S22-32
N88-18796
128238

TDA Progress Report 42-92 October–December 1987

Simulated Performance of an Order Statistic Threshold Strategy for Detection of Narrowband Signals

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The application of order statistics to signal detection is becoming an increasingly active area of research. This is due to the inherent robustness of rank estimators in the presence of large outliers that would significantly degrade more conventional mean-level-based detection systems. In this article, a detection strategy is presented in which the threshold estimate is obtained using order statistics. The performance of this algorithm in the presence of simulated interference and broadband noise is evaluated. In this way, the robustness of the proposed strategy in the presence of the interference can be fully assessed as a function of the interference, noise, and detector parameters.

I. Introduction

Development of a two million channel, FFT-based narrowband detection processor is currently under way at JPL for use in various applications of the Deep Space Network [1], [2]. It will also serve as a prototype for the Search for Extraterrestrial Intelligence (SETI) Sky Survey Processor [3]. The system is being designed to process contiguous spectra at a throughput rate of 40 MHz. The system output consists of detected spectral intervals. Each interval is composed of a run of one or more contiguous spectral bins for which the associated power levels all exceed the system threshold. The average power level, width, and location of each detected spectral interval are computed and passed along to the system computer which performs the final signal and interference assessment.

The key parameter in this system is the threshold level. For effective system performance, it is desirable that the threshold be adaptive to accommodate a typically time varying background (thermal) noise level, and that it be as insensitive as possible to the presence of both narrowband signal and interference components that lie within the threshold estimation window. Finally, it is desired that the threshold level be stable, i.e., that it exhibit a small variance. Toward these ends, we have considered an order-statistic-based threshold estimation scheme wherein the system threshold is a constant times a linear combination of successive nth order statistics computed from the power spectral data out of the FFT (see Section II). The scaling constant controls the false alarm rate.

The analysis and application of order statistics in general has become an important area of research [4]-[6], and the specific application of order statistics to signal detection is currently receiving some attention [7]. This is due to the inherent robustness of order statistics in the presence of large outliers (e.g., narrowband interference) that would significantly degrade the sensitivity of more conventional mean-level-based detection systems. The real issue in the application of order statistics to signal detection is the system performance for a given interference environment. An analysis of an order-statistic-based detection system presented in [7] clearly demonstrates the robustness of order statistic threshold estimators to the presence of a single narrowband interferer within the estimation window. Of course, in practice there will typically be multiple interferers with different amplitudes and bandwidths within the window depending on the specific interference environment.

This article summarizes the results of a preliminary computer-aided simulation analysis that has been carried out to evaluate system performance in the presence of interference. In performing this analysis, the interference environment has been simulated based on the results of limited survey data (collected between 1 and 2 GHz) which provides the percentage of spectral bins contaminated by RF interference (RFI) as a function of the RFI power level. In addition to RFI, a broadband Gaussian system noise component is included in this analysis. Ideally, the system threshold level will reflect the spectral level of the broadband system noise and not the RFI.

This system performance evaluation is carried out as a function of the system noise level relative to the RFI. The results of this analysis not only serve to assess system performance as a function of various system parameters, but also provide guidelines for choosing various system design parameters to enhance system performance.

II. Detector and RFI Models

The basic detector system model currently under consideration is depicted in Fig. 1. Here the digitized input data are transformed into the frequency domain via an FFT processor and the power in each FFT bin is accumulated over a specified number of transforms. The resulting accumulated power data is then split into two paths. The direct-through path is fed into a 5-point convolutional filter which forms the convolution of successive accumulated spectra with a 5-point finite impulse response (FIR) filter. Specifically, let $X_i(k)$ denote the level of the ith successive accumulated power spectrum at the kth spectral (FFT) bin. Then the output from the 5-point convolutional filter is given by:

$$Y_i(k) = \sum_{j=0}^{4} w_j X_{i-j}(k)$$

where the w_j are the FIR filter weights. As discussed in [3], the filter weights depend on the characteristics of the receive antenna beam pattern and are matched to the expected signature of a fixed source in the sky as it is traversed by the receive beam. Furthermore, a 5-coefficient FIR filter turns out to be sufficient to minimize signal-to-noise ratio (SNR) losses induced by the antenna beam in conjunction with the finite time interval between successive accumulated spectra [3]. For purposes of this analysis, the FIR filter weights are considered to be a set of fixed constants downloaded from the system computer.

In addition to being directly convolved with the FIR filter, the accumulated power spectral data are also utilized in determining the system threshold level. As indicated in Fig. 1, the threshold determination is composed of three steps: (1) compute the nth smallest power level; (2) convolve successive nth smallest power levels with the FIR filter; and (3) multiply the result from (2) by a fixed gain constant. The result of (2) is to further smooth the nth order statistics computed in (1) in a manner which is perfectly consistent with the convolution of the power accumulation data in the direct-through path. Note that this smoothing operation also reduces the variance of the order statistics. The final step effectively determines the number of detected noise intervals (or false alarm rate) out of the detector system. The gain constant in (3) is typically chosen based on a system-noise-only (no RFI) assumption. The goal of this analysis is to determine the threshold stability as well as the number of spectral interval detections in the presence of RFI.

After convolution and threshold level determination, the convolved data are thresholded and information concerning detected spectral intervals (interval width, location, and average power level) is passed on to the system computer. Ideally, the thresholding serves to discard most of the noise data (so that the system computer is not overloaded) while simultaneously retaining the desired signal information. The purpose of passing along detected intervals and not individual spectral bin detections is to reduce the amount of hit data which will arise from broadband interference sources with bandwidths well in excess of the FFT bin resolution ($\approx$30 Hz). Interference-related hit data which is passed on to the computer can then be identified (e.g., based on frequency or time discrimination) and eliminated from further analysis.

The RFI model developed for the system performance evaluation is based on limited survey data collected in the 1-2 GHz band. In collecting this data, a spectral resolution width of 10 kHz was used, and the average number of threshold detections attributed to RFI sources over a 1 GHz bandwidth was computed as a function of the threshold level. The fraction of spectral bins contaminated by RFI fit a power law model as the threshold level decreased over the range from -80 dBm to -120 dBm. Figure 2 represents the least squares fit to this data. In Fig. 2, the log (base 10) of the fraction of RFI-contaminated bins is plotted versus the RFI threshold level. For levels above -80 dBm, the fraction of spectral bins contaminated by the RFI is assumed constant. Below -120 dBm, the survey data has been extrapolated exponentially to -140 dBm. Below -140 dBm a constant profile of approximately 15 percent RFI contamination is assumed. The simulation results presented in Section III are based on this RFI density profile.

There are two basic limitations associated with this model. First, there are currently no available RFI data measurements below approximately -120 dBm. Even for a 10 kHz spectral resolution, this is well above the thermal noise level ($\approx$-150 dBm assuming a nominal 10 K system temperature and 10 kHz bandwidth). It was thus necessary to extrapolate the data into the low noise regions of interest as indicated in Fig. 2. A second limitation is that the RFI data used to construct this model profile have been collected using a spectral resolution (10 kHz) which is far coarser than the system goal ($\approx$30 Hz). Consequently, the RFI realizations based on this density profile will differ significantly from those corresponding to a narrowband RFI profile. Nevertheless, system performance results based on this model do highlight the RFI model attributes which most critically impact system performance in general.

III. System Performance Assessment

In the evaluation of system performance, a computer simulation test bed has been developed which generates realizations of RFI based on the amplitude density model depicted in Fig. 2. Specifically, the RFI amplitude range has been quantized into 2.5 dBm intervals, and the appropriate number of RFI components has been injected into each interval. Furthermore, the RFI components have been distributed into non-overlapping frequency bin intervals with all of the RFI components in a frequency interval having amplitudes lying within a given 2.5 dBm amplitude interval. Each RFI frequency interval is randomly positioned across the total number of spectral bins selected (i.e., total instantaneous bandwidth), and the width of each RFI interval is chosen randomly up to a maximum of 40 contiguous spectral bins. The resulting distribution of the RFI in frequency is termed the RFI "mask." A sample RFI mask is presented in Fig. 3, where the average interference-to-noise ratio (INR) is plotted across a total of 4096 spectral bins corresponding to a system noise level of -110 dBm. The power law increase in the number of RFI components with decreasing INR is clearly observed.

Each simulation run is composed of multiple realizations of RFI and additive broadband system noise corresponding to a fixed RFI mask (one independent mask per simulation run). The RFI amplitude (dBm) is uniformly randomized within each 2.5 dBm amplitude interval, and the phases of all RFI components are uniformly randomized over $[0,2\pi)$ once every spectral accumulation cycle. Independent broadband noise realizations (generated in the frequency domain) are computed for each power spectrum input to the accumulator.

The simulation input parameters include (1) total number of spectral bins (nominally 4096); (2) number of spectra per accumulation cycle (nominally 8); (3) average system noise level within a spectral bin (this varied between -100 and -150 dBm); (4) rank number, n, for the order statistic ($n = 10$ or 60); (5) gain constant for computing the system threshold corresponding to a 0.1 percent false alarm rate in the absence of RFI; and (6) total number of accumulated spectra (nominally 1000 per run). All of these parameters, including the RFI mask, are held constant during a simulation run. In addition, the 5 convolutional filter weights are always fixed (at the values 0.64, 0.89, 1.0, 0.89, and 0.64).

The two primary outputs from the system simulations are the nth order statistic and the number of detected noise intervals, averaged over all realizations, as a function of the system noise level. Plots of the order statistics (normalized by their respective means in the absence of RFI) are presented in Fig. 4 corresponding to the nominal simulation input parameters given above. As is seen, when the noise level is well above the majority of RFI components, i.e., above -90 dBm, then the spectral bins are dominated by system noise and the resulting nth order statistics approach those for the noise-only distribution. Conversely, as the system noise level decreases to well below the smallest RFI component, i.e., below -140 dBm, then the RFI components contaminate a fixed number of spectral bins and the order statistics increase due to the corresponding reduction in the number of noise-only bins. This is clearly observed in Fig. 4, where a significant inflation of both the 10th and the 60th smallest order statistics occurs as the noise level decreases. The net result of this inflation is a loss in detector sensitivity. However, the sensitivity loss associated with either order statistic is much less than would occur using a conventional average power estimator [7].

Plots of the average number of detected spectral intervals corresponding to both the 10th smallest and 60th smallest order statistics are presented in Fig. 5. As is seen for both cases, the average number of detected intervals increases from the noise-only limit of approximately 4 (0.1 percent of 4096 spectral bins) to over 80 at the -140 dBm noise level and then back to approximately 50 for noise levels below -150 dBm. At these lower levels, the detected spectral intervals are composed almost exclusively of the RFI frequency intervals–an average of 50 such intervals were generated in the RFI masks used for these runs. The number of additional detected noise-only intervals in this case is limited by the inflation of the nth order statistics as noted above. As the system noise level increases to -140 dBm, a level which corresponds to the majority of the RFI components (see Fig. 2), it interferes with the RFI to produce random "splittings" of the low-level, RFI frequency intervals. These splittings are manifested as an increase in the number of detected noise intervals to over 20 times that expected in the absence of RFI. Such an increase could impact the ability of the system computer to process all of the detected hit data. A more precise assessment of the impact of RFI on system performance will, in turn, require a more complete set of RFI survey data, which is clearly an important area for future investigation.

IV. Conclusions

Although the results of this preliminary simulation analysis depend critically on the assumed RFI density model, some general conclusions can be made. In particular, it is noted that system performance depends most critically on the distribution of RFI components at levels comparable to or greater than the broadband system noise level. RFI components well below the system noise level do not significantly impact system performance. RFI components well in excess of the system noise level contaminate a fixed number of spectral bins and thus produce a significant inflation of the system threshold due to the decrease in the number of noise-only spectral bins. This inflation has the effect of lowering the average number of detected noise-only spectral intervals as well as reducing detector sensitivity. Large RFI components also increase the total number of detected spectral intervals depending on the number of RFI intervals present. Note that the number of RFI intervals will, in turn, depend on the frequency distribution of the RFI. A small number of strong broadband RFI sources will not significantly increase the total number of detected spectral intervals, whereas a large number of strong narrowband RFI sources will produce a significant increase in the number of interval detections. Furthermore, as the RFI level approaches the system noise, additional spectral interval detections will occur due to RFI interval splitting caused by the interaction of the broadband system noise with the RFI. This splitting phenomenon will occur regardless of whether the RFI is narrow or broadband. Further analysis is currently being carried out to assess system performance in more realistic RFI environments.

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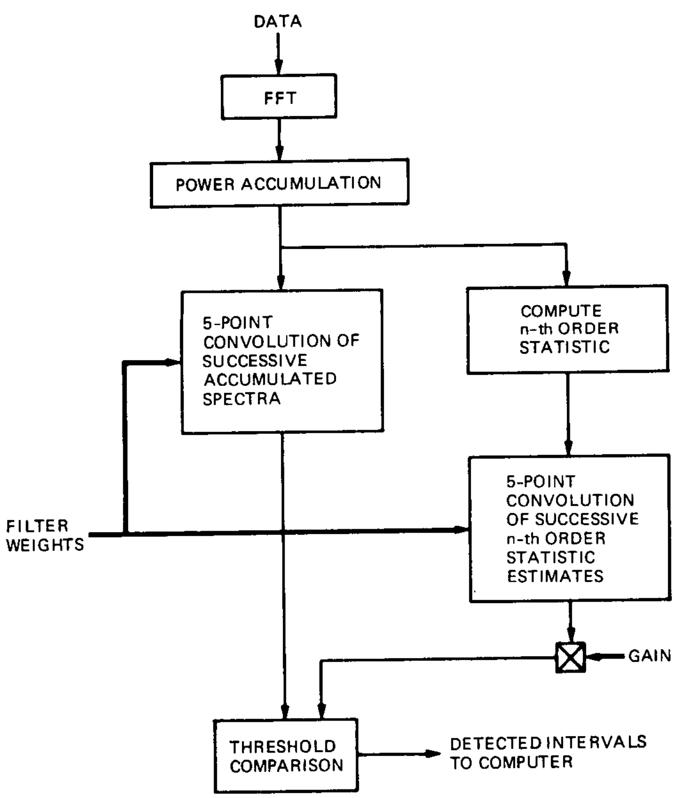

Fig. 1. Detector system model (heavy lines denote paths for detector parameters which are downloaded from the system computer)

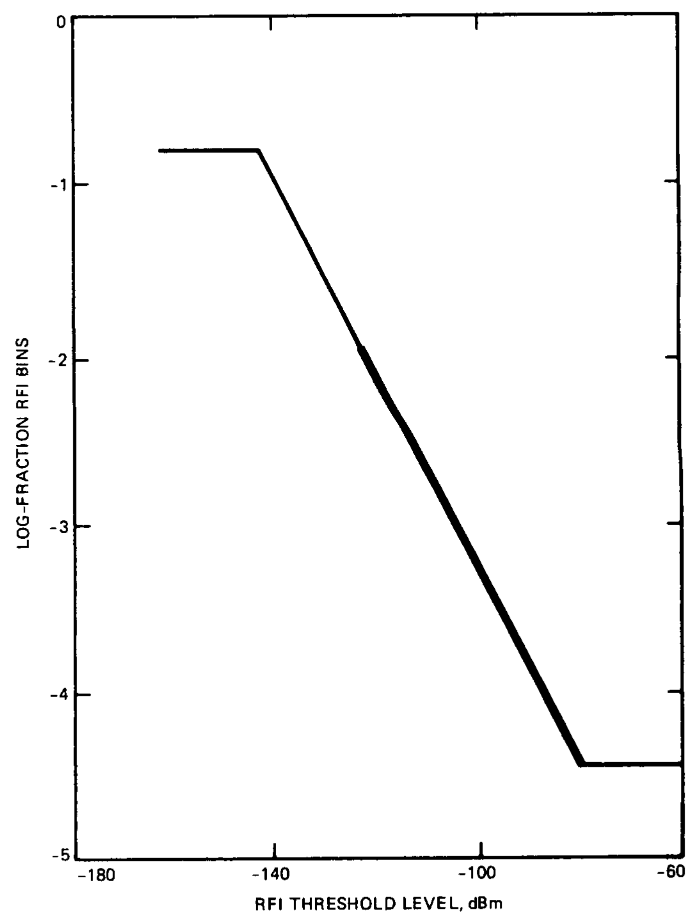

Fig. 2. RFI model density profile (heavy solid line denotes the region of valid survey data)

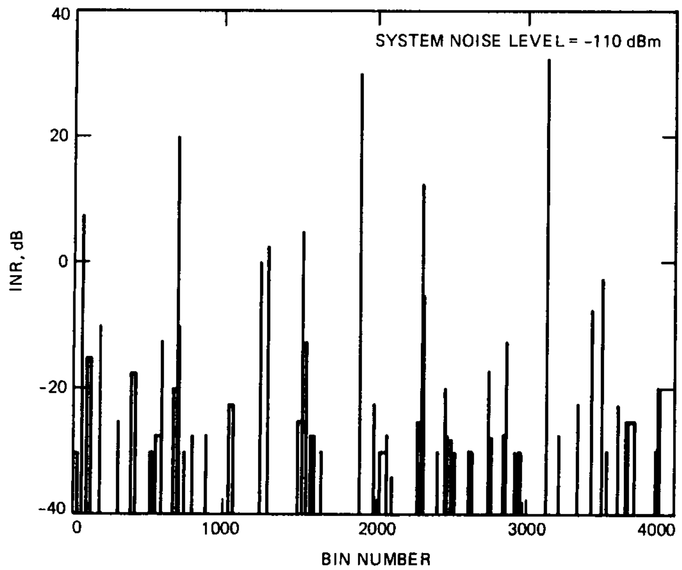

Fig. 3. Sample RFI mask

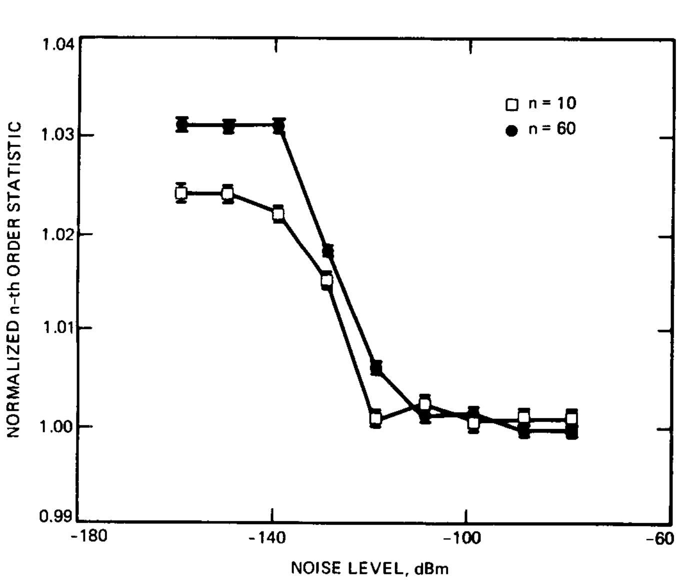

Fig. 4. Average *n*th order statistics (normalized by expected mean values in the absence of RFI)

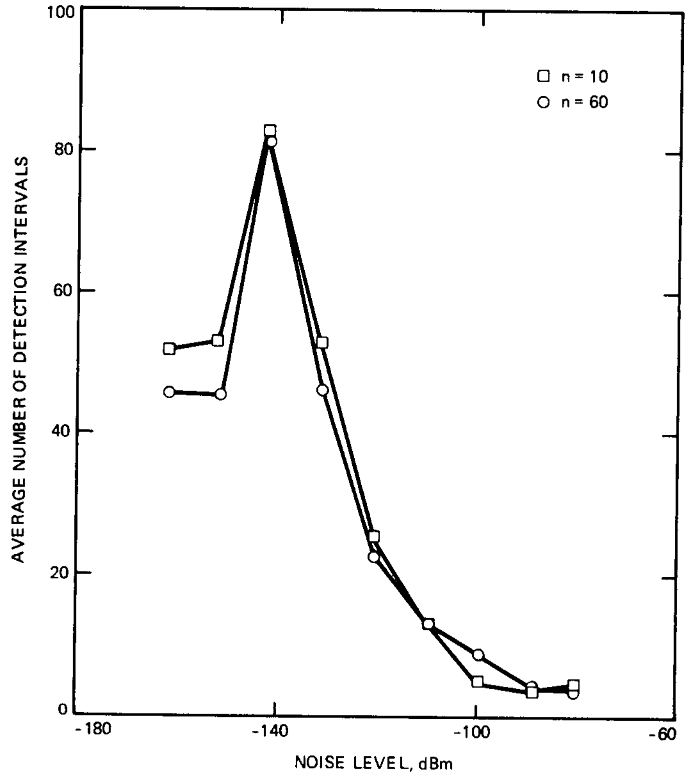

Fig. 5. Average number of detected spectral intervals