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A Fuzzy ARTMAP neural network based-approach for seismic signal discrimination between earthquakes and quarry blasts

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Motivation

Seismic source recognition based on acquired signals is a complex task to model using classical mathematical methods. In fact, seismic signals are affected by complex geological conditions and several types of noise sources. Nowadays, artificial intelligence techniques have attracted increasing attentions among scientists to handle real world problems which cannot be modeled using traditional mathematical techniques.

In this study we propose a simplified Fuzzy ARTMAP neural network based approach for discrimination between earthquakes and quarry blasts. This neural network provides several appealing features including flexible configuration, incremental learning capability, short training duration and good generalization even when the amount of training data is limited. These properties make it an attractive model for investigation into the problem of seismic signal classification.

Simplified Fuzzy ARTMAP

Fuzzy ARTMAP (FAM) refers to a competitive and supervised neural network. It is based on the Adaptive Resonance Theory (ART) which has been developed to address the stability-plasticity dilemma [1][2]; i.e., the ability of learning new patterns without losing the knowledge of previously learned patterns. This characteristic provides the network with a fast, stable and an incremental learning.

SFAM is a simplified version of FAM, which is more suited for classification problems [3][4]. The architecture of the SFAM is depicted in Fig. 1. It consists of four layers of nodes: an input layer F_0 which receives the normalized feature vector a of length M, two fully interconnected layers, called complement-coding layer F_1, composed of 2M nodes, and competitive layer F_2, composed of N nodes. Each F_1-to-F_2 layer connection is associated with its weight value $\omega_{ij} \in [0, 1]$, where i and j indicate the indices of the nodes in layers F_1 and F_2, respectively. The last layer, named classification layer, is connected to the F_2 through learned associative links which consist of many to one or one to one mappings. In this way, each F_2 node j represents a category that is characterized by its weight vector $\omega_j = (\omega_{j1}, \ldots, \omega_{j\,2M})$, and is associated with one of the output classes C_j.

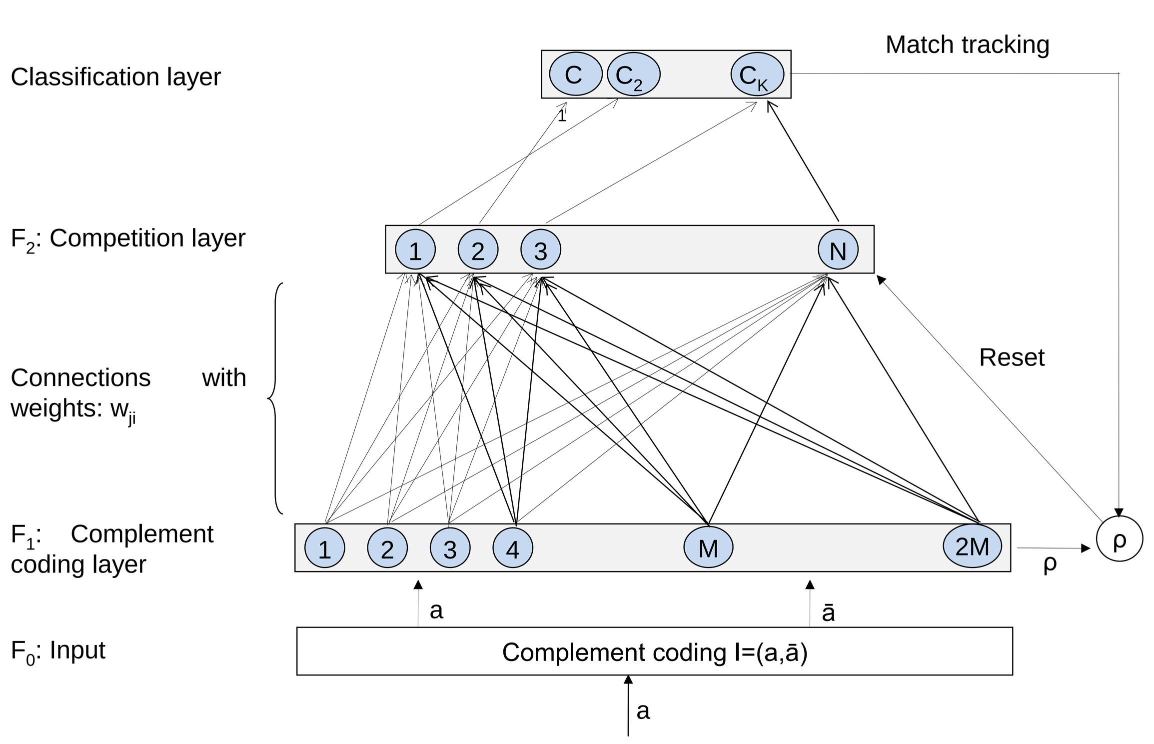

Fig.1. Architecture of the Simplified Fuzzy ARTMAP neural network.

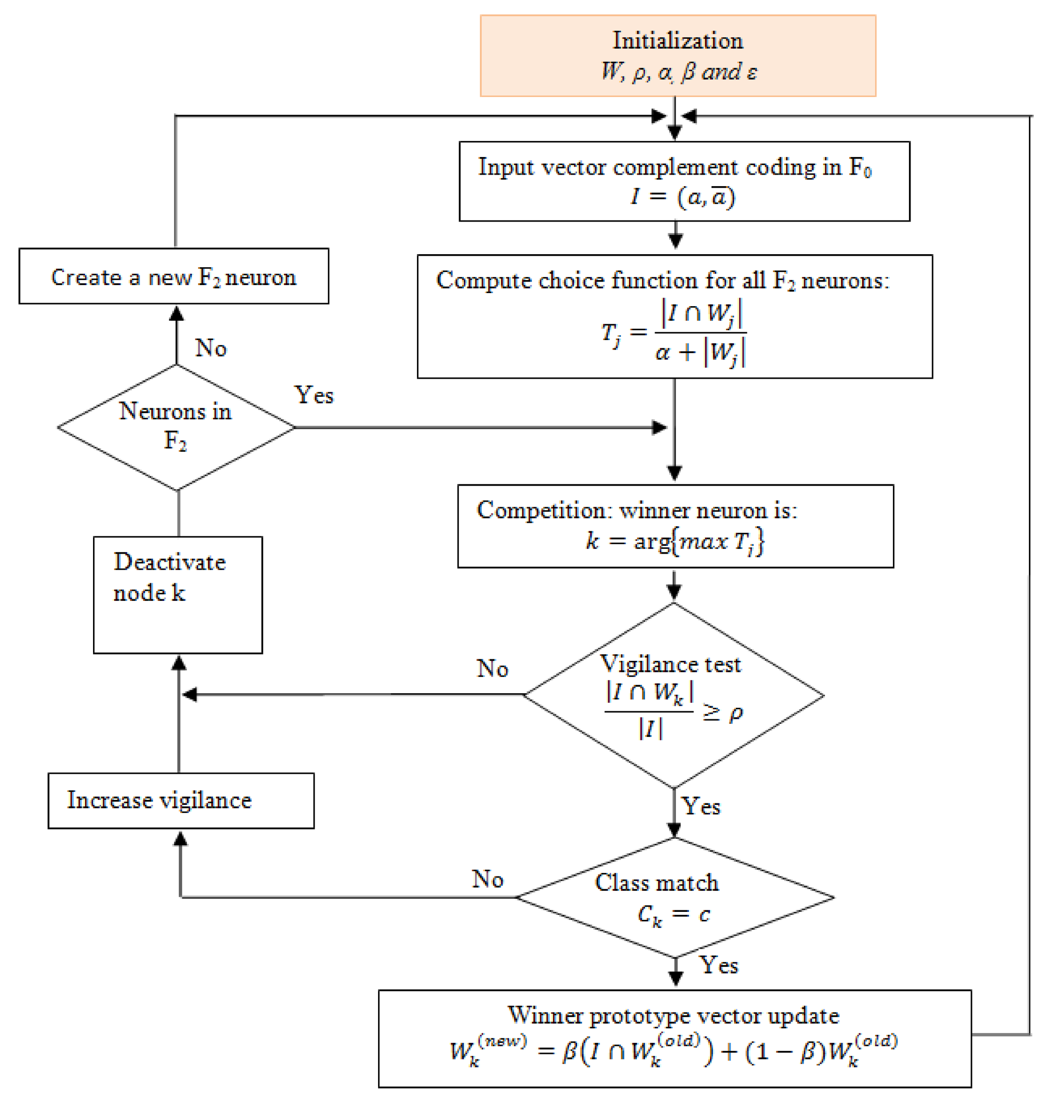

Fig.2. Flow chart of Simplified Fuzzy-ARTMAP training algorithm

Experimental result

A data set of 139 seismograms was chosen and classified by seismic analysts into two classes: earthquake (EQ) and quarry blast (QB). Figure 3 shows two seismograms from the two classes. This dataset is split randomly into three data sets: training set, validation set and test set.

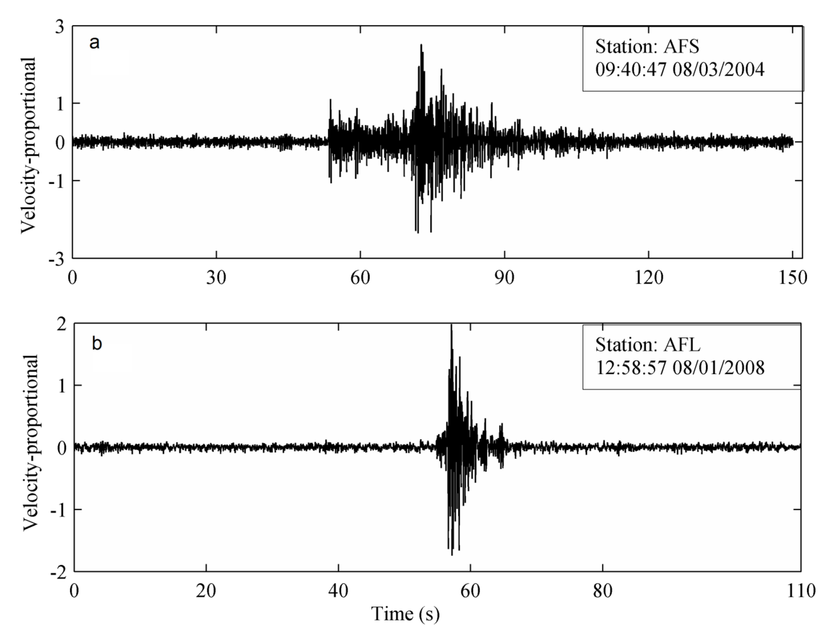

Fig.3. seismogram of an earthquake (a) and a quarry blast (b) .

An automatic classifier could not use directly the huge amount of seismogram samples as input. It is necessary to extract a set of pertinent attributes which represent the most distinctive characteristics among classes. The table below summarizes the features used here.

Feature	Description
Envelop similarity	The envelope similarity E_s measures the resemblance between signal shape of each incoming event and the reference shape.
Duration	The duration estimates the length of the signal.
Hour	The parameter hour determines the detection time.
Spectral centroid	The spectral centroid indicates the barycenter of the signal spectrum.
Spectral length	The spectral length measures the width of signal spectral.
Skewness	Skewness measures the degree of symmetry or asymmetry of a signal around its mean.

As the performance of SFAM is sensible to presentation order of training patterns, it is important to select firstly the presentation order that maximizes the SFAM classification performance. To do so, this experiment is divided into two separate phases. Pattern ordering phase and classification phase.

Pattern ordering using genetic algorithm

To select the best presentation order of the training pattern, the genetic algorithm GA is used. GA is a numerical multidimensional optimization algorithm motivated by natural selection and genetics. In recent years, genetic algorithms (GA) have been used to solve an increasing number of complex real-world problems [5].

Each solution is defined by a chromosome which is composed of genes. Each gene is a variable to optimize. These solutions are grouped in generations and evolve following a mechanism similar to natural selection. The solutions with better performance transmit their genetic information to next generation.

In this study, the chromosome encoding is as follows:

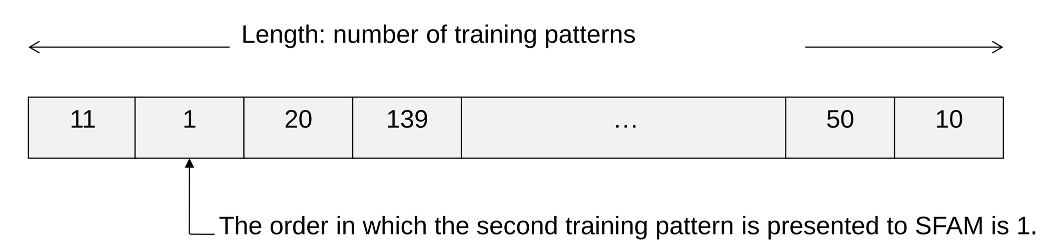

Fig.4. chromosome encoding

the index of each case indicates the order of the pattern in the training dataset and its value designates the order in which it should be presented to SFAM.

SFAM performance is evaluated for each presentation order on the validation data set. Fig.5 shows the steps involved in.

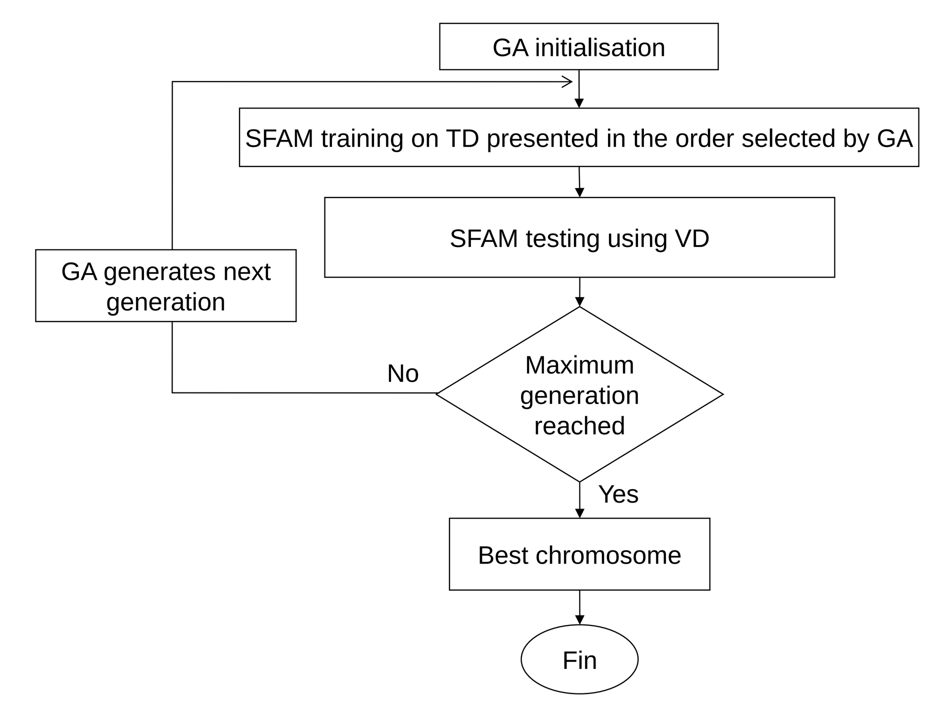

Fig.5. Flow chart of genetic based ordering algorithm.

The genetic algorithm is run until a maximum generation number of 20 is reached. The variation of the fitness function versus generation is showed in figure 6. The overall best chromosome (with the highest fitness value) is then stored. This chromosome represents the GA selected presentation order of training patterns for SFAM.

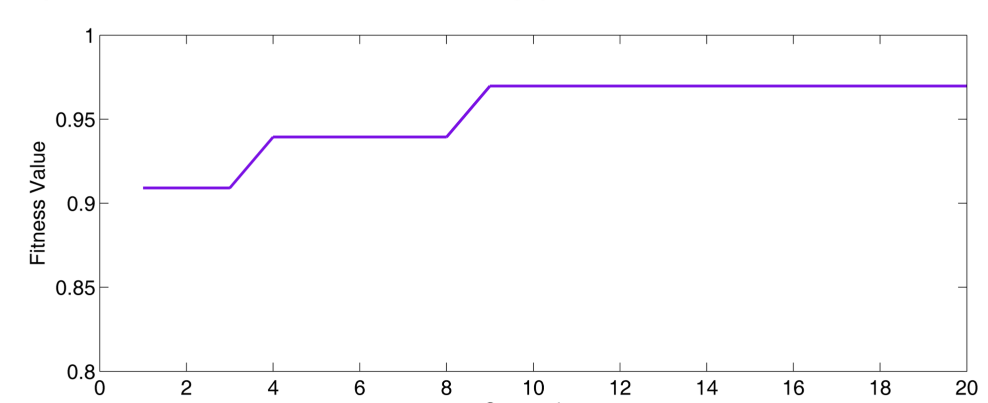

Fig.6. Fitness function.

Classification phase

The classification phase involves testing the performance of SFAM. To do so, the training data set is sorted in the selected presentation order and then used to train SFAM. Once trained, its performance is evaluated on the test data set. The classification accuracy is about 97%. To evaluate the effect of the initial vigilance parameter on the SFAM classification results and training time, SFAM performance is tested for different initial vigilance parameter values ranging from 0 to 0.9 (in steps of 0.1). Fig. 7 and Fig. 8 demonstrate the obtained results.

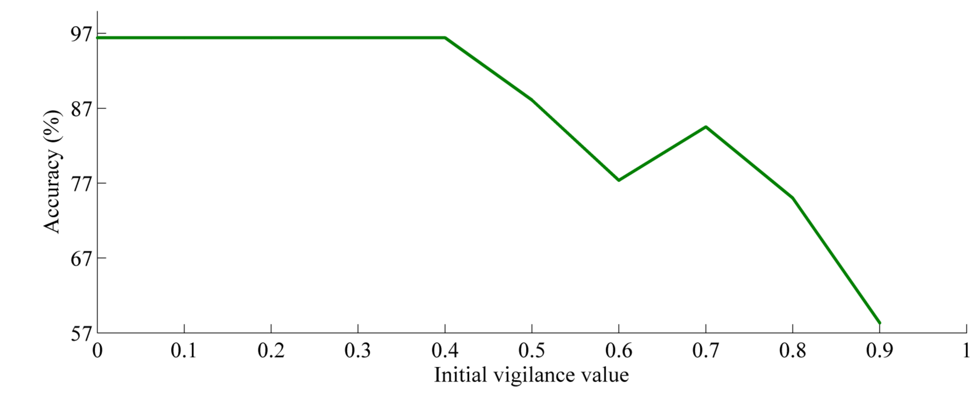

Fig.7. Classification performance versus baseline vigilance parameter.

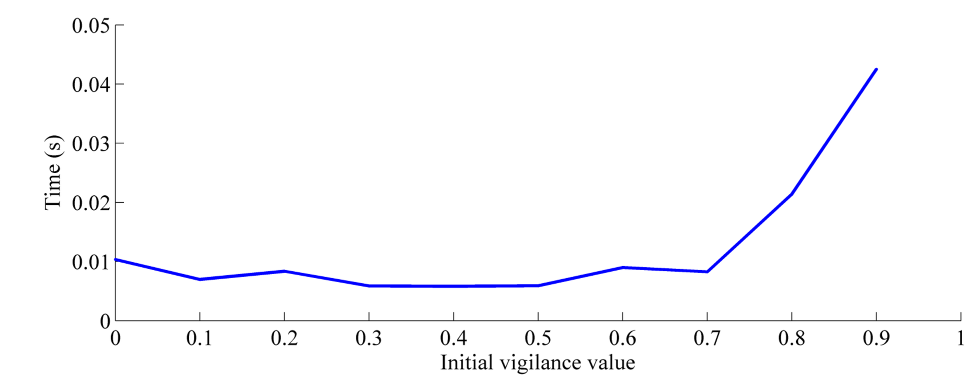

Fig.8. Training time versus baseline vigilance parameter.

To demonstrate the incremental learning capability of SFAM, we conducted a second experiment. we randomly partitioned the whole data set into ten sub-sets. Each sub-set contains data of the two classes. The experiment is then performed as illustrated by the following algorithm.

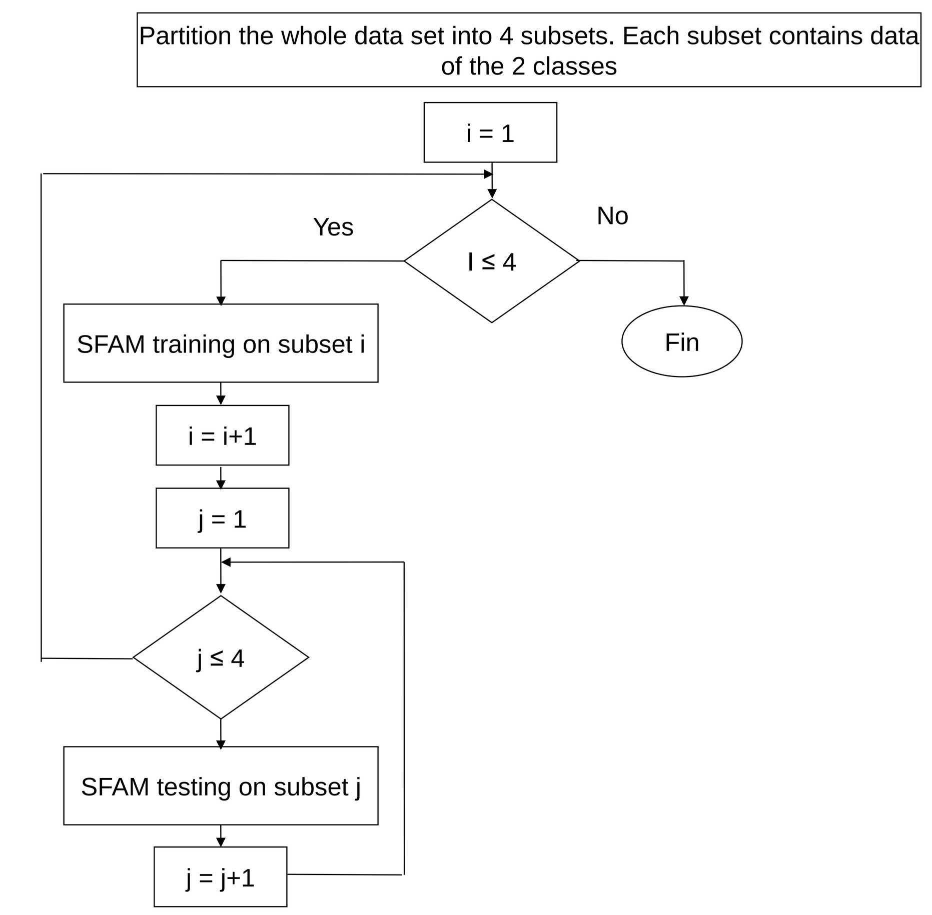

Fig. 9. Incremental learning capability testing algorithm

The table below shows the results.

Testing	Training: Subset 1	Subset 2	Subset 3	Subset 4
Subset 1	100.00	100.00	100.00	100.00
Subset 2	60.00	100.00	100.00	100.00
Subset 3	62.86	85.71	100.00	100.00
Subset 4	74.30	88.57	77.14	100.00

From the results, we clearly observe that the performance of SFAM on an old sub-set does not degrade after learning new information from new sub-sets.

Conclusion

SFAM has showed a number of desirable and attractive characteristics for seismic signal classification. These include high performance, fast learning and flexible configuration. Additionally, the capability of performing incremental learning remains unchallenged by other neural networks.

References

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