Artificial Neural Networks Algorithms for Earthquake Forecasts

Mostafa Allameh Zadeh, A. Mohseni

Abstract-Recent advances in machine learning make it possible to design efficient prediction algorithms for earthquake forecasts. Self Organizing Feature Maps (SOFM) technique can be used to detect precursory seismic activation or quiescence and make earthquake forecast.Here we apply the SOFM method for optimal forecasting of large earthquakes in Iran, using the data catalogue maintained by IIEES. The purpose of this paper is to describe the use of the neural network model to generate synthetics data catalogue in the local regions and propose a fast algorithm for synthetic earthquake catalog generation based on an original catalog. More specifically, we also propose a Monte Carlo simulation model which can generate data from a small number of earthquake aftershocks and discusses the relationship between the complexity of an earthquake and its aftershocks. This is a very stimulating article about the very important issue of making reliable decisions under uncertainty. This article shows how machine-learning techniques can be complemented with provably valid measures of accuracy and reliability. The experiments show this model can open new possibilities for earthquake forecasts.

Keywords—Pattern informatics, earthquake, forecasting, seismicity, Neural

I. INTRODUCTION

HE Earth's crust is clearly extremely complex and it is generally accepted that earthquakes are a chaotic phenomenon. Thus, as in the case earthquake forecasting must be considered on a statistical basis (Allamehzadeh and Mokhtari, 2003; Madahizadeh and Allamehzadeh, 2009). A
Fundamental question is whether the statistical properties of seismicity patterns can be used to forecast future earthquakes. Premonitory seismicity patterns were found for some strong earthquakes in Iran.
Premonitory seismicity pattern informatics (PI) approach has been proposed by RUNDLE et al. (2002), TIAMPO et al. (2002a, b, c).
This approach is based on the strong space-time correlations that are responsible for the cooperative behavior of driven threshold systems and arises both from threshold dynamics as well as from the mean field (long range) nature of the interactions. The PI technique can be used to detect precursory seismic activation or quiescence and make earthquake forecasts.
The purpose of this paper is to study the applicability of the pattern Recognition (PR) algorithm for forecasting large earthquakes in Iran. As an example, we will present a forecast of large (M>5) earthquakes during the time period 1990-2013 in the Alborz region:
the region that includes the epicenter of the 1990 Rudbar earthquake. First, we will briefly introduce the PR method. Next, we will describe the earthquake catalogues used in this paper.

II. PATTERN RECOGNITION

We suggest that the SOM is capable of identifying cohesive patterns of nonlinear measurements that would be difficult to identify using traditional linear data reduction procedures and that neural networks will be increasingly valuable in the analysis of a wide range of complex behaviors.

In this study we have employed the self-organizing map (SOM) in gene expression data
Analysis (figure 1). The SOM is an unsupervised neural network algorithm, which has been used
with great level of success in various clustering and visualization earthquakes aftershocks (see Allamehzadeh and Mokhtari, 2003; Allamehzadeh and Abbassi, 2005). Moreover, several studies report that for a noisy data set the SOM outperforms hierarchical clustering and many other clustering methods in various critical areas such as noise tolerance, speed and robustness (Mangiameli, Chen,&West, 1996; Chen et al., 2002; Gibbons & Roth, 2002).

Researchers in China have suggested that neural networks ensembles and support vector machines could be used to predict the magnitudes of strong earthquakes [5, 16], but more research needs to be done to corroborate their findings.

The purpose of this study is analysis and visualization of earthquake catalog data obtained from IIEES networks on simulation data using the SOM. The SOM has been used earlier in clustering aftershocks patterns by Allamehzadeh et al., 2003.

Rather than attempt to issue earthquake predictions, we hope to analyze past data for periodic patterns that may advance our understanding of earthquake dynamics.

With the exception of a brief period in the 1970s, earthquake prediction was generally considered to be infeasible by seismologists. Then, in 1975, Chinese scientists ordered the evacuation of Haicheng one day before a magnitude 7.3 earthquake struck. This led to a flurry of optimism toward earthquake prediction [9, 11], which was subsequently checked by the failed prediction of the magnitude 7.8 Tangshan earthquake of 1976.

Another failure occurred in Parkfield, California in the early 1980s. Up to then, magnitude 6.0 earthquakes had occurred at fairly regular 22-year intervals. This led researchers to predict that an earthquake would strike by 1993; no such earthquake arrived until 2004. To this day, the Haicheng earthquake remains the only successful earthquake prediction in history.

This paper describes a method for estimating earthquake recurrence interval and coefficient of variation from historic earthquake records by using SOM algorithms.

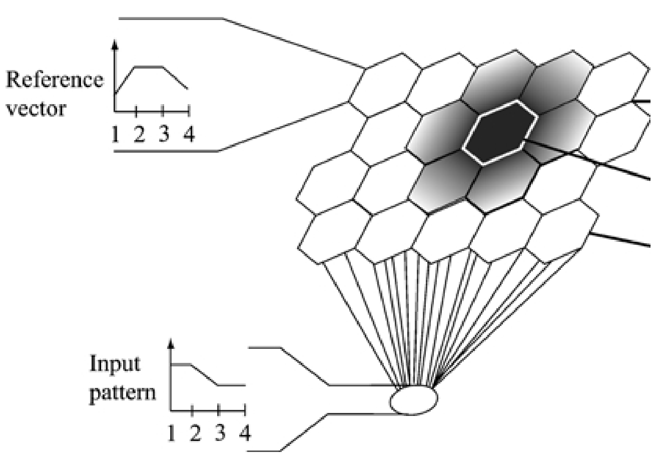

Fig. 1 Idea of the SOM. All neurons contain a reference vector, whose dimension is the same as the dimension of the input data. Earthquake location expression pattern is compared to all reference vectors and the neuron containing the closest reference (black with white boundaries) is permitted to update with neurons belonging to the neighborhood region (shaded).

Statistical practice between recurrence estimation and earthquake probability calculations can be a concern [e.g., Savage, 1991, 1992]. Optimally, we would have enough observations of earthquake intervals to fill out recurrence PDFs; these would eliminate the epistemic uncertainties surrounding recurrence parameters, and define the uncertainty inherent in earthquake recurrence.

As will be shown, Machine learning algorithms fitting tends to be most useful on short sequences and seems primarily sensitive to the histogram of the data. Results reflect epistemic uncertainties by showing the range and uncertainty in distribution parameters that are consistent with observations and their uncertainties.

In many pattern recognition systems, the methodology frequently used is the statistical approach, whereby decision theory derived from statistics of input patterns is used to design a classifier

[13]. Although this paradigm has been successfully applied to solve various problems in pattern classification, it has difficulty in expressing structural information unless an appropriate

choice of features is made possible. Furthermore, this approach requires much heuristic information to design a classifier [14]. Neural-networks-based paradigms, as new means of

implementing various classifiers based on statistical and structural approach, have been proven to possess many advantages for classification because of their learning ability and good generalization.

III. Methods

The methods described in this paper differ from other recurrence parameter estimation techniques. Most commonly, variants of maximum-likelihood techniques are applied to observed series to estimate recurrence parameters [e.g., Geller, Robert J. and Jackson, David D. and Ka-

gan, Yan Y. and Mulargia, Francesco (1997)]. The methods used to extract knowledge from earthquakes time series are described in this section. The goal is to find patterns in data that precede the appearance of earthquakes with a given magnitude by using Quadratic Neural Networks (QNN) and Radial Base Function (RBF) Neural Networks.

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[9]–[12], [14]–[16]. Generally speaking, multilayered networks (MLNs), usually coupled with the back propagation (BP) algorithm, are most widely used in face recognition [9]. Yet, two major criticisms are commonly raised against the BP algorithm: 1) It is computationally intensive because of its slow convergence speed and 2) there is no guarantee at all that the absolute minima can be achieved. On the other hand, RBF neural networks have recently attracted extensive interests in the community of neural networks for a wide range of applications [17]–[29]. The salient features of RBF neural networks are as

follows.

As the goal is to find patterns that precede quake occurrences, the magnitude of the current earthquake, Mb, has been forced to be the only attribute in the consequent.

The Mb attribute has been divided in three non-overlapped intervals: [3.0, 3.5) or small earthquakes, [3.5, 4.4) or medium earthquakes, and [4.4, 6.2] or large earthquakes (note that the largest retrieved earthquake magnitude is 6.2). Tables 1 show the data catalog is used for extracted to large, medium and small earthquakes, respectively. Note that ΔMw and Δt represent the increment of the b–value and the time elapsed between the previous and current earthquake, respectively. Also, the magnitude of the earthquake occurred prior the current one, Mw, has been covered only by one rule. Finally, all rules have been assessed by means of three well-known and widely used indices: Confidence, support, and lift [6].

Table1. Earthquakes used in this study

N	Date							Location			Magnitude
	Year	Month	Day	Hour	Min	Sec		Latitude (N)	Longitude (E)		Mw
1	1677	1	1	0	0	0		54.2	27.9		6.4
2	1703	1	1	0	0	0		54.9	26.6		6.8
3	1824	8	28	0	0	0		52.4	29.8		7.1
4	1890	3	25	0	0	0		53.7	28.8		7.1
5	1902	7	9	0	3	38		56.3	27.1		6.3
6	1927	5	9	0	10	31		56.7	27.7		6.4
7	1949	4	24	0	4	22		56.5	27.3		6.3
8	1956	10	31	0	14	3		54.7	27.3		6.6
9	1961	6	11	0	5	10		54.5	27.8		6.6
10	1972	4	10	6	2	6		52.8	28.4		6.7
11	1977	3	21	52	21	18		56.4	27.6		6.7
12	1990	11	6	53	18	45		55.5	28.2		6.6
13	1999	3	4	28	5	38		57.2	28.3		6.6
1	1919	10	24	0	20	32		62.05	26.11		5.8
2	1926	5	19	33	21	13		58.9	26.3		5.7
3	1929	9	3	0	12	7		62.07	26.59		6.3
4	1945	11	27	15	21	56		63.5	25		8.0

N	Date							Location			Magnitude
	Year	Month	Day	Hour	Min	Sec		Latitude (N)	Longitude (E)		Mw
5	1972	8	6	20	1	12		61.14	24.99		5.5
6	1979	1	10	45	15	5		60.99	26.491		6.1
7	1989	12	7	34	12	59		58.965	25.918		6.0
8	1992	1	30	0	5	22		62.88	24.25		5.9
9	2005	3	13	58	3	31		62	26.73		6.0
1	1824	6	2	0	0	0		51.5	29.7		6.1
2	1864	12	7	0	20	0		45.98	33.38		6.3
3	1868	8	1	0	20	0		52.5	34.9		6.4
4	1875	3	21	0	15	0		50.5	30.5		5.9
5	1890	2	7	0	0	0		51.22	34.18		6.3
6	1903	9	25	0	1	20		58.23	35.18		6.0
7	1907	3	31	0	14	12		50	30		6.1
8	1917	7	15	0	17	58		45.82	33.48		6.3
9	1923	9	22	0	20	47		56.63	29.51		6.7
10	1927	11	12	0	14	46		47.38	32.53		6.1
11	1929	7	15	0	7	44		49.48	32.08		6.1
12	1937	4	7	0	18	30		52.1	34.8		5.6
13	1939	11	4	0	10	15		48.52	32.4		6.1
14	1948	7	30	43	3	30		49.12	31.41		5.8
15	1957	3	16	46	0	43		52.87	34.91		5.6
16	1958	5	5	64	5	21		44.79	35.69		5.6
17	1962	6	29	15	22	35		48.76	32.21		5.7
18	1972	2	28	85	18	44		51.1	29.74		5.5
19	1980	12	18	0	12	34		44.25	35.89		6.2
20	1989	5	27	36	20	8		50.892	30.148		6.0
21	1998	8	5	15	14	27		46.266	33.183		5.6
22	2002	9	25	23.9	22	28		49.327	32.076		5.6
23	2008	8	27	12.5	21	52		47.36	32.23		5.8
24	2010	7	30	28.2	13	50		59.36	35.17		5.5
1	1868	8	1	0	20	0		52.5	34.9		6.4
2	1890	2	7	0	0	0		51.22	34.18		6.3
3	1903	9	25	0	1	20		58.23	35.18		6.0
4	1923	9	22	0	20	47		56.63	29.51		6.7
5	1937	4	7	0	18	30		52.1	34.8		5.6
6	1957	3	16	46	0	43		52.87	34.91		5.6
7	1962	9	4	20	13	30		49.72	35.56		5.7
8	2010	7	30	28.2	13	50		59.36	35.17		5.5
1	1641	2	5	0	18	0		46.1	37.9		6.7
2	1648	3	31	0	24	0		43.5	38.3		6.5
3	1696	4	14	0	0	0		43.9	39.1		7.0
4	1715	3	8	0	6	0		43.9	38.4		6.6
5	1840	7	2	0	19	0		43.9	39.5		7.3
6	1930	5	6	0	22	34		44.6	38.24		7.1
7	1957	12	13	0	1	45		47.8	34.55		6.8
8	1976	11	24	15	12	22		44	39.1		7.0
1	1909	1	23	0	2	48		49.13	33.41		7.4
2	1920	5	25	0	11	39		46.5	33.5		5.6
3	1932	5	7	0	14	54		45	36.2		5.7

N	Date							Location			Magnitude
	Year	Month	Day	Hour	Min	Sec		Latitude (N)	Longitude (E)		Mw
4	1939	1	25	0	11	2		50.81	30.93		5.7
5	1941	6	10	0	20	38		46.84	33.5		5.8
6	1944	6	28	33	2	57		45	36		5.8
7	1951	6	9	53	11	22		49.8	32.26		6.2
8	1960	3	24	0	23	21		51	31.25		6.1
9	1967	1	11	14	11	20		45.66	34.07		5.6
10	1978	12	14	21	7	5		49.634	32.128		6.2
11	1988	3	30	43	2	12		50.179	30.845		5.9
12	2006	3	31	17	1	17		48.73	33.74		6.1
1	1911	4	18	0	18	14		57.05	31.25		6.4
2	1933	10	5	0	13	29		57.07	34.52		6.2
3	1948	7	5	0	13	53		57.73	29.88		6.1
4	1978	9	16	54	15	35		57.382	33.243		7.4
5	1998	3	14	5	19	40		57.589	30.13		6.6
6	2005	2	22	12	2	25		56.81	30.76		6.4
1	1903	3	22	0	14	35		59.71	33.16		6.2
2	1923	11	29	0	3	36		59.4	33.62		5.8
3	1941	2	16	0	16	39		58.9	33.4		6.2
4	1947	9	23	0	12	28		58.7	33.7		6.9
5	1962	4	1	0	0	45		58.87	33.21		5.8
6	1968	8	31	12	10	47		58.96	34.04		7.1
7	1979	11	27	34	17	10		59.754	34.057		7.1
8	1997	6	25	8	19	38		59.435	33.916		5.9
1	1854	11	0	0	0	0		59.38	30.58		5.7
2	1923	9	14	0	8	10		59.33	28.97		5.8
3	1932	9	8	0	7	25		58.66	30.99		5.8
4	1960	8	23	15	8	58		59.85	29.09		5.7
5	1969	11	7	80	18	34		59.98	27.82		6.1
6	1980	1	1	56	2	45		60.346	27.341		5.5
7	2003	12	26	6	1	56		58.268	28.95		6.6
8	2010	12	20	58.1	18	41		59.24	28.35		6.5
1	1780	1	1	0	0	0		59	36		6.5
2	1804	1	1	0	0	0		57.18	36.33		5.8
3	1808	6	26	0	0	0		54.32	35.25		6.5
4	1931	8	8	0	8	54		57.63	35.56		5.7
5	1940	5	4	0	21	1		58.5	35.75		6.5
6	1953	2	12	10	8	15		54.88	35.39		6.5
7	1971	5	26	17	2	41		58.14	35.53		5.6
8	1979	12	9	3	9	12		56.82	35.105		5.6
9	2010	8	27	13.1	19	23		54.48	35.58		5.7
1	1838	1	1	0	0	0		59.96	29.5		6.9
2	1905	6	19	0	1	27		59.98	29.89		6.8
3	1927	7	7	0	20	6		62.26	27		6.3
4	1934	6	13	0	22	10		62.64	27.63		7.0
5	1950	9	24	0	22	56		60.7	34.5		6.0
6	1979	12	7	59	9	23		59.849	34.078		6.1
7	1994	2	24	13	0	11		60.51	30.79		6.3

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N	Date							Location			Magnitude
	Year	Month	Day	Hour	Min	Sec		Latitude (N)	Longitude (E)		Mw
8	1997	5	10	13	7	57		59.81	33.847		7.2
1	1786	10	1	0	0	0		45.77	38.36		6.2
2	1844	5	13	0	0	0		47.97	37.5		6.8
3	1862	12	19	0	5	0		47.8	39.3		6.2
4	1879	3	22	0	3	42		47.85	37.8		6.6
5	1896	1	4	0	18	28		48.32	37.7		6.6
6	1905	1	9	0	6	17		47.8	37.9		6.1
7	1924	2	19	0	7	1		48.32	39		6.8
8	1940	7	11	18	1	23		47.6	39.5		5.5
9	1976	2	3	57.5	16	40		48.326	39.898		5.6
10	1997	2	28	9	12	57		48.07	38.109		6.1
11	2002	6	22	11	2	58		49.02	35.597		6.5
1	856	12	22	0	0	0		54.14	36.23		7.3
2	958	2	23	0	0	0		51.35	35.82		7.3
3	1177	5	0	0	0	0		50.83	35.92		7.1
4	1209	0	0	0	0	0		59.22	36.05		7.3
5	1389	2	0	0	0	0		58.75	36.25		7.3
6	1405	11	23	0	0	0		58.75	36.25		7.3
7	1485	8	15	0	0	0		50.45	36.43		7.1
8	1608	4	20	0	0	0		50.5	36.37		7.3
9	1695	5	11	0	5	0		57.46	37.1		6.9
10	1825	0	0	0	0	0		52.45	36.05		6.6
11	1830	3	27	0	0	0		52.28	35.73		7.0
12	1851	6	0	0	0	0		58.5	36.78		6.8
13	1890	7	11	0	6	0		54.6	36.6		7.2
14	1957	7	2	0	0	42		52.45	36.05		7.1
1	1810	1	1	0	0	0		57.12	37.85		6.4
2	1833	1	1	0	0	0		58.1	37.3		6.2
3	1871	12	23	0	0	0		58.3	37.25		7.1
4	1893	11	17	0	19	36		58.4	37.12		7.0
5	1904	11	9	0	3	28		59.77	36.94		6.4
6	1929	5	1	0	15	37		57.8	37.7		7.1
7	1985	10	29	5	14	23		54.899	36.901		6.2
8	1997	2	4	8	10	37		57.312	37.729		6.5
1	1665	6	1	0	0	0		52.08	37.75		6.4
2	1678	1	1	0	0	0		52.6	36.3		6.5
3	1780	1	8	0	19	6		49.29	38.12		7.3
4	1854	10	1	0	15	0		50	38		6.0
5	1895	7	8	0	22	0		53.7	39.1		7.5
6	1935	4	11	0	23	14		53.3	36.35		6.6
7	1980	5	4	19	18	35		49.019	38.048		6.6
8	1990	6	20	10	21	0		49.222	36.997		7.4
9	2000	11	25	33	18	9		49.938	40.23		6.8

Statistical learning theory is for small-sample statistics. And support vector machine is a new machine learning method based on the statistical learning theory. The support vector machine not only has solved certain problems in many learning methods, such as small sample, over fitting, high dimension and local minimum, but also has a higher generalization (forecasting) ability than that of

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artificial neural networks. The strong earthquakes in Iran are related to a certain extent to the intensive seismicity along the main plate boundaries in the world; however, the relation is nonlinear. In the paper, we have studied this unclear relation by the support vector machine method for the purpose of forecasting strong earthquakes in Iran.
The used methodology is quite different from the usual seismotectonic methods that allow delineating seismogenic zones and calculating the seismic hazard inside these zones.
In the Alborz region, Gorshkov (2006) define seismogenic nodes prone to earthquakes M>6 and characteristic geomorphological-gelogical features that discriminate seismogenic nodes from non-seismogenic ones. Morphostructural nodes are formed around intersections or junctions of two or several lineaments. The nodes have been obtained by the morphostructural zoning (MZ) method. The compiled MZ map shows the hierarchical block-structure of the Alborz region, the network of boundary zones separating blocks formed at the intersections of boundary zones. The pattern recognition algorithm RBF was defined other nodes capable of such size earthquakes using topographic, morphometric, and morphostructural parameters that describe the nodes. Nodes prone to M>6 exhibit the high topographic contrast and the increased fragmentation of the crust. Results of the work were pointed out the high seismic potential of the Alborz region: this study was identified a number of seismogenic nodes, where the target earthquakes have not yet been recorded.

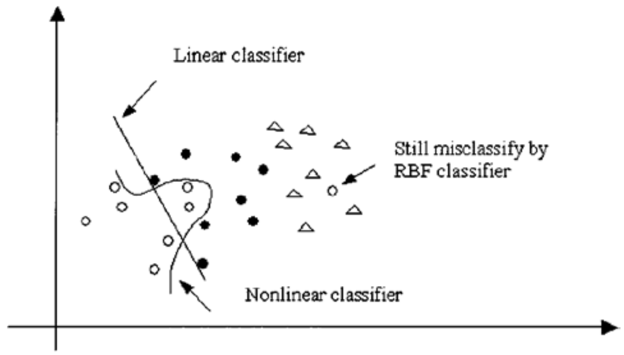

Fig. 2 An RBF neural classifier versus a linear classifier.

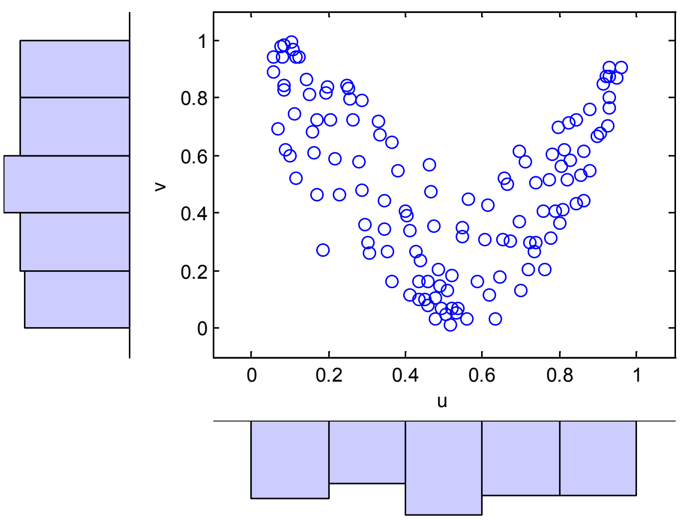

Fig. 3 shows the predicted of pattern recognition of Alborz region by this methods.

Machine learning will give us greater insight into the patterns underlying earthquake activity, even if we cannot predict the time, location, and strength of the earthquakes accurately, Machine learning algorithms available for us to understand and predict patterns of earthquakes activity.

Regression techniques have been widely used for forecasting time series [5]. Thus, an empirical study on sea water quality prediction can be found in [7]. The authors transformed quantitative data into statistical moments, and constructed a tree to estimate the forecasting interval of the target variable. Last, the problem of predicting the machinery degradation and trending of fault propagation before reaching the alarm was studied in [12]. In particular, the authors proposed an approach based on regression trees to forecast such time series.

IV. CONCLUSIONS

Earthquake data from two particular areas of the Iranian plate have been successfully mined by means of two different techniques: QNN and the RBF algorithm. In particular, QNN with a confidence of 83.0% and a lift of 5.6 on average have been discovered and a regression-tree with an error of 0.35 has been built. Both techniques have discovered the great influence that the b–value has in earthquakes occurrences as its variation along with the time elapsed have shown to be useful to model different earthquakes. Thus, the patterns discovered before an earthquake takes place may be useful in subsequent predictions.

It is well known that if the dimension of the network input is comparable to the size of the training set, which is the usual case in pattern recognition of earthquake, the system will easily bring about overfitting and result in poor generalization. In this paper, a general design approach using an RBF neural classifier for face recognition to cope with small training sets of high-dimensional problem is presented.

REFERENCES

- 2007 Working Group on California Earthquake Probabilities (2008), Working Group on California Earthquake Probabilities (2008), The Uniform California Earthquake Rupture Forecast, Version 2. Available: http://pubs.usgs.gov/of/2007/1437/ of 2007-1437 text.pdf
- [2] Allamehzadeh, M., M. Abbassi. “Recognition of seismic precursory activities using Self-Organizing Feature maps Neural Network” International Journal Diaster Advances, Vol I, (2008).
- [3] Allamezadeh, M., M. Mokhtari, “Prediction of Aftershokcs Distribution using Self-Organizing Feature maps (SOFM) and its Application on the Birjand-Ghaen and Izmit Earthquakes”Journal of Seismology and Earthquake Engineering (JSEE): Fall 2003. Vol. 5. No. 3. Page: 1-15.
- [4] 2007 Working Group on California Earthquake Probabilities (2008), The Uniform California Earthquake Rupture Forecast, Version 2. Available: http://pubs.usgs.gov/of/2007/1437/ of2007-1437 text.pdf
- [4] Press, Frank (1975), Earthquake Prediction. Scienti_c American, 232.5:14.
- [5] Liu, Yue and Wang, Yuan and Li, Yuan and Zhang, Bofeng and Wu, Gengfeng (2004), Earthquake Prediction by RBF Neural Network Ensemble. Advances in
- Neural Networks - ISNN 2004, 3174:13-17.
- [6] Stark, P. B. (1997), Earthquake prediction: the null hypothesis. Geophysical Journal International, 131: 495499. doi: 10.1111/j.1365-246X.1997.tb06593.x
- [7] USGS, Google Earth/KML Files. Available: http://earthquake.usgs.gov/learn/kml.php
- [8] USGS, Quaternary Faults in Google Earth. Available: http://earthquake.usgs.gov/hazards/qfaults/google.php
- [9] Wang, Kelin and Chen, Qi-Fu and Sun, Shihong and Wang, Andong (2006), Predicting the 1975 Haicheng earthquake. Bulletin of the Seismological Society of
- America, 96.3:757-795. doi:10.1785/0120050191
- [10] Wang, Wei and Liu, Yue and Li, Guo-zheng and Wu, Geng-feng and Ma, Qin-zhong and Zhao, Li-fei and Lin, Ming-zhou (2006), Support vector machine method for orecasting future strong earthquakes in Chinese mainland. Acta Seismologica Sinica, 19: 30-38.
- [11] S. Lawrence, C. L. Giles, A. C. Tsoi, and A. D. Back, “Face recognition:
- A convolutional neural-network approach,” IEEE Trans. Neural Networks, vol. 8, pp. 98–113, Jan. 1997.
- [12] S.-H. Lin, S.-Y. Kung, and L.-J. Lin, “Face recognition/detection by probabilistic decision-based neural network,” IEEE Trans. Neural Networks, vol. 8, pp. 114–132, Jan. 1997.
- [13] K. Fukunaga, Introduction to Statistical Pattern Recognition, 2nd ed. San Diego, CA: Academic Press, 1990.
- [14] H. H. Song and S. W. Lee, “A self-organizing neural tree for large-set pattern classification,” IEEE Trans. Neural Networks, vol. 9, pp. 369–380, Mar. 1998.
- [15] C. M. Bishop, Neural Networks for Pattern Recognition, New York: Oxford
- Univ. Press.
- [16] Wang, Wei and Liu, Yue and Li, Guo-zheng and Wu, Geng-feng and Ma, Qin-zhong and Zhao, Li-fei and Lin, Ming-zhou (2006), Support vector machine method for
- forecasting future strong earthquakes in Chinese mainland. Acta Seismologica Sinica, 19: 30-38.
- [16] J. L. Yuan and T. L. Fine, “Neural-Network design for small training sets of high dimension,” IEEE Trans. Neural Networks, vol. 9, pp. 266–280, Jan. 1998.
- [17] J. Park and J. Wsandberg, “Universal approximation using radial basis

- functions network," Neural Comput., vol. 3, pp. 246–257, 1991.
-
- [18] F. Girosi and T. Poggio, "Networks and the best approximation property," Biol. Cybern., vol. 63, pp. 169–176, 1990.
-