Optimized Forward Consecutive Mean Excision Algorithm for Adaptive Threshold Estimation in the Energy Detector

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Abstract—In this paper, we provide a new model for optimizing the parameters of the Forward Consecutive Mean Excision (FCME) algorithm for autonomous threshold estimation in Cogntive Radio (CR). Our new model ensures that the FCME algorithm is made capable of autonomously adjusting it's parameter values based on the Cuckoo Search Optimization (CSO) algorithm. The between-class variance function of the Otsu's algorithm was used as the objective function in the CSO algorithm towards ensuring optimal FCME parameter values. The new optimized FCME algorithm was tested using both simulated and real datasets. The comparative results obtained between the optimized and non-optimized FCME algorithm showed better threshold values been estimated via the optimized than the unoptimized algorithms leading to improved detection and false alarm probabilities.

1 INTRODUCTION

Cognitive Radios (CRs) are intelligent wireless communication devices capable of acquiring information about their surrounding Radio Frequency (RF) environment so as to dynamically adjust their radio operating parameters to increase communication reliability [1]-[3]. CRs become aware of their spectral environment based on some form of spectrum identification/awareness process, which is an important task in the CR cycle. This process was emphasized in the first cognitive radio wireless radio regional area network policy under the IEEE 802.22 draft standard, which specifically proposes spectrum sensing (SS) as the main approach for spectrum identification in CR. Spectrum Sensing (SS) detects the unused frequency spectrum by processing the received signal to decide on the presence or absence of primary user (PU) signals in a certain frequency band.

SS techniques are examined based on the sensing performance of the CR using factors such as the sensing reliability, sensing time and detection probability. Considering these factors, the energy detector (ED) is generally the most popular method for SS in CR because it is simple to develop, quickest to sense, and independent of any prior knowledge of the PU signal waveform [4]-[5]. The ED depends on a threshold value to make decision about the presence/absence of PU signals in a given channel [6]. This threshold system is required to adapt to the changing channel conditions, thus warranting the need for the development of adaptive threshold techniques (ATT). In this regard, the Forward Consecutive Mean Excision (FCME) algorithm stands out as one of the most effective ATTs for threshold estimation in the ED [7] - [11]. It is most useful when the noise statistics is unknown, and essential for setting the threshold value. The effectiveness of the FCME algorithm depends on the choice of its parameter values. These parameters are the Initial clean sample set (Q) and the threshold factor (T_{CME}), which both play an important role in estimating the detection threshold [8].

Most previous works on the FCME algorithm adopted a manual tuning method (trial and error approach) for setting the algorithm's parameter values, often leading to the poor performance of the algorithm. Furthermore, the parameter values obtained are local values that are specific only to the signal set under consideration. Consequently, these values cannot be considered to be global values, and they are often required to change per varying datasets [11]. This has been mentioned severally in works of Letomaki*et al*in [7],[8]. They noted that owing to the often local parameter values of the FCME algorithm, it may be necessary to obtain global parameter values and to develop automatic methods for estimating the parameter values of the algorithm for better performance.

Thus, in our work, we considered the development of an approach for optimizing the parameter values of the FCME algorithm towards automating and improving its SS performance in CR. This ensures that the FCME algorithm becomes capable of self-adjusting it's parameter values based on the particular input data under consideration. Our work involved the use of the Cuckoo Search Optimization (CSO) algorithm for computing the optimal parameter values of the FCME algorithm. It does so without prior knowledge of the spectral condition under consideration. We show in the result section that this enhancement provides more accurate threshold values leading to less false alarm rates and higher detection performance that the unoptimized FCME.

The rest of the paper is organized as follows: Section 2 provides the description of the system model, Section 3 provides the methodology used to achieve the work, In Section 4, results obtained are discussed, while Conclusion is provided in Section 5.

2 THE SYSTEM MODEL

The spectrum sensing technique (SS) used in this work was based on the Energy Detector (ED) model. It consists of eight 8 basic blocks (see Fig 1) made up of the antenna through which the signal is received, a band pass filter and a possible down converter unit. The sensed signal proceeds to the digitizer unit from the filter unit, where analogue to digital conversion (ADC) takes place. It is then passed to the Fast Fourier Transform (FFT) processor where the signal energy is computed. Thereafter, these values are squared and averaged by an averaging function.

Then, the output is passed to the threshold estimator to determine the status of the channel.

At the output of the ED, a test statistic i.e. the measured signal energy, is subjected to a threshold value, γ, to determine if the channel is vacant, H_0, or occupied, H_1. The H_0 hypothesis defines a noise only spectrum, while the H_1 hypothesis indicates the signal plus noise condition. Statistically, these hypotheses are defined as

$$H_0 : y(n) = w(n),\ n = 1,2,..,V \quad (1)$$

$$H_1 : y(n) = x(n) + w(n),\ n = 1,2,....,V \quad (2)$$

where n is the time sample index, V is the total number of measured samples, $x(n)$ is the transmitted signal, $w(n)$ is the Additive White Gaussian Noise (AWGN) and $y(n)$ is the received signal sample. Essentially, the entire detection process is expected to determine either H_0 or H_1, which strongly depends on the choice of the threshold, γ. Thus, the performance of the ED is determined by the probability of detection, PD and the false alarm PFA, giving by

$$P_D = Pr(Y(k) > \gamma \mid H_1),\ k = 1,2,.....,V \quad (3)$$

$$P_{FA} = Pr(Y(k) > \gamma \mid H_0),\ k = 1,2,.....,V \quad (4)$$

To analyze the performance of the estimated threshold after the optimization process, the values of P_D and P_{FA} were computed according to Fawcett [12]. Following Fawcett's method, different ground truths were generated and this came about by visually identifying the different portions in the displayed spectrum that corresponds to the actual signal, and that which corresponds to the noise. The signal points were labeled as true positives, while the noise samples were labeled as true negatives. For the real signals, we know the frequencies currently occupied by the licensed user in our local environment. Thus, we labeled the truly noise samples as 0, and the truly signal samples as 1. Furthermore, we used the maximum value of the noise samples to be the true threshold. Then, any sample above this threshold value is truly a signal sample, and below the threshold corresponds to the true noise sample. Using this approach, we can say that the ground truth was developed from the true dynamic range of the sample set. Then by relying on the knowledge of the confusion matrix in [12], we computed the probability of detection, P_D, using

$$P_D = \frac{TP}{P}, \quad (5)$$

Where TP is the number of truly detected signal samples if $Y(k) > \gamma \mid H_1$, and P is the total number of actual true signal samples. The probability of false alarm was computed using

$$P_{FA} = \frac{FP}{N}, \quad (6)$$

Where FP denotes the falsely detected signal samples if $Y(k) > \gamma \mid H_0$, and N is the total number of noise samples.

3 Description of the Algorithms

A. The FCME Algorithm

The FCME algorithm is computationally simple and effective. It calculates the threshold iteratively based on the noise properties. The algorithm will be discussed according to [10] for estimating a threshold value.

Initial Preparation: When the noise is assumed to be zero mean, independent, and identically distributed Gaussian noise, i.e., samples then the samples follow a Gaussian distribution, and the FCME algorithm calculates the threshold parameter based on [10]

$$\text{TCME} = -ln(\text{PFA,DES}) \quad (7)$$

where $P_{FA,DES}$ is the desired clean sample rejection rate (the target false alarm rate) and N is signal sample length [10]. Energy samples are calculated thereafter. Samples are then rearranged in an ascending order according to their energies. Then, m = 10% of smallest samples are selected to form the initial set Q (called also as a"clean set").

Algorithm: The FCME threshold is calculated based on [10]

$$Th = T_{CME} * Q \quad (8)$$

Where Q denotes the mean of m. Samples below the threshold are added to the set Q and new mean and threshold are calculated. This is repeated until there are no more new samples below the threshold. Usually, it takes 3-4 iterations to get the final threshold. In the end, the samples above the threshold are assumed to be signal samples, while samples below the threshold are assumed to be noise samples.

B. Cuckoo Search Optimization Algorithm

The optimization algorithm used to optimize the FCME's parameter values is the Cuckoo Search Optimization (CSO)

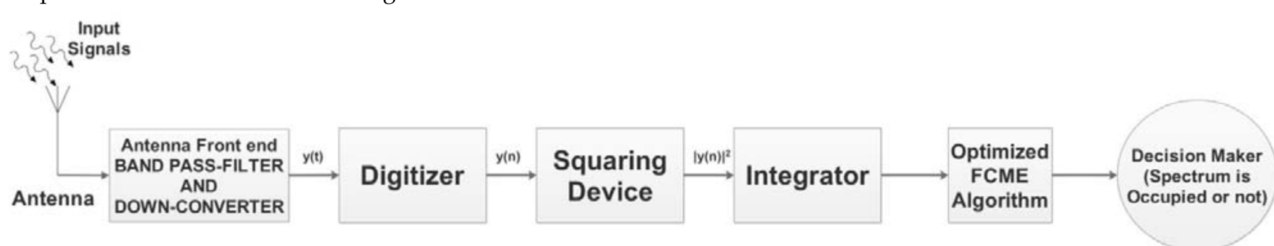


Fig. 1. The Detection System under Consideration

algorithm. The advantage of this algorithm lies in its simplicity, ease of implementation, and use of few parameters [13]. Essentially, the CSO concept can be described as follows: each egg in a nest represents a solution; a cuckoo egg represents a new solution. The aim is to use the new and potentially better solutions (cuckoos) to replace not-so-good solutions in the nests. In our adoption of the CSO algorithm, we consider the case for only a single egg, as we desire to determine only a single solution.

C. Proposed FCME-CSO Scheme

This is a combined scheme that seeks to show how the parameter values are optimized before estimating the detection threshold.

Algorithm: Unlike in the FCME algorithm where a single parameter value is estimated according to [10], in our combined FCME-CSO scheme, the CSO algorithm initializes the random parameter values, which are fed to the FCME algorithm. The initial threshold values are then estimated by the FCME algorithm. The initial threshold values are then evaluated by the CSO algorithm using the designed objective function (OF) given in eqn 9. The final optimal FCME parameters are estimated after several iterations by the CSO algorithm. Furthermore, these parameter values are fed into the FCME algorithm to estimate the final detection threshold.

$$\alpha(\gamma) = P_S(\gamma) \times P_N(\gamma) \times [\mu_S(\gamma) - \mu_N(\gamma)]^2 \qquad (9)$$

where, $P_S(\gamma)$ is the probability of a signal sample, $P_N(\gamma)$ is the probability of a noise sample, $\mu_S(\gamma)$ is the mean of the signal samples, and $\mu_N(\gamma)$ is the mean of the noise samples. The objective function of eqn 9 enables the FCME and CSO algorithms to estimate the best possible threshold value for the current dataset under consideration. The between-class variance function used according to Otsu in [14] was adopted. It uses linear discriminate analysis to segment an image into two or more classes by selecting a threshold automatically from a grey level histogram. The use of Otsu's model in optimizing the FCME algorithm marks a novel application in our work.

4 RESULTS AND DISCUSSION

In this section, we present the evaluation results for both the FCME and FCME-CSO algorithms. Both simulated and real data sets were used to evaluate both algorithms. The default parameter values used for the FCME algorithm were trained and tested using simulated noise samples under different noise uncertainties levels. This was done to obtain the best possible default parameter values that ensures the threshold value lies above the noise level. It is shown in Fig.2 that the T_{CME} value of 2.3 and Q value of 10% gave the best threshold value above the noise level with a low false alarm rate.

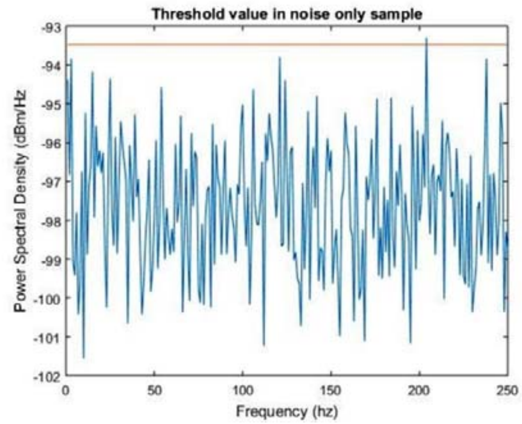


Fig. 2. The Detection System under Consideration

The FCME-CSO parameters were trained by varying the parameter values while keeping other parameters constant. This was done to determine the values that ensures maximum detection probability and lowest false alarm probability with the least computation time in each case. After training both algorithms, the following parameters were set: n (the population size or number of nests) was set at 5, Pa (probability of abandoning a nest) was set at 0.25, number of iteration was 100 and number of simulations was conducted only once.

Performance of the unoptimized FCME and optimized FCME-CSO Algorithms

1) *Under Simulated Datasets.:* The performance of the unoptimized FCME and optimized FCME-CSO algorithm were evaluated using different simulated datasets. Orthogonal Frequency Division Multiplexing (OFDM) signals and FM signals were simulated based on the method of Nee & Prasad [15]. The simulated signals were corrupted using AWGN based on eqn.2, while the signal strength was varied relative to the fixed noise level. The SNR was reduced from a high SNR level (SNR = 10dB), to a low SNR level of 1dB. For the high SNR condition (SNR = 10 dB) down until 5dB SNR for the OFDM signals, the result showed that both algorithms, FCME and FCME-CSO performed well (all typically producing above 90% detection rate, and 0% false alarm rate). However, at a SNR of 3dB and 1dB, FCME-CSO produced a 100% detection with a false alarm rate of 14.35% and 43.67% respectively. While FCME produced P_D = 8.8%, P_{FA} = 0%, and P_D = 20%, P_{FA} = 0%. It showed that better results were obtained using the optimized FCME-CSO model than the unoptimized FCME algorithm. Numerical details of the results are shown in Table 2. While for the simulated FM signal, the results showed that the unoptimized FCME algorithm performed better in terms of the P_{FA} = 0% for all SNR conditions. This confirms that the best parameter values (T_{CME} = 2.3, Q = 0.1) were used in training the algorithm considering the simulated AWGN samples. The higher SNR condition of 10dB, 5dB, 3dB and 1dB produced {(P_D = 66.67%, P_{FA} = 0), (P_D = 100%, P_{FA} = 42.86%), (P_D =

$100\%, P_{FA} = 44.08\%), (P_D = 100\%, P_{FA} = 45.78\%)\}$ respectively. The numerical details obtained are provided in Table 3.

2) Under Real Datasets.: Both algorithms were tested using real input datasets. The performances of both algorithms (FCME and FCME-CSO) were evaluated using the real OFDM signals and real FM band (89-95MHz). The results showed that both algorithms performed well for the real OFDM signal set producing above 90% detection rate and less than 10% false alarm rate. However, for the real FM signal set, the results showed that the FCME-CSO produced (P_D = 80%, P_{FA} = 0%) and FCME produced (P_D = 82%, P_{FA} = 47%). The numerical details are provided in Table 4. These results showed that optimized FCME-CSO produced a better performance compared to the unoptimized FCME, which has a higher false alarm rate as shown in the Figs. 3a and 3b.

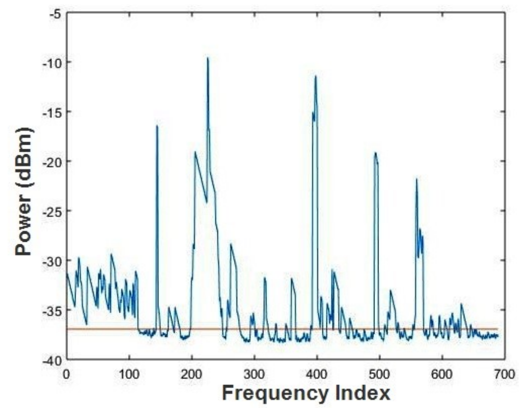
TABLE III

PERFORMANCE ANALYSIS FOR REAL DATASETS

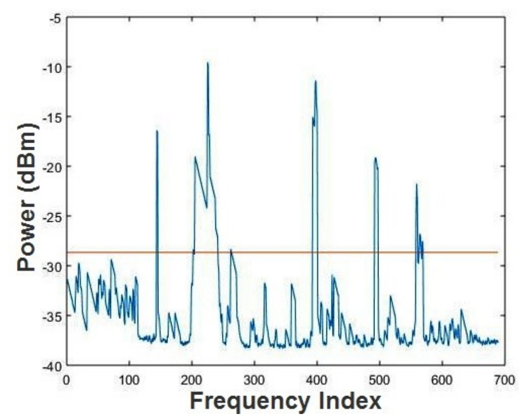
Algorithms	P_D	P_{FA}	$Th(dBm)$
Unoptimized-FCME	80	47	-74.76
Optimized-FCME	82	0	-74.31

5 CONCLUSION

This paper has presented an optimized Forward Consecutive Mean Excision (FCME) algorithm based on the Cuckoo Search Optimization (CSO) algorithm. The CSO algorithm was innovatively incorporated into the FCME algorithm to automatically estimate the FCME algorithm's parameter values for each unique input dataset. Thus, the fixed and manual tuning approach for determining the FCME's parameter values has now been fully automated. The new FCME-CSO model was evaluated using both simulated and real datasets. The results obtained shows an improvement in the detection and false alarm probability of the optimized FCME over the unoptimizedversion.The FCME-CSO model has been shown to perform well in very low SNR levels (<3 dB).



(a) Threshold Using Unoptimized FCME algorithm



(b) Threshold Using Optimized FCME algorithm

Fig. 3. Threshold Estimation using both Unoptimized and Optimized FCME algorithm

TABLE I
PERFORMANCE COMPARISON BETWEEN UNOPTIMIZED FCME AND OPTIMIZED FCME-CSO WITH DIFFERENT NOISE UNCERTAINTY FOR SIMULATED OFDM SIGNALS

Algorithms	SNR = 10dB			SNR = 10dB			SNR = 10dB			SNR = 10dB		
	P_{FA}	P_D	$Th(dBm)$	P_{FA}	P_D	$Th(dBm)$	P_{FA}	P_D	$Th(dBm)$	P_{FA}	P_D	$Th(dBm)$
Optimized-FCME	0	98.08	-96.22	0	96.08	-97.19	14.35	100	-98.67	43.67	100	-99.74
Unoptimized-FCME	0	98.08	-96/93	0	86.3	-96.28	0	8.8	-95.3	0	20	-96.24

TABLE II
PERFORMANCE COMPARISON BETWEEN UNOPTIMIZED FCME AND OPTIMIZED FCME-CSO WITH DIFFERENT NOISE UNCERTAINTY FOR SIMULATED FM SIGNALS

Algorithms	SNR = 10dB			SNR = 10dB			SNR = 10dB			SNR = 10dB		
	P_{FA}	P_D	$Th(dBm)$	P_{FA}	P_D	$Th(dBm)$	P_{FA}	P_D	$Th(dBm)$	P_{FA}	P_D	$Th(dBm)$
Optimized-FCME	0	66.67	-96.06	42.86	100	-99.86	44.08	100	-98.67	45.78	100	-99.97
Unoptimized-FCME	0	66.67	-96.58	0	60	-96.8	0	40	-96.57	0	10	-96.78

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