BAYESIAN DETECTION OF RADIO TRANSMITTER TURN-ON TRANSIENTS

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ABSTRACT

This paper describes an implementation of Bayesian change point detection for extracting transients captured from radio transmitter transmissions. When a radio transmitter is activated, it goes through a relatively short transient phase during which the signals generated by the unit have characteristics that can be unique. If these turn-on transients can be separated, they can be analyzed to identify the radio transmitter.

In this study, radio transmissions from 30 different radio transmitters were analyzed by using an experimental set-up. The estimated transient starting point is compared to the visually observed starting point. The probabilistic automatic segmentation algorithm has been found to be effective in detecting turn-on transients in the presence of noise.

1. INTRODUCTION

When a radio transmitter is engaged for transmission after the push-to-talk button is pressed, it is observed that its transient behavior, i.e., RF power and carrier frequency changing towards their nominal values, can exhibit unique features. These transients have been attributed to a variety of sources such as phase-lock-loop systems, modulator subsystems, RF amplifiers, antenna characteristics, switch and relay characteristics. Transient state duration depends on the make and model of a transmitter and can last from a few microseconds to tens of milliseconds. The analysis and classification of radio transmitters have been reported in [1]-[8].

The transient signals were acquired from the discriminator output of a communication receiver. Recording of transient data requires triggering information to indicate the beginning of the transient. The squelch signal of the receiver was used as a marker for this purpose. The problem with this approach is that there is an inherent delay between the onset of the actual transient and the trigger event. The capture system has to be continuously recording the received signal so that when a trigger is detected a portion of the pre-trigger samples is saved with the transient data.

The recorded transient signal contains ambient channel noise, which is followed by the start of a radio transmission similar to that shown in Figure 1. Due to the non-stationary nature of transmitter transients, though, the task of separating the transient from the channel noise is very difficult. It involves finding the exact time when the ambient channel noise, which is correlated to some unknown degree, ceases and the transient begins. However, despite being completely deterministic, many transients exhibit characteristics similar to noise due to their high degree of irregularity. Thus, to some extent, we are left with the problem of separating noise from noise with a different degree of correlation.

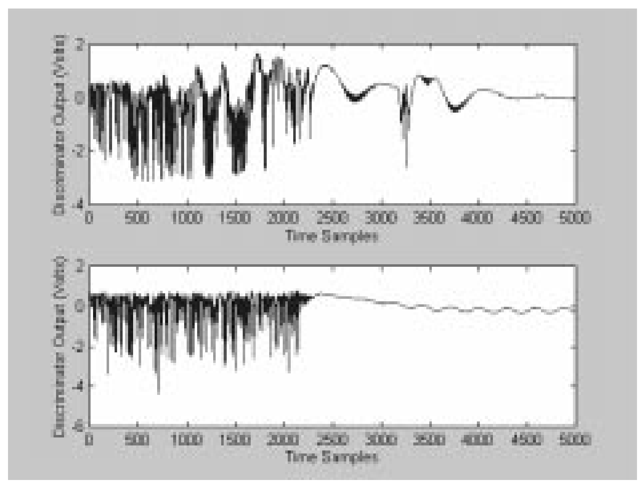

Figure 1. Transmission signals from two different radio transmitters showing the channel noise and the turn-on transients

Detecting the turn-on transient is then reduced to the determination of the transition point from noise to signal. This problem can be thought of as a change point detection problem because the signal statistics abruptly change after the transition point. The problem of detecting and estimating the location of change points in data is fundamental to many areas of data analysis such as quality control [9], navigation system monitoring [10], seismic data processing [11], speech signal segmentation [12] and edge detection in images [13]-[14].

Although there is a rough indication of the position of the change point from the squelch output of the receiver, more accurate determination of this point is required since it affects the performance of the transmitter identification system.

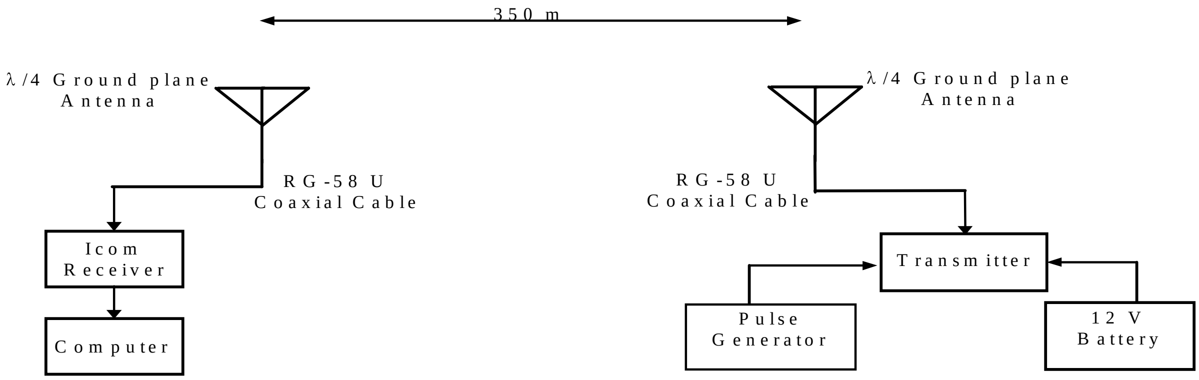

Figure 2. Experimental setup used for data acquisition.

2. EXPERIMENTAL SETUP

Radio transmission data used in this work were acquired by using the experimental setup shown in Figure 2. This setup was composed of two parts: the transmitter and the receiver.

The transmitters used in this experiment were installed in a vehicle approximately 350 meters away from the receiving location. The need for a human operator to key these transmitters was eliminated by using a pulse generator and relay arrangement to automatically control the push-to-talk lines of each radio. Using this set-up, test transmissions approximately 0.5 seconds in duration were repeated at 1 second intervals, i.e., the transmitter on for 0.5 seconds and then off for the next 0.5 seconds. A list of the transmitters used in this work is given in Table 1.

At the receiving location, a ICOM R-7100 receiver was used which was modified to access the squelch and discriminator signals. Both the discriminator output and the squelch signal of the receiver were recorded on a digital audio tape (DAT). The recordings from the DAT recorder were later digitized by a 16-bit personal computer sound card at a sampling rate of 44100 samples/sec.

Table 1. Transmitters used in the experiment.

Make	**Model**	**Output Power (W)**
Force	CMH350	35
Icom	IC251A	30
Motorola	MCX100	27
Motorola	MT500	5
Motorola	SHA-274	5
Motorola	HT1000	4.8
Motorola	Visar	4.0
Kenwood	TH25AT	0.1
Yeasu	FT208R	0.8

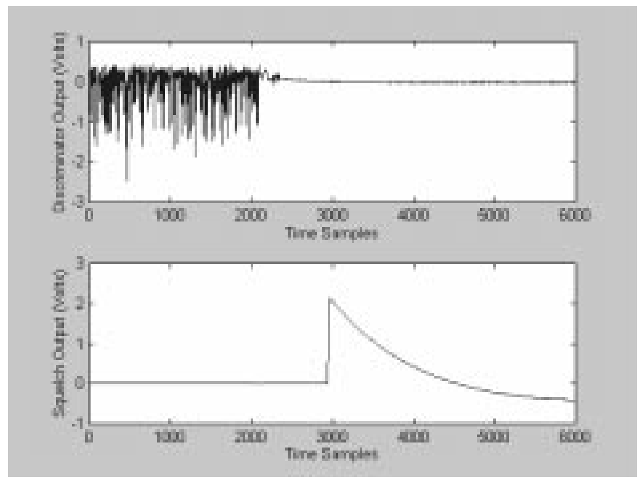

Figure 3. Digitized waveforms from the receiver. Top trace is the discriminator output, bottom trace is the squelch signal.

Figure 3 shows the digitized waveforms from the receiver. The top trace is the discriminator output and the bottom trace is the recorded squelch signal, which is a binary signal. The DAT recorder and analog to digital conversion subsystem have a combined low frequency cut-off of 10 Hz, and the shape of the recorded squelch waveform is due to the bandwidth of the recording and digitization equipment.

In order to analyze the relationship between the trigger event and the onset of the transient, 100 transmissions from each of 30 different transmitters were made. For each of these transmissions, the turn-on transient starting point was determined visually. The distance between the squelch trigger and the visually determined turn-on transient starting point was calculated. The histogram of the distance between trigger signal and the onset of the transmitter is plotted for all transmissions in Figure 4. This plot shows that, on average, the squelch trigger occurs approximately 800 samples after the onset of the transient. But the standard deviation of this distribution is sufficiently high that an accurate determination of the starting point of the transient is required.

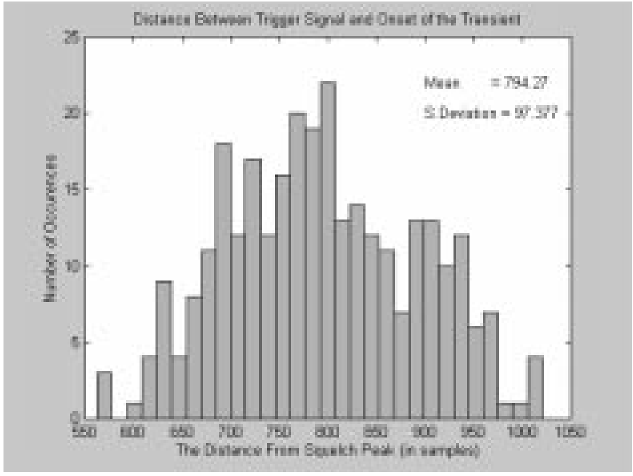

Figure 4. Histogram showing the relation between the onset of the transmitter and the squelch trigger

3. METHOD

The transmission data can be modeled as:

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

where

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

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

μ_1, μ_2, σ_1^2, σ_2^2 are mean values and 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. In choosing this model, we assume that the mean and the variance of the signal change abruptly after the change point m.

Derivation of the formula for the *a posteriori* probability of a simple step change point detector can be found in [15]. The same mathematical manipulations with minor modifications are used in the detection of the turn-on transient.

The likelihood function is the probability of realizing the data given the value of the parameters, the signal model and the noise statistics. By denoting the specific choice of signal model and noise statistics as M and signal model parameters and noise parameters as Φ, we may write:

$$p(d|\Phi, M) = L(\Phi; d)$$

where $\Phi = \{\mu_1\, \mu_2\, \sigma_1\, \sigma_2\ m\}$ in our case. The data are assumed to consist of the signal with added independent identically distributed (i.i.d.) noise with different statistics in each segment. In this case the likelihood function takes a particularly simple form and is identical to the joint density of the residuals that can be written as:

$$L(\Phi; d) = p(d|\{\mu_1\, \mu_2\, \sigma_1\, \sigma_2\, m\},\ M) = p(e_i) = \prod_{i=1}^{N} p(d_i)$$

$$= (2\pi\sigma_1^2)^{-N/2}(2\pi\sigma_2^2)^{(m-N)/2}\, e^{-\frac{1}{2\sigma_1^2}\sum_{i=1}^{m}(d_i-\mu_1)^2}\ e^{-\frac{1}{2\sigma_2^2}\sum_{i=m+1}^{N}(d_i-\mu_2)^2}$$

The Bayesian approach relies on Bayes' theorem for describing the learning process, by which prior information is updated in the light of new data as given by:

$$p(\Phi|d, M) = \frac{p(\Phi|M)\, p(d|\Phi, M)}{p(d|M)}$$

where $p(\Phi|M)$ is the *a priori* probability density that contains all knowledge of the values of the parameter prior to observing the data. $p(d|M)$ is called the Bayesian evidence and it is a normalizing factor. The term $p(\Phi|d, M)$ summarizes the state of knowledge about the values of the parameters after the data are observed.

The *a priori* probabilities of the location parameters like mean and change point can be written as below [16]:

$$p(\mu_1|\, M) = k_1\,,\ p(\mu_2|\, M) = k_2\,,\ p(m|\, M) = k_3$$

For the scale parameters (like variance, which is a measure of scale or magnitude as its name suggests), the *a priori* density is given due [17]:

$$p(\sigma_1|M) = 1/\sigma_1,\ \ p(\sigma_2|M) = 1/\sigma_2$$

After the marginalization of the nuisance parameters (i.e., parameters that are of no interest), the *a posteriori* probability of the change point can be found as:

$$p(\{m\}|d, M) \propto \frac{1}{\sqrt{m(N-m)}}\Gamma(\frac{m-1}{2})\Gamma(\frac{N-m-1}{2})S_1 S_2$$

where $S_1 = \left[\sum_{i=1}^{m} d_i^2 - \frac{1}{m}(\sum_{i=1}^{m} d_i^2)\right]^{\frac{1-m}{2}}$ and

$$S_2 = \left[\sum_{i=m+1}^{N} d_i^2 - \frac{1}{N-m}(\sum_{i=m+1}^{N} d_i)^2\right]^{\frac{1+m-N}{2}}.$$

4. RESULTS

Although the squelch trigger signal does not give a very good estimate for the change point, it provides a window in which to search for the change point. A 200 sample wide rectangular window that is offset by 800 samples prior to the start of the squelch trigger was created which defines the span of the search area. The method is to test each point in the time series as a potential change point using the expression p({m}|d,M).

As an example; the time series representation of discriminator signal inside the search window and the corresponding probability density is given in Figure 5. This figure shows that probability density has a peak around the change point. The inferred start of the transient position, corresponding to the maximum *a posteriori* probability density, is sample=115.

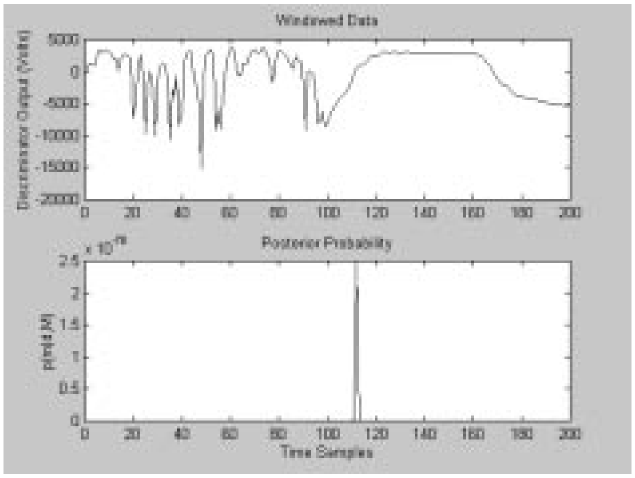

Figure 5. Windowed discriminator samples and calculated *a posteriori* probability density.

The resulting histogram of the detection error, which is the difference between the visually observed value and the estimated value, is plotted in Figure 6. This histogram shows that the mean error is about 10 samples and the standard deviation of the detection error is about 30 samples. The range of this error allows detection of the transient in less than 10 samples on the average, which is approximately equal to 25 microseconds at the sampling rate of 44100 samples/sec.

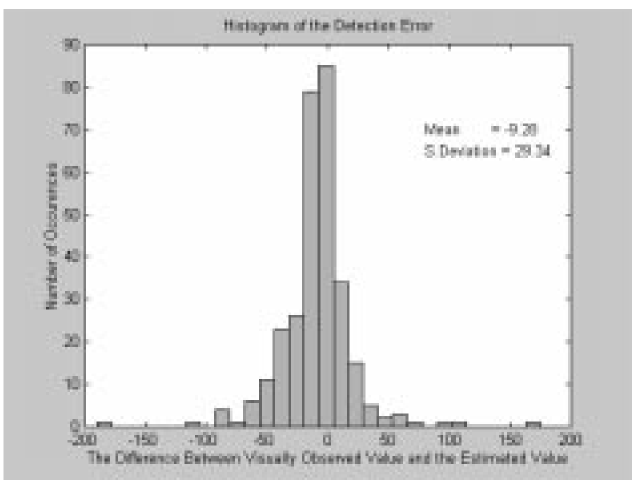

Figure 6. Histogram of the detection error.

5. DISCUSSION

In this work, a change model is used based on the assumption that the distributions before and after the change point are Gaussian and that the noise is uncorrelated. This assumption allows one to find the *a posteriori* probability of the change point analytically. In other cases, where the Gaussian assumption does not hold, we would need to solve the marginalization integrals by some numerical means such as Markov Chain Monte Carlo (MCMC) [18]-[19].

Another assumption was that there was only one change point in the transmission data. This is not always the case as illustrated in Figure 7. These multiple changes can be caused by frequency variations exceeding the transmitter and receiver IF bandwidths. The number of change points in the current data set is observed to be in the range of 1 to 3 although most of the transmitters have only one change. Assumption of more that one change point complicates the problem because the number of change points is an unknown and has to be estimated [20]-[21].

Despite the multiple change points the Bayesian detection technique was successful in estimating the start of the transients for the transmitters tested in this paper.

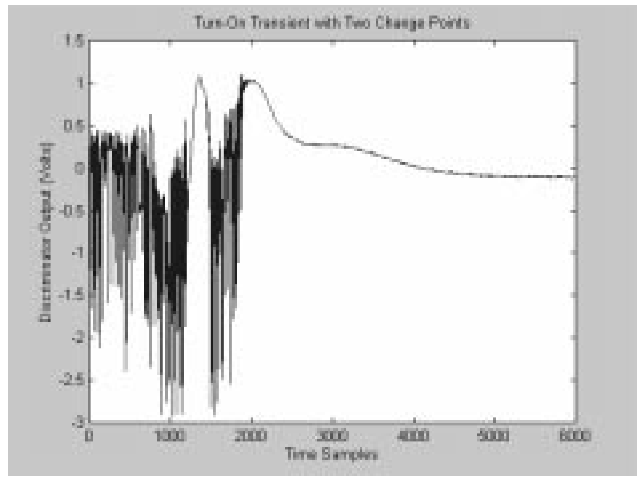

Figure 7. Turn-on transient that has more than one change point.

6. ACKNOWLEDGEMENTS

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