

**AUTOMATIC SECONDARY SEISMIC PHASE PICKING  
USING WAVELET TRANSFORMS**

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**ABSTRACT**

The primary objective of this study was to develop a new and innovative wavelet technique for accurate, reliable and semi-automatic arrival time determination, specifically for secondary phases in complex regional seismograms. For regional nuclear test monitoring applications, determining accurate locations for small-to-intermediate events ( $2.5 < m_b < 4.0$ ) using sparse stations or arrays is an important and difficult problem. Since relatively few *P*-wave observations will be available for hypocenter location, secondary seismic phases, such as *Lg* and *Pg*, must be considered to improve location accuracy to the level required for nuclear test monitoring. For these events, single array or single station locations may be used to determine an epicenter for an event, based on estimates of back azimuth and epicentral distance. Because *Lg* propagates at a consistent group velocity of approximately  $3.5 \pm 0.2$  km/s, the distance estimates using the travel time difference between this arrival and primary phases (e.g., *Pn*, *Pg*) are often quite reliable. However, *Lg* is a very complicated phase and identifying its onset time on seismograms remains one of the most difficult problems encountered in regional seismology. We have tested an improved version of the *Lg* wavelet picker, WAVELET1.0, based on a method developed by Tibuleac and Herrin (1999, 2001), and compared it with two other phase picking algorithms: CUMSQ and AR. CUMSQ is a method based on the cumulative sum of squares of a statistic whose minimum indicates the detection (Inclan and Tiao, 1994; Der and Shumway, 1999). AR is an autoregressive algorithm that picks arrivals at the location of the minimum of a function called the Akaike Information Criterion (AIC) and was developed by Taylor *et al.* (1992). We tested the three methods on *Lg* and *Pg* (as secondary arrivals), from a data set of 97 shallow ( $m_b < 4.0$ ) well-located mine explosions and collocated aftershocks recorded at the TXAR (Lajitas, Texas), NVAR (Mina, Nevada) and PDAR (Pinedale, Wyoming) seismic arrays. Based on a rigorous statistical evaluation, WAVELET1.0 estimates were more consistent for seven out of eight clusters located 300 to 700 km from three seismic arrays, and produced the lowest location sample standard deviations, in the 4.1 to 5.8 km range, while the other two methods had sample standard deviations well above 5.8 km. The 95% confidence intervals for location standard deviations were estimated as follows: standard deviation between 4.1 and 5.8 km for WAVELET1.0 picks, between 6.9 and 9.5 km for the analyst picks and between 5.8 and 8.0 km for CUMSQ picks. Our results show that WAVELET1.0 offers an improvement in semi-automatic secondary phase picking over the CUMSQ and AR algorithms and has the potential to be developed into a powerful and robust automatic tool for routine operations.

## **OBJECTIVES**

The primary objective of this research was to develop a new and innovative semi-automatic wavelet technique (WAVELET1.0) for accurate and reliable arrival time determination, specifically for secondary phases in complex regional seismograms.

To accomplish this objective we have:

- 1) Improved the performance of an existing *Lg* wavelet picking technique by Tibuleac and Herrin (1999). Improvements to the method include: a more flexible use of the algorithm's parameters based on the frequency content of the waveforms, an empirically variable threshold, and implementation of an algorithm to separate emergent from impulsive arrivals.
- 2) Compared WAVELET1.0 to results from two other phase picking methods based on Fourier transforms: CUMSQ (Inclan and Tiao, 1994; Der and Shumway, 1999) and AR (Takanami, 1991; Taylor *et al.*, 1992), to determine individual performance metrics. Each method was also compared to analyst picks to determine if any of the three methods offered more consistent picks than a trained analyst.
- 3) Developed a rigorous statistical framework to objectively evaluate the comparison. The phase picks from each method were used to estimate event locations and the 95% confidence intervals for the sample standard deviations of the location errors.

## **RESEARCH ACCOMPLISHED**

### **Introduction**

Different types of seismic phase pickers, in time or frequency domain, were previously developed (for a review, see Tibuleac and Herrin, 1999). However, most of these techniques were developed to pick first arrivals, and none has been demonstrated to be an optimal method for picking secondary phases. These methods pick phases based on changes in either amplitude or frequency of the signal. Most of the picking methods work well on first arriving impulsive *P* phases, but have difficulty picking later arrivals on regional seismograms. Also, all methods use windowing, and the length of the windows affects the precision of the picks.

Wavelet transforms are alternatives, rather than replacements for Fourier transforms. Their basis functions are short wavelets instead of cosine waves. As with any filtering technique, they have advantages and disadvantages. The advantage we exploit is that wavelet transforms are more local than Fourier transforms. When we deal with transient, *non-stationary* phases such as *Lg*, and we require computation speed, the wavelet transform represents the signal with a small number of rapidly computable base functions, localized in time and therefore better at extracting sharp features of the signal. To design and describe wavelets, we still use Fourier techniques. However, instead of transforming a pure "time description" into a pure "frequency description", the new methods find a good compromise: a time-frequency description that avoids the "blocking effect" at the edge of the time segments that is the nemesis of the Short Time Fourier Transform (Strang and Nguyen, 1996). In this study we use a class of wavelets that are orthogonal and are implemented using short digital filters (Daubechies, 1992).

Wavelet transform methods were used for *P* and *S* phase identification in three component seismograms by Anant and Dowlal (1997), for detection and classification of seismic events (Gendron *et al.*, 2000), for automatic *P* wave detection (Zhang *et al.*, 2002) and for identification of secondary phases in seismograms (Yomogida, 1994). However, these studies did not address in detail the problem of picking complicated *Lg* arrivals.

The *Lg* phase is typically of lower frequency than the first arrivals, and the surrounding coda and noise, and represents a change in process on the seismogram, meaning a change in both frequency and amplitude. The wavelet transform (see Tibuleac and Herrin, 1999, 2001) is the most effective technique for identifying *Lg* because it can detect changes in both time and scale (inverse frequency). In contrast, Fourier transforms can only globally detect changes in frequency.

These properties led to the development of a phase picker (Tibuleac and Herrin, 1999, 2001) based on the ability of the wavelet transform to represent the signal in time-scale space and using data from one vertical component of a regional seismic array. For waveform examples, the reader is referred to the 1999 study by Tibuleac and Herrin. The study also shows that the coefficients at scale 16 of a continuous *db2* (Daubechies order 2) wavelet decomposition (corresponding to a range of frequencies of 0.9 to 2.1 Hz) were empirically chosen as best to be analyzed for all events. The reason was that this frequency band (centered on 1.5 Hz) is a band with significant energy in the *Lg* Fourier spectrum (Campillo *et al.*; 1985, Nuttli, 1986; Herrmann *et al.*, 1997). In their 1999 and 2001 studies, Tibuleac and Herrin picked *Lg* arrival times by this semi-automatic method with a standard deviation of less than 1.5 seconds (less than 10 km location error) for explosions and earthquakes with high quality local to regional locations and for data recorded at three seismic arrays: TXAR (Lajitas, Texas), PDAR (Pinedale, Wyoming) and NVAR (Mina, Nevada).

We have developed an improved semi-automatic wavelet picking technique (which we have designated WAVELET1.0) based on the initial work of Tibuleac and Herrin (1999, 2001). The novelty of this technique is that it provides consistent arrival time picks of *Lg* phases previously identified and approximately picked by an analyst or by an automatic algorithm. Errors in *Lg* arrival time, when picked by an analyst, can be up to ten seconds. Our method ensures consistency of the measurements and we correct for the bias in each region.

We demonstrate in this study that the semi-automatic WAVELET1.0 outperforms the CUMSQ and AR methods as well as the analyst. It is important to note that we measured performance based on algorithm's capability to consistently pick the same phase feature for each event. We applied the three phase picking techniques on local to near-regional (100 to 700 km) array data for well-located, small ( $m_b < 4.0$ ) event clusters to compare algorithm performances.

### **Improved Wavelet Technique: WAVELET1.0**

**Pre-filtering.** We have allowed more flexible use of the picking parameters in this study than in the initial version of the wavelet picker. Specific parameters such as the search window length, the Continuous Wavelet Transform (CWT) scale and the Discrete Wavelet Transform (DWT) *Haar approximation* were chosen by the analyst as a function of the particular characteristics of the waveforms. In the case of high signal-to-noise ratio (*snr*) events, the analyst chose whether to pre-filter the data.

**Normalization.** In WAVELET1.0, the time series in the search window is normalized to the maximum value of the *Lg* amplitude in the window to avoid considering possible localized and very large amplitudes later in the *Lg* signal. In the initial version, the waveforms were normalized to the maximum value in the window and the following five seconds of the signal.

**Threshold.** In the new version of the algorithm, WAVELET1.0, an empirical variable threshold was calculated after wavelet filtering for all *Lg* picks:

$$th = 10^{\left[0.02 * snr\right]^{0.25}} \square 0.05$$

where *snr* (*dB*) is the ratio between the maximum value of the squared signal in a seven second window starting at the approximate pick and twice the sample standard deviation of the squared noise in a seven second window before the signal (Der and Shumway, 1999). This *snr* formula was chosen to compensate for short duration, very large amplitude pulses in the *Lg* signal. These large amplitudes were affecting the time picks for a waveform weighted to the maximum value of the signal in the search window. A second method used to eliminate these large amplitudes, before the threshold calculation, was to discard any amplitude maximum value larger than 3.5 times the standard deviation of the signal in the search window, and replace it with the second largest value.

We have observed that, by using squared waveforms after pre-filtering, WAVELET1.0 improves the *snr* more than the other techniques. In their study, Tibuleac and Herrin (1999) also showed that, in the same frequency range, the amplitude difference between the *Lg* signal and the coda before *Lg* is much less after Fourier pre-filtering than after wavelet pre-filtering.

**Phase Picking.** Finally, we have implemented an algorithm that separates and corrects for emergent arrivals. An arrival is considered impulsive when it exceeds the threshold plus 0.3 units within one second from the detection.

When the arrival is emergent, the algorithm picks the arrival time at the intersection of the threshold level with the line that fits the time series (L2 fit) in a four second window centered on the time pick. This procedure is a first step in improving the phase picks for emergent arrivals, before a completely automatic algorithm can be developed.

**Phase Picker Comparison**

**Dataset.** A dataset of 97 events was assembled for this study: two sequences of collocated aftershocks and five clusters of well-located mining explosions. We used data between 1995 and 2000 from elements of the TXAR (TX09), PDAR (PD03) and NVAR (NV08) seismic arrays in a distance range of 100 to 700 km to make the comparison between the different pickers. Events from this database (Table 1) have been described in detail in two previous studies by Tibuleac and Herrin (1999, 2001).

**Table 1. The seismic event database used to compare different pickers**

LOCATION	LATITUDE (DEGREES)	LONGITUDE (DEGREES)
Alpine, Texas (ALPINE)	30.3	-103.3
Minas des Hercules (Mexico) (HERCULES)	28.1	-103.8
MICARE Coal Mines (Mexico) (MICARE)	28.3	-100.5
Tyrone, New Mexico (TYRONE)	32.7	-108.4
Morenci, Arizona (MORENCI)	33.1	-109.4
Black Thunder, Wyoming (BTH)	43.7	-105.3
Scotty's Junction, Nevada (SCOTTY)	37.4	-117.0

**The CUMSQ and AR Algorithms.** To our knowledge, no generally accepted method for automatic phase picking has been developed. Therefore, we chose two methods to compare with WAVELET1.0 that were originally developed for first arrivals, and adapted them for secondary phase picking. Both methods were proven to be better than STA/LTA type pickers.

The first, developed by Der and Shumway (1999), from an initial version by Inclan and Tiao (1994), was based on the cumulative sum of squares (CUMSQ). The algorithm picks  $P_n$  onset time at regional distances by estimating the minimum of the cumulative sum of the squares of a test statistic (the absolute value of the trace amplitude). We chose from two versions of the algorithm developed by Der and Shumway (1999): CUMSQ and CUMSUM. CUMSQ is based on the accumulation of squares of amplitudes and a statistic whose minimum indicates the detection. CUMSUM is based on simulated annealing (randomized search) and the accumulation of amplitude absolute values. A Wiener pre-filter of order 15 was chosen over several other pre-filtering methods, e.g., a zero phase Butterworth 4 pole filter with a frequency range of 0.6 – 4.5 Hz, a  $S/N^2$  filter (ratio of the spectral amplitude of the signal  $S$  divided by the power spectrum of the noise  $N$ ) and a  $(S + N)/N^2$  filter. The CUMSQ method with a Wiener pre-filter proved to be the most stable, had the lowest distance standard deviations and was therefore adapted to be used in this study for secondary arrival time detection. However, a shortcoming of this algorithm was that it picked emergent arrivals too late for low *snr* events.

A second comparison was made with an autoregressive method (AR). This method uses a stable and fast technique initially developed by Takanami (1991). Taylor *et al.* (1992) extended the modeling procedure to develop a signal detection algorithm (AR) that can analyze continuous single-component data. The AR algorithm is based on developing a model of the background noise for a segment of data (typically 8 seconds). This noise model is used to predict the next short segment of data (typically 2 seconds). The detection occurs when the predicted and observed time series are different. The AR algorithm picks arrivals at the location of the minimum of a function called the Akaike Information Criterion (AIC). This function weighs the prediction error in each window (noise versus signal) by the length of the window, and its minimum (the onset time of the signal) defines the time where the data segment is best fit by the two different models. We applied a Wiener filter and different order zero phase Butterworth filters as pre-filters for the AR method. Based on these results, we chose a 4 pole zero phase Butterworth filter with a frequency range of 0.6 – 4.5 Hz as the optimal filter. An optimal search window of 14 seconds, centered on the approximate pick, was applied for both the AR and the CUMSQ algorithms. A drawback of the AR algorithm (for smaller signals) is that in the absence of white noise the autoregressive process cannot reliably predict the data.

Analyst *Lg* picks were performed after comparison of raw and filtered data. We consider these picks to be equivalent to those of an experienced analyst since all phases were identified using their horizontal phase velocity and back azimuth, estimated with array processing methods.

### **WAVELET1.0 parameters**

The WAVELET1.0 algorithm requires several input parameters that at this time are analyst options. The WAVELET1.0 parameters are: 10 or 12 second search window; the use of raw or filtered waveforms; the wavelet family; the CWT decomposition scale and the DWT decomposition *approximation* (depending on the frequency content of the signal). We have observed relatively small sensitivity (2 – 4 km variation) of sample standard deviation to the length of the search window and to the *Haar* DWT *approximation* level for most of the clusters. It also appears that WAVELET1.0 results are not significantly affected by the signal-to-noise ratio due in part to the proper choice of the threshold.

### **Results**

**Comparing the arrival time picks.** We have observed that choosing the correct type of pre-filtering method, which is not especially important when picking first arrivals (Der and Shumway, 1999), is essential when picking secondary arrivals.

We have used the pre-filtering method for which we had the lowest distance standard deviations for each algorithm. In order to give each algorithm the best chance of succeeding, we used the same carefully chosen analyst picks as the initial approximate picks for each algorithm. In operational practice, the *Lg* phase would be identified by an existing detection algorithm such as SLA/LTA (see as an example the PIDC *Lg* automatic detection algorithms in ‘IDC Processing of Seismic, Hydroacoustic and Infrasonic Data’ at [www.cmr.org](http://www.cmr.org)). Automatic secondary phase identification is a complicated problem, already the subject of extensive research (Harris *et al.*, 2001, Bai and Kennett, 2000) and was not addressed in this study. Our efforts were directed towards developing an automatic, consistent and reliable secondary phase picking method.

Table 2 shows that WAVELET1.0 has the lowest estimated location sample standard deviation in km in most of the clusters of the different tectonic regions we considered. The second best results are obtained using the CUMSQ algorithm. In fact, WAVELET1.0 and CUMSQ have similar results for clusters at distances less than 300 km, which is to be expected for local, larger *snr* events. However, for clusters between 300 and 700 km, the WAVELET1.0 algorithm performs best. The intrinsic WAVELET1.0 location error (see Tibuleac and Herrin, 2001) was calculated, taking into account the down-sampling when applying the *Haar* DWT decomposition. Both WAVELET1.0 and CUMSQ have lower variance than the analyst.

Given the number of failures (arrival time error more than 5 seconds) when using the AR algorithm, we considered only the CUMSQ and WAVELET1.0 methods for further analysis. It is important to mention that the AR algorithm and the analyst performed best for the high *SNR* *Pg* arrivals, even if they were secondary arrivals (with a small *Pn* in front of them) recorded at NVAR from Scotty’s Junction. This was to be expected because the AR algorithm was developed for these types of phases.

### **Statistical Analyses**

We define the error as the difference between the ‘true’ epicentral distance and the epicentral distance estimated using *P – Lg* arrival time differences and appropriate regional models. We are interested in the consistency of the picks for a certain cluster expressed by the sample standard deviation of the errors, since the location bias can be corrected by proper calibration. A plot of the location errors for the 113 samples (7 clusters) is presented in Figure 1. We designated the three methods: 1. Analyst, 2. CUMSQ, and 3. WAVELET1.0.

Note that all three methods have errors of varying degrees for some of the clusters. However, the analyst errors have the largest variance. Testing the hypothesis of equality of variances for the three methods (Table 3) leads to a strong rejection ( $P=.000$ ) under the normality assumption by the Bartlett test (Snedecor and Cochran, 1989) and a weak rejection ( $P=.076$ ) using Levene’s test (Levene, 1960), which is more robust relative to distributional

departures from normality. This means that we can be 93% confident that the standard deviations obtained by WAVELET1.0 are lower than those obtained using CUMSQ.

After examining the results it is clear that WAVELET1.0 produces consistent distance estimates with lower variance for seven out of eight clusters studied. The method is shown to produce good results for three different arrays in three different tectonic regimes in the Western US. Both WAVELET1.0 and CUMSQ methods have low variance estimates at local distances (< 300 km) and lower variance of distance estimates than the analyst. With 95% confidence, the standard deviation of the location error for WAVELET1.0 is between 4.1 and 5.8 km, while for CUMSQ it is between 5.8 and 8.1 km. Examination of Table 3, as well as Figure 1, indicates that the WAVELET1.0 standard deviations are substantially smaller than those measured by the other two methods, with the analyst having the largest variance. These results demonstrate clearly that the semi-automatic WAVELET1.0 significantly outperforms the CUMSQ and AR as well as the analyst.

**Table 2. Location standard deviation (km) obtained for each cluster, using each picking method. Bold numbers represent the lowest location sample standard deviation. Italics represent similar results of WAVELET1.0 and CUMSQ. The distance from clusters to arrays increases to the right. The numbers under the backslash (/) represent the number of arrival time errors larger than 5 seconds (picking failures).**

Method	Sample Standard Deviation (km) for cluster:							
	ALPINE	HERCULES	SCOTTYS	SCOTTYPg	MICARE	BTH	TYRONE	MORENCI
<b>ANALYST</b>	2.5	7.3	4.6	considered true	14.7	7.4	2.2	9
<b>CUMSQ Wiener</b>	3.4	5.7	3.6	1.5	8.6	10.7	2.1	11.3
<b>AR Butterworth</b>	6.4 /1	5.6 /14	4.7/7	<b>1.2</b>	13/13	2.9 /1	-	-
<b>WAVELET1.0</b>	<b>2.5</b>	<i>5.8</i>	<b>2.7</b>	<i>1.6</i>	<b>6.8</b>	<b>2.5</b>	<b>1.8</b>	<b>4.9</b>
<b>WAVELET 1.0 method location error (km)</b>	0.9	0.5	0.6	0.4	0.7	0.7	1.4	0.7
<b>Number of events</b>	15	21	16	16	22	7	9	7
<b>ARRAY</b>	TXAR	TXAR	NVAR	NVAR	TXAR	PDAR	TXAR	TXAR
<b>Epic. Dist. (km)</b>	108	150	157	157	329	360	579	681

**Table3. Estimated sample standard deviations (□ in km) and 95% confidence intervals for each method.**

Method	WAVELET1.0	CUMSQ	ANALYST
Estimated □	<b>4.9</b>	<b>6.7</b>	<b>7.9</b>
Confidence Interval	<b>(4.10, 5.79)</b>	<b>(5.80, 8.01)</b>	<b>(6.85, 9.45)</b>

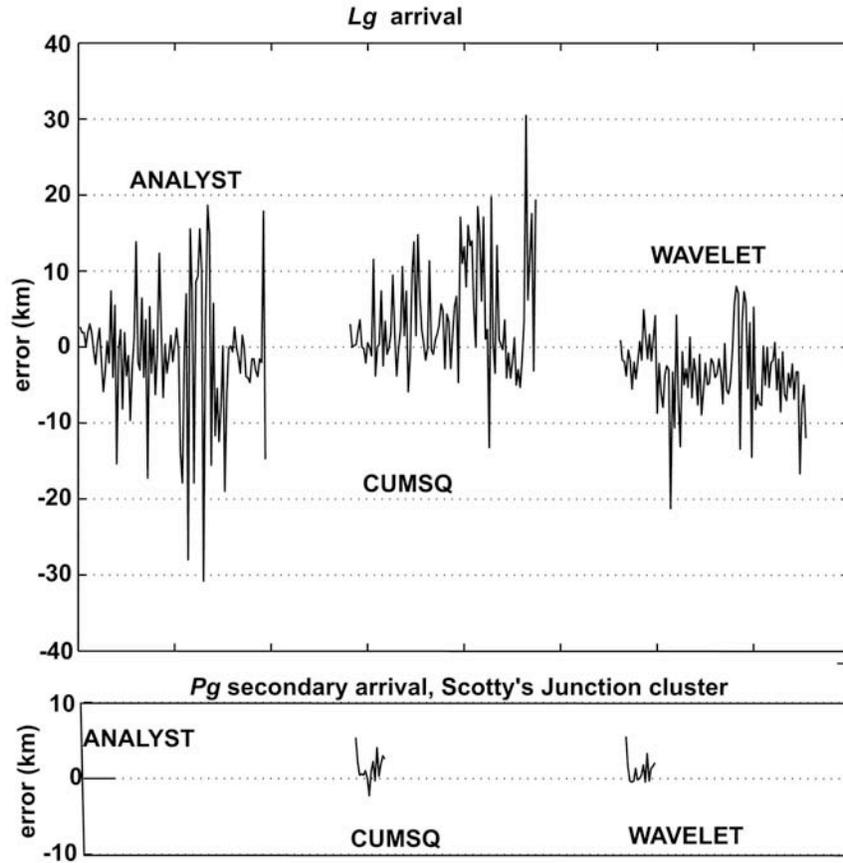


Figure 1. Errors in km from the three picking methods plotted by event number, in the same order of events for each method. Distance between clusters and arrays increase from left to right.

### CONCLUSIONS AND RECOMMENDATIONS

We have improved the original wavelet picker (Tibuleac and Herrin, 1999) and developed a robust and consistent semi-automatic secondary phase picker designated WAVELET1.0. The improved version corrects for the delay of emergent arrivals. It empirically calculates a variable picking threshold based on the *snr* in the search window after wavelet pre-filtering. Although the success of this empirical threshold calculation method is encouraging, it remains to be determined by future research if the formula is transportable to different data sets or if it must be further modified. WAVELET1.0 was tested on a variety of events (earthquakes and commercial explosions) recorded at three arrays located within different tectonic regimes of the Western US. The results were compared to those obtained by applying two other techniques (CUMSQ and AR), which we modified to pick secondary arrivals for the same dataset. After considering the results, it is clear that WAVELET1.0 produces consistent distance estimates with lower variance for seven out of eight clusters of events studied. Both WAVELET1.0 and CUMSQ methods have low variance estimates at local distances (< 300 km) and lower variance of distance estimates than the analyst.

With 95 % confidence, the location standard deviation for WAVELET1.0 is between 4.1 and 5.8 km, while for CUMSQ it is between 5.8 and 8.1 km. The WAVELET1.0 distance standard deviation is smaller than the CUMSQ at a 93% confidence level. We therefore consider WAVELET1.0 to be a reliable and promising technique worth investigating in order to develop an entirely automatic phase picker.

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**REFERENCES**

- Anant, K. S. and F. U. Dowla, (1997), Wavelet transform methods for phase identification in three-component seismograms, *Bull. Seis. Soc. Am.*, **87**, 1598-1612.
- Bai, Chao-ying and B. L. N. Kennett, (2000), Automatic Phase – Detection and identification by full use of a single three component broadband seismogram, *Bull. Seis. Soc. Am.*, **90**, 187-198.
- Campillo, M., Plantet, J. L. and Bouchon, M., (1985), Frequency – dependent attenuation in the crust beneath Central France from *Lg* waves: Data Analysis and Numerical Modeling, *Bull. Seis. Soc. Am.*, **75**, 1395-1411.
- Daubechies, I, (1992), Ten lectures on wavelets, SIAM, New York, NY, 1992
- Der, Z. A, and R. H. Shumway, (1999), Phase onset time estimation at regional distances using the CUMSUM algorithm, *Phys. Earth Planet. Int.*, **113**, 227 –246.
- Der, Z. and R. H. Shumway, (2000), Automatic interpretation of regional seismic signals using the CUMSUM-SA algorithms, *Proceedings of the 21st Annual Seismic Research Symposium on Monitoring a Comprehensive Nuclear Test Ban Treaty*, 21-24 September 1999, Las Vegas, Nevada, 393 – 403.
- Gendron, P., J. Ebel and D. Manolachis, (2000), Rapid Joint Detection and Classification with Wavelet Bases via Bayes Theorem, *Bull. Seis. Soc. Am*, **90**, 764-774.
- Harris, D. B, Walter, W. R., Rodgers, A. J., Sichertman, A., Myers, S. and C. Shultz, (2001), LLNL detection program: Broad area characterization of phase detectability and empirical detectors for specific sources, *Proceedings of the 23'rd Annual Seismic Research Symposium on Monitoring a Comprehensive Nuclear Test Ban Treaty*, Oct. 2-5 Jackson Hole, Wyoming,
- Herrmann, R. B., Mokhtar, T. A., Raoof, M. and Ammon, C., (1997), Wave Propagation – 16 Hz to 60 sec, *Proceedings of the 19'th Annual Seismic Research Symposium on Monitoring a Comprehensive Nuclear Test Ban Treaty*, 23-25 September, 1997, 495-503.
- Inclan, C. and G. C. Tiao, (1994), Use of cumulative sums of squares for retrospective detection in the changes in variance, *J. Amer. Statist. Assoc.*, **89**, 913-923.
- Levene, H. (1960), In Contributions to Probability and Statistics: Essays in Honor of Harold Hotelling, I. Olkin *et al.* eds., Stanford University Press, pp. 278-292.
- Nuttli, O. W., (1986), Yield Estimates of Nevada Test Site explosions obtained from seismic *Lg* waves, *J. Geophys. Res.*, **91**, 2137-2151.
- Snedecor, G. W. and W. G. Cochran, (1989), *Statistical Methods*, Eighth Edition, Iowa State University Press, Ames, Iowa.
- Strang, G. and T. Nquyen, (1996), Wavelets and Filter Banks, Wellesley-Cambridge Press, 81-82.
- Takanami, T., (1991), A study of detection and extraction methods for microearthquake waves by autoregressive models, *J. Fac. Sci.*, Hokkaido U., Ser. VII, 9, 67-196.
- Taylor, D. W., Ghalib, H. A. and R. H. Kimmel, (1992), Autoregressive analysis for seismic signal detection and onset time estimation, ENSCO report, DCS-92-90.
- Tibuleac, I. M. and E.T. Herrin, (1999), An automatic method for determination of *Lg* arrival times using wavelet methods, *Seism. Res. Lett.*, **70**, 577–595.
- Tibuleac, I. M. and E.T. Herrin, (2001), Location capability at NVAR (Mina, Nevada) seismic array for events on the Nevada Test Site, *Seism. Res. Lett.*, **72**, 97-107.
- Zhang, H., C. Thurber and C. Rowe, (2002) Automatic P-wave Arrival Detection and Picking with Multiscale Wavelet Analysis for Single Component Recordings, , submitted to *Bull. Seis. Soc. Am.*
- Yomogida, K, (1994), Detection of anomalous seismic phases by the wavelet transform, *Geophys. J. Int*, **116**, 119-130.