# Constrained Coding Techniques for Advanced Data Storage Devices

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# Outline

- Digital recording channel model
- Constrained codes (track-oriented)
  - Bit-stuffing, bit-flipping, symbol-sliding
  - Information theory of constrained codes
- Constrained codes (page-oriented)
  - Bit-stuffing in 2-dimensions
- Concluding remarks

# **Digital Recording Channel**



## Hard Disk Drive – Magnetic Transitions



78µm

Courtesy of Fred Spada

32µm

## **CD** - Pits and Lands



#### Linear Density: 39.4 kb/in or 1.55 bits/µm



<b>T3</b>	0	833 nm
<b>T4</b>	$\bigcirc$	1111 nm
T5	$\bigcirc$	1388 nm
<b>T6</b>	$\bigcirc$	1666 nm
<b>T7</b>	$\bigcirc$	1944 nm
<b>T8</b>		2221 nm
Т9	$\bigcirc$	2499 nm
T10		2777 nm
T11		3054 nm
Note: this is at 1.2 m/sec, with a channel bit size of 277.662 nm GN		

#### Courtesy of Giesbert Nijhuis

## (d,k) Runlength-Limited Constraints

Modulation codes for digital recording channels

 *A* = minimum number of 0's between 1's

 *k* = maximum number of 0's between 1's



• CD uses (d,k)=(2,10); Disk Drive uses (d,k)=(0,4)

# **Constrained Coding**

## • Problem:

- How can we transform unconstrained binary data streams into (*d*,*k*) constrained binary code streams?
- Issues:
  - Invertibility of transformation (unique decodability)
  - > Rate R, i.e., average ratio of # data bits to # code bits
  - Complexity of encoding and decoding operations

# **Bit-Stuffing Encoder**

- Encoder "stuffs" extra bits into data stream, as needed to enforce the (*d*,*k*) constraint:
  - > Stuffs d **0**'s after every data 1
  - > Keeps track of total number of consecutive 0's
  - > Stuffs a 1 and d 0's after a runlength of k 0's



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#### Encoder

# Data sequence: 110000101

Code sequence:

Decoder

Code sequence:

#### Encoder

# Data sequence: 110000101 Code sequence: 1

Decoder

Code sequence:

#### Encoder

# Data sequence: 110000101

Code sequence: 10

Decoder

Code sequence:

#### Encoder

# Data sequence: 110000101

Code sequence: 101

Decoder

Code sequence:

- Data sequence: 110000101
- Code sequence: 1010
- Decoder
- Code sequence:
- Data sequence:

- Data sequence: 110000101
- Code sequence: 10100
- Decoder
- Code sequence:
- Data sequence:

- Data sequence: 110000101
- Code sequence: 101000
- Decoder
- Code sequence:
- Data sequence:

#### Encoder

# Data sequence: 110000101

Code sequence: 10100010

#### Decoder

Code sequence:

#### Encoder

Data sequence: 110000101

Code sequence: 101000100

Decoder

Code sequence:

#### Encoder

Data sequence: 110000101

Code sequence: 1010001000

Decoder

Code sequence:

#### Encoder

# Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0

Decoder

Code sequence:

- Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1
- Decoder
- Code sequence:
- Data sequence:

#### Encoder

# Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 1 0

Decoder

Code sequence:

#### Encoder

# Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0

Decoder

Code sequence:

#### Encoder

# Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 1 0 1

Decoder

Code sequence:

#### Encoder

- Data sequence: 110000101
- Code sequence:
   10100010010101010

Decoder

Code sequence:

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

Code sequence: 10100010001010010 Data sequence:

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

#### Encoder

Data sequence:110000101Code sequence:1010001000101010010

#### Decoder

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

#### Encoder

Data sequence:110000101Code sequence:1010001000101010010

#### Decoder

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

#### Encoder

Data sequence:110000101Code sequence:1010001000101010010

#### Decoder

#### Encoder

Data sequence:110000101Code sequence:1010001000101010010

#### Decoder

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder
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Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

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#### Decoder

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#### Decoder

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Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

Code sequence:1010001000101010010Data sequence:1010001000100010100010

#### Encoder

Data sequence:1 1 0 0 0 0 1 0 1Code sequence:1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 1 0

#### Decoder

Code sequence:1010001000101010010Data sequence:101000100010001010010

# **Biased Bits May Be Better!**

- For large values of *k*−*d*, it seems like bit-stuffing may be more efficient if the data stream is properly biased, with fewer 1's than 0's, since 1's always generate *d* stuffed 0's.
- How can we transform a sequence of independent unbiased (i.e., fair) coin flips, where

$$Pr(0) = Pr(1) = \frac{1}{2}$$

into a sequence of independent biased (i.e., not fair) coin flips, where, for  $p \neq \frac{1}{2}$ 

$$Pr(0) = p$$
$$Pr(1) = 1 - p$$

# **Distribution Transformer**

• A "distribution transformer" maps an unbiased data stream to a biased stream invertibly:

• There is a rate penalty, given by the binary entropy function:

$$h(p) = -p \log p - (1-p) \log (1-p) \le 1$$

### **Binary Entropy Function**

$$h(p) = -p \log p - (1-p) \log (1-p)$$



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# **Distribution Transformer Implementation**

- A "distribution transformer" can be implemented by using the decoder of a source code that compresses a *p*-biased sequence of bits with compression ratio 1/h(p) to 1.
- In practice, the transformer could be based upon stream-oriented arithmetic coding techniques and achieve a rate very close to h(p).



# **Bit-Stuffing Algorithm Flow**



# Bit-Stuffing Rate vs. Bias



# **Bit-Flipping**

 After k-1 consecutive 0's, a 1 seems preferable to another 0: 1 generates d stuffed 0's, whereas a 0 generates a stuffed 1 along with d stuffed 0's.



• No need for a second distribution transformer if we just complement the next biased bit at state k-1, i.e.  $p_2=1-p_1$ 

# **Bit-Flipping**

• After *k*-1 consecutive 0's, a 1 seems preferable to another 0: 1 generates *d* stuffed 0's, whereas a 0 generates a stuffed 1 along with *d* stuffed 0's.



• No need for a second distribution transformer if we just "flip" the next biased bit at state k-1, i.e.  $p_2=1-p_1$ 

# Bit-Flipping vs. Bit-Stuffing

• Theorem [Aviran et al., 2003]: Bit-flipping achieves average rate strictly higher than bit-stuffing for  $d \ge 1$ and  $d+2 \le k < \infty$ .

(Also, starting the bit-flipping at state k-1 is optimal.)

• Question: Can we improve on bit-flipping, at least for some (*d*,*k*) constraints, still using only one distribution transformer?

YES! (e.g., symbol-sliding [Yogesh S. et al., 2004])

- Can we determine the absolute highest possible coding rate of (*d*,*k*) codes?
  YES! [Shannon, 1948]
- Can we achieve it (or get arbitrarily close) using stuffing, flipping, sliding, multiple transformers, or other coding methods?

YES! [Shannon, 1948], and his followers...

### Claude E. Shannon



Claude Elwood Shannon 1916 - 2001



Shannon Statue – CMRR

### The Inscription on the Statue

# **CLAUDE ELWOOD SHANNON**

1916 – 2001

FATHER OF INFORMATION THEORY

HIS FORMULATION OF THE MATHEMATICAL THEORY OF COMMUNICATION PROVIDED THE FOUNDATION FOR THE DEVELOPMENT OF DATA STORAGE AND TRANSMISSION SYSTEMS THAT LAUNCHED THE INFORMATION AGE.

**DEDICATED OCTOBER 16, 2001** 

EUGENE DAUB, SCULPTOR

## Discrete Noiseless Channels (Constrained Systems)

• A constrained system S is the set of sequences generated by walks on a labeled, directed graph G.

Telegraph channel constraints [Shannon, 1948]



# **Constrained Codes and Capacity**

- Shannon showed that the number of length-n constrained sequences is approximately  $2^{Cn}$ .
- The quantity *C* is called the capacity of the constrained system.

Theorem [Shannon,1948] : If there exists a decodable code at rate R = m/n from binary data to S, then R *WC*.

Theorem [Shannon,1948] : For any rate R=m/n < Cthere exists a block code [*look-up table*] from binary data to *S* with rate *km:kn*, for some integer *k D1*.

# **Computing Capacity**

- Shannon also showed how to compute the capacity *C*.
- For (d,k) constraints,  $C_{d,k} = \log \lambda_{d,k}$ , where  $\lambda_{d,k}$  is the largest real root of the polynomial

$$f_{d,k}(x) = x^{k+1} - x^{k-d} - \dots - x - 1$$
, for  $k < \infty$ 

• For  $(d,\infty)$  constraints, use the relation [Ashley et al. 1987]:

$$C_{d,\infty} = C_{d-1, 2d-1}, \text{ for } d \ge 1.$$

# Achieving Capacity (sometimes...)

- Theorem [Bender-Wolf, 1993]: The bit-stuffing algorithm achieves capacity for (d,k)=(d,d+1) and  $(d,k)=(d,\infty)$ .
- Theorem [Aviran, et al., 2004]: The bit-flipping algorithm additionally achieves capacity for (*d*,*k*)=(2,4).
- Theorem [Yogesh S.-McLaughlin]: The symbol-sliding algorithm also achieves capacity for (d,k)=(d,2d+1).

# **Bit Stuffing Performance**

#### Relative Average Rate vs Parameter k



# Shannon Probabilities

- Shannon also determined the probabilities on the edges of the constraint graph that correspond to the highest achievable rate, i.e., that achieve capacity, in terms of  $\lambda$ .
- The constrained sequences are called "maxentropic."



# **Bit-Stuffing with Multiple Transformers**



Maxentropic encoder achieves capacity!

# The Formula on the "Paper"

Capacity of a discrete channel with noise [Shannon, 1948]

$$C = Max (H(x) - H_y(x))$$

For noiseless channel,  $H_y(x)=0$ , so:

$$C = Max H(x)$$



Capacity achieved by maximum entropy sequences

# Magnetic Recording Constraints

Runlength constraints ("finite-type": determined by finite list F of forbidden words)



0

Forbidden word F={11}



Forbidden words F={101, 010}

#### Spectral null constraints ("almost-finite-type")



Even



# **Practical Constrained Codes**



m bits

We want: high rate R=m/n low complexity

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### **Constrained Coding Theorems**

• Powerful coding theorems were motivated by the problem of constrained code design for magnetic recording.

Theorem[Adler-Coppersmith-Hassner, 1983]

- Let S be a finite-type constrained system. If  $m/n \leq C$ , then there exists a rate m:n sliding-block decodable, finite-state encoder.
- (Proof is constructive: "state-splitting algorithm.")

Theorem[Karabed-Marcus, 1988] Ditto if *S* is almost-finite-type. (Proof not so constructive...)

### **Two-Dimensional Constrained Systems**

- "Page-oriented" and "multi-track" recording technologies require 2-dimensional (2-D) constraints.
- Examples:
  - Holographic Storage InPhaseTechnologies
  - Two-Dimensional Optical Storage (TwoDOS) Philips
  - Patterned Magnetic Media Hitachi, Toshiba, …
  - > Thermo-Mechanical Probe Array IBM

### Holographic Recording



#### Array constraints:

- 2-D runlength limited
- 2-D non-isolated bit
- 2-D low-pass filter

### **TwoDOS**



#### Courtesy of Wim Coene, Philips Research

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### **2-D** Constrained Codes

- There is no comprehensive algorithmic theory for constructing encoders and decoders for 2-D constrained systems. (See, however, [Demirkan-Wolf, 2004] .)
- There is no known general method for computing the capacity of 2-D constraints.
- That being the case, let's try...

# 2-D bit-stuffing!

### **Constraints on the Integer Grid**

• 2-D (*d*,*k*) constraints satisfy the (*d*,*k*) constraint in rows and columns.

1	0	0	0	1	0	0
0	0	0	1	0	1	0
0	1	0	0	1	0	0
1	0	1	0	0	0	1
0	1	0	1	0	1	0
0	0	1	0	1	0	0
1	0	0	1	0	0	0

• $(d,k) = (1,\infty)$  constraint in rows and columns.

"Hard-Square Model"

#### 2-D Bit-Stuffing Encoder (Hard-Square Model)

• Biased sequence: 111000100100011000



Optimal bias Pr(0) = p = 0.6444

R(p) = 0.583056

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#### Enhanced Bit-Stuffing Encoder (Hard-Square Model)

• Use 2 source encoders, with parameters  $p_0$ ,  $p_1$ .



Optimal bias Optimal bias  $Pr(0) = p_0 = 0.671833$   $Pr(0) = p_1 = 0.566932$ 

 $R(p_1, p_2) = 0.587277$ 

### Capacity of 2-D (d,k) Constraints

- For 2-D (d,k) constraints, there is no known simple "formula" that lets us compute the capacity  $C^{d,k}$ .
- In fact, the only nontrivial (*d*,*k*) pairs for which  $C^{d,k}$ is known are those with zero capacity [Ashley-Marcus 1998], [Kato-Zeger 1999]:

$$C^{d,d+1} = 0$$
, for  $d \ge 1$ 

### **Capacity of Hard-Square Model**

• Sharp bounds on  $C^{1,\infty}$  have been computed:

 $0.587891161775 \le C^{1,\infty} \le 0.587891161868$ 

[Calkin-Wilf, 1998], [Nagy-Zeger, 2000]:

- Bit-stuffing encoder with one distribution transformer achieves rate R(p) = 0.583056 within 1% of capacity.
- Bit-stuffing encoder with two distribution transformers achieves rate  $R(p_1, p_2) = 0.587277$  within 0.1% of capacity.

### Bit-Stuffing Bounds on C<sup>d,∞</sup>

- Bit-stuffing encoders can also be extended to 2-D (d,∞) constraints.
- Bounds on the bit-stuffing encoder rate yield the best known lower bounds on  $C^{d,\infty}$  for d > 1 [Halevy, et al., 2004].
- Bit-stuffing can also be applied to 2-D constraints on the hexagonal lattice.
- Bounds on the bit-stuffing encoder rate yield the best known lower bounds on  $C^{d,\infty}_{hex}$  for d > 1 [Halevy, et al., 2004]

### Hard Hexagon Model

•  $(d,k)=(1,\infty)$  constraints on the hexagonal lattice



### Hard-Hexagon Model

### Hard Hexagon Capacity

• Capacity of hard hexagon model  $C_{hex}^{1,\infty}$  is known precisely! [Baxter, 1980]\*

$$C_{hex}^{1,\infty} = \log \kappa_h$$
, where  $\kappa = \kappa_1 \kappa_2 \kappa_3 \kappa_4$  and

$$\kappa_{1} = 4^{-1}3^{5/4}11^{-5/12}c^{-2} \qquad a = -\frac{124}{363}11^{1/3} \kappa_{2} = \left[1 - \sqrt{1 - c} + \sqrt{2 + c + 2\sqrt{1 + c + c^{2}}}\right]^{2} \qquad b = \frac{2501}{11979}33^{1/2} \kappa_{3} = \left[-1 - \sqrt{1 - c} + \sqrt{2 + c + 2\sqrt{1 + c + c^{2}}}\right]^{2} \qquad c = \left[\frac{1}{4} + \frac{3}{8}a\left[(b + 1)^{1/3} - (b - 1)^{1/3}\right]\right]^{1/3}$$

So,  $C_{hex}^{1,\infty} \approx 0.480767622$ 

Bit-stuffing encoder achieves rate within 0.5% of capacity!

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### Hard Hexagon Capacity\*

- Alternatively, the hard hexagon entropy constant K satisfies a degree-24 polynomial with (big!) integer coefficients.
- Baxter does offer this disclaimer regarding his derivation, however:

\*"It is not mathematically rigorous, in that certain analyticity properties of  $\kappa$  are assumed, and the results of Chapter 13 (which depend on assuming that various large-lattice limits can be interchanged) are used. However, I believe that these assumptions, and therefore (14.1.18)-(14.1.24), are in fact correct."

## **Concluding Remarks**

- The theory and practice of 1-D constrained coding, including bit-stuffing, is well-developed and powerful.
- The lack of convenient graph-based representations of 2-D constraints prevents the straightforward extension of 1-D techniques for information theoretic analysis and code design. Both are active research areas.
- Bit-stuffing encoders yield some of the best known bounds on capacity of 2-D constraints.
- There are connections to statistical physics that may open up new approaches to understanding 2-D constrained systems (and, perhaps, vice-versa).

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