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Seismic and acoustic signal identification algorithms

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ABSTRACT

This paper will describe an algorithm for detecting and classifying seismic and acoustic signals for unattended ground sensors. The algorithm must be computationally efficient and continuously process a data stream in order to establish whether or not a desired signal has changed state (turned-on or off). The paper will focus on describing a Fourier based technique that compares the running power spectral density estimate of the data to a predetermined signature in order to determine if the desired signal has changed state. How to establish the signature and the detection thresholds will be discussed as well as the theoretical statistics of the algorithm for the Gaussian noise case with results from simulated data. Actual seismic data results will also be discussed along with techniques used to reduce false alarms due to the inherent non-stationary noise environments found with actual data.

Keywords: detection, identification, seismology, acoustics, unattended ground sensors

1. INTRODUCTION

There has been considerable interest in using seismic and acoustic sensors to detect and identify continuous wave (CW) sources [1][2][3][4][5]. This paper addresses the challenge of monitoring such sources within a seismic environment having limited interfering sources and under the constraint that the algorithm runs in real time in an unattended ground sensor system and extends the techniques discussed in [4]. The focus of the paper is on a Fourier based technique that uses a running power spectral density estimate of the data in order to determine if there was a turn-off or turn-on of a CW source of interest.

It is assumed that equipment in steady state vibrate at distinct frequencies and in many situations one does not know *a priori* the frequencies that characterize the equipment. As such, the first section describes a technique that detects turning-on or turning-off a frequency or tone (state change). The detector is then constrained to report only when a settable number of tones change state. The statistical properties of the detector are described as well as how the detector adapts to the changing background level.

The second section describes a technique that can be used to identify the state changes for a particular piece of equipment if one can determine the characteristic frequencies of the equipment *a priori*. In this case, the signature, referred to as a template, can be used by the detector to determine when a particular set of frequencies, assumed unique, turn-on or turn-off, and thereby, make a classification decision. Two different procedures for developing templates are discussed: (1) a frequency list approach; and (2) a statistical regression analysis approach. In either case, the statistical properties of the classifier are derived from the statistical discussion in the first section, and the same adaptive technique is used to adjust to the background level.

In both sections, white Gaussian noise is used to establish the statistical properties and set the thresholds, which are tied to a probability of false alarm. Synthetic data is then used to demonstrate the theoretical performance of both the detector and classifier. Potential field performance is demonstrated by using actual seismic data. The last section provides a summary of the results and examines future efforts to address potential improvements in performance.

2. TONE DETECTOR

2.1 Background

Detecting the turning on and off of equipment without *a priori* knowledge of the equipment's characteristic frequencies essentially becomes a tone detection problem. That is, one wants to detect the turning on or off of a specified number of frequencies or tones that are associated with equipment. Figure 1 shows the spectrogram from a GS-14 geophone located 200 meters away from a representative CW source turning on, running for 90 seconds (enough time to reach steady state), and then turning off. Note the presence of many tones as well as the non-stationary properties during the turn-on. In addition to the generator running, a large transient occurred at approximately 02:13:40. The goal is for the detector to detect the state

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changes of the tones without a false alarm from the transient or missing the turn-on due to the variable frequency characteristics during the turn-on.

2.2 Assessing the frequency content of the signal

The FFT is a natural tool to use for the detector since it can be used to estimate the frequency content of a signal. Our detector uses the Bartlett method for estimating the power spectrum of a data segment [6]. Given a data buffer, the data is segmented into K partitions of length N where b_0 controls the amount of overlapping:

$$\begin{aligned} x_k(t_n) &= x\,(t_n + kb_0) \\ n &= 0,1,\ldots,N-1 \\ k &= 0,1,\ldots,K-1. \end{aligned} \tag{1}$$

Typically b_0 is selected such that there is a 50% overlap; 1/2N*(K+1) samples of data are required. For each segment a windowed periodogram estimate is formed (W represents the window weights and f_l is the frequency value for bin l)

$$\hat{X}_k(f_l) = \frac{1}{N}\left\|\sum_{n=0}^{N} x_k(t_n) W(t_n) \exp\left(\frac{-i2\pi f_l t_n}{N}\right)\right\|^2, \tag{2}$$

and the short-term average (STA) of the power spectrum estimate is calculated by averaging the periodogram values for the m^{th} data buffer

$$STA_m(f_l) = \hat{X}_m(f_l) = \frac{1}{K}\sum_{k=0}^{K-1} \hat{X}_k(f_l). \tag{3}$$

2.3 Thresholds

The STA at a specific frequency f_l will be used to decide if a tone at this frequency has turned on or off. But before this can be done, one needs an estimate of the noise floor or background power level that is present. Forming a long-term average (LTA) of the STA values as well as calculating the variance of the STA values (STAVAR) characterizes the background level where M is the number of data buffers used. Note that these values are calculated using "delayed" STA values in order to remove any bias that could be created by a state change during the current STA buffer of data. A delay greater than one is useful for detecting equipment that takes longer in time than a data buffer to reach steady state during a turn-on. Once a state change is detected, then one has to go through an initialization process to re-characterize the background level. This procedure is discussed later.

$$\begin{aligned} LTA_m(f_l) &= \frac{1}{M}\sum_{d=D}^{M+D-1} STA_{m-d}(f_l) \\ STAVAR_m(f_l) &= \frac{1}{M-1}\sum_{d=D}^{M+D-1} \left(STA_{m-d}(f_l) - LTA_m(f_l)\right)^2 \end{aligned} \tag{4}$$

With the background level established, one can perform a threshold test to determine if the STA value represents a state change or not. A simple test, having its roots in the Gaussian assumption, would be to check whether the STA value is within a set number of standard deviations of the LTA, such as

$$ON_m(f_l): \qquad STA_m(f_l) - LTA_m(f_l) > 3.090\sqrt{STAVAR_m(f_l)}. \tag{5}$$

This test represents a significance test, and, if the STA values are normal and stationary, then the probability this test will erroneously declare a turn-on is approximately 0.001. The test is concerned with detecting events that are highly unlikely if the background level is well characterized and not changing—indicating a state change. However, since the STA values are actually power spectral density estimates, they are not Gaussian but known to be related to the chi-square distribution if the input signal is Gaussian [7]. The chi-square distribution is defined by the degrees of freedom (ν); ν is approximately 2*K for the STA value. Note that this assumes that each periodogram value is independent (no overlap) and a rectangular window is used. For our case of 50% overlap and a Hanning window, we assume the values are independent.

The tests become

$$ON_m(f_l): \quad STA_m(f_l) > \frac{\chi^2_{\nu;1-\alpha}}{\nu} LTA_m(f_l)$$
$$OFF_m(f_l): \quad STA_m(f_l) < \frac{\chi^2_{\nu;\alpha}}{\nu} LTA_m(f_l) \tag{6}$$

where

$$P\left(\chi^2_\nu < \chi^2_{\nu;p}\right) = p. \tag{7}$$

The threshold value $\chi^2_{\nu;p}$ is found from the chi-square distribution tables for a specified probability of false alarm (α) and is normalized by the degrees of freedom. Note there are two different threshold values since the chi-square distribution is not symmetric. The test relies on the assumption that the LTA characterizes the background level very well, or in essence represents, in the absence of the source in question, the true power density value for f_l.

Figure 2 shows the output of the detector for noise (white, random Gaussian, data sampled at 1000 Hz) for f_l=75.2, using N=1024, K=4, M=12, and α=0.05. Calculating the degrees of freedom to be 8, the on threshold ($\chi^2_{8;0.95}$) is 1.9388 and the off threshold ($\chi^2_{8;0.05}$) is 0.3416. The x-axis is the data buffer index m, the y-axis is the STA, LTA, and the scaled threshold values, and stars are used to indicate when the STA value passes either of the tests. Ideally the LTA would be a flat line at one (the standard deviation of the noise was set at 32), but does have a variance. Note that the first 12 STA values are used to initialize the LTA and a test is not performed for these values. The graph shows 14 on-detects and 12 off-detects for the 200 tests performed (212 STA values) indicating a probability of false alarm (PFA) of 0.07 and 0.06 for on's and off's respectively. Creating a 30 minute time series of data yielded a PFA for on's of 0.059 and off's of 0.052.

The same data set was used, but the processing parameters M and the degrees of freedom were changed to examine the affects on the PFA; see Table 1. The results show that changing the degrees of freedom by 1 has much more of an affect on the PFA than reducing the variance of the LTA by half. In general terms, a fractional estimate for degrees of freedom between 7 and 8 is required, and increasing the LTA window length improves the accuracy of the test. For the purposes of this paper, the original estimate for the degrees of freedom (ν=8) and the shorter LTA window length (M=12) will be considered adequate for predicting the PFA.

LTA window length (M)	Degrees of Freedom (ν)	PFA Off	PFA On	PFA Avg
12	8	0.059	0.052	0.0555
48	8	0.057	0.054	0.0528
12	7	0.044	0.047	0.0455
48	7	0.049	0.045	0.0470

Table 1 PFA results for white Gaussian noise.

2.4 Adaptive thresholds

Figure 3 shows the output of the detector for the same noise data with a signal turning on and then off (sine wave with a frequency of 75.2 Hz). Notice that when the signal is present the thresholds are much too large and no false alarms occur. This is not surprising since the thresholds assume noise only and are tied to the processing parameters instead of the signal; a measure of the STA's variance needs to be factored in. Since the thresholds are controlled by the degrees of freedom, one could use STAVAR to estimate "equivalent degrees of freedom" and then calculate the threshold value, which would adapt to the signal characteristics. The variance of a chi-square random variable is related to the degrees of freedom by [8]

$$VAR\left(\chi_\nu^2\right) = 2\nu\,, \tag{8}$$

and the sampling distribution for the power spectral estimate is [7]

$$\frac{STA_m(f_l)}{LTA_m(f_l)} = \frac{\chi_\nu^2}{\nu}\,, \tag{9}$$

again assuming the LTA represents the true power spectral density (PSD) value for f_l. Thus, the equivalent degrees of freedom for a signal can be determined from

$$\nu_m(f_l) = \frac{2LTA_m^2(f_l)}{STAVAR_m(f_l)}\,. \tag{10}$$

From [8], the Chi-Squared table look-up to determine the on-threshold $\chi^2_{\nu;1-\alpha}$ can be approximated by

$$\chi^2_{\nu;1-\alpha} = \nu\left\{1 - \frac{2}{9\nu} + Z_{1-\alpha}\sqrt{\frac{2}{9\nu}}\right\}^3 \tag{11}$$

where $Z_{1-\alpha}$ sets the PFA and is determined from a Normal distribution table

$$P\left(z < Z_p\right) = p\,. \tag{12}$$

The approximation is very accurate for ν large (greater than 30), but for our purposes, will be considered adequate for even small ν (but greater than 4). The off threshold is determined by using the negative of $Z_{1-\alpha}$. Figure 4 shows the detector output using the same signal with the adaptive thresholds set at a PFA of 0.05 ($Z_{0.95}$=1.645). After the LTA has stabilized to the signal with noise level, there are nearly 100 tests performed before the turn-off. During this period there are 4 false turn-on's and 10 false turn-off's. A 30 minute test signal with additive noise yielded a PFA of 0.062 for on's and 0.066 for off's, which is high because the periodograms are not totally independent, and the statistics may not be exactly chi-square. However, the results are encouraging considering the approximations and assumptions used.

2.5 Persistence testing and non-stationary decision logic

Knowing that a signal should be persistent for some amount of time can be used to reduce significantly the number of false alarms from spurious noise sources and transient events. By insisting that the there are a certain number of detections (q) for a specified number of data buffers (r) one can create a "q out of r" persistence test, which has a PFA determined from the binomial distribution

$$PFA = \frac{r!}{q!\,(r-q)!}\,\alpha^q\left(1-\alpha\right)^{r-q}\,. \tag{13}$$

Requiring a signal to be persistent for ~16 seconds, but allowing for a few missed detections, would require r=8, q=6 and produce a PFA of approximately 4x10^-7 or one every 60 days for stationary Gaussian noise using the processing parameters previously specified. Of course, this represents the PFA only for frequency f_i, and it is highly unlikely that the background will be stationary Gaussian noise.

As seen in Figure 1, the turn-on and turn-off of a signal is a non-stationary process and decision logic is required to determine when a state change has taken place and put the detector into a wait state until the new background level is characterized. Figure 5 shows the flow diagram for detecting the state changes and performing the persistence test. When the process is started, or an event is declared, the algorithm goes into a wait state until the background statistics are learned. Once the detector has characterized the statistics there are three possible detection states:

(1) Detecting On (DON)
(2) Detecting Off (DOFF)
(3) Not Detecting (ND).

Once in one of these three states, three different test results can occur and have to be assessed: turn-on, turn-off, and no detect (none). As indicated, generally the first turn-on test result puts the algorithm into the DON state and likewise for a turn-off test result. If the algorithm is not in the ND state, then the q out of r persistence test is applied to the ensuing test results. Note that the persistence test resets after r-q misses and can declare an event before q tests are completed. When an event is declared, the algorithm goes into a wait state in order to re-learn the background statistics.

Adding such logic and the 8 out of 6 detector to the adaptive threshold technique provides the results shown in Figure 6 for the synthetic signal test case. There are no false alarms and the turn-on and turn-off were both detected.

2.6 Tone detector test with actual seismic data

The data depicted in Figure 1 is a subset of a test where ten turn-on's and off's were performed over a half-hour period. A large transient event occurred during each turn-off and turn-on period. Due to the inherent difficulties with false alarms for actual data, α was chosen to be 0.001 ($Z_{0.999}$=3.090). Data taken from a geophone, at a much farther distance, had a much weaker signal and is shown in Figure 7 for the entire test period. The weak signal had an SNR less than 15 dB for the 75.2 Hz tone, which was measured by integrating the area of the tone and dividing by the noise power for the same frequency range when the source was off. Note that the signal is undetectable in the time domain (time series data not shown in a figure). This is significantly less than the nearly 50 dB measured for the 75.2 Hz tone depicted in Figure 1.

The detector results are shown in Figures 8 and 9 respectively. Unfortunately, the first turn-on is missed since there is not enough data before the turn-on to characterize the background. For the high SNR signal, all the possible turn-on's and off's were detected with only one false turn-off during the half-hour period. For the low SNR signal, 7 of 9 possible turn-on's were detected and 4 of 10 possible turn-off's were detected. Evident in the plots is the significant jump in the LTA after the transient occurs while the source is off. We are currently exploring techniques to remove this undesirable affect.

2.7 Summary

The tone detector can be used to detect the turning on and off of frequencies in seismic data that may be indicative of equipment turning-on and off. The technique is based on the statistical properties of the FFT for random Gaussian data, with adjustments made to handle signals embedded in random noise. Adaptive thresholds are used to adjust to the variance of the background level with the thresholds controlled by a parameter determined from an acceptable PFA. A persistence test is used to reduce significantly the PFA. The next section describes how to use this detector when the characteristic frequencies of the equipment to be detected are known.

3. TEMPLATE DETECTOR

3.1 Background

If one can develop a template of characteristic frequencies for a particular type of equipment to be monitored, then one can use the same principals of the tone detector to build a template detector that identifies when that particular type of equipment turns on or off, and as such, classify the seismic signals. In essence, a dot product of the template is taken with the frequencies (zero to Nyquist) of the power spectral estimate to form the template detection statistic or short-term average

$$T\_STA_m = \sum_{l=0}^{N/2} STA_m(f_l)T(f_l), \tag{14}$$

where $T(f_l)$ is the template value at f_l. The long-term average (T_LTA_m) and the variance of the T_STA values (T_STAVAR_m) can be calculated in a similar manner as described above; the thresholds and test statistics are calculated in a similar manner as well. How to determine the template values is discussed in the next sections.

3.2 Frequency list template

A simple technique for determining a template is to identify unique and prominent frequencies one wants to use to detect the equipment. Careful analysis of the data shown in Figure 1 identifies prominent frequencies at 75.2, 100 and 150 Hz. The 75.2 Hz tone is much stronger than the other tones, and the template will reflect this through repetition in the list. Also, one may expect the frequencies to vary somewhat over time. Therefore, the template consists of a composite mask formed by creating a subset-template for each frequency with the following weights

$$T_1(f_{l-3}, f_{l-2}, f_{l-1}, f_l, f_{l+1}, f_{l+2}, f_{l+3}) = \{0.1,\ 0.3,\ 0.6,\ 1.0,\ 0.3,\ 0.1\}, \tag{15}$$

where all other frequencies are assigned a zero value. The template is the sum of the subset-templates

$$T(f_l) = \sum_i T_i(f_l), \tag{16}$$

and a particular frequency can be given more weight by repetition in the list. The template is then normalized by

$$T(f_l) = \frac{T(f_l)}{\sqrt{\sum_{l=0}^{N/2} T^2(f_l)}}. \tag{17}$$

Figure 10 shows the template detector results for the f_l={72.5, 72.5, 100, 150} template. The 9 turn-on's and the 10 turn-off's were detected with one false alarm. The next section describes a procedure for deriving templates using statistical regression analysis.

3.3 Statistical regression analysis template

As described above, templates can be determined by examining the spectral output associated with a known signal, and selecting obvious peaks. If there is considerable noise in the spectrum, or if there is more than one signal present within the spectrum, choosing the appropriate peaks can be difficult. If a series of spectra are available that encompass the on-off cycle of the equipment, factor analysis methods can be used to calculate a template, based on the variance of the signal. Factor analysis methods are those techniques that effectively reduce the dimensionality of the data matrix, while maintaining the information content of the data. By using the entire frequency range for the template greater prediction precision is possible.

One such method is principal components analysis (PCA), which creates a linearly independent basis set based on the maximum variance in the spectral data. The variance described by the basis vectors is largest in the first vector and decreases with additional vectors. Each subsequent vector is orthogonal to the previous. A spectral data matrix, X, with r samples, each sample containing n points ($r < n$), can be interpreted as an ensemble of r points in n dimensional space. PCA is the process of fitting a series of "lines and planes of closest fit to systems of points in space"[9]. The "closest fit" in this case is the least squares fit.

The vectors within this new basis set are referred to as PCA loadings and scores. If the noise within the data is randomly varying, it will be contained in later loadings and scores of the PCA decomposition. Estimating the data set by using only the significant PCA loadings can effectively filter random noise.
Mathematically, PCA can be described as the decomposition of a data matrix, X, with rank q, into a series of rank 1 matrices. If the variation in a given signal is linear, and there is no noise in the data, the resulting data matrix will be rank 1. For real data containing noise, $q = r$. For X with dimensions r x n

$$X = M_1 + M_2 + M_3 + ... + M_q. \tag{18}$$

Each of the rank 1 matrices can be written as outer products of two vectors: a score vector, t_h, and a loading vector, p'_h, where the apostrophe (') represents the transpose

$$X = t_1 p'_1 + t_2 p'_2 + t_3 p'_3 + ... + t_h p'_h + t_q p'_q. \tag{19}$$

Each vector t_h is r x 1 and each p'_h vector is 1 x n. The equation above can be represented in matrix notation as:

$$X = TP'. \tag{20}$$

The loading vectors, p_h, can be thought of as the spectral, or frequency features, while the scores, t_h, can be thought of as the concentration, or amount, of that spectral feature contained in the sample. This can allow for the separation of signals, as long as they do not co-vary within the calibration data. The insignificant loadings and scores can be deleted and the data matrix estimated using only the significant PCA factors, $1{:}k$, $k<q$

$$X = T_{rxk} P'_{nxk} + E \tag{21}$$

where

$$E = T_{(k+1):q} P'_{(k+1):q}, \tag{22}$$

represents the error. Note that

$$\hat{X} = T_{rxk} P'_{nxk} \tag{23}$$

where $\hat{X}$ is the estimate of X.

Many methods exist for calculating scores and loadings. Details will not be discussed here, but the reader is referred to work on the Nonlinear Iterative Partial Least Squares (NIPALS) method [10], [11], and the Singular Value Decomposition method (SVD)[12].

Once the scores and loadings are obtained, they can be used to relate the spectral information to external values, such as concentration, class or in this case, on-off status of equipment. Once the data matrix is estimated by the appropriate number of PCA loadings, a least squares solution can be found to relate the vector containing the state of the external variable, y, to $\hat{X}$. The relationship between y and $\hat{X}$ can be defined as:

$$y = \hat{X} * b + E_y \tag{24}$$

where b is a regression vector relating y to $\hat{X}$ in a least squares sense and E_y is the error vector. For the data shown below, the value of the external variable was set to 0 for the off state and 1 to the on state. Substituting scores and loadings for $\hat{X}$ gives:

$$y = [T_{rxk} * (P_{nxk})] * b + E_y \tag{25}$$

The regression vector b ($n \times 1$) can be estimated in a least squares sense by

$$b \cong [T_{rxk} * (P_{nxk})]^{-1} * y \ . \tag{26}$$

The resulting regression vector is the template, and statistics presented in previous sections can be used to evaluate the result of the template applied to an incoming signal. In the analysis to be shown, scores and loadings calculated were related to the instrument status as described above, often called Principle Components Regression, (PCR). Another commonly used multivariate method, known as Partial Least Squares (PLS), uses the external variable information (instrument status) to adjust the rotation of the loading or scores vectors at each step of the factor calculation, slightly altering the final regression vector. In either case, the resulting template can be plotted and the resulting peaks and valleys compared to the known signals. If there is more than one signal present within the data used to create the template, the template will account for the second signal orthogonally, resulting in a 'net' template for the signal of interest.

The PCR method for calculating templates was applied to the data discussed in section 2.6. For the high SNR data, templates were created for the equipment using data between data buffer index 260 and 430 with the small subsets of data removed (during the transients and when the equipment was in a transitioning between states). The resulting predicted values are shown in Figure 11. While the equipment template is sensitive to some of the transients, there are no false alarms and all the turn-on and turn-off events were detected.

4. SUMMARY AND CONCLUSIONS

This paper describes algorithms for detecting and classifying seismic and acoustic signals from unattended ground sensors in the sense that the algorithms are computationally efficient. The Fourier based technique compares the running power spectral density estimate of the data to a predetermined signature in order to determine if the desired signal has changed state. Detection thresholds adapt to the changing background level by forming an "equivalent degrees of freedom" measure that is used to form a Chi-Squared based significance test. The significance of the test (or PFA) is determined by the normal cumulative probability distribution and is easy to set. A persistence test that insures the significance test is passed at least q out of r times reduces the false alarm rate tremendously. The signatures or templates are developed either from a frequency list associated with a particular type of equipment or using statistical regression analysis. The algorithm was run on actual seismic data and shown to have a probability of classification of one for a strong SNR signal with 10 events and no false alarms over a half-hour test with 20 transients. The current method for characterizing the background level becomes significantly biased when transient events occur as seen by the LTA value plots for the seismic data. We are investigating techniques for fusing a time domain transient detector into the background level characterization process. Studies are also underway to explore the false classification statistics of the regression templates.

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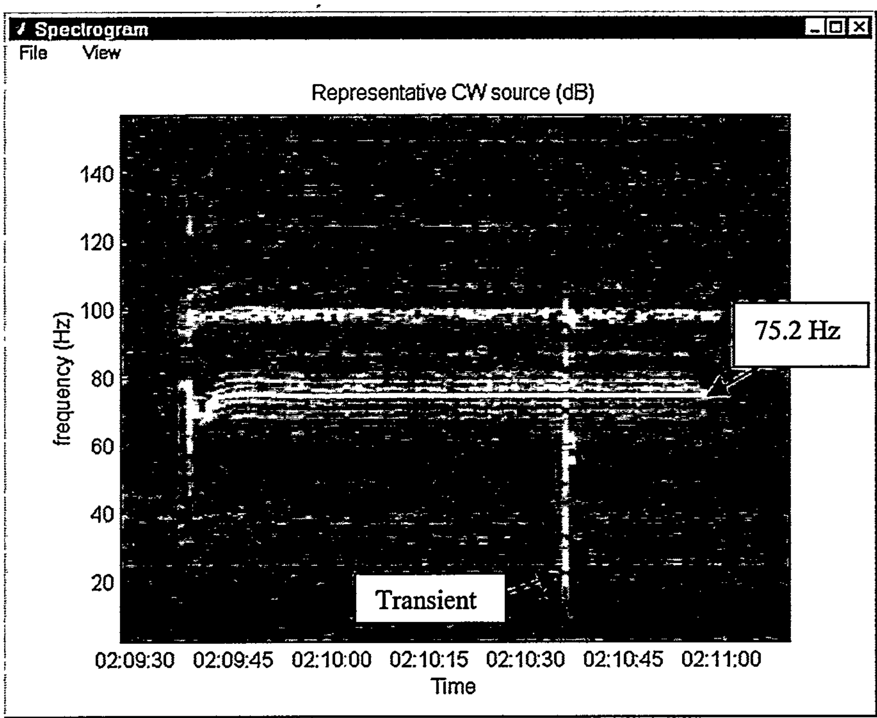
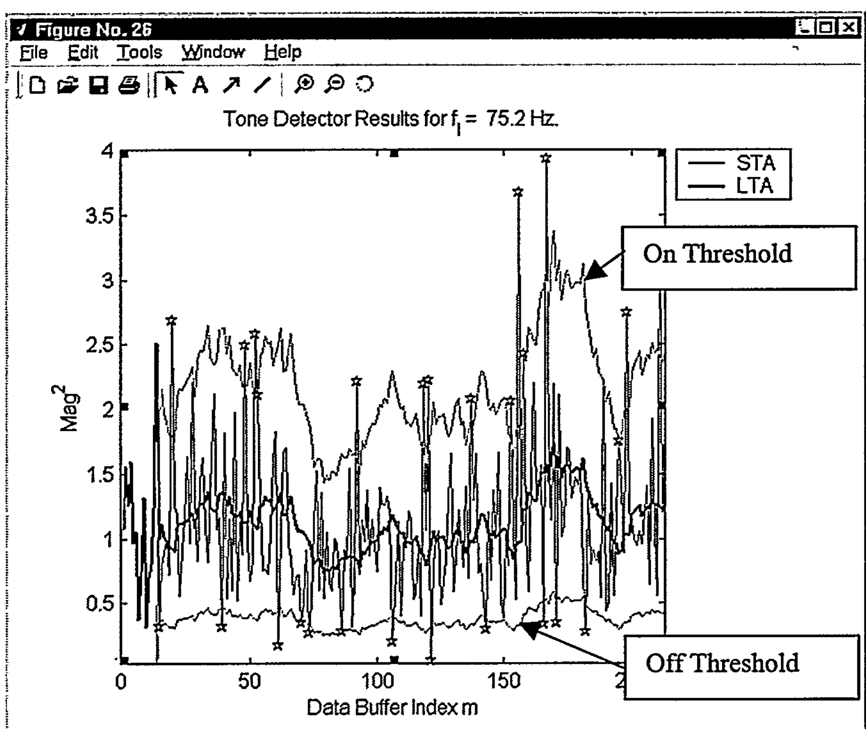
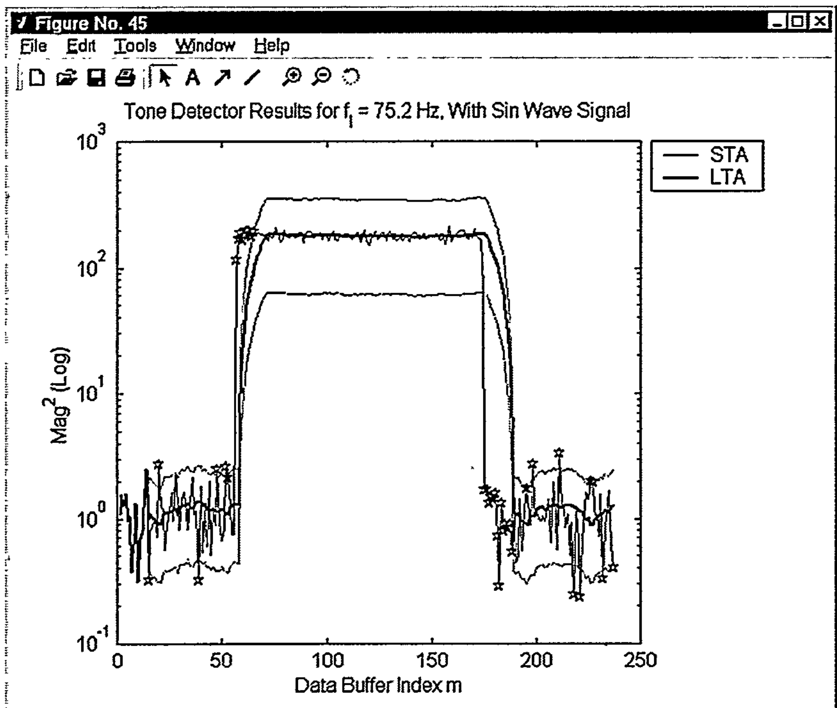


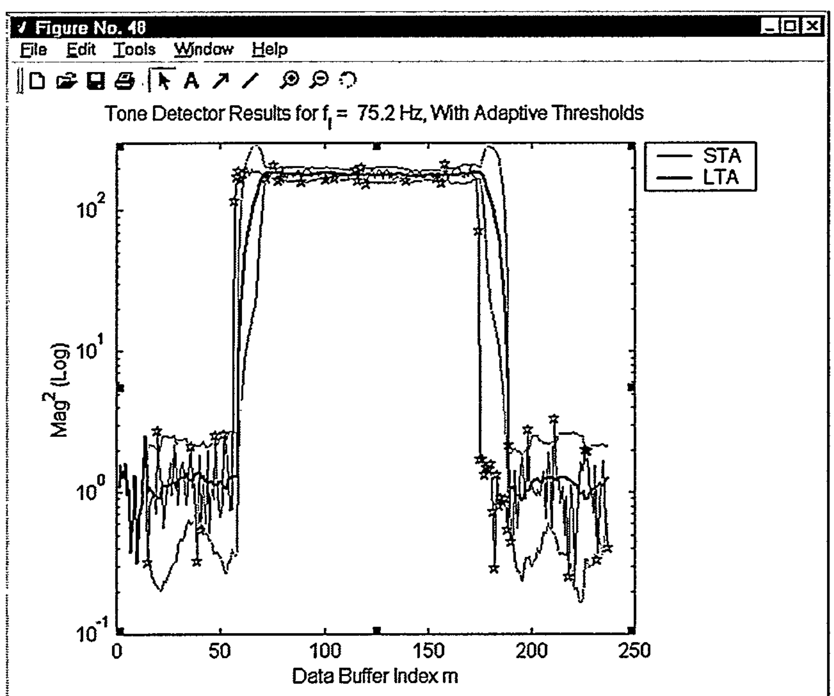
1. Figure 1 Spectrogram of representative CW source turning-on and off.



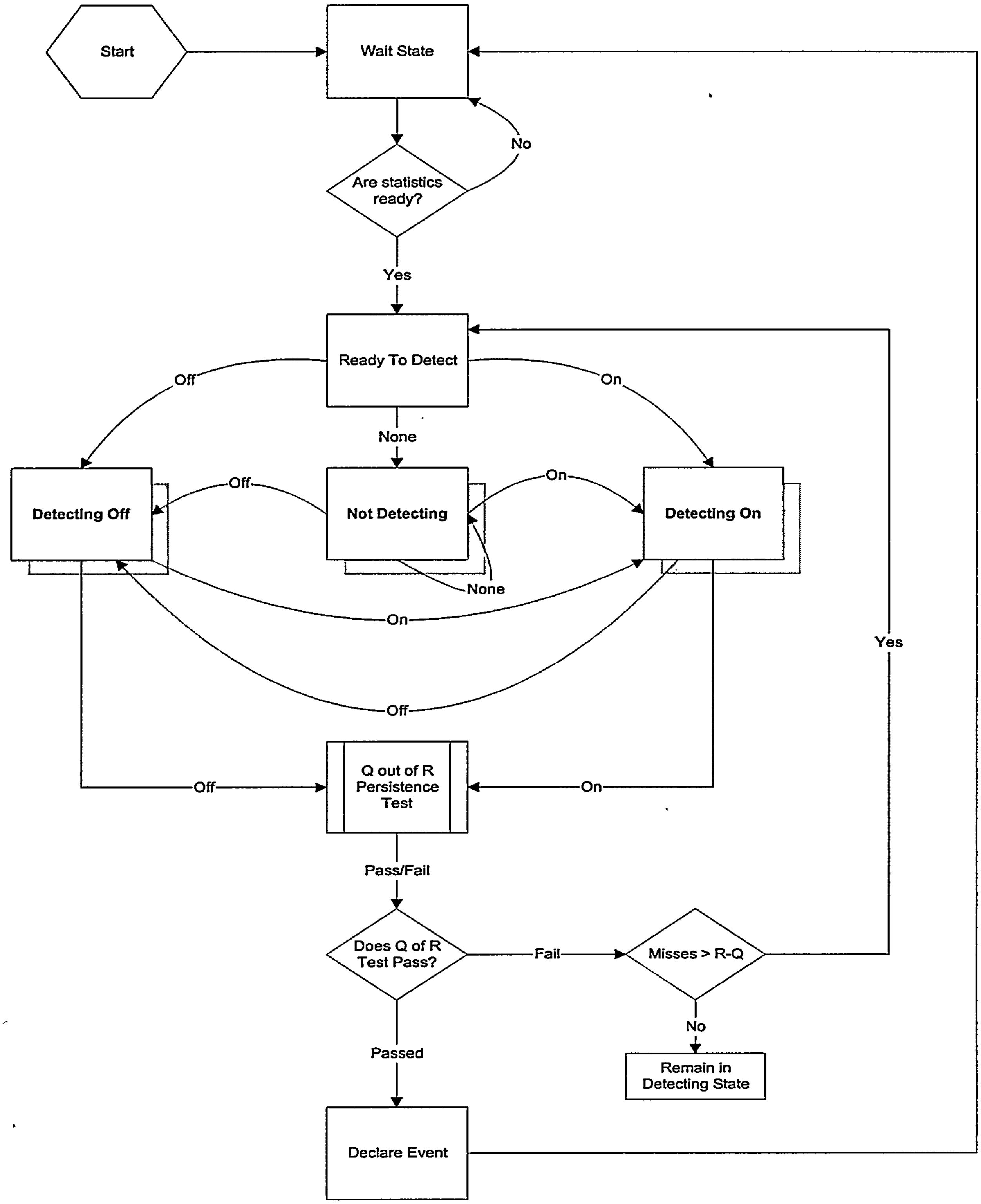
2. Figure 2 Tone detector results for random Gaussian noise. Stars indicate declared turn-on or turn-off event.



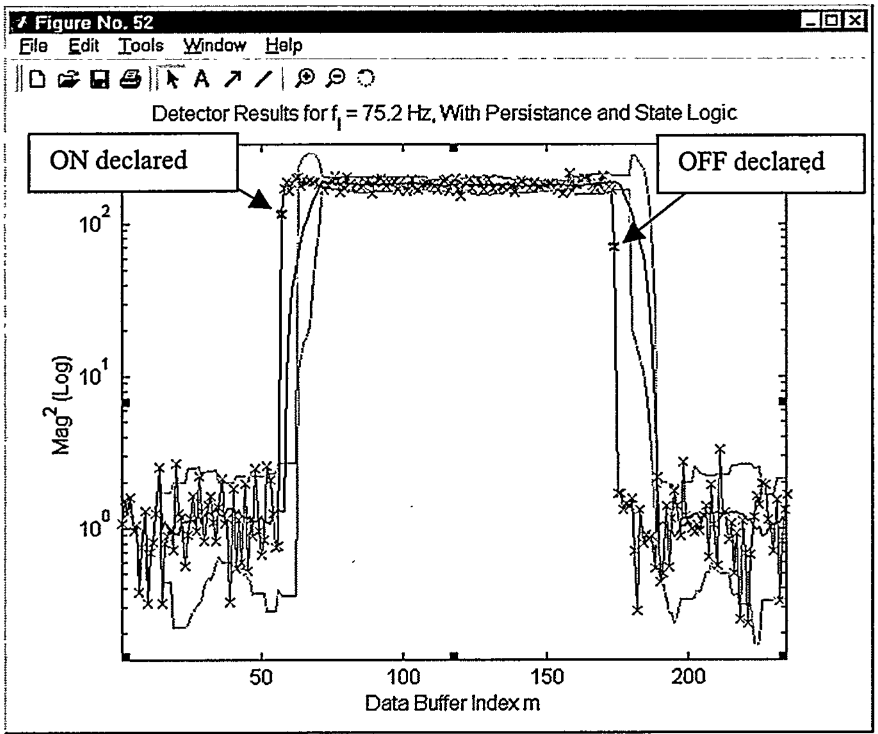
3. Figure 3 Tone detector results for sine wave and random Gaussian noise, fixed thresholds.



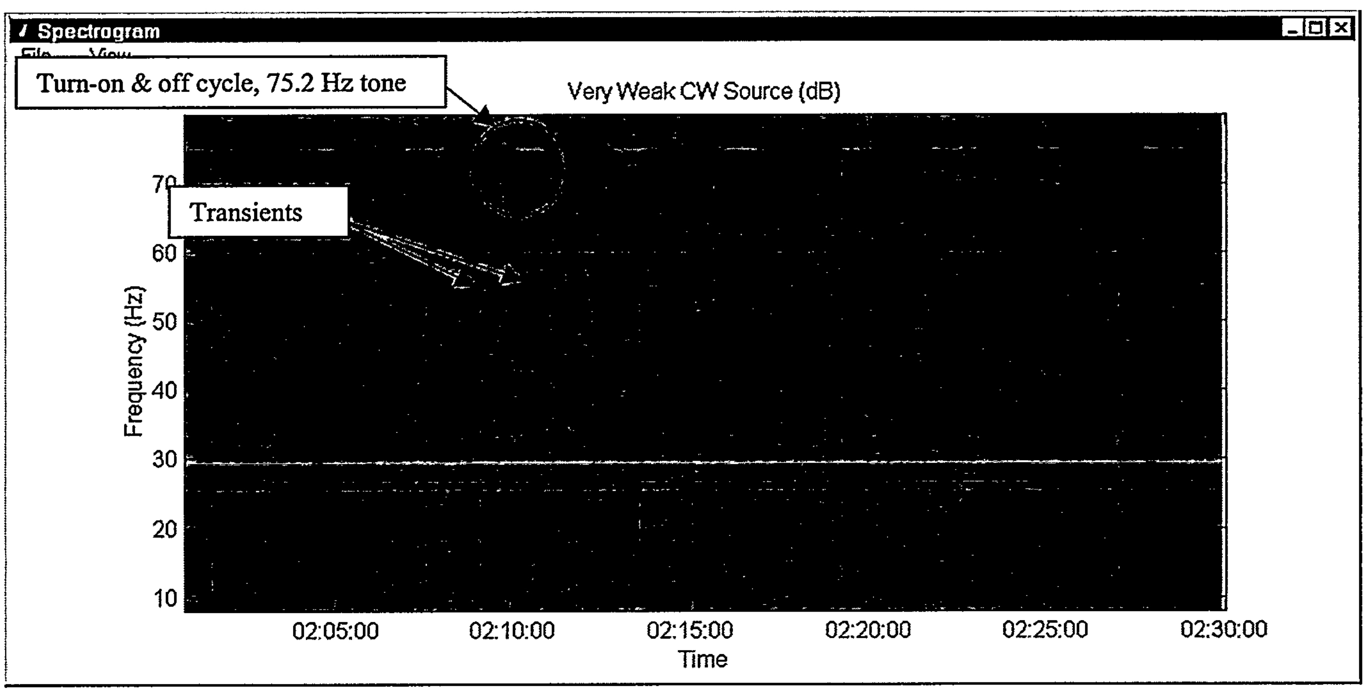
4. Figure 4 Tone detector results for sine wave and random Gaussian noise, adaptive thresholds.



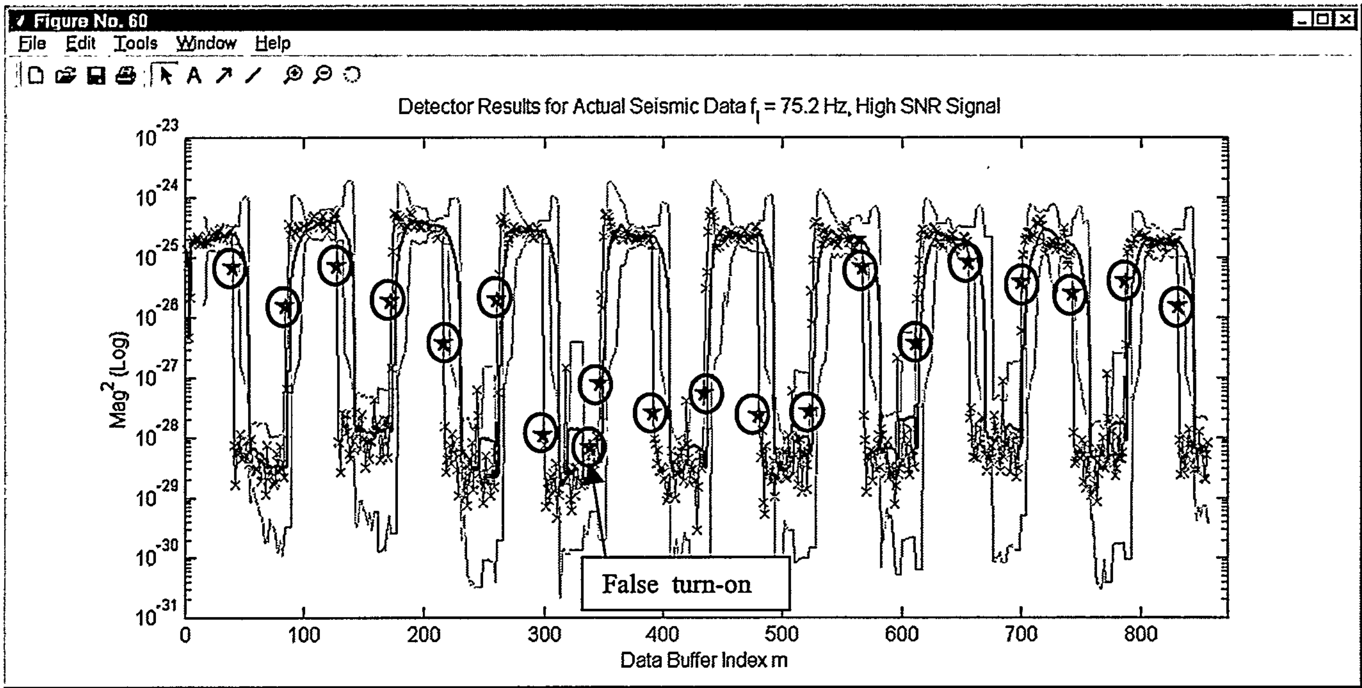
5. Figure 5 Flow diagram for state change (non-stationary process) detection and persistence test.



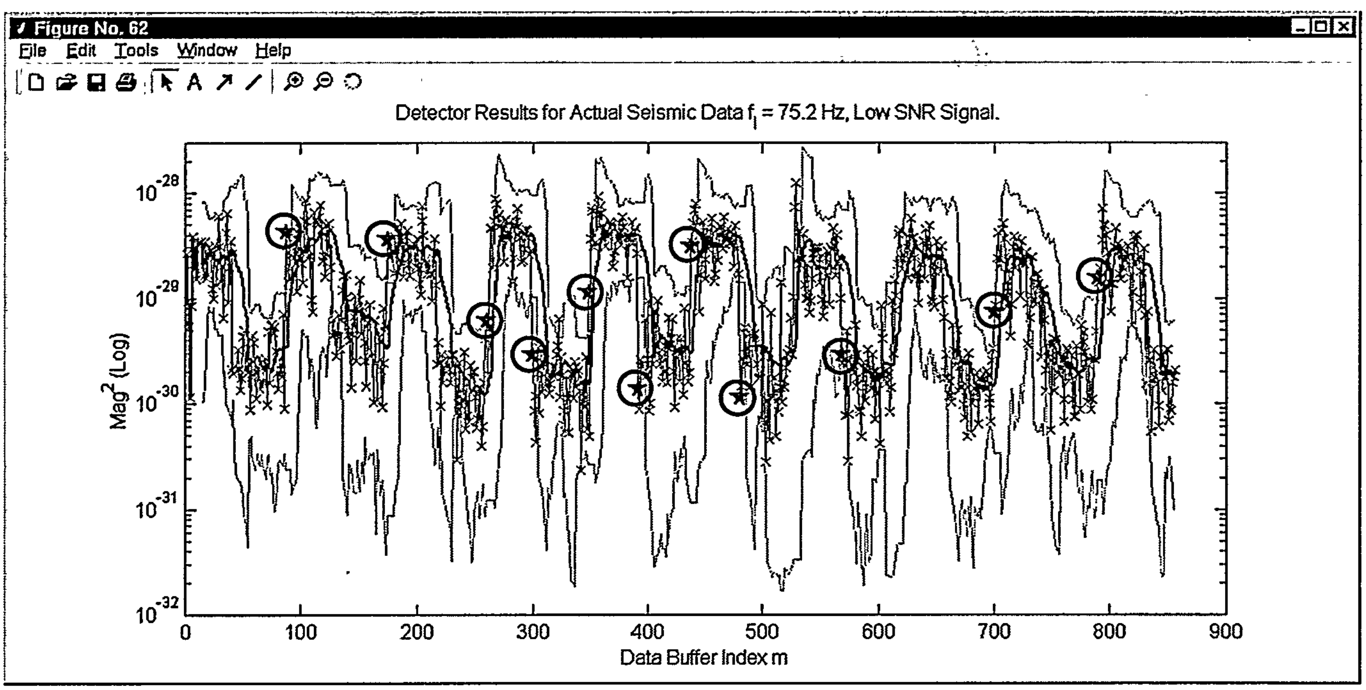
6. Figure 6 Tone detector results for sine wave with random Gaussian noise, adaptive thresholds, persistance test, and non-stationary state logic.



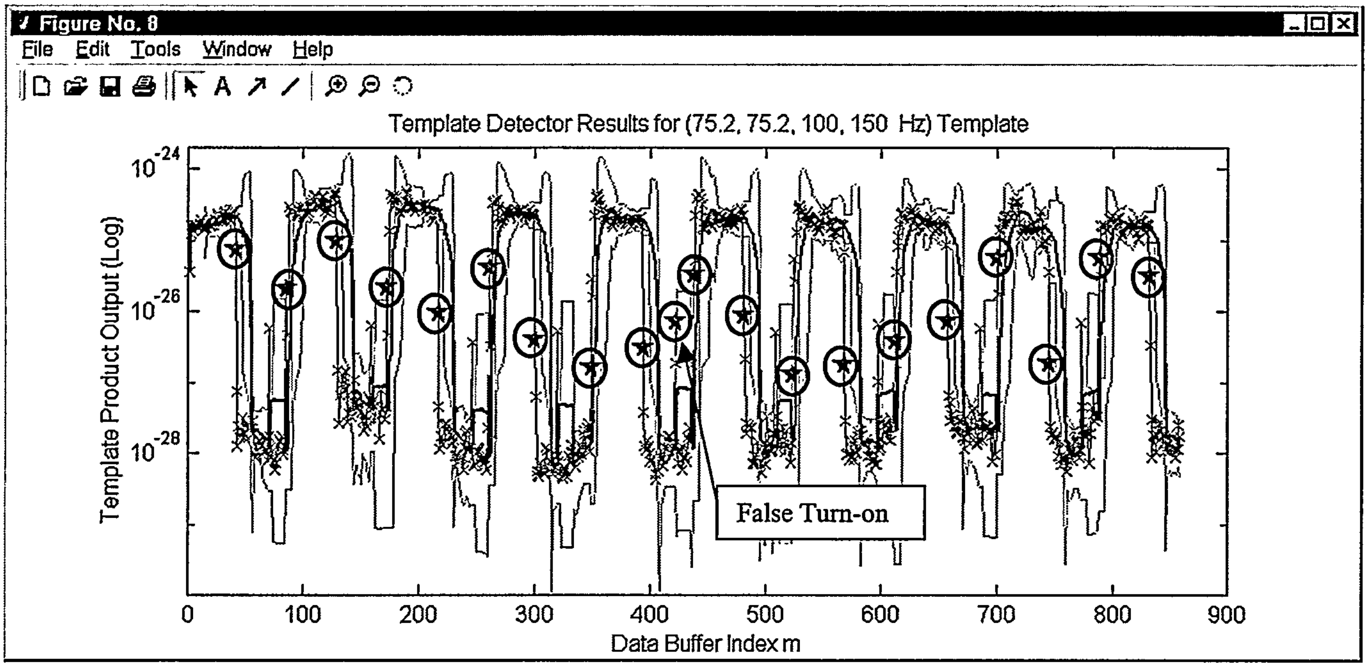
7. Figure 7 Weak CW source and transients. Ten turn-on and off events. Transient events occurred during each period the source was on and off. The event circled corresponds in time with the representative CW source shown in Figure 1.



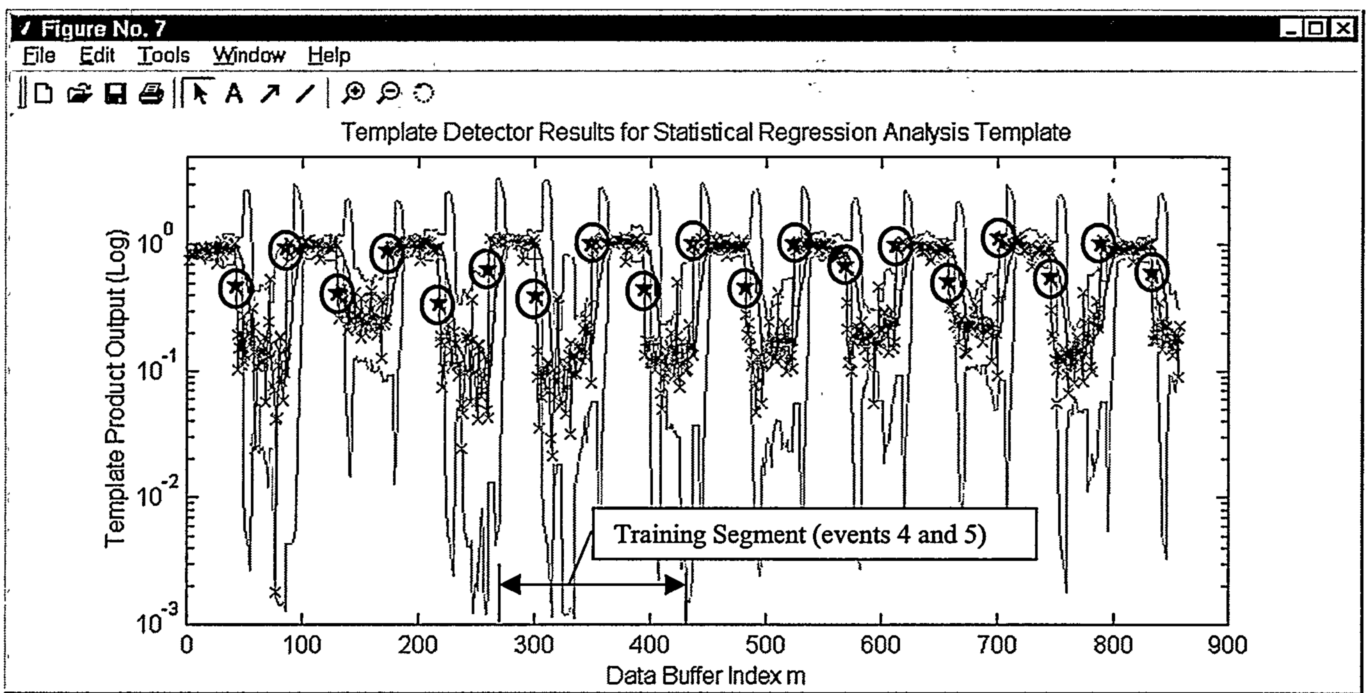
8. Figure 8 Detector results for seismic data with CW source and transients (see Figures 1 and 7).



9. Figure 9 Detector results for seismic data with weak CW source and weak transients (see Figure 7).



10. Figure 10 Template detector results for seismic data with CW source and transients. Frequency list template using {75.2, 75.2, 100, 150 Hz}.



11. Figure 11 Template detector results for seismic data with CW source and transients. Template derived from statistical regression analysis using the forth and fifth events.