

Efficient storage of genome data

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Outline

Introduction

State of research: different compression techniques

Reference-based read compression

Iterative dictionary construction: COMRAD

Robust relative compression with random access

Genome ReSequencing tool

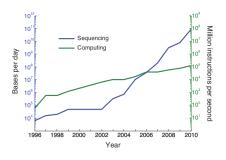
What is to come...



Genome size

Problem:

- ► Genomes are large: 10⁵ to 10¹⁰ BP
- New sequencing technologies allow fast and cheap sequencing
- Genome data grows faster than processing power (Moore's Law)





Genome size

But:

- ► Single genome almost incompressible
- ► Highly similar in same species (human: 1% difference)
- ightharpoonup if examining genome collections, only differences have to be stored

Demands:

- Reduce file size as much as possible
- Optional:
 - Fast compression
 - Random access/partly decompression



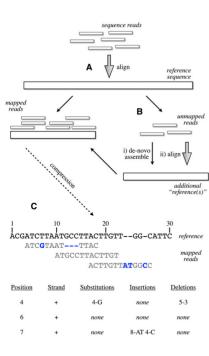
Different Approaches

- Reference based compression (Fritz, Leinonen, Chochrain et al. 2011)
- ▶ Iterative dictionary for large DNA datasets (Kuruppu et al. 2011)
- Robust relative compression with random access (Deorowicz, Grabowski 2011)



Reference-based read compression - Algorithm

- Stores short sequence reads
- Alignment of reads to reference sequence
- Store position of reads, strand, Indel information
- Postitions relatively stored als Golomb-codes





Reference-based read compression - Discussion

Problem: what to do with unaligned reads?

Discard: loss of information

► Keep: high storage cost → other compression technique?

Compression Results:

	reference based	raw FASTA	bzip2
human genome	0.41 bpb	11.45 bpb	1.84 bpb
bacterial genome	0.19 bpb	12.27 bpb	1.66 bpb

ightarrow 10- to 30-fold better compression than standard approaches



COMRAD - Algorithm

Dictionary construction by identifying repeated substrings in large DNA datasets

→ works best on highly redundant datasets

In each iteration:

- Modify frequency-dictionary
 - Count frequences of substrings
- Substitution
 - Substitute all new dictionary entries for new nonterminals
- result iteration k: Dictionary D_k , Alphabet Σ_k , set S_k of compressed sequences

final compression: Huffman

Input aabcbcaabcabc

Step 1 aa:2 ab:3 bc:4 cb:1 ca:2

Step 2 aabcbcaabcabc (no candidate) aabcbcaabcabc (no candidate) aabcbcaabcabc (cand cnt bc: 1) aabcbcaabcabc (cand ent be: 2) aabcbcaabcabc (no candidate) aabcbcaabcabc (no candidate) aabcbcaabcabc (cand cnt bc: 3) aabcbcaabcabc (no candidate) aabcbcaabcabc (cand cnt bc: 4) Step 3

$bc \rightarrow A$ aaAAaaAaA

Step 4 aa:2 aA:3 AA:1 Aa:2 bc:1

> $aA \rightarrow B$ aBAaBB

$$\begin{array}{c} aB \rightarrow C \\ CACB \end{array}$$



COMRAD - Discussion

- ▶ Provides random access and single sequence decompression
- ► Efficient on large dataset with many/long repeats
- Nearly no effect on small datasets with short repeats: disproportionately large codebook
- ► Influenza genomes 113 MB (1.97 bpb) to 6 MB (0.43 bpb)
 - ▶ time for compression: about $0.03h \rightarrow 1.04 \text{ MB/s}$
- Yeast genomes 485.87 MB (2.19 bpb) to 15.29 MB (0.25 bpb)
 - ▶ time for compression: about 0.19h \rightarrow 0.71 MB/s
- 4 human genomes 12 066,06 MB (2.18 bpb) to 2 176,06MB (1.44 bpb)
 - **•** time for compression: about $8h \rightarrow 0.42$ MB/s



Robust relative compression with random access - Algorithm

- Input sequence is parsed in sequence of matches and literals
- Hash array used to find matches
- Lookahead buffer
- Stores matches as pair of reference offset and match length
 - $\rightarrow \text{Huffman}$
- lacktriangle Literals and reference sequence ightarrow Huffman



Robust relative compression with random access - Discussion

- ▶ Allows random access to parts of compressed sequences due to blockwise coding
- ▶ 39 yeast genomes: 493.98 MB compressed to 6.88 MB, 33.15 MB/s
- ▶ 70 human genomes: 218 961,98 MB compressed to 1 201,15MB, 146.16 MB/s



Genome ReSequencing tool

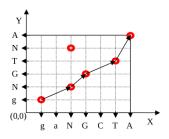
GRS Algorithm computes compressed difference files

- \blacktriangleright calculate varied sequence percentage δ for each chromosome based on a reference sequence
- \blacktriangleright if $\delta < 0.03$
 - compute different sequence file
- if $0.03 < \delta < 0.1$
 - cut chromosome into n pieces
 - calculate each δ_i
 - find position with minimal $\sum \delta_i$
 - compress each piece
- ightharpoonup if $\delta >$ 0.1: Data not suitable



Genome ReSequencing tool

- find longest common local nucleotide sequences
- example: gaNGCTA and gNGTNA





Genome ReSequencing tool

- method to compute difference file similar to UNIX diff program
- process diff file to reduce size
- encode using Huffman

)
N1, N2aN3, N4
> A
> T
N5, N6dN7, N8
< C
< G
N9, N10cN11, N12

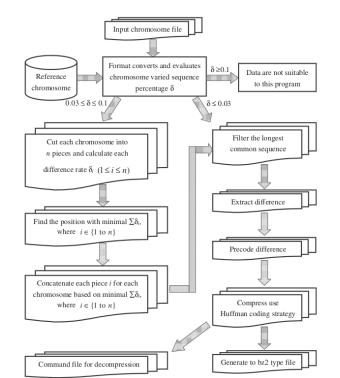
N11, N12

> c > g

< a

N1, N2 i N3, N4 AT N5, N6 dN7, N8 N9, N10 hN11, N12 cg

(c) N1 N2-N1 i N3 N4-N3 AT N5-N1 N6-N5 d N7-N3 N8-N7 N9-N5 N10-N9 h N11-N7 N12-N11 cg





Genome ReSequencing tool - Discussion

- Allows encoding without knowledge of reference SNPs map
- ▶ Rice genomes: 361 MB compressed to 4.4 MB, 0.26 MB/s
- ► Human genome: 2986,8 MB compressed to 18.8 MB, 1.81 MB/s
- ► No random access



Future development

Presented Algorithms:

- can compress effectively
- are efficient enough to store many genomes on available disk space

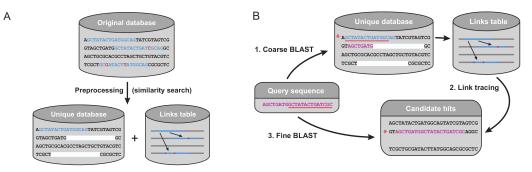
but...

- Decompression necesarry for computation
- Aim: algorithms computing on compressed data
- Next slides: a compressive BLAST algorithm is presented



CaBlast - Algorithm

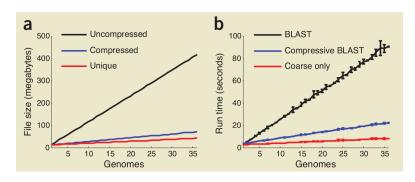
- Preprocession: compression of input data
 - fill unique database with first occurances of substrings
 - store repeats as pointers to subsequence from unique occurrence
- ► CaBLAST:
 - ▶ perform coarse BLAST Search on unique database →follow pointers to repeats of hits
 - perform fine BLAST Search on coarse-hits and decompressed repeats





CaBlast - Discussion

▶ improved runtime and space requirements





Bibliography

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