Type-Based Unsourced Multiple Access

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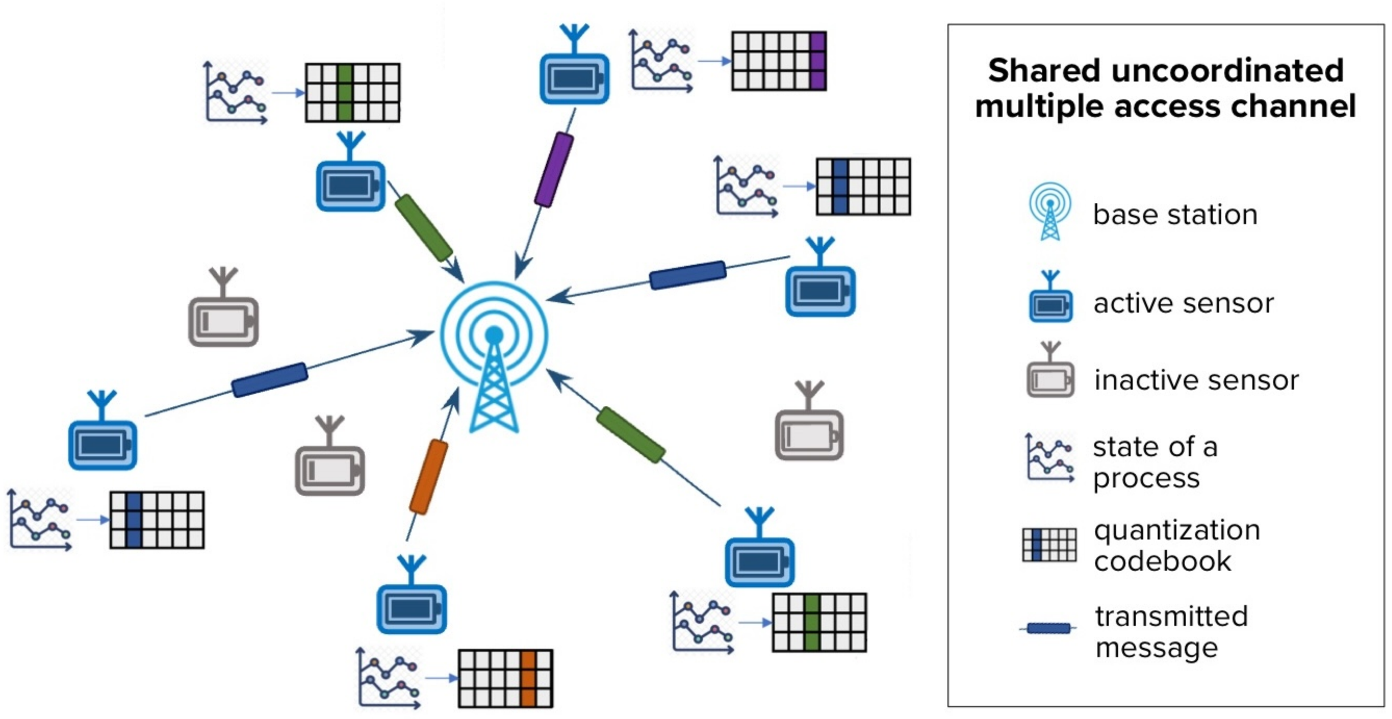
Motivation

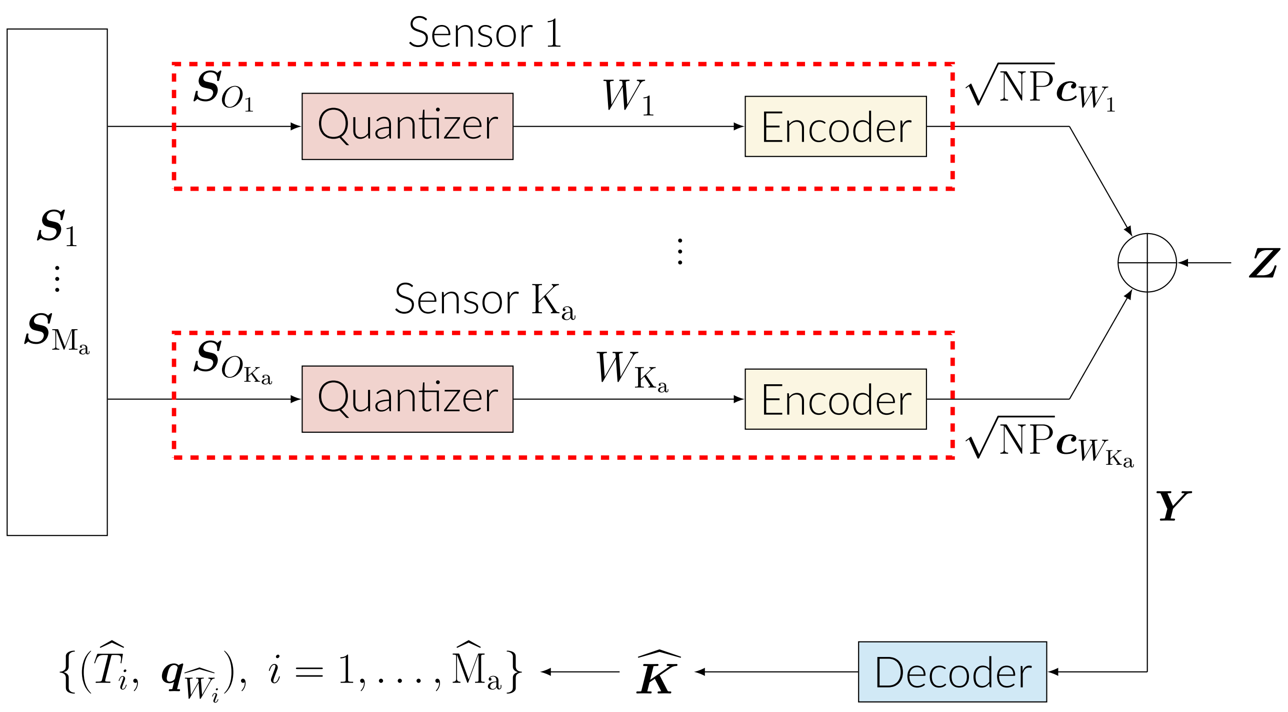


- Internet of Things (IoT) & 6G networks enable **massive** sensor connectivity.
- Sensors transmit digital data over a shared medium.
- Transmission: short and sporadic
- **Unsourced Multiple Access (UMA)** [1] models massive sensor communication
- Key feature: handles uncoordinated transmission from a multitude of sensors
- **Limitation**: no message multiplicity, i.e., each sensor sends a unique message
- Impractical for multi-target tracking, over-the-air federated learning, etc.
- In these applications, we require **empirical distribution (type)** of messages.

What's New?

1. **Type-Based UMA (TUMA)**: UMA + message multiplicity + type estimation
2. **Comparison** of TUMA decoding algorithms for multi-target tracking
3. **Characterization of trade-off** between quantization & communication error

System Model



- S_{O_i} : state of target O_i sensed by sensor i; W_i: index of quantized S_{O_i}
- c_{W_i}: codeword; Z: Gaussian noise
- Sensor i transmits $\sqrt{NP}c_{W_i}$, with power P in N channel uses
- $Y = \sqrt{NP}\mathbf{C}K + Z$; $\mathbf{C}$: codebook, K: message multiplicity vector
- $\widehat{K}_i$: estimate of message multiplicity i, $i = 1, \dots, M$
- $\widehat{W}_1, \dots, \widehat{W}_{\widehat{M}_a}$: estimated messages
- $\widehat{T}_i = \widehat{K}_i / \sum_i \widehat{K}_i$: type of estimated quantized state $q_{\widehat{W}_i}$

Goal: estimate states $S_1, \dots, S_{M_a}$ and their type $T_1, \dots, T_{M_a}$ from Y

How is Estimation Performance Measured?

Total variation distance

- Minimizes ℓ_1 distance between transmitted and estimated types
- Captures only communication errors

Wasserstein distance

- Minimizes average Euclidean distance between states and their estimates
- Captures overall performance, i.e., quantization and communication errors

Example: Multi-Target Position Tracking

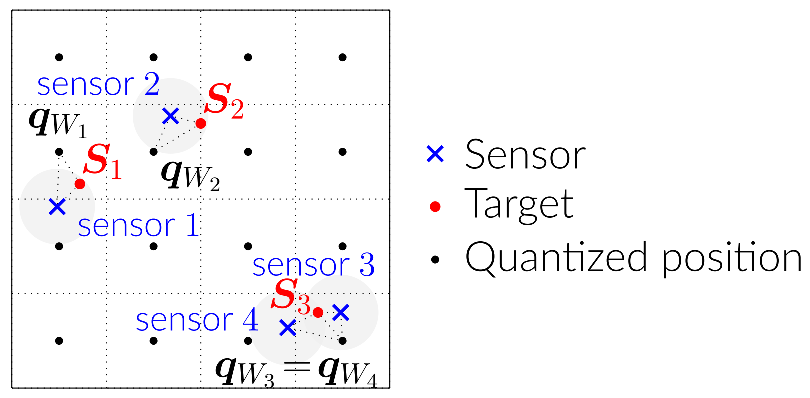


Fig . Multi-target position tracking with $K_a = 4$ sensors, $M_a = 3$ targets, and $M = 16$ cells

- Uniform, random target locations
- Quantized position: center of each cell
- Sensor i chooses a target uniformly at random & maps its location S_i to q_{W_i}.

Three Decoding Algorithms

Decoder's aim: estimate K given $Y = y$ for the model $Y = \sqrt{NP}\mathbf{C}K + Z$

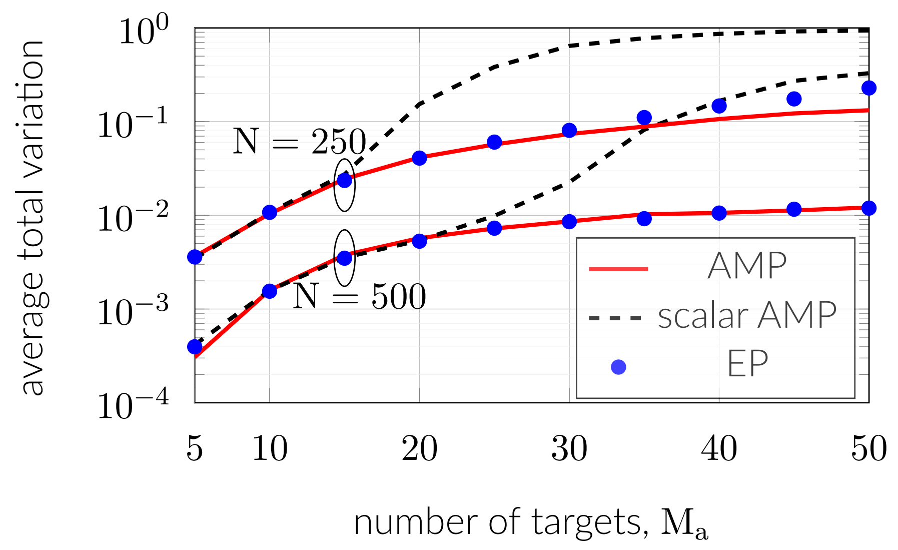
- Expectation propagation (EP) [2]: Gaussian factorization of Probability$[K|y]$
- Scalar approximate message passing (Scalar AMP): simplified EP
- Approximate message passing (AMP) [3]

AMP in a Nutshell

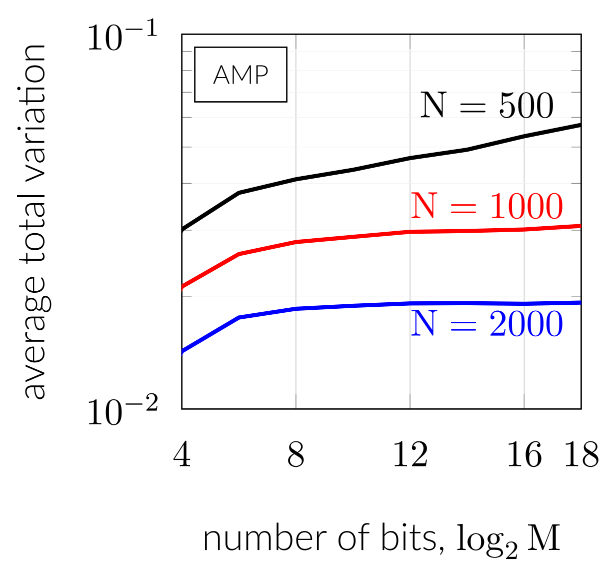
- Decouple: M scalar models $R_i = K_i + \mathcal{N}(0, \xi_i)$ (Gaussian approximation)
- Compute effective observation: $r^{(t)} = \mathbf{C}^T z^{(t-1)} + \sqrt{NP}\widehat{k}^{(t-1)}$
- Denoise: $\widehat{k}^{(t)} = f_t(r^{(t)})$, posterior mean of K given $r^{(t)}$
- Compute residual: $z^{(t)} = y - \sqrt{NP}\mathbf{C}\widehat{k}^{(t)} +$ *correction term*
- Iterate with $\xi_i = \|z^{(t-1)}\|^2/N$

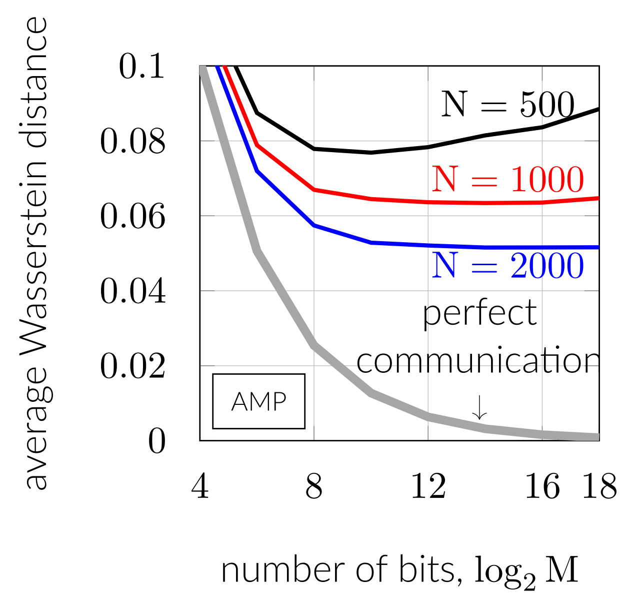
Complexity: $O(\max\{M, N\} \log \max\{M, N\})$ (lower than EP & scalar AMP)

Results



- **AMP outperforms EP & scalar AMP**: lower average total variation distance





- **Trade-off**: low M, quantization error>communication error; high M, vice versa
- **Scalability issue** (future work): for $\log_2 M > 18$, computational cost is high

Acknowledgements

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References

[1] Y. Polyanskiy, "A perspective on massive random-access," in *Proc. IEEE Int. Symp. Inf. Theory (ISIT)*, Aachen, Germany, Jun. 2017, pp. 2523– 2527.

[2] X. Meng, et al., "Advanced NOMA receivers from a unified variational inference perspective," *IEEE J. Select. Areas Commun.*, vol. 39, no. 4, pp. 934–948, Apr. 2021.

[3] A. Fengler et al., "SPARCs for unsourced random access," *IEEE Trans. Inf. Theory*, vol. 67, no. 10, pp. 6894–6915, Oct. 2021.