Abstract—We design new receiver structures suited for the ultra wide band (UWB) standard IEEE 802.15.4a. The design objective is a receiver robust to multiuser access interference (MAI), which is a particular severe impairment in simple wireless personal area networks (W-PAN). Unlike most approaches of the literature that focus on the optimisation of decoding, we jointly optimize both demodulation and decoding, deriving new maximum likelihood (ML) schemes with enhanced capabilities in MAI rejection. In particular, a generalized Gaussian mixture model is assumed for the description of MAI, which includes as sub-cases the Gaussian and Laplacian models but has the potential to describe much more general scenarios. Simulations carried out on the IEEE 802.15.4a standard and including channel estimation show that the proposed approach significantly outperforms existing solutions in various channel and interference scenarios.

I. INTRODUCTION

Spreading the transmission of information on a very large spectrum in order to allow multiuser access and multi-standard transmission has attracted increasing attention and lead to the definition of various ultra wide band (UWB) communication models. Some UWB techniques have been recently included in the IEEE 802.15.4a standard for wireless personal area networks. The standard defines a mixture of time hopping (TH) and direct sequence (DS) to implement a spread spectrum transmission, while the adopted modulation is a combination of pulse amplitude modulation (PAM) and pulse position modulation (PPM). Although the intent of spread spectrum is to reduce multiple access interference (MAI), the receiver must be carefully designed in order to exploit the benefits of the transmission technology and effectively cope interference. Indeed, the main issue in the receiver design is understanding the statistical behavior of the interference and derive appropriate demodulation and decoding techniques. The widely used model of MAI as additive white Gaussian noise (AWGN) does not capture the time-varying impulsive nature of interference and the maximum likelihood (ML) receiver derived for the AWGN model is therefore significantly suboptimal.

Various alternative approaches have been proposed in the literature. Most of them assume an AWGN model for demodulation, letting the subsequent decoding of error correction codes handling noise and interference. The existing solutions are characterized by different statistical models of MAI that lead to different decoders designs. For example, in [1] (see also [2]) a Laplacian model has been assumed for noise and interference, while in [3] a generalized Gaussian model has been considered for interference only. In [4] the concept is further extended, as decoding is performed by assuming a Gaussian-Laplacian description of interference. All these approaches are focused on decoding, while demodulation is performed as in the standard AWGN receiver.

In this paper we aim at optimizing both demodulation and decoding in order to mitigate MAI. This approach has been initiated by [5], [6] where a Gaussian mixture (GM) model has been applied to the sampled base band signal at the receiver input, and thus correspondingly deriving the ML receiver. We generalize the concept by introducing a class of receivers based on generalized Gaussian mixtures, having some existing solutions as sub-cases. We compare the receivers based on AWGN demodulation with those comprising a joint optimization of demodulation and detection. We show that the latter are much more efficient in rejecting MAI, an aspect which has not been previously clarified in the literature. All derivations and numerical results are referred to the new IEEE 802.15.4a standard and various reference interference scenarios.

II. SYSTEM MODEL

With reference to the IEEE 802.15.4a standard, let \( T_c \) and \( T_s = N_c T_c \) be the chip duration and the symbol period, respectively. TH is implemented by selecting the position for transmission in frame \( m \) according to the rule \( T_m = m T_s + \zeta_m T_c \), where \( \zeta_m \) is a pseudo-randomly generated code with range \( 0 \leq \zeta_m < N_c/4 \), where \( N_c \) is an integer multiple of \( 4 \). At frame \( m \), two symbols are transmitted, namely \( d_{1,m} = \pm 1 \) and \( d_{2,m} = 0, 1 \). The symbols are derived by convolutional encoding an original binary information sequence, \( b \). Moreover, the information is spread with a DS code \( c_{m,\ell}, \ell = 0, 1, \ldots, S - 1 \), and with an UWB impulse \( w(t) \).

After anti-aliasing filtering and sampling with rate \( 1/T \), the received signal can be written as

\[
\rho(nT) = r(nT) + \epsilon(nT),
\]

where \( \epsilon(nT) \) collects both AWGN and MAI, and the useful signal part \( r(nT) \) comprises the contribution of the \( M \) transmitted frames

\[
r(nT) = \sum_{m=0}^{M-1} d_{1,m} g_m(nT - T_m - d_{2,m} T_{PPM})
\]

Optimized Demodulation for MAI Resilient UWB W-PAN Receivers

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\[ g_m(nT) = \sum_{\ell=0}^{s-1} c_{m,\ell} h(nT - \ell T_c) \]  

with \( h(nT) \) the sampled received UWB waveform as modified by the channel. We assume that \( h(nT) \) is causal with extension \([0;N_h T]\), so that \( g_m(nT) \) is causal having length \( N_g = N_h + S - 1 \).

For the sake of simplicity we assume a time-invariant channel and we neglect inter symbol interference (ISI), as the IEEE 802.15.4a provides enough protection by means of a guard interval between frames. Moreover, we assume perfect synchronization in both time and frequency, as well as ideal correlation properties for the spreading sequences \( \{c_{m,\ell}\} \).

**AWGN receiver:** Commonly, an AWGN model is assumed for noise \( \epsilon(nT) \). The resulting AWGN receiver is presented here in an iterative fashion where channel estimation relies on data estimation, and vice versa, until convergence. The initial state is the channel estimate derived from a known packet preamble, here used as a training sequence. Specifically, channel taps \( h(nT) \) are directly estimated in time, using an estimate of symbols \( \hat{d}_{1,m} \) and \( \hat{d}_{2,m} \) as follows

\[ \hat{h}(nT) = \frac{1}{MS} \sum_{m=0}^{M-1} \sum_{s=0}^{S-1} \hat{d}_{1,m} c_{m,\ell} \cdot \rho(T_m + nT + \hat{d}_{2,m} T_{PPM} + \ell T_c). \]  

Then, demodulation collects the information needed by decoding, and is implemented with a filter matched to the pulse shape \( \hat{h}(nT) \), providing the two signals corresponding to each PPM position

\[ v_{1,m} = T \sum_{s=0}^{S-1} \sum_{\ell=0}^{L-1} \Re \left[ \rho(T_m + nT + \ell T_c) \hat{h}^*(nT) \right] c_{m,\ell} \]  

\[ v_{2,m} = T \sum_{s=0}^{S-1} \sum_{\ell=0}^{L-1} \Re \left[ \rho(T_m + nT + \ell T_c + T_{PPM}) \hat{h}^*(nT) \right] c_{m,\ell}. \]

Note that, in order to separate the useful signal part from noise, \( v_{1,m} \) and \( v_{2,m} \) can be written as

\[ v_{1,m} = d_{1,m} E_{\hat{g}_m} \delta(0, d_{2,m}) + w_{1,m} \]  

\[ v_{2,m} = d_{1,m} E_{\hat{g}_m} \delta(1, d_{2,m}) + w_{2,m} \]

where \( E_{\hat{g}_m} = T \sum_{s=0}^{S-1} |\hat{g}_m(iT)|^2 \) is the energy of \( \hat{g}_m(\cdot) \), and \( \delta(x, y) = 1 \) if \( x = y \) and zero otherwise.

**III. DECODING OPTIMIZATION FOR AWGN DEMODULATION**

When AWGN demodulation is considered, the various decoding strategies differ for the statistical model of the interference, but all have the form

\[ \hat{b} = \arg\max_b \sum_{m=0}^{M-1} \Psi_m(d_{1,m}(b), d_{2,m}(b)) \]

where

\[ \Psi_m(\alpha_1, \alpha_2) = \ln p_w(v_{1,m} - \delta_0, \alpha_2, \alpha_1 E_{\hat{g}_m}) \]  

\[ + \ln p_w(v_{2,m} - \delta_1, \alpha_2, \alpha_1 E_{\hat{g}_m}) \]  

with \( p_w(\alpha) \) the reference probability density function (PDF).

We now re-write (8) in a form which is customary for PAM systems, and which is suited extended to the combination of PAM and TH. We exploit the fact that \( \alpha_1 = \pm 1 \), and that \( \Psi_m(\alpha_1, \alpha_2) \) can be substituted in the maximization by

\[ \Psi_m(\alpha_1, \alpha_2) = -\ln p_w(v_{1,m}) - \ln p_w(v_{2,m}), \]  

since \( \ln p_w(v_{1,m}) \) and \( \ln p_w(v_{2,m}) \) are independent of \( \alpha_1 \) and \( \alpha_2 \). We obtain

\[ \Psi_m(\alpha_1, \alpha_2) = \left\{ \begin{array}{ll} f_1(v_{1,m}) + \alpha_1 f_2(v_{1,m}), & \alpha_2 = 0 \\ f_1(v_{2,m}) + \alpha_1 f_2(v_{2,m}), & \alpha_2 = 1 \end{array} \right. \]  

(9)

where

\[ f_1(x) = \frac{1}{2} [\ln p_w(x - E_{\hat{g}_m}) + \ln p_w(x + E_{\hat{g}_m})] - \ln p_w(x) \]  

\[ f_2(x) = \frac{1}{2} [\ln p_w(x - E_{\hat{g}_m}) - \ln p_w(x + E_{\hat{g}_m})] \]  

(10)

Observing (9) and (10), we note that in receivers with AWGN demodulation, \( v_{1,m} \) and \( v_{2,m} \) need to be suitably mapped in order to be used in the decoding process. Although \( f_2 \) is commonly adopted in PAM systems (e.g. see [3]), \( f_1 \) is typical of the TH access. Also, the channel estimation and demodulation processes are unvaried with respect to the AWGN solution. This assures the overall implementation complexity of the algorithm is very low, the only difference with an AWGN receiver being the complexity of the mapping functions (10).

We now specify (10) when using the most meaningful PDFs proposed in the literature for modeling impulsive MAI, namely generalized Gaussian and GM PDFs.

**Generalized Gaussian solution:** In the generalized Gaussian approach, \( p_w(a) \) is assumed to have the form

\[ p_w(a) = \frac{c_1(\nu)}{\sigma} \exp \left( -c_2(\nu) \frac{|a|}{\sigma} \right), \quad a \in \mathbb{R} \]  

(11)

where \( \sigma^2 \) is the variance, \( \nu > 0 \) is a shaping factor, and

\[ c_1(\nu) = \frac{\nu}{2} \Gamma\left(\frac{3}{\nu}\right) \]  

\[ c_2(\nu) = \frac{1}{2} \Gamma\left(\frac{1}{\nu}\right) \]  

(12)

In this case, (10) can be written as

\[ f_1(x) = -|x - E_{\hat{g}_m}|^\nu - |x + E_{\hat{g}_m}|^\nu + |x|^\nu \]  

\[ f_2(x) = -|x - E_{\hat{g}_m}|^\nu + |x + E_{\hat{g}_m}|^\nu \]  

(13)

where we dropped \( c_2(\nu) \) and \( \sigma^\nu \) since they are both positive constants. Note that, in the Gaussian case, \( f_1 \) provides a constant value, hence can be neglected, while \( f_2 \) provides a linear mapping. Instead, for a Laplacian model, \( \nu = 0.5 \) and \( f_1 \) is non constant, with an emphasis on values around \( \pm E_{\hat{g}_m} \), while \( f_2 \) lowers the weight for large inputs, thus mitigating impulsive MAI. Although it is possible to set \( \nu \) to a fixed value, it may be more useful to estimate it from the received samples [3].

**Gaussian mixtures solution:** GMs are known to be able to efficiently model impulsive MAI, even for low \( K \) values. Since \( v_{1,m} \) and \( v_{2,m} \) are real, the PDF of a real GM must be considered and we have [7]

\[ p_w(a) = \sum_{k=1}^{K} \lambda_k \frac{1}{\sqrt{2\pi \sigma_k^2}} e^{-\frac{1}{2} |a/\sigma_k|^2}, \quad a \in \mathbb{R} \]  

(14)
IV. JOINT OPTIMIZATION OF DEMODULATION AND DECODING

In the receivers revised in Section III only the decoding step is optimized with respect to MAI statistics, while demodulation is taken from the ML AWGN receiver, providing in general suboptimal solutions. Hence, we introduce new receivers, where both demodulation and decoding are optimized for specific MAI statistics.

In order to take into account all the various possibilities in the statistical description of the complex-valued noise $\epsilon(nT)$ in (1), spanning GM models, generalized Gaussian and Laplacian random variables, we develop a generalized Gaussian mixture (GGM) model for complex valued noises.

Specifically, the PDF for a complex-valued generalized Gaussian random variable with variance $\sigma^2$ is defined as

$$p_c(a) = \frac{c_1(\nu)}{\pi \sigma^2} \exp \left(-c_2(\nu) \frac{|a|^2}{\sigma^2} \right), \quad a \in \mathbb{C}$$  \hspace{1cm} (15)

where

$$c_1(\nu) = \frac{\nu}{2} \Gamma(4/\nu) \frac{1}{\Gamma(2/\nu)} , \quad c_2(\nu) = \left( \frac{\Gamma(4/\nu)}{\Gamma(2/\nu)} \right)^{\nu/2} \hspace{1cm} (16)$$

A GGM model is driven by three sets of parameters, namely: probabilities $\{\lambda_k\}$, variances $\{\sigma_k^2\}$, and shaping factors $\{\nu_k\}$. In our case we have

$$p_c(a) = \sum_{k=1}^{K} \frac{\lambda_k c_1(\nu_k)}{\pi \sigma_k^2} \exp \left(-c_2(\nu_k) \frac{|a|^2}{\sigma_k^2} \right)$$  \hspace{1cm} (17)

where $\sum_{k=1}^{K} \lambda_k = 1$ and $a \in \mathbb{C}$. Note that (17) may be interpreted as a generalized Gaussian random variable having variance and shaping factor $(\sigma_k^2, \nu_k)$ with probability $\lambda_k$.

A. Setup for maximum likelihood estimation

Our ML receiver design has been originally used for GM in [5], [6], [8] and here is further extended to GGM and the UWB PHY format. By denoting with $\varphi$ the quantities we wish to jointly estimate $(\lambda_k, \sigma_k^2, \nu_k, h(nT)$ or $b_k)$, according to the SAGE approach, the log-likelihood measure to maximize over $N$ samples is

$$Q(\varphi) = \sum_{n=0}^{N-1} \sum_{k=1}^{K} \ln \left( \frac{\lambda_k c_1(\nu_k)}{\pi \sigma_k^2} \exp \left(-c_2(\nu_k) \frac{|\epsilon(nT)|^2}{\sigma_k^2} \right) \right)$$  \hspace{1cm} (18)

where, from (2), $\epsilon(nT) = \rho(nT) - r(nT)$ is the noise sample and

$$\beta_{k,n} = \frac{\alpha_{k,n}}{\sum_{k=1}^{K} \alpha_{k,n}}, \quad \alpha_{k,n} = \frac{\lambda_k c_1(\nu_k)}{\pi \sigma_k^2} \exp \left(-c_2(\nu_k) \frac{|\epsilon(nT)|^2}{\sigma_k^2} \right) \hspace{1cm} (19)$$

with $\tilde{\epsilon}(nT)$ the available estimate of noise, and $\hat{\lambda}_k, \hat{\sigma}_k^2, \hat{\nu}_k$ the available parameters estimates. Then, the estimate update is obtained by

$$\varphi = \arg \max_{\varphi} Q(\varphi) \hspace{1cm} (20)$$

B. Formalization of the receive algorithm

Parameters estimation: An estimate of probabilities $\lambda_k$ provided in [6] as

$$\hat{\lambda}_k = \frac{1}{N} \sum_{n=0}^{N-1} \beta_{k,n}, \hspace{1cm} (21)$$

whereas an estimate of the variance is

$$\hat{\sigma}_k^2 = \left( \frac{\hat{c}_2(\hat{\nu}_k)}{\nu_k} \right) \frac{1}{\nu_k} \sum_{n=0}^{N-1} \beta_{k,n} |\tilde{\epsilon}(nT)|^2 \hspace{1cm} (22)$$

giving the classical GM solution for $\hat{\nu}_k = 2$.

Unfortunately, the estimate of $\hat{\nu}_k$ has no analytical solution and we resort to the alternative approach of [3] based upon the kurtosis estimate, which is related to $\nu$ by the following relation

$$\kappa = \frac{\nu}{\Gamma(2/\nu)} = 2$$  \hspace{0.5cm} (23)

According to [6], weights $\beta_{k,n}$ express the probability that the estimated sample noise $\tilde{\epsilon}(nT)$ belongs to the $k$th distribution model with parameters $\hat{\sigma}_k^2$ and $\hat{\nu}_k$. In particular, we have

$$\hat{\nu}_k = \kappa^{-1} \left( \frac{\sum_{n=0}^{N-1} \beta_{k,n} |\tilde{\epsilon}(nT)|^4}{\sum_{n=0}^{N-1} \beta_{k,n}} - 2 \right) \hspace{1cm} (24)$$

Channel estimation: Also for channel estimation we do not have an analytical solution, except in the GM case where $\nu_k = 2$ for all $k$. We thus follow an alternative approach and choose to rely on AWGN channel estimation (4). We verified in the GM case that this suboptimal estimation approach does not affect performance.

Demodulation and decoding: From (18), the reference criterion for decoding purposes is

$$\hat{b} = \arg \max_{b} -\sum_{n=0}^{N-1} \sum_{k=1}^{K} \beta_{k,n} c_2(\nu_k) \frac{\rho(nT) - \tilde{r}_n(b)}{\hat{\sigma}_k} \hat{\nu}_k \hspace{1cm} (25)$$

where

$$\tilde{r}_n(b) = \sum_{m=0}^{M-1} d_{1,m}(b) \tilde{g}_m(nT - T_m - d_{2,m}(b) T_{PPM}), \hspace{1cm} (26)$$

with the dependence on $b$ made explicit.

Mimicking (7), the contribution of the $m$th frame is obtained by restricting the summation in (25) to the $m$th frame, namely $n \in I_m = [mT_s, mT_s + T_s]$. We thus have

$$\Psi_m(\alpha_1, \alpha_2) = -\sum_{n \in I_m} \sum_{k=1}^{K} \beta_{k,n} c_2(\nu_k) \frac{\rho(nT) - \alpha_1 \tilde{g}_m(nT - T_m - \alpha_2 T_{PPM})}{\hat{\sigma}_k} \hat{\nu}_k, \hspace{1cm} (27)$$
By following similar steps to those leading to (9), we can separately and efficiently formulate demodulation and decoding strategies. The resulting method is reported in the following.

Demodulation: All measures that need to be extracted from the incoming signal can be described through the function

$$U_m(\alpha_1, \alpha_2) = \sum_{i=0}^{N_c-1} \sum_{k=1}^{K} c_2(\hat{d}_k) \beta_{k,m(i)} \cdot |\rho(n(i)T) - \alpha_1 \hat{g}_m(iT)|^{\hat{p}_k}$$

(28)

where \(n(i) = (T_m + \alpha_2 T_{PPM} + iT)/T\), and \(\hat{g}_m(iT)\) is the estimated value of sample \(g_m(iT)\).

Specifically, for the first PPM position we extract the measures (note the similarity with (10))

$$\begin{align*}
q_{1,m} &= \frac{1}{2} [U_m(1, 0) + U_m(-1, 0) - U_m(0, 0)] \\
u_{1,m} &= \frac{1}{2} [U_m(1, 0) - U_m(-1, 0)]
\end{align*}$$

(29)

while for the second PPM position we have

$$\begin{align*}
q_{2,m} &= \frac{1}{2} [U_m(1, 1) + U_m(-1, 1)] - U_m(0, 1) \\
u_{2,m} &= \frac{1}{2} [U_m(1, 1) - U_m(-1, 1)]
\end{align*}$$

(30)

The result takes a simpler form only with GMs, i.e., for \(\nu_k = 2\)

Decoding: The measures (29) and (30) are then used in the standard decoding process (7) where

$$\Psi_m(\alpha_1, \alpha_2) = \begin{cases} 
q_{1,m} + \alpha_1 u_{1,m}, & \alpha_2 = 0 \\
q_{2,m} + \alpha_1 u_{2,m}, & \alpha_2 = 1
\end{cases}$$

(31)

to obtain a criterion equivalent to (25). The decoding process is in close relation to (9).

V. NUMERICAL RESULTS

The chosen setup for evaluating performance is an operation mode of the IEEE 802.15.4a draft standard [9]. Specifically, we select the channel centered at 3993.6 MHz with bandwidth 499.2 MHz. To stress the presence of impulsive MAI, we use pure TH with \(S = 1\), \(N_c = 128\), \(T_s = 2\) ns, \(T_{c} = 256\) ns and a code range \(0 \leq \gamma_m < 32\). Also, the guard interval to combat ISI is \(32 T_c = 64\) ns.

The packet is made of a preamble for synchronization purposes and a payload containing data. The preamble is set to 500 symbols, while the number of data bits \(b_t\) is 1000.

The channel models used in simulations are both the CM1 and CM2 residential environment, and the CM3 and CM4 office environment models of [10] with a channel estimation window set to \(T N_0 = T_s/4 = 64\) ns, being able to collect more than 95% of the received energy. In our setting, the reference user is further away from the receiver than the disturbing user, which is the typical near-far scenario giving raise to strong MAI. We choose to model only one interferer, since this is the most common situation which we want to be robust at when using the ALOHA access mode. Also, we assume no line of sight (NLOS) propagation for the reference user and line of sight (LOS) propagation for the interfering user. In our simulations, the interfering user is kept active during the whole transmission time.

A. Performance in the presence of a strong interferer

In Fig. 1 we report packet error rate (PER) performance versus the signal to noise ratio (SNR) \(E_b/N_0\) in the presence of an interferer whose received power is 14 dB higher than the reference user power. This provides a first overview of algorithms robustness to strong and impulsive MAI. The performance bounds are set by state-of-the-art AWGN solution of [11] and by the idealized AWGN condition where MAI has been removed and there is complete channel state information (CCSI).

As statistical models of the demodulated signals we considered A1) GM variable with \(K = 2\) and \(\nu_1 = \nu_2 = 2\); A2) Laplacian variable [1]; A3) generalized Gaussian variable with \(K = 1\) [3] where \(\nu\) is estimated from the received samples. We verified that GM solutions with \(K > 2\) give almost the same
performance, which is appropriate for a scenario with a single interferer. We immediately note that all these solutions show a very similar behavior, with the generalized Gaussian approach giving slightly better results. However, they are not able to efficiently cope with strong MAI, showing a PER performance which is always bigger than $10^{-1}$.

Better results are given by the proposed solutions where both demodulation and decoding are optimized. We considered the same random variables as for AWGN demodulation, but the statistical description is now applied on $\epsilon(nT)$ instead of $v_{1,m}$ and $v_{2,m}$. In figure, these receivers are labeled B1 (the one proposed in [5, 6]), B2 and B3. We also considered a jointly optimized receiver where the random variable is a GGM with $K = 2$. This receiver structure is labeled as B4. Now, from Fig. 1 we clearly see that the proposed solutions are much more robust to strong MAI, with the GM receiver B1 providing a first improvement to PER performance, and with generalized Gaussian receivers B2, B3, and B4 giving a further impressive improvement down to a PER which is lower than $10^{-3}$ at $E_b/N_0 = 14$ dB. The best performance is obtained with the GGM approach B4 having $K = 2$.

Note that performance of all algorithms is similar in either residential and office environments, with slightly lower PERs in an office environment. The difference is easily explained by the fact that, with the chosen settings, the percentage of channel energy collected in CM4 is in the average close to 99%, while in CM2 it is of about 95%. This similarity further proves algorithm robustness in the presence of a limited number of reflections as in the spiky channel CM2.

B. Performance as a function of the interferer strength

Algorithm robustness has also been tested as function of the interference strength, measured by the interferer excess power where an excess power of 10 dB means that the interferer power is 10 dB higher than the reference user power.

Fig. 2 shows PER in the residential environment for $E_b/N_0$ to 16 dB, corresponding to a received power of $-96$ dBm for a 6 dB noise figure. The behavior of algorithms confirms the findings of Fig. 1, namely: receivers with AWGN demodulation give a small improvement to performance throughout the whole excess power range; the best behaving algorithms are the jointly optimized receiver based upon GGM. Note that, with $E_b/N_0 = 16$ dB at a reference PER of $10^{-4}$, B4 shows the impressive gain of about 10 dB with respect to the ordinary AWGN receiver.

VI. Conclusions

In this paper we have introduced new receiver structures for the UWB WPAN standard IEEE 802.15.4a, where both the demodulation and the decoding processes are jointly optimized according to an assumed statistical model of MAI. We have designed the optimized receiver for GGM that includes relevant sub-cases as Gaussian, generalized Gaussian and Laplacian random variables. By extensive simulation on the IEEE 802.15.4a standards for various propagation and interference scenario, we showed that the proposed receiver architectures significantly outperform existing approaches with robustness against MAI.

References