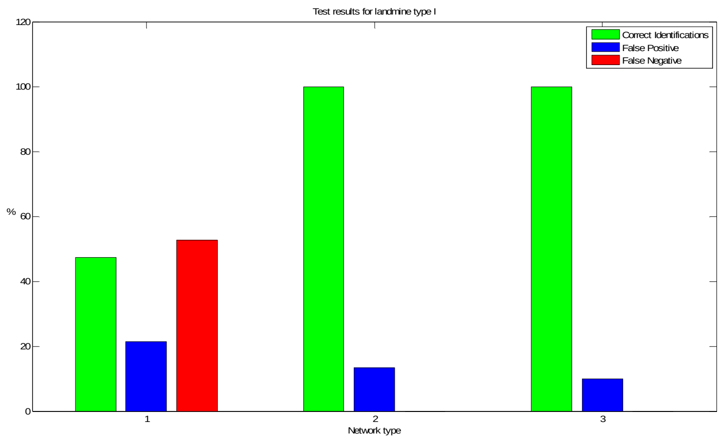

Figure 8
Test results for landmine type I

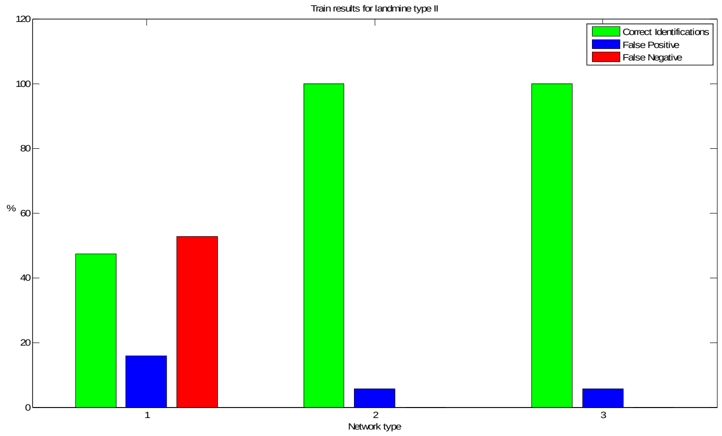

Figure 9
Train results for landmine type II

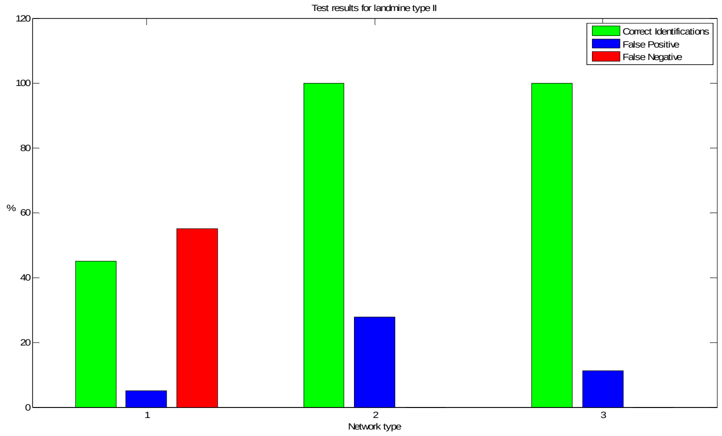

Figure 10
Test results for landmine type II

Conclusions

To summarize the achieved results, we presented a novel soft computing based demining method which can be successfully applied in landmine localization. The algorithm is very flexible and robust, thanks to the neural network approach. It is important to note that the ratio of correct identifications is very high and the false negative indications are rare, which is a reassuring result, considering security reasons.

As for practical aspects, the demining robot can be naturally divided to three major components: the moving platform, the sensors and the algorithm. The first two hardware type machines can be constructed on a very low budget, since high precision is not required, which was the financial objective. The last element, the neural network itself can be implemented on a microcontroller, so it is also a low-cost solution. Because of reasonable costs and high performance, the development can be commenced easily.

References

[1] International campaign to ban landmines, http://www.icbl.org/

[2] J. J. Bromenshenk et al.: Bees used in Area Reduction and Mine Detection. *Journal of Mine Action*, Issue 7.3, 2003

[3] H. Nyambura: Move over Sniffer Dogs, Here Come Africa's Rats. *Reuters New Media*, 27 September 2004

[4] Mine-sniffing plants. *ACF NewSource*, http://www.acfnewsource.org/ science/ mine_sniffing_plants.html

[5] R. S. Burlage, M. Hunt, J. DiBenedetto, M. Maston: Bioreporter Bacteria For The Detection Of Unexploded Ordnance. http://www.mech.uwa. edu.au/jpt/ demining/ others/ornl/rsb.html

[6] Vibrations could Reveal Landmine Locations. *NewScientistTech*, http://technology.newscientist.com/article/dn10868-vibrations-could-reveal -landmine-locations.html

[7] I. Yu-Hua, G. T. Tjahjadi: Detecting and Locating Landmine Fields from Vehicle- and Air-Borne Measured IR Images. *Pattern Recognition*, Volume 35, Issue 12, 2002, pp. 3001-3014

[8] L. Xuejun, L. Carin: Application of the Theory of Optimal Experiments to Adaptive Electromagnetic-Induction Sensing of Buried Targets. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Volume 6, Issue 8, 2004, pp. 961-972

[9] P. D. Gader, B. N. Nelson, H. Frigui, G. Vaillette, J. M. Keller: Fuzzy Logic Detection of Landmines with Ground Penetrating Radar. *Signal Processing*, Volume 80, June 2000, pp. 1069-1084(16)

[10] B. Zhang, K. O'Neill, J. A. Kong, T. M. Grzegorczyk: Support Vector Machine and Neural Network Classification of Metallic Objects Using Coefficients of the Spheroidal MQS Response Modes. *IEEE Transactions on Geoscience and Remote Sensing*, Volume 46, Issue 1, Jan. 2008, pp. 159-171

[11] M. Altrichter, G. Horváth, B. Pataki, Gy. Strausz, G. Takács, J. Valyon: Neurális hálózatok. *Panem Kiadó*, Budapest, 2006