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LMSS Modeling Status Report

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Abstract--The need to develop accurate models for secondary statistics of fading land mobile satellite signals has motivated a study of fading signal autocorrelations and multipath spectrum. Results of autocorrelations and power spectral densities from measured data are presented and comparisons to multipath spectrum models are made.

1. Background

Previously we have reported on the development of a software propagation simulator used to simulate fading of Land Mobile Satellite System (LMSS) signals for arbitrary propagation conditions (Stutzman, et al., 1988; Barts and Stutzman, 1988). The simulator generates signals using two data bases of signal components derived from experimental data.

The measures of performance used to evaluate the simulator are its ability to reproduce the primary fading statistics, cumulative fade distribution, and secondary (or conditional) fade statistics, average fade duration and level crossing rates, of experimental data. Previously reported results (Barts and Stutzman, 1988) have shown that the simulator reproduces primary fade statistics for a wide variety of experimentally measured propagation conditions. However, the simulator results for secondary statistics are not satisfactory.

The simulator is constructed to produce accurate primary statistics, but has no inherent model for secondary statistics. The secondary statistical behavior of the simulator is determined by the secondary statistical behavior of the data bases used to construct the simulated signal. Thus, it is important that we correctly process the experimental data when generating the simulator data bases to extract both the correct primary and secondary statistical behavior. However, the processing techniques in use only assure us of extracting primary statistics correctly.

The need for secondary statistics modeling capability led us to a review of the data processing used to generate the simulator data bases and a study of models for secondary statistics. We began these studies by looking at the dynamic fading signal behavior as represented by the signal autocorrelation. These were used as a stepping stone for examining the spectra of fading signals and comparing them with various multipath models. With these models we are attempting to develop models for the secondary statistics, for which no satisfactory models currently exist. Our approach is based on the modeling of Jakes (1974) wherein if we can establish an appropriate model for the multipath spectrum, we can derive analytical expressions for the secondary statistics.

2. Autocorrelation Studies

The autocorrelation of a signal is a measure of how fast the signal changes with time. We can also consider it a rough measure of the duration of a scatterer's influence upon a fading signal. The broader the autocorrelation function, the slower the signal fades and the longer the period of time an individual scatterer dominates the received signal.

The autocorrelation function is defined as

$$R_{zz}(\tau) = \langle z(t-\tau) z^*(t) \rangle \qquad (1)$$

where $z(t) = x(t) + j\, y(t)$ is a complex signal. A form of (1) more suitable for evaluation is

$$R_{zz}(\tau) = R_{xx}(\tau) + R_{yy}(\tau) - j[\, R_{xy}(\tau) - R_{yx}(\tau)\,] \qquad (2)$$

where $R_{xx}(\tau)$ and $R_{yy}(\tau)$ are the autocorrelations of the real and imaginary components of the complex signal, respectively. $R_{xy}(\tau)$ and $R_{yx}(\tau)$ are cross correlation between the real and imaginary signal components. We have found that for the experimental data we have that these cross correlations are usually approximately equal resulting in a real autocorrelation function, but this is not always the case, as discussed below.

The autocorrelation as defined in (1) is the expected value of $z(t-\tau)z^*(t)$. When we calculate the autocorrelation of a 1.024-second record of data, we are calculating the autocorrelation of but a single realization of a stochastic process. If we consider consecutive 1.024-second records of experimental data to be multiple realizations of the same process, we can average the resulting autocorrelations to find the expected value function. This is the technique we have used to analyze experimental data. This is also useful for calculating power spectral densities, as discussed below.

Figure 1 is an example of an autocorrelation of balloon data collected by Vogel (1985). Notice that the real part of the autocorrelation is smooth and slowly varying. This is indicative of signal data that is relatively smooth and does not have rapid fading. Figure 2 shows the signal data from which the autocorrelation function of Figure 1 was derived. Notice that, indeed, the signal data are relatively smooth and free of rapid fading. This is due in part to the slow vehicle speed (8 mph) during data collection, but the data also suggests a scarcity of scatterers or shadowing. Notice that the imaginary component of the autocorrelation in Figure 1, while small, is not negligible. This indicates a correlation between the real and imaginary signal components that is unexplained.

Figure 3 is an example autocorrelation for helicopter data collected by Vogel and Goldhirsh (1988). Figure 4 is the corresponding signal data. Notice that the helicopter autocorrelation function falls off more rapidly and is not smoothly varying. This is indicative of rapid fading and Figure 4 confirms this. The imaginary part of the autocorrelation function for the helicopter data is very small and can be considered negligible.

These examples were taken from single 1.024-second records of data, but the are indicative of the results using averaging. Data from Vogel and Goldhirsh's measurements with the MARECS-B2 satellite (Vogel and Goldhirsh, 1988) have also been analyzed (not included here for the sake of brevity) and are very similar to the helicopter data, which is expected since the two measurements were taken in the same geographical area.

These results give us some insight into processing the experimental data to create the databases used in the propagation simulator. To create the "lognormal" data base, the lognormal component of the signal is estimated by using a running average window. The size of the window was chosen empirically. When dealing with data that are markedly different, such as balloon and helicopter data, empirically choosing the window size is not an optimum technique. By examining the autocorrelation of the signal, we can make an informed judgement about the window size.

3. Power Spectrum Studies of Fading Signals

The fading signal power spectrum is related to the autocorrelation of the signal by a Fourier transform. Using the autocorrelation of the signal to obtain the power spectral density (psd) of a signal has several advantages over using a direct FFT of the signal data. When dealing with a signal in the presence of noise, the autocorrelation calculation acts as a noise filter, since Gaussian noise is decorrelated. This is particularly helpful when dealing with fading signals which are noisy. The resulting signal psd is not as corrupted as those from a direct FFT. Secondly, it is computationally easier to average the psds of multiple data records by averaging the record autocorrelations. By averaging the psds of multiple records, the important structures of the multipath spectrum become more clearly defined. Using this technique we calculated the multipath spectra for the experimental data from the balloon, helicopter, and satellite measurements. These spectra are used to develop and verify models for the multipath spectrum. They are also being used to design the filters for the data processing used in the propagation simulator.

Figure 5 is a spectrum average from 10 seconds of balloon data. The carrier is obvious at the edge of the graph and the multipath spectrum cuts off rather sharply at approximately 80 Hz. This was somewhat surprizing, since the vehicle speed during these measurements was approximately 8 mph. This spectrum taken alone suggests then that the velocity of the balloon was approximately 60 mph. The spike at the edge of the multipath spectrum is an important feature because it is predicted by the Jakes multipath model, which is discussed below.

Figure 6 is a spectrum average from 10 seconds of MARECS data. In this spectrum the multipath does not have a well defined cutoff. Notice also that the carrier-to-multipath ratio is much smaller than in the helicopter data. This is indicative of a larger number of scatterers in the propagation environment.

3.1 Multipath Spectrum Models

The purpose of the spectrum studies discussed above was to provide a basis for choosing a model of the multipath spectrum that could be used in developing a model for secondary statistics. The simplest and most commonly used multipath spectrum model employs an assumption of scattered waves uniformly spatially distributed around the vehicle. This is the Jakes model (Jakes, 1974). The theoretical spectrum for this model is shown in Figure 7. It has a width of $2f_m$ where f_m is the maximum doppler frequency. Notice the asymptotic behavior of the spectrum at the edges. The behavior of the balloon spectrum shown in Figure 5 corresponds closely to this model.

The MARECS spectrum of Figure 6 looks very different from the Jakes multipath model. This could be due to assumptions upon which the Jakes multipath model is based.

The model assumes that the scatterers are in the far field of the vehicle, and that the scattered fields are plane waves. This would not be true for roadside tree scatterers. Secondly, the Jakes model assumes a uniform spatial distribution for the scattered signal. This produces the asymptotes at the edges of the multipath spectrum, which are products of the scattered signals directly in front of and behind the vehicle. But, in reality, points directly in front of and behind the vehicle are relatively clear of scatterers. The assumption that the scattering from in front of and behind the vehicle is the same as the scattering from the sides is referred to as the "brick wall" fallacy.

Recent work by Campbell has produced a multipath spectrum model that agrees more closely with the result shown in Figure 6. Campbell has simulated a large number of random scatterers along the side of the road in the near field of the vehicle. Figure 8 is an example of the multipath spectrum predicted by Campbell's simulation. While this model still has a well defined cutoff, it is closer to the helicopter and MARECS spectra we observed than the Jakes model.

4. Conclusions

Our recent efforts in modeling and simulation of fading LMSS signals have concentrated on understanding the spectrum of the fading signals. In our effort we are have examined the autocorrelation of the signal as well as the signal power spectral density. In order to improve the signal processing used in the propagation simulator, we need to look at both the signal autocorrelation and power spectral density. These will allow us to make informed decisions on how to design filters used to extract the signal components.

Our study of multipath spectra is a step toward finding appropriate analytical models for the secondary fading statistics. The spectra from experimental data shown here have been compared to two different multipath spectrum models. The results indicate that the Jakes multipath model may be appropriate for slow, shallow fading, such as observed in the balloon measurements. Where there is rapid, deep fading and scatterers are in close proximity of the vehicle, the multipath spectrum produced by Campbell's simulation may be appropriate, as indicated by the helicopter and MARECS measurements.

References

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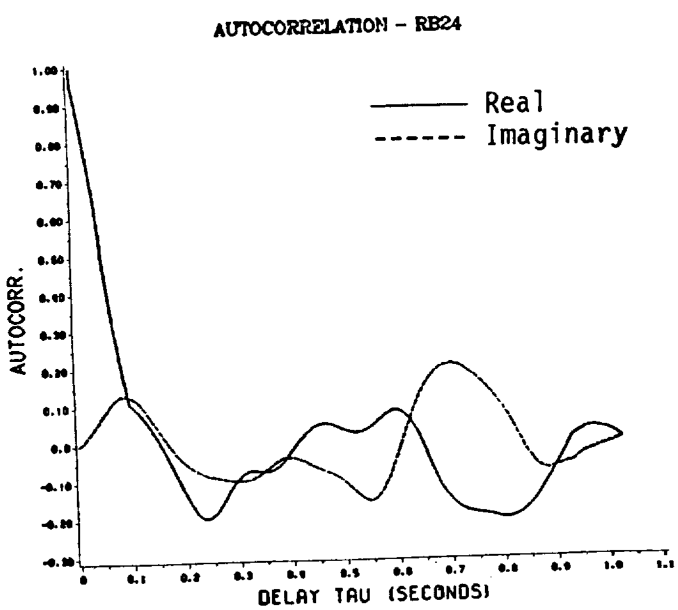

Figure 1. Autocorrelation of data from Vogel's balloon measurements.

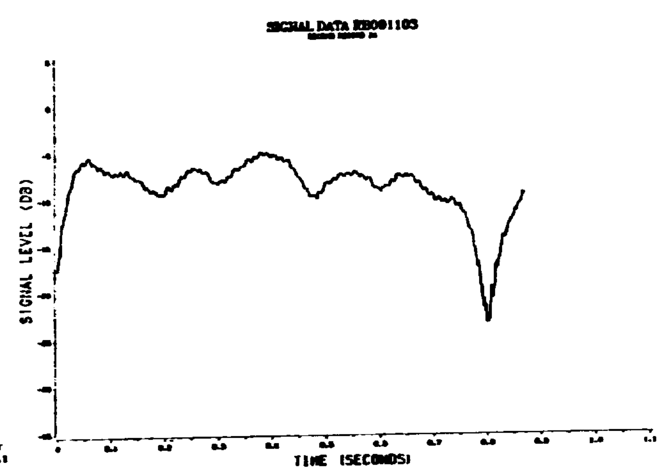

Figure 2. Signal data from Vogel's balloon measurements.

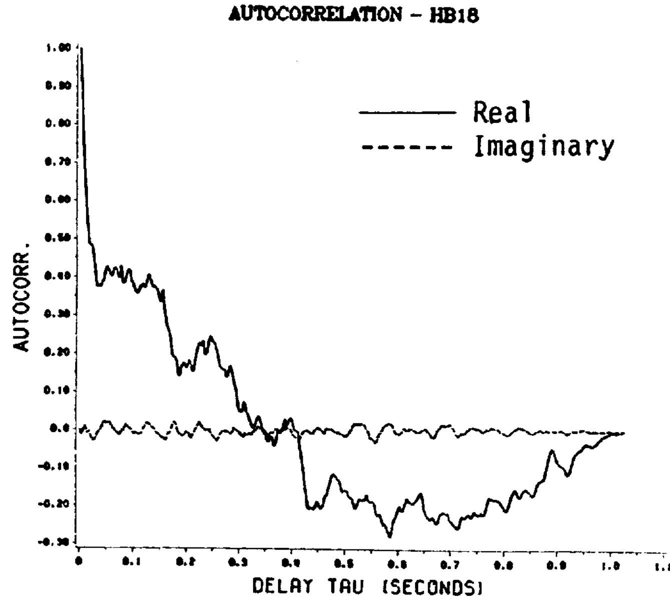

Figure 3. Autocorrelation of data from Vogel and Goldhirsh's helicopter measurements.

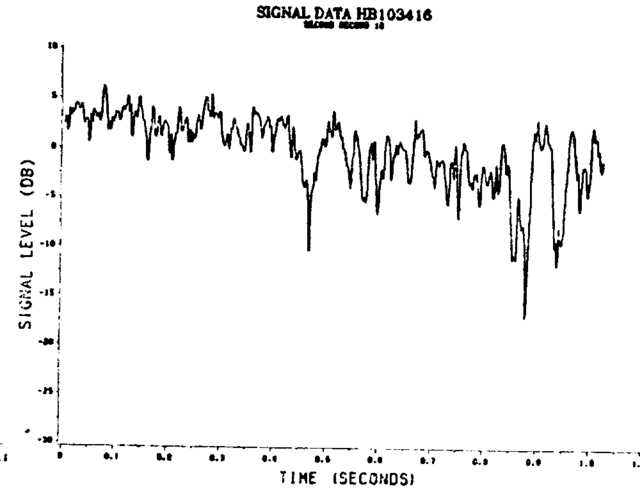

Figure 4. Signal data from Vogel and Goldhirsh's helicopter measurements.

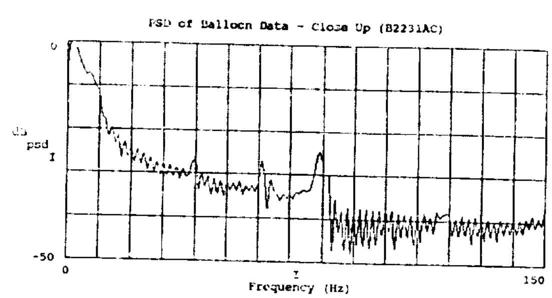

Figure 5. Signal spectrum from balloon data.

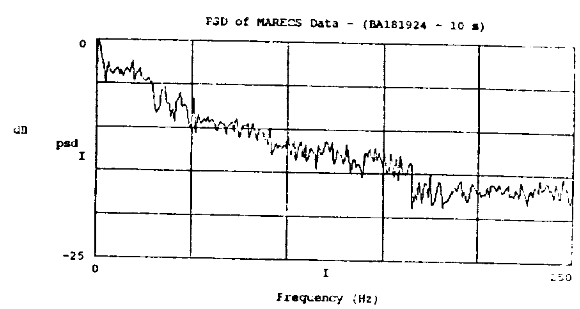

Figure 6. Signal spectrum from MARECS data.

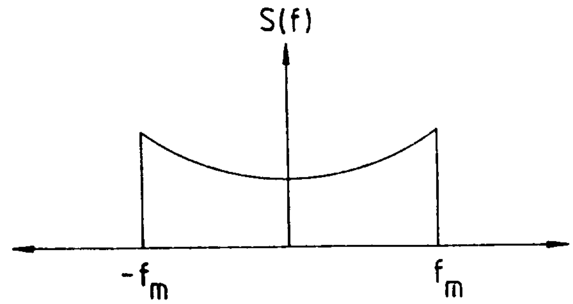

Figure 7. Multipath spectrum from Jakes' multipath model.

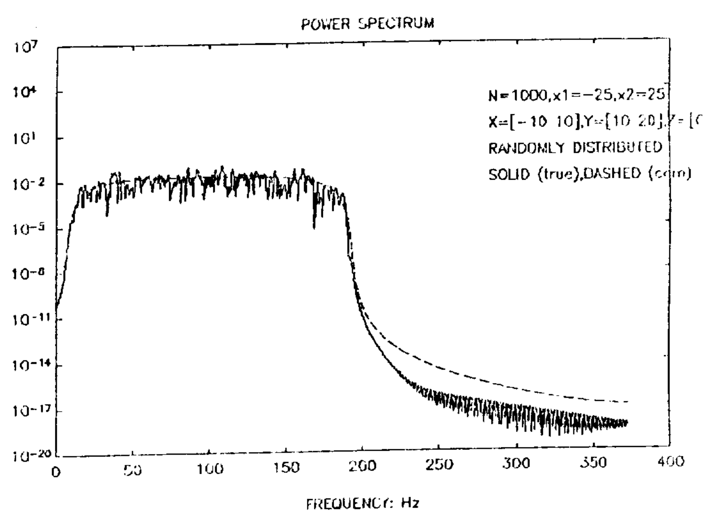

Figure 8. Multipath spectrum from Campbell's simulation.