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Intelligent Earthquake Prediction System Based On Neural Network

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***Abstract*—**Predicting earthquakes is an important issue in the study of geography. Accurate prediction of earthquakes can help people to take effective measures to minimize the loss of personal and economic damage, such as large casualties, destruction of buildings and broken of traffic, occurred within a few seconds. United States Geological Survey (USGS) science organization provides reliable scientific information about Earthquake Existed throughout history & the Preliminary database from the National Center Earthquake Information (NEIC) show some useful factors to predict an earthquake in a seismic area like Aleutian Arc in the U.S. state of Alaska. The main advantage of this prediction method that it does not require any assumption, it makes prediction according to the future evolution of the object's time series. The article compares between simulation data result from trained BP and RBF neural network versus actual output result from the system calculations. Therefore, this article focuses on analysis of data relating to real earthquakes. Evaluation results show better accuracy and higher speed by using radial basis functions (RBF) neural network.

***Keywords*—**BP neural network, Prediction, RBF neural network.

I. Introduction

EARTHQUAKE, one of the most devastating natural disasters occurs due to a sudden movement of the transition to the ground due to the release of elastic energy in a few seconds. The impact of the event is traumatic because it affects a large area to occur suddenly and unpredictably. An earthquake can cause large-scale loss of life, property and violates the basic services such as water, sanitation, energy, communication, transportation and so on. Earthquakes not only destroy cities and villages, but the effects lead to the destabilization of the economic and social fabric of the nation [1].

Alaska in 1964 resulted in a 9.2 magnitude earthquake, the largest ever recorded in North America. Earthquake, also known as the 1964 Alaska earthquake, the great earthquake of Alaska and the Friday earthquake, causing a lot of ground shaking at least 4 minutes and affected virtually all coastal communities in Alaska. The state has suffered enormous damage. A total of 139 people died in the earthquake, including 13 in California and Oregon 4 children. A damaged territory of the Pacific Coast was $ 311 million.

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Alaska-Aleutian arc marks as one of the most active tectonic margins in the world. It consists of 17 Flinn-Engdahl (F-E) seismic and geographical regions taking as input earthquake magnitude classes with day and month to predict the next one and seven day’s earthquake magnitude class warning over all regions in the Alaska-Aleutian arc.

II. The Review of Earthquake Prediction Systems

Many papers have talked about earthquake prediction and how to make a model that can predict the next earthquake in an area.

S. G. Chern, talked about Yuan-Lin Taiwan as his search area using Fuzzy Adaptive Resonance Theory network (Fuzzy ART) on the years of 1891 to 1980 For magnitude 5 to up deduce that the success rate in predicating liquefaction in Yuan-Lin area by using proposed Fuzz-ART neural network method is not so satisfactory [2].

In 2004, Yue Liu used Impulse Force based Supervised Adaptive Resonance Theory (IFART) Neural Network on attributes optimization by Genetic Algorithm to identify the different among the categories defined in his model using area of china for years of 1900 to 1998 and compare the results with Adaptive Resonance Theory (ART) Neural Network inferring that prediction accuracy of Category ART is almost 58.3% while IFART is almost 83.3% [3].

China searched using UCI benchmark datasets for the years of 1990 and 1991 by Yue Liu, in 2005 using Constructive Ensemble of RBF Neural Networks in which the number of hidden nodes in RBFNNs is determined automatically with high accuracy and efficiency by using the nearest-neighbor clustering algorithm and he determined that the same as or better than that of other ensemble learning methods [4].

In 2009, Wang Ying talked about the southwest Yunnan province as his search area. Data of year 2001 used by Radial Basis Function (RBF) neural network to predict the magnitude of the earthquake and compare the performance of RBF and Back-Propagation (BP) Neural Network and ratiocinate that the predicted speed of RBF Neural Network is much quicker than that of BP [5].

Southern California region, searched in 2009 using two chosen architectures for MLPs based neural networks Back Propagation (BP) and Conjugate Gradient descent (CG) for years data from 1950 to 1990. He draw that the model yields good prediction accuracies for earthquakes of magnitude between 4.5 and 6.0 [6].

Fangzhou Xu, in 2010 used Data Mining technology over the world for years from 2007 to 2008 by taking the way of Three-Layer Back-Propagation Neural Network on

DEMETER data, a series of physical quantities measured by the DEMETER satellite including Electron density, Electron temperature, ions temperature and oxygen ion density, together with seismic belt information in the range of a 30km x 30km region around the epicenter for analysis. The time span is about 30 days before the earthquake and he gets a total accuracy is about 69.96% [7].

Guangxi , far south of China area in 2010 searched using improved RBF neural network model for seismic time series by CHEN Yi understand that one-step prediction results were good, and when the multi-step prediction steps over a range of forecasts, forecast performance quickly declined [8].

Same year, Guang-yu used interpolation techniques on BP neural network deducing that the method of making use of neural network to process occultation data and analyzing the anomalies of seismic ionospheres' is feasible [9].

Probabilistic Neural Network (PNN) depended on the concept of the Parzen windows classifier used to predict an earthquake in northern China by HUANG, training dataset in 1960 is divided into seven input classes depending on the magnitude. HUANG concluded that The PNN models back propagation (BP) neural network and radial-basis function (RBF) neural network can be used to predict earthquakes with magnitude less than 5.0 while the Recurrent Neural Network (RNN) model can be used to predict earthquakes with magnitude bigger than 5.5 [10].

Habib Shah, searched in Southern California to predict the earthquake magnitude of more than 7.5 investigates the use of the Artificial Bee Colony (ABC) algorithm with the Back-Propagation (BP) algorithm concluding that the performance of MLP-ABC is benchmarked against MLP training with the standard BP [11].

California searched by K. Tomiyasu in 2012 using years data from 1812 to 2004 starting with Magnitude 8.25, down to 5.2. Calculations show that solar gravitational force is 176.1 times stronger that due to the moon. Ratiocinate that California Earthquakes cannot be predicted but a probability exists [12].

Chile country on the south western side of South America searched on magnitude equal or larger to 3.0 for data of the year 2001 by J. Reyesa, in 2013 and he determines that the back-propagation neural networks were able to predict [13].

In 2013 North Taiwan searched by Jui-Pin Wang using First-Order Second-Moment probability analysis since 1900 for magnitude greater than 6.0 and implemented the governing equation analysis on a probabilistic basis to evaluate the mean and variance of Peak ground acceleration (PGA), measure of ground acceleration during an earthquake. The result shows that there is a 30% probability that could exceed 0.3 g in 50 years, PGA associated with a major earthquake with its magnitude greater than 6.0 occurring within 200 km from the study site [14].

Beichuan Qiang County, in Sichuan, China searched by Zhuowei Hu in 2013 using the Geographic information system (GIS) platform made based on gathering fact for 1: 200,000 local geological map, 1: 250,000 geographic data, 30m SRTM DEM. The accuracy of precision using multiple Regression models is about 73.7% and the neural network model can be up to 81.28% determined. It can be concluded that in this area of study neural network model is more accurate in spatial landslide prediction [15].

East Anatolian Fault, Republic of Turkish searched using highly simplified ANN and cluster analysis on magnitude greater than 3 for data from 2005 to 2010 by S. Niksarlioglu conclude that according to the numerical methods the advantage of ANN is the optimization can be done very fast, no mathematical form of the relation between input and the output data is necessary. The disadvantage of neural network is that they require a lot of data to give better confidence in the results [16].

In 2013 North Taiwan searched by Jui-Pin Wang using First-Order In 2013, the Qeshm Island, south of Iran searched by Adel Moatti using the clustering method has been performed to pattern recognition from the years of 1995 to 2012 for magnitude greater than 6.0 and This result is similar to the past studies that reports The b-value of Gutenberg Richter law has been considered as precursor to earthquake prediction decrease as large earthquakes precursor [17].

A. Morales-Esteban used Feed Forward and Recurrent neural networks in the Iberian Peninsula area by The database of the Spanish Geographical Institute concluding that The networks predict the occurrence of large earthquakes for a seven-day [18].

In 2014, southwest areas of China searched by Feiyan Zhou using Back-Propagation (BP) Neural Network based on the Levenberg–Marquardt (LM) Algorithm, a nonlinear optimization method between Newton's method and gradient descent method For the overly parameterized problems has been performed for magnitude greater than or equal to three within half a year and The result is convergence speed of LM algorithm is fast and it has a good predictive effect and high accuracy [19].

Article idea is to make a relation between every region in Alaska-Aleutian arc. Every region could affect earthquake happened in other regions and may be this relation repeat in another date. Actual data were the data already happened in the next day for the period of one day and for seven days actual data were the data already happened in the next seven days.

This article train an RBF (Radial Basis Function) neural network by 19 factors as follow month, day and the F-E seismic regions of the Alaska-Aleutian arc earthquake data, and predict the earthquake though the trained network. Predicted results show that RBF neural network compares BP neural network to have the higher precision and the quicker speed.

III. Neural Network

The neural network system is a system that is very self-adaptive nonlinear dynamics. The network can extract the portion of hide samples through learning sample mass, and can analyze a complex nonlinear system. Thus, the earthquake prediction by the neural network is effective.

A. RBF Neural Network Model

With the development and use of radial basis functions (RBF) comes radial basis neural networks (RBFNNs) work in the late 1980s [21],

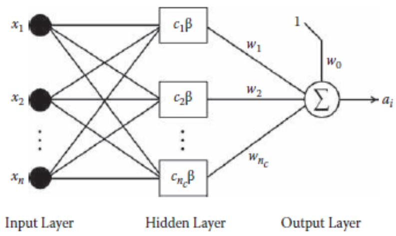

Fig. 1 Basic structure of a RBF neural network

Radial Basis Function displays a network in advance in three layers, with the output of a linear combination of the output of its hidden units. Each hidden unit implements a radial basis function (RBF).

Advantages compared with MLP. RBFNN has a good generalization capacity of the network structure of single avoiding lengthy calculations. The basic structure (Fig. 1) is a network of direct action with three layers, with a total production is a linear combination of the output of the hidden units (each hidden Unit for applying a radial basis function):

$$\phi(x) = \frac{\phi(\|x - c_i\|)}{\sum_{j=1}^{M} \phi(\|x - c_j\|)}$$

Using the neural network in MATLAB 7.0 Toolbox [22], it is easy to design, analysis and practical use of a neural network. The function that allows designing a radial basis network exactly as follows:

net = newrb (P, T, SPREAD)

This function takes two or three arguments: P -matrix RXQ input vectors Q. In this article, means a matrix includes 17 input factors. T -matrix SxQ Q vectors of the target class. In this article, means that 1 output target representing earthquake occurrence. SPREAD, default = 1. The largest SPREAD is the smoother the function Outputs = sim (net, P), this function to retain the output of radios basis function neural network.

IV. Application Analysis

Nineteen-element vector of indicators is computed for each time period forming 3825 training input vectors (training dataset) in the period of one day and 3821 training input vectors in the period of seven days. The training dataset is divided into four input classes depending on the magnitude of the largest earthquake that occurred during each time period. Input classes of the training dataset, the corresponding output classes, and the number of training input vectors available in each class are presented in Table III. The prediction success for a particular output class is expected to improve as the number of training input vectors available in the corresponding input class increases. Samples of the training dataset was obtained that showing the nineteen-element input vectors and the corresponding input classes for the two period times one and seven days between 1st January 2000 and 31st December 2010 for Alaska-Aleutian arc.

A. USGS NEIC Database

Prediction of earthquake can be one of the major aspects of knowledge discovery and also helpful in saving life and economy of most of the countries. Consequently, the following online databases from the USGS NEIC (U.S. Geological Survey National Earthquake Information Center) present Historical & Preliminary Data of earthquakes from Jan 2000 to Dec 2011 as Table I show samples earthquake information [20].

Preliminary determination of epicenters (PDE) Monthly listing is the most complete calculation of the hypocenter and values held by USGS NEIC. This is usually done several months after the events occur. A publication called "preliminary" because "final" Calculation hypocenter. Weekly Checklist PDE (PDE-W), this file covers the period since monthly data up to four weeks for the current week. Weekly PDE data are replaced PDE monthly data as they become available.

Origin time columns are the date and time when the earthquake initiates rupturing. This article uses month and day of the occurred earthquake.

MAGNITUDES_Ofc is the official or the preferred magnitude for this earthquake. Used in this article because it has the more available magnitudes rather than MAGNITUDES_mb and MAGNITUDES_ms.

F_E_reg is an automatically generated name from the Flinn-Engdahl (FE) seismic and geographical regionalization scheme proposed in 1965, defined in 1974 and revised in 1995. The boundaries of these regions are provided at intervals of power and therefore are distinguished from irregular political boundaries. The article uses the 17 regions of Alaska-Aleutian arc as factors to predict the next day occurrence class magnitude.

TABLE I
USGS Earthquake Sample

Catalog Source	Date Month	Date Day	Magnitudes Ofc	F_E reg
PDE	01	02	3.7	1
PDE	01	05	3.7	2
PDE	01	06	3.7	1
PDE	01	06	4.9	17

B. Parzen Windows Classification

Parzen window classification is a technique for non-parametric density estimation, which can be used for classification. Technology approaches a certain training set distributions by a linear combination of the kernel on the observation point centered. In this paper, we have separated approximately earthquakes count for each of the four classes, shown in Table II related to occurrence count in Table III.

TABLE II
ALASKA-ALEUTIAN ARC TRAINING DATASET INPUT CLASSES

Magnitude Rang	Input classes
Magnitude = 0	0
Magnitude < 3	1
3<= Magnitude < 5	2
Magnitude >= 5	3

TABLE III
ALASKA-ALEUTIAN ARC EARTHQUAKES COUNT FOR EACH CLASS

Region	No	Small	Moderate	Large
Central Alaska	2038	1001	930	5
Southern Alaska	2120	1104	780	15
Bering Sea	4008	1	9	1
Komandorsky Islands Region	3831	0	165	23
Near Islands, Aleutian Islands	3832	1	169	17
Rat Islands, Aleutian Islands	3816	162	620	51
Andreanof Islands, Aleutian Is.	2385	530	1012	92
Pribilof Islands, Alaska Region	4012	0	7	0
Fox Islands, Aleutian Islands	2506	648	823	42
Unimak Island Region, Alaska	3050	489	466	14
Bristol Bay	4007	3	8	1
Alaska Peninsula	2765	616	622	16
Kodiak Island Region, Alaska	3358	321	317	23
Kenai Peninsula, Alaska	3387	364	265	3
Gulf of Alaska	3766	123	127	3
South of Aleutian Islands	3904	50	63	2
South of Alaska	3453	215	340	11

Train data using RBF & BP neural networks and simulate samples using RBF compared with Back-Propagation neural network.

C. *Prediction Verifications*

In the test dataset, the ranges of values are obtained by the neural network relative to the actual output of the target class. 363 test input vectors (simulation dataset) in the period of one day and 357 test input vectors in the period of seven days. Three success rate statistics are calculated for each output class of the number of correct and incorrect predictions.

The probability of detection (POD), false alarm ratio (FAR), and R_score parameters is calculated using the following formulas:

$$POD = \frac{N_{pc}}{N_{pc} + N_{ni}}$$

$$FAR = \frac{N_{pi}}{N_{pc} + N_{pi}}$$

$$R = POD - FAR$$

where N_{pc} (predicted-correct) is the number of occurrence during a period which the magnitude earthquake class falls within the predicted magnitude range, N_{ni} (not predicted incorrect) is the number of occurrences during a period which the magnitude earthquake class is greater than the upper limit of the predicted magnitude range, and N_{pi} (predicted incorrect) is the number of occurrences during a period which the magnitude earthquake class is less than the lower limit of the predicted magnitude range.

The computed values of P0, POD, FAR, and R.score for each magnitude range based on the number of successful and unsuccessful predictions in the testing dataset is presented in the next section.

V. SIMULATION AND RESULTS

Simulation dataset fall within the period of 1st January 2011 to 31st December 2011. Results for one day Actual output versus RBF simulation output as shown in Table IV and actual output versus BP simulation out as shown in Table V.

TABLE IV
COMPUTED VERIFICATIONS VALUES FOR ACTUAL OUTPUT AND RBF SIMULATION OUTPUT

Class	p0	Pc	ni	pi	POD	FAR	R_Score
0	363	346	7	10	0.9802	0.0281	0.9521
1	363	349	1	13	0.9971	0.0360	0.9612
2	363	78	281	4	0.2173	0.0488	0.1685
3	363	333	25	5	0.9302	0.0148	0.9154

TABLE V
COMPUTED VERIFICATIONS VALUES FOR ACTUAL OUTPUT AND BP SIMULATION OUTPUT

Class	p0	Pc	ni	pi	POD	FAR	R_Score
0	363	349	4	10	0.9887	0.0279	0.9608
1	363	326	25	12	0.9288	0.0355	0.8932
2	363	268	53	42	0.8349	0.1355	0.6994
3	363	29	0	334	1	0.9201	0.0799

(1) Prediction of large earthquakes (Magnitude 5.0 or greater). RBF neural network predicts large earthquakes with percentage 92%. BP neural network predicts large earthquakes with percentage 8%. RBF is better at predicting large earthquakes than BP.
(2) Prediction of moderate earthquakes (Magnitude 3 or bigger but less than 5.0). RBF neural network predicts moderate earthquakes with percentage 17%. BP neural network predicts moderate earthquakes with percentage 70%. BP is better at predicting large earthquakes than RBF.
(3) Prediction of small earthquakes (Magnitude bigger than 0 while less than 3.0). RBF neural network predicts weak earthquakes with percentage 96%. BP neural network predicts weak earthquakes with percentage 89%. RBF is better at predicting weak earthquakes than BP.
(4) Prediction of no earthquakes (Magnitude equal 0).RBF neural network predicts no earthquakes with percentage 95%. BP neural network predicts no earthquakes with percentage 96%. BP is better at predicting large earthquakes than RBF.

For seven days of Actual output versus RBF simulation output as shown in Table VI and actual output versus BP simulation output as shown in Table VII.

TABLE VI
COMPUTED VERIFICATIONS VALUES FOR ACTUAL OUTPUT AND RBF SIMULATION RESULTS

class	p0	pc	ni	pi	POD	FAR	R_Score
0	357	355	1	1	0.9972	0.0028	0.9944
1	357	355	1	1	0.9972	0.0028	0.9944
2	357	355	1	1	0.9972	0.0028	0.9944
3	357	201	152	4	0.5694	0.0195	0.5499

TABLE VII
COMPUTED VERIFICATIONS VALUES FOR ACTUAL OUTPUT AND BP SIMULATION RESULTS

class	p0	pc	ni	pi	POD	FAR	R_Score
0	357	355	1	1	0.9972	0.0028	0.9944
1	357	355	1	1	0.9972	0.0028	0.9944
2	357	355	1	1	0.9972	0.0028	0.9944
3	357	174	15	168	0.9206	0.4912	0.4294

(1) Prediction of large earthquakes (Magnitude 5.0 or greater).RBF neural network predicts large earthquakes with percentage 55%. BP neural network predicts large earthquakes with percentage 43%. RBF is better at predicting large earthquakes than BP.

(2) Prediction of moderate earthquakes (Magnitude 3 or bigger but less than 5.0).RBF neural network predicts moderate earthquakes with percentage 99%. BP neural network predicts moderate earthquakes with percentage 99%. RBF is predicting moderate earthquakes same as BP.

(3) Prediction of small earthquakes (Magnitude bigger than 0 while less than 3.0). RBF neural network predicts weak earthquakes with percentage 99%. BP neural network predicts weak earthquakes with percentage 99%. RBF is predicting small earthquakes same as BP.

(4) Prediction of no earthquakes (Magnitude equal 0).RBF neural network predicts no earthquakes with percentage 99%. BP neural network predicts no earthquakes with percentage 99%. RBF is predicting no earthquakes same as BP.

Longer days in the future cause less accurate results.

VI. CONCLUSION AND DISCUSSION

Predict earthquake magnitude class by a neural network can be very effective. The article used the neural network RBF compared with the BP neural network. The RBF network is faster and the accuracy also much higher. Each of the two networks can be realized by software, which is very simple and easy to perform. But some of the measures should be taken to further improve the accuracy of the neural network, such as learning of the neural network with specific data much more efficient data processing. Results showed that RBF neural network is simple but effective too and the method of applying a certain value in the prediction of earthquakes in the future.

REFERENCES

[1] Amr S. Elnashai, Luigi Di Sarno” Fundamentals of Earthquake Engineering” A John Wiley & Sons, Ltd, Publication, 2008.
[2] S. G. Chern, R. F. Hu” FUZZ-ART neural networks for predicting chi-chi earthquake induced liquefaction in yuan-lin area” *Journal of Marine Science and Technology, Vol. 10, No. 1, pp. 21-32, 2002.*
[3] YueLiu, HuiLiu ” Extraction of If-Then Rules from Trained Neural Network and Its Application to Earthquake Prediction” the Third IEEE International Conference on Cognitive Informatics (ICCI’04) 2004.
[4] Yue Liu, Yuan Li” Constructive Ensemble of RBF Neural Networks and Its Application to Earthquake Prediction” ISNN 2005, LNCS 3496, pp. 532.537, 2005.
[5] WANG Ying, CHEN Yi ” The Application of RBF Neural Network in Earthquake Prediction” Third International Conference on Genetic and Evolutionary Computing 2009.
[6] Hojjat Adeli, Ashif Panakkat” A probabilistic neural network for earthquake magnitude prediction” H. Adeli, A. Panakkat / Neural Networks 22, 1018_1024, 2009.
[7] Fangzhou Xu, Xianfeng Song” Neural Network Model for Earthquake Prediction using DMETER Data and Seismic Belt Information” Second WRI Global Congress on Intelligent Systems, 2010.
[8] CHEN Yi , ZHANG Jinkui” Research on Application of Earthquake Prediction Based on Chaos Theory ” IEEE,2010.
[9] Guang-yu Geng, Chuang-hui Li” Research on Seismo-Ionospheric Anomalies Using Artificial Neural Network” IEEE,2010.
[10] HUANG Sheng-Zhong” The prediction of the earthquake based on neutral networks”, International Conference on Computer Design and Applications (ICCDA), 2010.
[11] Habib Shah, Rozaida Ghazali, and Nazri Mohd Nawi ”Using Artificial Bee Colony Algorithm for MLP Training on Earthquake Time Series Data Prediction”, Journal of Computing, 2011.
[12] *K. Tomiyasu* ”lunar, solar and earthquake projected positions of 138 mag. 8.25-5.2 events in california from 1769 to 2004” IEEE,2012.
[13] J. Reyes, A. Morales-Esteban” Neural networks to predict earthquakes in Chile” Reyes et al. / Applied Soft Computing 13, 1314–1328, 2013.
[14] Jui-Pin Wang1, Yun Xu” Earthquake statistics and a FOSM seismic hazard analysis for a nuclear power plant in Taiwan”
[15] Zhuowei Hu, Lai Wei “Spatial Prediction of Earthquake-Induced Secondary Landslide Disaster in Beichuan County Based on GIS” Research Journal of Applied Sciences, Engineering and Technology 6(20): 3828-3837, 2013.
[16] S. Niksarlioglu, F. Kulahci “An Artificial Neural Network Model for Earthquake Prediction and Relations between Environmental Parameters and Earthquakes” World Academy of Science, Engineering and Technology, 2013.
[17] Adel Moatti, Mohammad Reza Amin-Nasseri” Pattern Recognition on Seismic Data for Earthquake Prediction Purpose” International Conference on Environment, Energy, Ecosystems and Development, 2013
[18] A. Morales-Esteban, F. Martínez-Álvarez ”Earthquake prediction in seismogenic areas of the Iberian Peninsula based on computational intelligence” A. Morales-Esteban et al. / Tectonophysics 593, 121–134, 2013.
[19] Feiyan Zhou, Xiaofeng Zhu “Earthquake Prediction Based on LM-BP Neural Network” Proceedings of the 9th International Symposium on Linear Drives for Industry Applications, Volume 1, 2009.
[20] USGS National Earthquake Information Center, http://earthquake.usgs.gov.
[21] David Nettleton” Commercial Data Mining Processing, Analysis and Modeling for Predictive Analytics Projects” Elsevier Inc, 2014.
[22] Mark Hudson Beale,Martin T. Hagan” Neural Network Toolbox™ User’s Guide R2013b” The MathWorks, 2013.