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# PREDICTION OF AFTERSHOCKS PATTERN DISTRIBUTION USING SELF-ORGANISING FEATURE MAPS

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## SUMMARY

Pattern recognition techniques are able to predict the cluster of aftershocks of earthquake sequences. Self-Organizing feature maps (SOFM) have in recent years become powerful intelligent tools, used widely in pattern recognition and data clustering. These networks often used to predict the outcome of a future event based on current observations of the state of the environment. The aim of this paper is to show a reliable prediction of distribution of the location of aftershock patterns using Artificial Neural Networks (ANNs).These results strongly support this technique on investigating these spatial and temporal patterns in local and regional seismicity data.

## Introduction

The prevalence of earthquake clustering and its strong imprint on spatial and temporal patterns of seismicity, provide convincing arguments [1]. Shaw et al. in 1992 worked in patterns of seismic activity preceding large earthquakes. The recent of interest in neural networks has led to renewed research in the area of pattern recognition problems using SOFM.

In this work we present a method for prediction of aftershock patterns using SOFM.Self-Organizing feature maps originated by Kohonen[9], in the late 1970's, and refined since then, are the unsupervised network of choice. Several features of the maps make them desirable in our case. SOFM are a dimensionality reducing technique, which can be compared to, for example, principal components Analysis. This algorithm has been used to cluster the data. The SOFM defines a mapping from the input data space onto an output layer by the processing units of e.g. 2-D laminar network become sensitive to specific items of the input space in a topological order of the input items. Kohonen's algorithm creates a vector quantizer by adjusting weights from common input nodes to M output nodes arranged in a two dimensional grid as shown in Fig.1.

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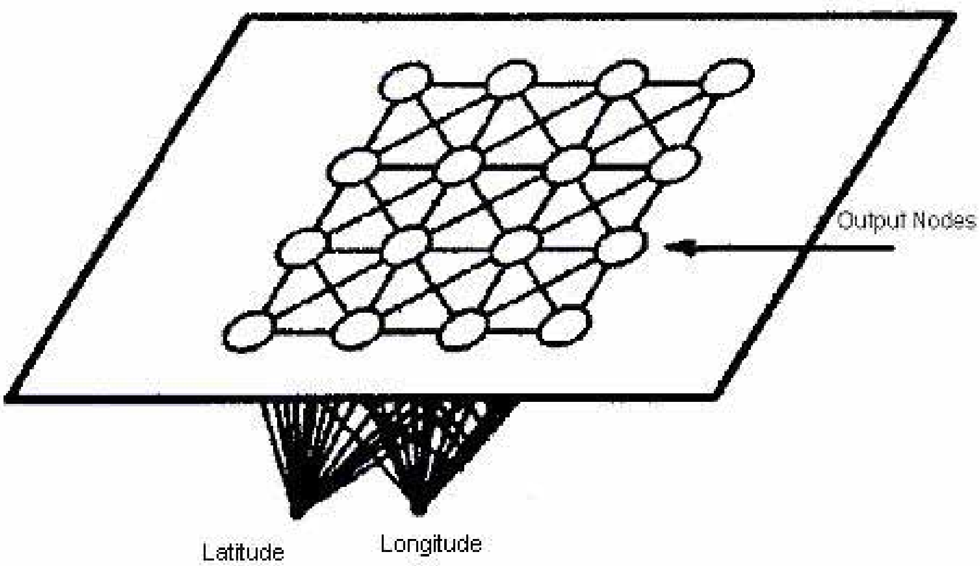

Fig 1. Two-dimensional array of output nodes used to form feature maps

Aftershocks pattern evolution and prediction in nonlinear systems is complicated by nonlinear mode coupling and noise, however understanding such patterns, which are the surface expression of the underlying dynamics, is critical to understanding and perhaps characterizing the physics which control the system.
Earthquake fault systems are examples of driven nonlinear threshold systems [8], comprised of interacting spatial networks of statistically identical, nonlinear units that are subjected to a persistent driving force [5]. Numerous examples of such systems exist, including neural networks [2].
. We apply neural network methods, Kohonen's Self-Organizing Feature Maps (SOFM) and then a supervised method which extends the map's usefulness, The SOFM algorithms has been tested on Bam's aftershocks (Fig.3.). These algorithms have been used to predict the cluster of pattern using Artificial Neural Networks (ANNs). Neural networks are non-parametric methods, and thus do not require the building of a comprehensive model. While a priori knowledge may sometimes be built into the network, this is not necessary, and excellent results may be obtained without such knowledge. Our simulations have suggested that the correlations in the seismicity represented by the SOFM modes above can be described by phase dynamics. Phase dynamics is a method used in various branches of physics to describe the behavior of important parameters of the physical system [3],[4].
In this report, we discuss a new
The SOFM map is a good approximation to the input space. This property is important since it provide a compact representation of the given input space( the location of aftershocks). The feature map naturally forms a topologically ordered output space such that the spatial location of a neuron in the lattice corresponds to a particular domain in input space. The advantage of this feature is that it can simplify local modeling of the input signal embedded in the space.

**Data Base**

In order to monitor the aftershock occurrence and the faulting mechanism, International Institute of Earthquake Engineering and Seismology (IIEES) had deployed a temporary seismic network of 5 stations in this area for a period of six weeks. Figure 2 shows the epicenter map of 31 aftershocks (Ml>2.5) recorder during this period. We found a clear tendency that aftershocks occur in clusters (Fig.3.), which implies strong heterogeneity in both the rupture process and the medium along the fault zone (Fig.4). The raw data consists of location (latitude and longitude) of Bam's aftershocks.

Self-organizing feature maps (SOFMs) originated by Kohonen in 1970's, and refined since then, are the unsupervised network of choice. Several features of the maps make them desirable in our case. The maps are topology conserving that is, relationships among points tend to be conserved in the mapping process. This occurs even if the intrinsic dimension of the data is larger than that of the map, although the topology conservation must necessarily become more local rather than completely global. While the clustering of a group of similar points may be done as well with a traditional k-means method, this will not indicate the relationship between the groups.

The unsupervised SOFM gives a good indication of the topology and grouping of the aftershocks data, but is not therefore necessarily an optimum classifier. The SOFM algorithm can be summarized as follows:

1. Initialize the weights w of a 1 or 2-dimensional network to small random weights.
2. For each input x, determine the closest or best-matching node, according to some predetermined criteria. Commonly used criteria are the minimum Euclidean distance or the maximum inner product.
3. Adjust the weights such that neurons in the neighborhood N of the best matching neuron move closer to the input,

$$w(n+1) = w(n) + h(n)[x(n) - w(n)], \text{ for } j \in N$$
$$w(n+1) = w(n), \text{ Otherwise}$$

Where h (n) , the learning rate and the size of N decrease with time.

Here, training begins with N including the full map and learning rate 1. Both of these parameters decrease approximately exponentially over the course of 2000 training runs.

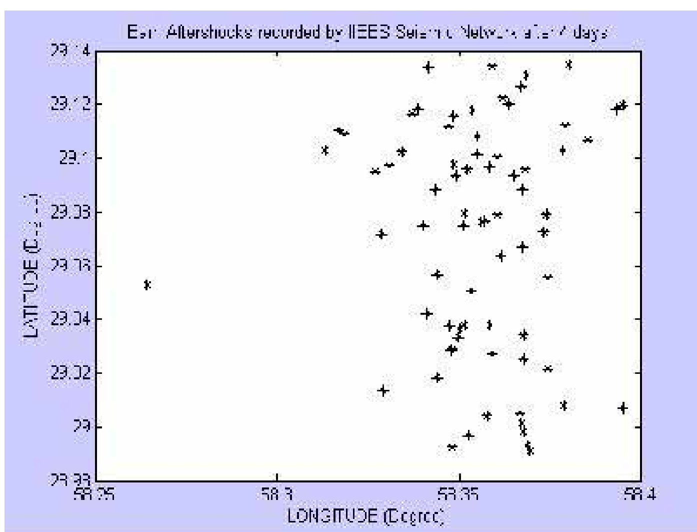

**Fig.2**. Bam's Aftershocks Recorded by IIEES Seismic Networks.

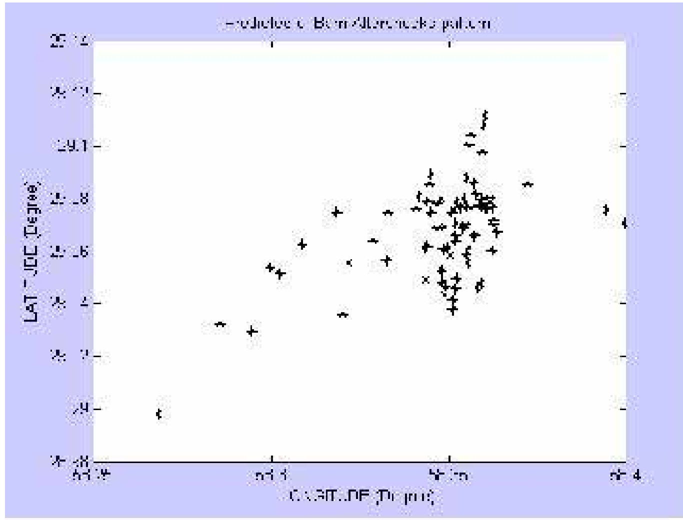

**Fig.3**. Predicted of Bam's Aftershocks Pattern for Next 2 Months.

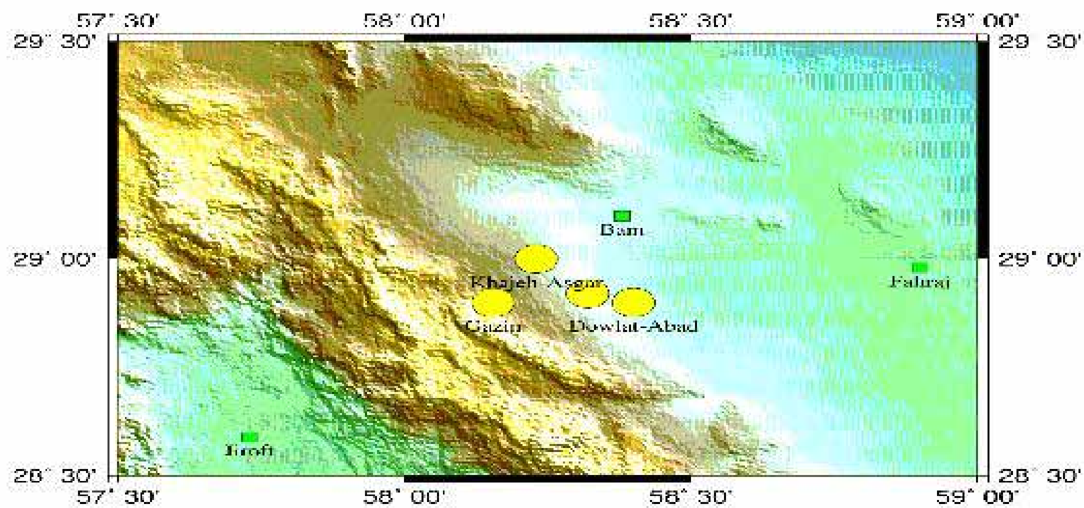


**Fig.4.** Location map of Bam aftershock's clusters which is predicted by Artificial Neural Networks

## RESULTS

To predict and identify seismic risk at high seismicity areas is very important work to asses the seismic hazard. In this paper, the possible of prediction the temporal and spatial distribution of aftershocks are searched for. The aim of this paper is shown a reliable prediction of patterns of aftershocks similar to the traditional methods using Artificial Neural Networks (ANNs); Investigation of the dynamics of aftershocks data requires the use of methods from the pattern recognition. The recent of interest in neural networks has led to renewed research in the area of pattern recognition problems. This paper has shown that SOFM can be used to predict the concentration and the trend of aftershocks of the BHUJ earthquake (26 January, 2001), India. Our experience confirmed that algorithm can be applied for local distribution in this aftershock region. In this work we present a method for identifying these areas of increased probability of an event. This pattern dynamics approach that we have applied to historical seismicity data in BHUJ earthquake (26 January, 2001 reveals wealth of interesting spatial patterns .These space patterns in the seismic activity directly reflect the existence of precondition for the occurrence of large earthquakes.

Aftershock distribution shows the rupture of the main shock, which is an important issue for estimating the risk of future disastrous earthquakes. Aftershocks tend to occur near the mainshock, but the exact geographic pattern of the aftershocks varies from earthquake to earthquake. Statistically, aftershocks are not mutually independent in space. In the weeks and months after a strong earthquake, there will be many aftershocks, some strong enough to cause additional damage to structures already weakened due to the main shock. Aftershock clustering is an unsupervised technique, which finds possible clusters in the data. In this research, the theory of Self-Organizing Feature Maps (SOFM) is applied in the learning procedure.

. During training SOFM, after enough input vectors, weights will specify cluster or vector centers in the input space, the point density function of the vector centers tends to approximate probability density function of the input vectors. The input vector position maps had been used *Latitude* and *longitude* and arranged as a neat assembly of rows and columns.

SOFM provides a topologically organized output of the input vectors and predicted clusters of aftershocks or distribution of earthquake swarms.

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