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Robust Over-The-Air Aggregation for uplink OFDM system under burst sparse interference

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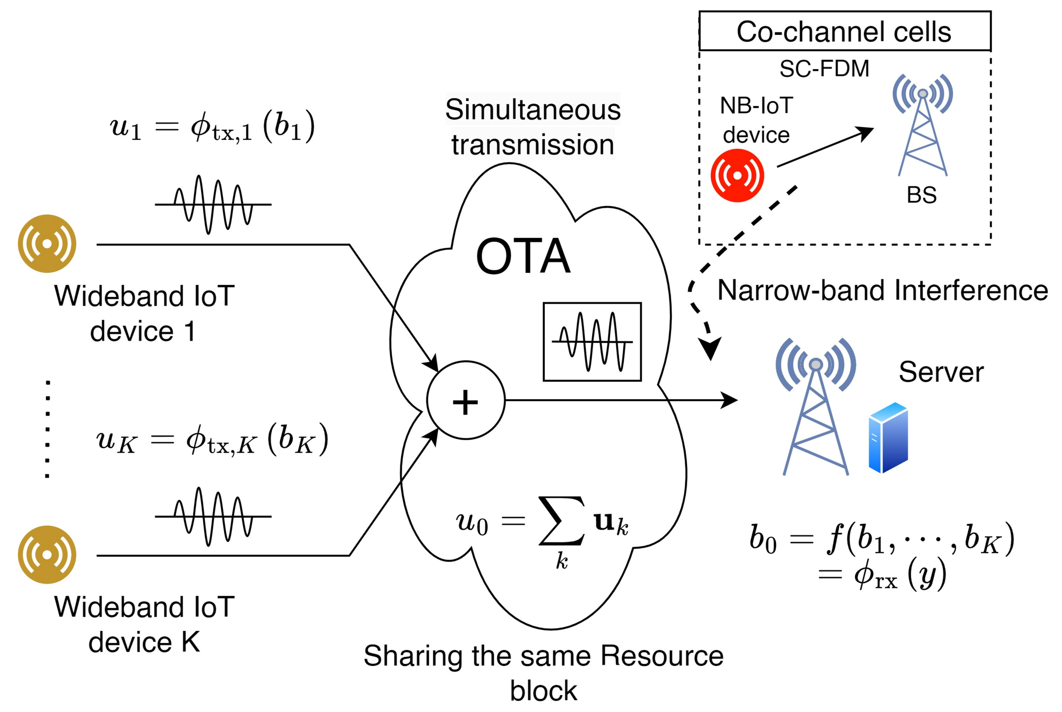
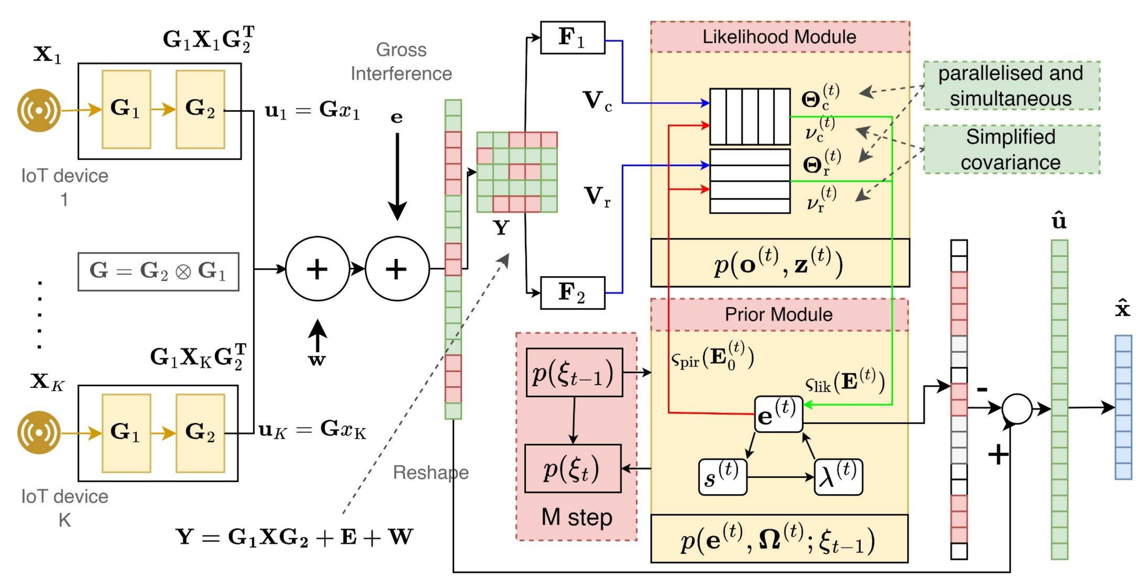
Abstract and Background:
Over-the-Air aggregation (OTA) is a promising technology for Internet-of-Things (IoT) applications, but it can be vulnerable to burst interference from co-channel non-cooperative IoT communications. Main challenges to mitigate interference include:

1. **Incompatibility with Digital FEC:** Digital FEC cannot be employed for OTA as superposition of digital codewords from edge devices results in a corrupted codeword
2. **Lack of interference models:** Practical interference is burst sparse in nature which has to be modelled properly.via Bayesian priors
3. **Unknown model parameters of the interference:** Interference burst properties and amplitude is unknown upon deployment
4. **High Decoding complexity of existing sparse estimators: I**nterference estimation can be cast as sparse estimation but they assume random sparsity and have high decoding complexity

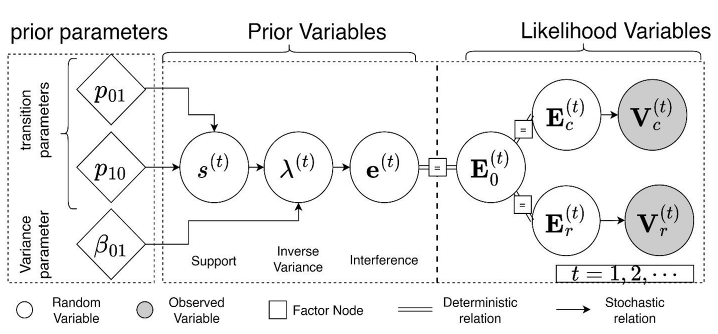
Thus, in this work, we propose a novel framework of **robust OTA** with product analog code in presence of burst sparse interference for IoT systems. We design:

1. **Analog code for robust aggregation:** We encode the message with Analog codes with product encoding matrices which reduces the decoding complexity.
2. **Markov Based prior:** We design and verify a Markov model based hierarchical prior to model the structural properties of the interference and enable algorithmic learning for the cluster as well as interference amplitude.
3. **Low-complexity Online Expectation-Maximisation (EM) algorithm:** We develop an online EM (online machine learning) algorithm with low-complexity to learn the interference model parameters on the fly.
4. **Encoder Optimisation:** We then propose an algorithmic unrolling based Stochasatic Manifold Optimization to improve encoding matrix under unknown interference patterns.





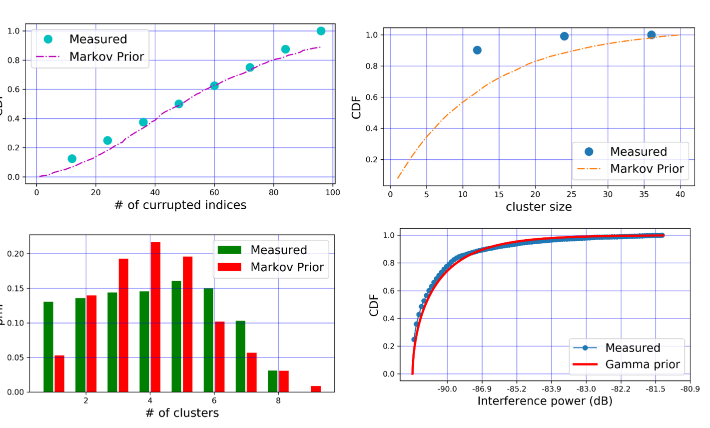
1. Modelling:



The first step is to design a Bayesian model which can incorporate the statistics of the interference via some probabilistic model, connecting the latent variables corresponding to the interference with the observations corresponding to the corrupted received signal.

The above graphical model shows the probabilistic model which is then considered for inference. The product code formulation allows us decompose the likelihood and the prior.

Figures below verify the ability of the proposed Markov based hierarchical prior to capture cluster statistics of real interference.

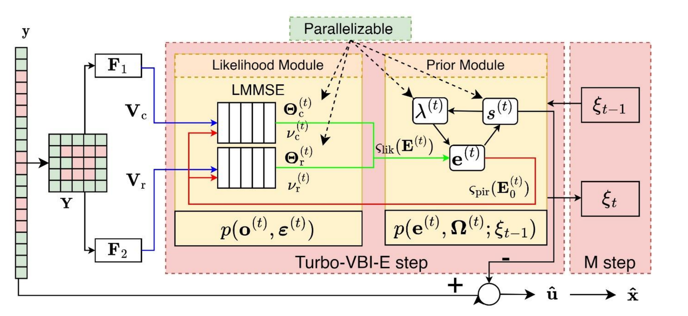


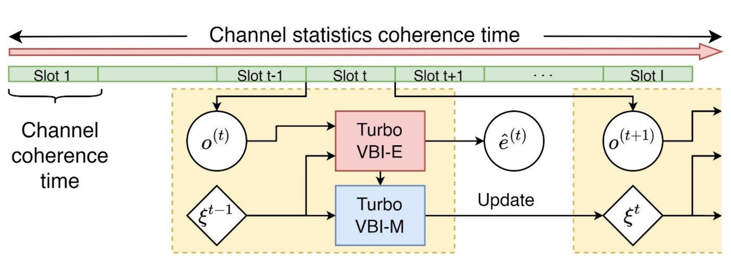
2. Inference Algorithm:

Algorithm 3 Proposed Online Turbo-VBI for Burst Sparse Interference Estimation

1: **Initialize** $\hat{\xi}_{(0)}$
2: **while** observation $\mathbf{o}^{(t)}$ in t-th slot comes **do**
3: **Initialize** $\boldsymbol{\Theta}_{\mathrm{pir}}^{(t)}$ and $\nu_{\mathrm{pir}}^{(t)}$;
4: *%% Online Turbo-VBI-E-Step*:
5: **while** not converged **do**
6: $[\boldsymbol{\Theta}_{\mathrm{lik}}^{(t)}, \nu_{\mathrm{lik}}^{(t)}] = f_{\mathrm{lik}}(\mathbf{o}^{(t)}, \boldsymbol{\Theta}_{\mathrm{pir}}^{(t)}, \nu_{\mathrm{pir}}^{(t)})$;
7: $[\boldsymbol{\Theta}_{\mathrm{pir}}^{(t)}, \nu_{\mathrm{pir}}^{(t)}, \varpi^{(t)}] = f_{\mathrm{pir}}(\boldsymbol{\Theta}_{\mathrm{lik}}^{(t)}, \nu_{\mathrm{lik}}^{(t)}; \hat{\xi}_{t-1})$
8: **end while**
9: **Output** $\hat{\mathbf{E}}^{(t)} = \boldsymbol{\Theta}_{\mathrm{e}}^{(t)}$ according to (77);
10: *%% Online Turbo-VBI-M-Step*:
11: Solve $\bar{\xi}$ by (81), (82) and (83) using $\varpi^{(t)}$;
12: Estimate $\hat{\xi}_t$ by (44);
13: **end while**

Based on the Bayesian model, we can then derive the inference algorithm. The posterior inference for the column and row-decoders are executed in the likelihood module whereas the posterior inference for interference and support for each frame is done using variational Bayesian inference (VBI). The global parameters corresponding to the variance and transition parameters are learnt via online EM algorithm.

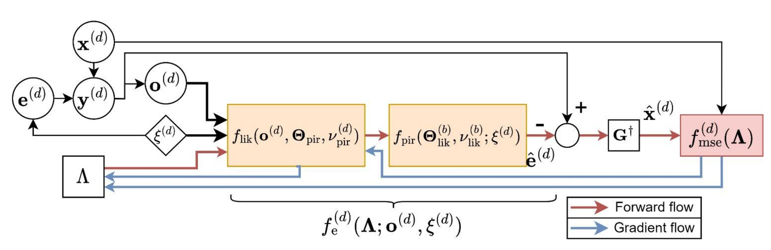




3. Encoder Optimisation:

Algorithm 4 Stochastic Manifold Optimisation for ($\mathcal{P}3$)

1: **while** not converged **do**
2: Sample index d from $\{1, \ldots, D\}$
3: Update $\boldsymbol{\Lambda}^{(j+1)} = R_{\boldsymbol{\Lambda}^{(j)}}\left(-\rho^{(j)}\nabla f_{\mathrm{mse}}^{(d)}(\boldsymbol{\Lambda}^{(j)})\right)$, where $\rho^{(j)}$ is the Robbins-Monroe sequence as stepsize.
4: **end while**



Optimization of the encoder using stochastic manifold optimzation. We first construct an offline dataset of interference realizations using ray-tracing techniques in COST2100 model.

Then a simple interference estimator is applied by unrolling the proposed Turbo-VBI estimator with only one iteration (Algorithm Unrolling).

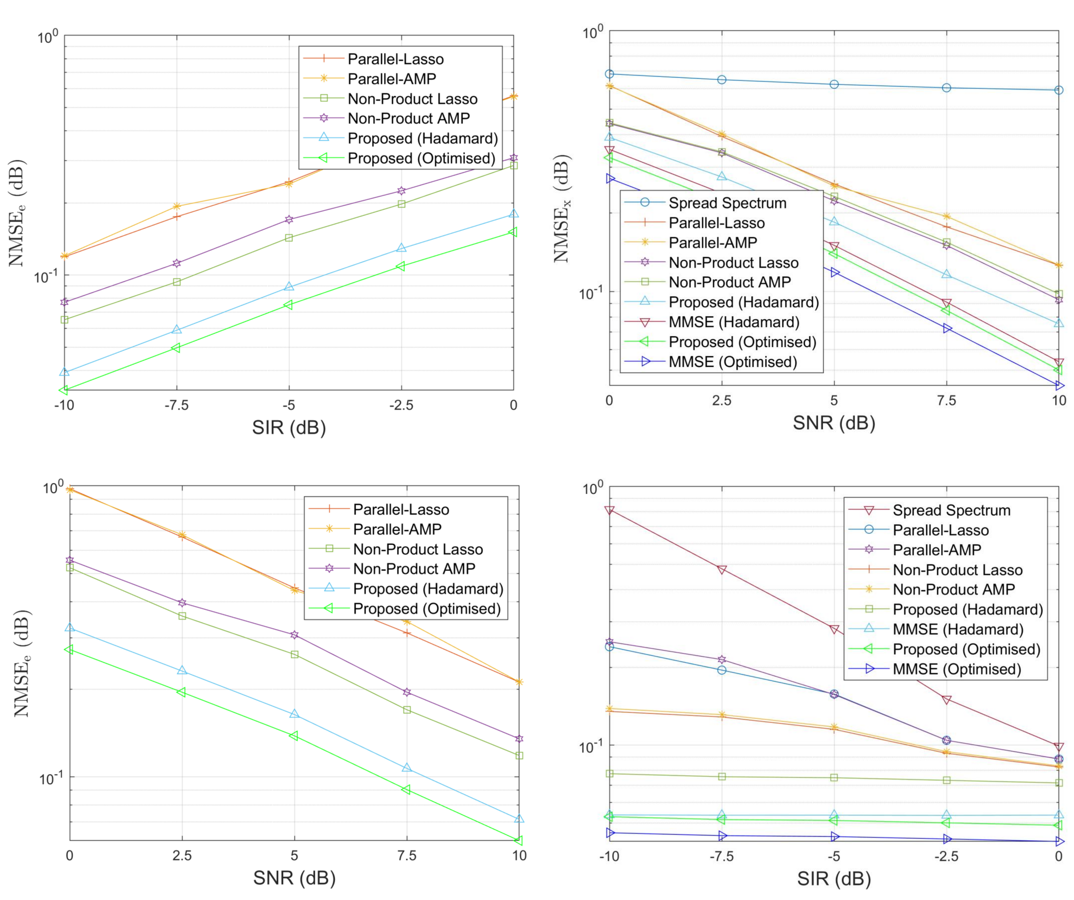
COMPARISONS OF COMPUTATIONAL COMPLEXITY AND COMPUTATION TIME.

Algorithm	Complexity	Computation Time
Proposed	$\mathcal{O}(\kappa M(\overline{M}_1 + \overline{M}_2))$	4.08 ms
Parallel Lasso	$\mathcal{O}(\kappa\overline{M}_1\overline{M}_2^3 + \kappa\overline{M}_2\overline{M}_1^3)$	29 ms
Lasso without product code	$\mathcal{O}(M^3)$	1080 ms
AMP	$\mathcal{O}(\kappa M^2)$	6.82 ms
Parallel-AMP	$\mathcal{O}(\kappa M(\overline{M}_1 + \overline{M}_2))$	4 ms

4. Results:

Provides an excellent near MMSE performance with good interference support estimation with SIR resistant recovery. For partially fixed interference support, the encoder is optimized providing improved interference estimation and message recovery.
Figures show NMSE of interference estimation and NMSE of message vs SNR and vs SIR.

- Message Length, N = 300 (25 Resource Blocks)
- # of subcarriers in the OTA bandwidth, M: 600 (50 RBs)
- Number of interference subcarriers: 72 (12%)
- With a total of 6 RB, with 3 RBs chosen from 8 candidate sets and 3 RBs chosen at random from the remaining (42 RBs).
- # of users, K = 20
- Optimized under Unitary constraint using stochastic manifold optimization.



Related Publications:

1. Jha, Nilesh Kumar, Huayan Guo, and Vincent KN Lau. "Robust Over-The-Air Aggregation for uplink OFDM system under burst sparse interference." In *2023* ***IEEE 24th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)***, pp. 31-35. IEEE, 2023.

2. Jha, Nilesh Kumar, Huayan Guo, and Vincent KN Lau. "Analog Product Coding for Over-the-Air Aggregation Over Burst-Sparse Interference Multiple-Access Channels." ***IEEE Transactions on Signal Processing*** 72 (2023): 157-172.

Acknowledgment

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