# Expectation Maximization for Multipath Detection in Wideband Signals

Salem Salem[1] and Mohamed El-Tarhuni[2(✉)]

[1] Phoenicia University, Beirut, Lebanon
[2] American University of Sharjah, Sharjah, UAE
mtarhuni@aus.edu

**Abstract.** In this paper, a new technique for delay estimation of multipath components in wideband communication systems is proposed. The proposed scheme uses the Expectation Maximization algorithm at the output of an energy detector in order to separate the multipath components from the noise components. The proposed scheme provides comparable performance to the conventional scheme based on maximum energy detector in terms of detection probability. However, it has two major advantages over the conventional scheme that make it more attractive in practical applications. Firstly, the proposed scheme does not require prior knowledge of the number of multipath components; and, secondly, it does not need to use a threshold to decide on the presence or absence of multipath components.

**Keywords:** Expectation Maximization · Delay estimation · Wideband signals

## 1 Introduction

Wideband digital communication over wireless channels has been a very important topic over the past several years. This continues to motivate the development of mobile radio systems that could support high rate applications with tens of Mbps speed through wideband transmission. Furthermore, ultra wideband (UWB) systems are of great interest for achieving even higher data rates and accurate localization applications [1]. However, as a consequence of using wideband signals, multipath propagation is the main characteristic of the wireless channel. The deployed systems need to not only mitigate the interference caused by multipath but also to exploit the diversity available in the multiple received copies of the transmitted signal. Hence, for such communication systems to operate properly, it is very crucial to device effective schemes for detecting multipath components. Another reason to detect multipath components is to improve the performance of location finding systems such as the Global Positioning Systems (GPS) and Global Navigation Satellite Systems (GNSS) [2–4].

There have been many techniques for delay estimation based on correlation and matched filtering for wideband systems using spread spectrum transmission [5–7]. All these schemes utilize the pseudo random (PN) code used in generating the spread spectrum signal to search for the multipath delays over a search window of a range of possible delays. The search window is typically searched at a discrete step that is a fraction of the PN code chip duration to produce a set of correlation results. These results


K. Long et al. (Eds.): 5GWN 2017, LNICST 211, pp. 120–131, 2018.
https://doi.org/10.1007/978-3-319-72823-0_13

are typically compared to a preset threshold to decide on how many multipath components are present and what their delays are.

In [8], multipath detection was done for a receiver with soft handover conditions with either full scanning or sequential scanning of all available multipath components is performed. The proposed scheme used the combined signal-to-noise ratio (SNR) to decide on the selection of the multipath components. Multipath detection based on per path signal-to-noise and interference was introduced in [9]. The authors extended their work to a system with space-time spreading in [10] and interference cancellation. In [11], selection of multipath components for a generalized rake (G-Rake) received based on a maximal weight criterion to maximize the signal energy and minimize interference was presented.

As indicated earlier, one of the most important reasons for multipath detection is to improve the accuracy of positioning systems. Multipath results in ranging errors that could lead to significant error in estimating the location. Most of the techniques presented in the literature were devised to mitigate the impact of multipath by compensating for the presence of multipath or eliminating the multipath after been detected [12–14]. Other techniques were recently introduced to mitigate multipath delays that are closely spaced to within a fraction of a chip [15, 16].

One of the difficult tasks in implementing an effective multipath detection scheme is the selection of the threshold to decide if a multipath component exists at a particular delay or not. The threshold is usually set to maximize the probability of correctly detecting the presence of the multipath component (detection probability) while minimizing or fixing the probability of deciding that a multipath component exists at a particular delay while no signal was present (called false alarm probability). The challenge comes from the fact that the threshold needs to be continuously optimized to maintain the desired performance due to the variation in the wireless channel. Furthermore, a major drawback of most existing multipath detection schemes is that they assume the number of multipath components in the received signal is known to the receiver apriori and they just need to estimate the delays for these components. This assumption is not realistic since the number of multipath components is actually a random value that depends on the physical objects surrounding the transmitter and receiver and how the transmitted wave is affected by these objects. This is further complicated because, in a mobile radio system, the physical objects vary as the transmitter, receiver, or both move during the data transmission leading to variation in the number of multipath components and their delays. These variations are especially significant for fast moving terminals.

In this paper, we develop a multipath detection scheme that overcomes both of the above issues. Namely, the proposed scheme does not use a threshold at all so there is no issue with setting the threshold value and optimizing it over time. Furthermore, the proposed scheme detects all multipath components without assuming prior knowledge of how many paths exist in the received signal. The proposed scheme works by modeling the multipath detection problem as a mixture model generated from two independent and unknown distributions; one for the noise and one for the signal. Then, each correlation result obtained from a conventional search algorithm is classified to belong to either the noise or signal distribution using the Expectation Maximization (EM) algorithm.

## 2 System Model

Let us consider a wideband signal generated using a PN code of length $N$ and transmitted over a frequency-selective Rayleigh fading channel with $L$ paths each with delay $\tau_l \in \{0, 1, 2, \ldots, N-1\}$. We assume $L$ to be a random integer value to be estimated by the receiver as well as to estimate the delays corresponding to these paths. The equivalent baseband transmitted signal from the $m^{th}$ user can be written as

$$s_m(t) = \sqrt{P_m} \sum_i d_i^{(m)} \sum_{k=0}^{N-1} c_m[k] p(t - iT_b - kT_c), \tag{1}$$

where $P_m$ is the transmitted power, $\left\{d_i^{(m)} \in \pm 1\right\}$ is the $i^{th}$ information bit, $\{c_m[k] \in \pm 1\}$ is the PN code of the desired user, $N$ is the PN code length which is the same as the number of chips pet bit, i.e. $N = T_b/T_c$, $T_b$ is the bit duration, $T_c$ is the chip duration, and $p(t)$ is the chip pulse shape.

The signal goes through a mobile radio channel and the received signal in presence of multiuser interference is written as

$$r(t) = \sum_{m=1}^{M} \sum_{l=1}^{L} \alpha_l^{(m)}(t) s_m(t - \tau_{ml}) + w(t), \tag{2}$$

where $\alpha_l^{(m)}(t)$ and $\tau_{ml}$ are the channel gain and path delay for the $l^{th}$ path of the $m^{th}$ user, respectively, $M$ is the number of users, and $w(t)$ is an additive Gaussian noise (AWGN) with zero mean and two-sided power spectral density $N_0/2$. The received base-band signal is sampled at a multiple of the chip rate such that there are $N_s$ samples per chip.

To find the delays of these multipath components, the received signal is correlated with different versions of the PN code each shifted with a specific delay offset within a search window of $N_D$ offsets. The smallest shift between the different PN codes is called the step size, $\Delta$, which is typically equal to 1-chip period or 1/2-chip. The correlation is done over a long period of time to ensure that enough signal energy is collected before making a decision. This period is typically the same as the PN code duration for short codes or could be a fraction of the PN code duration for long codes. Without loss of generality, we assume that the first user is the desired user and a step size of 1-chip is used, the correlation for every possible offset within the search window is calculated as:

$$h_n(v) = \frac{1}{N} \sum_{k=n}^{n+N} r[k] c_1[k+v] = f_{1n}(v) + f_{In}(v) + f_{wn}(v), \tag{3}$$

where $n = 0, 1, 2, \ldots,$ and $v = 0, 1, 2, \ldots, N_D - 1$. The term $f_{1n}(v)$ depends on the autocorrelation function of the desired user, while $f_{In}(v)$ depends on the cross-correlation function between the desired user and the other users. Finally, $f_{wn}(v)$ represents the AWGN contribution. The first term in (3) can be represented as:

$$f_{1n}(v) = \begin{cases} \sqrt{E_b}\alpha_l^{(1)}(n) & v = \tau_{1l} \\ 0 & otherwise \end{cases}, \tag{4}$$

where $E_b = T_b P_1$ is the energy per bit for the first user and $\alpha_l^{(1)}(n)$ is the channel coefficient for the first user during the $n^{th}$ bit duration. When a large number of users exist in the system, the second term in (3) can be represented by a Gaussian process with zero-mean and variance $\sigma_I^2$.

The receiver non-coherently combines the correlation results for the same offset over multiple bits to obtain the energy estimates at every offset as

$$x(v) = \frac{1}{N_a}\sum_{i=1}^{N_a}|h_i(v)|^2. \tag{5}$$

In a conventional multipath detection algorithm, the set of energy estimates $\{x(v)\}$ is compared to a preset threshold and the values that exceed this threshold indicate a presence of a multipath component at that delay offset. Optimization of this threshold is considered as a difficult task for the conventional algorithm. Another option is to choose the offsets with $L$ largest energy values as the multipath components. This assumes that the detector knows in advance that there are $L$ paths in the received signal. Such assumption is not realistic since the number of paths depends on the channel conditions and varies in a non-deterministic way with time.

Our proposed scheme for multipath detection is presented in the next section to overcome both restrictions of the conventional scheme. The proposed scheme uses the energy estimates in (5) to find the maximum likelihood estimates of the delay offsets based on an iterative Expectation Maximization (EM) algorithm.

## 3 Expectation Maximization

Suppose a mixture model is composed from $K$ independent, unknown probability distributions. Let $\mathbf{P} = \{p_k | k = 1 \ldots K\}$ be a set of prior probabilities of each $k^{th}$ distribution, where

$$\sum_{k=1}^{K} p_k = 1, \tag{6}$$

Let $\boldsymbol{\phi} = \{\phi_k | k = 1 \ldots K\}$ be a set of parameters that define the $K$ distributions, where each $k^{th}$ distribution is defined by its parameters $\phi_k$. Given a set of $N_D$ observed data points $\mathbf{X} = \{x_v | v = 1 \ldots N_D\}$ drawn from this mixture model, what are the parameters $\boldsymbol{\phi}$ and prior probabilities $\mathbf{P}$ that most likely generated $\mathbf{X}$?

The probability of a data point $x_v$ is

$$p(x_v|\boldsymbol{\phi}) = \sum_{k=1}^{K} p(x_v|\phi_k)p_k, \tag{7}$$

therefore the log-likelihood of the mixture model is

$$\ell(\boldsymbol{\phi}) = \sum_{v=0}^{N_D-1} \log\left(\sum_{k=1}^{K} p(x_v|\phi_k)p_k\right). \tag{8}$$

The parameters $\boldsymbol{\phi}$ and prior probabilities $\mathbf{P}$ can be estimated by maximizing (8). This is achieved by taking the derivative of (8) with respect to $\boldsymbol{\phi}$ and $\mathbf{P}$ then setting it to zero. For simple models, a solution could be achieved as an explicit function of $\mathbf{X}$. However, for models that are more complex a numerical solution is achieved through optimization methods, such as the Expectation Maximization algorithm [17]. The EM algorithm is a numerical method for maximizing (8) by iteratively estimating the mixture model parameters and the prior probabilities. The EM algorithm starts with an initial set of mixture model parameters $\boldsymbol{\phi}$. After that, it iterates between the two following steps:

1. **Expectation step:** Maximize (8) with respect to prior probabilities $\mathbf{P}$, subject to constraints in (6). For this one may use Lagrange multipliers [18]

$$\mathcal{L}(\boldsymbol{\phi}) = \sum_{v=0}^{N_D-1} \log\left(\sum_{k=1}^{K} p(x_v|\phi_k)p_k\right) - \lambda\left(\sum_{k=1}^{K} p_k - 1\right). \tag{9}$$

Taking the derivative of (9) with respect to $p(k)$ and equating to zero we get

$$\Delta_{p(k)}\mathcal{L}(\boldsymbol{\phi}) = \sum_{v=0}^{N_D-1} \frac{p(x_v|\phi_k)}{\sum_{k=1}^{K} p(x_v|\phi_k)p_k} - \lambda = 0. \tag{10}$$

After some manipulation, we get

$$p_k^{(new)} = \frac{N_K}{N_D}, \tag{11}$$

where

$$N_k = \sum_{v=0}^{N_D-1} \frac{p_k p(x_v|\phi_k)}{\sum_{k=1}^{K} p_k p(x_v|\phi_k)} = \sum_{v=0}^{N_D-1} w_{vk}, \tag{12}$$

where we define $w_{vk}$ as

$$w_{vk} = \frac{p_k p(x_v|\phi_k)}{\sum_{k=1}^{K} p_k p(x_v|\phi_k)}. \tag{13}$$

2. **Maximization step:** Maximize (8) with respect to mixture model parameters $\boldsymbol{\phi}$ by taking the derivative with respect to all model parameters, equating to zero, and finding a solution set.

$$\Delta_\phi \ell(\boldsymbol{\phi}) = \sum_{v=0}^{N_D-1} \frac{p_k \Delta_\phi p(x_v|\phi_k)}{\sum_{k=1}^{K} p_k p(x_v|\phi_k)} = 0, \tag{14}$$

where the outcome of (14) is dependent on the probability distribution assumption.

The above two steps are repeated until the value of the log-likelihood function (8) ceases to change. In the next section we discuss the problem of multipath detection from the maximum likelihood approach.

## 4 Problem Formulation

Let $\mathbf{X} = \{x_v | v = 0, 1, 2, \ldots N_D - 1\}$ be a set of $N_D$ possible delays, where each value $x_v$ is calculated as in (5). The set $\mathbf{X}$ contains an unknown number of signal delays, denoted $N_1$, and the remainder are noise delays, denoted by $N_2$, where

$$N_1 + N_2 = N_D. \tag{15}$$

Our goal is to correctly classify each delay $x_v$ as a signal or noise delay. This problem can be viewed as a classic mixture model problem: Given a set of observed points $\mathbf{X}$ generated from two independent and unknown distributions $\mathcal{Q}_1$ and $\mathcal{Q}_2$, where $\mathcal{Q}_1$ stands for a noise distribution and $\mathcal{Q}_2$ stands for a signal distribution, what are the parameters and prior probabilities of these two distributions that most likely generated $\mathbf{X}$? Once we estimate the distribution parameters, we can classify a delay $x_v$ to correspond to a signal complement if $p(x_v|\mathcal{Q}_2) > p(x_v|\mathcal{Q}_1)$ else it is classified as a noise component. Using the Central Limit Theorem, we may assume that $\mathcal{Q}_1$ and $\mathcal{Q}_2$ follow a Gaussian distribution, if enough bits are used to generate $\mathbf{X}$ in (5). The mixture model likelihood function in (8) becomes

$$\ell(\boldsymbol{\phi}) = \sum_{v=0}^{N_D-1} \log\left( \sum_{k=1}^{K} \frac{1}{\sqrt{2\pi}\sigma_k} e^{-\frac{(x_v-\mu_k)^2}{2\sigma_k^2}} p_k \right). \tag{16}$$

Our goal is to find the prior probabilities $p_k$ as well the distribution parameters $\mu_k$ and $\sigma_k$ that most likely generated $\mathbf{X}$. Using the EM algorithm outlined previously, we start with an initial set of model parameters $\boldsymbol{\phi}$ and prior probabilities $p_k$ and we iterate between calculating the prior probabilities and model parameters:

1. **Expectation step:**

$$p_k^{(new)} = \frac{1}{N_D} \sum_{v=0}^{N_D-1} w_{vk}, \tag{17}$$

where

$$w_{vk} = \frac{\frac{p_{\mathrm{k}}}{\sqrt{2\pi}\sigma_k} e^{-\frac{(x_v-\mu_k)^2}{2\sigma_k^2}}}{\sum_{k=1}^{K} \frac{p_{\mathrm{k}}}{\sqrt{2\pi}\sigma_k} e^{-\frac{(x_v-\mu_k)^2}{2\sigma_k^2}}}. \tag{18}$$

2. **Maximization step:**

$$\begin{aligned} \Delta_{\mu_k} \ell(\boldsymbol{\phi}) = \sum_{v=0}^{N_D-1} \frac{p_k \Delta_{\mu_k} p(x_v|\phi_k)}{\sum_{k=1}^{K} p_k \Delta_{\mu_k} p(x_v|\phi_k)} = 0, \\ \Rightarrow \sum_{v=0}^{N_D-1} \frac{p_k p(x_v|\phi_k)}{\sum_{k=1}^{K} p_k p(x_v|\phi_k)} \times \left(-\frac{(x_v-\mu_k)}{\sigma_k^2}\right) = 0, \\ \Rightarrow \sum_{v=0}^{N_D-1} w_{vk} \times \left(-\frac{(x_v-\mu_k)}{\sigma_k^2}\right) = 0. \end{aligned}$$

After some manipulation, we get

$$\mu_k = \frac{\sum_{v=0}^{N_D-1} w_{vk} x_v}{\sum_{v=0}^{N_D-1} w_{vk}}. \tag{19}$$

Now taking the derivative with respect to $\sigma_k$ we get

$$\begin{aligned} \Delta_{\sigma_k} \ell(\boldsymbol{\phi}) = \sum_{v=0}^{N_D-1} \frac{p_k \Delta_{\sigma_k} p(x_v|\phi_k)}{\sum_{k=1}^{K} p_k p(x_v|\phi_k)} = 0, \\ \Rightarrow \sum_{v=0}^{N_D-1} w_{vk} \left[-\frac{1}{\sigma_k} + \frac{2(x_v-\mu_k)^2}{2\sigma_k^3}\right] = 0, \\ \Rightarrow \sum_{v=0}^{N_D-1} w_{vk} \left[-\sigma_k^2 + (x_v-\mu_k)^2\right] = 0. \end{aligned}$$

After some manipulation, we get

$$\sigma_k^2 = \frac{\sum_{v=0}^{N_D-1} w_{vk}(x_v - \mu_k)^2}{\sum_{v=0}^{N_D-1} w_{vk}}. \tag{20}$$

We stop the EM iterations when the log likelihood in (16) stops changing after each iteration. The delays are then classified based on their posterior probability: A delay $x_v$ is classified as a signal delay if $p(x_v|\mathcal{Q}_2) > p(x_v|\mathcal{Q}_1)$, else it is classified as a noise delay.

We initialize the model parameters and prior probabilities as follows:

1. Assume signal and noise classes $\mathcal{Q}_1$ and $\mathcal{Q}_2$ are equally probable, with $p_1 = p_2 = 0.5$
2. Initialize class means as:$\mu_k = \min(\mathbf{X}) + k\left(\frac{\max(\mathbf{X}) - \min(\mathbf{X})}{3}\right)$
   where *min* and *max* are the minimum and maximum values of **X**, respectively. The 3 in the denominator places $\mu_1$ at a third of the range of **X** and $\mu_2$ at two-thirds of the range. It ensures the means are well spaced out and symmetric within **X**.
3. Initialize class standard deviations as $\sigma_k = \frac{\sigma_{\mathbf{X}}}{2}$, where $\sigma_{\mathbf{X}}$ is the standard deviation of the entire data set **X**. Any other initialization of the standard deviations is possible, so long as the initializations are not extremely unequal, which might cause one class to dominate erroneously.

## 5 Simulation Results

In this section, we compare simulation results from our EM-based algorithm to the conventional algorithm of picking the $N_D$ delays with the highest power. For our EM-based algorithm, the number of multipath delays is not known apriori, whereas for the conventional algorithm the number of delays $N_D$ is assumed known.

Our simulation is based on the case where the paths are widely spaced apart (multiples of chips apart). In general, performance is affected by three factors: number of delay paths ($N_D$), number of non-coherent accumulations ($N_a$), and the signal-to-noise ratio (*SNR*). For each variation of the factors we run the simulation 500 times. We consider a trial successful if the algorithm correctly finds at least half the multipath delays without adding a noise delay, else if is considered a failure. The probability $P_D$ is the percentage of the 500 trials that were successful.

Figure 1 shows the probability of multipath detection when the number of non-coherent accumulations and the SNR are fixed, and only the number of delay paths is varied. Two simulations are shown, the first where $SNR = -15\,\text{dB}$ (per chip), and $N_a = 200$, and the second where $SNR = -20\,\text{dB}$ and $N_a = 50$. The results show that the performance of our EM-based algorithm improves as the number of signal delays increases. This is expected with any statistical based approach: as more data is available for a model, the model estimate improves.

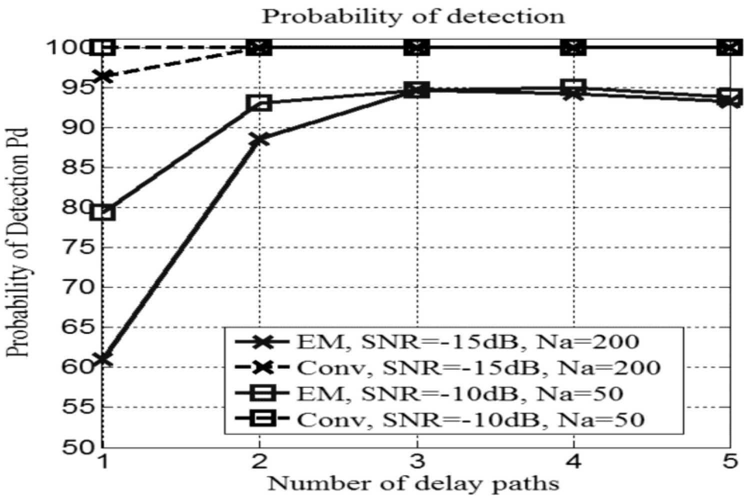


**Fig. 1.** Detection probability for different number of delay paths.

The results of varying the number of non-coherent accumulations $N_a$ while fixing the SNR and number of delay paths is shown in Fig. 2. Two simulations are shown, the first where $SNR = -15\,\text{dB}$ and the number of delay paths is $N_D = 3$ and the second is where $SNR = -20\,\text{dB}$ and the number of delay paths is $N_D = 4$. The figure shows that $P_D$ improves as $N_a$ increases for both the conventional algorithm and our EM based algorithm. The performance of our EM-based algorithm is comparable to the conventional methods, but trails in the required number of non-coherent accumulations for proper performance. At lower number of non-coherent accumulations, the delays are

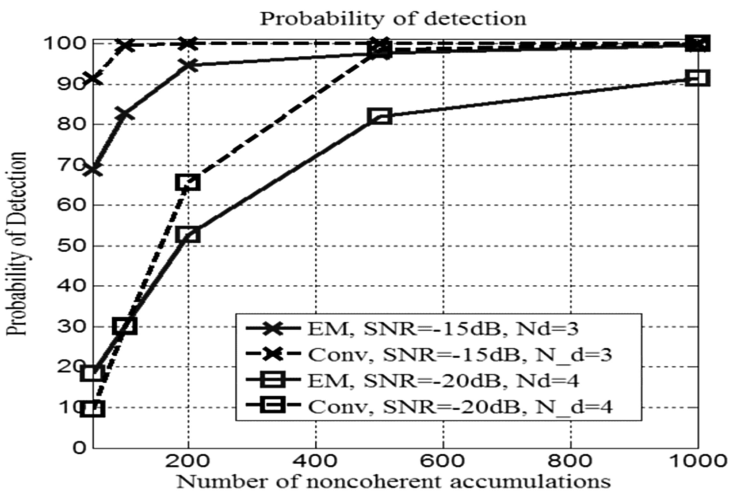


**Fig. 2.** Detection probability for different number of non-coherent accumulations.

sometimes too close to each other to be properly separated by the EM algorithm, and hence the lower performance at lower $N_a$. As the number of accumulations increases, the classes are more distinct, and performance of the EM algorithm increases to become comparable to the conventional algorithm.

Figure 3 shows the effect of SNR on performance, while keeping the number of delay paths to 5. The figure shows two simulations, one for $N_a = 100$ and one for $N_a = 200$. As expected, as SNR decreases performance decreases. This effect is compounded if the number of non-coherent accumulations is also decreased. Note that our EM-based algorithm outperforms the conventional algorithm at lower number of accumulations $N_a$. This is due to the fact that the conventional algorithm has to pick $N_D$ delays, and noise delays can be dominant at low *SNR* and low $N_a$, whereas our EM-based algorithm does not make any assumptions about the number of delays.

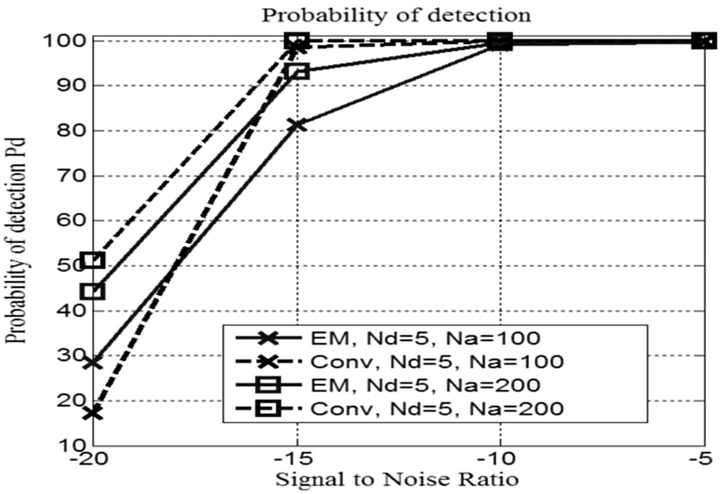


**Fig. 3.** Detection probability for different Signal to Noise Ratios

Tables 1, 2 and 3 show detailed comparison results of our EM-based algorithm to the conventional algorithm, where a simulation is considered a success if at least 50% of the signal delays are detected without adding a noise delay. Each experiment is repeated 500 times.

The data shows that our scheme performs comparably to the conventional one, without prior knowledge of the number of signal delays or a preset threshold. It generally requires more accumulations $N_a$ for the same performance, and the performance increases as the number of delays $N_D$ increases. This is typical of any statistical algorithm where performance increases when more data is available for parameter estimation.

**Table 1.** Simulation results for $L = 1$.

| $N_a$ | 50 | 100 | 200 | 500 | 1000 |
|---|---|---|---|---|---|
| $SNR = -5$ dB | $P_{EM} = 98.4\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ |
| $SNR = -10$ dB | $P_{EM} = 79.4\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 92.2\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 98.4\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 99.8\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 99.8\%$<br>$P_{conv} = 100\%$ |
| $SNR = -15$ dB | $P_{EM} = 19\%$<br>$P_{conv} = 62\%$ | $P_{EM} = 33.2\%$<br>$P_{conv} = 82.7\%$ | $P_{EM} = 61\%$<br>$P_{conv} = 96.4\%$ | $P_{EM} = 88.2\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 96.6\%$<br>$P_{conv} = 100\%$ |
| $SNR = -20$ dB | $P_{EM} = 1.8\%$<br>$P_{conv} = 22.8\%$ | $P_{EM} = 2.6\%$<br>$P_{conv} = 28.2\%$ | $P_{EM} = 8.6\%$<br>$P_{conv} = 39.4\%$ | $P_{EM} = 16\%$<br>$P_{conv} = 66\%$ | $P_{EM} = 37\%$<br>$P_{conv} = 90.8\%$ |

**Table 2.** Simulation results for $L = 3$.

| $N_a$ | 50 | 100 | 200 | 500 | 1000 |
|---|---|---|---|---|---|
| $SNR = -5$ dB | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ |
| $SNR = -10$ dB | $P_{EM} = 94.6\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 99\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 99.8\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ |
| $SNR = -15$ dB | $P_{EM} = 68.8\%$<br>$P_{conv} = 91.4\%$ | $P_{EM} = 82.8\%$<br>$P_{conv} = 99.6\%$ | $P_{EM} = 94.6\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 97.6\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 99.6\%$<br>$P_{conv} = 100\%$ |
| $SNR = -20$ dB | $P_{EM} = 21.8\%$<br>$P_{conv} = 12.8\%$ | $P_{EM} = 26.8\%$<br>$P_{conv} = 29.2\%$ | $P_{EM} = 45.2\%$<br>$P_{conv} = 63.8\%$ | $P_{EM} = 73.6\%$<br>$P_{conv} = 98.4\%$ | $P_{EM} = 87.4\%$<br>$P_{conv} = 100\%$ |

**Table 3.** Simulation results for $L = 5$.

| $N_a$ | 50 | 100 | 200 | 500 | 1000 |
|---|---|---|---|---|---|
| $SNR = -5$ dB | $P_{EM} = 99.8\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 99.8\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ |
| $SNR = -10$ dB | $P_{EM} = 93.8\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 99.2\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 99.6\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 100\%$<br>$P_{conv} = 100\%$ |
| $SNR = -15$ dB | $P_{EM} = 61\%$<br>$P_{conv} = 75.8\%$ | $P_{EM} = 81.4\%$<br>$P_{conv} = 98.6\%$ | $P_{EM} = 93.2\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 98.4\%$<br>$P_{conv} = 100\%$ | $P_{EM} = 99.8\%$<br>$P_{conv} = 100\%$ |
| $SNR = -20$ dB | $P_{EM} = 18.2\%$<br>$P_{conv} = 3.4\%$ | $P_{EM} = 28.4\%$<br>$P_{conv} = 17.2\%$ | $P_{EM} = 44.2\%$<br>$P_{conv} = 51.2\%$ | $P_{EM} = 77\%$<br>$P_{conv} = 96\%$ | $P_{EM} = 91.4\%$<br>$P_{conv} = 100\%$ |

## 6 Conclusion

We proposed an algorithm for multipath estimation in wideband communication systems. The proposed scheme is based on classifying an energy detector search results into either a signal component of a noise component using the Expectation Maximization algorithm. Simulation results have shown that the performance of our EM-based algorithm is comparable to the conventional energy detector scheme but without the need for prior knowledge of the number of multipath components and without the need to use a preset threshold for detecting the multipath components.

## References

1. Meissner, P., Leitinger, E., Witrisal, K.: UWB for robust indoor tracking: weighting of multipath components for efficient estimation. IEEE Wireless Commun. Lett. **3**(5), 501–504 (2014)
2. Chen, X., Dovis, F., Peng, S., Morton, Y.: Comprehensive studies of GPA multipath mitigation methods performance. IEEE Trans. Aerosp. Electron. Syst. **49**(3), 1555–1568 (2013)
3. Qu, B., Wei, J., Tang, Z., Yan, T., Zhou, Z.H.: Analysis of combined effects of multipath and CW interference on coherent delay lock loop. Wireless Pers. Commun. **77**(3), 2213–2233 (2014)
4. Wildemeersch, M., Slump, C., Rabbachin, A.: Acquisition of GNSS signals in urban interference environment. IEEE Trans. Aerosp. Electron. Syst. **50**(2), 1078–1091 (2014)
5. Holmes, J.: Coherent Spread Spectrum systems. R.E. Krieger Pub. Co., Malabar (1990)
6. Simon, M., Omura, J., Scholtz, R., Levitt, B.: Spread Spectrum Communications Handbook. McGraw-Hill Telecom Engineering, Electronic edn. McGraw-Hill Education, New York (2001)
7. Braun, W.R.: PN acquisition and tracking performance in DS/CDMA systems with symbol-length spreading sequences. IEEE Trans. Commun. **45**(12), 1595–1601 (1997)
8. Choi, S., Alouini, M.S., Qaraqe, K.A., Yang, H.C.: Finger assignment schemes for rake receivers with multiple-way soft handover. IEEE Trans. Wireless Commun. **7**(2), 495–499 (2008)
9. Abou-Khousa, M., Ghrayeb, A., El-Tarhuni, M.: An efficient multipath detection scheme for CDMA systems. IEEE Trans. Wireless Commun. **6**(8), 2776–2781 (2007)
10. Abou-Khousa, M., Ghrayeb, A., El-Tarhuni, M.: A multipath detection scheme for CDMA systems with space-time spreading. IEEE Trans. Veh. Technol. **57**(1), 146–156 (2008)
11. Fulghum, T., Cairns, D.A., Cozzo, C., Wang, Y.P.E., Bottomley, G.E.: Adaptive generalized rake reception in DS-CDMA systems. IEEE Trans. Wireless Commun. **8**(7), 3464–3474 (2009)
12. Van Nee, R.D.J.: The multipath estimating delay lock loop. In: ISSTA 1992, pp. 39–42, August 1992
13. Wilde, A.: The generalized delay-locked loop. Wireless Pers. Commun. **8**(2), 113–130 (1998)
14. Sheen, W.H., Tai, C.H.: A noncoherent tracking loop with diversity and multipath interference cancellation for direct-sequence spread-spectrum systems. IEEE Trans. Commun. **46**(11), 1516–1524 (1998)
15. Brenneman, M., Morton, Y., Zhou, Q.: GPS multipath detection with ANOVA for adaptive arrays. IEEE Trans. Aerosp. Electron. Syst. **46**(3), 1171–1184 (2010)
16. Closas, P., Fernandez-Prades, C.: A statistical multipath detector for antenna array based GNSS receivers. IEEE Trans. Wireless Commun. **10**(3), 916–929 (2011)
17. Dempster, P., Laird, N.M., Rubin, D.B.: Maximum likelihood from incomplete data via the EM algorithm. J. Roy. Stat. Soc. B **39**(1), 1–38 (1977)
18. Arfken, G., Weber, H.: Mathematical Methods for Physicists. Elsevier, Amsterdam (2005)