CONTINUOUS HMM-BASED VOLCANO MONITORING AT DECEPTION ISLAND, ANTARCTICA

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ABSTRACT

This paper shows a complete volcano monitoring system that has been developed on the basis of the seismicity observed during three summer Antarctic surveys at Deception Island Volcano (Antarctica). The system is based on the state of the art in hidden Markov modelling (HMM) techniques successfully applied to other scenarios. A database containing a representative set of different seismic events including volcano-tectonic earthquakes, long-period events, volcanic tremor and hybrid events recorded during the 1994-1995 and 1995-1996 seismic surveys was collected for training and testing. Simple left-to-right HMMs and multivariate Gaussian probability density functions (PDF) with diagonal covariance matrix were used. The feature vector consists of the log-energies of a filter-bank consisting of 16 triangular weighting functions uniformly spaced between 0 and 20 Hz plus the first and second order derivatives. The system is suitable to operate in real-time and its accuracy is close to 90%. When the system was tested with a different data set including mainly long-period events registered during several seismic swarms during the 2001-2002 field survey, more than 95% of the recognized events were correctly marked by the recognition system.

1. INTRODUCTION

Monitoring of precursory seismicity at restless volcanoes is the most reliable and widely used technique in volcano monitoring [1]. The rate of occurrence of seismicity in an active volcano is high, with presence of hundreds of events per hour during days or weeks. Each seismic event is related to different source processes. In order to understand the current state of the volcano, we should identify what these processes are. For this reason the conclusive identification of the signal is a primary and critical point in volcano monitoring. In a crisis situation, there is a need to make fast decisions that can affect the public safety. On the base of the number and type of seismic events, analysts working on volcanic observatories have to decide near real time the protocol to follow. In many situations, a visual classification on the sole basis of the seismogram appearance may be the only way to discriminate between internal, volcanic earthquakes and external or non-natural signals. The development of a robust automatic discrimination algorithm helps to this work, enabling technicians to focus their efforts in the interpretation of the situation or to analyze only a reduced number of signals.

Recently Del Pezzo et al. [2] and Scarpeta et al. [3] have presented the application of neuronal networks for discrimination and classification of volcanic and artificial signals at Vesuvius Volcano and Phlegraean Fields (Italy). These methods have been successfully applied to discriminate signals for local and volcanic seismicity. On the other hand, Ornhberger [4] has studied discrete hidden Markov modeling (HMM) tools for continuous seismic event classification. In this work we advance in the field and develop an HMM-based seismic event classification and monitoring system. This system is based on the state of the art of HMM-based pattern recognition techniques successfully applied to other disciplines such as robust automatic speech recognition (ASR) systems. As in continuous speech modeling where the signals are modeled as a concatenation of different acoustic events (eg: phone, words), seismic records can be also modeled as a time sequence of different seismic events. Furthermore, different realizations of the same seismic event have similar spectral patterns. Fig. 1 shows two different hybrid events registered at Deception Island (Antarctica). Note that the spectrograms have similar spectral patterns with the same instantaneous behavior, thus being suitable of being modeled with HMMs.

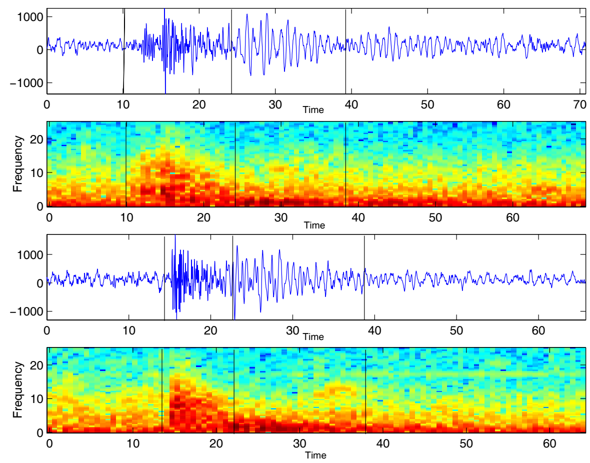

Fig. 1. Two different hybrid events recorded at Deception island during 1994/1995 summer Antarctic field survey.

2. SEISMIC DATA

Data used in this work were recorded in Deception Island Volcano (Antarctica) during three summer Antarctic surveys in the 1994-1995, 1995-1996 and 2001-2002 years. The data set consists of thousands of seismic events that contains volcano-tectonic earthquakes, long-period events, hybrids and tremor. The characteristics of this

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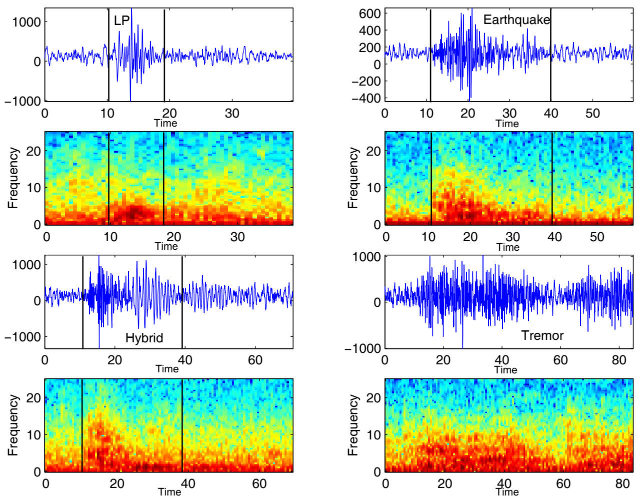

Fig. 2. Spectrogram of seismic events recorded at Deception Island.

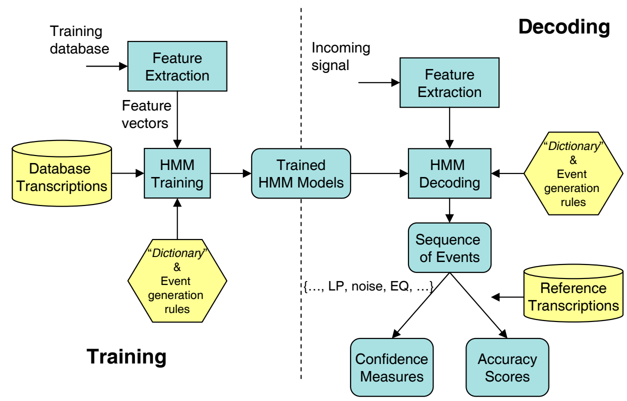

Fig. 3. Architecture of an HMM-based seismic monitoring system.

seismicity has been widely studied using different techniques as reported by Ibáñez et al. (2000, 2003). Fig. 2 shows the spectral characteristics of the different kind of events that are characterized as follows:

1. **Long Period** events recorded at Deception Island are signals with a fuse-shaped envelope with duration less than 60 seconds and almost pure monochromatic spectral content at frequencies below 4 Hz. In some cases, a high-frequency phase precedes some of these events. They are related to resonances of fluid-filled conduits and cracks driven by volcanic processes.
2. **Local Volcano-Tectonic** events are earthquakes with S-P time shorter than 4 seconds. This time limit ensures that the volcano-tectonic events are located inside of the island structure. They are usually characterised by impulsive direct *P* and *S* wave arrivals. The spectral content of this signal is very broad, reaching up to 30 Hz. The source of these local volcano-tectonic earthquakes can be interpreted as the brittle response of the volcanic environment under local and regional stresses. The origin of these stresses is related to volcanic processes within the island and varies from interaction of water with hot materials to the effects of shallow magma injections.
3. **Hybrid** events are signals which contain both double-couple and volumetric components. They are characterized by an initial high frequency phase, that corresponds to a volcano-tectonic earthquake in which *P* and *S* waves might be distinguished, followed by a monochromatic signal similar to those shown by the long period events. In some cases, long period events with an energetic initial high frequency signal can be interpreted as hybrids.
4. **Volcanic tremor** is a monochromatic signal with duration longer than that observed for long period events. Episodes of tremor that vary from minutes to several hours and days have been observed.

Tremor and long period events are different manifestation of the same process. A long period event is the response to a sudden pressure transient within a fluid filled crack, while tremor is the response to continuous fluctuation of pressure.

3. SEISMIC EVENT RECOGNITION SYSTEM

An HMM-based seismic event recognition system must assume that the signal is a realization of a sequence of one or more events. The recognizer decomposes the incoming signal as a sequence of feature vectors. This sequence is assumed to be a precise representation of the seismic signal while the length of the analysis window is such that the seismic waveform can be considered as stationary.

Let a sequence of seismic events $\mathbf{w}= w_1, w_2, ..., w_l$ be represented as a sequence of feature vectors $\boldsymbol{o}_t$ or observations $\boldsymbol{O}= \mathbf{o}_1, \mathbf{o}_2, ..., \mathbf{o}_T$. The recognizer selects the sequence of events $\mathbf{w}$ with the maximum probability $P(\mathbf{w}|\mathbf{O})$, that is:

$$\arg\max_{\mathbf{w}} P(\mathbf{w}|\mathbf{O}) \tag{1}$$

If a parametric model for seismic event production such as a Markov model is assumed, the problem is reduced to estimating the Markov model parameters. A Markov model is essentially a finite state machine with several states. A change of state takes place every time unit and a feature vector $\mathbf{o}_t$ is generated from a probability density $b_j(\mathbf{o}_t)$ determined during the training process. Moreover, transition from state *i* to state *j* is governed by the transition probabilities a_{ij} which are used to model the delay in each of the states and the transitions through the entire model.

Fig. 3 shows the architecture of a general purpose HMM-based pattern recognition system. The training database and transcriptions are used to build the models. Once the models are initiated, the recognition system performs feature extraction and decoding based on the Viterbi algorithm. The output is the sequence of recognized events, confidence measures and global accuracy scores.

3.1. Preprocessing

In the actual implementation of the recognition system it is not possible to accept the seismic signal in the format created for the array and based on multiplexed signals. The input signal for both, training and recognition, is a stream of 16-bit binary data without heading. Fig. 2 shows different events that was registered at Deception Island during the 1995-1996 field survey. It is shown that the energy of the signal is concentrated at frequencies below 20 Hz so that recordings initially sampled at 200 Hz were decimated to a 50Hz sample rate using a 101-tap linear phase FIR filter. The advantage obtained is double. First, redundant information which do not contribute to a

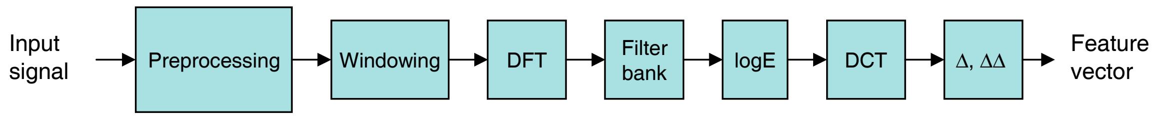

Fig. 4. Feature extraction.

clear identification of the different events is removed. Second, the computational cost of the recognition system is reduced.

3.2. Collecting the training database

The seismic array is composed by 24 different channels. In order to perform the data analysis we have selected the channel with the highest signal-to-noise ratio (SNR) for classification. The labelling process of the signal was performed in the following steps:

1. Visual recognition. The signal was analyzed on the screen of the computer and its shape was compared with the description of the signals performed by Ibáñez *et al*. [5].
2. Spectral shape. Those signals that could be mixed in different sets were analyzed observing their spectrogram.
3. On the base of both criteria each signal was labelled as "LP", "EQ", HYB", "TREMOR" or "NOISE" to denote long-period, earthquake, hybrid and tremor events or just seismic noise. The duration of the signal was established in the time domain inspecting the seismic waveform.

3.3. Feature extraction

The first step of the recognition process is the signal processing feature extraction which converts the volcano seismic waveform in a parametric representation, with less redundant information, for further analysis and processing. As the short-time spectral envelop representation of the signal has been widely used, with good results, in speech recognition systems [6], a similar representation for our volcano seismic recognition system is used in this work.

Fig. 4 shows a block diagram of the feature extraction process which is based on a filter-bank spectrum analysis model. The signal is arranged into 4 seconds overlapping frames with a 0.5 seconds frame shit using a Hamming window. A 512-point FFT is used to compute the magnitude spectrum which serves as the input of an emulated filter-bank consisting of 16 triangular weighting functions uniformly spaced between 0 Hz and 20 Hz. The overlap between adjacent filters is 50%. The purpose of the filter bank analyzer is to give a measurement of the energy of the signal in a given frequency band. Then, the natural logarithm of the output filter-bank energies is calculated resulting a 16-parameter feature vector. Since the log-filter bank energies are highly correlated and the recognition system uses continuous observation HMMs with diagonal covariance matrices, it is necessary to apply a decorrelation transformation. Thus, the Discrete Cosine Transform (DCT) is used to decorrelate the features and reduce the number of components of the feature vector from 16 to 13 coefficients. Finally, the feature vector is augmented with linear regressions of the features (derivatives and accelerations) obtaining a total of 39 parameters.

3.4. Recognition system

The recognition system presented in this work is based on continuous hidden Markov models (CHMM). CHMM are trained for each event (earthquakes, long-period, hybrid and tremors events) and a noise model is used to represent sequences with no events. Both, training and recognition processes are performed using HMM Tool Kit (HTK) software [7]. In a CHMM the emission probabilities for feature vector $\mathbf{o}_t$ in state $x(t)$, ($b_{x(t)}(\mathbf{o}_t)$ are defined to be:

$$b_{x(t)}(\mathbf{o}_t) = \prod_{s=1}^{S} \sum_{k=1}^{K} c_{ik} \mathrm{N}(\mu_k, \sigma_k, \mathbf{o}_t) \qquad (2)$$

where *S* is the number of parameters in the feature vector, and *K* is the number of probability density functions (PDFs) considered. It is worthwhile clarifying that multivariate Gaussian PDFs with diagonal covariance matrices are used in this work. In the training process it is necessary to fix:

- The topology of the models. In this case, classical left-to-right HMMs were used.
- The number of states for the models.
- The number of multivariate Gaussian PDFs.
- The number of iterations of the Baum-Welch algorithm.

As there is no statistical knowledge of possible event sequences, we assume that after a particular event, any other one or noise could appear with the same probability. The recognition process combines the probabilities generated by the models and the probabilities obtained by the allowed transition for the seismic events. It is necessary to generate all the possible sequences of events and evaluate all of them, thus selecting the one with maximum probability. There are several algorithms to expand and search the most probable sequence of events given a sequence of observations. The most popular algorithms used for speech recognition are: stack decoding [8] and Viterbi search [10]. Among them, Viterbi decoding [6, 11, 7] is adopted in this work. Additional details of the implementation of the training and decoding processes are:

1. Initial flat models are generated as HMM prototypes using the training database.
2. The Baum-Welch reestimation algorithm is performed using the training database which includes the labelled records. The number of iterations of Baum-Welch algorithm is fixed to 6.
3. Initial HMMs are obtained with one multivariate Gaussian PDF.
4. The number of multivariate Gaussian PDFs is increased from 1 to 24. The reestimation algorithm is performed in each iteration as in step 2 and recognition results using the Viterbi algorithm are obtained in each step.

4. EXPERIMENTAL RESULTS

The training database consists of 512 manually labelled, 150-s-long records which contain four classes of events as discussed in section I. It includes: *i*) 75 Local Volcano-Tectonic earthquake events (EQ), *ii*) 765 Long Period events (LP), *iii*) 54 Hybrid events (HYB) and *iv*) 77 Volcanic Tremor events (TREMOR). The experimental results are

Table 1. Recognition accuracy for different number of states (N_E) and number of Gaussians (N_G).

$N_E \backslash N_G$	4	8	12	16	20	24
9	61.89	70.65	74.77	79.30	81.46	83.11
11	74.15	82.29	84.65	87.23	89.29	91.04
13	76.31	81.57	84.76	86.71	88.67	89.50
15	73.94	81.15	84.14	86.41	86.82	87.95
17	74.56	79.40	81.26	83.32	84.45	85.38

shown in table 1. The performance of the system is given in terms of the recognition accuracy that is defined as:

$$Acc(\%) = \frac{C - I}{N} \times 100\% \tag{3}$$

where C is the number of correctly recognized events, I is the number of insertion errors and N is the total number of events present in the test. The table shows accuracy values for a variable number of Gaussians (4-24) when the number of states of the models varies from 9 to 17. It can be observed that the performance of the system increases with the number of Gaussians used to model each state of the HMMs; the upper bound depends on the size of the training database. The best results are obtained when the events are modelled with 11 states yielding accuracy values of up to 90%. Note that, the number of states of the models imposes a minimum duration for the events. In this work, 4 seconds analysis frames with a 0.5 seconds frame-shift were used. Thus, for the topology of the HMMs adopted in this work, the minimum duration that the system assigns to an event is obtained by multiplying the number of states by the frame-shift (0.5s).

In order to control the accuracy of the recognition method with other signals, not used in the training process, we selected the data recorded in the 2001-2002 field survey by the autonomous seismic station. In this period several seismic swarms were recorded, with durations ranging between hours and days. During the routine study performed in the field, a selection of the whole data set was done, containing thousands of events, mainly long-period events. This set of data has been used to control the recognition method. The result of the application of the recognition process to this data set reveals a great success that can be summarized as: *i*) no other type of signals was recognized, and only long period events were marked, *ii*) the seismic noise was recognized as noise, although the nature and amplitude of the noise was different between the training database and the testing one, *iii*) more than the 95% of the recognized LP events were marked by the recognition process, and *iv*) the recognition process marked other signals as long-period events, which initially did not appear classified as that in the data base. After an spectral analysis we observed that they also should be classified as long-period, but they were not labelled as events due to their low amplitude.

5. CONCLUSION

Monitoring of precursory seismicity at restless volcanoes is the most reliable and widely used technique in volcano monitoring. This paper showed a complete seismic event recognition and monitoring system that is based on the state of the art of hidden Markov modelling successfully applied to other disciplines including automatic speech recognition systems. A database containing a representative set of different seismic events including volcano-tectonic earthquakes, long period events, volcanic tremor or hybrid events was collected at Deception Island for training and testing. Simple left-to-right HMMs and multivariate Gaussian densities with diagonal covariance matrix were used. The feature vector includes the log-energies of a filter-bank consisting of 16 triangular weighting functions uniformly spaced between 0 and 20 Hz plus the first and second order derivatives. The system is suitable to operate in real-time and capable of discriminating between different types of seismic events with an accuracy of about 90%. On the other hand, when the system was tested with a different data set composed mainly by long-period events, more than 95% of the recognized events were marked correctly by the recognition system. Thus, the system enables monitoring the state of a volcano and the vicinity of a possible eruption by analyzing these seismic signals. As a conclusion, the system developed in this work is very useful to discriminate among different types of volcanic signals after a careful training process. With this valuable tool, analysts working on many volcanic observatories can decide in near real time the protocol to follow on the base of the number and type of seismic events.

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