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Contribution of Artificial Neural Networks to the Identification and Detection of Targets Concerning Mobility on Remote Sensing Images

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ABSTRACT

Targets identification on remote sensing images depends essentially on efficiency of the followed classification and analysis methods. In this context, this paper is to present a system for detection and identification of targets on a multi-band satellite image by connectionist methods. From a database comprising reflectance samples of four desired target, the proposed system performs a supervised classification of the wanted objects on a multispectral image by the gradient algorithms. Compared with principal component analysis (PCA), the method provides more meaningful results. Then, the system performs automatic identification of suspected targets on the studied image.

Keywords: *Multispectral Image, Supervised Classification, Identification, Principal Component Analysis, Artificial Neural Networks, Gradient Algorithms.*

1. INTRODUCTION

Topographic maps are still widely used in military field principally for preparing forces movement on unknown territory. Indeed, the movement of ground vehicles, especially in wartime, is generally based on conventional techniques of topographic maps reading, which provide an overview on roads and terrain reliefs to cross (Figure 1). However, these maps do not take into account the nature of soil and changes that can take place over time on the maneuver ground (appearance of woodlands, swamps and flooded areas ...). In this case, the maps will become less reliable and require additional data to enable the progression of the mobility means on the battlefield.
Given a portion of land, our work consists particularly in detecting areas with reduced mobility, such as swamps, dense forests and surface water.

We have a database of reflectance samples deduced from four classes, namely composed of sandy or low-density soil, non-deep water, mud or moist soil and wooded areas [1]. The connectionist classification of samples allowed the spatial separation of the four classes. Then, applying the same Artificial Neural Network (ANN) to a multi-spectral image of the MEKNES region, resulted in the extraction of the desired targets and their identification on the studied image.

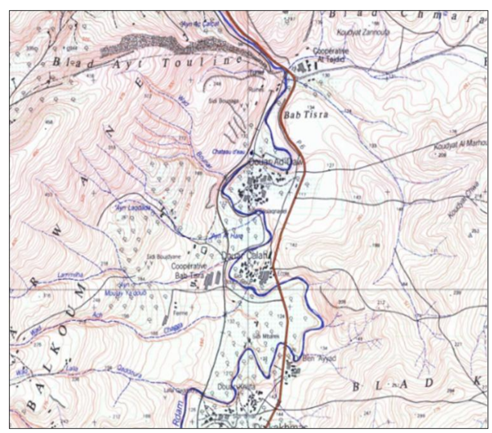

Fig. 1. Topographic map of SIDI KACEM region, scale: 1/25 000

2. CLASSIFICATION OF DEDUCTED TARGETS

To allow the detection of targets chosen on the studied image, we processed a supervised classification of the scene based on 32 samples representing four predefined targets (Table 1).

Table 1: Samples of targets taken from a multispectral image (Landsat 7 ETM+1)

Bands	SAND OR LOW DENSITY FLOOR							
1	0,21	0,21	0,21	0,21	0,20	0,21	0,21	0,21
2	0,33	0,32	0,32	0,32	0,35	0,34	0,34	0,32
3	0,35	0,34	0,34	0,34	0,36	0,4	0,33	0,41
4	0,33	0,33	0,32	0,33	0,34	0,33	0,33	0,32
5	0,28	0,29	0,26	0,3	0,31	0,32	0,27	0,29
6	0,52	0,52	0,52	0,52	0,53	0,52	0,52	0,52
7	0,27	0,21	0,29	0,21	0,31	0,36	0,29	0,3
	NON DEEP WATER							
1	0,61	0,61	0,61	0,61	0,62	0,62	0,69	0,68
2	0,72	0,68	0,67	0,67	0,67	0,67	0,69	0,66
3	0,55	0,64	0,53	0,54	0,54	0,55	0,54	0,53
4	0,45	0,54	0,53	0,54	0,54	0,54	0,55	0,54
5	0,46	0,45	0,45	0,45	0,45	0,45	0,45	0,44
6	0,42	0,42	0,42	0,42	0,42	0,42	0,42	0,42
7	0,54	0,43	0,47	0,57	0,64	0,75	0,4	0,6
	MUD OR WET FLOOR[1]							
1	0,51	0,51	0,51	0,51	0,51	0,51	0,50	0,51
2	0,61	0,59	0,58	0,56	0,61	0,59	0,57	0,56
3	0,34	0,34	0,33	0,33	0,34	0,34	0,34	0,33
4	0,34	0,34	0,33	0,33	0,34	0,35	0,34	0,34
5	0,65	0,64	0,64	0,64	0,65	0,64	0,64	0,64
6	0,02	0,01	0	0,01	0,02	0,02	0	0
7	0,41	0,39	0,38	0,36	0,41	0,38	0,37	0,34
	WOODED AREA							
1	0,31	0,31	0,31	0,31	0,31	0,31	0,31	0,31
2	0,41	0,39	0,38	0,36	0,31	0,39	0,34	0,36
3	0,34	0,34	0,33	0,34	0,34	0,33	0,33	0,34
4	0,34	0,34	0,43	0,33	0,34	0,35	0,34	0,04
5	0,01	0,01	0,01	0,01	0	0	0	0,01
6	0,05	0,04	0,01	0	0,01	0	0	0
7	0,01	0	0	0	0,01	0	0	0

For this, we used an ANN based on Multi-Layer Perceptron (MLP). This network uses at learning phase, the back-propagation gradient algorithm for modifying the synaptic weights until a minimum threshold equal to the mean square error (MSE) is reached. This processing leads to a more efficient system [2].

2.1 Network Configuration

The network built from the previous step, comprises of a layer with n inputs, m hidden layers and a layer S with m outputs (Figure 2).

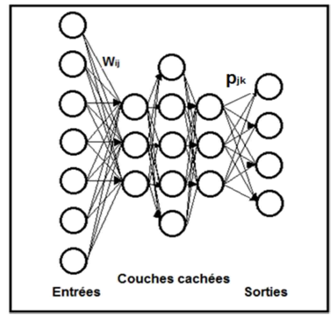

Fig. 2. Architecture of an MLP based Artificial Neural Network with supervised learning phase

The input layer E can be written as a matrix:

$$E = \begin{bmatrix} E_{11} & E_{12} & . & . & . & E_{1r} \\ E_{21} & E_{22} & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ E_{s1} & . & . & . & . & E_{sr} \end{bmatrix} \quad (1)$$

With: r=32 the total number of samples, and s=7 the number of bands (values of normalized reflectances).
The input values express the normalized reflectance of each band. As for the output layer, it contains four neurons that correspond to predefined classes.
Only the adjacent layers are interconnected (Figure 3).

[1] High resolution multispectral scanning Radiometer providing radiation in the visible and infrared eight distinct bands. It is an improved version of the sensor Thematic Mapper (TM), which provides increased spatial resolution thermal infrared band (band 6), improved radiometric calibration and addition of a panchromatic band. It is designed to collect and detect the radiation of earth in a 185 km band wide.

INPUTS	$\longrightarrow$	**HIDDEN LAYERS**	$\longrightarrow$	**OUTPUTS**	
E_{ij}		$y_j = f\left(\sum_i E_i w_{ij}\right) = f\left(a_j\right)$		$s_k = f\left(\sum_j y_j p_{jk}\right) = f\left(b_k\right)$	(2) (3)

Fig. 3. Inter-layers equations of a MLP based Artificial Neural Network

Where a_j : total input of the hidden layer y_j and b_k : total input of the output layer s_k

We use the sigmoid function as activation function, and a linear function for the output layer.

The activation function of the network used for the evaluation of outputs is a sigmoid f:

$$f\left(x\right) = \beta\left(\frac{e^{\alpha x}}{\left(1+e^{\alpha x}\right)}\right) \qquad (4)$$

Since the manipulated data is normalized, we take and we shall have:

$$f\left(x\right) = \frac{e^{x}}{1+e^{x}} \qquad (5)$$

2.2 Learning Algorithm

The learning phase starts with a forward propagation of the state of the inputs towards the hidden layers and the output cells, then a back propagation of the error with an adjustment of the connections weights [3] [4] [5] . The operation is repeated until the MSE minimized to the fixed threshold. The gap is defined as:

$$E\left(p_{jk}\right) = \frac{1}{2}\sum_k\left(sd_k - s_k\right)^2 \qquad (6)$$

Where:

- sd_k is the desired output ;
- s_k is the true output.

The algorithm updates the weights of the gradient of the highest slope.

$$\Delta p_{jk} = -\mu\frac{\partial E\left(p_{jk}\right)}{\partial p_{jk}} \qquad (7)$$

$\mu\left(0<\mu<1\right)$ is the step of the gradient thanks to which we can control the convergence speed of algorithm.

After deriving the MSE expression, with respect to the weights, we obtain:

$$\frac{\partial E\left(p_{jk}\right)}{\partial p_{jk}} = -\sum_k\left(sd_k - s_k\right)\frac{\partial s_k}{\partial p_{jk}} \qquad (8)$$

$$\frac{\partial s_k}{\partial p_{jk}} = \frac{\partial f\left(\sum_j y_j p_{jk}\right)}{\partial p_{jk}} = f'\left(\sum_k y_j p_{jk}\right)y_j \qquad (9)$$

$$\frac{\partial s_k}{\partial w_{jk}} = f'\left(\sum_j y_j p_{jk}\right)f'\left(\sum_i x_i w_{ik}\right)x_j \qquad (10)$$

Therefore, the updating weigth equations become:

$$\Delta p_{jk} = \mu_1\sum_k\left(sd_k - s_k\right)f'\left(\sum_j y_j w_{jk}\right)y_j \qquad (11)$$

$$\Delta w_{jk} = \mu_2 f'\left(\sum_j y_j w_{jk}\right)f'\left(\sum_i x_i w_{ik}\right)x_j \qquad (12)$$

And as $f'\left(x\right) = \left(\frac{e^{x}}{\left(1+e^{x}\right)}\right)' = f\left(x\right)\left(1-f\left(x\right)\right) \qquad (13)$

We can apply the Delta rule to compute the gradient of the output layer as follow:

$$\delta^{N} = \frac{\partial E\left(p_{jk}\right)}{\partial p_{jk}} = \left(sd_j - s_j\right)s_k\left(1-s_k\right) \qquad (14)$$

$$\delta^{N-1} = \sum_k \delta^{N} p_{jk} y_k\left(1-y_k\right) \qquad (15)$$

Then:

$$\Delta p_{jk} = \mu_1\sum_k \delta^{N}\cdot y_j \qquad (16)$$

$$\begin{aligned}\Delta w_{jk} &= \mu_2\left(\sum_j \delta^{N-1}.x_j\right)\\ &= \mu_2\sum_j\left(\sum_k \delta^{N}\cdot p_{jk} y_k\left(1-y_k\right)\right)x_j\end{aligned} \qquad (17)$$

NB: The weights w_{jk} between the cells j and k are modified proportionally to the output j and the delta of k .

2.3 Simulations

While using Matlab software, we were able to make a program that classify automatically the samples corresponding to the different targets according to our approach.

For the desired outputs, and in order to separate the classes in space, we chose the following vectors: [-1 1 1 1], [1 -1 1 1], [1 1 -1 1] and [1 1 1 -1].
The simulation was based on several tests using different values of the number of hidden layers and the number of cells.

For $K = 1$, $N_{C1} = 3$, $N_{C2} = 6$ et $N_{C3} = 3$, the graphical representation in 3D space is the following (Figure 4):

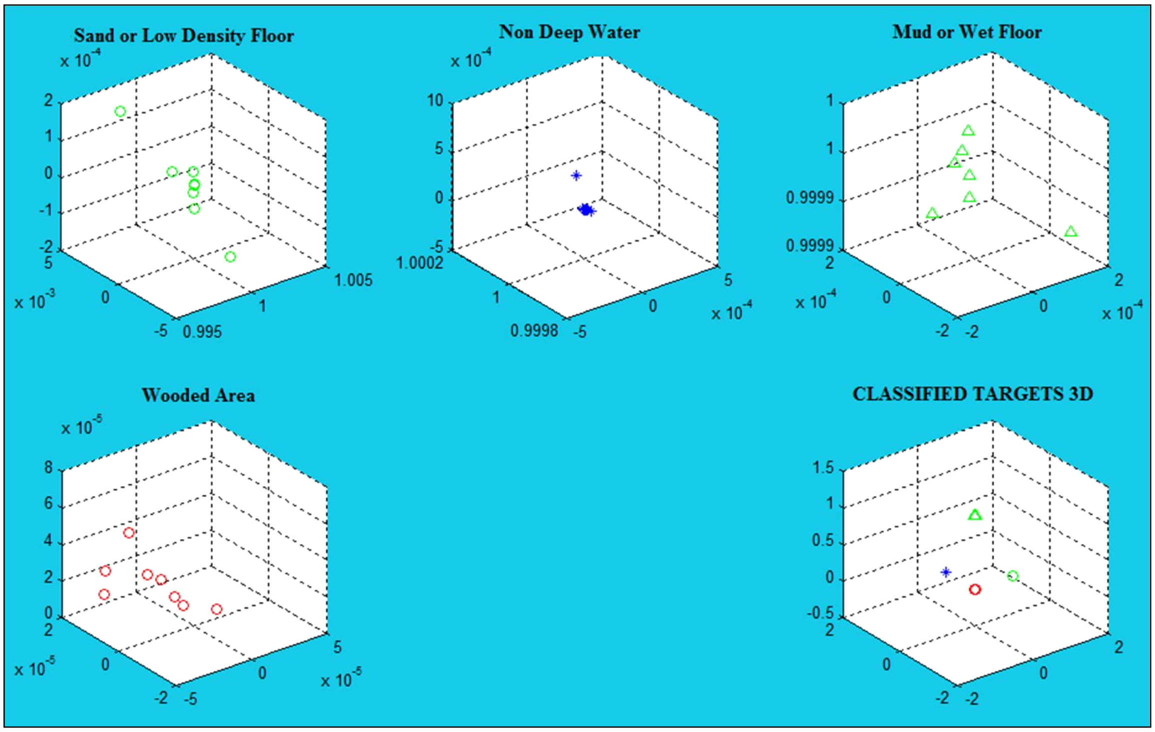

Fig. 4. Classification of the four targets using MLP

After one iteration, the network generates a mean square error of the order of 10^{-08} (Figure 5). Also, the gradient error is approximately 4,5772 10^{-06} (Figure 6). This indicates that the input classes are highly correlated with the output ones.

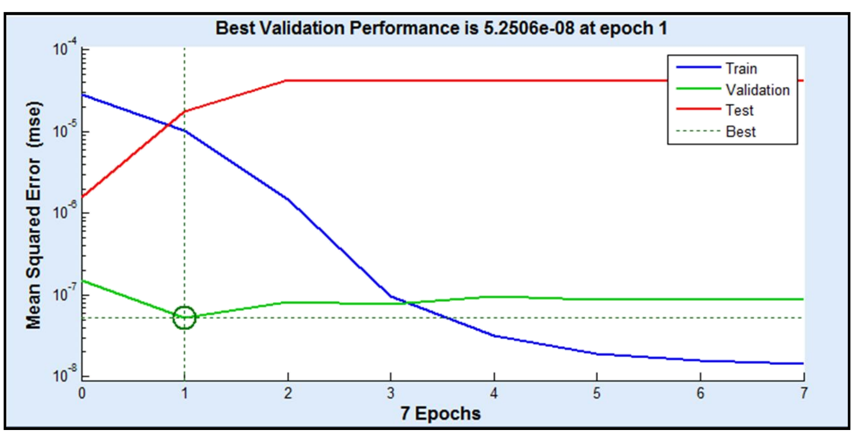

Fig. 5. Evolution of MSE, test and validation during learning phase

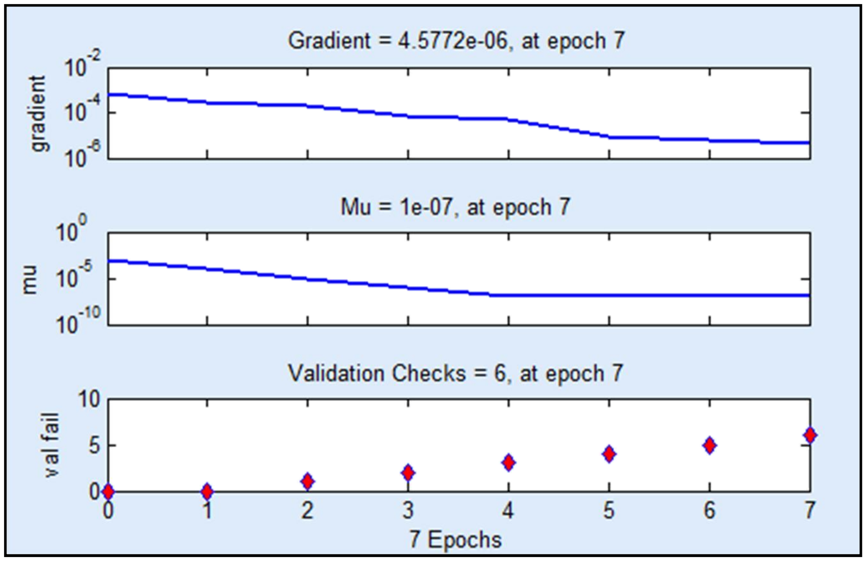

Fig. 6. Evolution of the Gradient, Mu (μ) and Validation

2.4 Principal Component Analysis based Comparison

The comparative study of this analysis with classical numerical methods such as the PCA shows that the MLP back-propagation gradient is more efficient and gives very conclusive results (Figure 7) [6] [7]. However, the iterative approximation along the highest slope could be improved by the conjugate gradient algorithm [8]. This results in the search for a minimum producing a faster convergence.

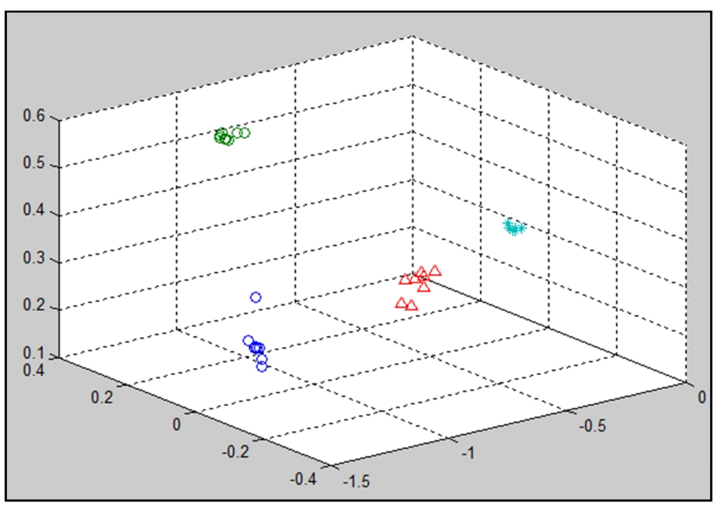

Fig. 7. Classification of the four targets using PCA.

3. TARGETS IDENTIFICATION ON THE STUDIED IMAGE

To test the effectiveness of our method, we used an image of the Meknes region taken by the same satellite reference sensor (Landsat 7 ETM +). We chose an area with a size of 769*593*7 which presents some field aspects containing the four targets of interest (Figure 8).

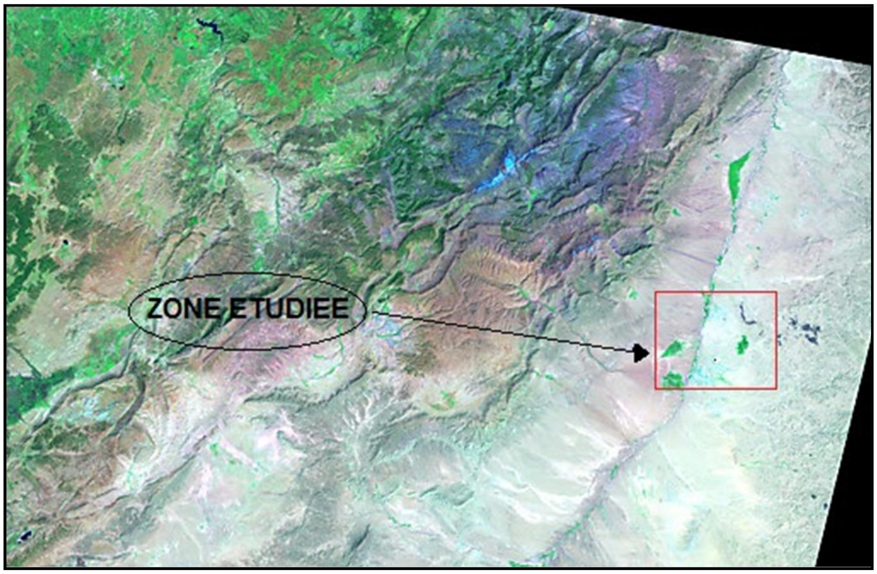

Fig. 8. Colored composition of 7 bands image of Meknès region

After the effective target classification established by the Matlab code (2.2), we record the weights and the biases of the network.
The neural network constructed becomes able to detect the presence of these targets and identify them on any multi-band image, provided it is acquired by the same sensor.

According to this assertion, the principle of identification is to resize the global matrix of the image to the size of 456017*7 (769*593*7) and then, inject it into the network. After assigning each voxel to the corresponding class, its position will be marked on the overall picture. From these positions, the program proceeds to reconstruct the image by assigning false colors to the four targets on the image (Figure 9).

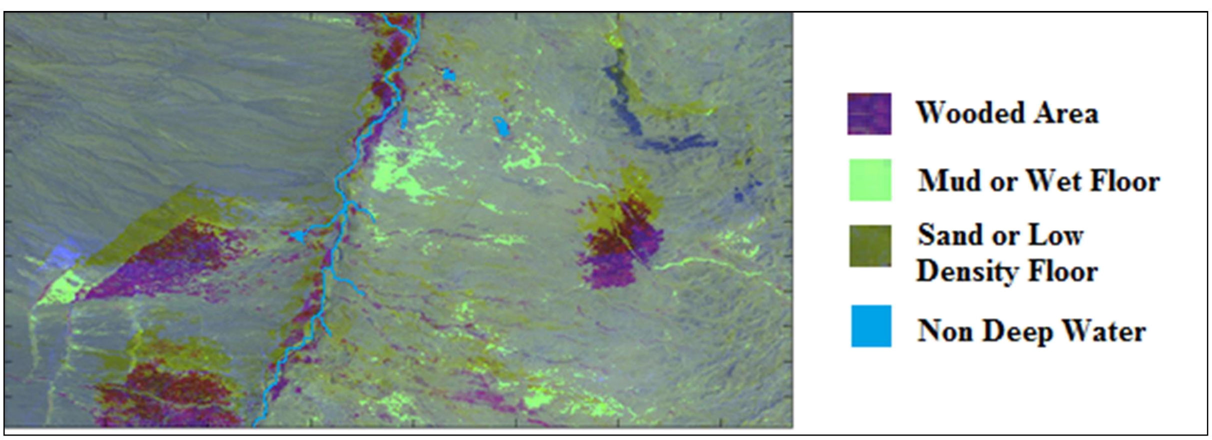

Fig. 9. Identification of the four targets on the 7 bands image (Meknes region)

4. CONCLUSIONS

In this paper, we presented a targets recognition method based ANNs. Indeed, from a database containing samples of four predefined targets, we performed a supervised classification through a MLP network. This classification allowed the spatial separation of the aforesaid targets based on the mean square error generated by the network with the back-propagation gradient. Thereafter, a comparison of the results of this method with those

obtained by the principal component analysis demonstrates the relevance and effectiveness of the Multi-Layer Perceptron networks for such classifications.
The identification involves a supervised classification of the images based on the desired target. It is performed by the same network, using the optimal settings resulting from the learning phase of the first classification. The results are very convincing.
In this way, thanks to the robustness of their models, Artificial Neural Networks appear to be remarkably well adapted to different targets. Adaptation to nonlinear problems, is a major asset for a very satisfactory solution to all types of targets reconnaissance.

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