NEURAL NETWORKS TO RETRIEVE SEISMIC SOURCE PARAMETERS BY SAR INTERFEROMETRY

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ABSTRACT

The use of supervised neural networks for the estimation of seismic source parameters from SAR interferometric data is presented in this paper. The RNGCHN software allowed the generation of the input-output pairs necessary for the learning phase of the net. After being trained, the net has been tested on real measured data. The obtained results encourage future developments of such an approach.

1 INTRODUCTION

SAR Interferometry (InSAR) technique has demonstrated to be a powerful tool for surface movements detection. From its first well known application in 1992 (Landers Earthquake) InSAR has been used in a number of strong (Kobe, 1997; Izmit, 1999; Hector Mine, 2000; Denali, 2002) and moderate earthquakes (Colfiorito, 1997). InSAR allows one to reconstruct the co-seismic surface displacement field with a centimetric accuracy using pre- and post-event SAR data. It can also show pre- and post-event movements, whenever present.
In the recent years InSAR potentialities, together with classic seismological and geophysical data such as strong motion and GPS, have also been used by geophysicists for the assessment of forward fault models [1], generally stemming from the Okada formulation [2]. In particular, for modelling radar interferometric data the RNGCHN software [3] calculates displacement components, expression at the surface of the seismic source in an elastic half-space. InSAR measurement contains information useful to define the fault geometry (dip and strike angle; width and length), the extension of the rupture, the distribution of slip on the fault plain. Of great interest and usefulness in this context is the solution of the inverse problem, that means to recover the source parameters from the knowledge of InSAR surface displacement field. To this aim, some significant results have been achieved by means of the simulated annealing technique [4] [5] [6]. However, due to the intrinsic ill-posedeness of the problem, some issues remain still open and more investigation is needed.
Neural networks have already been recognized as being a powerful tool for inversion procedure in remote sensing applications [7]. They are composed of many nonlinear computational elements (called neurons) operating in parallel and connected by the so called synapses. The use of neural networks is often effective because they can simultaneously address nonlinear dependencies and complex physical behaviour [8]. In this study we propose an alternative approach for the retrieval of fault parameters from interferometric data based on neural networks. The network is trained by using a data set generated by the RNGCHN software and then tested on real measured data. The input of the net consists of a set of features calculated from the interferometric image while the output vector contains the parameters characterizing the fault. For a preliminary analysis, we started focusing on a restricted number of parameters.

2 THE FORWARD PROBLEM

The RNGCHN software has been used for the generation of pairs consisting of the vector containing the fault parameters (input to the RNGCHN) and of the corresponding interferogram. To specify one fault patch RNGCHN requires 10 parameters: centroid latitude, longitude, depth; strike, dip, along-strike length, down-dip width, left-lateral slip U1, up-dip slip U2, and tensile slip U3. Given the values of these parameters, the program calculates the vector displacement U at the surface using analytic expressions from Okada [2] (Fig.1). For a preliminary analysis we decided to fix all parameters but two: the dip (δ) and the strike (α) angle. For these two quantities we considered the following intervals of variations:

- Dip: 45-90 degrees with step 5 deg
- Strike: 90 - 180 degrees with step 5 deg

A total of 190 fault parameters-interferogram patterns has then been generated. In Fig. 2 and 3 examples of generated interferograms are shown. We worked with 500x500 pixels interferograms. This corresponds to an area of 50x50 km^2.

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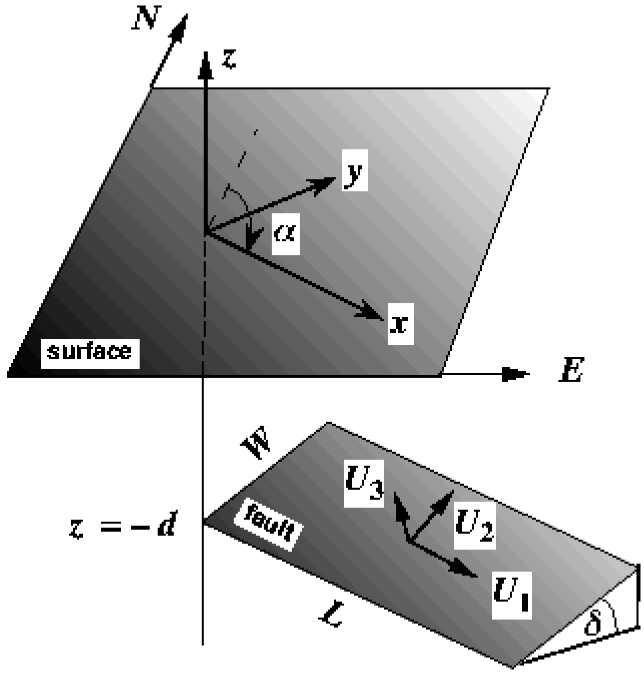

Figure 1. Fault geometry and symbols. The strike (α) and dip (δ) angles are shown. The slip vector U = [U1,U2,U3] represents the movement of the hanging wall with respect to the foot wall oriented such that positive U1 is left-lateral strike slip, positive U2 is thrusting dip slip, and U3 is tensile slip.

3 THE INVERSION PROBLEM

The neural inversion follows the general scheme illustrated in Fig. 4. Before the interferogram is given as input to the network, its dimension is reduced to 50x50 pixels. At this stage of the study we consider either sampling or clipping methods to decrease the size of data. We found out that a good procedure consisted in firstly subsampling the interferogram along both range and azimuth directions. The sampling rate was 1:5 which allowed to produce sub-images of 100x100 pixels. In a second step we cut the sub-images selecting a region of interest of 50x50 pixels. The region of interest has been chosen in order to include the highest fringe frequencies. In our first preliminary analysis the net is built by using one hidden layer and is described by the following topology: [50x50]-[10x10]-[2]. All values of the input vector have been scaled so that the values fed to the network vary in the range between -1 and 1. Similarly all values of the output vector ranged between 0 and 1. This stems from the fact of considering a sigmoid function for the output layer.

Few hundreds of epochs (Scale Conjugate Gradient algorithm) were enough to get the network trained. The final rms error on the two retrieved quantities is very low, less than one degree both for the strike and the dip angles. In Fig. 5 we show the interferogram representing the real data used for testing the trained net. The interferogram is relative to the September 26, 1997, Colfiorito (Central Italy) earthquake. The CMT solution for the two events (00:33 GMT, Mw=5.7; 09:40 GMT, Mw=6.0) is a purely normal fault with 140°-150° strike angle and 45° dip. In this case the output of the net gives for the two changing parameters the following values: Strike 141°, Dip 50°. The corresponding model is in Fig. 6. It should be added that to avoid uncertainties due to the random initialisation of weights of the network we repeated the process of training several times and the final estimation of the parameters values is based on averaged results.

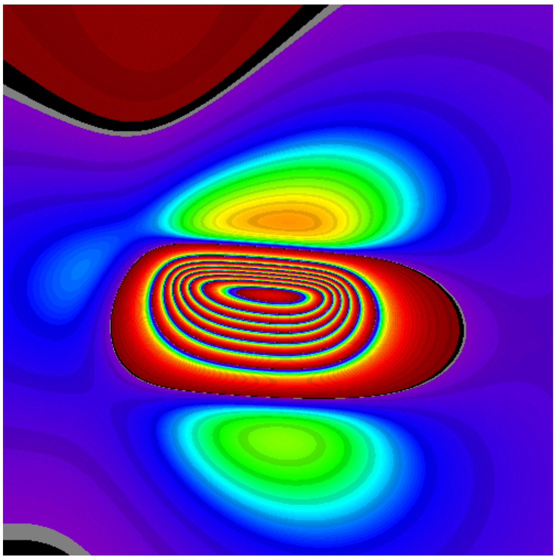

Figure 2. Surface fringe pattern by a 95° strike, 45° dip fault plane.

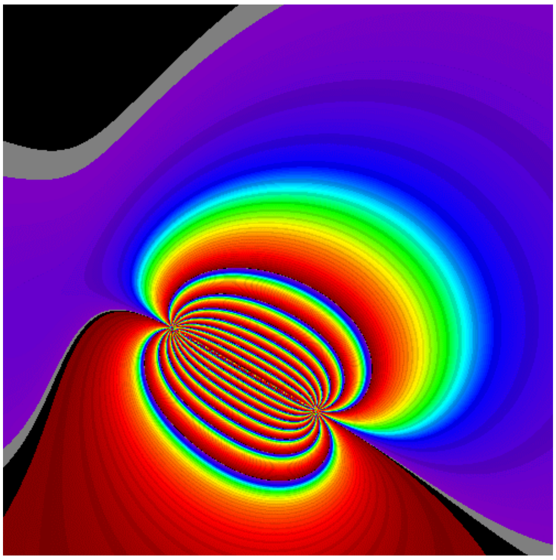

Figure 3. Surface fringe pattern by a 120° strike, 75° Dip fault plane

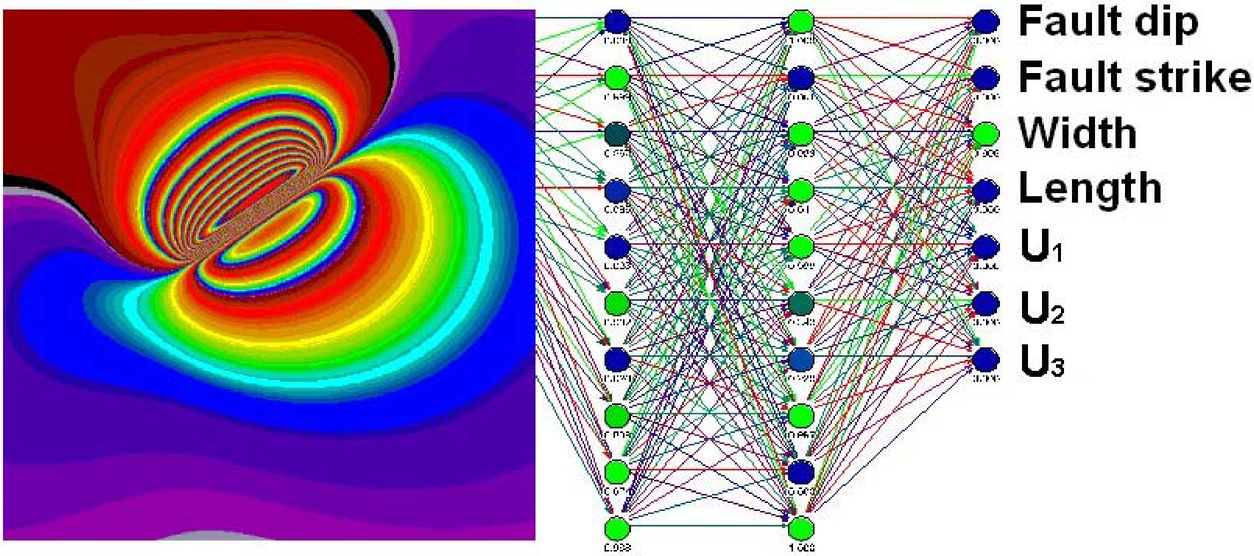

Figure 5. The general neural scheme used for the retrieval where the interferogram represents the input and the sought parameters the output. The solution for the test case is: strike 141°, dip 50°

4 CONCLUSIONS

The obtained results are encouraging and show the validity of the approach. After the training process the neural network is able to properly associate the tectonic parameters to the corresponding interferogram presented to it as input. Also a first result on real data is satisfactory. The solution found is in good agreement with CMT values. The very next steps will be to increase the number of fault parameters to be retrieved and to test the net with other real data. Also more sophisticated and efficient dimensionality reduction techniques such as PCA will be investigated and implemented. It has to be reminded that another advantage of neural networks is their flexibility and portability. Such a property could be exploited by adding in the input vector other pieces of independent information derived from several types of ancillary data.

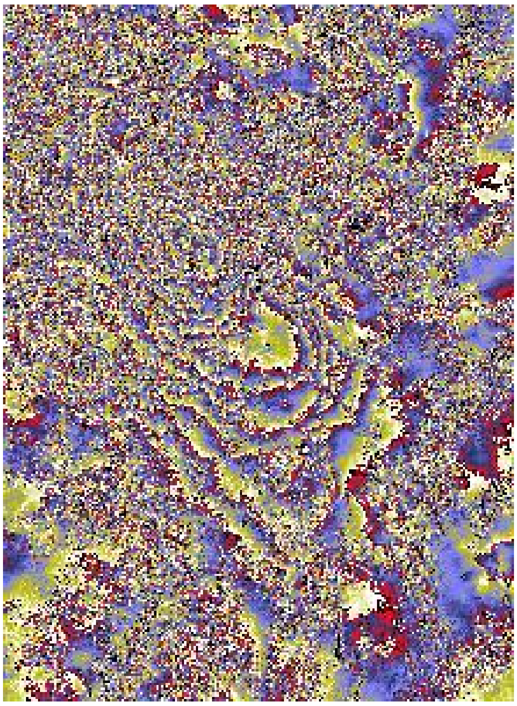

Figure 5. Differential interferogram relative to the 1997 Colfiorito Earthquake

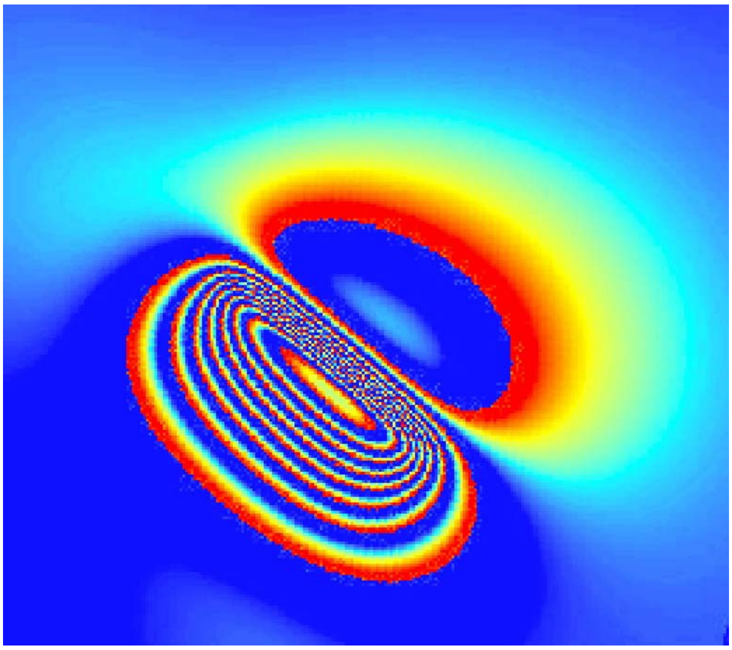

Figure 6. Surface displacement modelled by using the solution from the neural network

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