# Combining Hard and Soft Decoders for Hypergraph Product Codes

# Antoine Grospellier<sup>1</sup> ; Lucien Grouès<sup>1</sup>; Anirudh Krishna<sup>2</sup>; Anthony Leverrier<sup>1</sup>

<sup>1</sup>INRIA Paris, <sup>2</sup>Université de Sherbrooke

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### Hypergraph product codes (Tillich, Zemor, 2009)

A powerful quantum code construction

- ${\color{black}\bullet}$  2 classical codes  ${\color{black}\to}$  1 CSS code
- ${\scriptstyle \bullet}$  repetition codes  $\rightarrow$  toric code
- LDPC codes  $\rightarrow$  LDPC code
- $[n, \Theta(n), \Theta(n)] \rightarrow [[N, \Theta(N), \Theta(\sqrt{N})]]$  with  $N = \Theta(n^2)$
- expander codes  $\rightarrow$  fault tolerance with **constant overhead** (Fawzi and al., arXiv:1808.03821)

Yet we don't know how to decode them well :

- Small set flip decoder : proved theoretically to decode quantum expander codes under very low error rates
- Belief propagation decoder : works very well in the classical case but **not** in the quantum case

Our idea : combine both algorithms

### Small set flip (SSF) : a hard decoder

Generalisation of the classical bit flip :

decreases the syndrome weight by flipping small sets of qubits

- With quantum expander codes  $\rightarrow$  **constant overhead** fault tolerance
- Computation time  $\rightarrow \Theta(N)$
- $\bullet$  Theoretically  $\rightarrow$  decodes under very low physical error rate
- In practice  $\rightarrow$  decodes up to 4.6% on some LDPC hypergraph product codes (Grospellier, Krishna, arXiv:1810.03681)

### SSF: simulations (Grospellier, Krishna, arXiv:1810.03681)



- Product of a random 5,6-regular LDPC code with itself
- The threshold is around 4.6%

### Belief propagation (BP) : a soft decoder



- Computes for each bit  $\mathbb{P}(faulty|syndrome)$ 
  - Based on the Tanner graph
  - Message passing algorithm
  - Number of rounds = browsing depth
  - Exact on trees

#### Widely used in the classical case

- Tanner graph with large girth
   → good approximation
- $\bullet \,$  computes all probabilities at once  $\rightarrow \, {\rm very} \,$  fast

But limited by quantum specifics (Poulin and al., arXiv:0801.1241)

- many cycles of length 4  $\rightarrow$  girth too small
- code degeneracy
  - $\rightarrow$  computes wrong probabilities



#### Our contribution

#### Introducing BP+SSF :

- first decreases the size of the error with BP
- then corrects the residual error using SSF

### Our simulations results

Independent X-Z noise $(p_x = p_z)$											
Code	Rate	Stabilizers weight	Algorithm	Threshold							
Toric code	0%	4	MWPM	10.5%							
4,5-hyperbolic surface code	10%	4 and 5	MWPM	2.5%							
5,6 HGP code	1.6%	11	SSF	pprox 4.6%							
3,4 HGP code	4%	7	BP+SSF	pprox 7.5%							

[Kovalev and al., arXiv:1804.01950] Threshold around 7% on 3,4 HGP codes using estimated minimum weight decoder

[Panteleev and al., arXiv:1904.02703] Very good results on small cyclic HGP codes using BP+OSD (ordered statistical decoder)

4,5-hyperbolic

surface code 3,4 HGP code 10%

4%

4 and 5

7

### Our simulations results

	Independent X-Z noise $(p_x = p_z)$										
	Code		Rate	Stabilizers weight		Algorithm		Threshold			
	Toric code 4,5-hyperbolic surface code 5,6 HGP code 3,4 HGP code		0%		4	MWPM		10.5%		1	
			10%	4 and 5		MWPM		2.5%			
			1.6%	11		SSF		pprox 4.6%			
			4%	7		BP+SSF		pprox 7.5%			
Independent X-Z noise with syndrome errors ( $p_x = p_z = p_{check}$ )											
	Code	ode Rate Stabilizers weight		Algorithm		т	Threshold		igle iot		
T	oric code	0%	4	4		MWPM		2.9%	Ν	lo	

**MWPM** 

 $(BP)^{T}(BP+SSF)$ 

No

Yes

1.3%

 $\approx 3\%?$ 

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2 Noiseless syndrome





### Underlying classical code design

Several ways to build regular LDPC codes families :

- Random codes :
  - BP needs Tanner graphs with few small cycles
  - Progressive edge growth algorithm (PEG)

 $\rightarrow$  graphs with large girth very fast

- Random local modifications + adapted scoring system
   → slower algorithm but better results
- BP + small **cyclic codes** hypergraph product promising (Panteleev and al., arXiv:1904.02703v1)
- Quasi-cyclic codes are more general

We will use random 3,4-regular LDPC codes



#### Classical code construction

2 Noiseless syndrome



#### 4 Summary

### Error model and simulation protocol

Error model : independent X-Z errors with  $p_x = p_z = p$ 

- $\bullet\,$  Errors corrected independently  $\to\,$  graph girth length = 8
- Enough to simulate only X errors

#### Simulation protocol

- 1. We flip each qubit with probability  $p \rightarrow$  gives the error
- 2. We compute the syndrome
- 3. We run the decoder on the syndrome  $\rightarrow$  gives the correction
- 4. (error  $\Leftrightarrow$  correction)  $\longrightarrow$  decoder succeeded

### BP: simulations



- Performance worsen as we increase the code size
- No threshold found above 0.5%

### Common BP failing behaviour



- $\bullet~{\sf BP}$  doesn't converge  $\rightarrow$  starts to oscillate
- maximum likelihood ⇔ minimum syndrome weight

### Combining BP with SSF

#### Almost no logical error $\rightarrow$ BP often can't reach a codeword

- Yet BP decreases a lot the syndrome weight
   → use SSF to close the gap
- Often high amplitude oscillations
   → we shouldn't stop BP at an arbitrary time
- Syndrome weight looks relevant
  - ightarrow stop at its first local minimum
- Why the first minimum ?
  - easy to find and fast to compute
  - $\bullet~$  less rounds  $\rightarrow$  smaller depth  $\rightarrow~$  sees less cycles

### **BP+SSF**: simulation



- Threshold around 7.5% of physical errors probability
- Big improvement compared to the two algorithms alone

### Improving the BP stopping condition

The stopping condition is vulnerable to bad first local minimum

How to solve it :

- Big fixed number of rounds but come back to the best state
- The best state can be the one with :
  - the smallest syndrome weight
  - the highest likelihood

Both tried with 100 rounds  $\rightarrow$  overall unsatisfying results :

- improvement only for small codes
- curves having sweet values and crossing several times





2 Noiseless syndrome



### 4 Summary

### From noiseless to noisy syndrome

Fault tolerance context  $\rightarrow$  noisy syndrome measurement

- Are our algorithms still working in that case ?
- It might be needed to adapt them consequently
- We can't evaluate the performances the same way

Model used by Breuckmann and al. (arXiv:1703.00590):

- Several rounds of faulty syndrome and one last exact :
  - At the end of the calculus the information is classical and we can measure exactly the syndrome
- Unreliable syndrome measurement  $\rightarrow$  most algorithms need to repeat the measurement many times at each round (  $\sqrt{n}$  for the toric code)
- In our case only one measurement needed  $\rightarrow$  **single-shot** property

### How to evaluate the performance

Same method as Brown, Nickerson, Browne (arXiv:1503.08217) :

- The threshold depends on the number of faulty rounds (T)
- $\bullet$  Under this limit : larger codes  $\rightarrow$  information lasts longer
- The dependence on T is not trivial

 $\rightarrow$  we need to do a fitting of the curves (not done yet)

### Simulations protocol

Algorithm:  $(D_1)^T D_2$ 

input : A codeword

output: Whether we managed to conserve the codeword

for i=1 to T do

Apply on each qubit X error with probability p

Compute syndrome and flip each bit with probability p

Run decoder  $D_1$  on syndrome assuming the noise is still IID

Apply correction

#### end

Apply on each qubit X error with probability p

Compute syndrome

Run decoder  $D_2$  on syndrome assuming the noise is still IID

Apply correction

Succeeds if the new word is equivalent to the input codeword

### SSF and BP for the noisy syndrome case

#### Adaptation of the SSF

Acts as if the syndrome measurements were perfect :

- Tries to reduce the weight of the noisy syndrome
- Its guess on the syndrome error are the unsatisfied checks left



### $\mathsf{BP}{+}\mathsf{SSF}$ for the noisy syndrome case

- BP computes the probability of the new bits to be equal to 1  $\rightarrow$  this gives us a guess for the syndrome error
- BP applies both the qubits and syndrome correction
   → the SSF gets the *corrected* new syndrome as input
- Contrary to SSF the syndrome error guess of BP isn't equal to the unsatisfied checks left

# $(BP+SSF)^{T}(BP+SSF)$



- Too early to conclude but promising
- The limit looks above 2.5%

# $(BP)^{T}(BP+SSF)$



- Too early to conclude but even better results
- The limit should be around 3%

# $(BP)^{T}(BP+SSF) > (BP+SSF)^{T}(BP+SSF)$

#### Possible explanation

- BP isn't good at guessing the syndrome error : above 2.5% BP increases the weight of the syndrome error
- SSF doesn't take into account the syndrome errors
   → may take us very far from valid codewords
- BP takes these errors into account
  - ightarrow keeps us in the good area
- SSF still needed once the syndrome measurement is exact  $\rightarrow$  closes the gap

Gives better results with faster computation !





2 Noiseless syndrome





### Summary

#### What we did :

```
Heuristic combining BP and SSF
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- Noiseless syndrome case  $\rightarrow$  far better than SSF : better rate (1.6%  $\rightarrow$  4%) and threshold (4.6%  $\rightarrow$  7.5%)
- Noisy syndrome case  $\rightarrow$  started to get promising results : threshold  $\approx$  3%?

#### What's next?

- Try to improve our quantum codes  $\rightarrow$  e.g. use 2 different classical codes to deal with depolarising channel
- better version of BP for quantum LDPC codes (taking degeneracy in consideration)  $\rightarrow$  open question