Adaptive Spectrum Sensing of Wireless Microphones with Noise Uncertainty

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Abstract— **Many spectrum sensing techniques have been proposed in the literature to enable cognitive radio technology. However, their reliability when primary users have very low signal-to-noise ratio (SNR) in the presence of noise uncertainty remains a challenging problem. This paper focuses on detecting wireless microphone signals in the presence of noise uncertainty. Power Spectrum Density (PSD)-based sensing has been proposed in the literature as the best sensing algorithm for wireless microphones. However, when there is noise uncertainty, PSD-based sensing performance is severely degraded. To solve this problem, eignevalues-based blind sensing, which does not need noise information, have been proposed. In this paper, we present a new adaptive spectrum sensing algorithm that outperforms both PSD-based sensing and the eigenvalues-based sensing in the presence of noise uncertainty. The algorithm combines the decisions of the two algorithms, and then, adapts the decision threshold required for the PSD-based sensing in an iterative way. Simulation results show that the proposed spectrum sensing algorithm outperforms the PSD-based sensing in the presence of 1 dB noise uncertainty by more than 2 dBs. At the same level of noise uncertainty, our algorithm outperforms the eigenvalue-based sensing by 1.2 dBs.**

Keywords-**cognitive radio; spectrum sensing; noise uncertainty; wireless microphones.**

I. Introduction

Cognitive Radio (CR) technology has been first proposed by the USA Federal Communications Commission (FCC) to enable opportunistic spectrum sharing. It has provided a convenient solution to the problem of scarcity of the wireless spectrum and low spectrum usage efficiency. As a consequence, IEEE 802 standards committee established a working group named IEEE 802.22, also called WRAN Group, to develop a standard for a cognitive radio based PHY/MAC/air interface for use by unlicensed devices in the Digital TV white space (DTV) broadcast spectrum [1]. TV white space spectrum is considered prime real estate because its signals travel well, making it ideally suited for mobile wireless devices.

The basic idea of a cognitive radio is spectrum sharing, which allows secondary users to communicate over the spectrum allocated to primary users when they are not fully utilizing it. The operation of cognitive radio devices should be on a non-interfering basis in the spectrum that has already been allocated to the primary users, thus protecting the primary user's network functionalities. The FCC has taken steps to ensure that, including issuing a report on September 23rd, 2010 that reserves two vacant UHF channels for wireless microphones and other low power auxiliary service devices in all areas of the country. Wireless microphones are licensed devices operating in the DTV bands. The problem is that wireless microphones are more susceptible to interference by CR devices compared to DTV receivers; due to their lower transmit power (in the range of 10 mW). Therefore, the main task in spectrum sensing for IEEE 802.22 WRAN is to detect the existence of the DTV signal as well as wireless microphone signals that maybe operating in the DTV bands.

Many spectrum sensing methods have been proposed in the literature [3]-[9]. These sensing methods can be classified into three categories: (A) methods requiring both source signal and noise power information, (B) methods requiring only noise power information (semi-blind detection), and (C) methods requiring no information on source signal or noise power (totally blind detection). For example, likelihood ratio test [3], Matched Filter [4], and cyclo-stationary detection [5] belong to category (A); energy detection [6] and wavelet-based sensing methods [7] belong to category (B); eigenvalue-based sensing [8], covariance-based sensing [9], and blindly combined energy detection [6] belong to category (C).

The PSD-based sensing algorithm presented in [11] belongs to category (A) and it outperforms all other spectrum sensing algorithms when the receiver can estimate the true value of the noise power, as will be shown in section IV. However, in reality for the reasons mentioned in [9], the value of the estimated noise power is different than the true noise power. When the PSD-based sensing algorithm uses a wrong estimate of the noise power, its performance is highly degraded. And here comes the advantage of blind algorithms of category (C) which do not require any prior knowledge of the noise level in the system. Among these blind techniques, the eigenvalue-based sensing [8] provides the best performance and is most suitable to be used with wireless microphones in the presence of noise uncertainty.

In this paper, we propose a novel adaptive sensing algorithm that exploits the advantages of both the PSD-based sensing and the eigenvalue-based sensing, where the blind

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eigenvalue-based sensing algorithm is used to guide the PSD-based decision to overcome the effect of noise uncertainty. Our results show that the proposed algorithm outperforms both algorithms, and therefore, provides a reliable operation in noise varying environments.

The rest of the paper is organized as follows. Section II will compare between the PSD-based sensing algorithm and the eigenvalue-based sensing. Section III will present the proposed algorithm that combines these two algorithms. Section IV presents the simulation results. Finally, section V concludes the paper.

II. PSD AND EIGENVALUE BASED SENSING ALGORITHMS

A. Spectrum sensing using power spectral density:

Spectrum sensing using PSD [11] 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 WM signal is highly concentrated in the frequency domain, and there are a many apparent peaks in its PSD [12]. 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.

Wireless microphone signal is modeled by a sinusoidal signal that FM modulates a carrier signal, with a transmit power of 10 mW. The carrier frequency and FM deviation factor are chosen to model the WM signal in three cases:

1. Silence: that is the case when the wireless microphone is switched ON but the *microphone* user is silent. In this situation, the FM deviation factor is small.
2. Soft speaker : when the speaker speaks in a soft voice, the frequency deviation factor is medium.
3. Loud speaker: when the microphone user speaks in a loud voice, the frequency deviation factor is large.

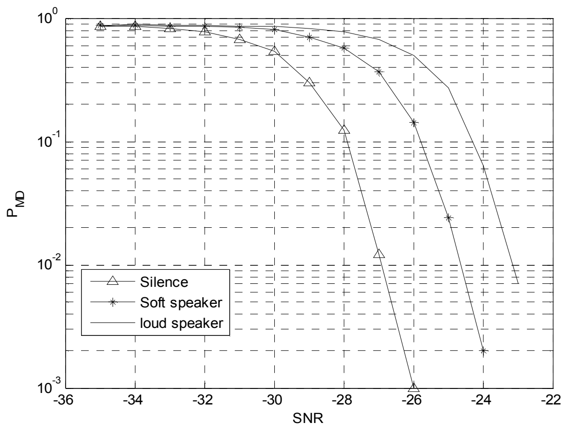

Fig. 1 . Performance of the WM spectrum sensing using PSD, at PFA =0.1 and sensing time = 10 ms.

The PSD-based sensing algorithm divides the signal's frequency domain into M windows each of size N samples, and finds the PSD in each band. The maximum value of all the bands is taken as a decision statistic and is compared to a certain threshold λ_{PSD} to decide the signal presence. This decision threshold is derived as a function of the probability of false alarm P_{FA} and estimated noise power as follows:

$$\lambda_{PSD} = M\theta + \sqrt{M}\theta . Q^{-1}\left(1-(1-P_{FA})^{\frac{1}{N}}\right) \quad (1)$$

θ is given by:

$$\theta = \frac{N\sigma^2}{(N-1)MT_s}$$

where T_s is the sampling period.

The performance of the algorithm is shown in Fig. 1 for the three types of speakers, where P_{MD} is the probability of miss detection. The performance is evaluated at P_{FA}=0.1, which is the maximum acceptable P_{FA} in the 802.22 standard. This is considered the best performance among all sensing algorithms in [3]-[9]. Note that the performance of the algorithm in case of silent speaker is better than the soft and loud speakers, because the spectrum is more concentrated in the first case than the two other cases.

It can be shown that the probability of false alarm achieved by this method is given by:

$$P_{FA} = 1 - \left[1 - Q\left(\frac{\lambda - M\theta}{\sqrt{M * \theta^2}}\right)\right]^N \quad (2)$$

And the probability of detection is:

$$P_D = 1 - \left[1 - Q\left(\frac{\lambda - M\theta - \left({NP}/{(N-1)T_s}\right)}{\sqrt{M * \theta^2 + \left({\mu}/{\Delta f}\right)}}\right)\right]^N \quad (3)$$

where Δf is the FM deviation factor and μ is a constant value depending on the signal power.

However, the dependency on accurate estimation of the noise power (through θ in (1)) is a drawback. As in practice, there is always noise uncertainty, where the estimated noise power is different than the true noise power by a factor α.

$$\hat{\sigma}_n{}^2 = \alpha \sigma_n{}^2$$

It is assumed that α in dB is uniformly distributed in an interval $[-B, B]$. Where B is known as the noise uncertainty bound [14]. Practical values of the noise uncertainty bound are between 1 dB and 2 dB.

It can be easily shown that the probability density function of α is given by [13]:

$$f_\alpha(\alpha) = \begin{cases} \dfrac{5}{\ln(10) * B * \alpha} & 10^{-B/10} < \alpha < 10^{B/10} \\ 0 & otherwise \end{cases} \quad (4)$$

And hence the average P_{FA} and P_D can be obtained by averaging (2) and (3) over the noise uncertainty factor in (4):

$$\overline{P_{FA}} = \int_{10^{\frac{-B}{10}}}^{10^{\frac{B}{10}}} \left(1 - \left[1 - Q\left(\frac{\lambda - M\theta}{\sqrt{M * \theta^2}}\right)\right]^N\right) * \frac{5}{\ln(10) * B * \alpha} d\alpha \quad (5)$$

$$\overline{P_D} = \int_{10^{\frac{-B}{10}}}^{10^{\frac{B}{10}}} \left(1-\left[1-Q\left(\frac{\lambda - M\theta - \left({NP}/{(N-1)T_s}\right)}{\sqrt{M*\theta^2+\left({\mu}/{\Delta f}\right)}}\right)\right]^N\right) * \frac{5}{\ln(10)*B*\alpha}\, d\alpha \qquad (6)$$

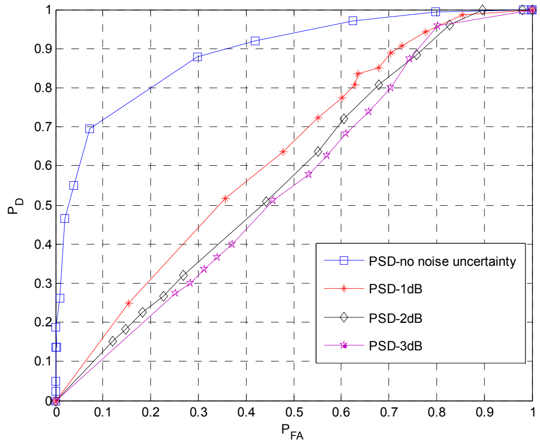

Fig. 2. ROC curve of the PSD sensing algorithm at SNR = -25dB, sensing time 10 ms, for loud speaker.

Using equations (5) and (6), we get the ROC (receiver operating characteristics) curves at different noise uncertainty values as shown in Fig. 2. In Fig.2, PSD-x dB means that the noise uncertainty level is x dB. As can be seen from the curve, the performance is severely degraded in the presence of noise uncertainty, and this degradation increases with the increase in the level of noise uncertainty. For a certain threshold λ_{PSD} in (1) set to achieve a specific P_{FA}, the resulting $\overline{P_{FA}}$ is larger than what was intended to be achieved when choosing λ_{PSD}, and the $\overline{P_D}$ is less than the target P_D. Moreover, noise uncertainty leads to formation of SNR walls. That is to say, for a given noise uncertainty bound B, there is a minimum SNR value below which we cannot achieve the required P_{FA} and P_D using the PSD sensing algorithm; even if sensing time tends to ∞ [13]. As we will show in section III, this effect can be alleviated by using one of the blind sensing algorithms to guide the PSD algorithm threshold in an iterative way.

B. Eigenvalue based detection:

Eigenvalue based detection [9] provides the best performance among all blind algorithms in case of wireless microphone signal detection [1]. The algorithm exploits the fact that the WM source signal has narrow bandwidth (200 kHz compared to 6 MHz of TV channels), and therefore, its samples are highly correlated. This is in contrast to the noise signal, which is a white random signal. Therefore, it has zero correlation between different samples.

The algorithm is based on estimating the covariance matrix of the transmitted signal from the received samples. First, the received samples are upsampled by a factor M. Then an estimation of the covariance matrix based on L consecutive symbols, which corresponds to (M L) received samples, is used to estimate the covariance matrix. An eigenvalue decomposition of the estimated covariance matrix is performed and the ratio between the maximum eigenvalue to the minimum eigenvalue is used as a decision statistic. That is why the algorithm is named maximum to minimum eigenvalue sensing algorithm (MME). The decision statistic is compared to a threshold that depends on the target probability of false alarm and does not depend on the. It has been shown in [10] that, as L increases, the estimated covariance matrix becomes more accurate. However the system complexity increases as well. A method to find the optimal L is given in [9]. The main advantage of this algorithm is that it is blind. The decision threshold depends only on the target probability of false alarm, and not on an estimation of the noise power. The decision statistic also does not depend on the noise power.

Note that the main idea of this algorithm is that the noise samples are assumed to be white i.i.d. random signal, so a pre-whitening process must be used prior to signal detection.
Numerical results that show the performance of the MME algorithm compared to the PSD-based algorithm are shown in section IV.

III. The Proposed Adaptive Algorithm

Although the PSD based sensing is the best sensing algorithm to detect the existence of wireless microphone signals, its performance is severely degraded in the presence of noise uncertainty, as has been shown in Fig. 2. The main reason for this performance degradation is that the decision threshold λ_{PSD} in (1) was chosen as a function of the true value of the noise power. However, as has been shown in [14], the estimated value of the noise power is different than the true value of the noise power. In this section, we propose a novel adaptive algorithm that uses the MME blind estimator to guide the selection of the decision threshold λ_{PSD} in the PSD technique when noise uncertainty exists. We show that this algorithm is superior in performance to both PSD and MME algorithms. We start by listing the steps of the proposed algorithm and follow by a description for its operation.

Algorithm 1:

1. Estimate the noise power, set iteration number i=1
   Calculate the PSD method decision threshold λ_{PSD} based on the required P_{FA} using the estimated noise power using equation (1).
2. Take decision D-PSD based on the decision threshold λ_{PSD} to determine if a packet has been detected or not.
3. Take decision D-MME based on the eignenvalues of the covariance matrix of the signal.
4. Combine D-PSD and D-MME based on Table 1.
5. i=i+1; If i >= *num_iterations* Goto 1, else continue
6. Based on the combined decision in step 4, if a packet has been detected, increase λ_{PSD} according to (7), otherwise, decrease λ_{PSD} according to (8)
7. Goto step 2

D-MME	D-PSD	Combined	
		Decision	λ_{PSD} adjustment
D	D	D	No adjustment
N	D	D	λ_{PSD} is increased
N	N	N	No adjustment
D	N	D	λ_{PSD} is decreased

Table 1: Combined decision based on PSD and MME algorithms.

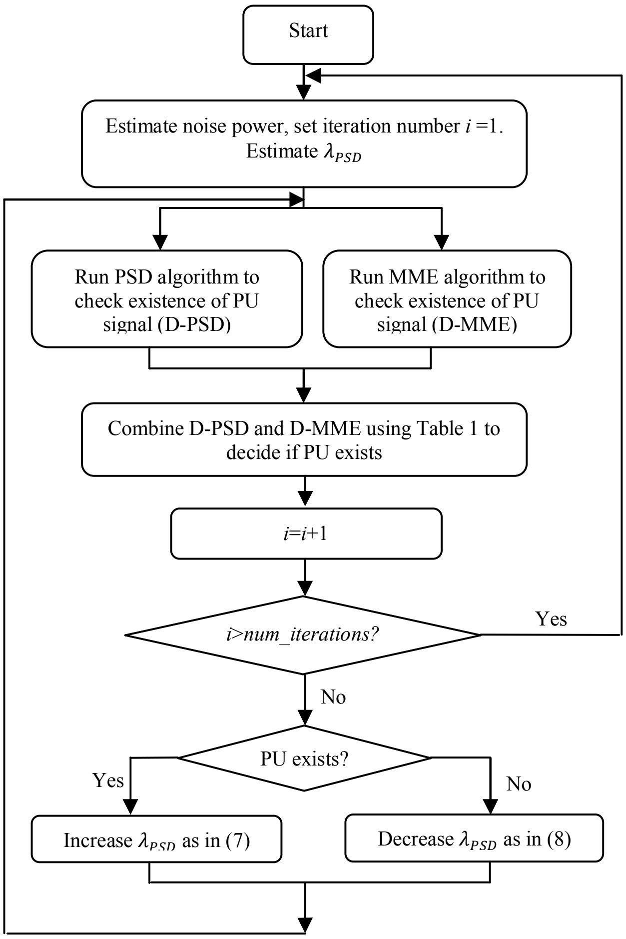

Fig. 3. Flow chart for the proposed adaptive algorithm.

The flow chart in Fig. 3 describes the steps of the proposed algorithm. The algorithm starts by calculating an estimate of the noise power to be used by the PSD spectrum sensing algorithm. In practice, as have been highlighted in [14], this noise estimate is not accurate. The noise estimate is used, along with the required P_{FA}, which is a system requirement, to estimate λ_{PSD} that will be used by the PSD spectrum sensing algorithm described in section II-A. The PSD sensing uses λ_{PSD} to take a decision concerning the existence of the PU in step 2. We call this decision (D-PSD). At the same time, in step 3, the covariance matrix of the received samples will be calculated and a decision based on the MME algorithm will be taken. We call this decision (D-MME).

In step 4, the decisions from the two sensing algorithms are combined based on table 1. Since the MME algorithm is blind, its performance is much worse than the performance of the PSD-based algorithm if the true noise information is available at the receiver (as we will show in section IV). Consequently, we will mainly consider the decision of the PSD-based algorithm in table 1, and use the MME decision as a feedback to adjust the value of λ_{PSD}. However, if MME detected a signal while PSD not (which is the last case in Table 1), that means that the noise power estimated was much larger than the true noise power value such that MME was able to detect the signal presence while PSD cannot. Therefore, we consider that a signal is detected.

In step 2, because the PSD threshold was based on an estimation of the noise power, and not the true value of the noise power, we will update this threshold to be used in the detection in the next iterations. Whenever the PSD algorithm detects a signal, while MME cannot (second case in Table 1), then there are two possibilities:

a) It can be an indication that the estimated noise power, and hence the calculated λ_{PSD}, is less than the actual value. Then we need to increase the value of λ_{PSD}.

b) The MME was unable to detect the signal because its P_D is low at that SNR.

Accordingly, λ_{PSD} increases in the next iteration by a value that varies directly with the P_D of the MME algorithm at the estimated SNR, which can be determined by an offline simulation and stored in a lookup table. Therefore, the value $1/(1-P_D)$ acts as a ratio that weights the decision of the MME algorithm and indicates the amount of trust we should give for. The update equation of λ_{PSD} in this case is:

$$\lambda_{PSD} = \lambda_{PSD}\frac{1}{1-P_D} \qquad (7)$$

Similarly, if MME detected a signal while PSD could not (case four in Table 1), there are two possibilities:

a) It can be because the estimated noise power and λ_{PSD} are larger than the actual value.

b) It can be just a false alarm from the MME algorithm.

Consequently, we need to decrease λ_{PSD}, but as before, the amount of decreasing λ_{PSD} should be in proportion to the P_{FA} value of the MME algorithm at the estimated SNR. The update equation of λ_{PSD} is given by:

$$\lambda_{PSD} = \lambda_{PSD} * P_{FA} \qquad (8)$$

Updating λ_{PSD} takes place in step 6. Adjusting λ_{PSD} continues for *num_iterations* iterations, and then the receiver estimates a new value of noise power.

IV. SIMULATIONS AND RESULTS

The proposed algorithm was tested in a typical PU sensing scenario, where the sensing interval was set to 10 ms. Fig.5 shows the probability of miss detection (P_{MD}) at different SNRs when the target P_{FA} = 0.1, which is the maximum acceptable by the 802.22 standard. The noise power uncertainty B in (4) is 1 dB. When true noise information is available, PSD based sensing outperforms MME based sensing by 3dB as shown in Fig.4. However, when the estimated noise is different than the true noise information, the performance of the PSD-based sensing becomes worse than the MME performance. This is emphasized in Fig. 6 for noise uncertainty of 2 dB. It is clear from Fig. 5 that the proposed algorithm is better than both PSD and MME based sensing. The results for one iteration show the validity of the decision fusion logic in table 1. Even for one iteration, the performance of the proposed algorithm is better than PSD and MME algorithms. As the number of iterations increase, the performance gets better. Fig.5 shows that going from three iterations to four iterations will not provide a significant gain. Fig.7 shows the ROC curve at a very low SNR (-25dB). Increasing the number of iterations will enhance the ROC curve of the system at all values of P_{FA} and P_D. Fig.6 shows also that the proposed algorithm outperforms the PSD sensing when noise uncertainty exists at all values of P_{FA} and P_D.

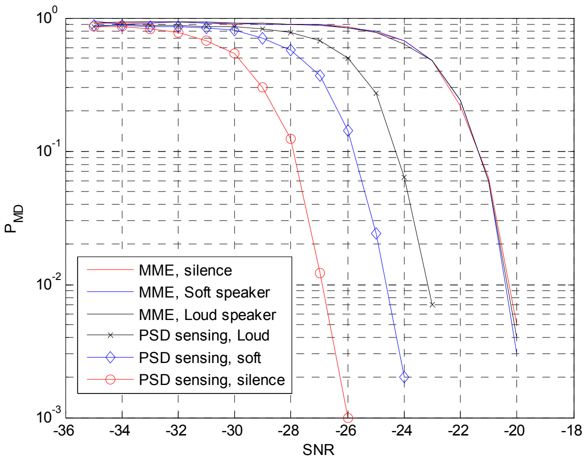

Fig. 4. Comparison between MME and PSD based sensing for P_{FA} =0.1

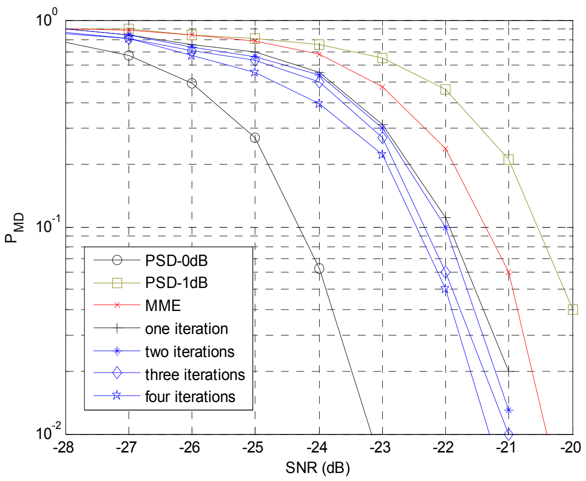

Fig. 5. Performance of different techniques with B=1dB at P_{FA} =0.1.

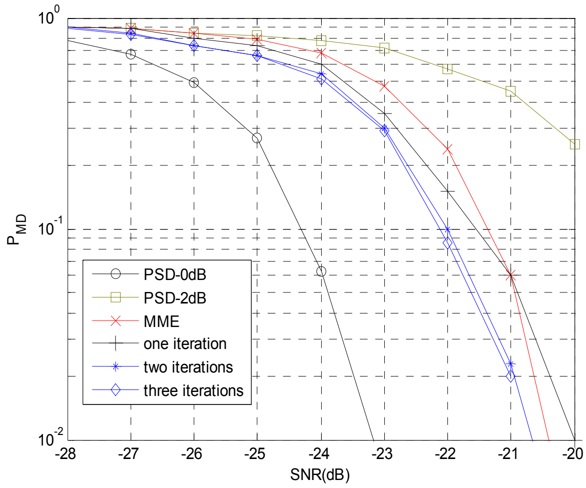

Fig. 6. Performance of different techniques with B=2dB at PFA =0.1.

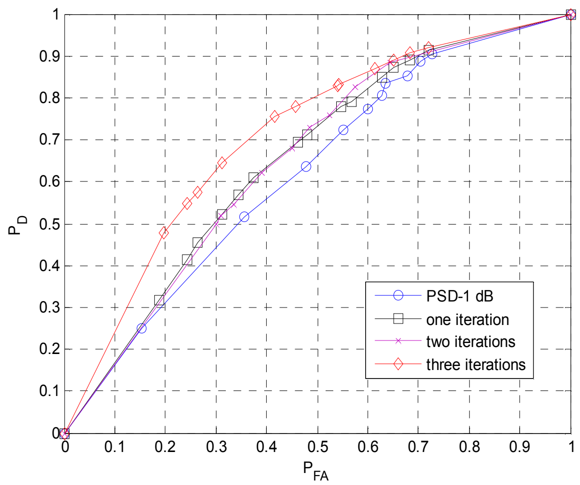

Fig. 7. ROC curve of the PSD, PSD with 1 dB noise uncertainty bound, and the proposed algorithm, for loud speaker at SNR -25 dB, 10 ms sensing time.

V. CONCLUSION

In this paper, we have introduced a new adaptive spectrum sensing algorithm to detect the existence of wireless microphone devices when true noise power is not available. The algorithm combines the decisions of the power spectrum density spectrum sensing and the eigenvalue-based sensing. Moreover, the power spectrum density decision threshold is adapted in an iterative way to mitigate the effect of noise uncertainty. Simulation results show that our algorithm outperforms both algorithms in the presence of noise uncertainty.

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