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Detection of subsurface Qanats by Artificial Neural Network via Microgravity data

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Abstract

A full automatic algorithm is designed to detect subsurface Qanats (sub terrains) via Artificial Neural Networks .We first gained the residual gravity anomaly from microgravity data and then applied it to a Multi Layer Perceptron (MLP) which was trained for the models of sphere and cylinder.

As a field example, the depth of a subsurface Qanat buried under the north entrance of the Geophysics Institute is determined through MLP (trained with noisy data).

Key words: Artificial Neural Network, Microgravity, Qanat

اکتشاف قنات‌های زیرزمینی مدفون از طریق شبکه‌های عصبی مصنوعی و با استفاده از داده‌های میکروگرانی‌سنجی

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چکیده

در این مقاله یک الگوریتم هوشمند جهت اکتشاف قنات‌های زیرزمینی مدفون با شبکه‌های عصبی و با استفاده از داده‌های میکروگرانی‌سنجی ارائه شده است.

به منظور برآورد عمق و اندازه قنات‌های زیرسطحی از روی بی‌هنجاری (آنومالی) گرانی باقی‌مانده یک شبکه عصبی مصنوعی با سرپرست، از نوع پرسپترون چندلایه (MLP) طراحی شد. از آنجاکه در طراحی شبکه عصبی سرعت پردازش داده‌ها از اهمیت خاصی برخوردار است و تعداد ورودی‌های زیاد باعث پیچیدگی غیر منطقی توپولوژی شبکه می‌شود، به جای اعمال همهٔ داده‌های تصحیح شده، میکروگرانی درحکم ورودی، مجموعه‌ای مشخصه‌های مناسب (Features) از روی آنومالی باقی‌مانده داده‌های میکروگرانی استخراج می‌شود، سپس با توجه به مدل‌های کره و استوانه که نزدیک‌ترین مدل‌ها به قنات‌های مدفون هستند، مجموعه‌ای از داده‌های آموزشی که برای آموزش شبکه عصبی طراحی شده‌اند، مورد استفاده قرار می‌گیرند، در واقع شبکه عصبی طراحی‌شده پس از این آموزش قادر خواهد بود که با توجه به مشخصه‌های استخراج شده از روی بی‌هنجاری باقی‌مانده، عمق و شعاع قنات مدفون را به‌دست آورد.

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از آنجاکه قاعده کلاسیک خاصی برای انتخاب تعداد نورون‌ها در لایه پنهان شبکه عصبی چندلایه وجود ندارد، شبکه‌های عصبی چندلایه گوناگونی با تعداد نورون‌های متفاوت در لایه پنهان مورد آزمایش قرار گرفت و نمودارهای عملکرد شبکه در هر حالت به‌دست آمد تا از روی آن بهترین مقدار تعداد نورون‌ها در لایه پنهان حاصل شود.

پس از این مرحله ابتدا با استفاده از مجموعه‌ای داده‌های مصنوعی، شبکه عصبی طراحی‌شده مورد آزمون قرار گرفت. سپس خروجی‌های شبکه با استفاده از داده‌های مصنوعی نوفه‌دار برای مدل‌های کره و استوانه بررسی شد که عملکرد مناسبی را نشان داد.

همچنین، عمق قنات زیرزمینی مدفون واقع در ورودی شمالی مؤسسه ژئوفیزیک درحکم نمونه‌ای عملی با شبکه عصبی طراحی شده، به‌دست آمد که با مقدار واقعی آن انطباق خوبی داشت.

واژه‌های کلیدی: شبکه‌های عصبی، میکروگرانی‌سنجی، قنات، پرسپترون چندلایه (MLP)

1 INTRODUCTION

In some parts of Isfahan, ran, there are many subsurface Qanats with a depth of few meters. They were excavated to make subsurface channels of water for water transmission systems which were invented by Iranians for the first time. But most of them have dried and been buried, so that they are now known as dangerous objects for the buildings and infrastructures located at the surface on top of them, because they can act as a trigger of down lifting of the ground. The municipality of Isfahan is trying to detect these subsurface Qanats to determine the risk areas of the city for new building sites and also old buildings to prevent down lifting.

The best geophysical method to detect these kinds of cavities is certainly the microgravity. Qanats have a clear gravity anomaly due to a significant density contrast with the host. In this paper an intelligent method is presented to locate the subsurface Qanats from microgravity data. Some methods like Euler De-convolution and Analytical Signals are very sensitive to noise and depending on interpreter experiments, but using the Artificial Neural Network method the interpreter will be able to determine the depth of the body intelligently.

2 NEURAL NETWORKS

Neural Networks are increasingly being used in prediction, estimation, and optimization problems. Neural networks have gained popularity in geophysics during the last decade.

They have been applied successfully to a variety of problems in geophysics. Nowadays, Neural Networks are also used in microchip technology for computer hardware.

Recent developments in gravity measurements and especially in microgravity tools have been prepaid excellent conditions for data acquisition to make better interpretation results specially detection of gravity sources. For these developments, combined with higher speed data acquisition technology, have made it possible to detect much smaller objects like small subsurface cavities.

The gravity data sets are naturally noisy so that it is very hard to estimate the gravity source depths precisely. Therefore, there an increasing need for a fully automatic interpretation technique that can be used to make decisions regarding the nature of the sources in real time. The massively parallel processing advantage of Artificial Neural Networks makes them suitable for hardware implementation; therefore, the detection of small gravity sources objects will be possible more precisely, especially for depth estimation of the cavities. Artificial Neural Networks are part of a much wider field called artificial intelligence, which can be defined as the study of mental facilities through the use of computational models (Charniak and McDermott, 1985). There are several types of artificial neural networks .For complete information covering the whole domain of neural networks kinds, the reader is referred to the excellent book of Fundamental of Artificial Neural Networks by Menhaj (2000).

Summarizing their reviews, neural networks can be divided into two main categories: supervised feed-forward networks and unsupervised recurrent networks. In the supervised feed-forward, information is only allowed to flow in one direction without any feedbacks. These nets are supervised because using a set of correct input-output pairs, called the training set, small changes in the connection weights are made in order to minimize the difference between the actual and the desired output values in a distributed way. Back propagation is the most popular supervised feed forward network. In the unsupervised recurrent type, the networks allow information to flow in either direction. These models are called unsupervised since the weight matrix is fixed at the beginning using global information and never changed. These networks are useful in optimization applications where a certain cost function should be maintained. One should merely choose a neural network whose energy function coincides with the given cost function. A Hopfield model is the most popular unsupervised recurrent network.

Application of neural network in microgravity is in its early stages. We hope to develop a more flexible intelligent method for Qanat detection by applying other methods like Fuzzy Logic and Genetic algorithms in the future, to develop a near-real-time processing system.

In this paper, we explore the supervised Multi Layer Perceptron (MLP) neural network for Qanat location estimation.

3 TRAINING DATA

To design the MLP neural network, it is necessary to have some available data as a set of input-outputs for training the network. To train the MLP with microgravity data, the problem is that if all the measured points are applied as inputs of the network it will have a lot of inputs and be time consuming in training .To prevent this problem we selected some features from microgravity data.

In this way, we prepared training data for two models in the shape of a sphere and a cylinder because the shape of most subsurface cavities is approximately sphere or cylinder. The features were calculated for these models with the equations (1), (2) and (3) (Emile Klingele, Alexandre Gret, 1998).

$$F_1 = \int_{t-}^{t+} g(x)dx \tag{1}$$

$$F_2 = xg50 \tag{2}$$

$$F_3 = xg75 \tag{3}$$

F1, F2, F3: Features calculated from gravity data; where F1 is the …
g(x): gravity value (in micro gal) at the point with horizontal distance of x (in meter)
xg50: x of the point where the gravity value is 50% of the maximum gravity value
xg75: x of the point where the gravity value is 75% of the maximum gravity value.

The domain of the integral in equation 1 is shown in figure 1. And gc is calculated from equation (4).

$$gc = g_{min} + 0.2*(g_{max} - g_{min}) \tag{4}$$

Where g_{min} is the minimum value of the measured gravity and g_{max} is the maximum value of the measured gravity. So gc is a definite value to find the domain of the integral equation (1).On the other hand in upper and lower domain of the integral in equation (1) the value of g(x) is equal by gc.

As has been shown in figure 2 the inputs of Artificial Neural Network (ANN) are F1, F2,F3 and outputs are R,Z where R is the radius of the Qanat and Z is its depth.

So the training set will be (F1, F2, F3), (R, Z). To prepare microgravity training data we used the equations (5) and (6) (Abdelrahman et al. 2001).

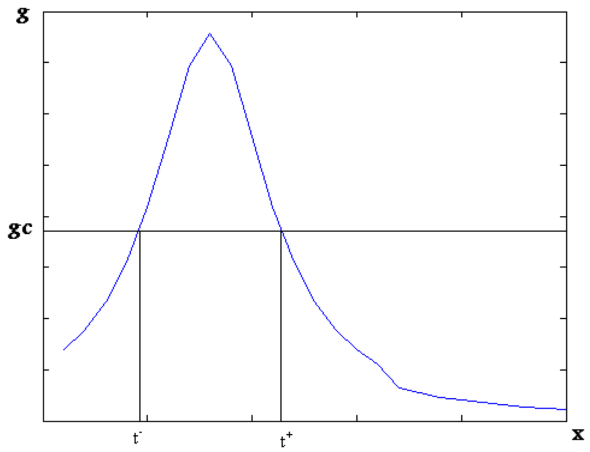


Figure 1. Integral domain for microgravity data.

Figure 2. Schematic of ANN with inputs and outputs.

$$g(x,z) = \frac{AZ}{(x^2+z^2)^q} \tag{5}$$

$$A = \begin{cases} \frac{4}{3}\pi GPR & \text{Sphere or Vertical cylinder} \\ 2\pi GPR^2 & \text{Horizontal cylinder} \end{cases} \tag{6}$$

R: Radius of the sphere or cylinder, Z: Depth of sphere or cylinder
X: Horizontal Distance, G: universal gravity constant (figure 3)
P: Contrast density

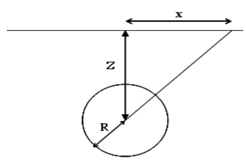


Figure 3. Values of R, Z, x in equation (3-5).

To prepare a set of training data first, the features F1, F2, F3 are calculated for various values of depth and radius in a domain of (Rmin, Rmax), (Zmin, Zmax) from equation (1). So the MLP network will be able to detect the Qanats which have radius between Rmin, Rmax and depth between Zmin, Zmax. For example if we are looking for the Qanats with a radius of 1 to 3 meter at a depth of 4 to 10 meter then Zmax=10 , Zmin=4, Rmax=3 and Rmin=1.

The briefly algorithm we used is that after that the neural network was trained by this set of data, the features (F1, F2, F3) were explored from real gravity data and fed to the trained neural network, and it is clear that the outputs of the trained neural network for this inputs are the depth and radius of the object.

4 MLP NETWORK STRUCTURE

The MLP we selected is a (3,n,2) network. It means a neural network with 3 neurons as inputs (F1, F2, F3) and n neurons in the hidden layer and 2 neurons as output layer, because outputs are (R,Z).

To gain the optimum value of the number of neurons in the hidden layer (n) we tested MLP's with n=3, n=4, n=5 and compared their accuracy of estimating depth and radius .As has been shown in figure 4 the optimum value for n is n=5. In figures 4 and 5 the horizontal axes shows the Epoch which means the number of iterations that the neural network gets to its minimum error.

Unfortunately there is no exact equation for calculating the best value of the number of neurons in the hidden layer but there is a simple rule that if the number of input vectors is n the number of neurons is better to be more than Ln(n).

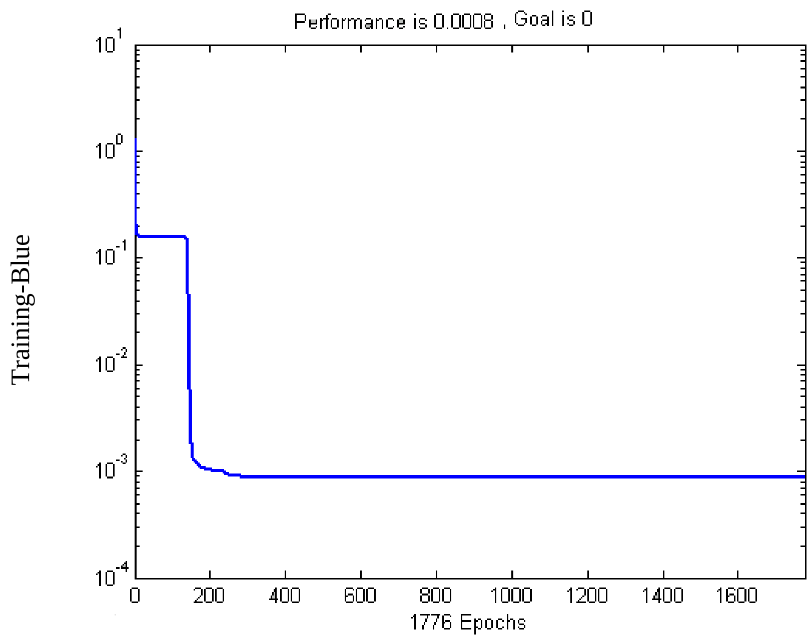
5 TEST OF MLP IN PRESENT OF NOISE AND FOR REAL DATA

After we gained the optimum value of n, we tested the (3, 5, 2) MLP neural network with noisy data which has 30% of noise(S/N=30%), it has good results for both models of Qanats. It is represented in table 1.

Also we tested the network for real data. The microgravity data was measured compared to the depth estimation of MLP with the Euler method and it was very close to that. We gained the depth of 3 meter for this Qanat.It has less than 15 centimeter difference compared with the Euler method. Some excavations were done there, and showed that the real depth was very near to the MLP output.

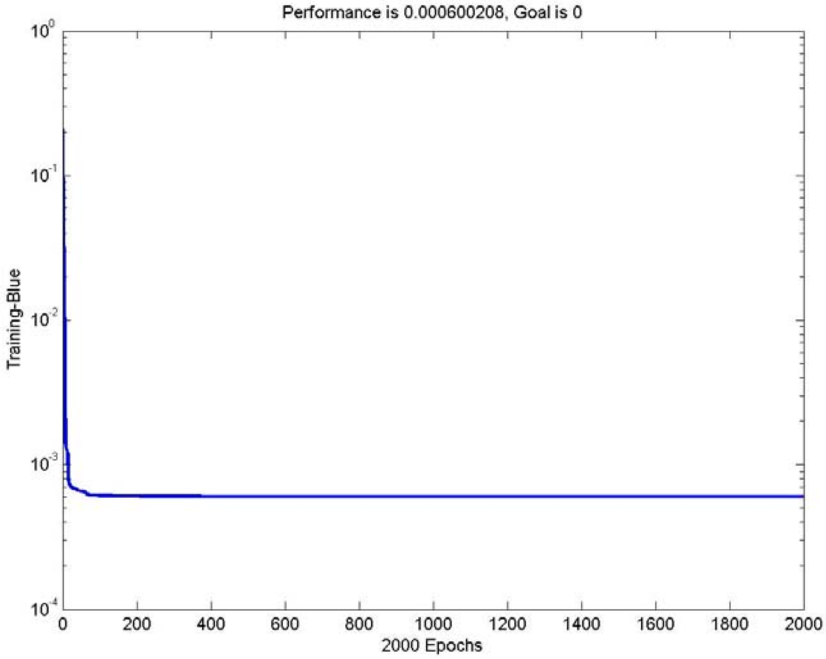
Table 1. Outputs of MLP (3, 5, 2) in present of 30% noise.

Training values for R,Z		**Outputs of MLP (3,5,2) in present of 30% noise**			
Horizontal cylinder	Sphere or Vertical cylinder	Horizontal cylinder		Sphere or Vertical cylinder	
R(m)	Z(m)	R(m)	Z(m)	R(m)	Z(m)
1	2	1.17	2.2	1.12	2.22
1	3	1.22	3.15	1.08	3.32
2	4	2.15	4.18	2.09	4.25
2	5	2.18	5.33	2.14	4.28
3	6	3.25	6.25	3.17	6.12
4	8	4.17	8.21	4.28	8.33
5	13	5.13	13.15	5.30	13.45
6	14	6.25	14.18	6.31	13.40
6	15	6.25	15.21	6.35	14.5



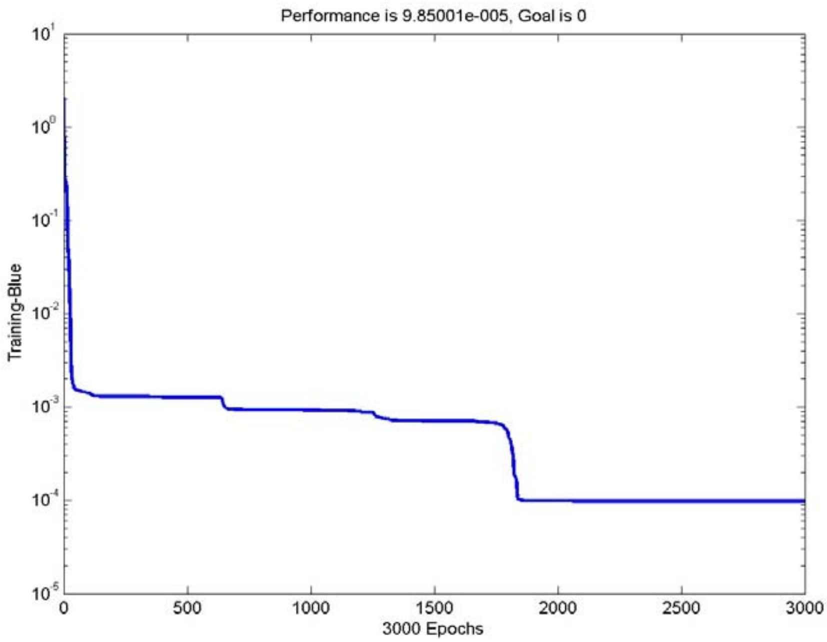
n=3

Figure 4. Responses of MLP network for n=3, n=4.



n=4

Figure 4 Continued.



n=5

Figure 5. Responses of MLP network for n=5.

6 CONCLUSIONS

In this paper a new method has been proposed for intelligent interpretation of gravity data for depth estimation of Qanats. The observed gravity anomaly of the buried Qanat is assumed to be produced by an equivalent source of cylinder or sphere. So we tested the network for synthetic data of the two models of sphere and cylinder in the presence of noise and saw the results have good adaptation to the actual values. For a testing of the field data we measured the gravity points on the top of a subsurface Qanat in the north entrance of the Geophysics Institute and fed the data corrected to the network to see the depth estimation by the network it was very near to the real depth of subsurface Qanat.

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