Content

- Cochlear Implant(CI)
- Audio signal processing(ACE)
- Theoretical principles(entropy,Markov source,etc.)
- Lossless coding(Huffman code,PPM,RNN)
- Future work and Timeline

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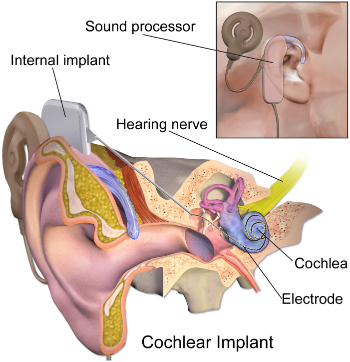
Cochlear Implant(CI)

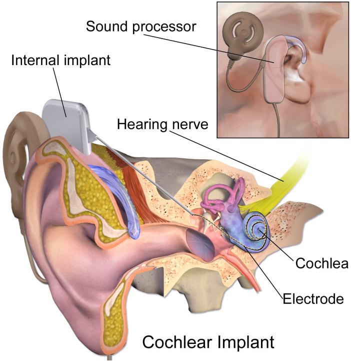
- Surgically implanted neuroprosthetic device
- Microphones,sound processor and electronics(outside)
- Coil to receive signals, electronics and electrodes which stimulate the cochlear nerve(inside)



Cochlear Implant

Problem

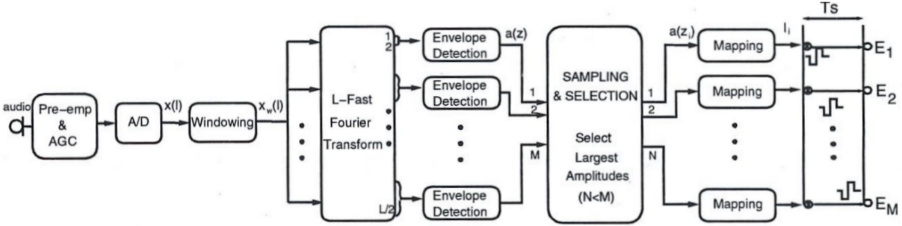
- Monaural implant, not enough in some noisy environment
- Binaural for improvement
- Coding and transmission time as low as possible



Cochlear Implant

Advanced combinational encoder(ACE)

- NofM-type strategy
- Largest amplitude envelopes are picked
- 22 electrodes(channels)



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Advanced combinational encoder(ACE)

- 1 sentence which last 3 seconds
- ACE generated current amplitude
- 22 channels, around 3000 to 8000 stimulations

22x6379 double

	5250	5251	5252	5253	5254
1	112	116	121	125	129
2	125	123	120	109	106
3	113	109	108	111	114
4	0	0	0	0	0
5	0	0	0	NaN	NaN
6	NaN	0	NaN	NaN	NaN
7	0	0	0	NaN	NaN
8	NaN	NaN	NaN	NaN	NaN
9	NaN	NaN	NaN	NaN	NaN
10	NaN	NaN	NaN	0	0
11	0	0	0	0	0
12	0	0	0	0	0
13	0	NaN	NaN	0	0
14	0	0	0	0	85
15	NaN	NaN	0	0	0
16	NaN	0	0	0	88
17	0	0	0	0	0
18	0	NaN	NaN	NaN	NaN
19	NaN	NaN	NaN	NaN	NaN
20	NaN	NaN	NaN	NaN	NaN
21	NaN	NaN	NaN	NaN	NaN
22	NaN	NaN	NaN	NaN	NaN

Entropy

- Lower bound of average codeword length
- Conditional entropy for Markov source (source with memory)
- $H(X|Y) = \sum_{x \in X} P(Y = y) \bullet H(X|Y = y)$

22x6379 double

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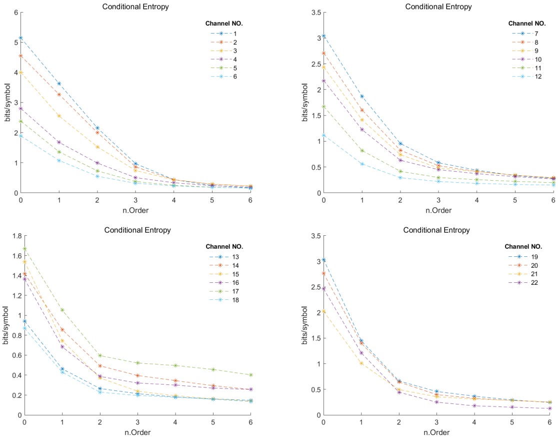
8	NaN	NaN	NaN	NaN	NaN
9	NaN	NaN	NaN	NaN	NaN
10	NaN	NaN	NaN	0	0
11	0	0	0	0	0
12	0	0	0	0	0
13	0	NaN	NaN	0	0
14	0	0	0	0	85
15	NaN	NaN	0	0	0
16	NaN	0	0	0	88
17	0	0	0	0	0
18	0	NaN	NaN	NaN	NaN
19	NaN	NaN	NaN	NaN	NaN
20	NaN	NaN	NaN	NaN	NaN
21	NaN	NaN	NaN	NaN	NaN
22	NaN	NaN	NaN	NaN	NaN

Conditional entropy

- Random selected 10 files are assembled together
- Unneeded zeros are deleted for clear trend



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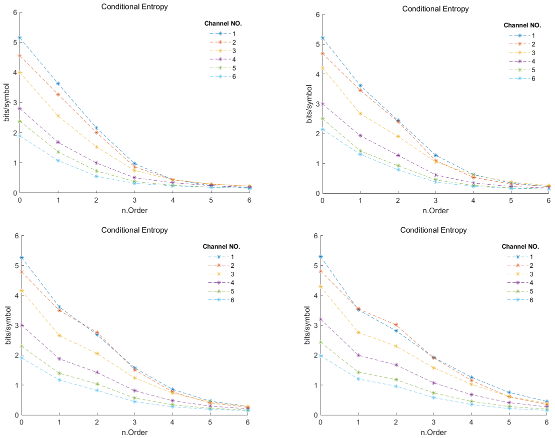
Conditional entropy

- Random selected 10, 20, 50 and 100 files
- channel 1 to 6



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Huffman code

- Optimal prefix code for lossless coding
- $\frac{H(U_N|U_1,...,U_N-1)}{log_2 D} \leq \overline{\mathrm{n}} < \frac{H(U_N|U_1,...,U_N-1)}{log_2 D} + 1$
- A Markov source of n order has up to $J = K^{n-1}$ different states, means J different prefix codes required
- For our ACE generated source, $K \approx 72$. The order 6 Huffman code requires 1.9349×10^9 different prefix codes
- Impracticable because of high computational effort

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Prediction by partial string matching(PPM)

- Very high compression rates
- Use a set of previous symbols in the uncompressed symbol stream to predict the next symbol
- Particularly suitable for our Markov source data

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Prediction by partial string matching(PPM)

- Use Markov Modelling with Partial String Matching to estimate probability
- Estimates escape probabilities for 'zero frequency problem'
- Probability table is fed to arithmetic coder in order to encode data

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Prediction by partial string matching(PPM)

- Probability of symbol φ: $p(\varphi) = \frac{c(\varphi)}{1+C}, c(\varphi) > 0$
- Escape probability $1 - \sum_{\varphi \in K, c(\varphi)>0} p(\varphi) = \frac{1}{1+C}$
- $p(133) = \frac{1}{12} \times \frac{1}{4} \times \frac{1}{27} \times \frac{32}{105}$
- If current symbol is novel even to the zero order context, final escape, encoded as an 8 bit code

order	context	symbol occurrence counts							total
		0	81	85	110	112	121	133	
3	(112,116,121)	9	2						11
2	(112,116)	10	2	3					15
1	(116)	15	6	18	25	1			65
0	empty	30	15	41	68	24	72	32	282

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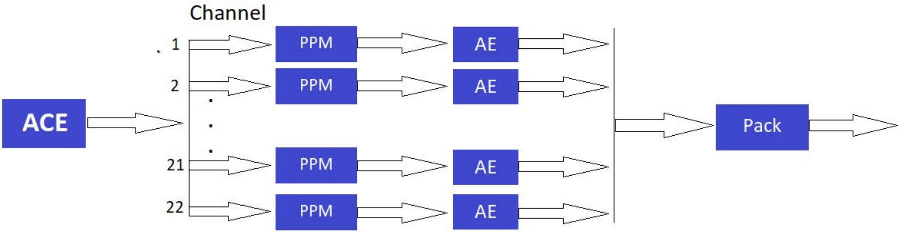
Prediction by partial string matching(PPM)

- Individual encoding for every channel
- Pack all 22 channels for transmission



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Lossless Compression using Recurrent Neural Networks

- RNN(LSTM/GRU) based models are good at capturing long term dependencies
- RNN(LSTM/GRU) can predict the next symbol very well
- RNN(LSTM/GRU) is highly potential for lossless compression (according to existing research, DeepZip)

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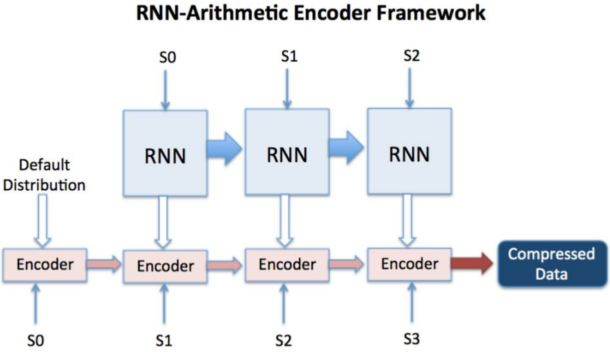
Lossless Compression using Recurrent Neural Networks

- Similar structure to PPM
- Both consist of probability estimator and arithmetic encoder
- DeepZip estimates conditional entropy distribution through RNN



Timeline

- In 3 weeks test PPM for our project
- In 6 weeks test DeepZip for our project
- Compare 2 different coding methods
  - Computational effort(code and decode time)
  - Storage memory demands
  - etc.