Monitoring the HF spectrum in the presence of noise

James E. Giesbrecht[a,b,c], Russell Clarke[c], and Derek Abbott[a,b]

[a]Centre for Biomedical Engineering, The University of Adelaide, SA 5005, Australia
[b]School of Electrical & Electronic Engineering, The University of Adelaide, SA 5005, Australia
[c]Ebor Computing, 147 Henley Beach Rd., Mile End, SA 5031, Australia

ABSTRACT

This paper reviews modulation recognition in the context of HF radio-communications. We investigate entropic distance measures and coherence measures for recognizing HF modulations. Preliminary results shown that it may be possible to identify a modulation and its transmit power level based on the entropic distance between it and another modulation. Coherence estimates may provide characteristic signatures that can be used to identify modulation types.

Keywords: Modulation Recognition, Entropy, Coherence, Spectrum Monitoring, HF

1. INTRODUCTION

The HF radio band (nominally 2 MHz to 30 MHz) can be used for long-distance wireless communications because the ionosphere and its various layers refract transmissions in this band. Such refraction enables signals to propagate beyond the horizon to distant receivers unable to be reached by higher frequency (VHF and above) signals. This fact makes the HF band attractive for private and commercial interests as well as for defense forces spread across the globe. For example, spectrum management agencies monitor the HF band for unlicensed operators and military agencies use the HF band for communications.

In the past, HF communication systems were analog. This meant that signals received by an antenna were down-converted to baseband using filters, oscillators, and many discrete components. Receivers were generally constructed in a super-heterodyne configuration.[1] The baseband signals were then passed through demodulators to extract the information content. Often special demodulators had to be switched in to demodulate signals with different modulation schemes.

Today, there are many different modulation techniques. Many of these are of the family of space-time layered signals. Some techniques include direct-sequence spread spectrum (DSSS), frequency-hopped spread spectrum (FHSS), time-domain multiplexing (TDM), frequency-domain multiplexing (FDM), and parallel transmission of data through multiple antennas and/or frequencies. Traditional HF monitoring, processing, and analysis cannot easily handle these signals.

Monitoring and detection of such signals using traditional methods would require numerous HF receivers. Monitoring and detection would also require some prior knowledge of the signals so as to choose the correct receiver. This is a difficult task. Early computers made processing easier, but only recently has enough processing power been available in one package to perform such tasks.

Software radio aims to replicate hardware functions in software running on a generic platform. In so doing many of the problems associated with hardware implementations are avoided. In addition, the receiver and transmitter chains can easily be changed to accommodate various modulation schemes. The idea is to digitize the incoming radio-frequency (RF) signal directly and then to perform down-conversion and demodulation in digital hardware. High resolution Analog-to-Digital Converters (ADCs) and Digital Down-Converters (DDCs) are now available for operation at sampling rates in the 100 MHz range. These sampling rates allow for direct digitization of RF signals up to around 50 MHz.

Send correspondence to:
The University of Adelaide - E-mail: james@eleceng.adelaide.edu.au; Phone: +61 (8) 8303 6296
Ebor Computing - E-mail: james.giesbrecht@ebor.com; Phone: +61 (8) 8238 0300; Fax: +61 (8) 8238 0304

Noise in Communication, edited by Langford B. White, Costas N. Georghiades, Michael H. Hoffmann, Lluís Pradell, Proceedings of SPIE Vol. 5473 (SPIE, Bellingham, WA, 2004) · 0277-786X/04/$15 · doi: 10.1117/12.546672

This paper continues the work presented in a critical review of contemporary papers on modulation recognition, signal separation, and Single Station Location (SSL) in the context of HF radio-communications by Giesbrecht, Clarke, and Abbott.[2] The paper investigates possible methods for recognizing HF modulations. One method[3] that is being used for language, text, and author identification may also be useful for HF modulation recognition. Another method relies on coherence estimates of HF signals. Hence the objective of this paper is to compare these methods and comment on their use in HF modulation recognition.

2. MODULATION RECOGNITION

The process of determining the modulation type of a signal with no foreknowledge of the signal modulation characteristics is known as modulation recognition. This field has been a topic of research since the mid-1980s. During those early days, modulation recognition was accomplished through multiple hardware demodulators – one for each modulation type of interest. With the advent of software radio, these multiple demodulators are being combined in software. With either method, the purpose of modulation recognition is to determine the type of modulation so that the correct demodulator can be chosen to demodulate the signal.

Fundamental processes of modulation recognition are feature extraction and classification (see Figure 1). Feature extraction determines unique characteristics of the signal so that a classifier can establish the modulation type. Common features include instantaneous amplitude, variance of phase, spectral symmetry, transmission models, and higher order statistics. Classification associates features with modulation types. These associations are normally made through threshold detection logic, artificial neural networks (ANNs), or pattern recognition algorithms.

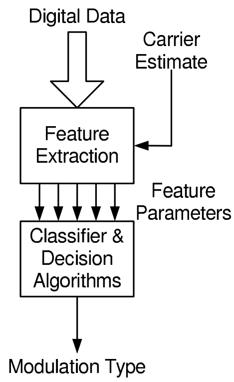

Figure 1. A typical modulation recognition structure.

Hero[4] and Nolan *et al*[5] described statistical methods for feature extraction and used threshold detection logic for feature classification. Their methods were able to correctly recognize various types of phase-shift-keying (PSK) and frequency-shift-keying (FSK). However, their assumptions of additive white Gaussian noise (AWGN), ideal bandpass filtering, Rayleigh fading, Doppler effects, or uniformly distributed phase noise are not generally valid for HF communications. Nor have they included in their papers any field-testing of their methods. Ketterer[6] *et al* also applied statistical methods and threshold detection to tackle the modulation recognition problem. But in this case, they demonstrated the robustness of their algorithm by applying it to a *real-world* short-wave radio signal having symbols identical to their synthetic data.

Others have taken a hybrid approach to modulation recognition. Wong and Nandi[7] described a feature extraction and classification algorithm for discriminating PSK, FSK, V.29 and V.32 (modem modulation standards), and QAM. Feature extraction was obtained through statistical methods, while classification was based on ANNs. Without noise and with suitable training, their method was capable of recognizing the modulation types with no error. With signal-to-noise ratios (SNRs) of 15 dB and 20 dB, their algorithm was able to recognize the modulation types with less than 10% error. The authors, however, do not mention the noise model for their simulations and do not consider the effects of real noise (an SNR of less than 15 dB is quite common for radio communications), multi-path, or Doppler shifts on the performance of the system. All of these strongly influence HF communications and so it is doubtful that the performance figures they quote are achievable for practical HF transmissions.

Waller and Brushe[8] addressed the problem of modulation recognition in a completely different way. Instead of pattern recognition, parameter estimation, or neural networks, the authors chose the best model of the transmission system based on observations of the noisy received signal. They focused on frequency modulation (FM) and phase modulation (PM) and used a cross-correlation approach that gave rise to characteristic peaks for FM or PM. This was based on the assumption that another recognition system had already determined that the signal was some form of angle modulation (FM or PM). For the estimation, the researchers passed the signal through parallel FM and PM demodulators. The output signal from each of the demodulators was re-modulated with parallel FM and PM modulators using an estimate of the carrier frequency of the received signal. The outputs of the four modulators were then correlated with the original received signal to determine the type of modulation. However, their identification of correlation peaks relies on appropriate threshold detection and in this sense, their method is no different from many other researchers.[4,5,9]

It is clear that much current research on modulation recognition concentrates on trial-and-error and statistical methods, threshold detection logic, pattern recognition techniques, or artificial neural networks. A number of these have been described above. All perform two basic functions: feature extraction and signal classification; and all suffer a common problem.

The problem is that of practical validity. Many researchers claim success of their methods based on assumptions of additive-white-Gaussian-noise, propagation characteristics, simulated data, and somewhat arbitrary thresholds. Validation raises many questions. Are the chosen correlation thresholds valid for HF communications? What is the real noise distribution for the HF band? Are the assumed propagation characteristics valid in all situations? What is the best way to determine the modulation type? Are *brute-force* methods (e.g. those of Waller and Brushe or the Coherence method) better than statistical methods? Is there a benchmark signal or benchmark noise distribution that could be used to verify modulation recognition methods for the HF band? If a recognition technique fails in the field, why did it fail, and how can it be improved to operate successfully? Which recognition method is the most robust and able to handle real data?

The modulation recognition methods presented above do not adequately rationalize the choice of thresholds and feature functions. Moreover, they do not assume appropriate noise and channel models[10,11] for application of their methods to the HF band, and they do not apply their methods to *real* signals (cf. Ketterer[6]). A key difference of the research presented here is that *real* HF signals containing *real* noise and interference are used instead of simulated data.

3. METHODS

Two methods are discussed that may, with suitable modification, be useful for identifying various HF modulations. The metric of entropy between information sources provides a promising approach to the problem. Estimates of coherence functions may also provide useful signatures for signal identification.

3.1. Entropic Distance

Benedetto, Caglioti, and Loreto[3] presented a method whereby the similarity or dissimilarity of two information sources, $\boldsymbol{A}$ and $\boldsymbol{B}$, was defined by their relative entropy. They compressed a long sequence A from $\boldsymbol{A}$ and subtracted the compressed length from the length of the compressed sequence $A+b$, where $A+b$ was the concatenation of A and a small sequence b from $\boldsymbol{B}$. This was defined as the *entropy* of $\boldsymbol{A}$ (designated by Δ_{Ab}). In a similar manner they computed the *entropy* of $\boldsymbol{B}$ as Δ_{Bb}. They then defined the relative entropy between A and B as

$$S_{AB} = \frac{\Delta_{Ab} - \Delta_{Bb}}{|b|}, \tag{1}$$

where $|b|$ was the length of b, and the relative entropy between B and A as

$$S_{BA} = \frac{\Delta_{Ba} - \Delta_{Aa}}{|a|}, \tag{2}$$

where $|a|$ was the length of a small sequence of A. The total relative entropy, or entropic distance, between the two information sources was then

$$S_T = S_{AB} + S_{BA}. \tag{3}$$

By applying the algorithm to language recognition, authorship attribution, and classification of sequences they were able to successfully identify languages and authors. For example, the method was able to successfully distinguish between Dutch, Danish, English, French, Finnish, German, Italian, Portuguese, Spanish, and Swedish. It was also able to correctly identify the author of a text 93.3% of the time. And for language classification, the method was able to correctly classify the romance, celtic, germanic, slavic, and baltic languages.

In the research presented here, the information source $\boldsymbol{A}$ consists of a down-converted HF signal of the types in Table 1. Furthermore, $\boldsymbol{B}$ also consists of a down-converted HF signal of types in the table. The idea then, is to determine the entropic distance between various combinations of different HF signals.

The entropic distance is computed for pairs of down-converted signals at various transmit power levels (see Section 5) and at various $|b|$ and $|a|$. The length of b or a is varied between 0.1% and 10%, in 0.1% steps, of the total length of a reference sequence. The reference sequence is either B in Equation 1 or A in Equation 2.

3.2. Coherence

Another method that may be useful for modulation recognition is the coherence function. In general, the coherence function is analogous to correlation coefficients in the frequency domain. Consider the power-spectral density of a signal X. It is defined as

$$P_{xx}(f) = \int_{-\infty}^{\infty} \rho_{xx}(\tau) e^{-j2\pi f\tau} d\tau \tag{4}$$

where f is frequency, τ is time delay, and $\rho_{xx}(\tau)$ is the auto-correlation function of X. In a similar manner, the cross-spectral density is defined by

$$P_{xy}(f) = \int_{-\infty}^{\infty} \rho_{xy}(\tau) e^{-j2\pi f\tau} d\tau \tag{5}$$

where $\rho_{xy}(\tau)$ is the cross-correlation of signals X and Y. From these definitions the coherence function is the cross-spectral density normalized by the respective power-spectral densities;

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)}. \tag{6}$$

For each frequency, the coherence function varies between 0 and 1 and indicates the similarity between X and Y. If the value of the function at a particular frequency is close to unity, it indicates that X and Y are similar at that frequency. On the other hand, if the value of the function is near zero it implies that the two signals are dissimilar at the particular frequency.

This work estimats the coherence function, using Welch's[12] averaged periodogram method, of pairs of down-converted signals at various transmit power levels (see Section 5). Welch's method breaks the sequences into overlapping sections. Each overlapping section is detrended and windowed by a 2048-point Hanning window before a 2048-point Fast Fourier Transform (FFT) is applied.

4. RESEARCH PLATFORM

An HF Monitoring System and research platform is currently under development at Ebor Computing. This monitoring system consists of an array of antennas, followed by signal conditioning electronics, multiple digital receivers, and a data processing sub-system (see Figure 2).

The Analog RF Subsystem consists of antennas, amplifiers, attenuators, and filters. Outputs of this subsystem are fed to a rack of digital receivers that directly sample RF signals up to 50 MHz and down-convert the HF channels to baseband. The digitization of the RF signals is achieved by high-speed analog-to-digital converters (ADCs). Down-conversion is accomplished with digital-down-converters (DDCs). The Data Processing

Subsystem collects the baseband information and processes it. Processing includes functions such as modulation recognition, signal separation, and SSL. A Remote Management System oversees the operation of the entire system. The research platform operates independently of the Data Processing Subsystem and Remote Management System. It also includes a remotely-controlled test-transmitter with HF modem (not shown) that sends groundwave signals to the HF Monitoring System.

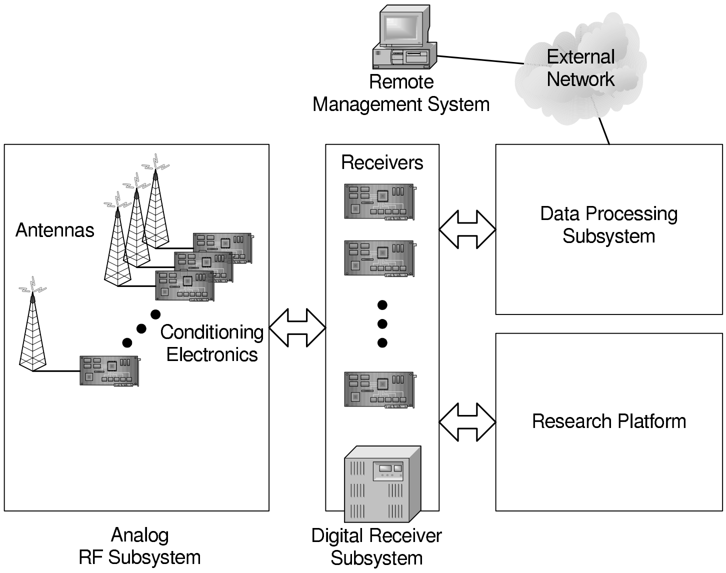

Figure 2. Architecture of the HF monitoring system.

5. DATA COLLECTION

An HF modem (British Aerospace ARM-9401) was setup with a 1 W HF transmitter approximately 300 m from the antenna array of the HF Monitoring System. At this distance, the HF Monitoring System was able to receive groundwaves from the transmitter that arrived relatively unattenuated and undistorted but still containing noise and possibly interfering signals. The modem was capable of a number of different modulation schemes, however, only the four in Table 1 were considered in this work.

In turn, each of the four different modulation schemes were transmitted by the HF modem on 15.824 MHz USB (upper side-band). The research platform applied a 3 kHz low-pass filter on the received signal since channels in the HF spectrum are generally 3 kHz wide and the chosen modulations had bandwidths of 3 kHz. Furthermore, each modulation type was transmitted at various power levels: -30 dBm, -24 dBm, -18 dBm, and -12 dBm.

6. RESULTS

6.1. Entropic Distance Results

There are six unique pairs (see Table 2) of the four modulation types. Computing the entropic distances between each pair results in two groups of distances: Group I and Group II. Pairs in Group I are separated by small entropic distances while pairs in Group II have relatively large entropic distances between them. Figure 3 is typical of signal pairs in Group I except for self-pairs (i.e. any one modulation versus itself such as 8-PSK vs. 8-PSK) which always results in entropic distances of zero. Figure 4 is typical of signal pairs in Group II. Clearly, the shape and magnitude of the curves for Group I differ from those of Group II.

Entropic distances between pairs in Group I are quite small, generally between 0.1 and 0.4, whereas distances between Group II pairs vary between 0.25 and 2.7. What this implies is that for all lengths, $|b|$ or $|a|$, the pairs in Group I are more similar to each other then the pairs in Group II.

Table 1. HF Modulation Types

Modulation	Standard	Characteristics
8-PSK	Stanag 4285	75 baud long interleaving Single Tone Sub-Carrier 1800 Hz Bandwidth 600-3000 Hz
FSK Alt. Wide	Mil-Std-188-110A Sec. 5.1.1 (HF Narrow)	75 baud no interleaving Mark:1915 Hz Space:2085 Hz
FSK Narrow	Mil-Std-188-110A Sec. 5.1.3 (LF UHF Speech+Telephony)	75 baud no interleaving Mark:2762.5 Hz Space:2847.5 Hz
FSK Wide	Mil-Std-188-110A Sec. 5.1.2 (HF Wide)	75 baud no interleaving Mark:1575 Hz Space:2425 Hz

Another noticeable difference between the two groups is that the transmit power level does not affect the entropic distances in a linear manner. For example, one would expect that as the transmit power was varied up or down the entropic distance between pairs of signals would change accordingly. However as both figures show, the -18 dBm curve is below the -12 dBm curve, but the -24 dBm and -30 dBm curves are above the -12 dBm curve. It could be expected that the -12 dBm curve and -18 dBm curve should be interchanged.

Nevertheless, the figures do reveal that for longer appended sequences (i.e. b or a), a difference in transmit power level can be detected as a change in entropic distance. It may also be possible to identify the signal modulation if it can be proven that particular entropic distances are associated with particular signal pairs and signal levels. This is a subject of further work.

Table 2. Pairs of modulation types

Group	Pair	Combination
I	1	8-PSK vs. FSK Alt. Wide
I	2	8-PSK vs. FSK Wide
I	3	FSK Alt. Wide vs. FSK Wide
II	4	8-PSK vs. FSK Narrow
II	5	FSK Narrow vs. FSK Wide
II	6	FSK Alt. Wide vs. FSK Narrow

6.2. Coherence Results

The coherence function is estimated for each of the signal pairs discussed above. For reference, Figure 5 illustrates the power-spectral densities of the individual signals in Table 1 and clearly shows the differences between the signals.

Figure 6 shows coherence functions that are typical for each pair of signals at the various transmit levels. As implied by the power-spectral densities, the coherence functions illustrate the dissimilarities between the four modulation types. That is, the values at each frequency are quite small. However, for self-pairs the coherence function is always unity. This highlights the weakness and strength of the coherence function. For example, though FSK Alt. Wide and FSK Wide differ only in the mark and space frequencies the coherence function indicated a low score (i.e. highly dissimilar modulations). One would expect that a somewhat higher score would be have been achieved because both methods were FSK. On the other hand, the coherence function yielded a high score if it was applied to self-pairs or signal pairs that were nearly the same so that a definite identification was possible. It is therefore obvious that the coherence function must be considered a *brute-force* approach.

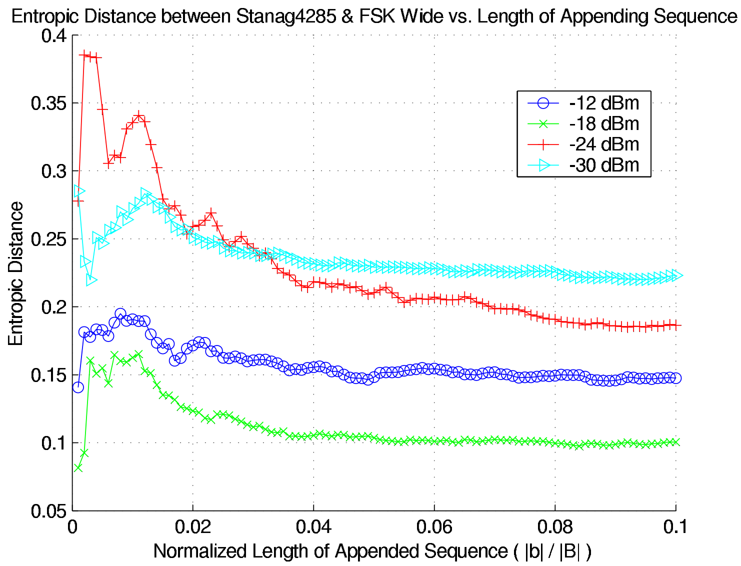

Figure 3. Entropic distances between 8-PSK and FSK Wide (Group I).

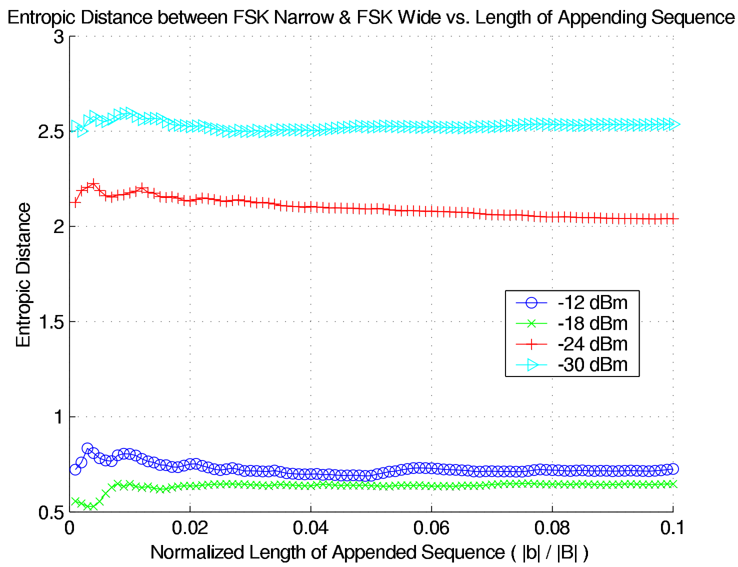

Figure 4. Entropic distances between FSK Narrow and FSK Wide (Group II).

The coherence functions also appear to vary with the transmit power levels, though not in a consistent manner. The differences may have been due to variations in the HF environment as much as they were due to changes in transmit power level.

For now, the results raise more questions than they answer. Does the coherence function for a signal pair convey the same relative closeness (or distance) that the previous method shows? Does a signal pair have a characteristic coherence function that can be used as an identifying signature? These questions stimulate directions for research.

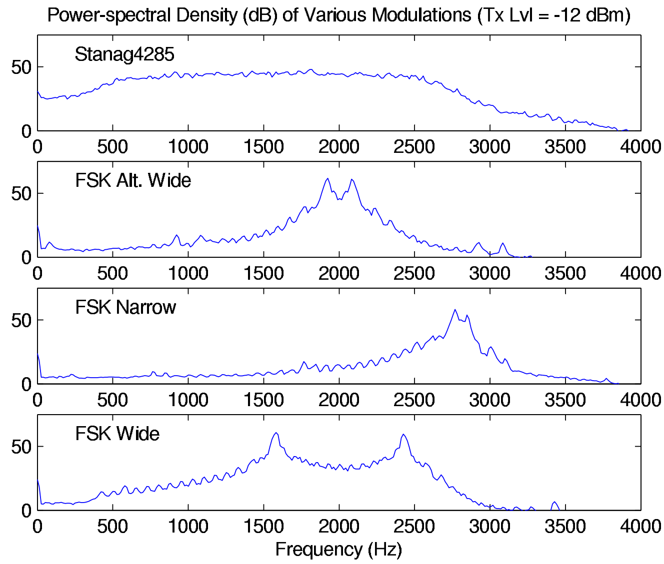

Figure 5. Power-spectral densities of various HF modulations.

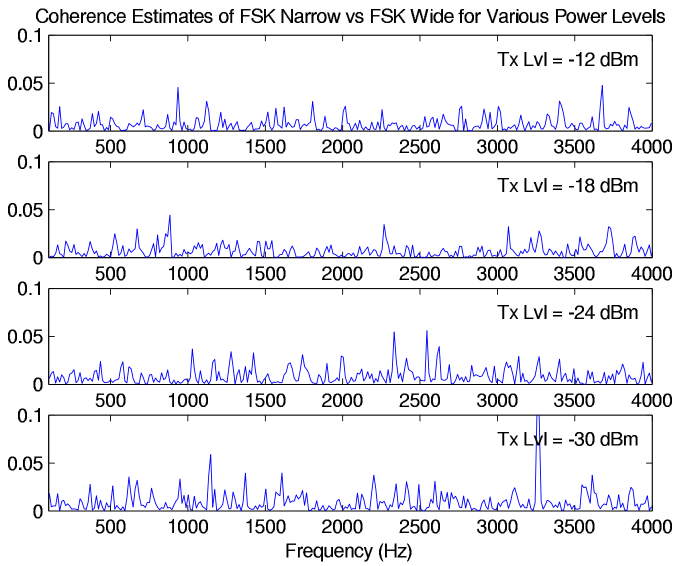

Figure 6. Coherence functions for FSK Narrow and FSK Wide.

7. SUMMARY AND FUTURE WORK

Two methods for recognizing HF modulation schemes were discussed. One technique measured the entropy between pairs of modulated HF signals. The other method attempted to identify similarities between pairs of HF signals based on estimates of the coherence function.

Preliminary results show that it may be possible to identify a modulation based on the entropic distance between it and another modulation. It may also be possible to detect a difference in transmit power level between two modulated HF signals.

The coherence function does not, at first glance, appear to easily identify the modulation type of a HF signal. However, it may be that the coherence function can provide a signature that is identifiable with a particular modulation type.

Additional sample sets of *real* HF signals need to be collected and analyzed to validate the suitability of the presented methods for HF modulation recognition. Furthermore, a benchmark for each modulation type needs to be found and established so that other methods can be measured against it.

ACKNOWLEDGMENTS

Financial support for this work is provided by the The University of Adelaide and Ebor Computing.

REFERENCES

1. J. Smith, *Modern Communication Circuits*, McGraw-Hill Series in Electrical Engineering, McGraw-Hill Inc., New York, 1st ed., 1986. pp. 1-13.
2. J. E. Giesbrecht, R. Clarke, and D. Abbott, "Improved techniques for monitoring the HF spectrum," in *Proceedings of SPIE*, **5274**, 2003.
3. D. Benedetto, E. Caglioti, and V. Loreto, "Language trees and zipping," *Physical Review Letters* **88**(4), p. 048702, 2002.
4. A. O. Hero III and H. Hadinejad-Mahram, "Digital modulation classification using power moment matrices," in *Proceedings of the IEEE 1998 International Conference on Acoustics, Speech, and Signal Processing*, **6**, pp. 3285–3288, (Seattle), 1998.
5. K. E. Nolan, L. Doyle, P. Mackenzie, and D. O'Mahony, "Modulation scheme classification for 4G software radio wireless networks," in *Proceedings of the IASTED International Conference on Signal Processing, Pattern Recognition, and Applications (SPPRA 2002)*, pp. 25–31, (Crete, Greece), 2002.
6. H. Ketterer, F. Jondral, and A. H. Costa, "Classification of modulation models using time-frequency methods," in *Proceedings of the IEEE 1999 International Conference on Acoustics, Speech, and Signal Processing*, **5**, pp. 2471–2474, (Phoenix, Arizona), 1999.
7. M. L. D. Wong and A. K. Nandi, "Automatic digital modulation recognition using spectral and statistical features with multi-layer perceptrons," in *Proceedings of the IEEE International Symposium on Signal Processing and its Applications*, **2**, pp. 390–393, (Kuala Lumpur, Malaysia), 2001.
8. J. R. Waller and G. D. Brushe, "A method for differentiation between frequency and phase modulated signals," in *Proceedings of IEEE Information, Decision, and Control 1999*, pp. 489–494, 1999.
9. H. C. Tan, K. Sakaguchi, J.-I. Takada, and K. Araki, "*DOA based Signal Combining aided Automatic Modulation Recognition/Demodulation for Surveillance System*," tech. rep., The Institute of Electronics, Information and Communications Engineers (IEICE), 2002.
10. L. Sevgi and A. M. Ponsford, "*An HF Radar Based Integrated Maritime Surveillance System*," tech. rep., Raytheon Systems Canada Ltd, 1999. `http://www3.dogus.edu.tr/lsevgi/LS_PROF/SYMP/siu99.pdf`.
11. M. Goris, "*Categories of Radio-Frequency Interference*," tech. rep., National Foundation for Radio Astronomy, Holland, February 1998.
12. P. D. Welch, "The use of the fast fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms," *IEEE Transactions on Audio and Electroacoustics* **AU-15**, pp. 70–73, June 1967.