Spectrum sensing methods and implementations

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***Abstract*—With the likely transition of radio communications from static to dynamic spectrum access in the near future, spectrum sensing has become an interesting topic of research. Even though many signal detection methods have a long history, economical implementations of consumer devices employing spectrum sensing are still missing. We present an overview of current state-of-the-art spectrum sensing methods, limited to the binary decision of channel occupancy. Existing methods are classified into energy detector, covariance, cyclostationary and matched filter methods. For each we give a brief introduction and theoretical background of their operation and comment on practical benefits and drawbacks. In the second part of the paper we describe what implementations of these methods appear in the literature. Both analog and digital electronic implementations are considered.**

I. Introduction

In the context of wireless communications, *spectrum sensing* refers to the act of measuring and characterizing the electromagnetic field in the environment where the communication is taking place. It is typically limited to the wavelengths used for radio telecommunications (e.g. a subset of the 3 kHz - 300 GHz band). In most cases the goal of spectrum sensing is detection and characterization of other users of the radio frequency spectrum, but in a broader sense it can also include for instance measurement of signal propagation properties of the environment and the noise spectral density.

Spectrum measurements can have various purposes. In the simplest case, they can be used to optimize an existing radio link. Given an accurate picture of activity in its frequency band, a radio communications link can avoid interference and maximize its data rate by changing its central frequency, transmit power and bandwidth. Such applications are common in cases where users are unregulated, like for instance in unlicensed frequency bands or in military applications. For example, if an administrator knows day-to-day activity of Wi-Fi hotspots in his vicinity, she can select a channel for a new hotspot with minimal interference to existing equipment. However even in regulated frequency bands, spectrum sensing can be useful as propagation models and theoretical calculations only have a limited accuracy. It can provide valuable input to frequency planners by providing the picture of the actual state of spectrum use.

Another use case for spectrum sensing is finding *spectrum opportunities* and white spaces. If a sufficiently advanced radio system can detect that a certain frequency band is unused in its region at a certain time, it can automatically use that opportunity to increase its data rate without causing interference with other users. This for example enables unlicensed secondary users to coexist with primary users in a licensed frequency band. In the future such systems could drastically increase the efficiency at which the limited radio spectrum is used. They would enable transition from static to *dynamic spectrum access* and in the ideal case remove the need to centralized management of the radio spectrum, as it exists today[1].

Historically, spectrum sensing has mostly been employed in expensive, specialized applications like military communications, monitoring equipment by radio regulatory agencies and by engineers working for large network operators. However in recent years we were witness to a drastic growth in the demand for bandwidth in wireless communications, mostly in consumer devices. This increased the demand for technologies that would enable a more efficient use of the limited spectrum. Lack of free spectrum for exclusive licensing and overcrowding of unlicensed bands was is another contributing factor. Dynamic spectrum access is a promising way of getting more value out of the limited amount of usable spectrum. However the most efficient implementation of dynamic spectrum access depends on accurate spectrum sensing.

Another indicator that shows that adoption of dynamic spectrum access is at hand is the so-called digital dividend. With the transition from analog to digital television broadcasts large swaths of valuable UHF spectrum have been freed. While this created large white spaces, these frequencies are still in use by incumbents and new devices must assure a very low probability of interference with these primary users. Despite that, TV white spaces are just starting to see first trials of consumer applications based on dynamic spectrum access.

If consumer devices are to adopt spectrum sensing, the methods they employ must be well understood, reliable and cheap to implement. Despite its seemingly simple task and the amount of research that has already been done on different methods, spectrum sensing is not a solved problem today. There still remain plenty of theoretical and most of all practical problems before it can come to wide spread use.

The rest of this paper focuses on one specific spectrum sensing task: the binary decision whether a certain frequency channel is occupied by another transmitter or is free to use. We decided on this focus since in the context of dynamic spectrum access, providing an up-to-date *channel occupancy table* is the most important task of a spectrum sensor. The goal of a spectrum sensor in this context is to provide control logic in a transceiver with high quality information about which channels are safe to transmit on and which are occupied by a primary or another secondary user and must be avoided.

In the following sections we give an overview of existing methods the we found to be popular in the literature. Some theoretical background is given on each group of methods, but we mostly limit ourselves to details relevant to the implementation of these methods. We comment on each method's benefits and drawbacks and give comments about practical experience with their applications. Finally we provide a short overview of how spectrum sensors employing these sensing methods are typically implemented in practice and draw some conclusions and pointers for further study.

II. Spectrum sensing methods

As mentioned above, the goal of a spectrum sensing method in the context of this section is to make a binary decision. The null hypothesis $\mathcal{H}_0$ is that a channel is vacant. Alternative hypothesis $\mathcal{H}_1$ is that the channel is occupied by another user.

The spectrum sensor must make this decision based on the observed signal values on the channel during a limited time window. Observed values can be represented as a continuous function $x(t)$ defined for $t \in [0, T]$ in case of analog implementations. More commonly however, a more useful representation is a vector $\mathbf{x}$ of observed samples in the time domain.

$$\mathbf{x} = [x_n] = \{x_0, x_1, \dots x_{N_s-1}\} \quad (1)$$

In the case of a vacant channel, the observed samples are presumed to consist of only noise. Practically all theoretical analyses of spectrum sensing methods assume that noise samples u_n are independently produced by a random process. Often this process is assumed to be frequency independent or have a Gaussian probability distribution, which is a good approximation for receiver thermal noise.[1]

On the other hand, in the case of an occupied channel, the observed samples contain noise in addition to some information-carrying signal s_n. Various spectrum sensing methods make different assumptions about properties of s_n to distinguish it from noise.

Written more formally[2]:

$$\mathcal{H}_0 : x_n = u_n \quad (2)$$

$$\mathcal{H}_1 : x_n = u_n + s_n \qquad n \in [0, N_s - 1] \quad (3)$$

An event when $\mathcal{H}_0$ is true, but the sensor reports an occupied channel is called a *false alarm*. On the other hand an instance when $\mathcal{H}_1$ is true, but the sensor reports a vacant channel is called a *missed detection*. In analyses of sensing methods both of these events are assigned probabilities, P_{fa} and P_{md} respectively. For describing the reliability of signal detection a more common metric is the probability of correct detection P_d.

$$P_d = 1 - P_{md} \quad (4)$$

An ideal spectrum sensor would have $P_{fa} = 0$ and $P_d = 1$. However in reality these two probabilities are related. Typically in practical applications priority is given to maximizing P_d (avoiding interference) over P_{fa} (increasing spectrum use efficiency). A typical relation between these two probabilities is shown in Fig.2.

In addition to error probabilities, another metric for evaluating and comparing spectrum sensing methods is the signal-to-noise ratio SNR at which they are still able to reliably detect a signal.

$$SNR = \frac{\frac{1}{N_s}\sum_{n=0}^{N_s} s_n^2}{\sigma_u^2} \quad (5)$$

Here σ_u^2 is the noise variance. Relationship between SNR and P_d with fixed P_{fa} and time of sensing N_s, as shown on Fig.3, is another characteristic of a spectrum sensing method. A good spectrum sensing method will keep P_{fa} high even for low SNR and short sensing time N_s.

In practical applications probability of detection must stay above a certain threshold, for instance $P_d = 0.9$. Given a relationship like one shown on Fig.3, one can determine the SNR range in which the sensor will reliably operate.

Spectrum sensing methods considered in this paper all operate by defining a test statistic γ as a function of observed signal samples:

$$\gamma = \gamma(\mathbf{x}) \quad (6)$$

A threshold γ_0 is also defined, which is then used to make the binary decision as follows:

$$\begin{array}{lll} \mathcal{H}_0 & \text{if} & \gamma(\mathbf{x}) \leq \gamma_0 \\ \mathcal{H}_1 & \text{if} & \gamma(\mathbf{x}) > \gamma_0 \end{array} \quad (7)$$

Calculation of the threshold depends on the test statistic of the method and typically also on other factors, such as time of sensing N_s and desired probability of false alarm P_{fa}.

In practically all cases P_{fa}, rather than P_d, is considered when deriving γ_0. This is because P_d depends on details of the signal to be detected which are typically unknown in advance. On the other hand P_{fa} depends only on properties of the detector, like noise level, and those are usually better defined.

Exact analytical expressions or approximations for threshold γ_0 exist for majority of test statistics. While these are useful for gaining insight into how the threshold is related to different method parameters, these expressions are rarely useful in practice. As mentioned before, in practice many assumptions made during the derivation of these expressions do not hold

[1] It should be added at this point that the goal is to detect channels where a *harmful* interference might occur. Generally speaking it's not necessary to flag as occupied channels with stray emissions, electromagnetic interference or even internal interference from components of the spectrum sensing receiver itself. While these signals may appear as legitimate transmissions from the standpoint of signal analysis, they can be considered noise for all other practical purposes.

sensing method	**detected property**
energy detection	signal energy
CAV, eigenvalue	sample correlation
cyclostationary	periodicity
matched filter	known waveform

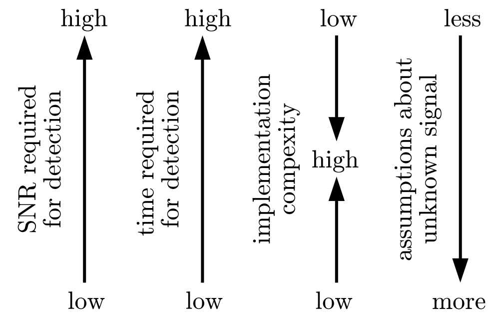

Fig. 1. Overview of spectrum sensing methods and their basic properties.

true. A common cause for this discrepancy is the noise, which is often not Gaussian, uncorrelated or frequency-independent.

Therefore in practical use γ_0 is typically empirically determined. Using the chosen sensing hardware, method parameters and test statistic, a large number of trials is performed observing a known-empty channel. This data is used to approximate the complementary cumulative distribution function (CCDF) for γ in the case of $\mathcal{H}_0$.

The approximate γ_0 for a desired probability of false alarm P_{fa} can then be simply read of the graph, as illustrated in Fig.4 [3].

A high-level overview of spectrum sensing methods is given in Fig.1. The method themselves are described in more detail in the following subsections.

Finally, it should be mentioned that the list of methods described in this paper is of course not comprehensive. In addition to general purpose spectrum sensing methods we might have missed in the large amount of literature written on this topic, there are also methods specialized on detecting certain waveforms. For example, a large amount of work has been done on detecting OFDM-based signals[4]. These specialized methods were considered to have a too narrow focus to be covered in this paper.

A. Energy detection

Energy detection, also called radiometry, is the simplest spectrum sensing method. It is also the best understood, both theoretically and practically. As such it is often used as a baseline when evaluating other spectrum sensing methods.

As the name implies, this method is based on detecting energy emitted by the transmitter. All radio transmitters by definition emit energy into the electromagnetic field and hence this method is also the most universal. It can detect all transmissions, regardless of bandwidth, modulations and other signal properties.

The test statistic γ for energy detectors is based on definition of signal energy, which is related to the physical concept of energy. For a continuous signal:

$$\gamma = \int_0^T x^2(t)dt \tag{8}$$

For sampled-time real signals, previous equation transforms into:

$$\gamma = \sum_{n=0}^{N_s} x_n^2 \tag{9}$$

The limit of detection for energy detection stems from the fact that all receivers exhibit a certain amount of noise $u(t)$ with variance σ_u^2, which is always added to the received signal. This makes $x(t)$, as well as γ, a random variable.

$$x(t) = s(t) + u(t) \tag{10}$$

Given a constant signal power, the noise term adds a certain amount of uncertainty to γ. If noise is assumed to be zero-mean Gaussian, this uncertainty can be in theory arbitrarily decreased with longer integration times T or taking more signal samples N_s.

This fact is taken into account in the derivation of the theoretical threshold for energy detector in the presence of additive Gaussian noise for the desired probability of false alarm P_{fa}[2][5]:

$$\gamma_0 = N_s \sigma_u^2 \left(1 + \frac{\sqrt{2}Q^{-1}(P_{fa})}{\sqrt{N_s}}\right) \tag{11}$$

Somewhat counterintuitively, taken long enough time, a theoretical energy detector is capable of detecting an arbitrarily weak signal. In fact, theoretically, energy detection is the optimum algorithm for detecting Gaussian signals in Gaussian noise.[2]

In practice however this is not possible. Firstly, in spectrum sensing applications the time given for sensing is limited. And secondly, the noise variance is not constant in practice. Internal receiver noise changes with production tolerances, temperature and other environmental factors. Environment noise changes with time as well.

This basic problem with energy detection is illustrated in Fig.5.

[2]In this paper, Q denotes the Gaussian Q-function, where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{+\infty} e^{-\frac{u^2}{2}} du$. Q^{-1} denotes the inverse, which can expressed as $Q^{-1}(x) = -\sqrt{2} \cdot \mathrm{erf}^{-1}(2x-1)$, where erf^{-1} is the inverse error function.

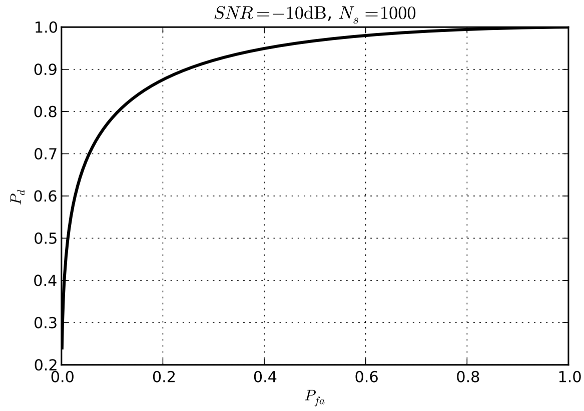

Fig. 2. Theoretical probability of detection P_d versus probability of false alarm P_{fa} for energy detector. This graph is also called *receiver operating curve*. Methods with better performance lie above the energy detector curve.

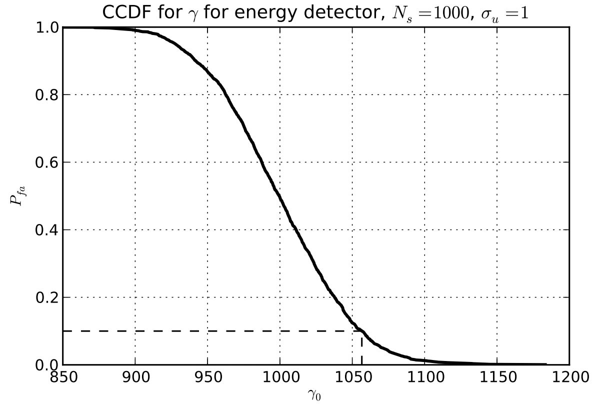

Fig. 4. Complementary cumulative distribution function for energy detector test statistic γ obtained through numerical simulation of 2000 measurements. Dashed lines indicate the threshold value γ_0 for a chosen $P_{fa} = 0.1$.

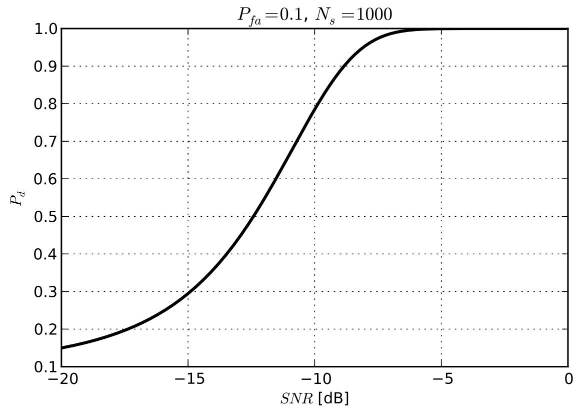

Fig. 3. Theoretical probability of detection P_d versus signal-to-noise ratio SNR for energy detector. Methods with better performance lie above the energy detector curve.

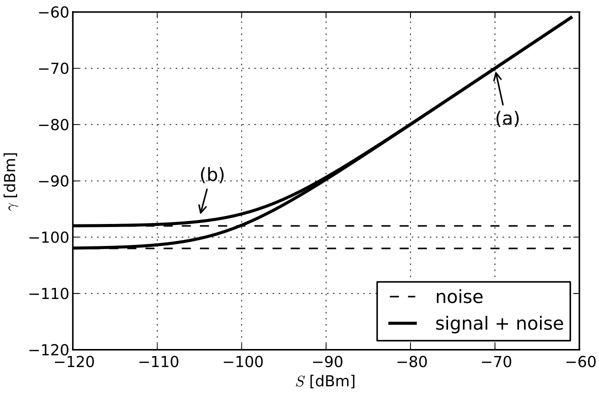

Fig. 5. Energy detector test statistic γ versus signal power S in log-log scale for two slightly different receiver noise floors. Detector output is relatively independent of noise power when the signal is strong (a), but with signal power at or below noise, reliable detection depends on accurate knowledge of the noise level (b).

This drawback doesn't only invalidate the theoretical derivation in Equation 11. It puts a hard limit on the minimal signal to noise ratio under which the energy detector is capable of reliably discerning the signal. This is often referred to as the *signal-to-noise wall*. In practice, energy detectors are rarely effective with SNR below -10 dB.

B. Covariance methods

To overcome the problem with noise floor uncertainty, covariance methods derive their test statistic from sample covariance instead of the mean. In this section we cover a broad group of methods of varying computational complexity. All of them have the common characteristic that they work on two assumptions: firstly that noise samples are independent and hence uncorrelated and secondly that samples of realistic information-carrying signals are correlated to some degree.

The second assumption is not a given. An ideally encoded signal has no correlation between samples. However in practice most signals do exhibit some correlation between samples[6]:

- Samples will be correlated if the sample rate is higher than the Nyquist frequency of a signal. An example of such a case is a narrow-band transmission that is over sampled.
- Correlation can be added if the propagation channel has time dispersion. This can happen for example in multipath environment.
- Signal samples observed through multiple antennas and RF pipelines can be phase-shifted and hence correlated.
- A signal itself can be correlated, for example many analog transmissions.

It should be noted that these characteristics can be also exhibited by certain electromagnetic emissions that, while are not noise, strictly speaking, are also not signals that have to be avoided in practical spectrum sensing. Such examples for example include out-of-band emissions, EMI and other man-made noise.

These methods require that sample covariance estimates λ_l

are calculated based on an array of observed signal samples:

$$\lambda_l = \frac{1}{N_s} \sum_{n=0}^{N_s-1} x_n \cdot x_{n-l} \qquad l \in [0, L-1] \tag{12}$$

Here L is an input parameter called a *smoothing factor*, which determines the minimum time window within which the signal must exhibit correlation.

Typically covariance methods then derive the test statistic from a Toeplitz matrix of covariance estimates $\mathbf{R}$.

$$\mathbf{R} = [r_{ij}] = \begin{bmatrix} \lambda_0 & \lambda_1 & \dots & \lambda_{L-1} \\ \lambda_1 & \lambda_0 & \dots & \lambda_{L-2} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{L-1} & \lambda_{L-2} & \dots & \lambda_0 \end{bmatrix} \tag{13}$$

In general, non-diagonal elements of $\mathbf{R}$ will be near zero in case of a vacant channel while diagonal elements are related to signal power and are not affected by correlations in the signal. Comparing total signal power to correlations present in the signal gives covariance methods a certain immunity to noise level uncertainty.

This matrix form also lends itself to an elegant and computationally efficient correction in case noise samples are themselves correlated due to a time-invariant filter in front of the detector. The correction algorithm is based on the Cholesky decomposition of a matrix of noise samples and is described in the appendix of [6].

We can find several different approaches to deriving a single test statistic. A simple and effective method is to compare a sum of absolute values of all elements T_1 to a sum of absolute values of diagonal elements T_2. This is the so-called *covariance absolute value* method[6].

$$T_1 = \frac{1}{L} \sum_{i=1}^{L} \sum_{j=1}^{L} |r_{ij}| \tag{14}$$

$$T_2 = \frac{1}{L} \sum_{i=1}^{L} |r_{ii}| \tag{15}$$

$$\gamma = \frac{T_1}{T_2} \tag{16}$$

Variations on this method include for example summing $|r_{ij}|^2$ (*covariance Frobenius norm*) or taking a maximum instead of a sum (*maximum auto-correlation detection*).

Another class of methods is based on eigenvalues of the covariance matrix $\mathbf{R}$ or similar matrices (see references in [3] and [7]). These trade off computational simplicity of former methods for better signal detection performance.

For example, *maximum-minimum eigenvalue* method computes the test statistic from the ratio of maximum and minimum eigenvalue of the covariance matrix $\mathbf{R}$:

$$\gamma = \frac{\lambda_{max}}{\lambda_{min}} \tag{17}$$

Analytical derivation of the threshold γ_0 for a desired probability of false alarm P_{fa} is possible for some of these methods. For example, for the covariance absolute value detector given in Equation 16, the threshold can be calculated as:

$$\gamma_0 = \frac{1 + (L-1)\sqrt{\frac{2}{N_s \pi}}}{1 - Q^{-1}(P_{fa})\sqrt{\frac{2}{N_s}}} \tag{18}$$

It can be seen that the threshold only depends on the smoothing factor L and the number of observed signal samples N_s. However, similarly to energy detection, this analytical expression is only useful to give an insight into the functioning and behavior of the detector. In case of Equation 18 the approximations are actually severe enough that the threshold does not give the exact probability of false alarm even in otherwise ideal conditions of a numerical simulation. In practice the thresholds must be determined empirically.

For many methods based on covariance matrix the analytical calculation of the threshold and other properties of the detector is still an open mathematical problem in the theory of random matrices.

C. Cyclostationary detection

Cyclostationary detectors exploit the fact that practical information carrying signals often include some level of periodicity. This can be the consequence for example of the fact that a digital transmission divides a stream into constant sized blocks, or it can be the result of guard intervals inserted between individual symbols. Periodicity can also be artificially introduced, for example by adding a carrier signal into the waveform.

In the context of cyclostationary spectrum sensing methods we use a stochastic definition of periodicity rather than a more conventional deterministic one. Instead of considering signal samples for decomposition into a sum of harmonic functions, as in Fourier analysis, we consider periodicity of statistical properties, like mean μ and covariance c.

$$\mu_n = E(x_n) \tag{19}$$

$$c_{n,\tau} = E(x_n \cdot x_{n+\tau}) \tag{20}$$

A *cyclostationary signal* with a period N_p has the following properties:

$$\mu_n = \mu_{n+N_p} \tag{21}$$

$$c_{n,\tau} = c_{n+N_p,\tau} \tag{22}$$

This broader definition of signals is more realistic for weak signals buried in noise and fading. In such conditions it is common to encounter deterministic signals with additive as well as multiplicative noise[8].

Cyclostationary signals are contrasted with stationary signals, for which these same statistical properties do not change in time. Gaussian noise with a time-invariant mean and deviation is a stationary signal.

Cyclostationary detectors can also be seen as an extension of covariance detectors. However the smoothing factor in covariance methods is typically shorter than the characteristic period of a signal, while cyclostationary methods by definition require that the number of observed samples contains multiple signal periods.

Cyclostationary detectors base the test statistic on the assumption that a vacant channel only has a stationary component, while an occupied channel has a cyclic component as well. If we consider only covariance $c_{n,\tau}$:

$$c_{n,\tau} = c_\tau + c'_{n,\tau} \qquad n \in [0, N_p - 1] \tag{23}$$

Here, c_τ is the noise-contributed time-invariant and $c'_{n,\tau}$ the periodic term. The binary decision hypotheses from Equation 3 hence become:

$$\mathcal{H}_0 : c'_{n,\tau} = 0 \tag{24}$$
$$\mathcal{H}_1 : c'_{n,\tau} \neq 0 \tag{25}$$

We can find many methods in the literature to calculate a test statistics for detecting cyclostationarity in a signal (see e.g. [9] and its references). In general the methods are quite computationally intensive and involve matrix operations. Generally it is required that $N_s \gg N_p$ (i.e. time window of the signal considered includes multiple periods).

Typical cyclostationary detectors are most efficient when the period of the signal is known, or at least is known to be an integer fraction of a base period. Performance decreases when the base period is not known. We can also find reports in the literature that practical limitations of spectrum sensing receivers affect the performance of cyclostationary detectors. For example, [10] investigates effect of sampling rate uncertainty.

One of the unique benefits of cyclostationary detection is the property that in addition to detection it also enables the detector to classify the signal without decoding it and with little extra computational effort. Waveforms produced by different wireless technologies have different characteristic periods and can be thus distinguished from each other. This feature can also be further exploited by artificially adding periodicity to signals. For example signals of primary users can be tagged with a certain cyclostationary pattern which can be detected by secondary devices and given priority.

D. Matched filter

If energy detector is a method that makes minimal assumptions about the signal being detected, then matched filter methods lie in the other extreme. They assume perfect knowledge of the signal that we want to detect. In fact, a matched filter is theoretically an optimal detector for a known signal in stationary, frequency independent noise[11].

Matched filter here refers to a linear filter that maximizes signal-to-noise ratio for a known signal $\mathbf{s}$. Such a filter has an impulse response $\mathbf{h}$ that is a time-reverse of the signal:

$$\mathbf{s} = \{s_0, s_1, \ldots, s_{N_s-1}\} \tag{26}$$
$$\mathbf{h} = \{s_{N_s-1}, s_{N_s-2}, \ldots, s_0\} = [h_n] \tag{27}$$

The test statistic in this case is simply the time-domain response of such a filter, obtained through convolution.

$$\gamma = \sum_{n=0}^{N_s-1} x_n \cdot h_{N_s-1-n} \tag{28}$$

Combining Equations 27 and 28 reveals that γ is also equal to correlation between the known and input signal. Because of this matched filter detectors are also called *correlation detectors* in some literature.

Deriving the threshold γ_0 for a matched filter detector is similar to the energy detector. In fact in the case of Gaussian noise, the test statistic is a linear operation over Gaussian random variables which is itself again a Gaussian random variable. Given a desired probability of false alarm, the threshold can be calculated as:

$$\gamma_0 = \sigma_u Q^{-1}(P_{fa}) \sqrt{\sum_{n=0}^{N_s-1} |h_n|} \tag{29}$$

Here P_{fa} is the probability of false alarm and σ_u^2 variance of the additive noise.

At first glance it might appear from Equation 29 that the matched filter is plagued by the same problem as the energy detector - the uncertainty in the value of σ_u^2. However the test statistic γ is in this case more sensitive to the presence of the desired signal than in the energy detector. This means that the uncertainty in noise level, and hence in γ_0 has a much smaller effect on the overall performance of the detector.

Obviously, the drawback of this kind of detector is the requirement that at least part of the signal being detected is known in its entirety. Typically this can be a block preamble or a synchronization part of transmission. Several matched filters can be run in parallel to detect multiple signatures.

Another problem is the fact that the window of N_s samples tested must include the known part of the signal in its entirety, or the probability of detection will suffer. This means that either the detector must be synchronized to the transmitter or test statistic must be calculated on multiple overlapping windows of samples.

The derivation above also does not take into account that even a perfectly known signal transmitted over a wireless channel will be subject to frequency-dependent fading, time dispersion and other distortions which cannot be known in practice. Since matched filter needs to coherently process the signal, it shares the same sensitivity to time-domain errors in the spectrum sensing receiver as cyclostationary detectors. These effects all severely impact the performance of matched filters in practice.

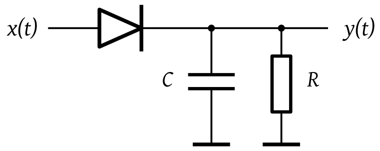

Fig. 6. Diode detector

III. IMPLEMENTATIONS

A spectrum sensing method that performs well in theoretic analysis and numerical simulations is only one part in a successful, practical spectrum sensor. A good method must also be simple to implement in a physical device and be robust to errors, uncertainties and engineering tolerances that are unavoidable in practical implementations.

One important feature that a practical implementation must provide and that was not yet mentioned is that all theoretical methods considered above only provide a decision for a single channel. They assume that the observed samples have already been filtered down to a single frequency channel that is of interest. This consideration for instance is important in software defined radio architectures, where the bandwidth of the signal chain can be significantly wider than the bandwidth of the channel we are interested in sensing.

Another consideration in this regard is the fact that some methods can be extended to provide more efficient sensing for multiple channels at once if the bandwidth of the signal chain allows for that. One such popular example is energy detection, which can be performed on multiple channels at once by averaging power spectral density obtained through fast Fourier transform of observed signal samples.

The following sections provide a brief overview of existing work on spectrum sensor implementations we found in the literature.

A. Analog

Of the sensing methods considered in Section II, only energy detection and matched filter can be practically implemented in analog electronic circuits. Analog matched filters have been important historically, but presently only analog energy detection still holds some benefits over digital implementations.

Analog energy detectors are surprisingly common in practical spectrum sensing experiments and also in wide-spread devices. Their main benefit is simplicity, low power usage and low cost of implementation. Hence one can find them in practically all digital integrated transceivers. Manufacturers are adding them to be used for example in carrier-sense MAC protocols, clear-channel assessment or as a received signal strength indicator. However they are often also used in research as low-cost sensing hardware for mounting on wireless and mobile sensor nodes[12]. An example of such a spectrum sensor is shown in Fig.7[13].

Analog implementations of energy detectors are typically implemented as a diode detector circuit shown on Fig.6. The output of such a detector is then coupled with a logarithmic amplifier to expand its useful dynamic range before being sampled by an analog-to-digital converter (ADC).

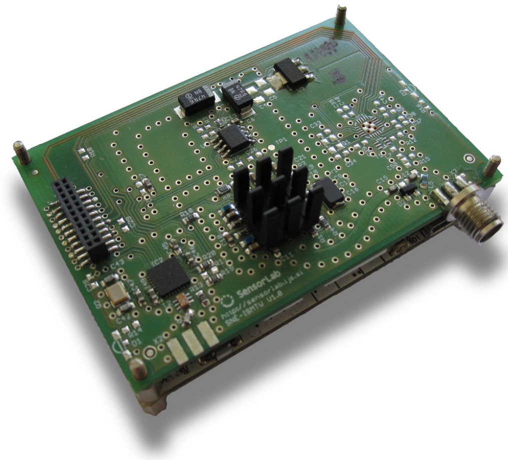

Fig. 7. SNE-ISMTV-UHF energy detector for the VHF/UHF band mounted on a VESNA sensor node is an example of a simple, low-cost analog implementation of a spectrum sensor.

A semiconductor diode provides non-linearity while the RC circuit approximates integration over a time interval. Compared to Equation 8, it should be noted that this circuit performs a somewhat different operation: A semiconductor diode has an exponential characteristic, not quadratic. The effective integration interval T is related to the time constant RC, however the output signal $y(t)$ of this circuit is also not exactly equal to the integral in Equation 8. While the exact analysis of this circuit is not trivial, for the purposes of the energy detection method its behavior is close enough to the theoretical evaluation in Section II.

In practical implementations of energy detectors, the output of circuit in Fig.6 is typically further averaged in the digital domain to improve the minimal signal-to-noise ratio. The effect of the time constant RC in that case complements the digital averaging.

B. Digital

Implementing spectrum sensing in the digital domain has several benefits over the analog circuitry: it allows for more complex algorithms, simpler development and higher flexibility. On the other hand, it typically requires more expensive hardware and consumes more power. Some of these drawbacks however can be mitigated by using the same radio hardware for spectrum sensing as well as for communication, which is typically possible on software defined radio architectures.

Digital spectrum sensing implementations typically consist of three parts:

The analog front-end amplifies the signal, performs filtering to prevent aliasing at the analog-to-digital converter and shifts the signal in the frequency domain to baseband or a low intermediate frequency. Typically this stage includes some

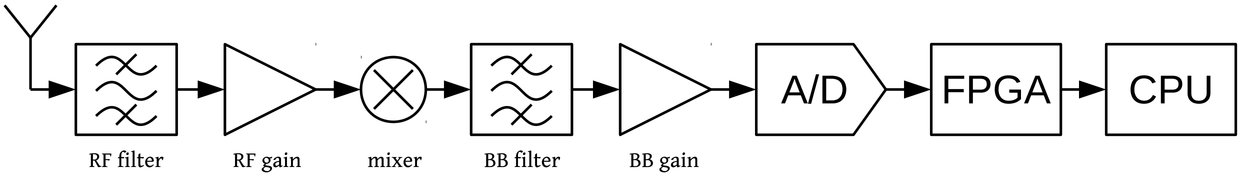

Fig. 8. A typical block diagram of a spectrum sensor based on a software-defined radio architecture. Analog front-end conditions the signal at radio (RF) and base-band (BB) frequencies. Digital part consists of a front-end implemented in a FPGA or an ASIC. High-level operations are done in software on a general-purpose CPU.

form of automatic gain control (AGC) to optimize the signal-to-noise ratio of the receiver and minimize the effect of any non-linearities in the analog signal chain.

It should be noted that AGC often presents a problem for digital spectrum sensing methods, especially if the absolute level of a signal needs to be known or if the level of the signal level needs to be compared over longer time periods[14]. Many commercial tuners also do not allow software inspection or control of the AGC state, which makes controlling or calculating the total gain in the signal chain impossible. This makes methods that require such information less practical.

Due to engineering constraints of anti-aliasing filters, the ADC typically samples the signal at a much higher frequency than is the usable bandwidth of the signal chain. To shed the unnecessary samples as early as possible in the digital signal processing, the first stage after the ADC is typically a fast digital front-end.

Digital front-end performs digital filtering and decimation to a sample rate that is close to the Nyquist frequency of the channel being analyzed. This front-end is typically implemented in a reprogrammable circuit like a FPGA in research applications or an application-specific circuit (ASIC).

The front-end can also implement other functionality, like for example calculating a fast Fourier transform to off-load computationally intensive tasks from the general-purpose processor. Some low-bandwidth and embedded applications however may skip the digital front-end altogether.

The actual sensing algorithm is most often implemented in software running on a general purpose processor. In such case and using modern software development tools the implementation is usually straightforward from the mathematical definition. This is the path followed by many experimenters using common software-defined radio platforms targeted at research community, like the Ettus Research USRP series.

Software implementations however can be problematic when very low latency is required between a change in the channel and its detection. General purpose processors also generally consume more power than a dedicated integrated digital circuit. Therefore in some cases, sensing methods are implemented in a dedicated integrated circuit as well (e.g. Imec Digital Interface for Sensing (DIFFS) chip in [15]).

IV. Conclusions

In this paper we have presented a general overview of current state of the art in spectrum sensing methods and their implementations.

Even though a large amount of literature exists on the topic and some of the methods described here have a research history of more than 50 years, practical applications are still lacking.

One of the possible reasons we see is that the application of signal detectors to the dynamic spectrum access problem is relatively novel and not well researched (most of these methods were initially developed for other uses).

Another reason is likely a lack of engineering knowledge on how to implement them. We have seen a lot of scientific literature about novel spectrum sensing methods where reproducing a working implementation from the mathematical description alone is highly non-trivial. Many theoretical analyses of sensing methods also assume knowledge about the signal being detected that is unrealistic. One such assumption is synchronization of the spectrum sensor with the transmitter - if such a synchronization is possible then the signal is already known to exist and the sensing is unnecessary in the first place.

Another consideration that is often missing from the analysis of spectrum sensing methods is the computational complexity of their implementations. Recent developments in covariance based methods seem to be the most promising in the respect. We have found the covariance absolute value method for example to be a good compromise between detector performance and implementation complexity.

Experimental experience with spectrum sensing is still largely based on energy detection. Especially with large scale surveys, when implementations using laboratory equipment become impractical. It also appears that commercial solutions tend to stay away from theoretically researched and mathematically well-defined methods and rather choose heuristical methods. We have not seen enough evidence in the literature to decide whether the reason for that is because such methods are more economical to implement or because they perform better in practice.

We believe that further research into practical spectrum sensing methods and their economical implementations would be aided significantly by a hardware platform that would be closer to practical implementations than the research platforms we see in the literature today. Hence our future focus will be on developing such a platform based on our previous work on spectrum sensing on wireless sensor platforms.

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