Improving Seismic Monitoring System for Small to Intermediate Earthquake Detection

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Abstract

Efficient and successful seismic event detection is an important and challenging issue in many disciplines, especially in tectonics studies and geo-seismic sciences. In this paper, we propose a fast, efficient, and useful feature extraction technique for maximally separable class events. Support vector machine classifier algorithm with an adjustable learning rate has been utilized to adaptively and accurately estimate small level seismic events. The algorithm has less computation, and thereby increased high economic impact on analyzing the database. Experimental results demonstrate the strength and robustness of the method.

Keywords: Feature extraction, Support Vector Machines, Kernels, Seismic signals, Wavelet decomposition Energy.

1. INTRODUCTION

Seismic recorder based on 24-bit digitizer could not provide desired resolution for entire spectrum of seismic signals emanated from micro to intermediate level earthquakes [13]. Therefore it is necessary to characterize much small size seismic signals by employing a special algorithm to distinguish between seismic and non-seismic sources. Several algorithms are there in literature. Freiberger developed the theory of the Maximum likelihood detector assuming Gaussian signal superimposed on Gaussian noise. But real seismic data are not so statistically predictable [3]. Allen described an event detector based on an envelope that is equal to the square of the first derivative. The scheme well suited for short period data (frequency > 1Hz). It missed events from tele-seismic and volcanic events [1]. Clark and Rodger developed an adaptive prediction scheme suitable for small event detection. The drawback of the algorithm is that the signal becomes distorted during processing and event and noise components in the same frequency range are not separated well [2]. Similarly, Stearns and Vortman algorithm could not provide event and noise components in a separate manner [14].

Fretcher et. al. described an approach to seismic event detection based on the Walsh transform theory. This method has complicated computing and unsuitable for online real time seismic applications [4]. Houliston et. al. have described a Short term to Long term average ratio (STA/LTA) algorithm for multichannel seismic network system. This algorithm is based on three components which is STA, LTA and Threshold value. The scheme depends on the amplitude fluctuations of seismic signals rather than signal polarization and frequencies [6]. Improved version of STA/LTA algorithm for 24 bit seismic data recording system has been developed by Kumar et. al. [9]. Even though STA/LTA algorithm performs better, sometimes it provides false event identification and incorrect time picking [13]. Ahmed et. al. developed wavelet based Akaike Information Criteria (AIC) method. It gives good result for event signal having different type of frequency [8] [18] [21]. But this could not be provided desired result when the local noise (Induced seismic events) is overlapping. Therefore the objective of our present work is to provide additional new features in existing 24-bit seismic monitoring system for reducing false events.

2. METHODOLOGY

An aim in this research was to identify small to intermediate seismic events. We began this study with feature extraction technique, which is used to extract the information from the signals. Then the data is aligned into a single row as a vector for the *SVM* training and testing. The SVM is a learning machine for two-group classification problems that transforms the attribute space into multidimensional feature space using a kernel function to separate dataset instances by an optimal hyperplane. Subsequent section explained entire structure of methodology.

2.1. Data Source

Our seismic monitoring network has included 8 substations and 1 head station. The purpose of this monitoring is to compile a complete database of earthquake activity in South India to predict as low magnitude as possible to understand the causes of the earthquakes in the region, to assess the potential for future damaging earthquakes, and to have better constrain in the patterns of strong ground motions from earthquakes in the region. Andaman and Java-Sumatra ridges where active collision and sudden changes taking place, have resulted very high seismicity in the northeast coast of India and Andaman belts. Therefore, station locations were fixed in and around this region. In this research, we used three years (2007-2010) of seismic data acquired from above mentioned seismic monitoring network.

2.2. Feature extraction

We proposed a combined algorithm to extract the features from real time data. The combined algorithm includes Amplitude statistics, Phase statistics and Wavelet Decomposition Energy.

2.2.1. Statistical parameters

Standard statistical techniques have been established for discriminate analysis of time series data [12], and structural techniques have been shown to be effective in a variety of domains involving time series data [17][19][20]. Mainly we focused four standard statistical parameters to extract the features from the seismic signals. Those parameters are Mean, Standard deviation, Skewness and Kurtosis. Mean and variance are fundamental statistical attributes of a time series. The arithmetic mean of a time series is the average or expected value of that time series. In some cases, the mean value of a time series can be the operating point or working point of a physical system that generates the time series.

The Skewness and Kurtosis are higher- order statistical attributes of a time series. Skewness indicates the symmetry of the probability density function (PDF) of the amplitude of a time series. A time series with an equal number of large and small amplitude values has a Skewness of zero. A time series with many small values and few large values is positively skewed (right tail), and the Skewness value is positive. A time series with many large values and few small values is negatively skewed (left tail), and the Skewness value is negative. Amplitude and Shape Statistical parameters are shown in Table 1.

Methods	Parameters	Notation
Amplitude	Mean	$A = \frac{1}{N}\sum_{i=1}^{N} X(i)$, Where $X(i)$ is the spectral magnitude for the i th frequency bin
	Standard deviation	$B = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X(i)-A)^2}$
	Skewness	$C = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X(i)-A}{B}\right)^3$
	Kurtosis	$D = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{X(i)-A}{B}\right)^4 - 3$
Shape	Mean	$E = \frac{1}{Q}\sum_{i=1}^{N} iX(i)$, Where $Q = \sum_{i=1}^{N} X(i)$
	Standard deviation	$F = \sqrt{\frac{1}{Q}\sum_{i=1}^{N}(i-E)^2 X(i)}$
	Skewness	$G = \frac{1}{Q}\sum_{i=1}^{N}\left(\frac{i-E}{F}\right)^3 X(i)$
	Kurtosis	$D = \frac{1}{Q}\sum_{i=1}^{N}\left(\frac{i-E}{F}\right)^4 X(i) - 3$

TABLE 1: Amplitude and Shape Statistical Parameters

2.2.2. Wavelet Decomposition Energy

We derive a set of features from Wavelet Decomposition Energy generated from a discrete Wavelet Transform [20]. Decomposition energy equation (Equation 1) and its results (see figure 1) are described below.

$$E = -\sum_{i} p(i)\log\left|p(i)\right|, \qquad (1)$$

Where, $p(i) = \frac{\left|X(i)^2\right|}{\sqrt{\sum_{i}\left|X(i)\right|^2}}$ and $X(i)$ is a samples of the decomposition signals.

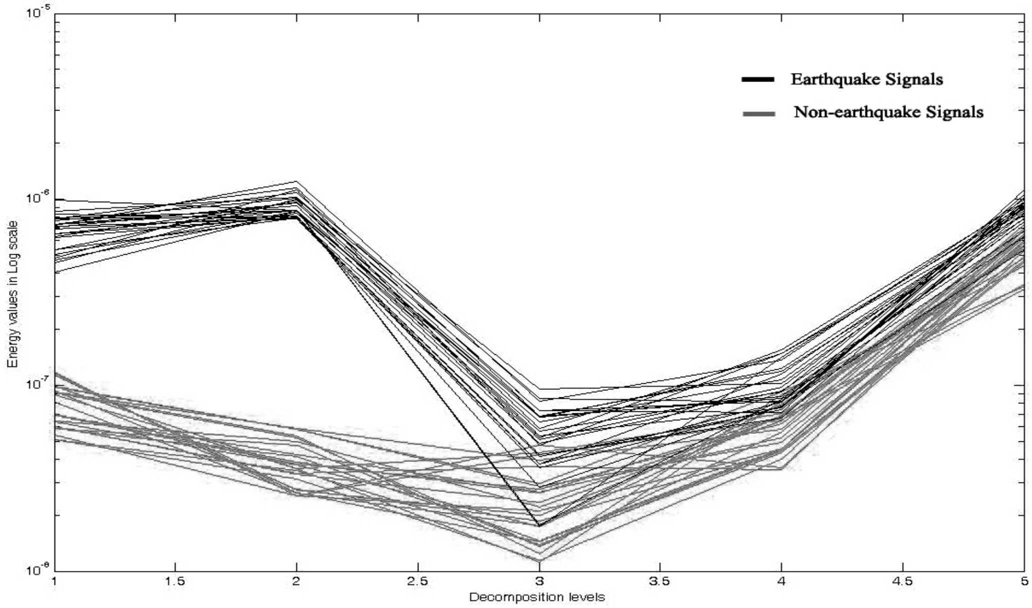


FIGURE 1: Energy difference between Earthquake and Non-earthquake signals

The result in Figure 1 is a good example to show that level 1 and level 2 of earthquake and non-earthquake signals are well separable. Finally thirteen features have been developed from both statistical and wavelet decomposition energy. Next subsection illustrates SVM classifier mechanism.

2.3. SVM classifier

In support vector machines, the learning machine is given a set of examples (training data) and its associated class labels. SVM tries to construct a maximally separating hyperplane between classes, thus by differentiating the classes [5]. The maximally separating linear hyperplane in support vector binary classifiers can be expressed as $\mathbf{w}^T \boldsymbol{x} - \gamma = 0$ and two bounding hyperplanes can be expressed as $\mathbf{w}^T \boldsymbol{x} - \gamma = 1$ and $\mathbf{w}^T \boldsymbol{x} - \gamma = -1$. The training data belonging to +1 class obey the constraint $\mathbf{w}^T \boldsymbol{x} - \gamma \geq 1$ and the training data point belonging to -1 class obeys the constraint $\mathbf{w}^T \boldsymbol{x} - \gamma \leq -1$. However, there are cases where our training data points will be deviated from their respective bounding plane, such deviation of data points from their respective bounding planes are called as error. A positive quantity called ξ is added or subtracted to the training data that constitutes to error to obey the constraints. SVM aims at obtaining a maximum margin and minimum error classifier. General formulation of SVM is given in equation 2.

$$\min_{\mathbf{w},\gamma,\xi} \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{m}\xi_i$$
$$\text{subject to } d_i(\mathbf{w}^T\mathbf{x}_i - \gamma) + \xi_i - 1 \geq 0, \quad 1 \leq i \leq m$$
$$\xi_i \geq 0, \quad 1 \leq i \leq m$$

The quantity $\frac{1}{2}\mathbf{w}^T\mathbf{w}$ ensures maximum margin, which is the reciprocal of the distance between the two bounding hyperplanes from the origin. Minimization of the quantity $\sum_{i=1}^{m}\xi_i$ ensures minimum error. The parameter 'C' controls the weightage for maximum margin requirement and sum of error. Maximum margin and minimum error are contradictory and the value ‘C’ controls these parameters to achieve optimum results.

3. EXPERIMENTAL WORK

3.1. Training

The dataset contains two classes (earthquake and non-earthquake) of seismic signals with 200 feature vectors. We have analysed our training data using linear, polynomial and RBF kernels. Ten fold cross validation is done for training set and for best ‘C’ value and classification accuracy is calculated. Training results are listed below.

- Linear Kernel = 88.35%
- Polynomial Kernel = 94.68%
- RBF Kernel = 95.87%

From the training results, it is found that RBF kernel gives a good training accuracy and the accuracy of polynomial kernel is comparable to RBF. Training accuracy of linear kernel seems to be less compared with the other two. In order to evaluate the effectiveness of our algorithm, classified results were compared with other well-known algorithms. Misclassification cases were given in Table 2.

S.No	Type of classifier	Number of Input patterns	Misclassification cases	Time elapsed (S)
1	Euclidean	90	11	5.33
2	SVM	90	5	5.91
3	K-nn	90	8	13.52
4	Weighted average	90	7	5.94

TABLE 2: Algorithm Evaluation

From the results in table 2, it is understood that SVM based classification gives good classification accuracy with less computational time. In other hand, Euclidean distance gives less classification accuracy with more computation time and also K-nn classifier takes more time to construct the rules.

3.2. Prediction

The real time acquisition allows the recognition of the electrical precursors and their analysis well before the earthquake occurrence. Hence predictions are issued well in advance, which include estimation of the parameters such as epicenter, time and Magnitude of the impending. Main shock seismic signals can be recognized on a real time basis. Our database contains three years of real time seismic signals, from that 90 were chosen randomly. In first, STA/LTA ratio is calculated and optimum threshold values have been determined. STA/LTA is already well established technique so that detailed part of this algorithm is omitted. Based on STA/LTA threshold values, event locations were established. This technique predicted some false events due to higher threshold level. To improve these results, we applied Support Vector Machine classifier. The value ‘C’ controls the marginal parameters to achieve optimum results. In this application, the best value of ‘C’ for Linear kernel is 0.1 and Non-linear 0.01. Prediction of new class values is done using the SVM classifier for all the three kernels. Prediction results are:

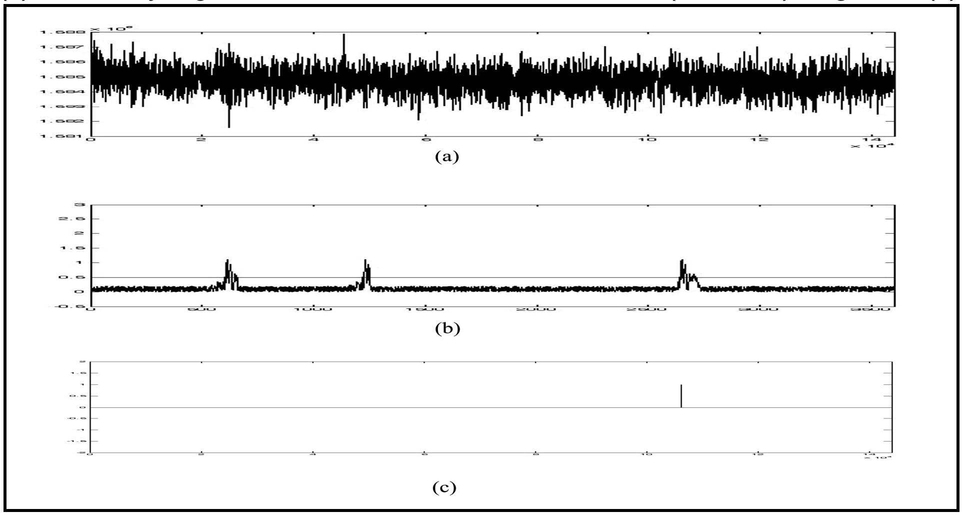
- Linear Kernel = 85.11%

- Polynomial Kernel = 92.88%
- RBF Kernel = 93.91%

From prediction accuracy, it is found that RBF kernel performs much better, and the polynomial is nearly comparable. Linear kernel gives low percentage of accuracy compared with other two. Figure 2 illustrates step-by-step procedure of prediction process.

FIGURE 2: (a) Noisy data, (b) STA/LTA result, (c) Prediction using SVM

Figure 2(a) is a noisy signal which is emanated from sensors (raw data). Figure 2 (b) shown



results obtained from STA/LTA algorithm. This figure illustrates three possible earthquake events based on STA/LTA threshold level (We obtained 0.5). But the result has produced two false predictions. In order to improve the performance we evaluated these results by SVM classifier. Figure 2 (c) shown optimum predicted results. SVM may prevent the overfitting problem and makes its solution global optimum since the feasible region is convex set. SVM classifier has been evaluated with 90 test samples and few of them we listed below (Table 3).

S.No	Magnitude	Co-ordinates		Event location	Data acquisition time		Prediction Result
		Lat (N)	Long (E)		USGS (UTC) (hh:mm:ss)	Station (UTC) (hh:mm:ss)	
1	3.4	19.0	84.4	Gajapathi district, Orissa	0:55:30	0:59:28	Correct
2	4.3	23.3	70.3	Kachchh, Gujarat	11:10:45	11:55:30	Incorrect
3	3.8	12.8	78.8	Vellore, Tamilnadu	18.5.23	18: 06:01	Correct
4	5.0	10.7	92.0	Andaman	18:5:5	18:08:43	Correct
5	4.9	10.6	92.2	Little Andaman	9:12:53	9:46:33	Incorrect
6	5.3	14.1	93.2	Andaman	19:39:50	19:43:32	Correct
7	3.4	8.29	76.59	Tiruvananthapuram	13:15:12	13:15:30	Correct

TABLE 3. Prediction result

The SVM classifier could detect the magnitude of very low ranging between 3 to 5.5 particularly the regions of Tamilnadu and Andaman. Whereas the magnitude of 4.9 could not be predicted by the SVM classifier due to the local explosives used in opencast limestone mining resulting heavy noise (see Table 3). To evaluate the prediction performance of this model, we compared its prediction time with USGS record. The present method could also be validated through long term generated data with time and different earthquake magnitudes. The obtained results in the present method have showed good for prediction of small scale seismicity.

4. CONCLUSION

The SVM classifier has been tested on different real seismic datasets and works well even when the S/N ratio is low. However, this greater reliability is achieved at the expense of speed. To validate the prediction performance of this model, we statistically compared its training accuracy with Euclidean, K-nn and Weighted average methods respectively. The results of empirical analysis showed that SVM outperformed the other methods. In the search of best kernels for SVM it is found that RBF kernel performs better. Some misclassifications occurred in Table 3 due to overlapping of local mining effect. The proposed algorithm would give the accuracy of 93.91% in the seismic events as cataloged earthquake of USGS record. Besides the continuous database in a specific location or other network station may enhance the prediction accuracy by using this classifier. We perceived a high reliability method to detect the seismic events as better as the classical algorithm such as STA/LTA. This research work is purely software approach and there by reduced the cost of expenditure in data analysis.

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