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Stochastic Threshold for Spectrum Sensing of Professional Wireless Microphone Systems

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Abstract - In recent years, the professional wireless audio transmission systems such as Program Making andSpecial Event (PMSE) devices have been risen causing the need for a higher spectrum efficiency. Cognitive radio (CR) paradigm has been proposed to maximize the audio quality and ensuring interference free operation all the time. The motivation to a reliable spectrum sensing (SS) technique for the detection of PMSE devices has been considered, e.g. the detection of ProfessionalWireless Microphone Systems (PWMS). In this paper, anovel threshold estimation technique for the spectrum sensing (SS) using stochastic approach for energy detection (ED) has been presented. The performance of stochastic threshold estimation approach under noise uncertainty environment has been tested. Under noise uncertainty and obeying the 802.22 standard, our stochastic thresholdhas achieved comparable results and even outperform the doublethreshold in a low signal to noise ratio (SNR).

Keywords - *Cognitive radio, Spectrum Sensing, Energy Detection, Wireless Microphone, Threshold, Power Spectral Density , Stochastic Approach, Noise Uncertainty.*

1. Introduction

Cognitive radio has been considered an innovative solution to the problem of scarcity of the wireless spectrum and low spectrum usage efficiency0.In accordance to the provisions of the ITU World Radio Conference[2],and FCC [3] as well. The IEEE [4] has developed a standard to allow parts of the digital dividend in the TV UHF band might be reassignedtoProgram Making and Special Event(PMSE) devicesand Internet service providersexclusively [5], e.g. for providing Cognitive Radio (CR)devices[4]. CR has utilized the unused frequency bands of the spectrum to the problem of spectrumscarcity by allow the Secondary or unlicensed Users (SU) to use it in absence of Primary or licensed Users (PU) while keeping unharmful interference to it. TV White Space (TVWS) is the unused spectrum on TV broadcasting frequencies in UHF band in an arbitrary location [3] .TVWS is currently the first area that is considered for SU such as a White Space Devices (WSD). The reason is that due to the network planning strategies there is available a relatively good amount of white spaces. Also, the TV signal which is the PU and its coverage area are more stable than for many other communication systems. Program Making and Special Event (PMSE) devices also use the same band with the TV signal and WSD but it is a SU for the first one and a PU for the second. For PMSE devices, such as Professional Wireless Microphone Systems (PWMS) andIn-Ear monitoring systems for TV shows, theater, opera, etc., this situation, however, was quite convenient. These devicesoperate so far in locally unused TVWS channels that presenta quite static and predictable spectrum usage. In order tooperate a PMSE system in licensed frequency bands, a manualfrequency allocation process during system setup is performed.

In addition, white space devices have toprotect both incumbents: TV signal and PWMS. Theincumbent use is also called as PU while white spaceutilization is referred to as SU in this paper. Spectrum sensing has many techniques such as energy detection, matched filter and cyclostationary feature detection [6] .Among these techniques, energy detection has been a preferred approach due to its simplicity and quick performance. The main

drawback of energy detection is its sensitivity to noise power fluctuations, small variations in noise power may cause a high degradation in energy detection performance due to SNR wall[7][8]. Most studies on energy detection technique are based upon constant noise power [9][10]; however, the noise is an aggregation of various sources like thermal noise, aliasing from front end filters and leakage of signals. Therefore, using constant noise power during the detection period is non-practical approach; hence the noise uncertainty has to be considered.

Here, Probability of Detection (P_D) is defined as the probability that the sensing algorithm has successfully detected the presence of the primary signal , Probability of Missed Detection (P_{MD}) equals (1- P_D) and Probability of False Alarm (P_{FA}) is the probability that the sensing algorithm assumes the presence of the primary signal even when the primary signal is absent;meanwhile the noise is present only. Calculating the threshold by fixing a target P_{FA} is called the constant false alarm rate (CFAR) principle;while setting a target P_D is called the constant detection rate (CDR) principle [13].

There are other ways to set the threshold as well, for instance as in [13],where a static threshold which is neither CFAR based nor CDR based has been used. Many researchers have been focused on adaptive setting of the threshold;furthermore on multi-level setting of threshold in [14][15][16]. In [14], the threshold has been assumed to be adaptively based on themean and standard deviation of the input signal. This approach has the advantage that it does not have to depend on the noise variance and SNR, but the analysis is restricted to positive (relatively high) SNR channels. In [15],the threshold has been calculated based on physical parameters like the transmission power of the PU, SU, the distance between the PU and the SU, minimum decodable signal-to-interference noise ratio. The threshold is changed adaptively by changing the transmission power of the SU. The algorithm proposed in [16]changes the threshold after comparing the sensed energy with the current threshold. The threshold is varied as a function of the current threshold and the total energy calculated from the collected samples. Furthermore, In [17], the operating environment hasbeen modeled as a Suzuki channel for relatively high SNR values.

The physical systems in which they are uncertain about the values of parameters, measurements, expected input and disturbances is referred as a "stochastic systems". In probability theory, a purely stochastic system is one whose state is randomly determined, having a random probability distribution or pattern that may be analyzed statistically but may not be predicted precisely. According to this, it could be classified as non-deterministic (e.g., "random") so that the subsequent state of the system is determined probabilistically[18].

The remainder of this paper is organized as follows. SectionII gives a background about the Spectrum sensing using energy detection technique in frequency domain and the periodogram method to find the power spectrum density (PSD) of the PWMS signal, in addition the threshold expression at noise uncertainty environment using a stochastic approach is explained. Section III introduces our stochastic threshold forthe detection for PMSE systems using energy detection technique. In Section IV, simulation resultsof our proposed algorithm in different noise uncertainty levels. Finally, Section Vconclusions and future work.

2. Basic Concepts

In the following; energy detection in frequency domain has been highlighted. Moreover, thestochastic approach for noise uncertaintyhas been explained. Those basic concepts are reviewed in this section as follow:

2.1 Energy Detection in Frequency Domain

Energy detector based approach, also known as radiometry or periodogram, is the most common way of spectrum sensing because of their low implementation complexity and quick performance.Conventional frequency domain ED consists of *A/D*converter using Nyquist sampling condition, then a Fourier transform N_f-*FFT* to transfer the signal to frequency domain. Hence; the squared and averaged value of the signal is used to estimate the PSD;Afterword; the detector compares the PSD peak to a certain threshed expression.

The detection decision process is generally described under the testof the following two hypotheses:

$$\begin{aligned} &H_0: y[n] = g[n] && \textit{signal absent} \\ &H_1: y[n] = x[n] + g[n] && \textit{signal present} \\ &\quad n=1, 2,....., N; && \end{aligned} \tag{1}$$

where$y[n]$ is received sampled signal, $x[n]$ is transmitted sampled signal, $g[n]$ is the additive white Gaussian Noise (AWGN) with zero mean and variance σ_n^2 and N is the number of observation samples which they are depend on the sensing (detection) time and the signal bandwidth.Assuming that noise uncertainty does not exists, poses a limitation on the performance of the given system. Thus, noise uncertainty factor has to be incorporatedfor the system at reliable performance. The conventional energy detection technique, which is based upon our old fixed threshold, is sensitive to noise uncertainty which isunavoidable in practical cases. This noise uncertainty gets

the fixed threshold energy detector un-optimized in its performance[18].

The power spectral density (PSD) of a signal is a Fourier transformation of its autocorrelationsequence. Welch-Bartlett method estimates PSD with high signal resolution as well as high noise variance. It reduces the large fluctuations and high noise variance of the periodogram, by dividing the data sequence into segments, andaverages the periodograms obtained from the segmentation [19][20].The variance and spectralresolutionoftheWelch-Bartlett methodisreduced proportional tothe number of segments as it was examined in [10].

Spectrum sensing using PSD makes use of the fact that wireless microphone devices use analog frequency modulation (FM), with a bandwidth less than 200 KHz. The power of the Professional Wireless Microphone Systems (PWMS) signal is highly concentrated in the frequency domain, and there are a many apparent peaks in its PSD. Using this property, the power spectral density of the received FM signal can be easily estimated, and its maximum value, is used as the decision statistic.

For simplicity, we assume that the signal is FM with a carrier frequency f_c = 2 MHz and a frequency deviation $\Delta f$is chosen to be 15 kHz in order to be suitable for a soft speakerPWMS with single tone modulation signal with 3.9kHz frequency. The PWMS signal generally concentrates within a small frequency band which is less than 200 kHz.Moreover, there are apparent peaks contained in the PSDs of the various PWMS signal models. In this paper thus far, we present results for 15 kHz frequency deviations, representing soft speakerPWMSuser.

2.2 Stochastic Approach for Noise Uncertainty

Noise fluctuations could be characterized as random signalsbecause we cannot determine their values precisely, that is, they are uncertainty values.

Let the estimated noise variance be denotaed by[21][22].

$$10\log(\hat{\sigma}_n^2) = \alpha + 10\log(\sigma_n^2) \quad (2)$$

Where α obey uniform distribution in the interval [-UdB ,UdB] and U =0 denotes no noise uncertainty. The corresponding estimated noise $\hat{\sigma}_n^2$falls into $[(1/r)\sigma_n^2,\ r\sigma_n^2]$

$$r = 10^{(U/10)} \quad (3)$$

Under noise uncertainty condition, signal powerP_s should be larger than the whole noise power interval size to distinguish signal presented situation from only noise fluctuationσ_n^2[11], e.g.

$$P_s > r\sigma_n^2 - (1/r)\sigma_n^2 = (r - 1/r)\sigma_n^2 \quad (4)$$

$$SNR = P_s/\sigma_n^2 > (r - 1/r) = SNR_{wall} \quad (5)$$

When *SNR* below SNR_{wall}, signal could not be robustly detected. Evaluated from equations (1) to equations (5). The mean of the test statistic under both hypotheses is related to the noise variance. Instead of noise variance σ_n^2, estimatednoise variance $\hat{\sigma}_n^2$ is used for calculation in practice. To better fit practical implementaion environment, noise uncertanity is considerd in simulations.

The noise uncertainty will being two main problems in spectrum sensing, e.g., the false alarm probability P_{FA}increases and the detection probability P_D decreases. Moreover; Energy detection algorithm which involves fixed threshold offers degraded performance with noise uncertainty. That indicates the dynamic threshold would yield better performance in presence of noise uncertainty [23][24].

The mathematical framework for the description of these discrete-time random signals is provided by discrete-time stochastic processes. The word stochastic is derived from the Greek word stochasticos, which means skillful in aiming or guessing. In general, although random signals are evolving in time in an unpredictable manner, their average properties can often be assumed to be deterministic; that is, they can bespecified by explicit mathematical formulas. This concept is a key to the modeling of a random signal as a stochastic process. Thus, random signals are mathematically described by stochastic processes and can be analyzed by using statistical methods instead of explicit equations. The theory of probability, random variables, and stochastic processes provides the mathematical framework for the theoretical study of random signals. The simplest description of any random signal is provided by an amplitude-versus-time plot. Inspection of this plot provides qualitative information about some significant signal features that are useful in many applications.

These features include the frequency of occurrence of various signal amplitudes, described by the probability distribution of samples which is obtained by plotting the histogram. Hence, the histogram is an estimate of the first-order probability density of the underlying stochastic process. Mindful examination of the shape of the histogram curve clearly indicates the highest frequently value between consecutive samples with large number of iterations. In other words, the probability of large increments is significant. In general, the shape of the histogram, or more precisely the probability density, is very important in applications such as signal coding and signal detection. Although many practical signals follow a

Gaussian distribution, many other signals of practical interest have distributions that are non-Gaussian. The histogram function uses an automatic binning algorithm that returns bins with a uniform width, chosen to cover the range of elements in a certain observation period and reveal the underlying shape of the distribution. The bins display as rectangles such that the height of each rectangle indicates the number of elements in the bin.

3. The Proposed Threshold Expression

In above paragraphs, energy detection and noise uncertainty have been explained separately. By combining both those conceptsour proposed stochastic threshold could be constructed. Our stochasticthreshold could be computed by using equation (2)& (3).

3.1 The Old Threshold Under Noise Uncertainty

The threshold value λ_0 is obtained as follows. For hypothesis H_0, which corresponds to the presence of noise only, we know that $g[n]$is independently and identically distributed (*i.i.d.*) Gaussian random variables with zero-mean and variance σ_n^2. Using the Central Limit Theorem (CLT), when the samples are sufficiently large, the noise approaches Gaussian distribution (μ_n,σ_n^2) which can be calculated from simulation. Then the threshold value λ_0 will be[9]

$$\lambda_0 = \mu_n + \sigma_n . Q^{-1}(1-(1-P_{FA})^{1/N_f}) \qquad (6)$$

where$Q^{-1}(\cdot)$ is the inverse of the Q-function

$$Q(x) = \int_x^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2} du$$

Probability of detection, P_D, defines, at the hypothesis H_1 (signal present), the probability of the sensing algorithm having detected the presence of the primary signal $(P\{Y> \lambda| H_1\})$. Probability of false alarm, P_{FA}, defines, at the hypothesis H_0(signal absent), the probability of the sensing algorithm claiming the presence of the primary signal $(P\{Y> \lambda| H_0\})$.

3.2 Stochastic Threshold

When the exact noise σ_n^2 is larger than estimated noise variance$\hat{\sigma}_n^2$, the false alarm probability P_{FA},e.g., the false alarm probability in traditional signal threshold detection with U dB uncertainty will get increased because the test statistic will be above the threshold more times than usual. The decision threshold λ could be chosen for an optimum trade-off between detectionprobability (P_D) and false alarm probability (P_{FA}). Theknowledge of noise power and signal power is necessary toget optimum value of threshold λ_S. Noise power can beestimated but to get the signal power, transmission andpropagation characteristics of Signal are necessary. Inpractice, the threshold is normally chosen to satisfy a certainP_{FA}, which only requires the noise power to be known.When *SNR* of signal is low, the situation is similar to hypothesis H_0, the detection probability P_D ,*e.g.*the detection probability in traditional signal threshold detection with U dB uncertainty will be increased. When *SNR* of signal increases,the test statistic will be below the threshold more times when σ_n^2 is lower than$\hat{\sigma}_n^2$, which is equivalent to increase the threshold. The detection probability P_D then will be decreased.Since the estimated noise variance can be any value within the interval [-UdB, UdB].This variable has independent zero-mean real and imaginary parts each with variance $\sigma^2/2$ under the null hypothesis.

The maximum noise uncertaintyvalue can be used to set the high threshold[25]

$$\lambda_H = \lambda_0 + U \qquad (7)$$

The minimum noise uncertaintyvalue can be used to set the low threshold

$$\lambda_L = \lambda_0 - U \qquad (8)$$

According to equation (7) and equation (8), there are three sections for signal decision;

1) The signal is decided to be present when the test statistic is above the high threshold λ_H.
2) The signal is decided to be absent when the test statistic is below the low threshold λ_L.
3) There was no decision when the test statstic is between the two thresholds. In this case, the sensing will fail and the receiver will request the cogintive user toperform anew spectrum sensing again [25].

Our proposed stochastic threshold has to solve this problem by exploring the different values of the threshold in between the lower and the higher limits and draw the histogram of it, Afterthe histogram has been constructed then the most iterative valuethat has the higher histogramwould bechosen to be used when the signal isin between the two higher and lower thresholds. The stochastic thresholdλ_s will be:

$$\lambda_S = Max_n \left(\sum_{i=1}^{k} \lambda_i \right) \qquad (9)$$

where i is the iterations number and λ_i is the histogram function that counts the number of observations that fall into each in between values of the threshold(known as

bins). In addtion, n is the total number of observations and k is the total number of bins ($k = \frac{\lambda_H - \lambda_L}{h}$)and h is the bin width. The largest value of the identical threshold value summation is chosen and it will be used as the stochastic threshold.

4. Simulation Results

The proposed algorithm was tested in a typical PU sensing scenario, where the sensing interval was set to 8.2ms using the MATLAB simulator for PWMS at soft speakercase.

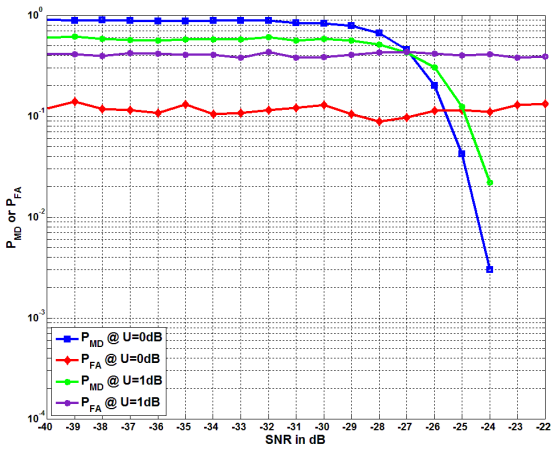

Fig1. The probability of missed detection and probability offalse alarmversus SNR for noise uncertainty U=0dB and U=1dB respectively, using the old threshold.

Figure 1. Shows the probability of missed detection and probability of false alarm versus SNR for noise uncertainty U=0dB and U=1dB respectively, using the old thresholdexpression.

The histogram as the number of iterations versus the values of threshold in dB at noise uncertainty environment has been shown in figure 2. The value number six will be chosen as it has the highest iteration number; the stochastic values of the threshold will be equal to -28.2dB which is in between the highest -27.2dB limit and the lowest threshed limits -29.4dB.

In Figure 3. The probability of missed detection and probability of false alarm versus SNR for noise uncertainty U=1dB using the double and Stochastic thresholds respectively has been plotted.

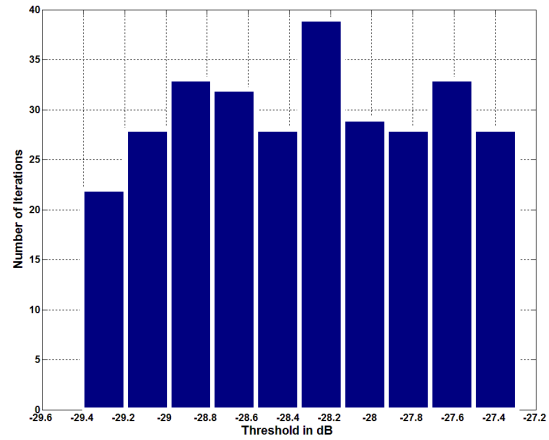

Fig 2. The histogramof stochastic threshold in dB at noise uncertainty environment.

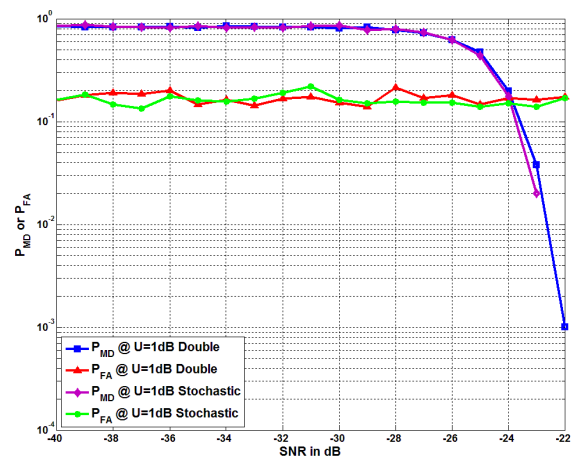

Fig3. The probability of missed detection and probability offalse alarmversus SNR for noise uncertainty U=1dB using the double and stochastic thresholds respectively.

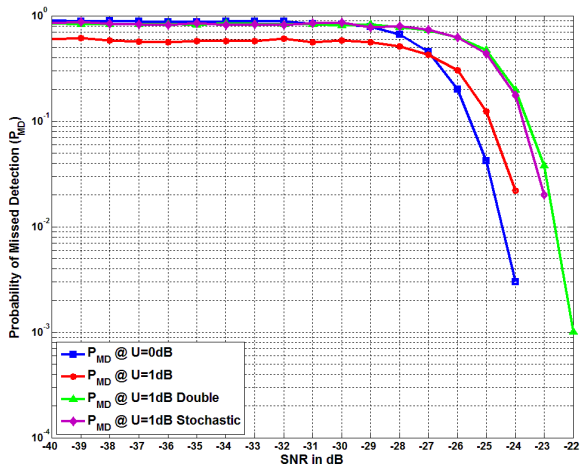

Fig4. The probability of missed detectionversus SNR for noise uncertainty U=0dB and U=1dB using the old, double and stochastic threshold respectively.

Figure 4. Shows the probability of missed detection versus SNR for noise uncertainty U=0dB and U=1dB using the old, double and stochastic threshold respectively. In addition; P_{MD} = 0.1 have been achieved corresponding to a value of P_{FA} = 0.1, which is the maximum acceptable by the 802.22 standard, at sensing time equals 8.2 ms are 25.5dB for old threshold at U= 0dB and 25dB for old threshold at U= 1dB with P_{FA} = 0.4 that is not acceptable by the standard, 22.5dB for double threshold at U= 1dB with P_{FA} = 0.1, and22.6dB for stochastic threshold at U= 1dB with P_{FA} = 0.1 as well.

SNRs when the target P_{FA} = 0.1. The noise power uncertainty U in equation (3) is 0 dB. When true noise information is available, old thresholdoutperforms double and stochastic threshold by 3dB as shown in Fig.4. However, when the estimated noise has uncertainty U= 1dB, the performance of the old threshold becomes worse than the double and stochastic threshold performance with respect to the P_{FA} = 0.1 condition. Furthermore; the performance of stochastic thresholdoutperforms double threshold by 0.1dB as shown in Fig.4.

5. Conclsion and Future Work

Simulation results show that the proposed stochastic threshold outperforms the double threshold at aP_{FA} = 0.1andsensing time 8.2ms in the presence of 1 dB noise uncertainty by more than 0.1 dB.. Further experimental work using stochastic threshold equations could be needed to try it for U= 2dB and 3dB and measure its performance w.r.t P_{MD} and P_{FA} condition. Thenthe validity of the stochastic thresholddecision could be achieved. Also; it needs to be tested if the number of iterations increase, the performance gets better or it will not provide a significant gain. The receiver operating characteristic(ROC)curve as the P_D verses P_{FA} at a very low SNR (-25dB) is need to be tested also. In addition; Increasing the number of iterations will enhance the ROC curve of the system at all values of P_{FA} and $P_D$or not.

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