Modulation Mode Detection and Classification for In Vivo Nano-Scale Communication Systems Operating in Terahertz Band

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Objective

Designing an intelligent/cognitive nano receiver operating in terahertz band:

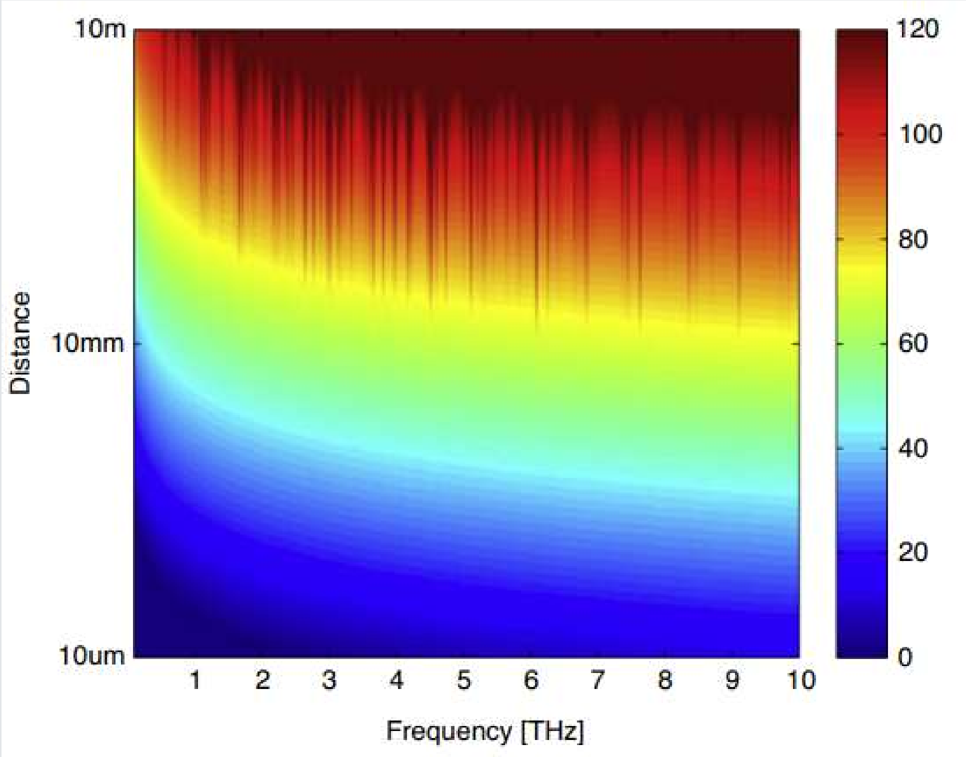
- Modulation mode detection (to differentiate between pulse-based modulation and carrier-based modulation)
  - Binary hypothesis test in nano-receiver's passband -> provide closed-form expressions for the two error probabilities
- Modulation classification (to identify the exact modulation scheme in use)
  - Represent the received signal of interest by a Gaussian mixture model (GMM) -> THz channel estimation is needed
  - Learn the GMM parameters via Expectation–Maximization algorithm
  - Gaussian approximation to compute symmetric Kullback–Leibler divergence in order to differentiate between various modulation schemes

Introduction – TeraHertz Band

TERAHERTZ (THz) band (0.1 – 10 THz) is a promising candidate for nano-scale communication because of its non-ionization and robustness to the fading characteristics. Moreover, novel nano-materials with remarkable electrical properties has led to a surge of interest in development of nano-scale devices for THz band

Terahertz band will be enabled by the use of novel nano-antennas. The **energy efficiency** of the process to mechanically generate EM waves in a nano-device is predictably very low so nanosensor devices will not communicate among themselves by using the megahertz frequency range. [2]

Nanosensor devices will potentially communicate among them in the terahertz band (0.1–10.0 THz). The first research challenge for nanosensor device communication is to develop new **channel models for the terahertz band**.



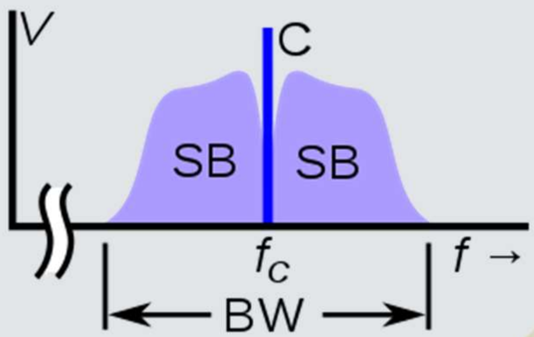
Total path-loss in dB as a function of frequency and distance in a standard medium with 1% of water vapor molecules (the values for path-loss have been truncated at 120 dB to avoid masking relevant transmission windows in the short range) [2]

Introduction – Intelligent nano receivers

Intelligent/cognitive receiver design for nano-scale communication in THz band finds its utilization in defense, security and military applications. A cognitive nano receiver performs various statistical inference tests on the received signal of interest to implement **modulation mode detection** and **modulation classification** in a systematic manner.

Modulation mode detection arises due to the fact that the nano-scale communication systems operating in THz band either do (few hundred femto-seconds long) pulse-based communication or utilize classical carrier-based modulation schemes (if form factor is not a constraint)

In carrier-based communications a waveform (usually sinusoidal) is modulated with an information-bearing signal for the purpose of conveying information. This carrier wave usually has a much higher frequency than the input signal does. The purpose of the carrier is usually either to transmit the information through space as an electromagnetic wave or to allow several carriers at different frequencies to share a common physical transmission medium by frequency division multiplexing



Introduction – Pulse-based communication

In pulse-based communications, the pulse occupies a large bandwidth, so it can be directly emitted without using carriers or any IF processing, greatly reducing the transceiver complexity and the overall power consumption.

In THz band, due to the expectedly very limited power of nano-devices, the feasibility of nanonetworks would be compromised if ranges are long. Graphene antennas can efficiently operate at Terahertz Band frequencies by exploiting the behavior of Surface Plasmon Polariton (SPP) waves. Nano-antennas are just tens of nanometers wide and few micrometers long and can potentially be easily integrated in nano-devices. [3]

In this context, only very short pulses, just a hundred femtosecond long, can be generated, with a power of just a few μW per pulse. While this might not be enough for long range Terahertz Band communication, it opens the door to communication in nanonetworks [3]

Introduction – Modulation Classification

Modulation classification automatically identifies the modulation scheme in use, from the received signal of interest. It is the intermediate step between signal detection and demodulation. It was originally motivated by military applications but now, it finds its application in various cooperative communication problems, e.g., cognitive radios etc.

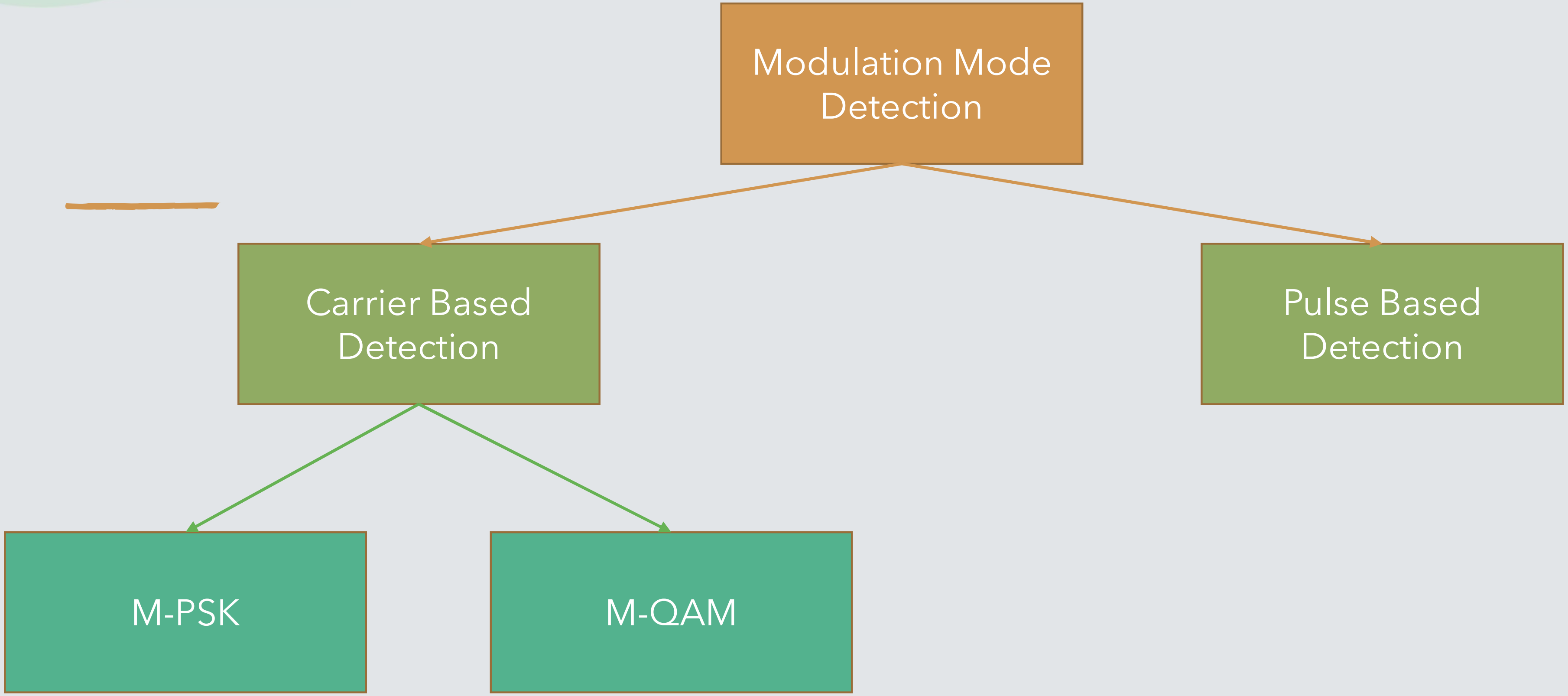
For modulation classification in traditional wireless networks, the solutions could be classified as either **feature-based** (e.g., cyclic cumulants, moments, amplitude, phase etc.), or, **decision-theoretic** (based on likelihood functions).

- Decision-theoretic approaches are optimal, but are computationally prohibitive, and sensitive to model mismatch.
- Pattern recognition based approaches could perform very close to optimal if designed properly. More recently, there is a growing interest in applying machine learning techniques to automatic modulation recognition/classification.

A summary of related works [4]

Frequency (THz)	Data Rate (Gbit/s)	Distance (m)	Modulation
0.125	10	200	ASK
0.25	8	0.5	ASK
0.2	1	2.6	ASK
0.12	10	5800	ASK
0.3	0.096	0.7	64QAM
0.625	2.5	< 10	Duobinary
0.22	15–40	10	OOK
0.24	25	60	OOK
0.0875	100	1.2	16QAM
0.135	10	0.2	ASK
0.3	24	0.5	ASK
0.146	1	0.025	OOK
0.22	30	20	ASK
0.542	2	0.01	ASK
0.14	10	1500	16QAM
0.24	30	40	8PSK
0.196	0.1	0.5	QPSK
0.34	3	0.3	16QAM
0.3	24	0.3	ASK
0.3	48	1	OOK
0.237	100	20	16QAM
0.4	40	2	ASK

Introduction – Design



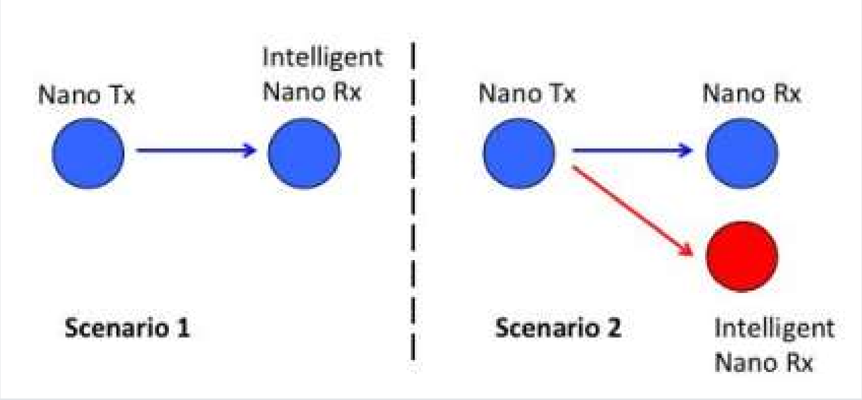
System Model

An intelligent/cognitive nano receiver listening to a signal of interest in THz band is considered.

With the objective of modulation mode detection and modulation classification, two distinct application scenarios are foreseeable:

1) the nano receiver is the intended recipient of the signal transmitted by the nano transmitter;

2) the nano receiver is not the intended recipient; rather, it overhears the signal intended for some other nano receiver in the nearby vicinity



THz Channel Model

The THz channel is extremely frequency-selective due to absorption by the water molecules. Water vapors constitute the main factor altering the Terahertz channel. As the THz signal propagates through the channel, it is attenuated due to the resonance of some molecules in the atmosphere at specific frequencies.

$$h(t) = h_{ant}^T(t) * h_c(t) * h_{ant}^R(t)$$

$$H_c(f) = H_{spread}(f) H_{abs}(f),$$

$$h_{ant}^T(t) = \frac{\partial}{\partial t} \int \mathbf{J}(t,(x,y))dV,$$

$$h_{ant}^R(t) = \int_0^t h_{ant}^T(\tau)d\tau$$

H_{spread}(f) due to expansion of a wave as it travels through the medium

$$H_{spread}(f) = \frac{1}{\sqrt{4\pi d^2}} \exp\left(-j\frac{2\pi f d}{c}\right),$$

The molecular absorption loss H_{abs}(f)

$$H_{abs}(f) = \exp\left(-\frac{k(f)d}{2}\right),$$

k(f) is the medium absorption coefficient

$$k(f) = \frac{p}{p_0}\frac{\mathbb{T}_{stp}}{\mathbb{T}}\sum_i Q^i \sigma^i(f)$$

Modulation Mode Detection

A nano-scale communication system operating in THz band could either utilize pulse based modulation (**PBM**) or carrier based modulation (**CBM**).

Under the classic CBM approach, the nano transmitter and nano receiver both tune to a center frequency where absorption loss due to atmospheric molecules is minimum; then, standard modulation schemes—phase shift keying (PSK), quadrature amplitude modulation (QAM)—are used.

The PBM approach relies upon transmission and subsequent successful reception of extremely short-lived (few hundreds of femto-seconds long) pulses to realize simple modulation schemes (e.g., on-off keying, amplitude shift keying etc.).

To choose the modulation mode a **binary hypothesis test** at the nano receiver is constructed.

Modulation Mode Detection – Binary Hypothesis

Gaussian pulse p(t) for **pulse based modulation**

$$p(t) = \frac{1}{\sqrt{2\pi\sigma_p^2}} exp(-\frac{(t-\mu_p)^2}{2\sigma_p^2}) = \alpha\ exp(-\frac{(t-b)^2}{2c^2})$$

a=amplitude b=pulse's center c=pulse's spread

Duration -> c = $T_p < T$

Transmitted signal $u_0(t) = \sum_k p(t-kT)$

Raised-cosine (RC) pulse q(t) for **carrier based modulation**

$$q(t) = sinc\left(\frac{t}{T}\right)\frac{cos\pi\alpha(\frac{t}{T})}{1-\left(\frac{2\alpha t}{T}\right)^2}$$

Roll−off → $0 < \alpha < 1$ T=symbol duration

Transmitted signal $u_1(t) = (\sum_k b[k]q(t - kT))\cos(2\pi f_c t + \phi)$

b[k] = transmitted symbol

$$\begin{cases} H_0: & \text{(PBM)}\ r(t) = s_0(t) + w(t) \\ H_1: & \text{(CBM)}\ r(t) = s_1(t) + w(t) \end{cases}$$

s_0(t) = u_0(t) ∗ h(t) = $\sum_k f(t-kT)$ f (t) = p(t) ∗ h(t)

s_1(t) =u_1(t) ∗ h(t) = = $(\sum_k b[k]g(t-kT))\cos(2\pi f_c t + \phi)$ g(t) = q(t)∗h(t)

Modulation Mode Detection – Binary Hypothesis

$$\begin{cases} H_0: & \text{(PBM) } r[n] = s_0[n] + w[n] \\ H_1: & \text{(CBM) } r[n] = s_1[n] + w[n] \end{cases}$$

r[n] = r(nT_s) T/$T_s = N$ $N = samples\ of\ r(t)\ during\ each\ slot$

w[n] ~ N (0, σ^2)

The assumption T_p < T is the key to observe that the energy in u_0(t) is less than the energy in u_1(t) during any observation interval of length To. Therefore, the modulation mode detection problem boils down to an **energy detection** problem

$A = \sum_{n=0}^{N-1}(\tilde{r}[n])^2$ $chi\text{−}squared\ distribution$

T = $\frac{\sigma^2}{N}$ A = $\frac{\sigma^2}{N}\sum_{n=0}^{N-1}(\tilde{r}[n])^2 \quad \gtrless_{H_0}^{H_1} \eta$ η is a threshold

Modulation Classification - LSBE

GMM Representation → Expectation Maximization → symmetric Kullback-Leibler divergence → Modulation Classification

The representation of the received signal as a GMM, and subsequent learning of the GMM parameters via the EM algorithm is valid for a noise-limited channel only.

For communication in THz band, one needs to explicitly estimate the channel impulse response (CIR), and then compensate it before applying the GMM+EM based framework.

$\hat{h}(t)$ = obtained LS channel estimate

$R(f) = \mathcal{F}(\mathrm{r(t)})$
$\hat{H}(\mathrm{f}) = \mathcal{F}(\hat{\mathrm{h}}(\mathrm{t}))$

$$\hat{r}(t) = \mathcal{F}^{-1}\left(\frac{R(f)}{H(f)}\right)$$

Modulation Classification - LSBE

GMM Representation → Expectation Maximization → symmetric Kullback-Leibler divergence → Modulation Classification

$$\mathbf{B} = \begin{pmatrix} b[k_1+L] & b[k_1+L-1] & \cdots & b[k_1] \\ b[k_1+L+1] & b[k_1+L] & \cdots & b[k_1+1] \\ \vdots & \vdots & \ddots & \vdots \\ b[k_m] & b[k_m-1] & \cdots & b[k_m-L] \end{pmatrix}$$

Received signal -> r = Bh + w

Least Square Based Estimation -> $\hat{h} = (B^H B)^{-1} B^H r$

The proposed least-squares based solution exists only when B is a full column-rank matrix. In other words, the length of training data should be: $k_m - k_1 \geq 2L$

Modulation Classification – GMM

GMM Representation → Expectation Maximization → symmetric Kullback-Leibler divergence → Modulation Classification

PDF of the mixture random variable U is the convex/weighted sum of the Q component PDFs

$$u(x) = \sum_{q=1}^{Q} \pi_q \phi_q(x)$$

$\phi_q(x)$ = Gaussian PDF

$\pi_q \geq 0$

$\sum_{q=1}^{Q} \pi_q = 1$

$\phi_q(x) > 0$

$\int_{x\epsilon} \phi_q(x)dx = 1$

d = dimension of the data x

d = 1 for BPSK

d = 2 for M-PSK, M-QAM

Modulation Classification - EM

GMM Representation → Expectation Maximization → symmetric Kullback-Leibler divergence → Modulation Classification

The GMM has 3Q unknown parameters which are learned using iterative Expectation Maximization algorithm applied on training data $\{x_m\}_{m=1}^{M}$
The posterior probability for each point x_m in the training data:

$$p_{m,q}^{(j)} = \frac{\pi_q^{(j)} \phi_q(x_m, \mu_q^{(j)}, \Sigma_q^{(j)})}{\sum_{\hat{q}=1}^{Q} \pi_{\hat{q}}^{(j)} \phi(x_m, \mu_{\hat{q}}^{(j)}, \Sigma_{\hat{q}}^{(j)})}$$

$$\pi_q^{(j+1)} = \frac{1}{M} \sum_{m=1}^{M} p_{m,q}^{(j)}$$

The Q number of priors are updated

$$\mu_q^{(j+1)} = \frac{\sum_{m=1}^{M} p_{m,q}^{(j)} x_m}{\sum_{m=1}^{M} p_{m,q}^{(j)}}$$

The Q number of means are updated

$$\Sigma_q^{(j+1)} = \frac{\sum_{m=1}^{M} p_{m,q}^{(j)} (x_m - \mu_q^{(j)})(x_m - \mu_q^{(j)})^T}{\sum_{m=1}^{M} p_{m,q}^{(j)}}$$

The Q number of (co-)variances are updated

Modulation Classification – Kullback-Leiner

GMM Representation → Expectation Maximization → symmetric Kullback-Leibler divergence → Modulation Classification

Kullback-Leibler divergence (KLD) is a (directional) measure of the distance between the two probability density functions y(x) and z(x) sharing a common probability space X

$$D(y||z) = \int_x y(x) log \frac{y(x)}{z(x)} dx$$

Received signal $y(x) = \sum_{q=1}^{Q} \pi_{y,q} \phi(x, \mu_{y,q}, \Sigma_{y,q})$

Database signal $\mathrm{z}(x) = \sum_{q'=1}^{Q'} \pi_{z,q'} \phi(x, \mu_{z,q'}, \Sigma_{z,q'})$

y and z are replaced with their Gaussian approximations $\hat{y}$ and $\hat{z}$ respectively

$$\mu_{\hat{y}} = \sum_{q=1}^{Q} \pi_{y,q} \mu_{y,q}$$

$$\Sigma_{\hat{y}} = \sum_{q=1}^{Q} \pi_{y,q} \left[\Sigma_{y,q} + (\mu_{y,q} - \mu_{\hat{y}})(\mu_{y,q} - \mu_{\hat{y}})^T \right]$$

Modulation Classification – Kullback-Leiner

GMM Representation → Expectation Maximization → symmetric Kullback-Leibler divergence → Modulation Classification

$$D(y||z) = \frac{1}{2}[\log\left(\frac{|\Sigma_{\hat{z}}|}{|\Sigma_{\hat{y}}|}\right) + Tr\left[\Sigma_{\hat{z}}{}^{-1}\Sigma_{\hat{y}}\right] + \left(\mu_{\hat{y}} - \mu_{\hat{z}}\right)^T \Sigma_{\hat{z}}{}^{-1}\left(\mu_{\hat{y}} - \mu_{\hat{z}}\right) - \mathrm{d}]$$

Due to the fact that $D(\hat{y}||\hat{z}) \neq D(\hat{z}||\hat{y})$, we utilize the symmetric KLD instead for decision-making for modulation classification:

$$D_{sym}(\hat{y}||\hat{z}) = 0.5D(\hat{y}||\hat{z}) + 0.5D(\hat{z}||\hat{y})$$

Modulation Classification

GMM Representation → Expectation Maximization → symmetric Kullback-Leibler divergence → Modulation Classification

An offline database at the nano receiver which contains the constellation points of the following modulation schemes M = {BPSK,QPSK,8-PSK,16-QAM} is constructed .

Template signals $\tau_i(t)$, i = 1,...,|M| are generated and assume a noise-limited channel to represent each of them as a GMM. The template signal $\tau_i(t)$ serves as the ground truth under hypothesis i which states that the received signal of interest utilizes the modulation scheme on i-th index of M.

Finally, |M| symmetric KLDs are computed, between the Gaussian approximation of the GMM representing the received deconvolved signal and the Gaussian approximation of the GMM representing $\tau_i(t)$.

The index i for which the symmetric KLD is the minimum is utilized to pick the corresponding modulation scheme from the set M to declare it as the modulation scheme used by the nano transmitter of interest during the current time-slot.

Modulation Classification

GMM Representation → Expectation Maximization → symmetric Kullback-Leibler divergence → Modulation Classification

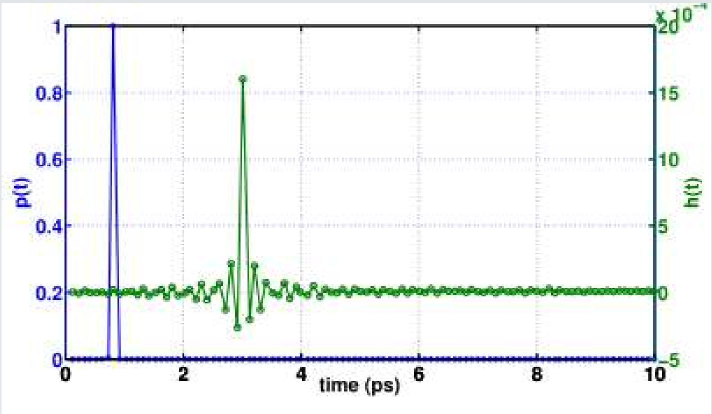
1) Obtain the least-squares estimate $\hat{h}$(t) of the THz CIR by utilizing the (samples of) received signal r(t) and the known training symbols
2) Obtain the deconvolved signal as $\hat{r}(t) = \mathcal{F}^{-1}(\frac{R(f)}{H(f)})$
3) Represent $\hat{r}(t)$ as a Gaussian mixture model and learn the GMM parameters via the iterative EM algorithm
4) Approximate the GMM PDF due to $\hat{r}(t)$ as well as the GMM PDFs due to the template signals τ_i(t) in the database each as a Gaussian PDF
5) Compute the |M| symmetric KLDs between the Gaussian approximation of the GMM representing the received deconvolved signal $\hat{r}(t)$ and the Gaussian approximation of the GMM representing τ_i(t)

The index i for which the symmetric KLD is the minimum is utilized to pick the corresponding modulation scheme from the set M to declare it as the modulation scheme in use.

Numerical Results – THz Channel Response

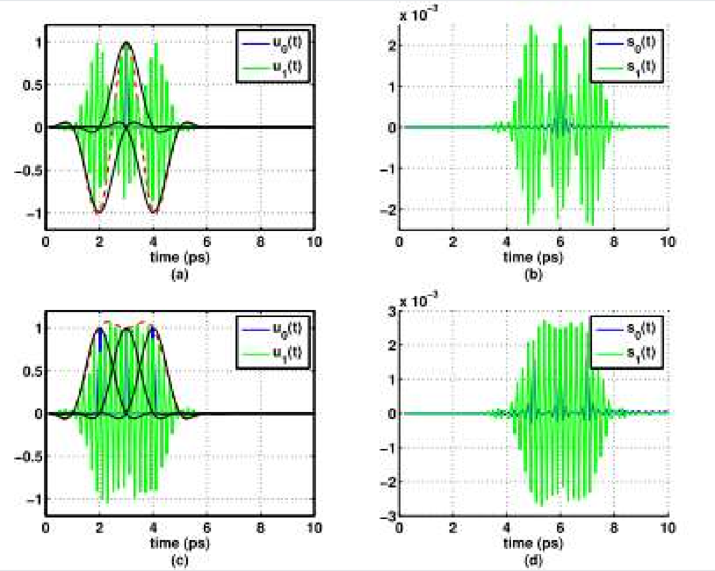
THz channel impulse response h(t) observed by the nano receiver when a 100 femto seconds long Gaussian pulse p(t) is transmitted by the nano transmitter at t = 800 fs. For this plot, we placed the nano receiver at a distance of 1 mm from the nano transmitter.

The channel impulse response shows that the transmitted pulse is delayed and spread in time (which could potentially lead to inter-symbol interference). The CIR is used to simulate the performance of modulation mode detection and modulation classification in the sequel.



Numerical Results – Modulation Mode Detection

The transmitted CBM signal has more energy than the transmitted PBM signal during any observation interval. This fact holds even when the transmitted signal passes through the THz channel.



α = 0.8, T = 1 ps, To = 3T , ρp = 20 fs, a = 1, and N = 40.
fc = 5 THz

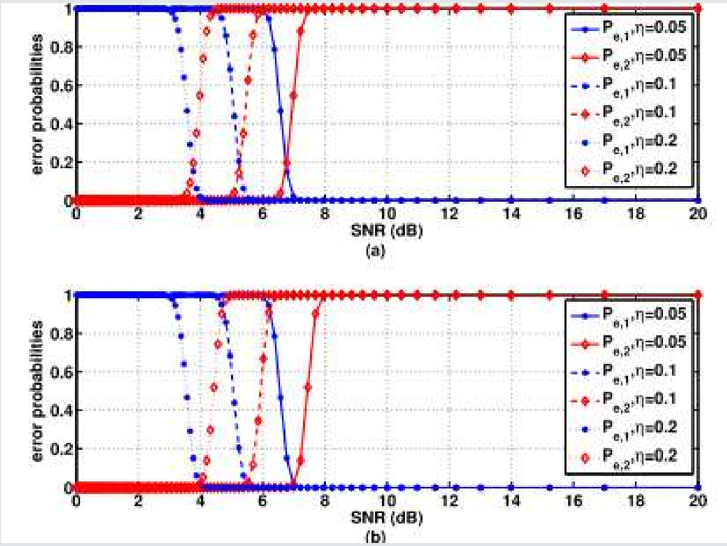
For PBM, OOK was used.
For CBM, BPSK scheme (thus ϕ = 0) was used.

In (a)-(b), the transmitted symbol sequence is {−1, +1, −1}
In (c)-(d), the transmitted symbol sequence is {+1, +1, +1}.

Numerical Results – Modulation Mode Detection

Error probabilities $P_{e,1}$ (wrongly declaring CBM) and $P_{e,2}$ (wrongly declaring PBM) against the signal-to-noise ratio (SNR) for three different values of the threshold η

$P_{e,1}$ and $P_{e,2}$ are complementary



For a fixed value of η, there is only one (pareto-) optimal SNR where both errors are jointly minimized.

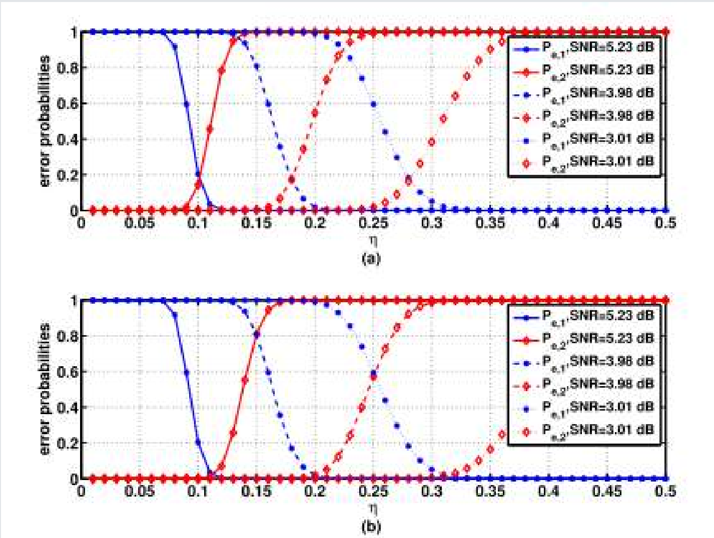
In Fig. (a) for η = 0.05, η = 0.1, η = 0.2, SNR_{opt}= 6.8 dB, SNR_{opt} = 5.5 dB, SNR_{opt} = 3.9 dB and $P_{e,min}$ = 0.2.
In Fig. (b), for η = 0.05, η = 0.1, η = 0.2, SNR_{opt} = 7.1 dB, SNR_{opt} = 5.7 dB, SNR_{opt} = 4 dB and $P_{e,min}$= 0.01.

Thus, $P_{e,min}$ depends upon specific symbol sequence {b[k]} actually sent from the nano transmitter.

Numerical Results – Modulation Mode Detection

Error probabilities $P_{e,1}$ (wrongly declaring CBM) and $P_{e,2}$ (wrongly declaring PBM) against the signal-to-noise ratio (SNR) for three different values of the threshold η

$P_{e,1}$ and $P_{e,2}$ are complementary



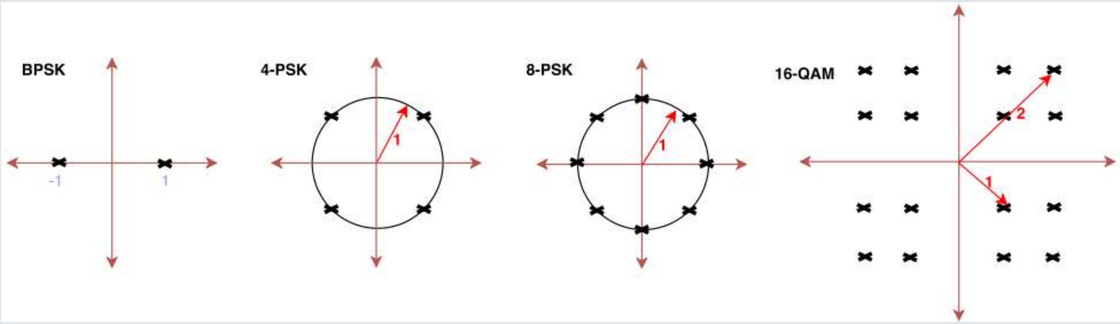
For a fixed value of η, there is only one (pareto-) optimal SNR where both errors are jointly minimized.

In Fig. (a), for SNR= 5.23 dB, SNR= 3.98 dB, SNR= 3.01 dB, we have η_{opt}= 0.1, η_{opt} = 0.18, η_{opt} = 0.28 and $P_{e,min}$ = 0.2.
In Fig. (b), for SNR= 5.23 dB, SNR= 3.98 dB, SNR= 3.01 dB, we have η_{opt} = 0.11, η_{opt} = 0.21, η_{opt} = 0.32, and $P_{e,min}$ = 0.01.

$P_{e,min}$ depends upon specific symbol sequence {b[k]} actually sent from the nano transmitter.

Numerical Results – Modulation Classification

The proposed GMM+EM based modulation classification framework applies to noise-limited signals only. Therefore, for all the results on modulation classification below, first the deconvolved signal $\hat{r}(t)$ by compensating for the THz CIR using the LS based method is obtained



Constellation plots for each of the modulation schemes considered in this work. They are used to construct the database M which contains the constellation points for each of the four modulation schemes considered. The constellation points of i-th modulation scheme, in turn, become the Q means of the GMM representation of the template signal $\tau_i(t)$.

Numerical Results – Modulation Classification

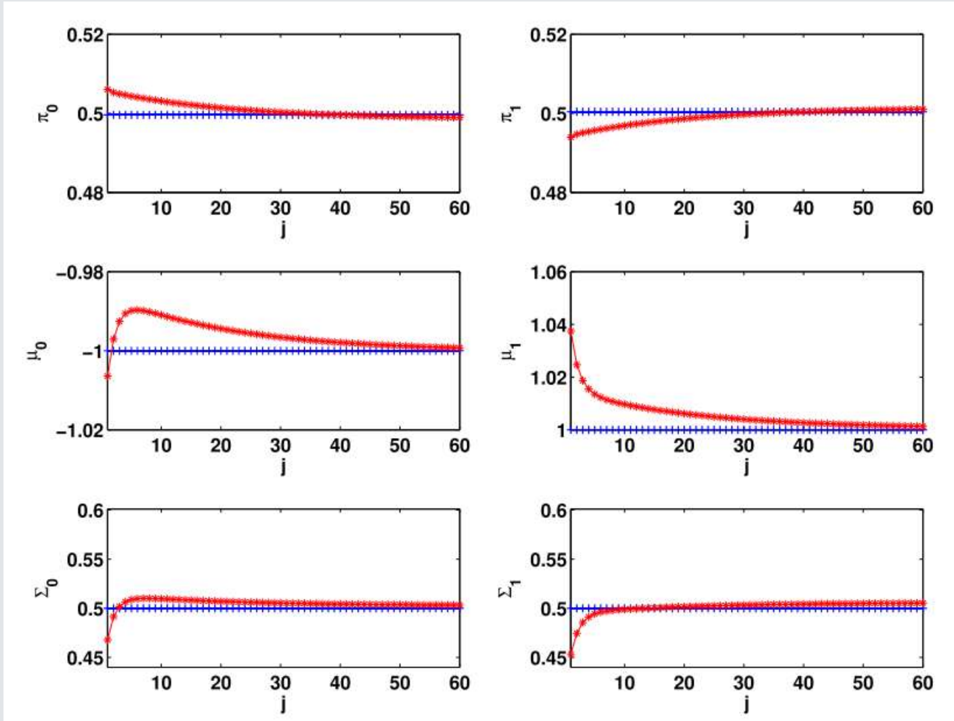
Plotting of the performance of the EM algorithm in the noise-limited channel.

Case where the GMM represents the BPSK modulation scheme

The true parameters for the training data were: $\beta_0 = 0.5$, $\beta_1 = 0.5$, $\mu_0 = -1$, $\mu_1 = 1$, $\Sigma_0 = 0.5$, $\Sigma_1 = 0.5$

EM algorithm is initialized with the following guess at iteration 0: $\widehat{\beta_0}\,(0) = 0.6$, $\widehat{\beta_1}\,(0) = 0.4$, $\widehat{\mu_0}\,(0) = -1.2$, $\widehat{\mu_1}\,(0) = 1.3$, $\widehat{\Sigma_0}\,(0) = 0.4$, $\widehat{\Sigma_1}\,(0) = 0.6$.

EM algorithm learns the 3Q number of parameters of the GMM model for BPSK scheme (d = 1) very efficiently (in about 60 iterations)

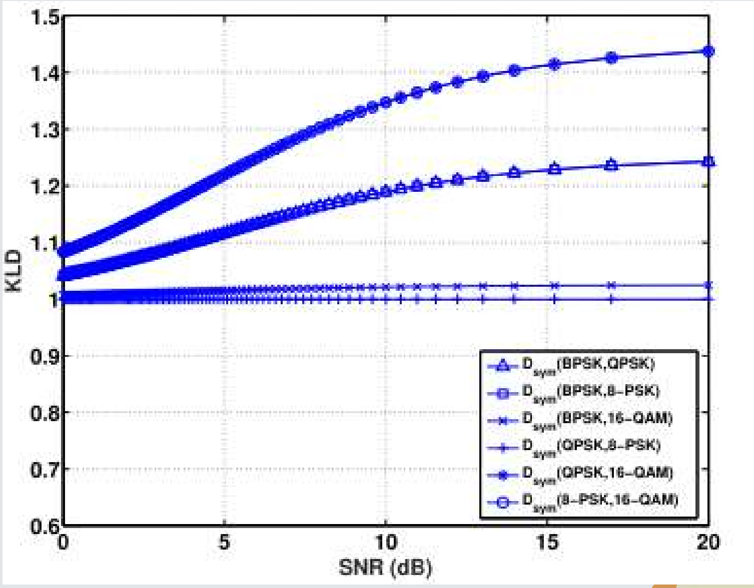


Numerical Results – Modulation Classification

Plotting of all the pair-wise symmetric KLDs for the considered modulation schemes against the SNR. An ideal situation is considered where the GMM parameters for all the modulation schemes are perfectly known

All the pair-wise symmetric KLDs show a monotonic (non-decreasing) trend with increase in SNR.
This is because all the self-KLDs are zero regardless of the SNR value.
Therefore, the distance between a self-KLD and the corresponding pairwise symmetric KLDs increases with increase in SNR.

The overall takeaway message is that the symmetric KLD is indeed a viable (and sufficient) feature for modulation classification



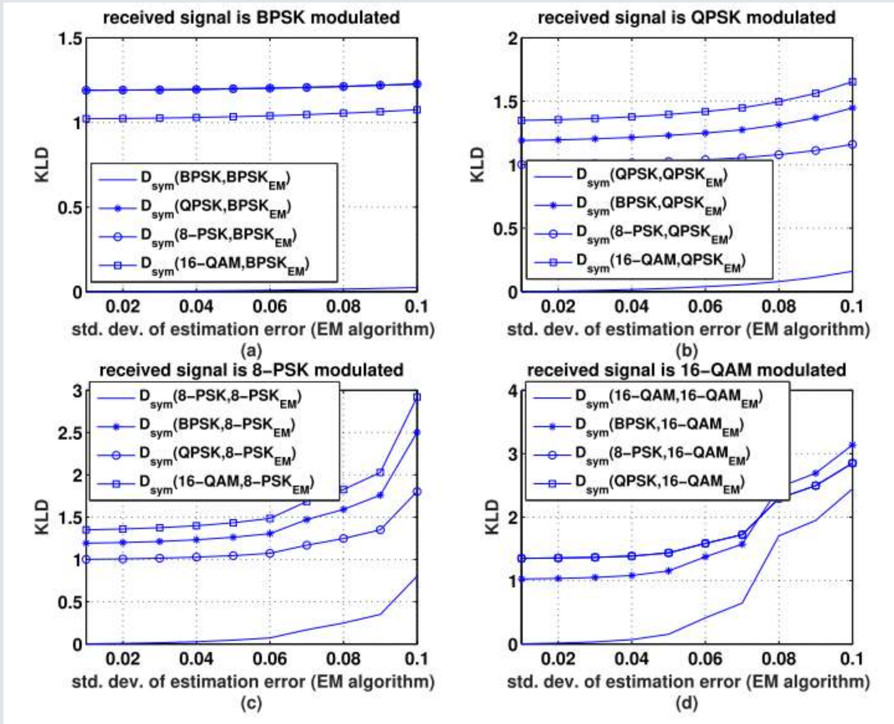
Numerical Results – Modulation Classification

Plotting of the self-KLD and corresponding pair-wise symmetric KLDs for each of the four considered modulation schemes against the (standard deviation of) estimation error of the EM algorithm.

The training data $\{x_m\}_{m=1}^{M}$ with increasing noise levels is considered

Given a received deconvolved signal $\hat{r}$(t) (whose GMM parameters are learned by the EM algorithm), the KLDs between $\hat{r}$(t) and all the template signals τ_i(t), in the database (whose GMM parameters are perfectly known to the nano receiver) are computed.
The values of both the self-KLDs as well as the pair-wise symmetric KLDs increase with increase in estimation error, but the gap between any self-KLD and the corresponding pair-wise symmetric KLDs remains constant.

This in turn implies that the proposed method could correctly classify the modulation scheme in use very efficiently, even in the presence of large estimation errors by the EM algorithm

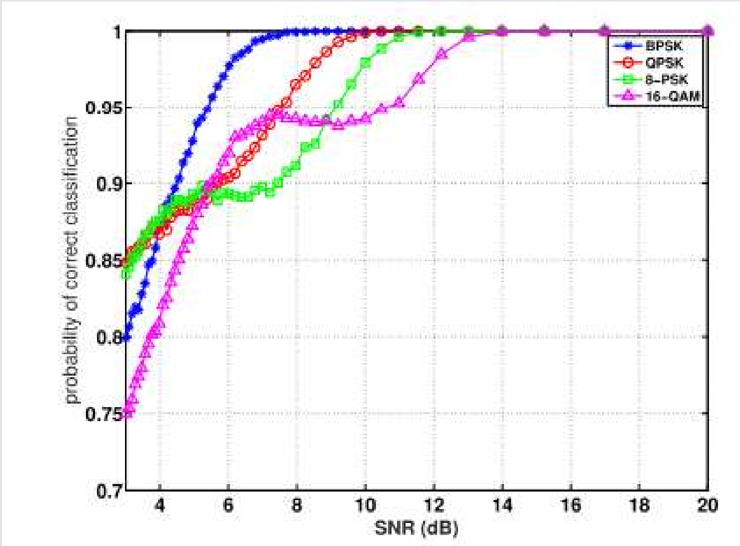


Numerical Results – Modulation Classification

Plotting of the main result–probability of correct classification P_{cc} against the SNR

P_{cc} for all modulation schemes increases with increase in SNR and converges to the maximum value of 1 for moderate SNR values.
However, for a pre-specified P_{cc}, the required SNR for higher-order constellations schemes is larger and viceversa (higher-order constellations are successfully decoded at higher SNRs only).

The reason for such behavior is that for the higher order modulation schemes, the gap between the self-KLD and the corresponding pair-wise symmetric KLDs reduces slightly with increase in estimation error of the EM algorithm which in turn reduces the P_{cc} for higher order modulation schemes at low SNRs.



Conclusion

The problem of designing an intelligent/ cognitive nano receiver operating in THz band was considered.

Two essential ingredients of an intelligent nano receiver—modulation mode detection and modulation classification were investigated.

For modulation mode detection, a binary hypothesis test in nano-receiver's passband was constructed and provide closed-form expressions for the two error probabilities.

For modulation classification, explicit least-squares based THz channel estimation and subsequent compensation via deconvolution were done.

Then, the received deconvolved signal by a Gaussian mixture model was represented and its parameters were learned via Expectation-Maximization algorithm.

Finally, Gaussian approximation of each mixture density was performed to compute symmetric Kullback-Leibler divergence in order to differentiate between various modulation schemes

References

[1] M. O. Iqbal, M. M. Ur Rahman, M. A. Imran, A. Alomainy and Q. H. Abbasi, "Modulation Mode Detection and Classification for In Vivo Nano-Scale Communication Systems Operating in Terahertz Band," in *IEEE Transactions on NanoBioscience*, vol. 18, no. 1, pp. 10-17, Jan. 2019, doi: 10.1109/TNB.2018.2882063.

[2] I. F. Akyildiz and J. M. Jornet, “Electromagnetic wireless nanosensor networks,” Nano Commun. Netw., vol. 1, no. 1, pp. 3–19, Mar. 2010

[3] J. M. Jornet and I. F. Akyildiz, “Femtosecond-long pulse-based modulation for terahertz band communication in nanonetworks,” IEEE Trans Commun., vol. 62, no. 5, pp. 1742–1754, May 2014.

[4] F. Moshir and S. Singh, “Modulation and rate adaptation algorithms for terahertz channels,” Nano Commun. Netw., vol. 10, pp. 38–50, Dec. 2016. [Online]. Available: http://www.sciencedirect.com/science/ article/pii/S1878778916300412

[5] I. F. Akyildiz and J. M. Jornet, “Electromagnetic wireless nanosensor networks,” Nano Commun. Netw., vol. 1, no. 1, pp. 3–19, Mar. 2010

[6] I. F. Akyildiz, F. Brunetti, and C. Blázquez, “Nanonetworks: A new communication paradigm,” Comput. Netw., vol. 52, no. 12, pp. 2260–2279, 2008.

[7] M. Nafari and J. M. Jornet, “Metallic plasmonic nano-antenna for wireless optical communication in intra-body nanonetworks,” in Proc. 10th EAI Int. Conf. Body Area Netw. (ICST), Brussels, Belgium, 2015, pp. 287–293, doi: 10.4108/eai.28-9-2015.2261410.

[8] J. M. Jornet and I. F. Akyildiz, “Channel modeling and capacity análisis for electromagnetic wireless nanonetworks in the terahertz band,” IEEE Trans. Wireless Commun., vol. 10, no. 10, pp. 3211–3221, Oct. 2011.

[9] Q. H. Abbasi, H. El Sallabi, N. Chopra, K. Yang, K. Qaraqe, and A. Alomainy, “Terahertz channel characterization inside the human skin for nano-scale body-centric networks,” IEEE Trans. THz Sci. Technol., vol. 6, no. 3, pp. 427–434, May 2016.

[10] A. Gupta, M. Medley, and J. M. Jornet, “Joint synchronization and symbol detection design for pulse-based communications in the THz band,” in Proc. IEEE Global Commun. Conf. (GLOBECOM), Dec. 2015, pp. 1–7.

References

[11] R. G. Cid-Fuentes, J. M. Jornet, I. F. Akyildiz, and E. Alarcón, “A receiver architecture for pulse-based electromagnetic nanonetworks in the terahertz band,” in Proc. IEEE Int. Conf. Commun. (ICC),Jun. 2012, pp. 4937–4942.

[12] J. M. Jornet, J. C. Pujol, and J. S. Pareta, “Phlame: A physical layer aware MAC protocol for electromagnetic nanonetworks in the terahertz band,” Nano Commun. Netw., vol. 3, no. 1, pp. 74–81, 2012.

[13] C. Han, J. M. Jornet, E. Fadel, and I. F. Akyildiz, “A cross-layer communication module for the Internet of Things,” Comput. Netw., vol. 57, no. 3, pp. 622–633, 2013.

[14] K. Iwaszczuk, “Terahertz technology for defense and security-related applications,” Ph.D. dissertation, Dept. Photon. Eng., Tech. Univ. Denmark, Lyngby, Denmark, 2012, vol. 172.

[15] O. A. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, “Survey of automatic modulation classification techniques: Classical approaches and new trends,” IET Commun., vol. 1, no. 2, pp. 137–156, Apr. 2007

[16] J. G. Liu, X. Wang, J. Nadeau, and H. Lin, “Modulation classification based on Gaussian mixture models under multipath fading channel,” in Proc. IEEE Global Commun. Conf. (GLOBECOM), Dec. 2012, pp. 3970–3974

[17] H. C. Wu, M. Saquib, and Z. Yun, “Novel automatic modulation classification using cumulant features for communications via multipath channels,” IEEE Trans. Wireless Commun., vol. 7, no. 8, pp. 3098–3105, Aug. 2008

[18] S. Peng, H. Jiang, H. Wang, H. Alwageed, and Y.-D. Yao, “Modulation classification using convolutional neural network based deep learning model,” in Proc. 26th Wireless Opt. Commun. Conf. (WOCC), Apr. 2017, pp. 1–5.

[19] A. Ali and F. Yangyu, “Unsupervised feature learning and automatic modulation classification using deep learning model,” Phys. Commun., vol. 25, pp. 75–84, Dec. 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1874490717300435

[20] Z. Zhu and A. K. Nandi, “Machine learning for modulation classification,” in Automatic Modulation Classification. Hoboken, NJ, USA: Wiley, 2014, ch. 6, pp. 81–95. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/9781118906507.ch6, doi: 10.1002/9781118906507.ch6.

References

[21]] A. K. Vavouris, F. D. Dervisi, V. K. Papanikolaou, and G. K. Karagiannidis, “An energy efficient modulation scheme for body-centric nano-communications in the THz band,” in Proc. 7th Int. Conf. Mod. Circuits Syst. Technol. (MOCAST), May 2018, pp. 1–4.

[22] R. Zhang, K. Yang, Q. H. Abbasi, K. A. Qaraqe, and A. Alomainy, “Analytical characterisation of the terahertz in-vivo nano-network in the presence of interference based on TS-OOK communication scheme, ”IEEE Access, vol. 5, pp. 10172–10181, 2017.

[23] J. R. Hershey and P. A. Olsen, “Approximating the Kullback leibler divergence between Gaussian mixture models,” in Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP), vol. 4, Apr. 2007, pp. IV-317–IV-320.