# Magnetic anomaly separation usıng Genetic Cellular Neural Networks

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*Abstract: In this paper, a contamporary stochastic image processing novel, Genetic Cellular Neural Networks (GCNN) is applied the first time in geophysics. The new approach has been applied to gravity anomaly separation problem. The advantages of CNN method are that it introduces little distortion to the shape of the original image by using neighbourhood locations and stochastic properties of 2-D images and that it is not effected significantly by factors such as the overlap power spectra of regional and residual fields. Genetic algorithm is a statistical optimisation technique using a natural selection. In this paper, coefficients of CNN templates A, B and I are trained using genetic algorithm for geophysical data. Here the proposed method is tested using a synthetic examples and satisfactory results have been found.*

## INTRODUCTION

Potential-Field maps usually contain a number of ano-malies that are superposed on each other. For instance, a magnetic map may be composed of regional, local, and micro-anomalies. In this case the determination of the cousitive sources boundaries suffers from the nearby source interference that yields mislocations. Since one type of anomaly often masks another, the need arises to separate the various anomalies from each other.

On a regional scale, aeromagnetic and gravity maps are some of the most useful tools presently available. Other techniques such as conductivity mapping (Palacky, 1986) or remote sensing (Watson 1985) are also very helpful in locating lithologic boundaries. Interpretation of magnetic and gravity anomalies makes extensive use of enhanced maps as an initial step to eliminate or atte-nuate unwanted field components in order to isolate the desired anomaly (e.g., residual-regional separations). These initial filtering operations include the radial weights methods (Griffin, 1989), least squares minimi-sation (Abdelrahman *et al*. 1991), the Fast Fourier Transform filtering methods (Bhattacharya and Navolio, 1976) and recursion filters (Vaclac *et al*. 1992) and rational approximation techniques (Agarwal and Lal, 1971). Gravity anomaly separation is possible when the gravity response from the geologic feature of interest (the signal) dominates one region (or spectral band) of the observed gravity field's power spectrum.

Nowadays, in literature there are some new image processing techniques in geophysics. Roth *et al*. (1994) have found inversion of seismic data waveform by artificial neural network (ANN) and Macies *et al*. (2000) have estimated parameters in geophysical resistivity models using ANN. Ucan *et al*. (2000a) have applied a new stochastic approach, Differential Markov Random Field (DMRF) to gravity anomaly separation problem. A specific space-scale wavelet analysis, Multi-Resolution Analysis (MRA) which allows decomposition of the signal with respect to a vast range of scales has been proposed by Fedi and Quarta 1998. Fedi *et al*. (1999) have analysed upward continuation of potential field data to enhance the signal of deeper sources when shallower ones are present. Ucan *et al*. (2000b) have also evaluated magnetic dipole anomaly using wavelet approach. A stochastic image processing technique based on neighbourhood and stochastic properties of 2D images, denoted as Cellular Neural Network (CNN) is introduced by Chua (1988). Albora *et al*. (2001) have applied CNN in geophysics the first time in literature and they have extracted the coordinates of Akdag iron ore reserves of Turkey using this update technique.

In this paper, we have applied Genetic Cellular Neural Network (GCNN) for the separation of magnetic dipoles. We have optimised CNN templates A, B and I using genetic algorithm. Genetic algorithm is a statistical technique using a natural analogy to biological evolution. A detailed account of genetic algorithms has been given by Ji et al. (2000).

## GENETIC CELLULAR NEURAL NETWORKS

Cellular Neural Networks (CNN) were introduced by Chua and Yang in 1988. CNN structure is well-suited for image processing (Figures 2-3). Its normalised differential state-equation (1,2) can be described by matrix-convolution operators:

$$\frac{dX}{dt} = -X + A*Y + B*U + I \qquad (1)$$

$U, X, Y$ are the $M*N$ input, state and output matrices while $I$ is an $M*N$ offset matrix. There is a nonlinear function between the state and the output:

$$Y_{ij} = 0.5 * \left[ \left| X_{ij} + 1 \right| - \left| X_{ij} - 1 \right| \right] \qquad (2)$$

$A$ and $B$ represent the feedback and feedforward connections, respectively. According to Equation (1) CNN output changes till derivative of the state variable of the CNN is zero. So, the last stable output defined as

$$Y_{ij}^{\infty} = Y_{ij} \text{ where } \frac{dX}{dt} = 0 \qquad (3)$$

For designing stable CNN, $A$ and $B$ should be symmetric and $A_{22}$ must be greater than one if size of A has been selected as 3*3. CNN is used for various special image processing application with various templates (Figure 4-6).
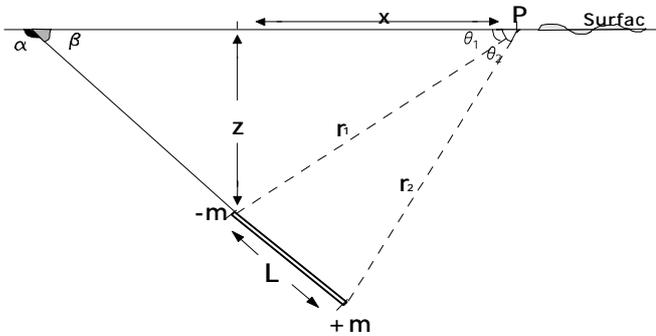


**FIG. 1.** Polarized Magnetic Dipole Model.

Genetic algorithm is a learning algorithm based on the mechanism of natural selection and genetics, which have proved to be effective in a number of applications. It works with a binary coding of the parameter set searches from a number of points of the parameter space. It uses only the cost function during the optimisation, it need not derivatives of the cost function or other information (Kozek *et al.* 1988). Processes of natural selection cause chromosomes that encode successful structures to reproduce more often than those that do not. In addition to reproduction, mutations may cause the chromosomes of children to be different from those of their biological parents, and crossingover processes create different chromosomes

in children by changing the some parts of the parent chromosomes between each other. Like nature, genetic algorithms solve the problem of finding good chromosomes by manipulating in the chromosomes blindly without any knowledge about the problem they are solving. The underlying principles of GA were first published by Holland (1962). The mathematical framework was developed in the 1960s and is presented in his pioneering book (Holland, 1975). In optimisation applications, they have been used in many diverse fields such as function optimisation, image processing, the travelling sales-person problem, system identification and control. In machine learning, Gas has been used to learn syntactically simple string IF-THEN rules in an arbitrary environment. A high-level description of GA has been done by Davis in 1991 as follows:
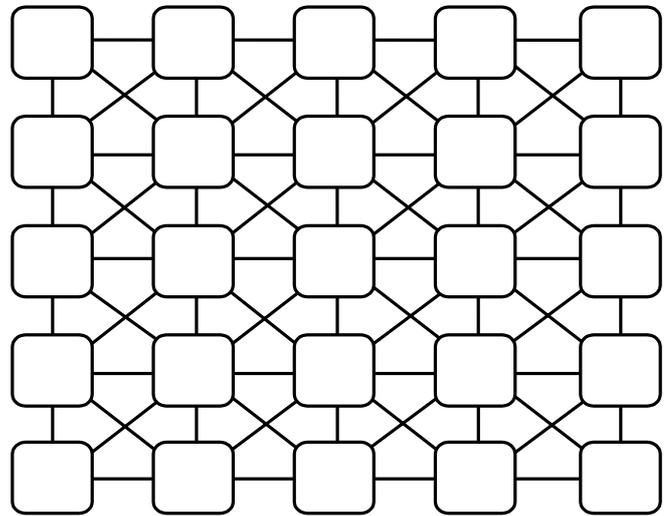


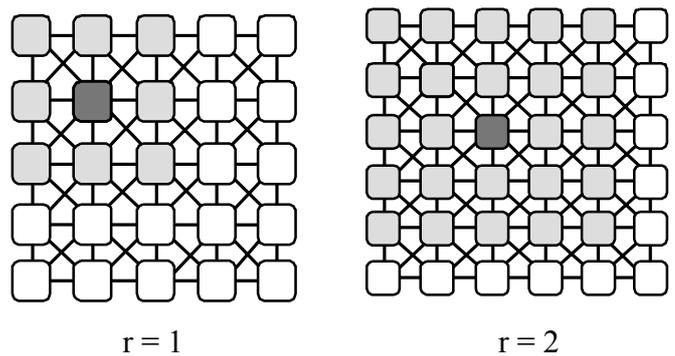**FIG. 2.** General CNN Neighbourhood Structure.



**FIG. 3.** Representation of Neighbourhood Relation of CNN.

Given a way or a method of encoding solutions of problem into the form of chromosomes and given an evaluation function that returns a measurement of the cost value of the following steps:

Step 1: Initialise a population of chromosomes
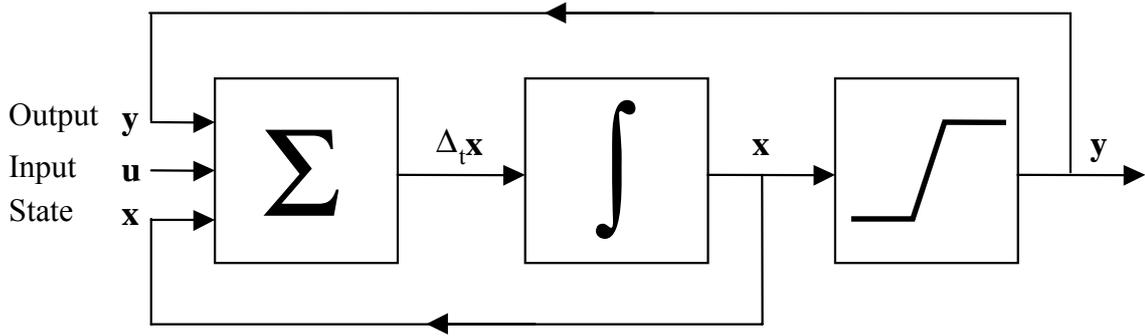Step 2: Evaluate each chromosomes in the population.

**FIG. 4.** CNN Model Input-Output Relationship.

Step 3: Create new chromosomes by mating current chromosomes; apply mutation and recombination as the parent chromosomes mate.

Step 4: Delete members of the population to make room for new chromosomes.

Step 5: Evaluate the new chromosomes and insert them into the population.

Step 6: If the stopping criterion is satisfied, then stop and return the best chromosome; otherwise, go to step3.

**Construct initial population**

A matrix is constructed called as population matrix. Each row of the population matrix represents chromosomes. Because of selecting number of chromosomes are 30, there are 30 rows in population matrix. Number of columns of this matrix is 352, because there are 352 bits in each chromosome. At the beginning this matrix is constructed randomly.

**Extract the CNN template**

Chromosomes represents the binary codes of the elements of the CNN template *A, B, I*. In this step, each chromosomes are decoded the elements of the CNN are computed in [-8,8] interval. Since each element is coded as 32 bits, each parameter can take $2^{16}$ different value in [-8,8] interval. In each chromosomes first 11 bits represents first bits of the template elements. And second 11 bits of chromosomes represents the second bits of the template elements and so on. These elements are

$$S = \left[ A_{1,1}, A_{1,2}, A_{1,3}, A_{2,1}, A_{2,2}, B_{1,1}, B_{1,2}, B_{1,3}, B_{2,1}, B_{2,2}, I \right].$$

**Evaluate cost function value for each chromosomes**

In this step, an image which was selected as training image is given as input to CNN. Normally in this Gary-level image, brightness varies in 0 (black) through 1 (white) interval. To fit this image to CNN operation, brightness of the image is converted from [0,1] to [-1,1]. According the same rule, brightness of the CNN output image is converted from [-1,1] to [0,1]. Then CNN works

with templates belonging with first chromosome. After the CNN output appears as stable, cost function is computed between this output image and target image which we want to obtain. This process is repeated with template sets belongs each chromosomes in the population. Cost function has been selected in this study as follow

$$\cos t(A,B,I) = \sum_i^m \sum_j^n P_{i,j} \oplus T_{i,j} \qquad (4)$$

where *A,B,I* represents CNN templates, *m,n* represents number of pixels of the image, *P* and *T* represent input and target image, respectively, notation $\oplus$ represents XOR operation between each elements of the *P* and *T*.

After the finding the cost function, fitness function is evaluated for each chromosome according this rule;

$$fitness(A,B,I) = m*n - \cos t(A,B,I) \qquad (5)$$

Another definition has been defined for stopping criterion as follows;

$$stcriterion = 0.99*m*n$$

where *m* represents the number of rows of the image matrix and *n* represents the number of the columns of the image matrix.

If the maximum fitness value of the chromosomes is greater than stop criterion, algorithms is stopped and the chromosome whose fitness value is the maximum fitness in the population is selected. The templates which have been extracted from this selected chromosomes are the most proper the templates which satisfy the task we wanted to realise.

**Creating new generation**

Before creating next generation, fitness values of the population are sorted by descendent order. And all of the fitness values are normalised related to the sum of the fitness values of the population. A random number *r* between 0 and 1 is generated. Then the first population member is selected whose normalised fitness, added to normalised fitnesses of the proceedings population members, is greater than or equal to *r*.
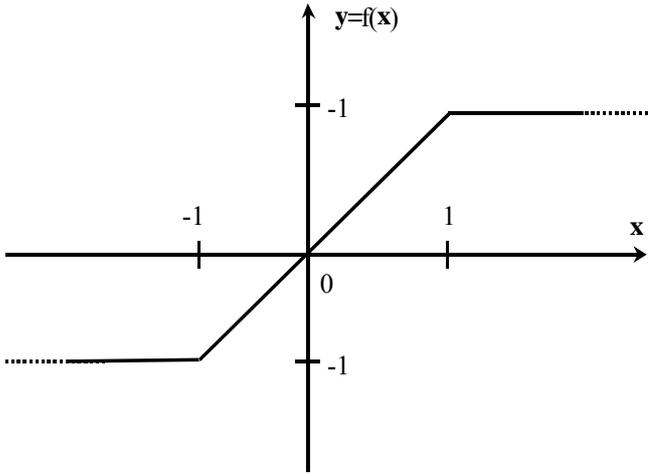
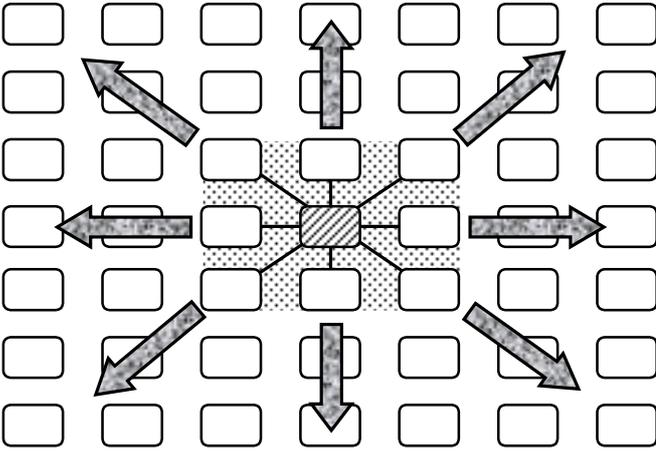**FIG. 5**.  Piece-wise Linear Output Characteristics of CNN cell.



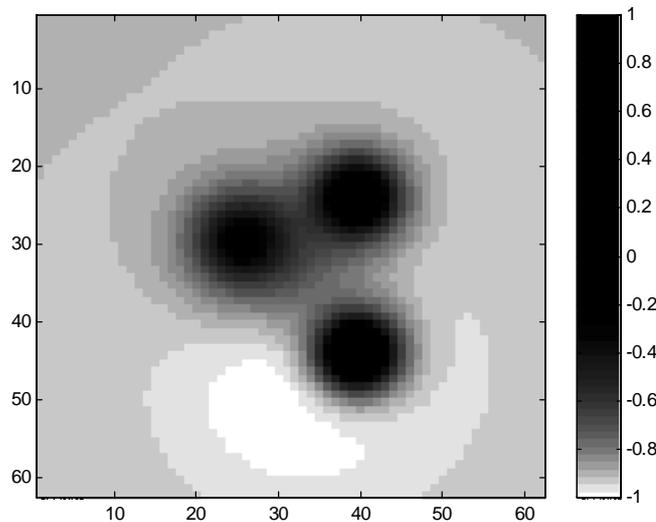**FIG. 6.** CNN Propagation Effect on 2-D Images.



**FIG. 7.** Vertical Magnetic Field for 4 Different Dipole with properties given in Table I.

# EXAMPLES ON GENETIC CELLULAR NEURAL NETWORKS APPROACH

Geophysical maps usually contain a number of features (anomalies, structures, etc.) which are superposed on each other. For instance, a magnetic map may be composed of regional, local, and micro-anomalies. The aim of an interpretation of such maps is to extract as much useful information as possible from the data. Since one type of anomaly often masks another, the need arises to separate the various features from each other.

In our model, we investigate a two-dimensional magnetic structure as shown in Figure 1. Here the vertical component Z of the field can be expressed as (Telford *et al.* 1981),

Z = (Vertical component of field due to –m)-(Vertical component of field due to +m)

$$Z = kF_0 S \left\{ \left( \frac{1}{r_1^2} \right) \left( \frac{z}{r_1} \right) - \left( \frac{1}{r_2^2} \right) \left( \frac{z + L\sin\alpha}{r_2} \right) \right\} \qquad (6)$$
$$= kF_0 S \left\{ (z/r_1^3) - (z + L\sin\alpha)/r_2^3 \right\}$$

$k$ is susceptibility, $F_o$ is earth's total field and $S$ is surface area. Since we have assumed that the rod is magnetised along its axis, these expression are valid only under one or both of the following conditions:

  (i)   the intrinsic field of the rod is very much larger than the external field;
  (ii)  the rod is oriented along the field direction.

Magnetic anomaly separation can be affected by such wavelength filtering when magnetic response from the geologic feature of interest dominates one region of the observed magnetic field's power spectrum.

**Table I**: Magnetic Data Model with 4 dipoles

| Parameters | Dipole 1 | Dipole 2 | Dipole 3 | Dipole 4 |
|---|---|---|---|---|
| (x,y) coordinate | (32,32) | (40,45) | (40,25) | (25,30) |
| Z (dip) | 15 | 5 | 6 | 8 |
| L (along) | 20 | 10 | 8 | 8 |
| α (angle) | 20 | 90 | 90 | 90 |

**Table II**: Magnetic Data Model with 2 Dipoles having the same (x,y) coordinates.

| Parameters | Dipole 1 | Dipole 2 |
|---|---|---|
| (x,y) coordinate | (0,0) | (0,0) |
| Z (dip) | 5 | 25 |
| L (along) | 8 | 30 |
| α (angle) | 90 | 90 |

In this paper, we have studied on two synthetic data, formed according to Equation 6, with different susceptibility, depth, length and angles of the dipoles with surface as in Table I and II. The vertical magnetic anomaly of dipoles defined in Table I, is shown in Figure 7. One of the dipole is deeper than the others. In Table II, the dipoles are overlapping each other with the same angles at different depths, which is the one of the worst case.

The deeper dipole effects the shallow one completely. The vertical magnetic anomaly of this situation is given in Figure 9.

In optimisation of A, B and I templates of CNN, genetic algorithm is used. The chromosomes are deleted from the population after 30 iteration if their fitness given by Equations 4-5 are not good. This procedure mentioned is called as reproduction process in genetic algorithms. Reproduction process does not generate new chromosomes. It elects the best chromosomes in the population and increases the number of the chromosomes whose fitness values are relatively greater than the others. After the reproduction 15 pairs of chromosomes are selected as parents randomly. Two numbers *s1,s2* between 1 and length of chromosomes, 352 are generated. The bit strings between s1 and s2 are called crossover site. During the crossing over process, bit strings in crossover site in each pair of chromosomes are interchanged. Then two new chromosomes are created from a pair of old chromosomes. At the last, 30 new chromosomes which are called children are generated to build new population. Over these chromosomes, mutation operation is processed. Since mutation probability has been set to %1, 105 bits are selected randomly in the population and they are inverted. And the chromosome whose fitness value was the best before the reproduction process is added instead of deleted a chromosome, which randomly selected in the population that was obtained after the mutation process population to save the best chromosome. This new population is the next generation population. After the obtaining the new generation searching procedure goes to second step and goes on until the stopping criterion was happened in the second step.

At the end of the training process following templates were found after the 326 generation

$$A = \begin{bmatrix} 0.3687 & 0.5448 & -1.6049 \\ -1.1611 & 6.1781 & -1.1611 \\ -1.6049 & 0.5448 & 0.3687 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.7582 & -1.5600 & 3.6032 \\ -1.2928 & 3.6401 & -1.2928 \\ 3.6032 & -1.5600 & 0.7582 \end{bmatrix} \tag{7}$$

I = 7.7892

The best chromosome, which gives these templates, is:

$$Gen = [10000101111001100001000000000001110001000101101111001010101101001011001100101001001010000000010111011011010101101100010101011110110010100101011011001100100000100000100100011000010000110011111100101000110011100001010010101010000001100101110011010010110101100100100000001101011010100001011011101100010101110100011110110100111110110001111111001010000010100110000000010] \tag{8}$$
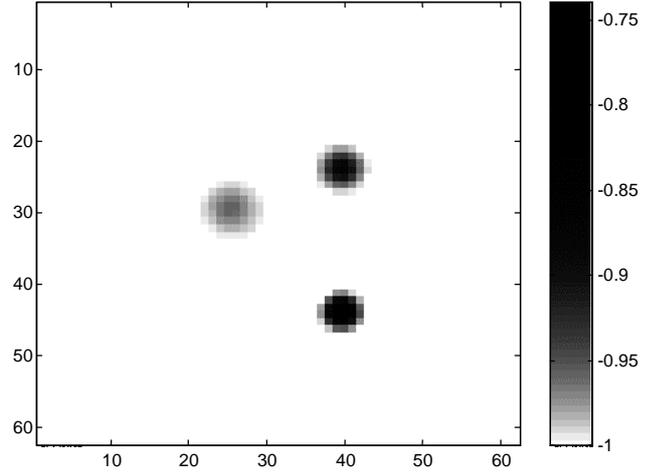


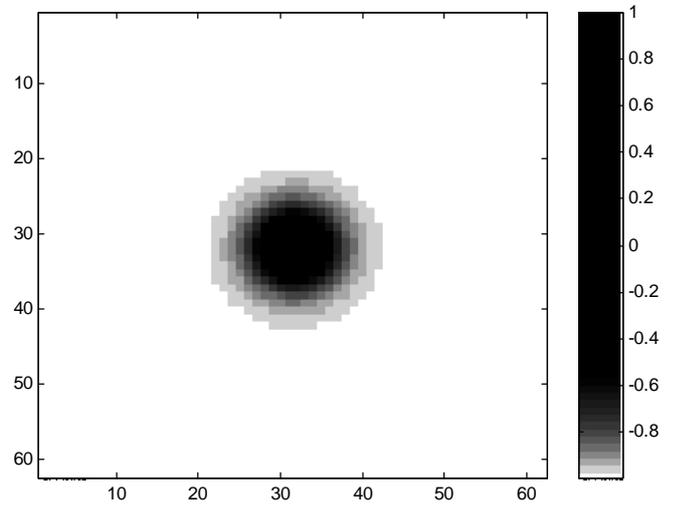**FIG. 8**. Genetic CNN Output of Total Magnetic Field given in Figure 7.



**FIG. 9.** Vertical Magnetic Field for 2 Different Dipole with the same z-axis as given in Table II.
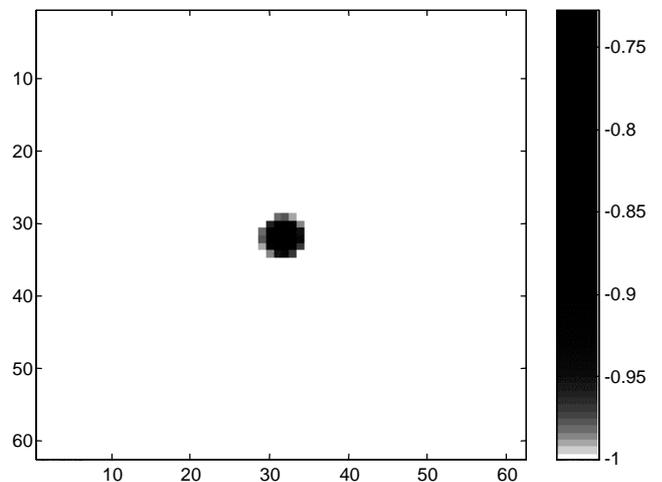


**FIG. 10**. Genetic-CNN Output of Total Magnetic Field given in Figure 9.

Using Equations (7, 8), for Table I and related Figure 7, GCNN output is given in Figure 8. The separation of GCNN is satisfactory since its performance of evaluating dipoles close to surface. In the similar way, for Table II and Figure 9, GCNN output is as in Figure 10. It is clear that GCNN has solved this overlapping problem.

## CONCLUSION

In this paper, Genetic Cellular Neural Networks (GCNN) is applied the first time in geophysics. This approach has been evaluated on various synthetic examples. Especially the dipoles with the same z-axes are interesting. The results are obtained after training of CNN templates using genetic algorithm.

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