Enhanced Low-Complexity Detector Design for Embedded Cyclostationary Signatures

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***Abstract*—This paper presents a novel cyclostationary signature detector designed for robust detection of embedded signatures under frequency-selective fading conditions. Cyclostationary signatures are features which may be intentionally embedded in a digital communications signal, detected through cyclostationary analysis and used as a unique identifier. It has been shown that such signatures can also be employed to derive key signal parameters including carrier frequency and bandwidth, making them a powerful tool to support network coordination in dynamic spectrum access scenarios. Signature detection can be compromised under conditions of frequency-selective fading whereby a deep fade can destroy an individual signature. The detector presented in this paper can reduce the destructive effects of such fading conditions, greatly improving detection performance. These improvements are illustrated through simulation results which compare the performance of our detector with that of existing designs.**

I. INTRODUCTION

A signal is cyclostationary if there exists some nonlinear transformation of that signal which will generate finite-strength additive sine-wave components [1]. A signal is said to exhibit *second-order* cyclostationarity if its mean and autocorrelation are periodic.

Many of the communications signals in use today exhibit second and higher-order cyclostationarity due to underlying periodicities introduced through coupling stationary message signals with periodic sinusoidal carriers, pilot sequences, spreading codes and repeating preambles. It has been shown that these cyclostationary properties can be used to achieve a number of critical tasks including signal detection [2], classification [3], synchronization [4], [5] and equalization [6].

Cyclostationary signal analysis is a powerful tool when applied to the inherent cyclostationary features of transmitted communications signals. However, the authors have shown that it is also possible to generate intentionally embedded cyclostationary features and use these known *signatures* to achieve key tasks while reducing the computational complexity typically associated with cyclostationary analysis [7]. In this way, real-time cyclostationary analysis can become a practical tool for use in reconfigurable wireless networks.

Nodes within a reconfigurable wireless network may dynamically change the properties of their transmitted waveform in order to improve the quality of a given wireless link, to efficiently use available spectral resources, to avoid the creation of harmful interference or to respond to changes in their operating environment. A key challenge in this context is network coordination. If, for example, the carrier frequency or bandwidth of the waveform in use can be dynamically changed, how do nodes in the network maintain communication links? How do new nodes join the network?

One approach to achieve self-configuration and self-coordination in such networks is to adopt a common control channel with fixed waveform parameters which are known in advance. This control channel can be used as a bootstrapping mechanism, allowing nodes to retrieve the information needed to join the network and maintain communication links. However, the use of such a control channel requires a static allocation of resources and presents a bottleneck and single point of failure for the network.

A more flexible solution to the problem is to embed a cyclostationary signature in the waveform transmitted by nodes in the network. While the properties of the waveform may change, the properties of the signature are fixed. This permits nodes to detect that signature and use it to discover key waveform parameters before establishing communication links.

Previous work by the authors has shown how cyclostationary signatures can be embedded in multicarrier waveforms and used to achieve signal detection and identification, as well as to estimate the carrier frequency and bandwidth of the signal [7], [8]. It was also seen that frequency-selective fading can destroy signatures by causing a deep fade at the subcarriers used to generate the signature. This paper builds on previous work and presents a novel signature detector design which provides robust detection in a frequency selective fading environment.

The remainder of the paper is structured as follows. Section II gives an overview of cyclostationary signatures and their generation in multicarrier waveforms. The use of signatures in reconfigurable wireless networks is discussed and the effect of frequency-selective fading is examined. The enhanced signature detector design is presented in Section III and its performance is examined through simulation results in Section IV. Section V concludes the paper.

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II. CYCLOSTATIONARY SIGNATURES

Second order cyclostationarity manifests as a correlation pattern in the spectrum of a signal. This spectral correlation completely describes the cyclostationarity of the signal and may be examined using the spectral correlation function (SCF) [2],

$$S_x^\alpha(f) = \lim_{\Delta f \to \infty} \lim_{\Delta t \to \infty} \frac{1}{\Delta t} \int_{-\Delta t/2}^{\Delta t/2} \Delta f X_{1/\Delta f}(t, f + \frac{\alpha}{2}) \cdot X^*_{1/\Delta f}(t, f - \frac{\alpha}{2}) dt \qquad (1)$$

where

$$X_{1/\Delta f}(t, v) = \int_{t-1/2\Delta f}^{t+1/2\Delta f} x(u) e^{-i2\pi v u} du \qquad (2)$$

represents the complex envelope of the narrow-band-pass component of $x(t)$ with centre frequency v and bandwidth Δf.

The spectral coherence (SC) [9], C_x^α, can be used to normalize the cyclic spectrum estimates in the range [0,1]:

$$C_x^\alpha(f) = \frac{S_x^\alpha(f)}{\sqrt{S_x^0(f+\alpha/2) S_x^0(f-\alpha/2)}} \qquad (3)$$

where $S_x^0(f)$ is the SCF at cyclic frequency $\alpha = 0$.

In order to generate an artificial cyclostationary signature, we can intentionally generate a correlation pattern in the spectrum of a signal. This can be easily achieved in multicarrier waveforms where individual subcarriers can be manipulated to alter the spectral properties of the overall waveform.

Orthogonal Frequency Division Multiplexed (OFDM) waveforms consist of many subcarriers, separated in frequency and individually modulated by a sequence of message symbols. Due to the efficient implementation of OFDM transceivers using the Fast Fourier Transform (FFT) and the robustness of the waveform to multi-path fading, OFDM currently forms the basis for many of the most common wireless standards including IEEE 802.11g, IEEE 802.16, ETSI DAB, ETSI DVB and 3GPP LTE.

OFDM signals may be represented as a composite of N statistically independent subchannel Quadrature Amplitude Modulated (QAM) signals [10]:

$$w(t) = \sum_k \sum_{n=0}^{N-1} \gamma_{n,k} e^{j(2\pi/T_s)nt} q(t - kT) \qquad (4)$$

where $w(t)$ is the complex envelope of an OFDM signal with a cyclic prefix, $\gamma_{n,k}$ is the independent, identically distributed message symbol transmitted on subcarrier n during OFDM symbol k, N is the number of subcarriers and $q(t)$ is a square shaping pulse of duration T. T_s is the source symbol length and T_g is the cyclic prefix length such that $T = T_s + T_g$.

A cyclostationary signature may be embedded in an OFDM waveform simply by mapping one subset of subcarriers onto a second subset so that message data transmitted on the first subset is identically transmitted on the second:

$$\gamma_{n,k} = \gamma_{n+p,k}, \qquad n \in M \qquad (5)$$

where M is the set of subcarrier values to be mapped and p is the number of subcarriers between mapped symbols. This approach is illustrated in Fig. 1.

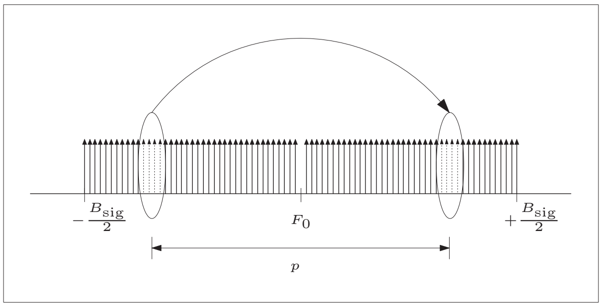
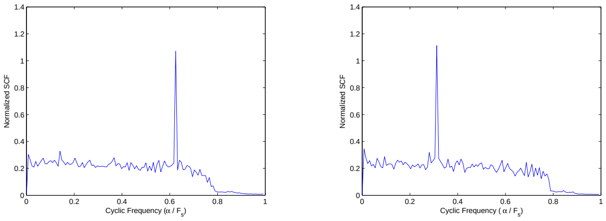


Fig. 1. Embedding a cyclostationary signature in an OFDM waveform.

Cyclostationary signatures generated by mapping a single subset of subcarriers consist of a single feature occurring at cyclic frequency $\alpha = \frac{p}{T_s}$. If this cyclic frequency is known in advance, the computational complexity associated with detecting the signature can be greatly reduced. As the signature is continuously present in the transmitted waveform, it may be detected by capturing and analyzing any part of that waveform.

A key advantage of cyclostationary signatures generated through subcarrier set mapping is the ability to create unique identifiers by choosing different cyclic frequencies, α for the embedded feature. This is achieved simply by choosing the subcarrier mapping distance, p. This can be seen in Fig. 2 which shows the alpha profile of two signals, each containing a signature generated at a different cyclic frequency.



(a) Signature at α_1 (b) Signature at α_2

Fig. 2. Unique cyclostationary signatures at two different cyclic frequencies.

In addition to their use to detect and identify signals of interest, signatures can be used to determine key signal parameters such as carrier frequency and bandwidth. Carrier frequency acquisition is required for network rendezvous, where a wireless node wishes to receive a signal, establish a communication link and join the network. Fig. 3 shows the spectral frequency of a signal at the cyclic frequency of an embedded signature. In this case the subcarrier subsets used to generate the signatures are equidistant from the carrier frequency of the signal and the feature can be used directly to determine that carrier frequency.

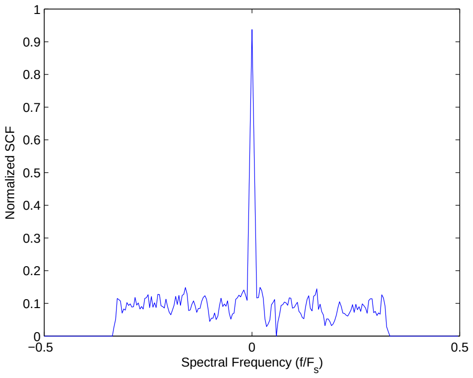


Fig. 3. Spectral frequency at α_{sig}, the signature cyclic frequency.

One challenge associated with using cyclostationary signatures in reconfigurable wireless networks is detection in the presence of frequency-selective fading. A deep fade at the location of a mapped subcarrier subset can distort the resulting signature. This can be seen in Fig. 4 where the spectral frequency of the signal is shown at the cyclic frequency of the embedded signature.

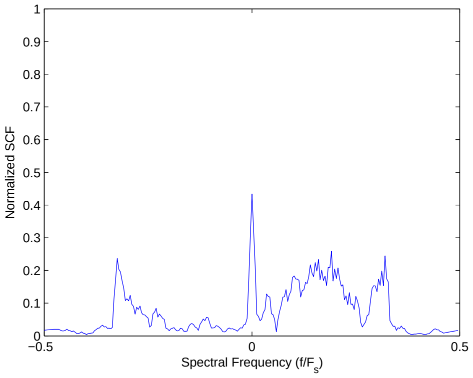


Fig. 4. Distortion of cyclostationary signature caused by frequency-selective fading.

OFDM waveforms exhibit robustness to frequency-selective fading due to the conversion of a single high-rate data stream to multiple low-rate streams and the use of a cyclic prefix to collect multipath components. However, in order to benefit from these features, close time and frequency synchronization is required. In the context of signal detection, identification and parameterization, this is not possible and the effects of multipath must be overcome in other ways.

The next section presents a signature detector which provides robust detection in the presence of multipath.

III. ENHANCED DETECTOR

Optimum cyclostationary feature detection can be performed through correlation of the estimated SCF with the ideal SCF [2]:

$$y_\alpha(t) = \int_{-\infty}^{\infty} S_s^\alpha(f) * \tilde{S}_x^\alpha(f) df e^{i2\alpha\pi t} \tag{6}$$

where $\tilde{S}_x^\alpha(f)$ is the estimated SCF following notch filtering to remove strong narrow-band interference. Estimation of the SCF may be performed using the time-smoothed cyclic cross periodogram (TS-CCP), a consistent, asymptotically unbiased and complex normally distributed estimator for the cyclic cross spectrum [11]:

$$\hat{S}_x^\alpha[k] = \frac{1}{L}\sum_{l=0}^{L-1} X_l[k]X_l^*[k-\alpha]W[k] \tag{7}$$

where $W[k]$ denotes a smoothing spectral window and $X_l[k]$ is the Fourier transform of the discrete-time signal $x[n]$ after sampling the received signal $x(t)$,

$$X_l[k] = \sum_{n=0}^{N-1} x[n] \exp^{\frac{-i2\pi nk}{N}} \tag{8}$$

Estimates are calculated using L windows of length N where N is the duration of a single OFDM symbol.

Previous work has shown that an SCF signature detector can be implemented using the TS-CCP directly and used to achieve signal detection, identification and frequency acquisition [7]. However, the performance of such a detector in frequency-selective fading conditions can be greatly improved through estimation of the spectral coherence (SC) (Eqn.3). The spectral coherence normalizes the SCF with the power of the signal on a per-frequency bin basis. This can compensate for some of the effects of multipath distortion.

Our low-complexity single-cycle signature detector may be implemented through estimation of the SC as:

$$y_\alpha = \max_{0 \le k \le N-1} \sum_{m=0}^{M-1} H[m]\hat{C}_x^\alpha[k-m] \tag{9}$$

where $H[m]$ is a rectangular window and $\hat{C}_x^\alpha[k]$ is computed as

$$\hat{C}_x^\alpha[k] = \frac{\hat{S}_x^\alpha[k]}{\sqrt{\hat{S}_x^0[k]\hat{S}_x^0[(k-\alpha)_N]}} \tag{10}$$

with $(.)_N$ denoting the modulo-N operation. Then, y_α is compared to a threshold for feature detection.

IV. PERFORMANCE

Simulations were used to examine the performance of our SC detector and to compare it with that of the simpler SCF detector.

256-subcarrier OFDM signals were considered, with subcarriers distributed as follows: 192 data, 55 guard, 8 pilot and 1 DC. Data was randomly generated and QPSK modulated with a 16 sample cyclic prefix prepended to each OFDM symbol. Cyclostationary features were embedded at cyclic frequency $\alpha = 16/T_s$ using mapped sets of 3 subcarriers. A 4 MHz signal was simulated with a number of frequency-selective multipath channels modeled using the COST 207 [12]

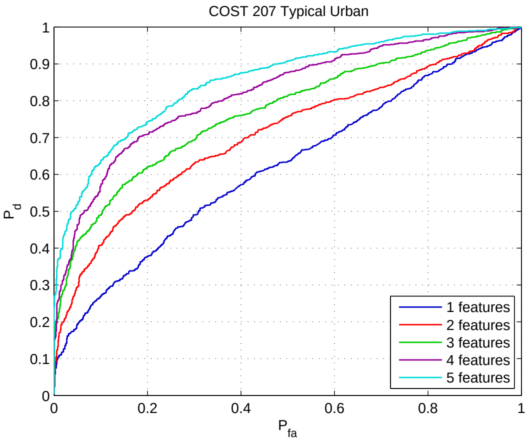


Fig. 5. SCF detector performance - Typical Urban channel.

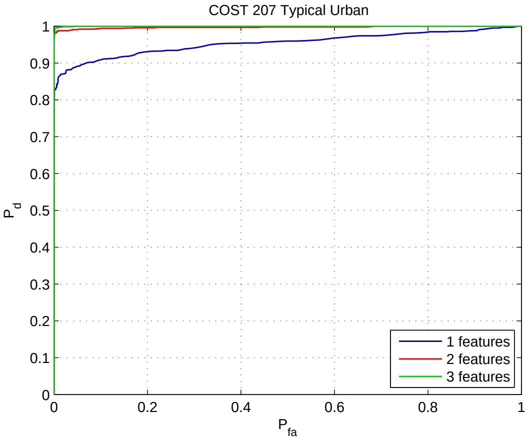


Fig. 6. SC detector performance - Typical Urban channel.

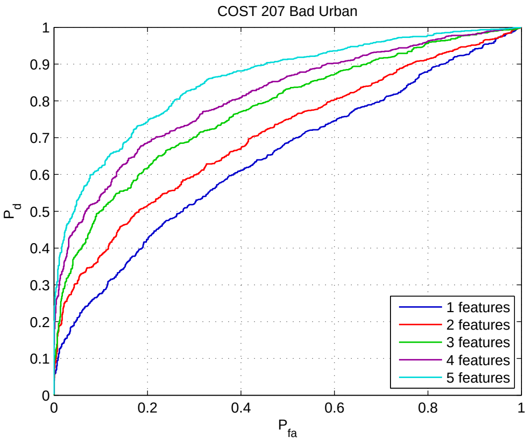


Fig. 7. SCF detector performance - Bad Urban channel.

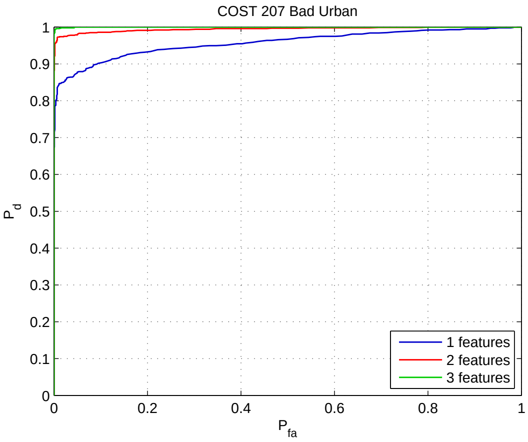


Fig. 8. SC detector performance - Bad Urban channel.

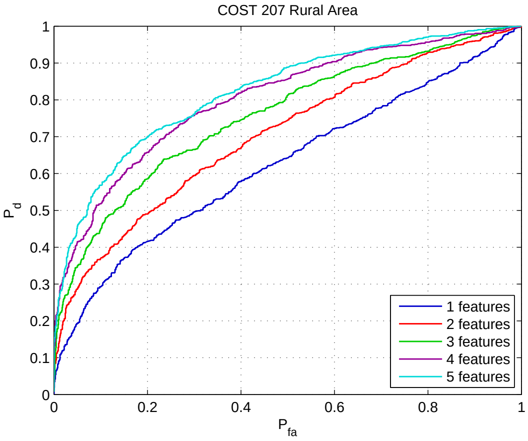


Fig. 9. SCF detector performance - Rural Area channel.

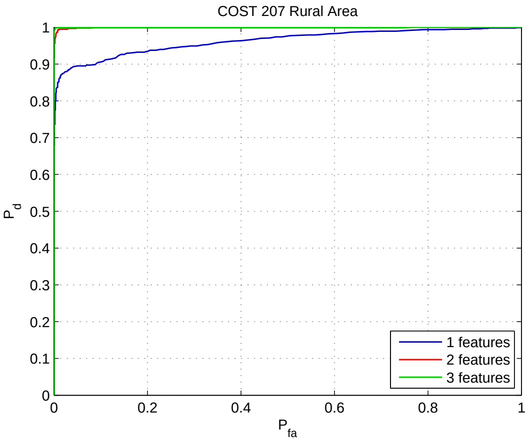


Fig. 10. SC detector performance - Rural Area channel.

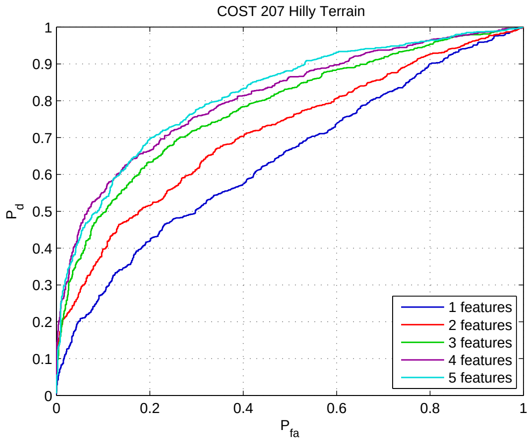


Fig. 11. SCF detector performance - Hilly Terrain channel.

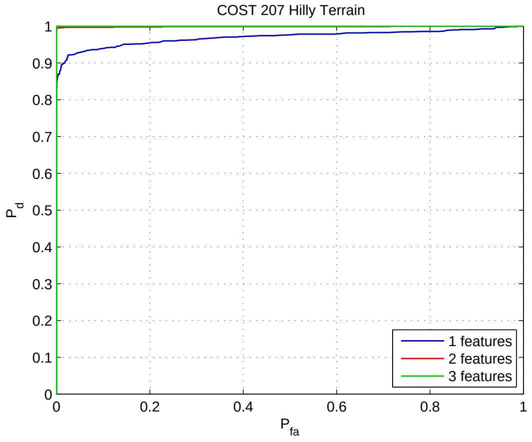


Fig. 12. SC detector performance - Hilly Terrain channel.

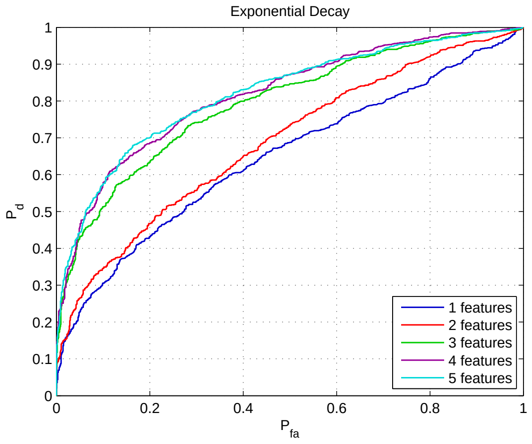


Fig. 13. SCF detector performance - Exponential Decay channel.

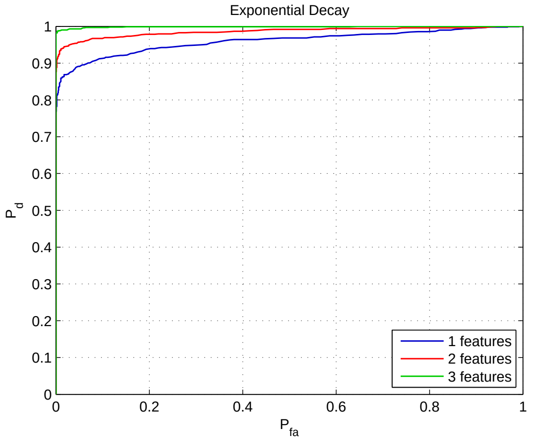


Fig. 14. SC detector performance - Exponential Decay channel.

channel profiles as well as an exponentially decayed channel model. Signatures were generated using between 1 and 5 unique features and Receiver Operating Characteristic (ROC) performance was examined for each using Monte Carlo simulations. Probabilities of detection (P_d) and false alarm (P_{fa}) were recorded over 2000 simulations. Gaussian white noise was added for $SNR \approx 5\,\mathrm{dB}$ and a single feature detector with signal observation time of $\Delta t = 30T$ was used. Fig. 15 illustrates the spread profile of our exponential decay channel model.

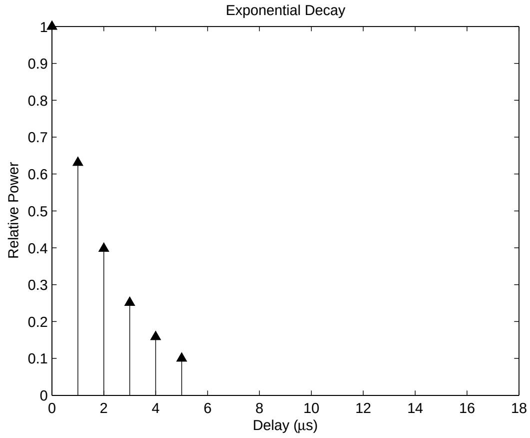


Fig. 15. Exponential Decay channel spread profile.

Examining the performance of our signature detectors under conditions of frequency-selective fading illustrates the importance of power normalization in estimating spectral correlation. Power normalization is achieved through use of the SC (Eqn.3). For each of the channel models examined, it can be seen that the SCF detector performs poorly for an observation time of 30 OFDM symbols. Performance improves slightly with an increased number of features per signature but even with 5 features, a P_d of just 0.75 incurs a P_{fa} of 0.25 using an exponential decay channel model. Previous work has shown that the SCF detector can perform well under these conditions with increased observation times [13]. However, results show that the SC detector achieves very good performance with these short observation times and a low number of features per signature. For each of our channel models, it can be seen that near-perfect detection performance is achieved using just two features per signature.

V. CONCLUSIONS

Cyclostationary signatures are a powerful tool for realizing self-coordinating and self-configuring wireless networks. Intentionally embedded in transmitted multi-carrier waveforms, signatures can be used for signal detection and identification, carrier frequency acquisition and bandwidth estimation. This paper has examined how existing detector designs based on the spectral correlation function (SCF) can be improved through estimation of the spectral coherence (SC) which provides power normalization and compensates for some of the distortion introduced by frequency-selective fading.

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