Signal Discrimination via Non-Gaussian Modeling with Application to Termite Detection

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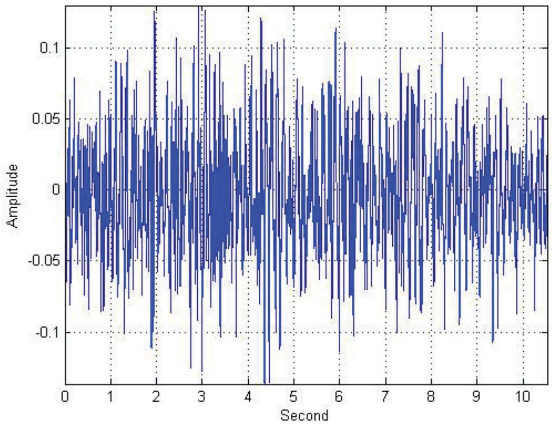
Abstract: *Detection of weak signals in a low SNR environment is generally difficult, particularly, when the underlying signal noise is not only not Gaussian distributed but essentially unknown. A good example of such a case is the detection of termite biting signals from noisy audio data recorded by a passive acoustic sensor. In this paper, we present a novel technique to discriminate weak signals in data from noise of a learned non-Gaussian distribution. The proposed method, proceeds via the framework of generalised likelihood ratio test, and consists of two fundamental steps. First, an entropy-based incremental variational Bayesian inference is adopted to learn the non-Gaussian distribution from data using a Gaussian mixture model. An information geometric mapping of the data is then carried out via the total Bregman divergence (tBD), where the ambient noise distribution is approximated by the tBD-based* l_1*-norm center of the neighboring data points over a specified time window. Experiment results show that the proposed method yields a significantly improvement in detection probability in low SNR and a robust detection performance compared with existing detection techniques.*

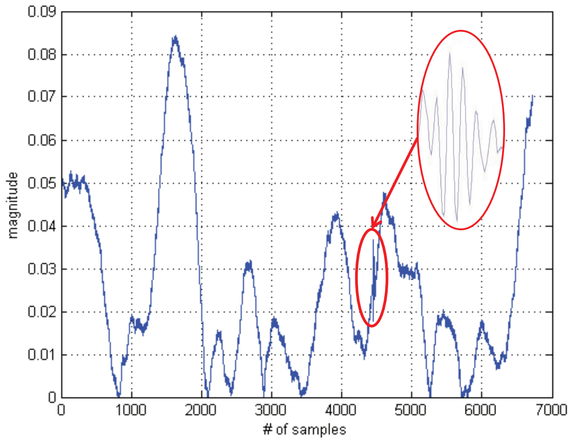
1. Introduction

In many signal detection problems, the underlying signal is corrupted by a non-stationary noise of non-Gaussian distribution. A particular instance is the detection of termites using termite biting signals recorded by a microphone in heavy ambient noise [1]. Others include medical examinations using neuroimaging data and ECG signals [2], various object detections via ultrasonic signals [3], radar return detection in clutter [4], etc. In general, this type of signal detection is non-trivial because the underlying noise distribution is unknown and the signal power spectrum is similar to that of the ambient noise. Moreover, the sampled data is often collected in low Signal-to-Noise Ratio (SNR) situations [5, 6].

In this work, we address a generic low SNR signal detection problem under additive non-Gaussian noise by considering the problem of termite signal detection from acoustic data. Termites are sometimes referred to as *white ants* because of their appearance. Termites are attracted to wood and water, and may cause massive damage to furniture, trees and properties. Early detection of the presence of termites and their localization enables timely targeting of the infestation, which is very important for both environmental protection and cost reduction compared to an comprehensive and indiscriminate program of eradication. A popular way to detect termites is to listen termite activity "noise" caused by the banging of the termite head, eating, etc using passive acoustic sensors. In practice, however, several challenges for such a detection problem arise from the fact that 1) the recorded acoustic signal suffers from a very low SNR; 2) the signal model is ill-defined; 3) and the underlying noise statistics is unknown. Fig. 1 illustrates a short recording of acoustic data alongside a termite activity signature. The presence of termites may be confirmed from recorded acoustic data by the detection of several acoustic signal patterns, though with



(a)



(b)

Figure 1: (a) Recorded Termite "noise" at sampling frequency 48000 Hz. (b) Illustration of Termite signature signal pattern.

considerable incertitude. The underlying signal detection problem falls into the category of composite hypothesis testing and can be addressed using the GLRT technique but as we will demonstrate, detection performance using the standard detection techniques are poor.

These challenging issues have been addressed in recent literature in several areas including supervised data mining, statistical data analysis and information geometry, etc. Principle Component Analysis was used in [1] to identify termite noise from acoustic data. The work in [7] analyses and models termite signals using a wavelet-based approach. Such techniques attempt to maximise the difference between the signal of interest and background noise. The problem has also been considered as a precise distribution discrimination problem using information divergence measures, for example, the approach in [8] treats the problem as Riemannian Median detection and the study in [9] addresses the outlier detection problem using the Total Bregman divergence.

In this paper we propose a new GLRT method to detect termite signals from acoustic data recorded in wood by a acoustic sensor. We assume Gaussian mixture models with unknown parameters data both in the presence and absence of termite activity signals. The method then uses an entropy-based incremental variational Bayesian (EBIVB) inference approach to learn the distribution from data as a Gaussian mixture. Then an information geometric mapping of the data is carried out using the total Bregman divergence (tBD), where the ambient noise distribution is approximated by the tBD-based l_1-norm center (known as the tBD center) of the neighboring data over a specified time window. This procedure significantly improves the SNR of the detection system as we have observed from experiments. Both simulated and real data test show that the proposed detector yields a better detection performance with a significantly improved probability of detection for low SNR case compared with existing standard detection techniques.

2. Problem

Our generic framework is that of binary decision to be made based on the observation of a finite time sequence

$$\mathbf{x} = [x_1, x_2, \dots, x_N]^T \tag{1}$$

which is assumed to be independently sampled. It is assumed that x is a sample which can only be drawn from one of the two events $\theta = \theta_1 \in \Theta_1$ and $\theta = \theta_0 \in \Theta_0$:

$$\begin{array}{lll} \theta_1: & \text{signal } s \text{ present in noise } n. & (\text{hypothesis } \mathcal{H}_1) \\ \theta_0: & \text{only noise } n \text{ present.} & (\text{hypothesis } \mathcal{H}_0) \end{array} \tag{2}$$

In this work, we assume that the termite-free background noise follows a Gaussian mixture distribution. In particular, the data model is given by

$$\begin{array}{ll} \mathcal{H}_0: & p_0(\mathbf{x}|\theta, \mathcal{H}_0) \sim \sum_{i=1}^{M} w_i \mathcal{N}(\mathbf{x};\, \mu_i^0, \Sigma_i), \quad \theta = \{\mu_i^0, \Sigma_i, w_i, M\} \\ \mathcal{H}_1: & p_0(\mathbf{x}|\theta, \mathcal{H}_1) \sim \sum_{i=1}^{M} w_i \mathcal{N}(\mathbf{x};\, \mu_i^1, \Sigma_i), \quad \theta = \{\mu_i^1, \Sigma_i, w_i, M\}. \end{array} \tag{3}$$

where the number of components M, the mean vector $\{\mu_1, \cdots, \mu_M\}$, the associated covariances $\{\Sigma_1, \cdots, \Sigma_M\}$ and the weights $\{w_1, \cdots, w_M\}$ associated with each of components are unknown and to be estimated from the data. Under the GLRT framework, several decision rules may be considered. For example, a multi-mode matched filter can be designed from the known termite signatures of acoustic signals; or we can build a CFAR detector with an adaptive threshold proposed in [10]. Nevertheless, it is observed that the detection probability P_D drops quickly as SNR decreases for a fixed false alarm rate P_{fa} with these decision rules. This motivates the authors to consider an information geometric approach to compare signals under the two hypotheses using an information metric. It is worth mentioning that it is difficult to extract termite signals from data via spectrum analysis technique as it is essentially a "wideband" signal similar to that of additive noise.

3. EBIVB-tBD Detector

As illustrated in Fig. 2, the proposed EBIVB-tBD method combines three techniques. First, we apply a variational Bayesian learning method to estimate unknown parameters of the Gaussian mixture distribution where the number of Gaussian components is determined by an entropy based component splitting method [11]. Having obtained these estimated parameters, we then perform a GLRT-based hypothesistest, where the threshold may be determined by either Neyman-Pearson or Bayes decision criteria; the third function. To enhance the difference between the distributions of termite signal and background noise, we introduce the second technique, in which the tBD between empirical distribution and the distribution in the absence of termite signal is computed. The latter is approximately represented by the l_1 norm tBD center.

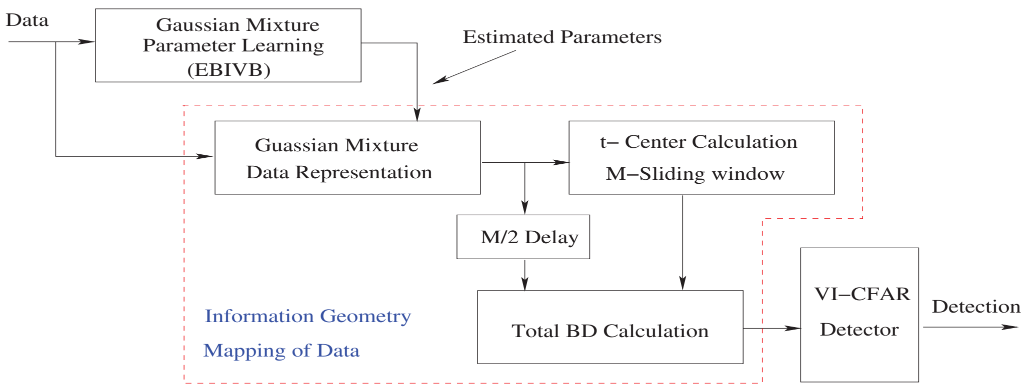


Figure 2: Flowchart of EBIVB-tBD algorithm.

3.1. Entropy-based Incremental VB

Standard variational Bayesian (VB) optimization iterations are applied to estimate the parameters of the Gaussian mixture distribution (3) from data. The algorithm starts with a single component and adds new components iteratively by splitting the worst fitted component in terms of its Gaussian deficiency (GD) which is measured in entropy [11]. When a worse fitted component is split, a new VB iteration is carried out to estimate the parameters to maximize the marginal likelihood for the current number of components. This entropy-based incremental VB algorithm is denoted by EBIVB.

3.2. Total Bregman Divergence and tBD-Center

While the empirical data distribution parameterized by a Gaussian mixture is estimated with the EBIVB algorithm, the underlying noise distribution is estimated using a non-parametric approach, i.e., the tBD center computed over a set of N data points. In this work, the tBD center is the data point $x^* \in \mathbf{x}$ such that

$$x^* = \arg\min_x \mathrm{tBD}_f(x,\, \mathbf{x}) = \arg\min_x \sum_{i=1}^{N} \mathrm{tBD}_f(x,\, \mathbf{x}) \tag{4}$$

where $\mathrm{tBD}_f(x, y)$ is the total Bregman divergence between points $x, y \in X$. It is defined with a real valued strictly convex and differentiable function $f : X \mapsto \mathbb{R}$ as

$$\mathrm{tBD}_f(x, y) = \frac{f(x) - f(y) - < x - y, \nabla f(y) >}{\sqrt{1 + ||\nabla f(y)||^2}} \tag{5}$$

We should remark that the tBD between a specific point and a set of points defined in (4) is also called l_1 norm and the tBD center represent intrinsic property of data $\mathbf{x}$ since tBD is a coordinate independent quantity. Therefore, the noise distribution at each data point is approximated by the data point $x^* \in \mathbf{x}$ selected from a set of neighboring points that yields least “fluctuation”.

Finally, the GLRT at every data point is performed between the empirical data distribution (or the likelihood under alternative hypothesis) and the noise distribution (or the likelihood under the null hypothesis), which, in fact, is equivalent to the tBD between the two distributions. The detection threshold is then chosen for a given P_{fa}.

3.3. Justification

It can be shown that the Neyman-Pearson hypotheses test for signal of length N is equivalent to

$$\mathrm{KLD}\big(q(\mathbf{x})||p_0(\mathbf{x})\big) - \mathrm{KLD}\big(q(\mathbf{x})||p_1(\mathbf{x})\big) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \frac{1}{N}\gamma \tag{6}$$

where $q(\mathbf{x})$ is measurement distribution approximated by empirical distribution for a large sample size N, and γ is a constant for a given false alarm rate P_{fa}. $\mathrm{KLD}\big(q(\mathbf{x})||p_0(\mathbf{x})\big)$ is defined as the Kullback Leibler divergence between $q(\mathbf{x})$ and the null hypothesis distribution $p_0(\mathbf{x})$. Eq. (6) indicates that the likelihood ratio test is equivalent to comparison of the difference between the KLDs of the empirical distribution to each of the two hypotheses with a threshold $\frac{\gamma}{N}$, i.e. choosing the hypothesis that is “closer” to the data in the sense of Kullback-Leibler divergence.

In our case, $p_1(\mathbf{x})$ in (6) is a Gaussian mixture with parameters estimated by the EBIVB algorithm. When termite signal is present in data $\mathbf{x}$, the second term of (6) vanishes. Instead of using Kullback Leibler divergence, we use the total Bregman divergence. Therefore, Equation (6) reduces to

$$\mathrm{KLD}\big(q(\mathbf{x})||p_0(\mathbf{x})\big) \equiv \mathrm{tBD}_f\left(q(\mathbf{x}), p_0(\mathbf{x})\right) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \frac{1}{N}\gamma. \tag{7}$$

As indicated in [9], an analytical expression may be obtained for non-Gaussian case when tBD is used. In addition, tBD is robust to outliers.

4. Experimental Results

Experiments based on both simulated data and real data were carried out. Results are presented here to demonstrate the detection performance of proposed detector along with that of a CFAR detector (VI-CFAR) [10] and a multi-model matched filter (Matched filter).

4.1. Detection Performance Comparison

In the simulation, several acoustic signal patterns from termites' activities, which are typically narrow impulses in milliseconds, identified from real data were used to synthesize the termite activity signal as shown in the top plot in Fig. 3. These termite "signatures" were also used as the signal model in the multi-mode matched filter. Additive noise drawn from a Gaussian mixture distribution with known parameters was added in various SNR levels as shown in the middle and bottom plots in Fig. 3.

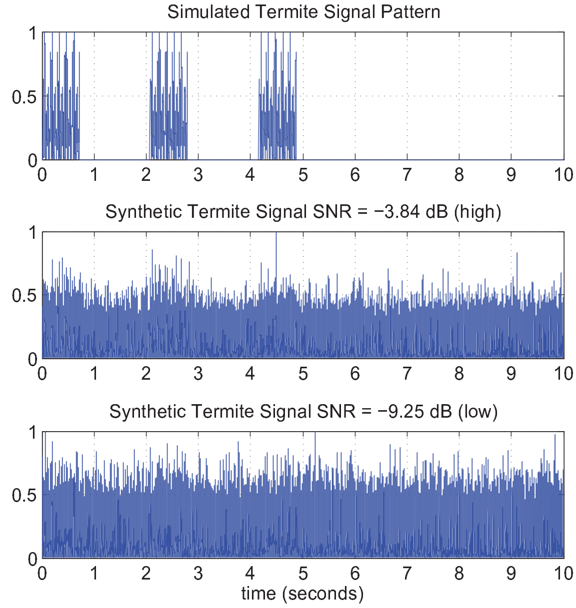


Figure 3: Realizations of two synthetic Termite signals.

Fig. 4 shows the performance comparison between the detectors of EBIVB-tBD, VI-CFAR and Matched filter. The result is obtained from a 1000 Monte Carlo runs. It indicates that in low SNR case the proposed EBIVB-tBD detector outperforms the other two in terms of detection probability.

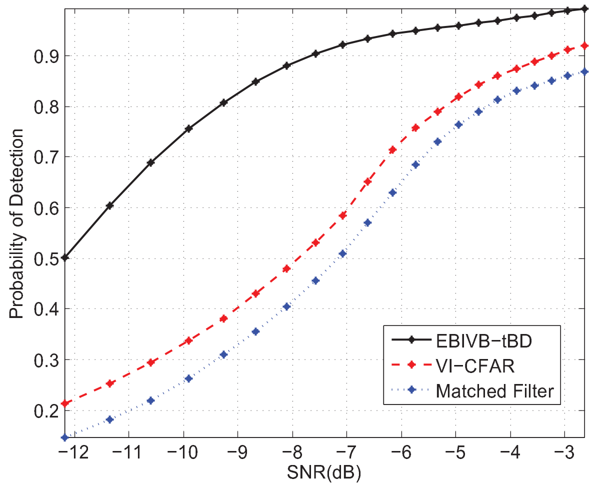


Figure 4: Detection probabilities vs. SNR averaged over 10000 Monte Carlo runs on simulated termite data.

4.2. Real Data Termite Detection

The real data used were recorded from a tree infested by termites taken from the sound track of in nest video. While significant perceptible noise from environment can be removed from the recorded data using standard noise cancelation techniques, the SNR of data collection is still very low as termite signals are sparsely distributed over time. With the help of in nest video recorded during data collection, a few (ground truth) termite signal points are identified and marked by red arrows as shown in the top plot of Fig. 5. The detection performance comparison is based on the detection results observed from these data points.

The detection performance is shown in Fig. 5. While we observed that both EBIVB-tBD and VI-CFAR algorithms have detected the termite signal in the specified data points without false alarm, the EBIVB-tBD provides the largest margin between "signal" and "noise". On the other hand, the Match filter based detector will suffer from a high false alarm rate in order to detect the termite signal in the specified data points by lowering the threshold.

5. Conclusions

In this paper, a new algorithm EBIVB-tBD for detecting sparsely distributed signal under non-Gaussian noise is proposed. The novelty of this detector is in that it interprets the GLRT in terms of the total Bregman divergence between data distributions under alternative and null hypotheses respectively. Significantly better detection performance is observed from both simulated and real data in the application of termite activity detection, in particular, when SNR is low. Nevertheless, the improved detection performance comes up with the cost of increased algorithm complexity, which is currently under investigation in our ongoing research.

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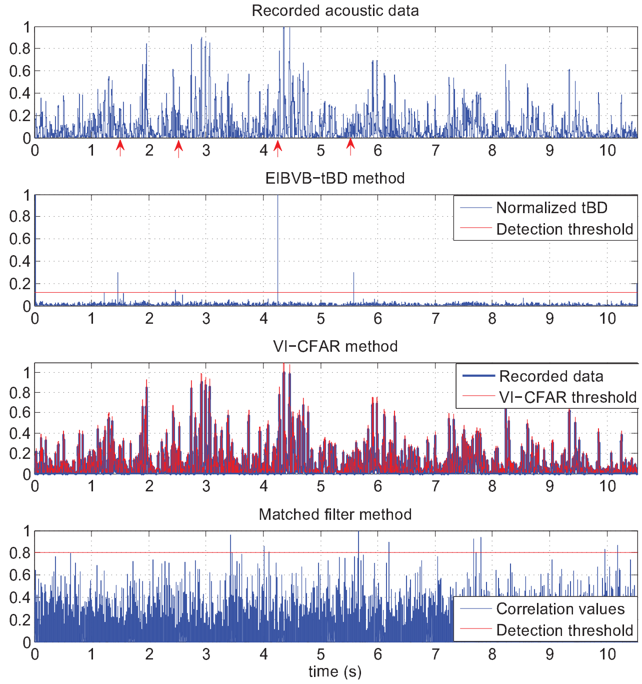

Figure 5: Detection performance comparison for the proposed EIBVB-tBD, VI-CFAR and Matched filter algorithms using real data. Top row: recorded acoustic data, where the red arrows at 1.5, 2.5, 4.2 and 5.6 seconds indicate termite activity signals were observed.

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