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# Adaptive threshold spectrum sensing based on Expectation Maximization algorithm

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ABSTRACT

In this article we address a novel method for spectrum sensing, based on the Expectation Maximization algorithm applied to the histogram of the moving average signal power. The method enables the estimation of the number of active users in a given frequency band, the power received from each user, the occupied time slots and the front-end noise floor. The proposed approach takes advantage of the statistical properties of the averaging estimator output, which allows to model the received estimated power as a Gaussian mixture. This model represents the distributions of the users transmitted signal power as well as the system noise floor. Moreover, the Gaussian with the lowest mean that is related with the noise floor, can be used to estimate an adaptive threshold for a constant false alarm rate detector. Finally, the method was validated in a Wi-Fi experimental setup, where real-world data was acquired with a software defined radio.



## 1. Introduction

The Long-Term Evolution (LTE) is the current standard for high-speed wireless communication systems and has reached its maturity. The new releases only consider incremental improvements to the standard without any additional spectral bands [1]. In the recent Visual Network Index (VNI) report [2], it is foreseen that an incremental approach will be unable to meet the future demands of the mobile data by 2019 when an increase of traffic is expected compared to 2014.

Therefore, with a limited amount of available spectrum and the necessity of increasingly higher data-rates, spectrum sharing became a relevant research topic in 5G mobile communication systems [3]. This approach allows the dynamic assignment of spectrum resources to RF devices in an opportunistic way, even for frequency bands that may be already assigned to primary users. This is especially true provided that it is possible to prevent collisions between opportunistic users and the primary users. However, this strategy presents a huge challenge to spectrum regulators in order to control interference.

The future spectrum sharing implementations can be used in licensed spectrum if the opportunist users sense any incumbent signals, being constantly aware of the medium in order to avoid conflict with the primary users that have priority in that frequency band [4]. It can also be applied to an unlicensed spectrum where users need to sense the occupation of these unlicensed bands in order to allocate their communication data on channels without interfering with other users.

For sharing unlicensed and licensed spectra, the key element will be the need to sense the occupation of the spectral bands by opportunistic RF devices. Spectrum sensing is thus the key mechanism for any multiple access communication medium. It avoids collisions between users that share the access to the medium, and reduces the contention delay experienced in dense user environments. Even in a scenario where a central database assigns spectrum resources to the users taking into consideration frequency, time and space, the spectrum sensing will be mandatory in order to supervise the behavior of the RF systems. This option is currently tested in pilot project by the Microsoft Spectrum Observatory [5].

The main goal of spectrum sensing is to determine when a certain frequency band is being used [6]. In this work the proposed channel utilization analysis is based on the Expectation Maximization (EM) algorithm. The EM algorithm is usually employed for the extraction of unknown parameters where the observed data set has a known distribution function. The most common estimation problem is usually to obtain the mean and variance of a given set of signals in the presence of noise [7]. For this reason, EM has typically been associated with reconstruction and segmentation of data, with a clear emphasis on image processing [8,9].

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More recently, the application of EM has been studied for Spectrum Sensing. In [10] the instantaneously received power of a single transmitter is detected. The received signal suffers multipath propagation that can be modeled approximately by a gamma distribution and the parameters estimated with the EM. The noise-floor is also approximated to a gamma distribution to account for non-Gaussian sources of noise. In [11] measured spectra are acquired by a spectrum analyzer and evaluated using EM. In this article the authors state that the amplitude of the transmitted wireless signals follows a Rayleigh distribution while the noise follows a Gaussian distribution. This statement allows the use of a Rayleigh–Gaussian mixture as a model for the analyzed data with the EM algorithm. In [12] EM is used for a multi-antenna Spectrum Sensing network to detect the primary user transmissions. In the article a Rayleigh fading channel is assumed but the noise and the signal are both modeled by Gaussian distributions due to power averaging. The discrete Fourier Transform of the data is then analyzed by the EM algorithm using a complex Gaussian Distribution Mixture model. The method expects a single transmission in each channel and assumes perfect knowledge of the frequency responses of each receiver channel and the noise floor variances.

In the method proposed in this paper as the signal analysis is performed after a moving average of the signal energy, the central-limit theorem ensures that the distribution of the signals and noise will be close to the Gaussian mixture model. Allowing to sense both the signal received from a predominant direct path as well as those scattered by a heavy multi-path channel. The proposed method works in multi-transmitter scenario and does not need to know the number of transmitters in a given frequency channel due to *a priori* knowledge of the energy estimation variance. This method also makes a novel use of the EM algorithm on the RF data energy estimation, by using a histogram to identify the spectrum occupation through time allowing for a higher algorithmic efficiency. This method is also able to determine the number of active users on a given channel and the time slot that each one occupies based on the analysis of the signal received energy. The noise-floor is also dynamically estimated from the EM and is used for a Constant False Alarm Rate (CFAR) threshold calculation for signal detection.

## 2. Spectrum sensing with Gaussian mixture models

### 2.1. Signal model

Consider a spectrum sensing front-end that is constantly analyzing the RF spectrum. The sensed spectrum is divided into multiple sub-bands, where each sub-band may be vacant (only noise-floor is present) or it is occupied by one of $U$ possible users. We assume that each possible user will be sensed by the RF front-end with a unique power level that is due to the uniqueness of each path from the transmitting user to the sensing unit. At a particular instance of time $n$, the received signal will then be one of the $U$ users or, if no one is transmitting, the received signal will be the background noise floor. This scenario is modeled by the following hypothesis:

$$H_o : x(n) = w(n)$$
$$H_k : x(n) = s_k(n) + w(n) \qquad (1)$$

where $x(n)$ is the discrete received time signal in the front-end, $s_k$ denotes the signal transmitted by the user $k = 1, 2, \ldots, K-1$ and $w(n)$ the additive zero-mean white Gaussian noise. A sensing interval, encompassing $N$ samples, will be a sequence of received user signals, represented by $H_i$, and also a noise floor, described by $H_o$. Let $\mathbf{x}$ denote the signal vector with a sample size of $N$, this vector is given by the concatenation of a set of $H_i$ and $H_o$ states. The vector $\mathbf{x}$ contains a mixture of various transmitted users signals and the noise floor. As we assume that each sensed user has a unique power level, an energy estimation analysis of the $\mathbf{x}$ data vector will be able to differentiate the different users of the spectrum.

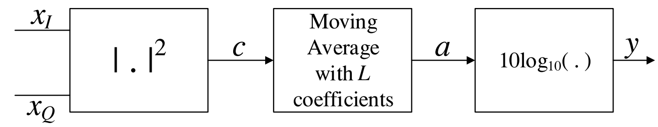


**Fig. 1.** Functional diagram of the used energy estimator.

### 2.2. Signal energy estimation

#### 2.2.1. Energy estimator

In order to analyze the occupation, the spectrum can be divided into individual sub-bands. This spectrum division can be performed, for example, by a band-pass filter-bank, with the necessary bandwidth for the required specifications. For each individual sub-band, the filtered signal can be analyzed to detect occupation. On the other hand, each $i$ user of the shared medium will transmit different data at a different power level. Then, to characterize the energy in the sub-band, the processing steps illustrated in Fig. 1 are proposed. The input $x$ is the acquired complex signal with component in phase ($x_I$) and quadrature ($x_Q$). The complex absolute square of the signal is calculated in order to obtain its instantaneous energy. The instantaneous energy is filtered by an $L$ order moving average. The last step ensures that the output of the filter has an approximate Gaussian distribution [13]. Finally, the smoothed energy estimation is converted to decibels.

Considering the transmission scenario described in Eq. (1) the smoothed energy can correspond to either user or noise. The probability density function of the output $y$ can be modeled as a mixture of $K$ Gaussian distributions corresponding to $K-1$ active users and the noise-floor. The output can be modeled by a Gaussian Mixture Model, where each Gaussian has an unknown mean, which corresponds to its received energy, and a variance that will only depend on the order $L$ of the moving average as will be proven latter.

#### 2.2.2. Complex absolute square

For convenience of calculation, let us assume the front-end input as zero-mean Gaussian complex data, then the absolute square of the input is given by the sum of the squares of the phase and quadrature part of the signal.

$$c = |x|^2 = \left(\sqrt{x_I^2 + x_Q^2}\right)^2 = x_I^2 + x_Q^2. \qquad (2)$$

By definition the Chi-Squared distribution is the result of squaring a standard normal random variable [14]. So, if $x \sim \mathcal{N}(0, \sigma^2)$, $x^2 \sim \sigma^2 \chi_1^2$, where $\chi_1^2$ is the Chi-Squared distribution with 1 degree of freedom. The mean and the variance of Chi-Squared are $\mathrm{E}[\chi_1^2] = 1$ and $\mathrm{Var}[\chi_1^2] = 2$, respectively. The mean of the squared signal is given by $\mathrm{E}[x^2] = \sigma^2$ and the variance by $\mathrm{Var}[x^2] = 2\sigma^4$ [15]. By assuming that the two components of the complex value are normally distributed independent variables $x_I, x_Q \sim \mathcal{N}(0, \frac{1}{2}\sigma_x^2)$, i.e. both with zero mean and the same variance. Then, the square of the quadrature and phase components of the signal will follow the Chi-Squared distribution $x_I^2, x_Q^2 \sim \chi_1^2(\frac{1}{2}\sigma_x^2, \frac{1}{2}\sigma_x^4)$ with the mean and variance calculated as previously explained.

The output of the first block, $c$, is the sum of the squared phase and quadrature components. Therefore, the $c$ signal is the sum of two independent components which have identical Chi-Squared distributions. The distribution of the signal at the output of the first block of Fig. 1 is also a Chi-Squared distribution $c \sim \chi_1^2(\sigma_x^2, \sigma_x^4)$. Therefore the mean is equal to the variance of the input signal, while the variance is the square of the input variance.