Coding and Compressed Sensing for Unsourced Multiple Access

J.-F. Chamberland
Krishna Narayanan, Vamsi Amalladinne, Avinash Vem

Electrical and Computer Engineering
Texas A&M University

Vehicular Technology Conference, Hawaii
September 22, 2019

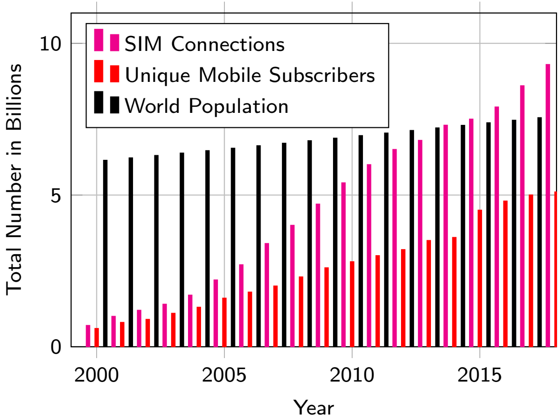
This material is based upon work supported, in part, by NSF under Grant No. 1619085
This material is also based upon work support, in part, by Qualcomm Technologies, Inc., through their University Relations Program

Part I

Motivation behind Research Agenda: Can One Discern the Future of Wireless?

Mobile Device Market Penetration

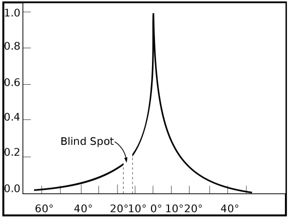
There are now more subscribed wireless devices than humans on Earth



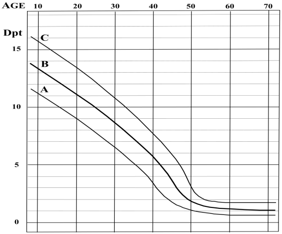
Sources: United Nations, GSMA

©Google Earth

Clarity of Vision – Reaching the Limit



©Vanessa Ezekowitz



©Hans Strasburge

©Samarskaya

Visual Resolution

Peak visual resolution of 20/20 human is

$$\frac{1}{\text{Visual Acuity}} = \frac{1}{20/20} \text{ min. of arc}$$

$$\approx 0.0167 \text{ degrees}$$

Sharp drops limit viewing angle to ± 20 degrees

Amplitude of Accommodation

Diopters capture eye adaptability in reciprocal of focal length, Crystalline limits minimum range

Visual Acuity and Display Technology

Apple Super Retina HD

Screen Distance

The distance at which the super retina HD display matches this resolution is

$$\begin{aligned} \text{Distance} &= \frac{1}{2} \cdot \frac{1}{458} \cdot \cot \frac{1}{120} \\ &= 1.876 \text{ in.} \end{aligned}$$

Mobile VR Headsets

Content-Rich Applications

Video and Mobile Statistics

- 63% of all US online traffic comes from smartphones and tablets – Stone Temple
- More than 70% of YouTube viewing happens on mobile devices – Comscore
- 65% of all digital media time is spent on mobile devices – Business2Community

©Real

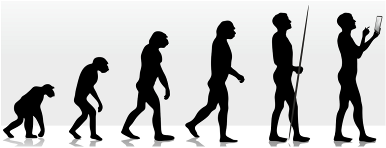
Options to Stay the Course

Spend More Time on Mobile Devices

Average time spent on mobile phone in US is 3h45m per day

– eMarketer

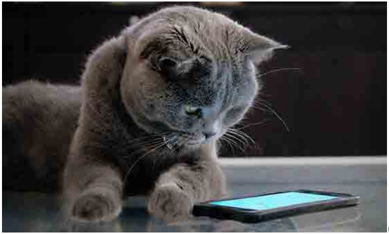
Wait for Eye Evolution



ⒸRavishly

ⒸDreamworks

Diversify User Population



ⒸAsurobson

Summary of Quality of Experience

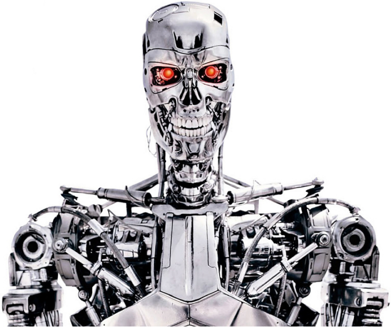
Current Wireless Landscape

- **Growth and Market Penetration**: Near saturation
  - Number of connected wireless devices exceeds world population
  - Almost every human who wants mobile phone has one (or more)
- **Screen Quality**: At limit of eye acuity
  - Screens are near boundary of visual resolution
  - Viewing distance is constrained by amplitude of accommodation
- **Content-Rich Apps**: Video watching & gaming are prevalent
  - On average, a person spends 4 hours on mobile device per day
  - More videos are watch on phones than elsewhere

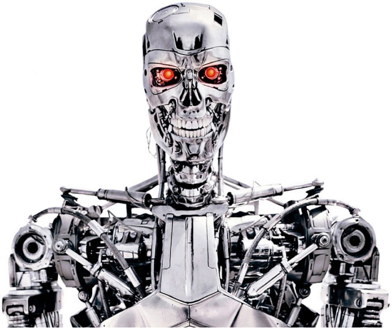
Wireless Research and the Future

What's Next?

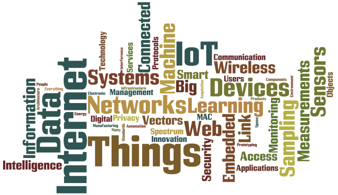
The Rise of the Machine



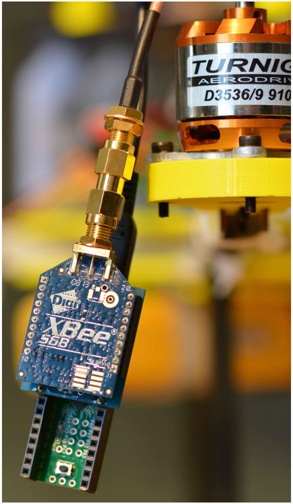
The Rise of the Machine



©Warner Bros.



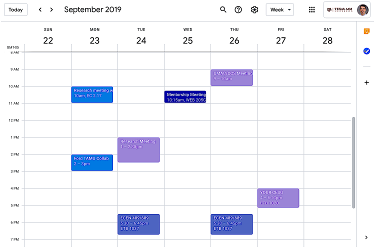
Internet of Things



Contrasting Machines and Human Behaviors

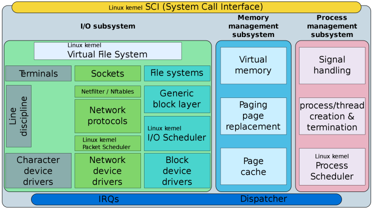
Typical Human Calendar

- YouTube video earns 1 view when watched for ≥ 30 sec
- 47% of visitors expect website to load in ≤ 2 sec
- Callers notice roundtrip voice delays of ≥ 250 ms



Machine Scheduler

- OS timeslice ≈ 10 ms
- LTE schedule ≈ 1 ms (transmission time interval)
- Microcontroller interrupt latency is $\leq 10\ \mu s$



ⒸScotXW

Information and Inference

IEEE TRANSACTIONS ON SIGNAL PROCESSING, VOL. 51, NO. 2, FEBRUARY 2003 407

Decentralized Detection in Sensor Networks

Jean-François Chamberland, *Student Member, IEEE,* and Venugopal V. Veeravalli, *Senior Member, IEEE*

***Abstract*—In this paper, we investigate a binary decentralized detection problem in which a network of wireless sensors provides relevant information about the state of nature to a fusion center. Each sensor transmits its data over a multiple access channel. Upon reception of the information, the fusion center attempts to accurately reconstruct the state of nature. We consider the scenario where the sensor network is constrained by the capacity of the wireless channel over which the sensors are transmitting, and we study the structure of an optimal sensor configuration. For the problem of detecting deterministic signals in additive Gaussian noise, we show that having a set of identical binary sensors is asymptotically optimal, as the number of observations per sensor goes to infinity. Thus, the gain offered by having more sensors exceeds the benefits of getting detailed information from each sensor. A thorough analysis of the Gaussian case is presented along with some extensions to other observation distributions.**

***Index Terms*—Bayesian estimation, decentralized detection, sensor network, wireless sensors.**

problem have been studied in the past. Notably, the class of decentralized detection problems where each sensor must select one of D possible messages has received much attention. In this setting, which was originally introduced by Tenney and Sandell [1], the goal is to find what message should be sent by which sensor and when. See Tsitsiklis [2] and the references contained therein for an elaborate treatment of the decentralized detection problem. More recently, the problem of decentralized detection with correlated observations has also been addressed (see, e.g., [3] and [4]).

In essence, having each sensor select one of D possible messages upper bounds the amount of information available at the fusion center. Indeed, the quantity of information relayed to the fusion center by a network of L sensors, each sending one of D possible messages, does not exceed $L\lceil \log_2 D \rceil$ bits per unit time. In the standard decentralized problem formulation, the number of sensors L and the number of distinct messages D are

Payload Design Guideline

- Most of information for inference is contained in first few bits!

Information and Inference

A Telemetering System by Code Modulation — Δ-Σ Modulation*

H. INOSE†, MEMBER, IRE, Y. YASUDA†, AND J. MURAKAMI‡

Summary—**A communication system by code modulation is described which incorporates an integration process in the original delta modulation system and is named delta-sigma modulation after its modulation mechanism. It has an advantage over delta modulation in dc level transmission and stability of performance, although both require essentially an equal bandwidth and complexity of circuitry. An experimental telemetering system employing delta-sigma modulation is also described.**

the input signal before it enters the modulator so as to generate output pulses carrying the information corresponding to the amplitude of the input signal. The delta-sigma modulation (Δ-ΣM) system is a realization of this principle.

THE PRINCIPLE OF THE Δ-ΣM SYSTEM

Payload Design Guideline

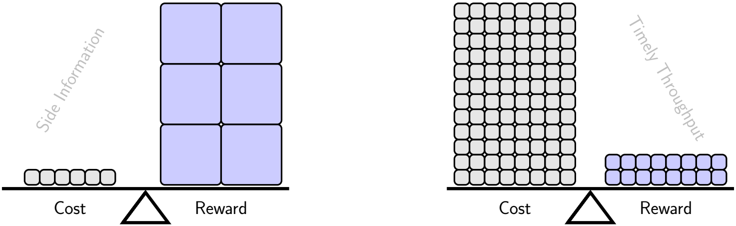
- Signals are tracked well using small, yet frequent updates
- Δ-Σ modulation

Losing the Connection

Emerging M2M Traffic Characteristics

- Device density – Massive versus small
- Connectivity profile – Sporadic versus sustained
- Packet payloads – Minuscule versus moderate-to-long

Anticipated traffic characteristics invalidate the acquisition-estimation-scheduling paradigm!



Revival of Uncoordinated Access

A New Reality

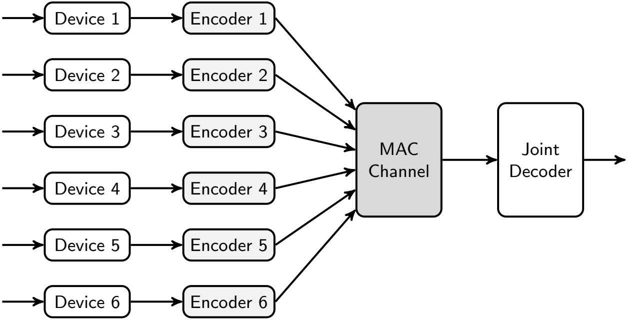
- Must address sporadic nature of machine-driven communications
- Transfer of small payloads without ability to amortize cost of acquiring channel and buffer states over long connections
- Preclude use of opportunistic scheduling
- Evinced by departure from scheduling-based solutions

Communication and Identity

When number of devices is massive, with only subset of them active, problem of allocating resources (e.g., codebook, subcarriers, signature sequences) to every user as to manage interference becomes very complex

Uncoordinated, Unsourced MAC

Uncoordinated Multiple Access Channel (MAC)



LoRa-Inspired Parameters

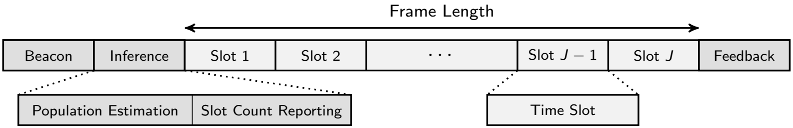
- K active users out of K_{tot} total users, $K \in [25 : 300]$
- Each user has B-bit message, B is small ≈ 100
- N channel uses available, $N \approx 30,000$

M. Berioli, G. Cocco, G. Liva and A. Munari, *Modern Random Access Protocols*. Foundations and Trends in Networking, 2016

F. Clazzer, A. Munari, G. Liva, F. Lazaro, C. Stefanovic, P. Popovski, *From 5G to 6G: Has the Time for Modern Random Access Come?*, arXiv 2019

Uncoordinated MAC Frame Structure

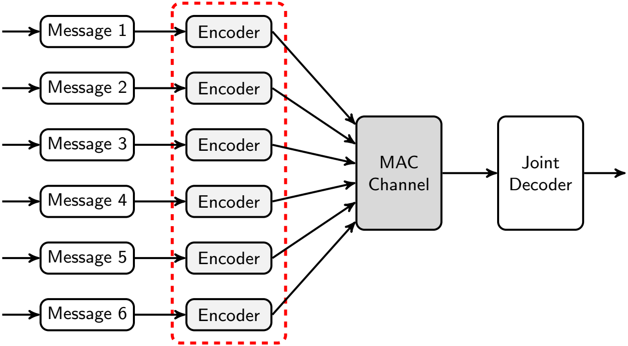
- K active devices out of many, many devices
- Framework of gathering channel and queue states does not apply



- Beacon employed for coarse synchronization
- Same devices transmit within frame
- Each device may or may not use slot

X. Chen and D. Guo. *Many-access channels: The Gaussian case with random user activities*. ISIT, 2014

Uncoordinated and Unsourced MAC



Without Personalized Feedback

- All devices employ same encoder
- No explicit knowledge of identities
- Need only return unordered list

Math Model

$$\vec{y} = \sum_{i \in \mathbf{S}_{\mathrm{a}}} \vec{x}_i + \vec{n}$$

where $\mathbf{x}_i = f(w_i)$ is codeword, only depends on message

Y. Polyanskiy. *A Perspective on Massive Random-Access.* ISIT, 2017

Gaussian Random Codes & Performance Bounds

A perspective on massive random-access

Yury Polyanskiy

***Abstract*—This paper discusses the contemporary problem of providing multiple-access (MAC) to a massive number of uncoordinated users. First, we define a random-access code for K_a-user Gaussian MAC to be a collection of norm-constrained vectors such that the noisy sum of any K_a of them can be decoded with a given (suitably defined) probability of error. An achievability bound for such codes is proposed and compared against popular practical solutions: ALOHA, coded slotted ALOHA, CDMA, and treating interference as noise. It is found out that as the number of users increases existing solutions become vastly energy-inefficient.**

MAC [11], [12]). Already 30 years ago R. Gallager [13] called for "a coding technology that is applicable for a large set of transmitters of which a small, but variable, subset simultaneously use the channel." It appears (to this author) that this call has not been completely answered still. One reason for this could be that the models in each of three categories are different and thus solutions are not directly comparable. Our first goal, thus, is to define a notion of random-access code that would appeal to all three communities. This we do next.

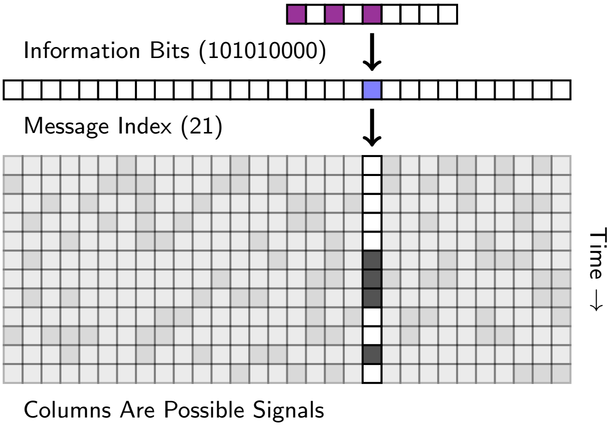
Theorem: Fix $P' < P$. There exists an (M, n, ϵ) random-access code for the K-user GMAC satisfying power-constraint P and

$$\epsilon \leq \sum_{t=1}^{K} \frac{t}{K} \min(p_t, q_t) + p_0,$$

where constants p_0, p_t, and q_t are complicated

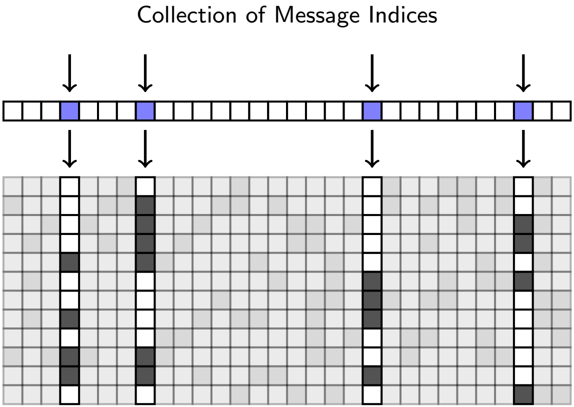
Y. Polyanskiy. *A Perspective on Massive Random-Access*. ISIT, 2017

UMAC – Compressed Sensing Interpretation



- Bit sequence $\underline{w}_i \in \{0,1\}^B$ converted to index in $[1, 2^B]$
- Stack codewords into $N \times 2^B$ *sensing* matrix
- Message index determines transmitted codeword

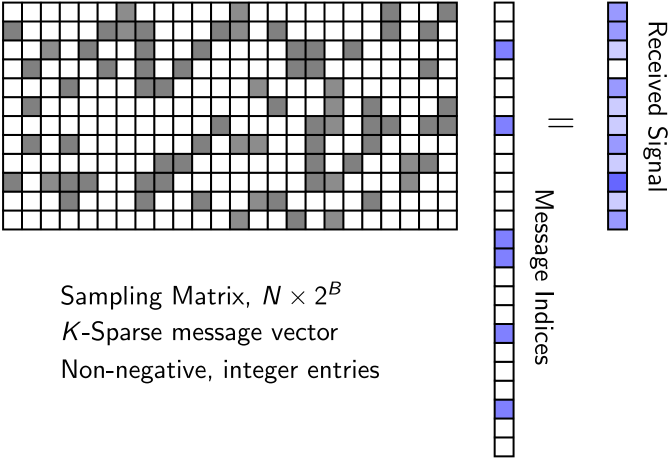
UMAC – Compressed Sensing with Multiple Messages



Conceptual MAC Framework

- Devices share same codebook (sensing matrix)
- Received signal is sum of K columns plus noise

UMAC – Exact CS Analogy



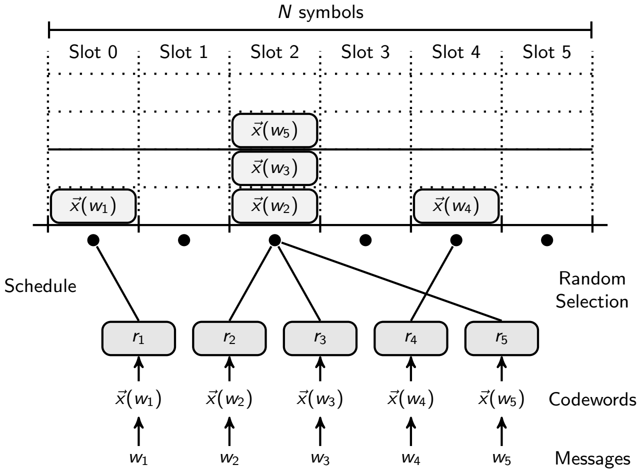
- $\vec{y} = A\vec{x} + \vec{z}$ with $\|\vec{x}\|_0 = K$
- Dimensionality of CS problem is **huge**
- Computational complexity of conventional CS solvers: $\mathcal{O}(\mathrm{poly}(2^B))$

Part II

A Quest for Low-Complexity: Sparsifying Collision

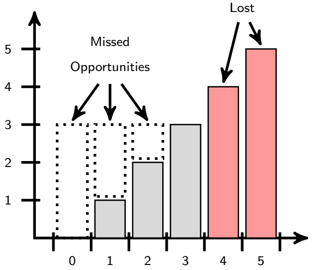
Quest for Low-Complexity Unsourced MAC

Idea 1: Stochastic Binning

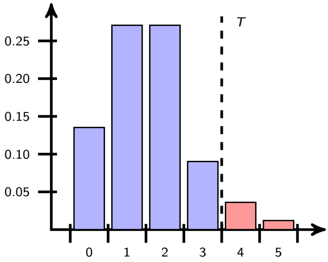


O. Ordentlich and Y. Polyanskiy. *Low Complexity Schemes for the Random Access Gaussian Channel*. ISIT, 2017

Caveat – The Poisson Wall



Sum Reward

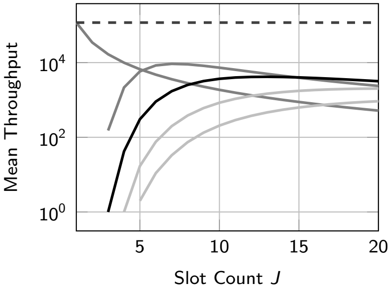


Count Distribution

Effects of Decoding Threshold

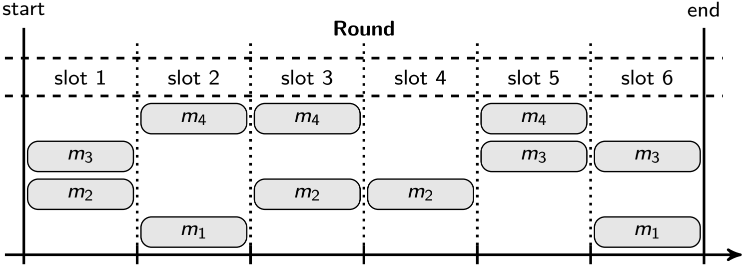
- More slots reduces parameter of Poisson/binomial distribution
- More slots reduces bit count per decoded slot

$\sum_{k=0}^{T} \frac{N}{J} \frac{k}{T} \log_2 (1 + JT \cdot \mathrm{SNR}) \, \mathrm{pmf}(k)$



Quest for Low-Complexity Unsourced MAC

Idea 1++: Slotted with Successive Interference Cancellation



Leveraging Prior Work on Uncoordinated Access

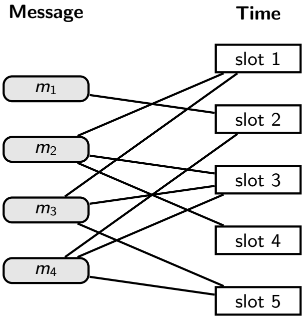
- K **uncoordinated** devices, each with one packet to send
- Time is **slotted**; transmissions occur within slots
- Successive interference cancellation

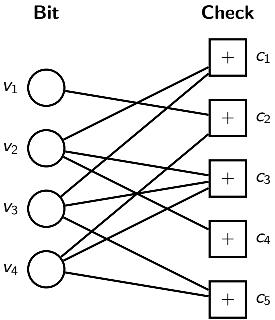
E. Casini, R. De Gaudenzi, and O. Del Rio Herrero. *Contention resolution diversity slotted ALOHA (CRDSA): An enhanced random access scheme for satellite access packet networks.* IEEE Trans on Wireless Comm, 2007

E Paolini, G Liva, M Chiani. *Coded slotted ALOHA: A graph-based method for uncoordinated multiple access.* IEEE Trans on Info Theory, 2015

Amenable to Graphical Representation

- Tanner graph representation for transmission scheme
- Variable nodes ↔ packets; check nodes ↔ received signals
- Message-passing decoder ↔ peeling decoder for erasure channel



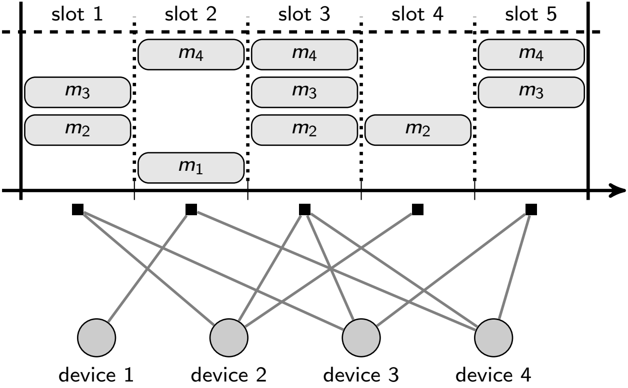


G. Liva. *Graph-based analysis and optimization of contention resolution diversity slotted ALOHA*. IEEE Trans on Comm, 2011

E. Paolini, G. Liva, and M. Chiani. *Coded slotted ALOHA: A graph-based method for uncoordinated multiple access*. IEEE Trans on Info Theory, 2015

Decoder – Peeling Algorithm

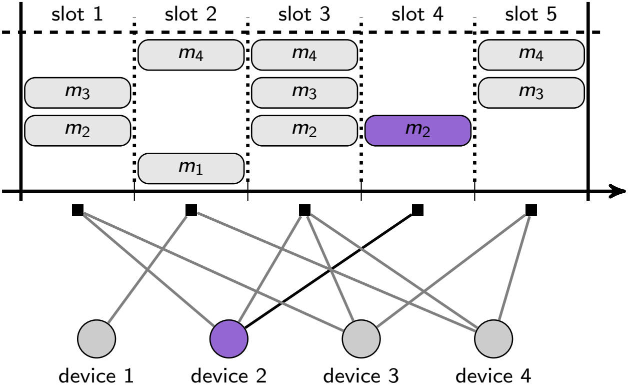
Joint decoding via successive interference cancellation



Instance of Random Access

Decoder – Peeling Algorithm

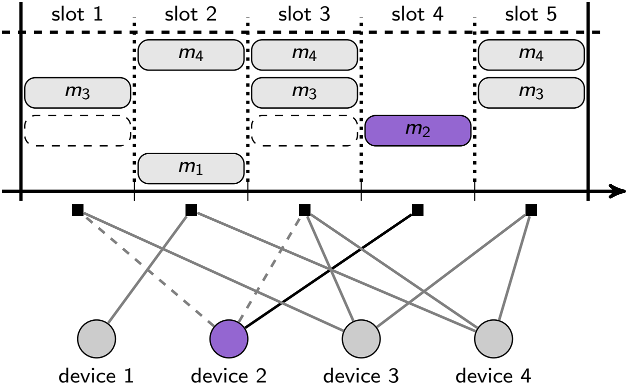
Joint decoding via successive interference cancellation



Step 1

Decoder – Peeling Algorithm

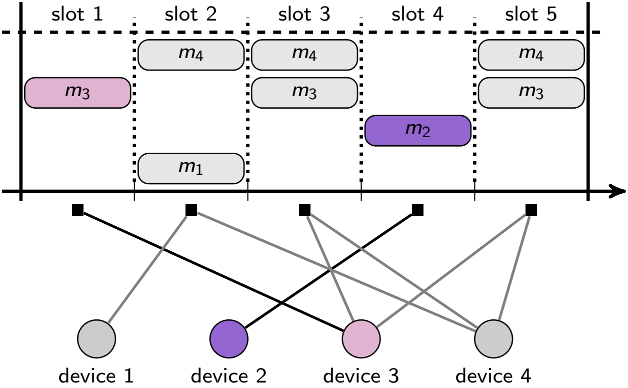
Joint decoding via successive interference cancellation



Step 1

Decoder – Peeling Algorithm

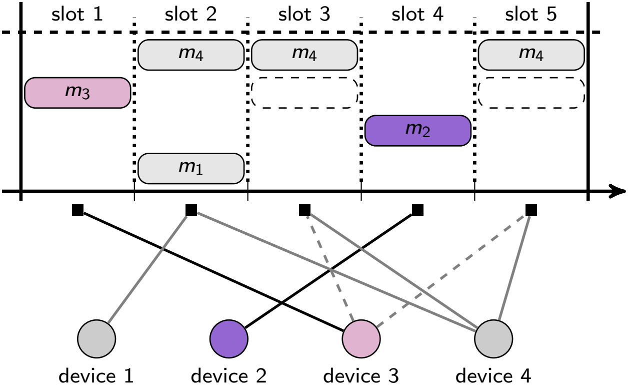
Joint decoding via successive interference cancellation



Step 2

Decoder – Peeling Algorithm

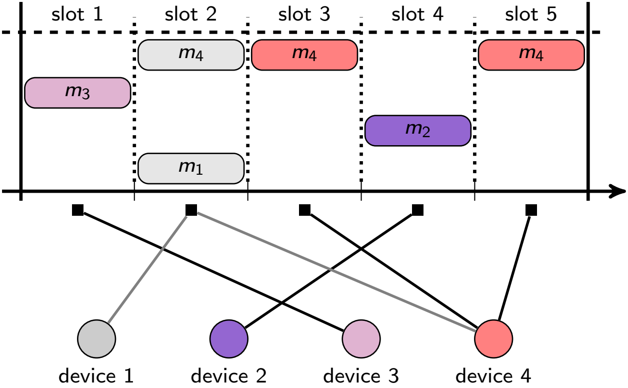
Joint decoding via successive interference cancellation



Step 2

Decoder – Peeling Algorithm

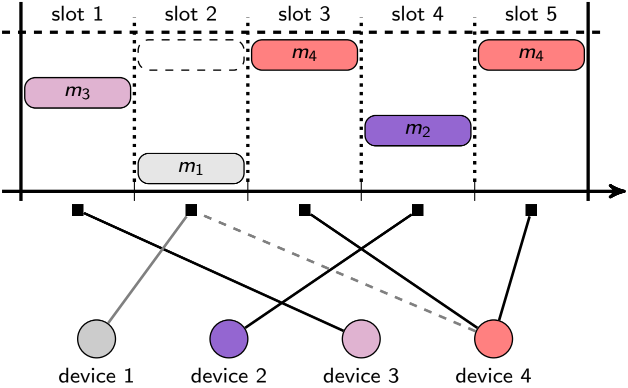
Joint decoding via successive interference cancellation



Step 3

Decoder – Peeling Algorithm

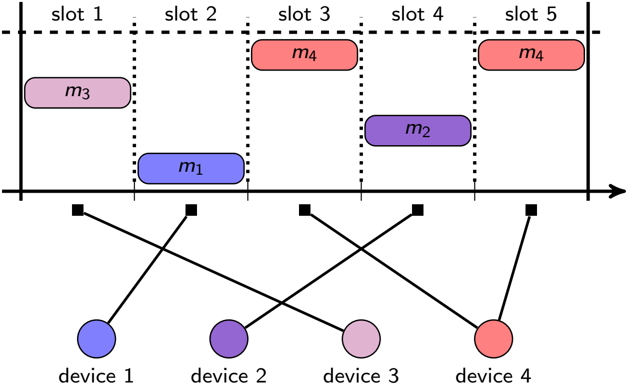
Joint decoding via successive interference cancellation



Step 3

Decoder – Peeling Algorithm

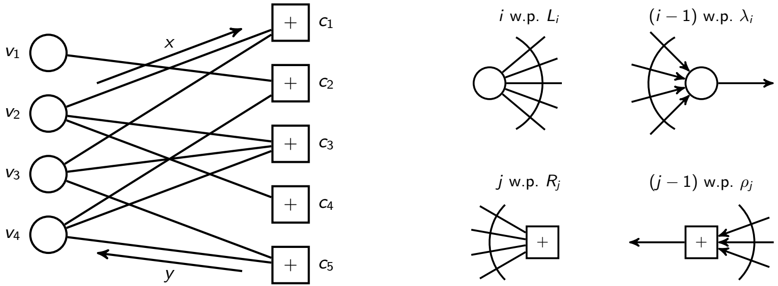
Joint decoding via successive interference cancellation



Step 4

Graphical Methods: Tools from Iterative Decoding

- $L(z) = \sum_i L_i z^i$ variable dist. from node
- $\lambda(z) = \sum_i \lambda_i x^{i-1} = L'(z)/L'(1)$ variable dist. from edge
- $R(z) = \sum_j R_j z^i$ check dist. from node
- $\rho(z) = \sum_j \rho_j x^{j-1} = R'(z)/R'(1)$ check dist. from edge



V. Zyablov, and M. Pinsker. *Decoding complexity of low-density codes for transmission in a channel with erasures.* Problemy Peredachi Informatsii, 1974

M. Luby, M. Mitzenmacher, A. Shokrollahi, and D. Spielman. *Efficient erasure correcting codes.* IEEE Trans on Info Theory, 2001

Graphical Methods: Tools from Iterative Decoding

- x: Prob. outgoing message from variable node erased
- y: Prob. outgoing message from check node erased

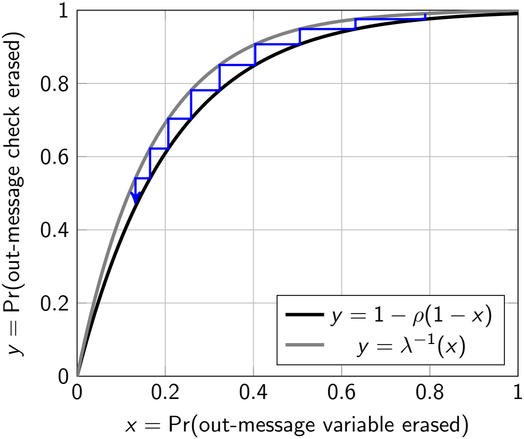
- Outgoing variable message is erased when all incoming check messages are erased

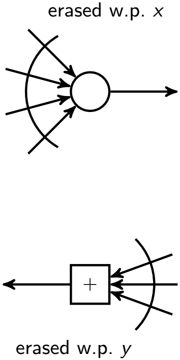
$$x = \mathrm{E}\left[y^{i-1}\right] = \lambda(y)$$

- Outgoing check message is erased when one incoming variable message is erased

$$y = \mathrm{E}\left[1-(1-x)^{j-1}\right] = 1-\rho(1-x)$$

Extrinsic Information Transfer (EXIT) Chart

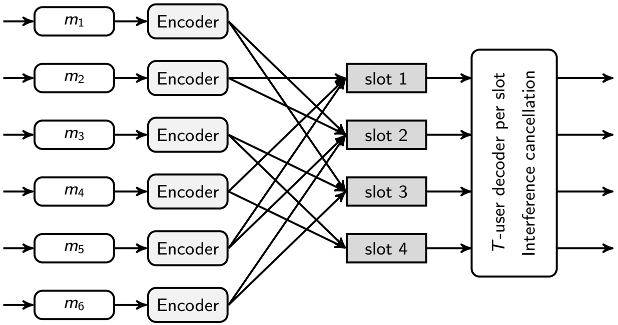




Step-by-Step Progression

$$y = 1 - \rho(1 - x) \qquad\qquad x = \lambda(y) \quad \text{(flipped)}$$

Unsourced MAC – SIC UGMAC Scheme

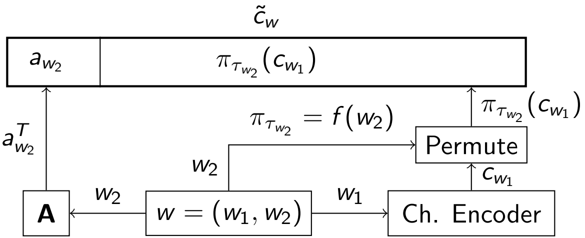


Key Features

- Schedule selected based on **message bits**
- Devices can transmit in multiple sub-blocks
- Scheme facilitates peeling decoder

A. Vem, K. Narayanan, J. Cheng, JFC. *A User-Independent Successive Interference Cancellation Based Coding Scheme for the Unsourced Random Access Gaussian Channel*. IEEE Trans on Comm, 2019

What Really Happens within Slot?



Implementation Notes

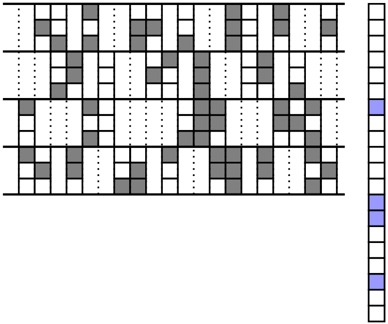
- Message is partitioned into two parts $w = (w_1, w_2)$
- Every device uses identical codebook built from spatially-coupled LDPC-type codes tailored to T-user real-adder channel
- w_2 dictate permutation on encoder and recovered through CS
- Non-negative ℓ_1-regularized LASSO

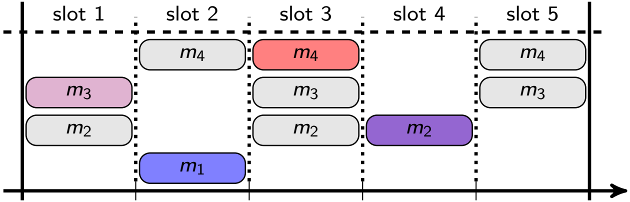
A. Vem, K. Narayanan, J. Cheng, JFC. *A User-Independent Successive Interference Cancellation Based Coding Scheme for the Unsourced Random Access Gaussian Channel*. IEEE Trans on Comm, 2019

Limitations of Sparsifying Collisions

Drawbacks of Slots

- Stochastic binning and expectation of concave rewards
- Second order dispersion effects comes into play in FBL
- Energy expended solely to resolving collisions
- Gray slots are discarded during decoding process (60%)



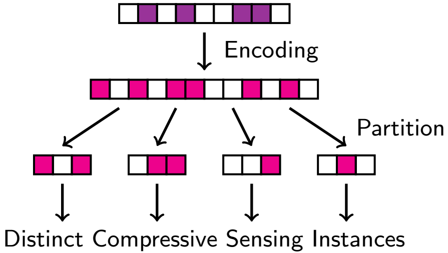


Part III

Quest for Low-Complexity: Coded Compressed Sensing

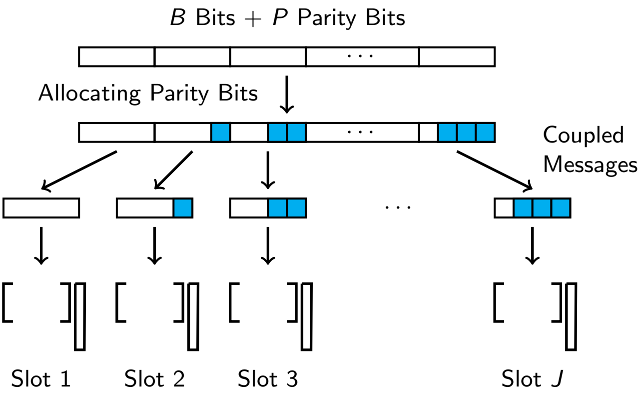
Quest for Low-Complexity Unsourced MAC

Idea 2: Divide and Conquer Information Bits



- Split problem into sub-components suitable for CS framework
- Get lists of sub-packets, one list for every slot
- Stitch pieces of one packet together using error correction

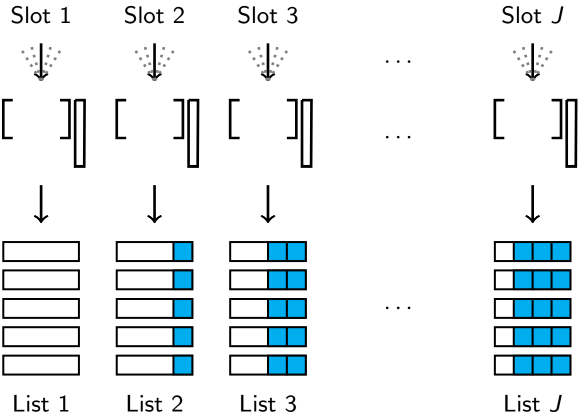
Coded Compressive Sensing – Device Perspective



- Collection of J CS matrices and 1-sparse vectors
- Each CS generated signal is sent in specific time slot

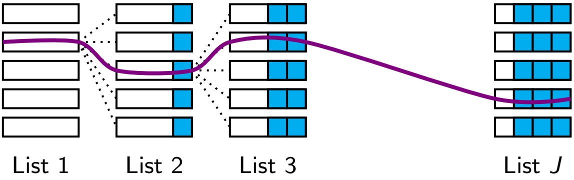
V. Amalladinne, A. Vem, D. Soma, K. R. Narayanan, JFC. *Coupled Compressive Sensing Scheme for Unsourced Multiple Access*. ICASSP 2018

Coded Compressive Sensing – Multiple Access



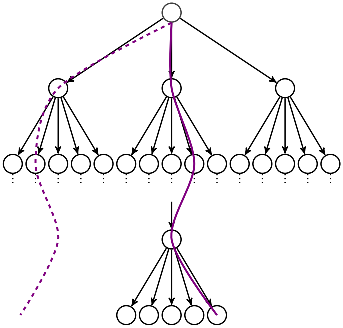
- J instances of CS problem, each solved with non-negative LS
- Produces J lists of K decoded sub-packets (with parity)
- Must piece sub-packets together using tree decoder

Coded Compressive Sensing – Stitching Process

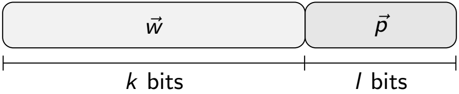


Tree Decoding Principles

- Every parity is linear combination of bits in preceding blocks
- Late parity bits offer better performance
- Early parity bits decrease decoding complexity
- Correct fragment is on list



Coded Compressive Sensing – Understanding Parity Bits



- Consider binary information vector $\vec{w}$ of length k
- Systematically encoded using generator matrix G, with $\vec{p} = \vec{w}G$
- Suppose alternate vector $\vec{w}_{\mathrm{r}}$ is selected at random from $\{0,1\}^k$

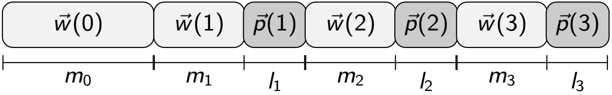
Lemma

Probability that randomly selected information vector $\vec{w}_{\mathrm{r}}$ produces same parity sub-component is given by

$$\Pr(\vec{p} = \vec{p}_{\mathrm{r}}) = 2^{-\operatorname{rank}(G)}$$

Proof: $\{\vec{p} = \vec{p}_{\mathrm{r}}\} = \{\vec{w}G = \vec{w}_{\mathrm{r}}G\} = \{\vec{w} + \vec{w}_{\mathrm{r}} \in \operatorname{nullspace}(G)\}$

Coded Compressive Sensing – General Parity Bits



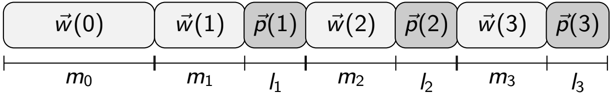
- True vector $(\vec{w}_{i_0}(0), \vec{w}_{i_0}(1), \vec{w}_{i_0}(2), \vec{w}_{i_0}(3))$
- Consider alternate vector with information sub-block $(\vec{w}_{i_0}(0), \vec{w}_{i_1}(1), \vec{w}_{i_2}(2), \vec{w}_{i_3}(3))$ pieced from lists
- To survive stage 3, candidate vector must fulfill parity equations

$$\left(\vec{w}_{i_0}(0) - \vec{w}_{i_1}(0)\right) \begin{bmatrix} G_{0,0} \end{bmatrix} = \vec{0}_{1 \times l_1}$$

$$\left(\vec{w}_{i_0}(0) - \vec{w}_{i_2}(0), \vec{w}_{i_1}(1) - \vec{w}_{i_2}(1)\right) \begin{bmatrix} G_{0,1} \\ G_{1,1} \end{bmatrix} = \vec{0}_{1 \times l_2}$$

$$\left(\vec{w}_{i_0}(0) - \vec{w}_{i_3}(0), \vec{w}_{i_1}(1) - \vec{w}_{i_3}(1), \vec{w}_{i_2}(2) - \vec{w}_{i_3}(2)\right) \begin{bmatrix} G_{0,2} \\ G_{1,2} \\ G_{2,2} \end{bmatrix} = \vec{0}_{1 \times l_3}$$

Coded Compressive Sensing – General Parity Bits



- When indices are not repeated in $(\vec{w}_{i_0}(0), \vec{w}_{i_1}(1), \vec{w}_{i_2}(2), \vec{w}_{i_3}(3))$, probability is governed by

$$\operatorname{rank}\left(\begin{bmatrix} G_{0,0} & G_{0,1} & G_{0,2} \\ \mathbf{0} & G_{1,1} & G_{1,2} \\ \mathbf{0} & \mathbf{0} & G_{2,2} \end{bmatrix}\right)$$

- But, when indices are repeated, sub-blocks may disappear

$$\operatorname{rank}\left(\begin{bmatrix} G_{0,0}\mathbf{1}_{\{i_1 \neq i_0\}} & G_{0,1}\mathbf{1}_{\{i_2 \neq i_0\}} & G_{0,2}\mathbf{1}_{\{i_3 \neq i_0\}} \\ \mathbf{0} & G_{1,1}\mathbf{1}_{\{i_2 \neq i_1\}} & G_{1,2}\mathbf{1}_{\{i_3 \neq i_1\}} \\ \mathbf{0} & \mathbf{0} & G_{2,2}\mathbf{1}_{\{i_3 \neq i_2\}} \end{bmatrix}\right)$$

Allocating Parity Bits (approximation)

- l_i: # parity bits in sub-block $i \in 2, \ldots, J$,
- L_i: # erroneous paths that survive stage $i \in 2, \ldots, J$,
- Complexity C_{tree}: # nodes on which parity check constraints verified

Expressions for $\mathbb{E}[L_i]$ and C_{tree}

- $L_i | L_{i-1} \sim B((L_{i-1}+1)K - 1, p_i)$, $p_i = 2^{-l_i}$, $q_i = 1 - p_i$

$$\begin{aligned}\mathbb{E}[L_i] &= \mathbb{E}[\mathbb{E}[L_i | L_{i-1}]] \\ &= \mathbb{E}[((L_{i-1}+1)K - 1)p_i] \\ &= p_i K \mathbb{E}[L_{i-1}] + p_i(K-1) \\ &= \sum_{r=1}^{i} K^{i-r}(K-1) \prod_{j=r}^{i} p_j\end{aligned}$$

- $C_{\mathrm{tree}} = K + \sum_{i=1}^{J-2} [(L_i + 1)K]$
- $\mathbb{E}[C_{\mathrm{tree}}]$ can be computed using the expression for $\mathbb{E}[L_i]$

Optimization of Parity Lengths

- l_i: # parity bits in sub-block $i \in 2, \ldots, J$,
- L_i: # erroneous paths that survive stage $i \in 2, \ldots, J$,

(Relaxed) Geometric Programming Optimization

$$\begin{aligned}
\underset{(l_2,\ldots,l_J)}{\text{minimize}} \quad & \mathbb{E}[C_{\text{tree}}] & \\
\text{subject to} \quad & \Pr(L_J \geq 1) \leq \varepsilon_{\text{tree}} & \text{Erroneous Paths} \\
& \sum_{i=2}^{J} l_i = M - B & \text{Total \# Parity Bits} \\
& l_i \in \{0, \ldots, N/J\} \quad \forall\, i \in 2, \ldots, J & \text{Integer Constraints}
\end{aligned}$$

- Can be solved using standard convex solver (e.g. CVX)

Choice of Parity Lengths

- $K = 200,\ J = 11,\ N/J = 15$

$\varepsilon_{\text{tree}}$	$\mathbb{E}[C_{\text{tree}}]$	Parity Lengths $l_2, \ldots, l_J$
0.006	Infeasible	Infeasible
0.0061930	3.2357×10^{11}	$0, 0, 0, 0, 15, 15, 15, 15, 15, 15$
0.0061931	3357300	$0, 3, 8, 8, 8, 8, 10, 15, 15, 15$
0.0061932	1737000	$0, 4, 8, 8, 8, 8, 9, 15, 15, 15$
0.0061933	926990	$0, 5, 8, 8, 8, 8, 8, 15, 15, 15$
0.0061935	467060	$1, 8, 8, 8, 8, 8, 8, 11, 15, 15$
0.0062	79634	$1, 8, 8, 8, 8, 8, 8, 11, 15, 15$
0.007	7357.8	$6, 8, 8, 8, 8, 8, 8, 8, 13, 15$
0.008	6152.7	$7, 8, 8, 8, 8, 8, 8, 8, 12, 15$
0.02	5022.9	$6, 8, 8, 9, 9, 9, 9, 9, 9, 14$
0.04	4158	$7, 8, 8, 9, 9, 9, 9, 9, 9, 13$
0.6378	3066.3	$9, 9, 9, 9, 9, 9, 9, 9, 9, 9$

Leveraging CCS Framework

CHIRRUP: a practical algorithm for unsourced multiple access

Robert Calderbank, Andrew Thompson

(Submitted on 2 Nov 2018)

Unsourced multiple access abstracts grantless simultaneous communication of a large number of devices (messages) each of which transmits (is transmitted) infrequently. It provides a model for machine-to-machine communication in the Internet of Things (IoT), including the special case of radio-frequency identification (RFID), as well as neighbor discovery in ad hoc wireless networks. This paper presents a fast algorithm for unsourced multiple access that scales to 2^{100} devices (arbitrary 100 bit messages). The primary building block is multiuser detection of binary chirps which are simply codewords in the second order Reed Muller code. The chirp detection algorithm originally presented by Howard et al. is enhanced and integrated into a peeling decoder designed for a patching and slotting framework. In terms of both energy per bit and number of transmitted messages, the proposed algorithm is within a factor of 2 of state of the art approaches. A significant advantage of our algorithm is its computational efficiency. We prove that the worst-case complexity of the basic chirp reconstruction algorithm is $\mathcal{O}[nK(\log_2 n + K)]$, where n is the codeword length and K is the number of active users, and we report computing times for our algorithm. Our performance and computing time results represent a benchmark against which other practical algorithms can be measured.

Subjects: **Signal Processing (eess.SP)**
Cite as: **arXiv:1811.00879 [eess.SP]**
(or **arXiv:1811.00879v1 [eess.SP]** for this version)

Submission history
From: Andrew Thompson [view email]
[v1] Fri, 2 Nov 2018 14:25:46 UTC (470 KB)

- Robert Calderbank, Andrew Thompson on arXiv
- Hadamard matrix based compressing scheme + CSS
- Ultra-low complexity decoding algorithm

Part IV

Quest for Low-Complexity: Hybrid and Emerging Paradigms

Extending CCS Framework

SPARCs for Unsourced Random Access

Alexander Fengler, Peter Jung, Giuseppe Caire

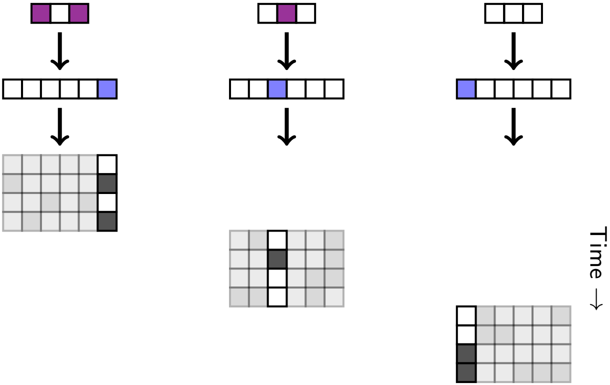
(Submitted on 18 Jan 2019)

This paper studies the optimal achievable performance of compressed sensing based unsourced random-access communication over the real AWGN channel. "Unsourced" means, that every user employs the same codebook. This paradigm, recently introduced by Polyanskiy, is a natural consequence of a very large number of potential users of which only a finite number is active in each time slot. The idea behind compressed sensing based schemes is that each user encodes his message into a sparse binary vector and compresses it into a real or complex valued vector using a random linear mapping. When each user employs the same matrix this creates an effective binary inner multiple-access channel. To reduce the complexity to an acceptable level the messages have to be split into blocks. An outer code is used to assign the symbols to individual messages. This division into sparse blocks is analogous to the construction of sparse regression codes (SPARCs), a novel type of channel codes, and we can use concepts from SPARCs to design efficient random-access codes. We analyze the asymptotically optimal performance of the inner code using the recently rigorized replica symmetric formula for the free energy which is achievable with the approximate message passing (AMP) decoder with spatial coupling. An upper bound on the achievable rates of the outer code is derived by classical Shannon theory. Together this establishes a framework to analyse the trade-off between SNR, complexity and achievable rates in the asymptotic infinite blocklength limit. Finite blocklength simulations show that the combination of AMP decoding, with suitable approximations, together with an outer code recently proposed by Amalladinne et. al. outperforms state of the art methods in terms of required energy-per-bit at lower decoding complexity.

Comments:	16 pages, 7 Figures
Subjects:	**Information Theory (cs.IT)**
Cite as:	**arXiv:1901.06234 [cs.IT]**
	(or **arXiv:1901.06234v1 [cs.IT]** for this version)

- Alexander Fengler, Peter Jung, Giuseppe Caire on arXiv
- Connection between CCS indexing and sparse regression codes
- Circumvent slotting under CCS and dispersion effects

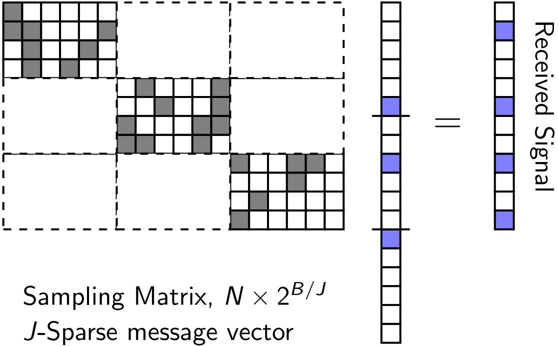
UMAC – CCS Revisited



Columns Are Possible Signals

- Bit sequence split into J fragments
- Each bit + parity block converted to index in $[1, 2^{M/J}]$
- Stack sub-codewords into $(N/J) \times 2^{M/J}$ sensing matrices

UMAC – CCS Unified CS Analogy

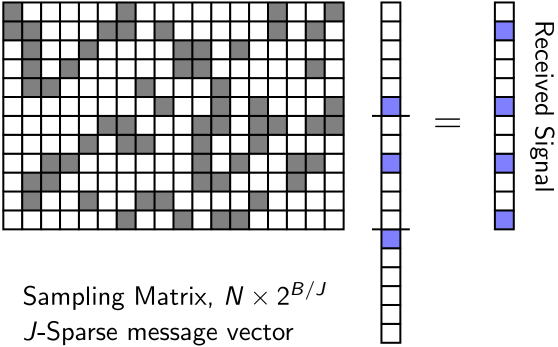


Sampling Matrix, $N \times 2^{B/J}$

J-Sparse message vector

- Initial non-linear indexing step
- Index vector is J-block sparse
- Connection to sparse regression codes

UMAC – Exact CS Analogy



- Complexity management comes from dimensionality reduction
- Use full sensing matrix on sparse regression codes
- Decode using low-complexity AMP

The Big MAC

A Joint Graph Based Coding Scheme for the Unsourced Random Access Gaussian Channel

Asit Pradhan, Vamsi Amalladinne, Avinash Vem, Krishna R. Narayanan, and Jean-Francois Chamberland
Department of Electrical and Computer Engineering, Texas A&M University

***Abstract*—This article introduces a novel communication paradigm for the unsourced, uncoordinated Gaussian multiple access problem. The major components of the envisioned framework are as follows. The encoded bits of every message are partitioned into two groups. The first portion is transmitted using a compressive sensing scheme, whereas the second set of bits is conveyed using a multi-user coding scheme. The compressive sensing portion is key in sidestepping some of the challenges posed by the unsourced aspect of the problem. The information afforded by the compressive sensing is employed to create a sparse random multi-access graph conducive to joint decoding. This construction leverages the lessons learned from traditional IDMA into creating low-complexity schemes for the unsourced setting and its inherent randomness. Under joint message-passing decoding, the proposed scheme offers superior performance compared to existing low-complexity alternatives. Findings are supported by numerical simulations.**

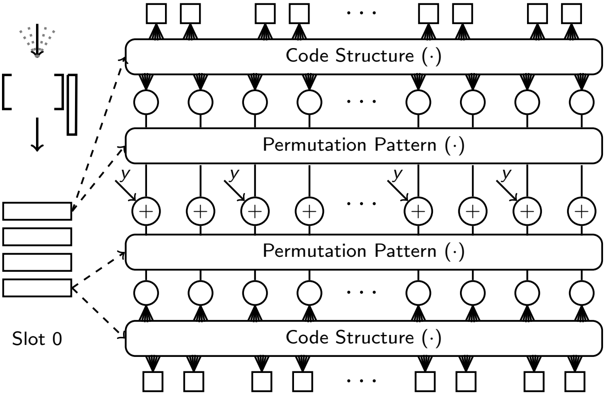
***Index Terms*—Communication, unsourced multiple access, joint-Tanner graph, belief propagation, compressive sensing.**

for the uncoordinated random access channel which is closely related to the unsourced MAC.

In [6], Vem et al. devise a coding scheme which uses a slotted structure. Therein, information bits are encoded into codewords using a combination of compressed sensing and low density parity check (LDPC) codes and these codewords are repeated across several slots. The decoder uses message passing decoding within each slot and employs successive interference cancellation across slots. More recently, in [7], Amalladinne et al. cast the unsourced MAC as a very large-dimensional compressive sensing problem. They then adopt a divide-and-conquer approach to obtain a pragmatic, low-complexity solution. In [8], Fengler et al. propose using the approximate message passing (AMP) algorithm as the inner decoder in combination with the outer decoder found in [7]. This latter scheme represents the current state-of-the-art in terms of error performance.

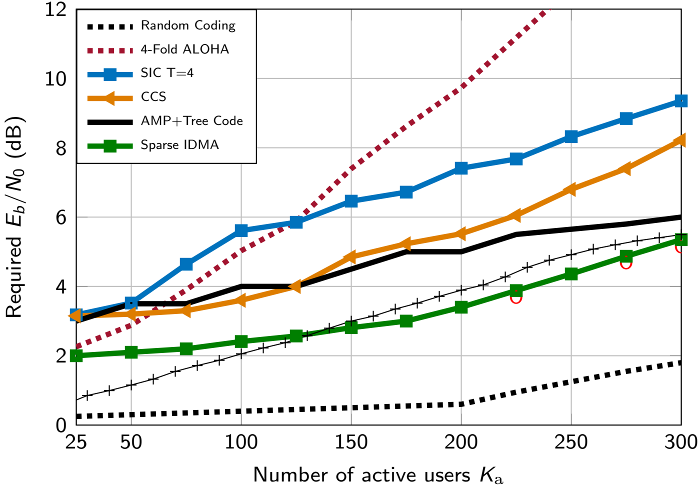
- A. Pradhan, V. Amalladinne, A. Vem, K. Narayanan, JFC
- IEEE Global Communications Conference, December 2019

Sparse IDMA



- Compressed sensing preamble with information bits
- Sparse random multi-access graph conducive to joint decoding.

Performance of Unsourced GMAC Schemes



Discussion – Unsourced Multiple Access Channel

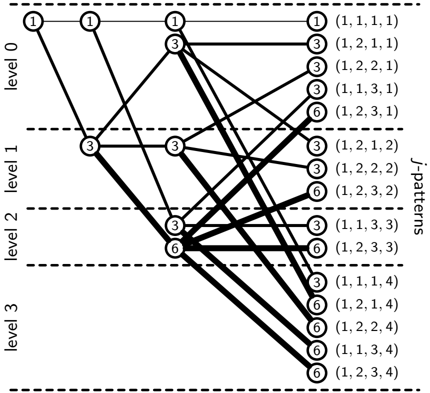
Summary

- Reviewed several frameworks for unsourced multiple access
- There are close connections between graph-based codes, compressive sensing, and UMAC
- There remains a gap from information-theoretic results
- Many theoretical and practical challenges exist

Current Approach

When carefully designed, single sparse joint Tanner graph that spans across all transmissions offers state-of-the-art performance

Questions?



Thank You!

This material is based upon work supported, in part, by NSF under Grant No. 1619085

This material is also based upon work support, in part, by Qualcomm Technologies, Inc., through their University Relations Program

Asynchronous UMAC

Asynchronous Neighbor Discovery Using Coupled Compressive Sensing

Vamsi K. Amalladinne, Krishna R. Narayanan, Jean-Francois Chamberland, Dongning Guo

(Submitted on 2 Nov 2018)

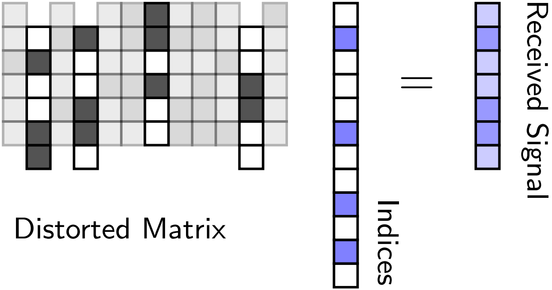
The neighbor discovery paradigm finds wide application in Internet of Things networks, where the number of active devices is orders of magnitude smaller than the total device population. Designing low-complexity schemes for asynchronous neighbor discovery has recently gained significant attention from the research community. Concurrently, a divide-and-conquer framework, referred to as coupled compressive sensing, has been introduced for the synchronous massive random access channel. This work adapts this novel algorithm to the problem of asynchronous neighbor discovery with unknown transmission delays. Simulation results suggest that the proposed scheme requires much fewer transmissions to achieve a performance level akin to that of state-of-the-art techniques.

Subjects: **Signal Processing (eess.SP)**; Information Theory (cs.IT)
Cite as: **arXiv:1811.00687 [eess.SP]**
(or **arXiv:1811.00687v1 [eess.SP]** for this version)

Building Robust Sensing Matrices

- Extending CCS framework with low sample complexity
- Addressing issues pertaining to asynchrony
- Context of neighbor discovery

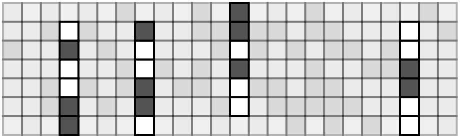
Dealing with Jitter and Asynchrony



Asynchronous Signals

- $\vec{y} = \tilde{A}\tilde{\vec{x}} + \vec{z}$ with $\|\vec{x}\|_0 = K$
- $\tilde{A} \in \mathbb{C}^{(n+\mathcal{T})\times 2^B}$ unknown due to unknown random delays
- Max delay $\mathcal{T}$ known to the decoder

Expanded Codebook through Sensing Matrix

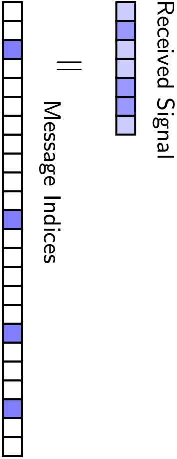


Expanded Codebook **A**

$(n + \mathcal{T}) \times 2^B(\mathcal{T} + 1)$ matrix

Accounts for all possible delays

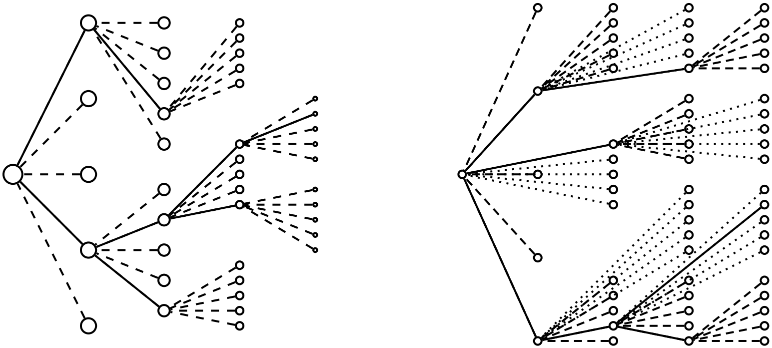
K out of $2^B(\mathcal{T} + 1)$ sparse



- Computational complexity of CS solvers: $\mathcal{O}(\mathrm{poly}(2^B(\mathcal{T} + 1)))$

Hybrid Methods and Alternatives

Intermittent CCS



- Trading off flexibility and complexity