Decision Fusion Using a Hybrid Spectrum Sensing Technique for Multiple Channels in a Cognitive Radio Network: Evaluation and Simulation

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Abstract:
Hybrid spectrum sensing techniques that combine matched filtering and cyclostationary feature detection have been shown to improve the detection accuracy and reliability of CRN. MF is a technique that uses a filter coordinated to the shape of the expected signal to perceive the existence of a known signal in noise. It is designed to match the waveform of the primary user signal of interest. CFD is a method for identifying the presence of PU by taking advantage of the regularity in the statistical features of the signal. The CFD looks for the cyclic correlation in the signal, which is the correlation between the signal and a time-delayed version of itself. This combination is particularly useful in environments where the primary user signals are weak or the noise level is high. It provides a robust and reliable way of detecting the occurrence of PU in a dynamic and uncertain environment. The technique can also decrease the number of false detections and get better the overall efficiency of spectrum usage in the CRN.
Keywords: Cognitive Radio Network, Hybrid Detection, Spectrum Sensing.

Introduction:
Hybrid spectrum sensing techniques are a combination of two or more SST used to perceive the existence of PU signals in CRN. The goal of HSST is to improve the accuracy and reliability of SS while reducing the false detection and false non-detection probabilities. [1]
There are several HSST that have been evidence and studied in the literature. Some of the most popular techniques are:
1. MF and ED: This technique combines the MF and ED techniques. To determine whether a PU signal is present, an MF is first applied to the acknowledged signal. If the MF output is above a certain threshold, the signal is assumed to be present. If the MF output is below the threshold, energy detection is used to make the decision.[2][5]
2. ED and CFD: This technique combines the ED and CFD. The received signal is first processed by the ED to perceive the existence of a PU information. If the ED output is above a certain threshold, the signal is assumed to be present. If the ED output is below the threshold, the CFD is used to make the decision.[3][4][6]
3. MF, ED, and CFD: This technique combines all three techniques to provide a more robust and reliable spectrum sensing solution. [7][8]

Hybrid spectrum sensing techniques can provide significant improvements in the detection accuracy and reliability of cognitive radio networks. By combining multiple SST, HSST can exploit the strengths of each individual technique while mitigating their weaknesses. [9] However, the choice of the appropriate HSST depends on the specific characteristics of the PU signal, the noise level, and the environment in which the CRN operates.[10][11]

CSS is a technique used in CRN to improve the precision and consistency of SS by merging the sensing outcome from multiple users. The basic design behind cooperative SS is that by merging the local sensing outcomes from multiple clients the overall sensing performance can be improved, and the P_{fa} and P_{md} can be reduced. [12] There are several CSS techniques that can be used in cognitive radio networks, including: Hard decision fusion: In this technique, each user performs local SS and sends a binary decision (i.e., signal present or signal absent) to a FC. The FC combines the binary decisions using a majority voting rule or other fusion rule and produces a final binary decision. Hard decision fusion is simple and easy to implement, but it assumes that all users have the same sensing performance and ignores the uncertainty and variability of the sensing results. Soft decision fusion: In this technique, each user sends a real-valued decision statistic or likelihood ratio to the FC, which coalesced the likelihood ratios using a weighted averaging or other fusion rule.[13] The resulting combined likelihood ratio is then evaluated to a threshold to produce a final binary decision. Soft decision fusion takes into account the uncertainty and variability of the sensing results and can improve the overall sensing performance.[14] Maximal ratio combining (MRC) is a widely used diversity technique in wireless communications to look up the consistency and performance of wireless transmissions. It is a soft fusion rule that combines the signals from multiple receives antennas to improve the received signal quality. [15]

In a CRN, a fading channel refers to a channel in which the strength of the signal varies over time due to various factors such as multipath interference, atmospheric conditions, and obstacles between the transmitter and receiver. The variability in signal strength can cause considerable fluctuations in the received signal power, resulting in errors in decoding the transmitted information. To overcome the effects of fading in a CRN, various techniques can be employed. [16][17]

The effectiveness of the initial phase of SS in the CR cycle is crucial to the success of cognitive radio [4]. Non-cooperative detection is divided into MFD, ED, and CFD categories. This article focuses on the HSST, which combines the MFD scheme with the CFD of Non-cooperative sensing systems [6]. In segment II, the Literature Review is covered. Segment III provides an explanation of the proposed work. The findings of the simulation are discussed in segment IV. Segment V of the manuscript concludes.

Literature Review:

Due to its ability to raise SS precision and dependability in CRN, HSST have attracted significantly more attention over the past few years. The most recently published and important studies that have looked into HSS approaches will be covered in this part.

The authors proposed a HSST method that combines clustering and cooperative decision-making for CRN. In this method, secondary users are grouped into clusters based on their sensing results, and each cluster makes a cooperative decision on the existence or nonexistence of the PU information. The presented method is authenticated by the outcomes of simulations, achieves higher detection accuracy and lower false alarm rate compared to traditional SS methods. [1]

The authors proposed a novel HSST that combines deep learning and Dumpster-Shafer theory for cognitive radio networks. The deep learning algorithm is used to extract features from the acknowledged signal, and the Dumpster-Shafer theory is used to fuse the results from multiple sensors. Research results show that the proposed technique achieves higher detection accuracy and lower false alarm rate compared to traditional spectrum sensing techniques. [2]

The authors proposed a HSST that combines compressed sensing and machine learning for CRN. In this technique, compressed sensing is used to reduce the dimensionality of the received signal, and machine learning algorithms are used to classify the signal as either primary or secondary user. Results from experiments indicate that the suggested method achieves higher detection accuracy and lower false alarm rate compared to traditional spectrum sensing techniques. [3]

The authors propose a HSST that combines ED and CFD. The proposed method first uses ED to sense the presence of PU and then uses CFD to identify the modulation type of the detected signal. The outcomes show that the suggested method outperforms conventional spectrum sensing techniques. [4] [22]

In this paper, the authors proposed a HSST that combines ED and MF. The proposed method first uses ED to sense the existence of the PU signal and then uses MF to identify the primary user signal. Modeling outcomes indicate that the suggested method is effective outperforms conventional ED and MF methods in terms of P_d and P_{fa} rate. [6][26]

This paper proposed a technique that combines ED and CFD. The proposed method first uses ED to sense the existence of the PU signal and then uses CFD to identify the PU signal. Simulation findings demonstrate that the suggested approach is appropriate ED and CFD methods in terms of P_d and P_{fa} rate. [7][28]

System Model

The system model for a HSST that come together MF and CFD can be described as follows:

Signal generate by the primary unit is of 100 bit where each digital information is transform into analog signal. So carrier signal was involved where BPSK modulation was applied. This formation of signal is done at primary user side, in case data is not present at primary signal than channel has carrier waveform only. So if channel is utilized by primary user than channel has data, carrier waveform and noise while in case if primary user has no data than channel has carrier waveform and noise.

1. Received Signal: The conventional signal y[n] at the CR receiver is a superposition of the PU signal and the noise.

2. Matched filter: This is used to correlate the conventional signal with a known template of the PU signal. The MF output is given by:

$$\mathrm{zMF}[n] = \mathrm{y}[n] * \mathrm{hMF}[n]$$

Where hMF[n] is the impulse response of the MF and * denotes convolution.

3. Cyclostationary Feature Detection: This is utilized to detect the cyclic features of the PU signal. The PU signal's cyclic characteristic can be mark as:

$$\mathrm{Sf}(t,\tau) = \mathrm{E}\{\mathrm{y}(t)\ \mathrm{y} * (t-\tau)\}$$

where E{} denotes expectation, y(t) is the received signal, y*(t-τ) is the conjugate of the received signal delayed by τ seconds.

The CFD can be implemented by calculating the cyclic autocorrelation function (CAF) of the received signal. The CAF is defined as:

$$\mathrm{Ryy}(\tau, f) = \lim \mathrm{T}{-}{>}\infty\ (1/\mathrm{T}) * \int\_(0)\hat{}(\mathrm{T})\ \mathrm{y}(t)\ \mathrm{y} * (t-\tau)\ e\hat{}(-j2\pi f t)\ dt$$

Where f is the cyclic frequency and T is the observation time.

4. Decision rule: The decision rule combines the MF output and the CFD output to compose the ultimate result on the existence or nonexistence of the PU signal. The decision rule can be expressed as:

H_0: No PU signal present

H_1: PU signal present

If zMF[n] > Tmf and CAF[f] > Tcaf, then the decision is H_1, where Tmf and Tcaf are the detection thresholds for the matched filter output and the CAF, respectively. Otherwise, the decision is H_0.

Proposed Algorithm

```
Input: N // Number of Nodes
Output: CS // CS: Channel Status (Available /Blank)
Initialize_Network(N)
Loop 1:s // s: number of time random signal generate
R←Rand() // Generate 1 or 0
If R is 1
S←Signal + Gaussian_Noise()
Otherwise
S← Gaussian_Noise()
EndIf
```

S←Channel(S)

Loop 1:N // Each Node Sense Channel
m←match_filter (S)
c←cyclostationary(S)
m←Normalize(m)
c←Normalize(c)
F←[m c]
EndLoop
CS←Fusion_Center (F)

In closing, the HSST based on MF and CFD combines two distinct techniques to find the existence of the PU information. The PU signal's cyclic properties are detected by the CFD, while the signal's signal energy is detected by the MF. To determine whether the PU signal is in use or not, the decision rule combines the outputs of the MF and the CFD.

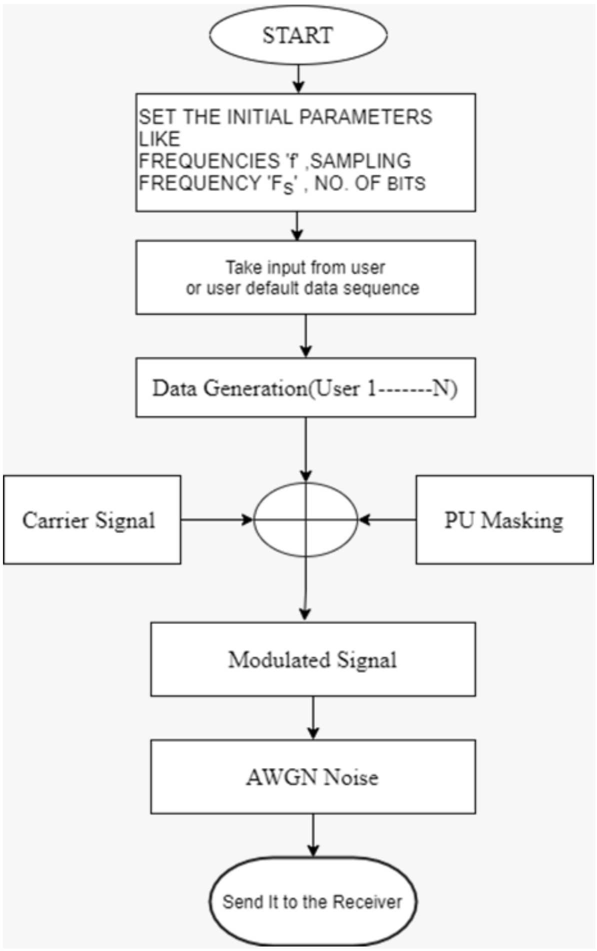

Figure 1: Flow Chart of Proposed Transmitter Section

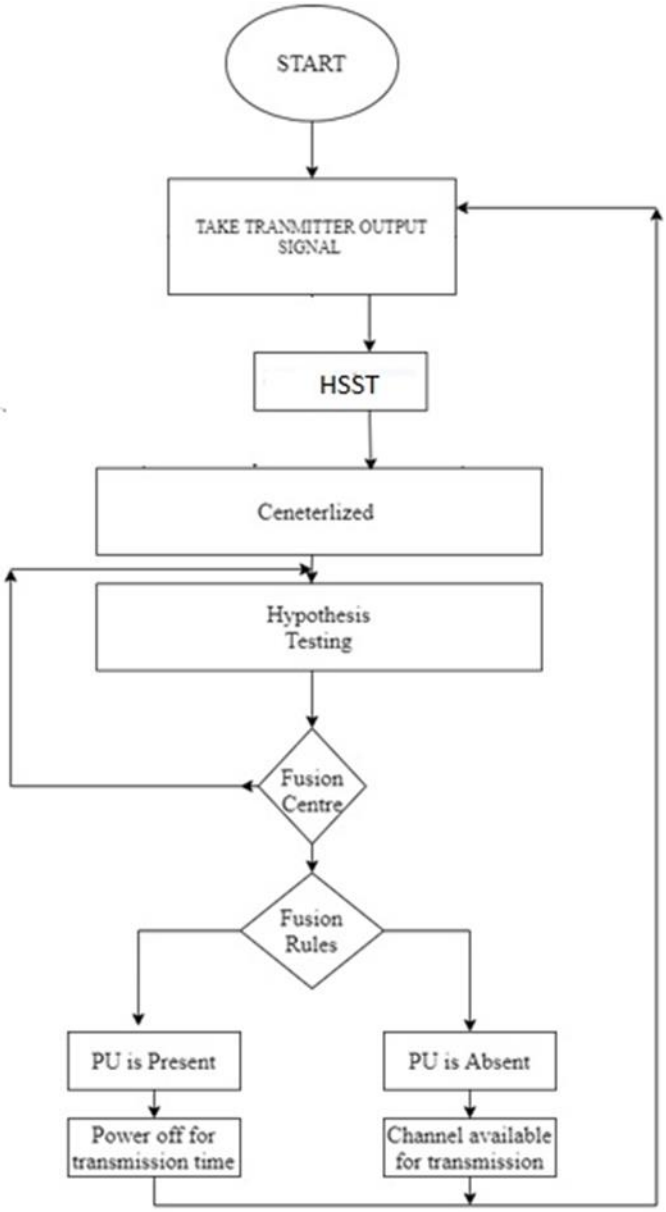

Figure 2: Flow Chart of Proposed Receiver Section

Simulation Results

The performance measurement metrics P_d, P_{fa}, and $P_{md} = 1 - P_d$ are used to examine the performance of HSST techniques. The ROC curve, which is a plot of P_d versus P_{fa} or P_{md} versus P_{fa}, depicts the performance of a HSST technology. The simulations were run on three different wireless fading channels: AWGN, Rayleigh, and Rician. Complementary ROC curves for different values of P_{md}, P_{fa}, P_d, and SNR are used to describe receiver performance.

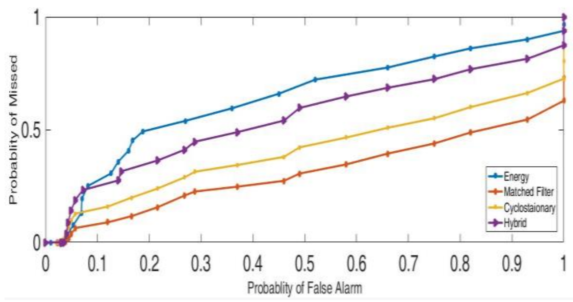

Figure 3: ROC curves between P_{fa} & P_{md} of AWGN Channel for all Spectrum Sensing Techniques

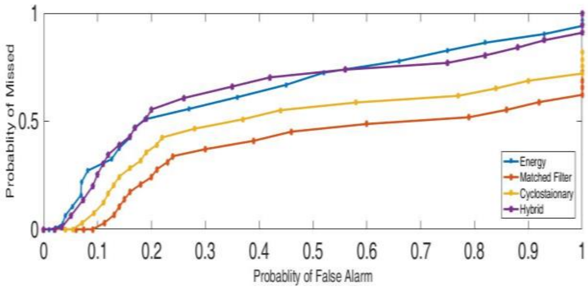

Figure 4: ROC curves between P_{fa} & P_{md} of Rayleigh Channel for all Spectrum Sensing Techniques

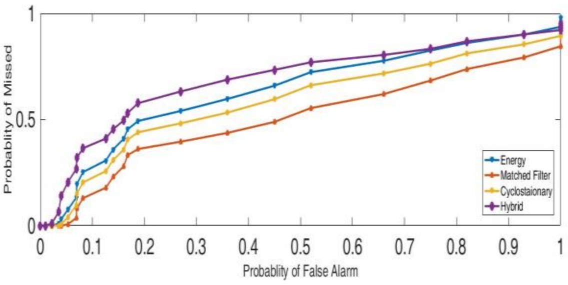

Figure 5: ROC curves between P_{fa} & P_{md} of Rician Channel for all Spectrum Sensing Techniques

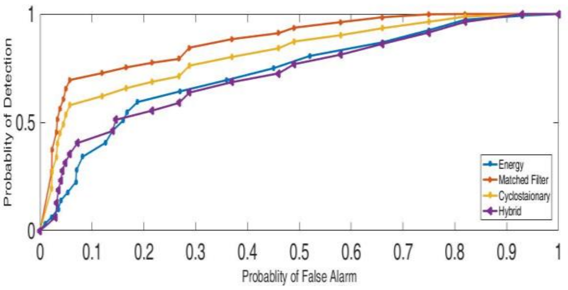

Figure 6: ROC curves between P_{fa} & P_d of AWGN Channel for all Spectrum Sensing Techniques

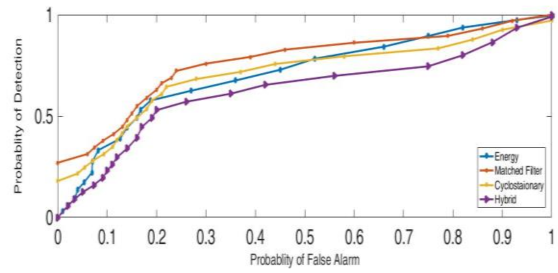

Figure 7: ROC curves between P_{fa} & P_d of Rayleigh Channel for all Spectrum Sensing Techniques

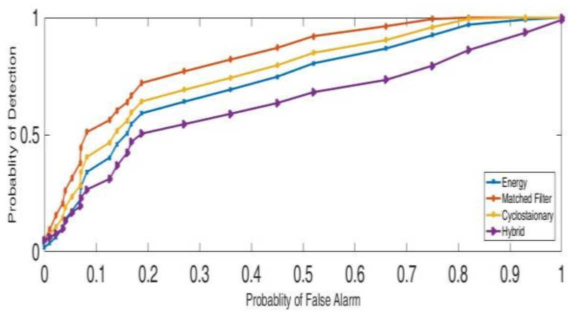

Figure 8: ROC curves between P_{fa} & P_d of Rician Channel for all Spectrum Sensing Techniques

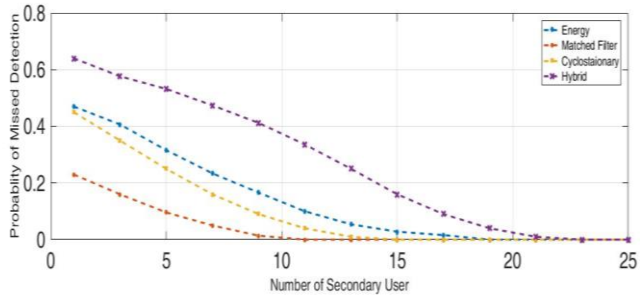

Figure 9: ROC curves between P_{md} Vs number of secondary user

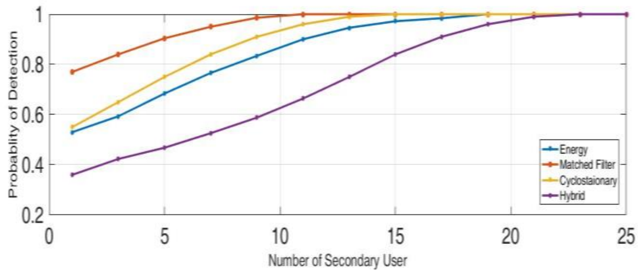

Figure 10: ROC curves between P_d Vs number of secondary user

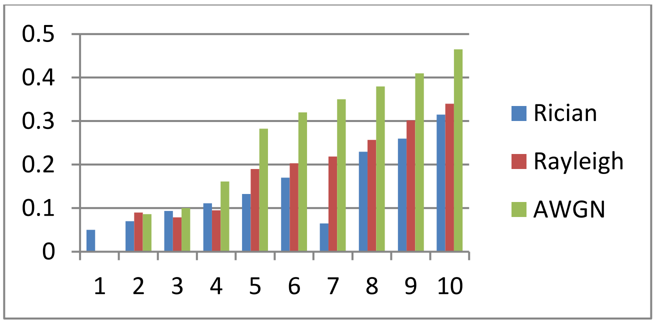

Figure 11: P_d for different channels

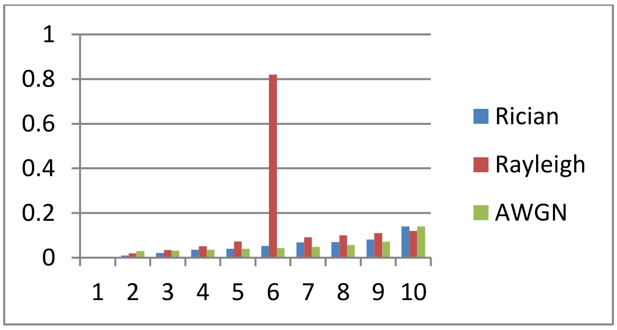

Figure 12: P_{fa} for different channels

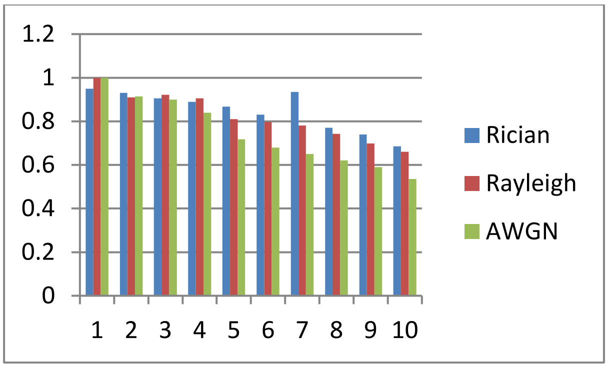

Figure 13: P_{md} for different channels

Conclusion

Hybrid spectrum sensing techniques that combine MF and CFD have been shown to improve the detection precision and consistency of cognitive radio networks. The matched filter is utilized to detect the existence of a known PU signal in noise by matching the waveform of the primary user signal of interest. CFD is employ to detect the periodicity in the statistical properties of the signal by exploiting the cyclic correlation in the signal. In this technique, the received signal is first matched filtered to detect the presence of the primary user signal. This hybrid technique can provide additional information about the signal by detecting the cyclic correlation in the signal, which can further improve the detection accuracy and reliability of the cognitive radio network. HSST are particularly useful in environments where the primary user signals are weak or the noise level is high. They provide a robust and reliable way of detecting the presence of primary users in a dynamic and uncertain environment. Overall, the hybrid spectrum sensing technique can enhance the performance of cognitive radio networks by providing a more accurate and reliable way of detecting the existence of PU signals.

Table 1: The following abbreviations are used in this manuscript:

CR	Cognitive Radio	HD	Hard Decision
CRN	Cognitive Radio Network	PU	Primary User
CFD	Cyclostationary Feature Detection	ROC	Receiver Operating Characteristic
ED	Energy Detection	SU	Secondary User
FCC	Federal Communications Commission	SD	Soft Decision
HSST	Hybrid Spectrum Sensing Technique	SS	Spectrum Sensing
P_d	probability of detection	SNR	Signal to Noise Ratio
P_{fa}	probability of false alarm	P_{md}	probability of miss detection

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