



Universitätsklinikum Essen



SFB 876 Verfügbarkeit vor Information durch Analyse unter Ressourcenbeschränkung



Alignment-free detection of copy number variations (CNVs) using strongly unique k-mers and fused lasso regularization

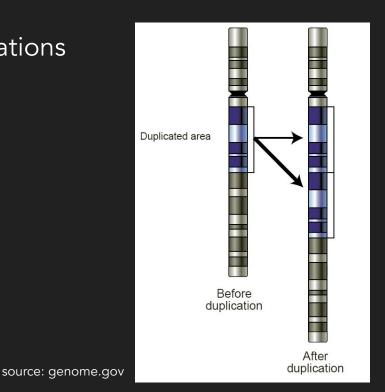
Till Hartmann^{1,2}, Elias Kuthe^{2,3}, Alicia Tüns^{2,4}, Alexander Schramm^{2,4}, Jens Zentgraf^{2,3}, Sven Rahmann^{1,2,3}

(DSB online, 12-Feb-2021)

¹ Genome Informatics, Institute of Human Genetics, University of Duisburg-Essen, Essen, Germany ² Collaborative Research Center SFB 876, Dortmund/Essen, Germany ³ Bioinformatics, Computer Science XI, TU Dortmund University, Dortmund, Germany ⁴ Laboratory for Molecular Oncology, Department of Medical Oncology, West German Cancer Center, University Hospital Essen, University of Duisburg-Essen, Essen, Germany

copy number variations (CNVs)

- segmental duplications & amplifications
- segmental deletions & losses
- may change gene copy numbers
- may influence gene expression
- frequently happen in cancer cells

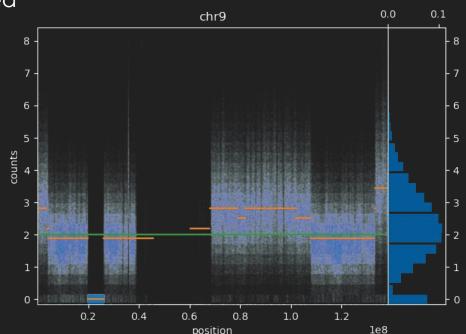


why alignment-free CNV calling?

- alignment-free approaches more efficient than mapping-based
- avoids mapping bias
- k-mer count: direct CN estimate
 if k-mer is unique in genome

GGCTCAGAACCCTGAATTCTAGTCTC GCGCCCGGCCCTGGGTGGGGAGATAT AGGTTAGAGATACTCAAGCTCCCCTT TGTCCCTTTTCTGCGCCTCAAAGGGG TGTGACATGAACAAAACCAAAACCTT

...



overview

• determine robust *k*-mer probes:

strongly unique k-mer : unique in genome & no hamming distance 1 neighbours

• bit vector indicator of these probes in reference (aka "index")

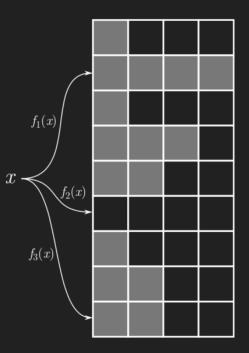


- for each sample:
 - deduplicate raw reads (bloom filter)
 - count *k*-mers (any k-mer counter will do)
 - \circ counts \rightarrow copy number via k-mer count histogram
 - "measure" copy number signal on robust probes across reference
 - segment signal with fused lasso

Part I: choosing strongly unique *k*-mer probes

hashing genomic k-mers

- Hash and count genomic *k*-mers (up to 2)
- Use 3-way bucketed Cuckoo hashing *
- 3 hash functions, each maps a *k*-mer to a bucket
- each bucket can store up to 4 elements (such that a bucket fits within a cache line)
 → 12 possible locations for each element
- at worst 3 memory lookups (cache misses), often only 1 or 2, depends on load factor
- use quotienting* for saving space (only part of the key needs to be stored)



* as featured in: "Fast lightweight accurate xenograft sorting", Jens Zentgraf & Sven Rahmann, WABI 2020 (with an extended version being under review at Algorithms in Molecular Biology)

marking weak vs. strong k-mers

• determine robust probes:

strongly unique k-mer : unique & has no hamming distance 1 neighbours

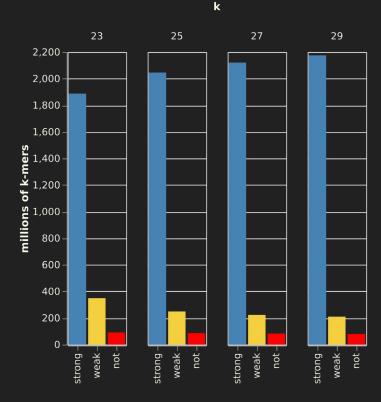
 naïve: for each k-mer, look up each of its 3·k neighbours, mark those with any neighbour as weak (remainder as strong)

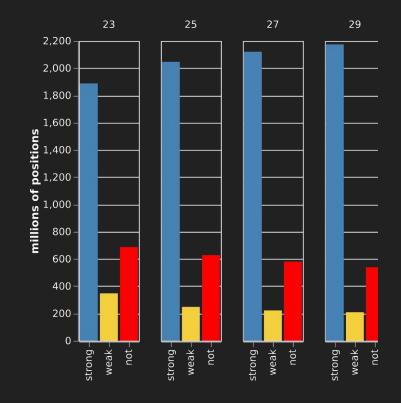
• better:

- sort list of *k*-mers *and* their reverse complements
- partition into blocks by k-mer prefix of length k/2
- for each block: test all suffix pairs for HD 1.
- \circ using fast bit-magic test for HD 1
- blocks can be processed in parallel

ΑΑΑΑ	ACGA	weak
ΑΑΑΑ	ACGT	weak
ΑΑΑΑ	GGGC	strong
A A A C	ΑССΑ	weak
A A A C	ACGA	weak

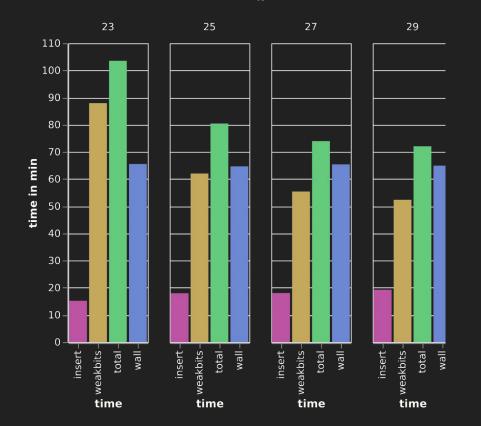
k-mer type distribution \rightarrow pick *k*=27





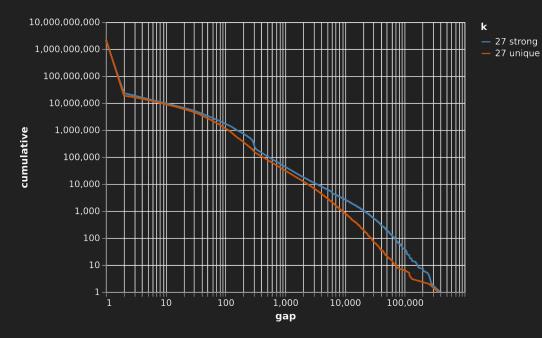
k

build times (reference k-mer hash)



- times in CPU minutes (except wall: wall minutes)
- insert time (serial) increases
 with number of *k*-mers:
 2.33 G (*k*=23) to 2.47 G (*k*=29)
- marking time of weak k-mers is dominant, but decreases with k (smaller blocks)
- parallelization over blocks more effective for smaller k (fewer, but larger blocks)
- wall clock time constant ~65 min
- genome: UCSC "analysis set"

gaps between strong vs. all unique k-mers



cumulative gap length distribution
 for k = 27

(both axes logarithmic)

- not counting invalid k-mers (containing Ns)
- very often k-mers directly adjacent (gap 1)
- only few long gaps \geq 10k:
 - strong 27-mers: 2665 gaps
 - all unique 27-mers: 814 gaps
- maximal gap lengths:
 - strong 27-mers: 389,890
 - all unique 27-mers: 362,527
- caused by exact repeats, also affects alignments !

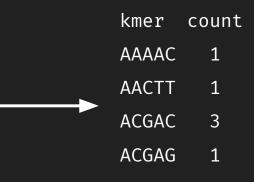
Part II: calling CNs in WGS samples using strongly unique *k*-mers

sample processing: counting k-mers

- deduplicate paired end reads (large bloom filter with very low fpr)
- use *k*-mer counter of choice (kmc3)

...

GGCTCAGAACCCTGAATTCTAGTCTC GCGCCCGGCCCTGGGTGGGGAGATAT AGGTTAGAGATACTCAAGCTCCCCTT TGTCCCTTTTCTGCGCCTCAAAGGGG TGTGACATGAACAAAACCAAAACCTT



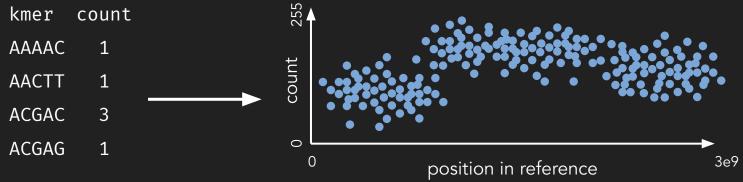
. . .

k-mer counts at strong positions

• bitvector of strong k-mers in reference

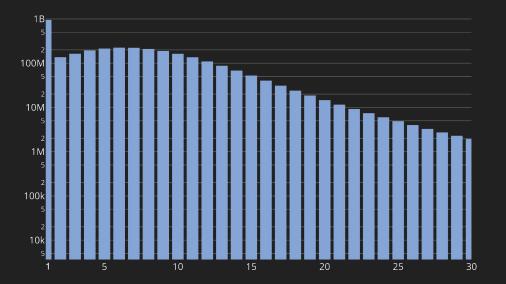


- iterate over reference sequence and bitvector
- for each strongly unique kmer: query sample *k*-mer count (kmc3 API)



from counts to copy numbers

- find "normcount" corresponding to CN 2 (for diploid genomes)
 from k-mer (log-)count histogram: then CN := 2 · count / normcount
 - fit quadratic polynomial locally around mode (low coverage)
 - fit negative binomial mixture model using EM (high coverage)



segmentation

fused lasso signal approximator (FLSA)

$$f(x) := \sum_{i=1}^n \mu_i (\underline{y_i} - \underline{x_i})^2 + \sum_{i=1}^{n-1} \lambda_i \left| x_{i+1} - x_i
ight|$$

where

 $\lambda_i = \lambda^{(0)}/{ ext{dist}_i}$: weighting factors

dist_i : distance between (strongly unique) k-mer i and i +1 in the reference

 $\lambda^{(0)}$: constant, iteratively adapted

segmentation

fused lasso signal approximator (FLSA)

$$f(x) := \sum_{i=1}^n \mu_i (\underline{y_i} - \underline{x_i})^2 + \sum_{i=1}^{n-1} \lambda_i \left| x_{i+1} - x_i
ight|$$

where

 $\lambda_i = \lambda^{(0)}/{ ext{dist}_i}$: weighting factors

dist_i : distance between (strongly unique) k-mer i and i +1 in the reference

 $\lambda^{(0)}$: constant, iteratively adapted

segmentation

fused lasso signal approximator (FLSA)

$$f(x) := \sum_{i=1}^n \mu_i (\underline{y_i} - \underline{x_i})^2 + \sum_{i=1}^{n-1} \lambda_i \left| x_{i+1} - x_i
ight|$$

where

 $\lambda^{(0)}$

 $\lambda_i = \lambda^{(0)}/{
m dist}_i$: weighting factors

dist_i : distance between (strongly unique) *k*-mer *i* and *i* +1 in the reference

: constant, iteratively adapted

exemplary results

- 2 ~5x coverage WGS samples:
 - Capan1 (Human Pancreatic Adenocarcinoma Cell Line (ATCC HTB-79))
 - Capan2 (Human Pancreatic Adenocarcinoma Cell Line (ATCC HTB-80))
- 1 ~35x coverage WGS sample (normal)

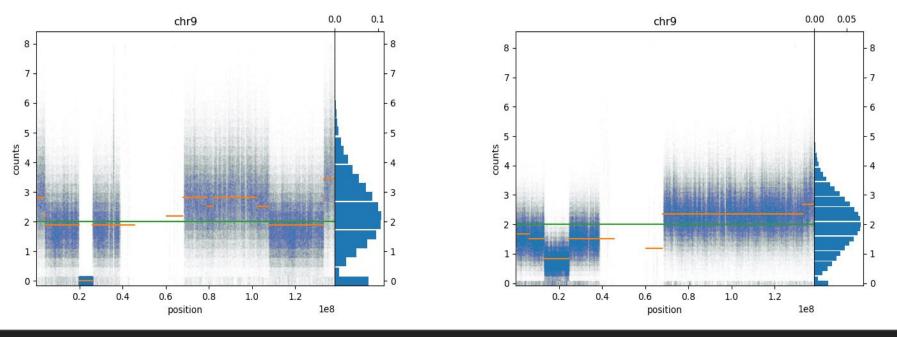
whole genome



amplification normal reduction



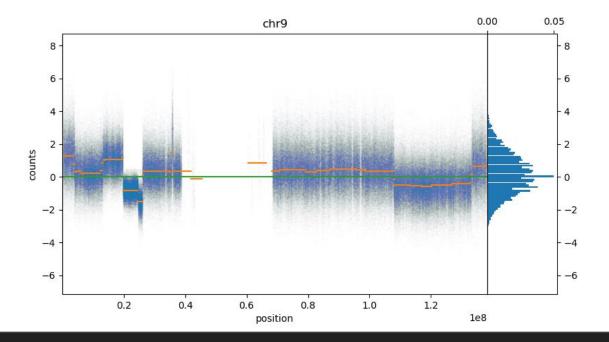
chromosome details



Capan1

Capan2

chromosome details - difference



summary

- what: from raw WGS reads to CNV calls
- how:
 - count strongly unique k-mers in sample \rightarrow copy number signal along genome
 - fused lasso for segmentation of signal
- why:
 - avoid read mapping & alignment: save resources (energy, cpu hours, memory usage, storage space)
- work in progress:
 - include *k*-mers from known frequent variants
 - further speed-up of weak *k*-mer detection
 - count strongly unique *k*-mers only
 - optimize fused lasso parameters and evaluate on large datasets

appendix (technical details)

reference genome

- We use the non-redundant "analysis set" from <u>https://hgdownload.soe.ucsc.edu/goldenPath/hg38/bigZips/analysisSet/hg38.analysisSet.fa.gz</u>
- note: there may be a problem with the X and Y chromosome, which share some very homologous regions that may lead to non-unique (repeated) k-mers even though we may not want to analyze Y at all.
- note: they hard-masked (Ns) the so-called PAR regions in the analysis set.

memory for reference index

k-mer hashes need between

7.2 GB for 2.33 G *k*-mers (*k*=23) and 11.3 GB for 2.47 G *k*-mers (*k*=29) (3.090 bytes / 23-mer to 4.575 bytes / 29-mer) (exact representation, no probabilistic filter, efficient because of quotienting)

- for CNV calling, we only need the bit vector (1 bit / reference position) of size approx. 350 MB, independent of k
- bit vector may even be compressed (allowing fast left-to-right access)
- but we also need a huge k-mer counter of the sample...
 (size depends on sequencing depth, easily over 16 GB)