# AN EVALUATION OF VARIOUS CHANGE POINT DETECTION MODELS FOR RADIO TRANSMITTER IDENTIFICATION USING TURN ON TRANSIENTS

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### ABSTRACT

In this paper, three different change point detection models that can be used for radio transmitter identification using turn on transients have been evaluated. Detection errors of each algorithm have been calculated for a set of experimentally obtained transmitter turn-on transient signals and the results are presented as histograms. The ability to preserve the significant features of transient signals has been discussed versus complexity of each algorithm. It is observed that detection algorithms should be justified together with the feature extraction algorithm for a successful classification.

## 1. INTRODUCTION

Radio transmitters exhibit a unique frequency versus time turn-on characteristics until they stabilize to their operating frequency. These turn-on characteristics stem from a combination of effects such as phase locked loop systems, modulator subsystems, RF amplifiers, antenna, switch and relay characteristics. Transient state duration depends on the make and model of a transmitter and can last from a few hundred microseconds to tens of milliseconds. By capturing and analyzing these turn-on transient signals from the radio transmission data, one can identify a particular radio transmitter. The analysis and classification of radio transmitters are addressed in (Choe, Poole, and Szu, 1995) , ( Hippenstiel and Payal, 1996 ) , ( Kolakowski, 1998)  and (Shaw and Kinsner, 1996). If a transmitter identification system is coupled with a direction finding system, they will serve as a powerful tool for frequency monitoring applications.
The turn-on transient signals can be acquired from the discriminator output of a communication receiver (Toonstra and Kinsner, 1996)  . In order to record the transient data, a trigger information is required to indicate the beginning of the transient. Although the squelch trigger of the receiver can be used as a marker for this purpose, there is a delay between the actual onset of the transmitter and the trigger event. Moreover, the amount of the delay is not constant even for the same

transmitter. An analysis of the relation between the squelch trigger and the onset of the transmitter is discussed in Reference (Ureten and Serinken, 1999) .

A method for recording the transient data is to save a portion of the pre-trigger samples with the turn-on transient signal. A typical transient data obtained in this way contains ambient channel noise followed by the start of a radio transmission similar to that shown in Figure 1. The aim of the transient detection is to find the exact time when the ambient channel noise stops and the transient begins. This problem is complicated because of the non-stationary nature of the transient signal and the noise like characteristics of the turn-on transient. In this respect, the problem is to separate noise from noise having a different degree of correlation.
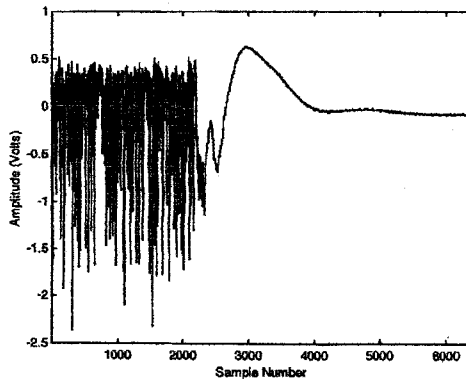


Figure 1. Typical radio transmission data showing the channel noise and the turn-on transient

The most important feature of a good transient detection algorithm is its ability to preserve the significant characteristics of the transient signal. This means that the algorithm should neither destroy the significant features by filtering nor obscure them by delaying the start of the transient.

A common approach for noise cancellation is to design an optimal filter in order to remove the noise from the data. These filtering methods work fine if there is no significant overlap between the noise spectrum and the signal spectrum. However, a typical channel noise spectrum and the transient signal spectrum totally overlap as shown in Figure 2. Therefore, any filter which is used to remove the channel noise will have a significant impact on the signal spectrum thus destroying the important characteristics of the transient signal
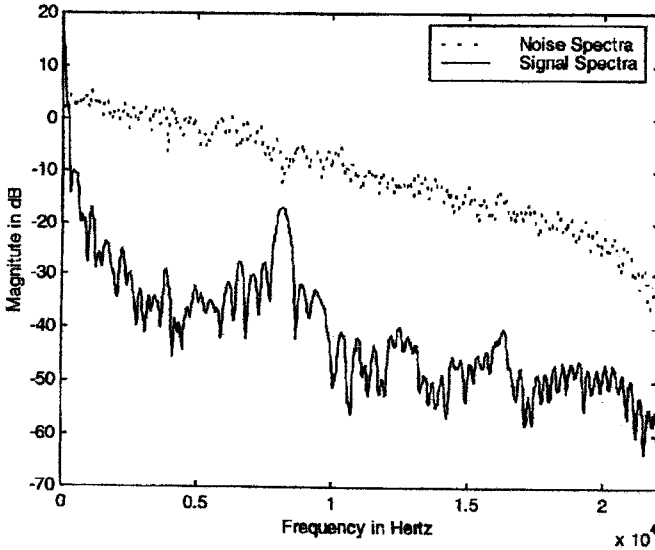
Figure 2. Overlapping noise spectrum and the transient signal spectrum

The main goal of detecting the transmitter turn-on transient signal is to find the exact time when channel noise stops and transient begins. This problem can be thought as a change point detection problem because the signal statistics abruptly change after the transition point. The most important issue with this approach is the accuracy of the estimation of the change position. An early detection may destroy the significant features of the turn-on transients by capturing some channel noise which has a wide band characteristic. On the other hand, a late detection may completely obscure the significant features because most significant characteristics are placed at the very beginning of the transient signal. An example of the effects of an early detection and late detection of the transient signal is shown in Figure 3.

Variety of signal models can be considered for the transmission data depending on the statistics that is assumed to be changing at the transition point. The chosen model has an important effect on the detection error. In this work, 3 different change models have been tested in a Bayesian framework. The detection errors are computed and presented as histograms for each model. Complexity of each algorithm is also discussed. Finally, the ability of preserving the significant features of the transient signals is evaluated.
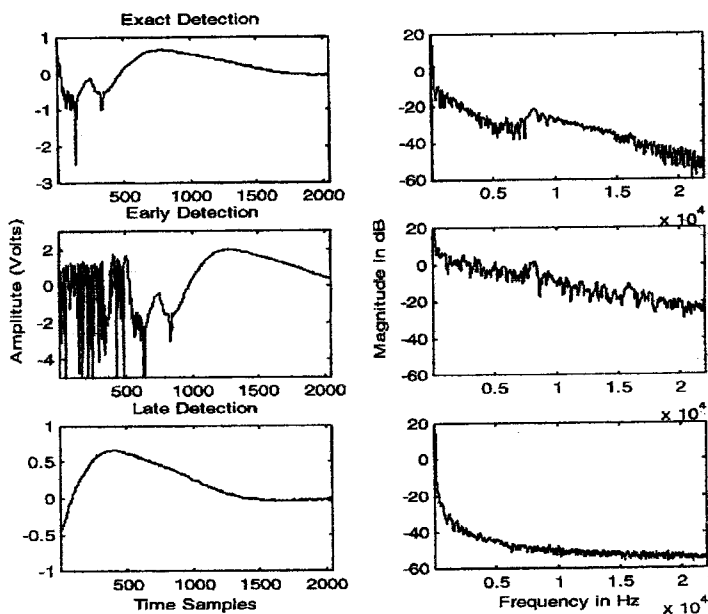
Figure 3. An example of the effect of an early and a late detection

## II. CHANGE MODELS

Three different change models have been proposed for turn-on transient detection. The first model *i)* Assumes that mean and variance of the data have abrupt changes after the transition point. The second model is *ii)* Based on the difference in the fractal dimension between the channel noise and the turn-on transient signal. The third model *iii)* Assumes that the number of zero crossing points introduce an abrupt change at the transition point. The first model is applied directly on the data without the need of a transform. The second and third models however transform the data into new features called fractal  trajectory and zero cross trajectory respectively. Additional change models may  also be proposed; such as entropy, correlation dimension or other information measures (Pawelzik and Schuster, 1987). By introducing these transformations step changes that are relatively easier to detect is aimed to be obtained.

### i)       Abrupt Changes in Mean and Variance
The radio transmitter data is modeled as:

$$di = \begin{cases} \mu_1 + u_i & 1 < i \le m \\ \mu_2 + v_i & m+1 < i < N \end{cases} \tag{1}$$

where

$$u \sim N(0,\sigma_1^2), \, p(u) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{u^2}{2\sigma_1^2}} \text{ and } v \sim N(0,\sigma_2^2), \, p(v) = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{v^2}{2\sigma_2^2}} \tag{2}$$

are the mean values and the variances before and after the change point respectively, N is the number of data points and $m$ is the change point, $u$ and $v$ are assumed to be Gaussian for the sake of mathematical simplicity. By choosing this model, it is assumed that the mean and variance of the signal change abruptly after the change point $m$. If model parameters are not known, uniform priors may be set. These uninformative priors are updated using the likelihood function which is a measure of realizing the data given the signal model and parameters. Change point m is the only parameter of interest. Other parameters are called "nuisance" parameters and they can be integrated out by marginalization .

Marginalization integrals can be carried out analytically because of the Gaussian assumption. In other cases, where the Gaussian assumption is not acceptable some numerical means, such as Markov Chain Monte Carlo (MSMC), would be needed to solve the marginalization integrals (Hastings, 1972) .

The derivation of the posteriori probability of the change point in a Bayesian framework can be found in (Ureten and Serinken, 1999) and it is given as follows:

$$p(\{m\} \mid D,M) \propto \frac{1}{\sqrt{m(N-m)}} \Gamma(\frac{m-1}{2}) \Gamma(\frac{N-m-1}{2}) \left[ \sum_{i=1}^{m} d_i^2 - \frac{1}{m}(\sum_{i=1}^{m} d_i^2) \right]^{\frac{1-m}{2}}$$

$$\left[ \sum_{i=m+1}^{N} d_i^2 - \frac{1}{N-m}(\sum_{i=m+1}^{N} d_i)^2 \right]^{\frac{1+m-N}{2}} \tag{3}$$

and M is the specific choice of the signal model.

## ii)     Abrupt Changes in the Fractal Dimension

Fractals refer to objects that are self-similar. The fractal dimension, D can be interpreted as the "degree of irregularity" of a fractal. A non-stationary signal, such as a transient, is not a pure fractal because its fractality changes with time. Multifractality deals with signals or objects that have varying local fractal dimensions. To calculate the local fractal dimensions of a signal, a sliding rectangular window is used whereby the fractal dimension is determined for successive portions of the signal. In this study, Higuchi's method (Higuchi, 1988) is

used for calculating the fractal dimension of a signal. Higuchi defines the length of the curves constructed from a given time series $X(1)$, $X(2)$, ..., $X(N)$ as follows:

$$L_n(k) = \{ ( \sum_{i=1}^{[(N-n)/k]} |X(n+ik) - X(n+(i-1).k)|) \frac{N-1}{[(N-n)/k]k} \}/k \qquad (4)$$

where [] denotes the integer part of the number, | | denotes the absolute value, $n$ is the initial time and $k$ is the interval time. $k$ determines the number of subset time series constructed from the original time sequence while m is the starting point of each subset. If $L_n(k)$ is plotted against $k$ on a log-log scale, the data should fall on a straight line as $k$ varies from $N$ to zero. A straight line is fitted according to the least-square procedure. The slope of this line is an estimation of the fractal dimension D and it is in the range of 1.0<D<2.0. The typical values for D are 1.0 for a highly periodic and well-behaved function such as a sine wave and merges 2.0 for completely uncorrelated white noise.

The fractal trajectory data is modeled as:

$$d_i = \begin{cases} f_n + u_i, & \text{if } 1 < i < m \\ f_t + u_i, & \text{if } m+1 < i < N \end{cases} \qquad (5)$$

where $f_n$ and $f_t$ are the fractal dimensions of the noise and transient signal respectively. N is the number of data points on the fractal trajectory, $m$ is the change point and $u$ is a zero mean Gaussian process. By choosing this approach, it is assumed that there is a step change in fractal trajectory after the transition point. Derivation of the formula for a posteriori probability density of a simple step change detector can be found in (Ruanaidh and Fitzgerald, 1996 ) and it is given as follows:

$$p(\{m\} | d, I) \alpha \frac{1}{\sqrt{m(N-m)}} \left[ \sum_{i=1}^{N} d_i^2 - \frac{1}{m}(\sum_{i=1}^{m} d_i)^2 - \frac{1}{N-m}(\sum_{i=m+1}^{N} d_i)^2 \right]^{-(\frac{N-2}{2})} \qquad (6)$$

where $I$ denotes the specific choice of the signal model. Using Equation 6, each point on the fractal trajectory is tested whether it is a change point or not. Please note that there is no need to know the probable step position or step size.

### iii)     Abrupt Change in the Number of Zero Crossings

A zero cross trajectory of the data is obtained in the same way as the fractal trajectory. The zero cross trajectory can be modeled as:

$$d_i = \begin{cases} z_n + u_i, & 1 < i < m \text{ ise} \\ z_t + u_i, & m+1 < i < N \text{ ise} \end{cases} \qquad (7)$$

where $z_n$ and $z_t$ are the number of zero crossings of the noise and transmitter signal respectively, N is the number of data points on the zero cross trajectory, $m$ is the change point and $u$ is a zero mean Gaussian process. By choosing this model, it is assumed that there is a step change in the number of zero crossings after the transition point is encountered. Equation 6 is then used in order to detect the step change in zero cross trajectory as mentioned in the second model, Abrupt Changes in the Fractal Dimension.

## III. APPLICATON EXAMPLES

Application of the first model on transmission data differs from the second and third as the first model is not involved with any transformation and is applied directly onto the data. A search window is determined by using squelch trigger information for the first model. 300 sample rectangular window with offset by 800 samples prior to the start of the squelch trigger is created. Each sample in this search area is tested as a potential change point using Equation 3.

Time series representation of discriminator signal inside the search window and the corresponding posteriori probability density of change point are shown in Figure 4. This figure shows that probability density has a peak around the change point. The inferred start of the transition point is the maximum a posteriori (MAP) estimator.
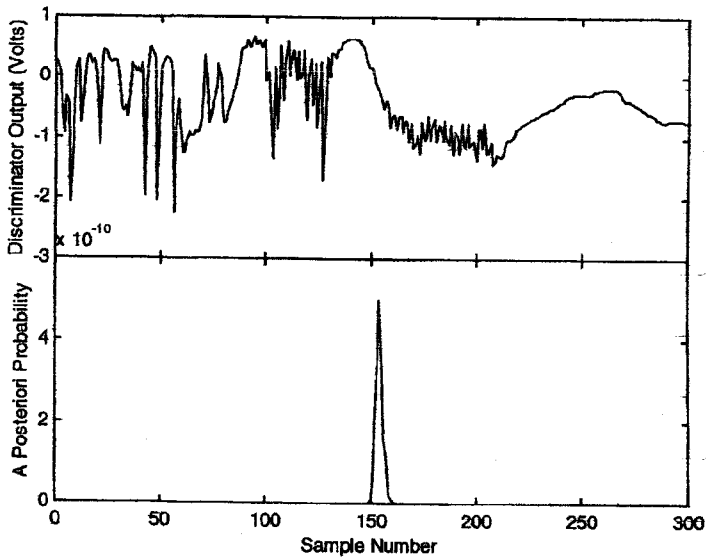


Figure 4. Discriminator output inside the search window and corresponding *a posteriori* probability of the change point

For the second model, a sliding rectangular window is applied to the sampled discriminator data. A window size and spacing of 64 samples were determined experimentally. Fractal dimension of each sliding window was calculated. This resulted in a 100 sample long fractal trajectory for a 6400 sample long transmission data. In order to locate the change point in the trajectory, a simple Bayesian step change detector was used. This method tests each point in the fractal trajectory as a potential change point using Equation 6. The inferred position of the change point is the MAP estimate of the a posteriori.

Fractal trajectory of a transmission signal containing channel noise followed by a turn-on transient signal and corresponding a posteriori probability of the change point are shown in Figure 5.
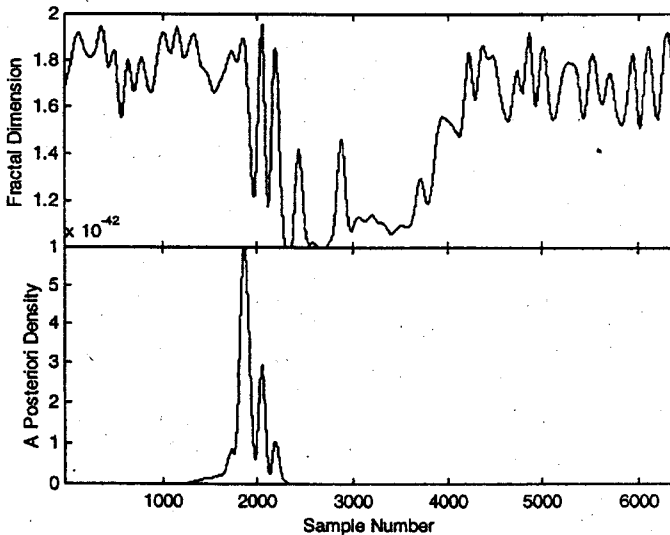


Figure 5. Fractal trajectory of a transmission signal including channel noise followed by a turn-on transient signal and corresponding *a posteriori* probability density of the change point

The third model is very similar to the second with one exception that the number of zero crossing points of the sliding windows are calculated rather than the fractal dimension. The change in the number of zero crossings is then estimated using the Bayesian step change detector.
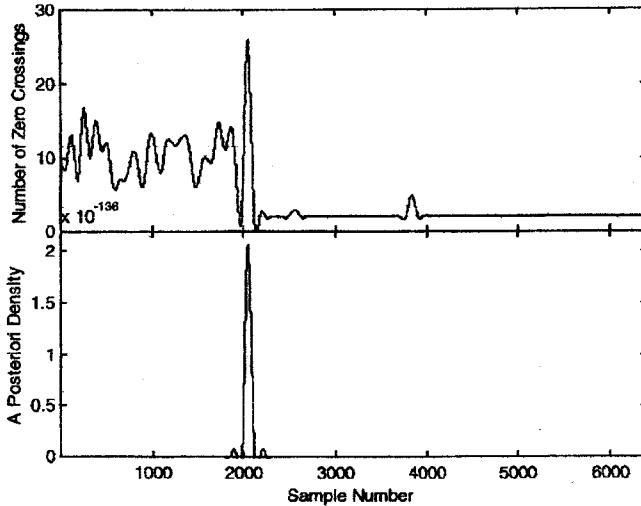
Figure 6. Zero cross trajectory of a radio transmission signal and corresponding *a posteriori* probability of change point

## IV. EXPERIMENTAL RESULTS

Each model has been tested with the data collected from 8 different makes of 20 VHF transmitters with 5 transients per unit resulting 100 transient signal in total. Data is obtained from the discriminator output of a generic communications receiver and sampled at a rate of 44.1 kHz.

Detection errors which are the differences between the visually observed values and the estimated values were calculated for each model. The histograms of the detection errors for each model are presented in Figure 7.

The first, second and third models have a mean error of –431, -229 and –288 samples respectively. A negative error indicates the delay. It is clear from the results that second model based on the fractality of data gives better results.
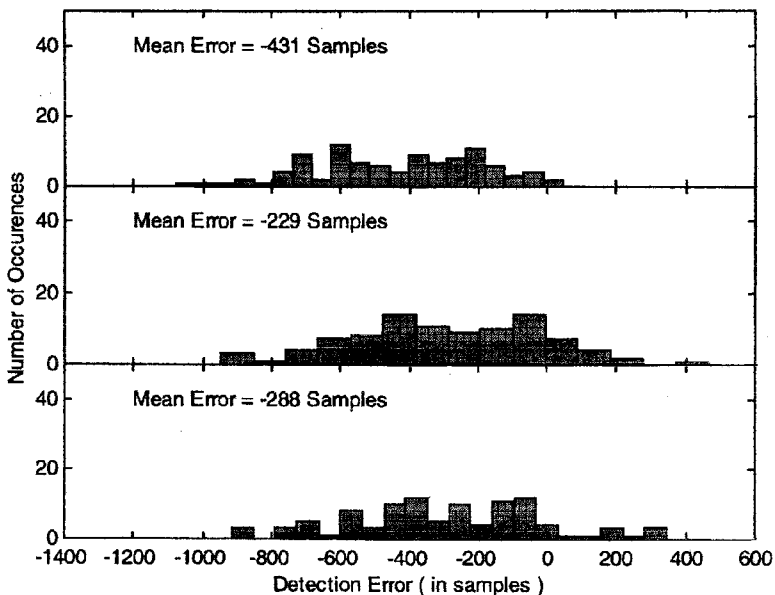
Figure 7. Detection errors for three models. Top to bottom: Changes in mean and variance, change in fractal dimension, change in the number of zero crossing points

Figure 7 illustrates that all three models have delay in the detection of transient signals. The assumption that both mean and variance change as opposed to variance change only allows an analytical solution within a Beyesian framework for the first model. However the first model fails for some classes of transmitter transients for which the change in the mean occurs considerably later than the variance thus delaying the detection of the start of the transient. Although combined models have delay in detecting the start of transients, this delay is mainly due to the noise like characteristics of some transients of which fractal dimension and number of zero crossings are very close to the channel noise.

The preservation of the characteristic features of the turn-on transients is an important feature in the detection of transmitter identity. However change point detection and transmitter identification should be performed jointly in order to asses the model success. The performance of each algorithm has been tested by using heuristic features of five selected transmitters experimentally. These features were obtained by using a high resolution power spectrum estimation called multi-taper method (Choe, Poole and Szu, 1995). Turn-on transient signals were separated from the channel noise by a human observer. Spectrum of these signals were then

computed using the multi-taper approach. Characteristic peaks of these spectrums were determined visually. Transmissions were made from each of these five transmitters and turn-on transient signals from these transmissions were detected using proposed models in conjunction with multi-taper method. The spectra of these signals were then calculated. It was checked whether the visually determined characteristics were contained in these spectrums. The number of successful events were counted in a set of 100 transmissions. The results are given in Table 1.

Table 1. The number of successful events

| Change Model | Motorola SHA-274 Serial#144 | Motorola SHA-274 Serial#209 | Kenwood TH25AT Serial #9080840 | Kenwood TH21AT Serial #5056533 | Motorola MT500 Serial#5000 |
|---|---|---|---|---|---|
| I | 94 | 95 | x | 99 | 98 |
| II | 94 | 93 | 90 | 100 | 96 |
| III | 96 | 95 | 99 | 99 | 100 |

x: Misses the characteristic feature
*I: First Change Model (Change in the mean and variance)*
*II: Second Change Model (Change in Fractal Dimension)*
*III: Third Change Model (Change in the number of zero crossing points)*

## V. CONCLUSIONS

Three different change point detection models for transmitter identification using turn-on transient were tested. In addition a high resolution power spectrum estimation called multi-taper method is employed in conjunction with these models in order to identify the transmitter identities. Although the fractal change model produced better results for change point detection, zero crossing model preserves the significant features of the transient signal and it is computationally more efficient. This result indicates that the overall performance of the transmitter identification algorithm depends on both feature extraction and change point detection.

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