AUTOMATIC INTERPRETATION OF REGIONAL SHORT PERIOD SEISMIC SIGNALS USING THE CUSUM-SA ALGORITHMS

Zoltan A.Der[1] , Matthew W. McGarvey[1], and Robert H. Shumway[2]
[1] Ensco Inc, Springfield VA.
[2] University of California at Davis, Davis CA.

Sponsored by the Defense Threat Reduction Agency
Contract DSWA01-98-C-0155

1.0. ABSTRACT

Automatic seismogram interpretation and onset estimation are desirable goals facilitating the rapid location and discrimination of seismic events, automation also relieves the human operator from onerous repetitive tasks. At regional distances the onsets of seismic phases are associated with gradual, rather than sudden, changes in the statistical properties of the seismic time series, i.e. changes in autoregressive models and mean square amplitudes. The work presented combines two aspects of the onset time estimation, the detection of the onset as a change in the trend of the cumulative sum (CUSUM) of a suitable test statistic, and a randomized search for its location, simulated annealing (SA). The latter is applied repeatedly, thus, resulting in multiple onset time estimates. These typically form clusters around the arrival times of the known seismic phases, but there are some scattered values as well, that have to be discarded. The uncertainties in the onset times estimated can be quantified in terms of the spread in the values of the best defined clusters. Various standard cluster analysis methods can be applied to define individual clusters. The system is presently developed using MATLAB, utilizing its graphical user interface capabilities.

2.0. OBJECTIVES

The objective of this work is to develop automated methods for interpreting regional and teleseismic short period seismograms using ideas and algorithms from the statistical literature. In the analyses of seismic data, onset times of the various seismic arrivals are of great importance, because they are used in locating the sources and segmenting the seismograms into wave groups used in discrimination of various types of events. Although various onset time (or change point) estimation methods have been tested in the past, with success, for time series where the properties (amplitudes and frequency spectra) suddenly change, actual seismograms are more complex. Amplitudes increase and decrease and spectra of various arrivals may be different. Because of the great variability of the seismic data, it is necessary to make the methodology work reliably under varying conditions. It is likely that several approaches that have been tried may have to be combined to achieve reliability and robustness to achieve these goals.

3.0. RESEARCH ACCOMPLISHED

3.1. Background.

Automatic phase arrival time estimation for regional arrivals is of considerable interest because of the need for rapid location and identification of numerous seismic events by networks monitoring natural and man-made seismic activity. Times of seismic ‘phase’ arrivals can be defined as time instants, where some visible characteristic, such as amplitude, frequency content or wave polarization changes in some recording. Typically, regional arrivals are high frequency, broadband, emergent wave groups containing numerous cycles. Generally, later arrivals have no clear, impulsive waveforms and are preceded by the codas of earlier ones and their onset times can only be defined to within a few cycles. Besides locating events from multiple *Pn* times at several stations, onset time estimation is useful in facilitating location using multiple arrivals in the same seismogram and in automated application time and frequency domain discriminants.

The methods developed in this paper differ from the semi-automatic computer guided onset time determination methods presently used by analysts in current systems, in which preliminary phase onset predictions suggest picks to the analysts. We find that these suggested onset times often take precedence over what the analysts actually sees in the seismogram leading to biased or censored onset times. What we are trying to do is to teach

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **SEP 2000**	2. REPORT TYPE	3. DATES COVERED **00-00-2000 to 00-00-2000**

4. TITLE AND SUBTITLE **Automatic Interpretation Of Regional Short Period Seismic Signals Using The Cusum-Sa Algorithms**	5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Ensco Inc,5400 Port Royal Rd,Springfield,VA,22151**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S) 11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES
Proceedings of the 22nd Annual DoD/DOE Seismic Research Symposium: Planning for Verification of and Compliance with the Comprehensive Nuclear-Test-Ban Treaty (CTBT) held in New Orleans, Louisiana on September 13-15, 2000. U.S. Government or Federal Rights.

14. ABSTRACT
See Report

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**10**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

the computer to pick multiple phase onsets based on the seismograms only, as if it were the first time in an unknown region.

There are numerous statistical approaches in the literature to determining the arrival time of 'phases'. Onsets of packets of seismic energy associated with various paths, i.e. seismic phases, are usually associated with sudden changes in amplitudes, spectra, polarization and slowness. Generally it is assumed that it is known that the change occurs somewhere in a predefined time interval and that the statistical model of the time series changes abruptly. It is also assumed that the time series are stationary before and after such a change and that the statistical distributions are multivariate Gaussian (e.g. Basseville and Nikiforov 1993).

Depending on the autoregressive models applied one may test for spectral and amplitude changes (single channnel model), slowness changes (multichannel model applied to array sensor outputs) or polarization (three-channel model) as described by several workers (Kushnir 1996, Leonard and Kennett 1999). The model fitting can be performed for each guess of the onset time (Taylor et al 1992, Takanami 1991) or the fit to two fixed models fitted at each side of the possible arrival times may be used (Kvaerna 1966a,b). The minimum of the summed squared residuals occurs when two models are fitted such that the boundary of the fitting regions correspond to the onset time. In any case, the estimation process decreases the degrees of freedom in the process, thus decreasing the stability and its sensitivity. Common to all these methods is the assumption that the time interval where the phase onset occurs is known and there are sufficient segments of the time series preceding and following the onset for effect the estimation models. The approach described above is quite general and is applicable to many kinds of problems involving changes in time series.

Subtle changes in the frequency content in noisy records often give clue to a human indicating the onset of a seismic phase arrival. On the other hand, when such human capabilities are needed it simply indicates a failure of applying appropriate frequency domain prefiltering that could produce an enhanced amplitude contrast between the noise and the arrival. Appropriate prefiltering in frequency is a prerequisite for further onset time determination regardless of the method (Kvaerna 1996a,b). Various schemes for optimum pre-filtering were suggested and most of these seem to work well in practice and the exact nature of filter is not critical as long as they are reasonably close to the optimum S/N^2 shape (averages of signal amplitude spectrum divided by the squared noise amplitude spectrum). Minimum phase filters based on Kvaerna 's definition of "usable bandwidth" (Kvaerna 1995, 1996a), as well as those shaped according to S/N^2 , $S^2/(S^2+N^2)$ the latter is a Wiener filter (Whalen 1971), where S and N are signal and noise spectral amplitudes respectively, or noise-adaptive predictive filtering all enhance the amplitude contrast between the noise background preceding the onset of the signal.

This happens because both regional seismic signals and noise have similar spectral shapes in the 3-10 Hz band, in which they both fall off with frequency. These statements seem to be generally true for typical regional seismograms. Thus after suitable prefiltering has been performed, the problem reduces to, for most practical purposes, to a detection of a sudden or gradual change in trace amplitude levels.

3.2. Some CUSUM-based onset time estimation methods.

A step-like change in amplitude levels can be detected easier if a cumulative sum (CUSUM) of the squared or absolute amplitudes it is computed (Der and Shumway 1999, Iclan and Tiao 1994, Basseville and Nikiforov 1993, Shumway 1998). After imposing a linear trend to the CUSUM, a repetitive onset time estimation is performed, locating the minima or maxima of various chosen functions, by simulated annealing. The clustering in the multiple onset time estimates provides a means to assess the reliability of the process and the significance of each major arrival. In practical tests, the method has outperformed those based on testing for changes in autoregressive models.

The approaches based on the cumulative sum statistics are simple to apply and can be automated for applications in a CTBT monitoring environment. Inclán and Tiao (1996) developed a properly centered and normalized CUSUM test statistic and tabulated critical points for testing of significance. Furthermore, they developed an Iterative Cumulative Sum of Squares (ICSS) algorithm that allows sequential identification of multiple changepoints in a white noise series. In this work we have tested their approach on a set of regional seismic data.

Suppose first that a single channel time series x_κ, $\kappa=1,2,\ldots n$ is observed and we have a possible change point that is to be detected using a CUSUM type statistic. Assume that the time series x has been prewhitened and has a zero mean, so that the change in regime can be modeled simply by a change in the variance of the white noise process. Inclán and Tiao (1996) proposed using the centered and scaled cumulative sum of the squared amplitudes. First define the sum of squares function over the interval $[1\ \kappa]$ of length points as

$$C_k = \sum_{i=1}^{k} x_i^2 \qquad (1)$$

The scaled and normalized CUSUM statistic over the interval $[1,T]$ at the point $1<\kappa<T$ is defined as

$$D_\kappa = \frac{C_k}{C_T} - \frac{\kappa}{T} \qquad (2)$$

The F statistic for testing for a change of variance at time κ is

$$F_{T-\kappa,\kappa} = \left(\left(C_T - C_\kappa\right)/\left(T-\kappa\right)\right)/\left(C_\kappa/\kappa\right) \qquad (3)$$

This is, of course the standard power detector. With no change in variance in the time interval $1<\kappa<T$, $D(\kappa)$ is a monotone function of t. If the variance increases $D(\kappa)$ will have a maximum at the change point.

If we assume that the x_i are normally distributed with mean 0 and variances σ then we can obtain the likelihoods for testing one change against no change and let $NT=1$ represent one change. The likelihood for $NT=0$ is

$$l\left(N_T=0;x\right) = -\frac{T}{2}\log(2\pi) - \frac{T}{2}\log\left[C_T/T\right] - \frac{T}{2}$$
(4)

The likelihood function for $NT=1$, change at point t is

$$l\left(t,N_T=1;x\right) = -\frac{T}{2}\log(2\pi) - \frac{\kappa}{2}\log\left[C_\kappa/\kappa\right] - \frac{T-\kappa}{2}\log\left[\frac{C_T - C_\kappa}{T-\kappa}\right] - \frac{T}{2} \qquad (5)$$

The best estimate of the change point is where the likelihood ratio is maximized

$$\log\ L\left(\kappa,\sigma_1^2,\sigma_2^2\right) \approx -\max\left\{-\frac{\kappa}{2}\log\left(1+\frac{T}{\kappa}D_\kappa\right) - \frac{T-\kappa}{\kappa}\log\left(1-\frac{T}{T-\kappa}D_\kappa\right)\right\}$$
(6)

The function puts more weight on the middle of the time series. This is not a serious disadvantage since prior to applying the algorithm one has a fairly good idea where the main regional phases are (from standard detection algorithms and F-K analyses). All the previous formulas assume that the time series were pre-whitened. In doing F-tests with bandwidth limited data the degrees of freedom used in the assumed F distributions should be appropriately reduced to account for the limited bandwidth.

The paper by Chen and Gupta (1997) uses a corrected form of AIC, say

$$AIC\big(C(\kappa)\big) = -2\log L\left(\kappa, \sigma_1^2, \sigma_2^2\right) + \frac{4\left(T\kappa - \kappa^2 - T\right)}{(\kappa-2)(T-\kappa-2)}$$

(7)

for $2<\kappa<T-2$, and chooses τ as a minimizer of $AIC(C(\kappa))$ by introducing the second, penalty function term. Constructing an unbiased estimator leads to equation (7) above (Hurvich and Tsai 1989). The AIC likelihood is claimed to perform better if the break point is close to the ends of the segment, a situation that we try to avoid, however.

A binary iterative version of the CUSUM algorithm was proposed by Inclan and Tiao (1994) and Chen and Gupta (1997) which uses repetitive applications of the approach described above for subintervals of the first time interval. The method applies the following steps;

1) Calculate $D(\kappa)$ from the start to the endpoint of the initial time segment
2) Search for a significant maximum as defined by equation (3). If one is found at κ_1 then
3) Search the time interval $1<\kappa<\kappa_1$ for another significant maxima (that pass an F-test)
4) Similarly search the $\kappa_1<\kappa<T$ intervals for a significant maximum
5) Continue the same procedure in each subinterval until no more significant maxima are found.

3.3. Basic building blocks of the CUSUM-based onset time estimation system

In order to apply any of the search methods for locating onsets, first one needs to segment the seismograms such that each of the segments contain only one arrival. Typically, a regional seismogram contains multiple arrivals followed by either a coda where the amplitude decays with time or remains nearly constant.

Moreover, the minima of the variants of the CUSUM functions described above will provide reasonable onset time estimates, additional refinements can greatly improve the results. The exact locations of such absolute minima may be accidental and thus may be of lesser importance than the overall layout of the regions of minima, whether they are narrowly localized or broad. The latter case implies greater uncertainties in the onset times, while the former a lesser uncertainty. It is therefore desirable to use stochastic, randomized search methods repeatedly and use the multiple onset time picks to estimate more stable onset times and their uncertainties.

3.3.1. Leaky integration

Applying leaky integration to the absolute trace amplitude generates a function which has maxima close to the trace maxima but delayed in time. This function is useful, therefore, for segmenting the seismogram between such maxiam such that each segment will contain one sudden increase of trace amplitude envelopes (a phase onset).

3.3.2. F tests.

F tests are standard tools for verifying the arrival of a new package of energy from the source, i. e. a phase arrival. In this work we pick the arrival time from the modified CUSUM $D(\kappa)$ and test whether the variances on both sides of this arrival are indeed different. In performing an F test on seismic data that has not been prewhitened one must make sure that the number of degrees of freedom is adjusted appropriately. F statistics for the assumed phase onset within one segment must pass a significance test before the onset is accepted. Otherwise the segment is declared as containing no onsets.

3.3.3. Simulated annealing.

Simulated annealing (SA) was designed to find global minima of irregular functions where many local minima may exist. It tends to disregard minor local minima and converge to the lowest points. It uses the randomized Metropolis search algorithm which is based on a thermodynamic analogy (Press et al 1986). Initially, it allows a

search using large steps in the independent variables, which may even be associated with increased values of the function. This allows the solution to “jump out” from local minima and resume searching for other minima. As “cooling” occurs such steps are accepted less and less and finally the solution will settle in broad global minima. Repeated application of SA with random starting points will give rise to *populations* of onset time estimates that can be used for evaluation of the efficiency and accuracy of the method.

3.3.4. Cluster analysis

The multiple application of SA searches automatically provides means for assessing the stability and accuracy of the onset estimates derived from the SA method. Starting out with numerous randomly chosen positions for the onset time within a search window these will converge into positions of prominent CUSUM minima and form a varying number of tight clusters. Besides these there will be hopefully much fewer scattered ‘solutions’ that are obviously spurious and thus must be discarded. This approach was not pursued much in our recent work but it has a considerable potential (Der and Shumway 1999). We apply the well known K-means clustering algorithm (Tou and Gonzalez 1974, Theodoris and Koutroumbas 1999) for finding the clusters in a population of SA onset times or trace amplitude maxima in this report.

3.4 Flow diagram of the process.

Figure 1 shows two ways such a process may be put together from its building blocks. One applies the SA algorithm, the other does not. The F-test makes the decision whether in a given segment a phase onset is declared or not. The one involving SA is more refined, but it takes more time for computations. The optimization of the whole process requires optimum choices in the numerous parameters required. Such are those appropriate to the prefiltering methods, the leaky integration constants, the temperatures and cooling rates and number of trials for SA, specifications needed for cluster analysis. Optimizing such parameters requires the testing of the algorithms on large amounts of data and minimizing the number of false or missed onset times

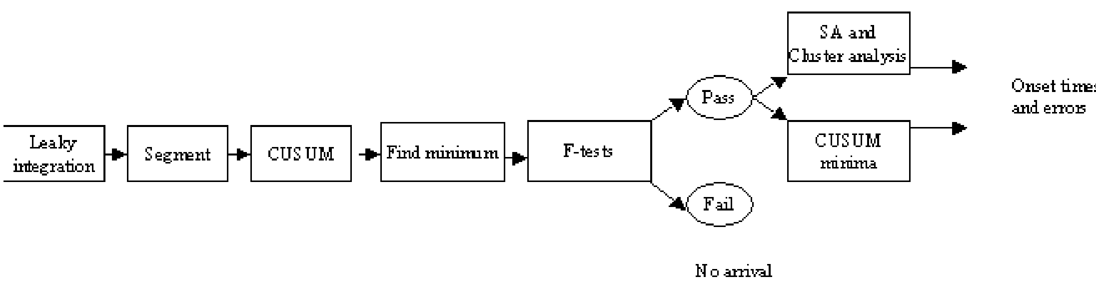

Figure 1. Flow diagram of the process.

3.4. PRACTICAL EXAMPLES OF THE APPLICATIONS OF THE METHODOLOGIES DESCRIBED ABOVE.

3. 4.1. Performance of the CUSUM Procedure for Estimating Pn Onset Times.

During the early phase of this work we have made evaluations of the performance of the CUSUM minimum and the combined CUSUM-SA procedure for picking onset times of first-arriving Pn phases under various S/N scenarios. The evaluation was based on comparing the performance of **a)** human analysts **b)** picking the absolute minimum of normalized CUSUM and keeping the arrival if the F tests is passed **c)** picking the median of multiple picks using SA on the CUSUM and taking the median of these, but discarding the result if the SA arrivals are highly scattered.

The results, reported at the annual research review meeting last year and in a subsequent annual report, will not be repeated here. We simply state that the performance of the second of these options was comparable to a human analysts picking the initial Pn arrival times. The module for Pn onset time estimation will be tested more

extensively in the near future.

3.4.2. Application of the binary iterative version of normalized CUSUM method to Segment Complete Regional Seismograms.

The iterative binary segmentation method method of Inclán and Tiao (1996) was applied to many regional seismograms. Typically, three iterations were used. During the first iteration, the largest arrival was commonly picked. In the succeeding iterations the smaller arrivals were identified. Although this binary segmentation approach works well for events where the various arrivals have grossly unequal amplitudes, it fails in many cases where there are several arrivals with comparable amplitudes. Therefore, we need more general segmentation methods while retaining much of the statistical testing machinery contained in the papers of Inclán and Tiao (1996) and Chen and Gupta (1997).

3.4.3. Methods based on seismogram segmentation.

The approach proposed below seems to work much better than the binary segmentation methods. In order to find the rapid increases in amplitude we have leaky-integrated the absolute trace amplitudes of the seismogram. The maxima of traces thus processed will be located at times later than the maximum amplitude portions of the respective phases due to the time delay introduced by the leaky integral low-pass filter. If we segment the seismogram from beginning to end using these maxima as the intermediate point then the actual onsets will be interior to these segments. If we locate the minima of the functions $D(\kappa)$ within these initial segments then we shall have the approximate locations of the phase onsets. Now, if we create windows that are centered on this preliminary onset time with the end points at the maxima of the leaky-integrated absolute amplitudes.

We have tested two methods for finding the broad maxima. One method consisted of the monitoring the amplitude differential (gradient) in the leaky-integrated absolute amplitude trace over a set time interval (typically tied to the time constant of the leaky integrator), finding a maximum and set the segment separation such that this gradient decreased by a set factor (typically 0.9). Automatic onset time picks for seismograms segmented this way are shown in **Figure 2**. The examples shown were taken from the Ground Truth data base compiled by Multimax Inc. and downloaded through the Internet. Many of these seismograms are not strictly regional, some distances are teleseismic. Consequently some broader bandpass prefiltering was needed to enhance these arrivals.

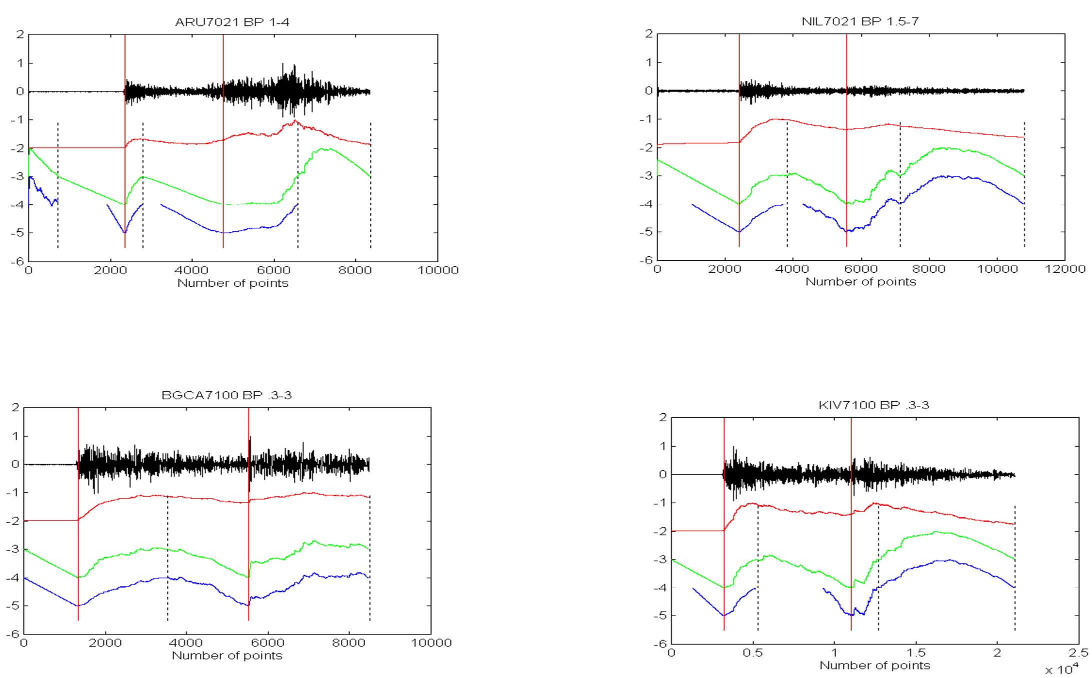

Figure 2 continued

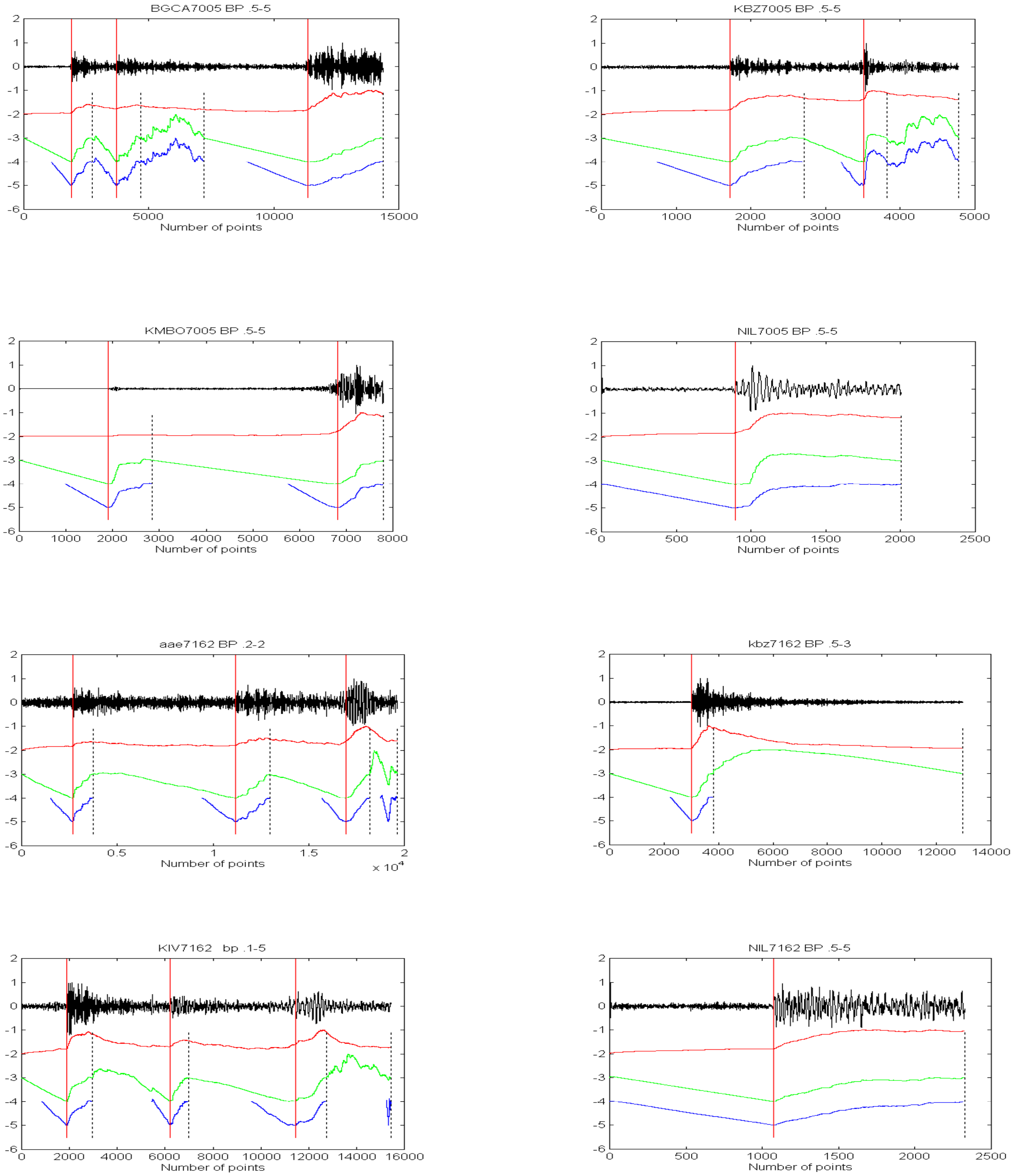

Figure 2. Examples of the decomposition of seismograms into segments bounded by the decreasing portions of the maxima of the leaky-integrated absolute amplitudes (second trace. This is followed by looking for the minima in the function D(t) of Incl n and Tiao (1994) in each segment (third trace). This is followed by the redefinition of shorter segments designed to be centered on this minimum be bounded by the previous right side of the segment (shorter segments below). This is followed by an F-test around the minimum to determine whether the change in amplitudes is significant. An onset (vertical lines) is declared if this is the case. Such onsets can be further refined by actually defining the onsets as maxima of F or the statistics of Chan and Gupta (1997).

Another approach we have tried for finding the broad maxima was based on a cluster analysis of multiple solutions produced by simulated annealing (SA) . Since our SA program was designed for finding minima, we have simply reversed the sign of the leaky-integrated trace for such computations. The centers of the clusters for the picks of minima thus produced can be used as limits of the segments to be searched for single increases in amplitude. Note that this procedure is the same as the one we have applied for finding onset times previously (Der and Shumway 1999). Illustrations of the results of such procedures are shown in **Figure 3**. We have found that this method was somewhat more robust than the previous one.

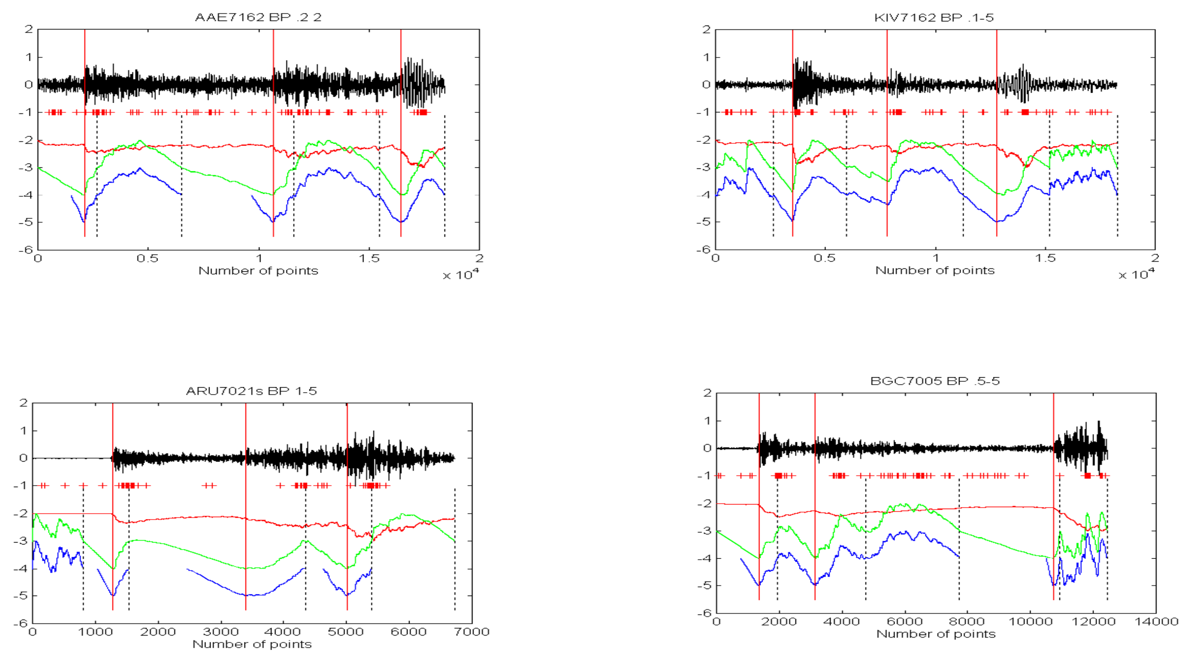

Figure 3. Examples of the decomposition of seismograms (top trace) into segments bounded by the clusters of the SA picks (plus signs) of the mimima of the sign-inverted leaky-integrated absolute amplitudes (second trace), followed by looking for the minima in the function D(t) of Inclán and Tiao (1994) in each segment (third trace). This is followed by the redefinition of shorter segments designed to be centered on this minimum be bounded by the previous right side of the segment (shorter segments below). The next step is an F-test around the minimum to determine whether the change in amplitudes is significant. An onsets (vertical lines) are declared if this is the case. The first letters in the titles are the station names and the following digits are the event 'orid'-s (see data base Schema 3.0 Manual), referring to Table I. The band-pass filters used are indicated in the rest of the title.

It appears, however, that reliable segmentation of high frequency seismograms and the automatic determination of the onset times of the various arrivals will require sophisticated algorithms. The algorithms need to have sufficient flexibility to recognize arrivals with quite different amplitudes, impulsive arrivals without codas, phases with long codas and phases where the seismogram essentially consists of a series of increases in amplitude without much decrease until the Lg coda. The latter is typical of Kola peninsula quarry blasts and the binary iterative segmentation procedures of Inclán and Tiao (1994) and Chen and Gupta (1997) seem to work well for these. For seismograms containing phases with codas the segmentation methods using SA work better. In actual implementation of such methods more than a single approach may have to be employed in interpreting seismograms in the automatic mode.

Since the methods have been tested in the interpretative MATLAB computing environment they run slow under MATLAB. This is misleading, however. According to our previous experience (Der and Shumway 1999), when implemented as compiled codes all the algorithms tested will run much faster than any human analyst could read the seismograms. SA is a very fast algorithm because it mostly involves comparisons of the magnitudes of various quantities (Press et al 1986) . In this prototyping stage we have not taken the pains, either, to fully exploit the efficient vectorized computation features in MATLAB. In the actual implementation MATLAB codes can also be compiled or linked to compiled C or FORTRAN modules.

4.0. CONCLUSIONS AND RECOMMENDATIONS.

CUSUM-based methods seem to be quite suitable for processing regional seismograms since these consist of long wavetrains and have emergent phase onsets. Since CUSUM methods emphasize changes in the properties of signals over several cycles this kinds of methods can be used to segment regional seismograms. CUSUM-based methods to pick seismic phase onset times can also be developed based on a variety of statistics that are diagnostic of polarization, slowness, and spectral changes (Jurkevics 1988, Der et al 1993). Other candidates may include instantaneous relative phase differences among components, adaptive slowness estimates or their combination.

During the course of previous work described in Der and Shumway (1999), and in the work summarized in this report, we have developed the essential building blocks for a practical implementation of an automatic seismogram interpretation algorithm. As stated above, not all the approaches that we have tried worked equally well for segmentation of seismograms and onset estimation under the various scenarios encountered in practice. For seismograms that contain steplike increases in the amplitudes of the successive phases binary iterative segmentation procedures of Inclán and Tiao (1994) and Chen and Gupta (1997) seem to work well. For seismograms containing phases with codas and variable amplitudes the segmentation methods using SA work better. Once the segments are defined numerous, previously developed approaches for the determination of the onset times described described in the literature can be applied (Inclán and Tiao 1994, Chen and Gupta 1997, Basseville and Nikiforov 1993).

Any practical algorithm package for the automatic interpretation of high frequency seismograms will have to possess sufficient intelligence to recognize various situations and chose the best algorithms. We shall implement the final code in a MATLAB environment complete with a suitable graphical user interface (Marchard 1990). Most of the algorithms described have been programmed as MATLAB M-files during the work described.

Key Words; onset times, change points, location, discrimination

5.0. REFERENCES

Basseville, M. and I.V. Nikiforov (1993), Detection of Abrupt Changes: Theory and Application. Prentice Hall Information and System Science Series, Prentice Hall, Englewood Cliffs, NJ.

Bendat, J. S., and Piersol, A. G. (1986), Random Data; Analysis and Measurement Procedures. John Wiley & Sons.

Chen, J. and Gupta, A. K. (1997), Testing and locating change points with applications to stock prices. J. Amer. Statist. Assoc., 92, 739-747.

Der, Z.A., Baumgardt,D.R. and R.H. Shumway (1993), The nature of particle motion in regional seismograms and its utilization for phase identification. Geophys. J. Int., 115, 1012-1024.

Der, Z. A. and R. H. Shumway (1999), Phase onset time estimation at regional distances using the CUSUM-SA algorithm. Phys. Earth and Planet. Int., 113,227-246.

Hurvich, C. M., and Tsai, C-L (1989, Regression and time series model selection in small samples. Biometrika, 76, 297-307.

Inclán, C., and G. C. Tiao (1994), Use of cumulative sums of squares for retrospective detection in the changes of variance. J. Amer. Statist. Assoc., 89,, 913-923.

Jurkevics, A. (1988), Polarization analysis of three-component array data. Bull. Seism. Soc. Am., 78, 1725-1743.

Kushnir, A. F. (1996), Algorithms for adaptive statistical processing of seismic array data. In 'Monitoring a Comprehensive Test Ban treaty', E. S. Husebye and A. M. Dainty Eds., Kluwer Academic Publishers.

Kvaerna, T. (1995), Automatic onset time estimation based on autoregressive processing. Semiannual Technical Summary, 1 April-30 September 1995. NORSAR, Sci. Report No. 1-95/96, Kjeller, Norway.

Kvaerna, T. (1996a), Quality assessment of automatic onset times estimated by the autoregressive method. Semiannual Technical Summary, 1 April-30 September 1995. NORSAR, Sci. Report No. 1-95/96, Kjeller, Norway.

Kvaerna, T. (1996b), Time shifts of phase onsets caused by SNR variations, Semiannual Technical Summary, 1 October 1995-31 March 1996. NORSAR, Sci. Report No. 2-95/96, Kjeller, Norway. Leonard, M., and Kennett, B. L. N. (199), Mul;ti-component autoregressive techniques for the analysis of seismograms. Phys. Earth Planet. Int., 113, 247-264.

Leonard, M., and Kennett, B. L. N. (1999), Multi-component autoregressive techniques for the analysis of seismograms. Phys. Earth. Planet. Int., 113, 247-264.

Maeda, N. (1985), A method for reading and checking phase time in auto-processing ssystem of seismic wave data (in Japanese with English abstract), J. Seismol. Soc. Jpn., 38, 365-379.

Marchard, P. (1996), Graphics and GUIs with MATLAB. CRC Press.

Press, W.H., Flannery, B.P., Teukolsky, S.A. and W.T. Vetterling (1986), Numerical Recipes: The Art of Scientific Computing. Cambridge University Press.

Shumway, R. H. (1998), An iterative cumulative sum of squares algorithm for phase onset estimation. ENSCO Technical Memo.

Takanami, T. (1991), A study of detection and extraction methods for earthquake waves by autoregressive models. J. Fac. Sci. Hokkaido, U., Ser VII, 9, 67-196.

Taylor, D. W. A., Ghalib, H. A. A. and Kimmel, R. H. (1992), Autoregressive analysis for seismic signal detection and onset time estimation. ENSCO Inc. Technical Report DCS-92-90 prepared for AFTAC.

Theodoris, S., and Koutroumbas, K. (1999), Pattern Recognition, Addison-Wesley.

Tou, J. T., and Gonzalez, R. C. (1974), Pattern Recognition Principles. Addison-Wesley.

Yokota, T., Zhou, S., Mizoue, M., and Nakamura, I. (1981), An automatic measurement of arrival time of seismic waves and its application to an on-line processing system (in Japanese with English abstract), Bull. Earthquake. Res. Inst. Univ. Tokyo, 55, 449-484.

Whalen, A. D., (1971), Detection of Signals in Noise. Academic Press.