Exome Sequencing Data Analysis

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Exome sequencing workflow



1) Next generation sequencing (NGS)

- Platform
- Productivity
- 2) Exome sequencing
- 3) Experimental design
- 4) Mutation study resources

Sanger sequencing: dye-terminator sequencing, 1977-present





Next generation sequencing technology 2004-present



illumına











Mardis ER. (2017) Nat Protoc. 12(2):213-218.

Comparison of sequencing methods



http://ueb.vhir.org/NGS; https://www.qiagen.com



https://flxlexblog.wordpress.com

Next generation sequencing applications



1) Next generation sequencing (NGS)

- 2) Exome sequencing
 - Benefit
 - Capture technology
- 3) Experimental design
- 4) Mutation study resource

Whole exome sequencing: Why?

- Focuses on the part of the genome we understand best, the exons of genes
- About 85% of known mutations in Mendelian diseases affect the exome
 - Nonsense, missense, splice, indel mutations
- Depending on the annotation and coverage of flanking sequencing: ~35-60Mb => 1-2% of human genomes
- There are ~200,000 coding exons in ~20,000 genes
- A whole exome is 1/6 the cost of whole genome and 1/15 the amount of data

Exome sequencing balances the coverage and cost

Sanger	Targeted	Exome	Whole Genome
 Accurate Cheap per exon High turn-around 	 Optimization possible Low chance of incidental findings Easy analysis 	 No bias for genes Standardized workflow Re-use of performed exomes to interpret new ones 	 No sequencing bias Detect SVs and SNVs
•Low diagnostic yield for genetically heterogeneous diseases	 Design and re-design required Different designs for different disorders 	 No non-coding regions Sequencing bias Incidental findings 	 Data analysis bottleneck Interpretation of non-coding regions Expensive, time- consuming

Exome sequencing detects mutations

Somatic mutations

- Occur in nongermline tissues
- Cannot be inherited



Mutation in tumor only (for example, breast)

Germline mutations

- Present in egg or sperm
- Can be inherited
- Cause cancer family syndrome



Somatic mutation calls require tumornormal paired samples

Human (b37)	- 17	- 17:7,57	78,400-7,578,439	Go f	₫ • ►	🤣 🗖 🗙 🛛	-					111111 <mark>1</mark> 🛨	
	p13.3 p13.2	p13.1	p12 p11.2	911.1	q11.2	q12 q21.1	q21.31 q2 40 bp	1.32	q22 q23.1	q23.3 q24.2 7.578,430 bp	q24.3 q25.1	q25.3	
cuttu7hE-selectedregion-readgro p.bam Coverage	[0 - 901]										I		
cufru7hE-selectedregion-readgro p.bam			>		•								norma
kUdruc®d-selectedregion-readgro p.bam Coverage	[0 - 45]												4
kUdruc8d-selectedregion-readgrc p.bam			_										tumor
Sequence →	G G G	C A G C	C G C C R R	T C A C	A A V	C C T C	C G T	C A T	G T G H	C T G T Q	GACT 5 Q	G C T	

SureSelect Target Enrichment workflow





Application	Number of san Manual	n ples/week* Automated
Whole Genome Sequencing (library preparation only)	100	960
Target Enrichment	20-40	192

Automated NGS Sample Preparation

http://www.genomics.agilent.com

Comparison of commercial human wholeexome capture platforms





(a) Targeted genomic regions;(b) Targeted coding regions;(c) Targeted untranslated regions.

NimbleGen:	63,564,965 bases
Agilent:	50,390,601 bases
Illumina:	45,112,692 bases

Coverage of target regions



%Coding regions covered at 10x at different read depth



Shigemizu D et al. (2015) Sci Rep. 5:12742.

On-target enrichment

1) Next generation sequencing (NGS)

- 2) Exome sequencing
- 3) Experimental design
 - Sample size
 - Sequencing coverage
- 4) Mutation study resource

Whole exome DNA sources



Variants detected in exome sequencing data from the paired FF/FFPE samples



Hedegaard, J. et al. (2014) PLoS ONE 9(5): e98187.

High genetic diversity in a single tumor (HCC)





Ling, S. (2015) Proc Natl Acad Sci U S A. 112(47):E6496-505

Map of the mutation clones



Ling, S. (2015) Proc Natl Acad Sci U S A. 112(47):E6496-505

Single cell exome sequencing demonstrates the sample heterogeneity



Wang, Y. et al. (2014) Nature. 512(7513):155-60.

Certain mutations only occur in a subset of TNBC cell populations



Wang, Y. et al. (2014) Nature. 512(7513):155-60.

The number of samples needed to detect significantly mutated genes



Lawrence, M.S. et al. (2014) Nature. 505(7484):495-501

Sequencing terminology



Sequencing coverage

Average coverage =

read length × number of mapped reads/ genome size



Normand, R. et al. (2013) Methods Mol Biol. 1038:1-26.

Diploid genome and coverage



Wendl, M.C. et al. (2008) BMC Bioinformatics. 9:239.

The complexity of cancer genome



OVCAR-3, NCI60 cell line, Ovarian cancer

http://www.ncbi.nlm.nih.gov/projects/sky/skyquery.cgi

Polyploid genome and coverage



Wendl, M.C. et al. (2008) BMC Bioinformatics. 9:239.

High coverage is needed for low tumor fraction samples



Ding, L. et al. (2014) Nat Rev Genet. 15(8):556-70

The depth-VAF scatter plot of SNV candidates in WES



Steps to bring in projects to CCR–SF



/fnl-cores/sequencing-facility

Courtesy of Yongmei Zhao, CCR-SF



Comments

Please complete the Sample Manifest form and e-mail it to the attention of Jyoti Shetty at shettyju@mail.nih.gov prior to shipping your samples. Please include any Quality Control documentation available such as gel images or electropherograms.



1) Next generation sequencing (NGS)

- 2) Exome sequencing
- 3) Experimental design
- 4) Mutation study resources
 - Genome in a Bottle
 - DREAM mutation challenge

Genome in a Bottle Consortium

- No widely accepted set of metrics to characterize the fidelity of variant calls from NGS...
- Genome in a Bottle Consortium is developing standards to address this...
 - well-characterized human genomes as *Reference Materials* (RMs)
 - characterized and disseminated by NIST
 - tools and methods to use these RMs
 - Global Alliance for Genomics and Health Benchmarking Team





The data sets for NA12878 are available at the Genome in a Bottle ftp site at NCBI

Source ^a	Platform	Mapping algorithm	Coverage	Read length	Genome/exome
1000 Genomes	Illumina Gallx	BWA	39	44	Genome
1000 Genomes	Illumina Gallx	BWA	30	54	Exome
1000 Genomes	454	Ssaha2	16	239	Genome
X Prize	Illumina HiSeq	Novoalign	37	100	Genome
X Prize	SOLiD 4	Lifescope	24	40	Genome
Complete Genomics	Complete Genomics	CGTools 2.0	73	33	Genome
Broad	Illumina HiSeq	BWA	68	93	Genome
Broad	Illumina HiSeq	BWA	66	66	Exome
Illumina	Illumina HiSeq	CASAVA	80	100	Genome
Illumina	Illumina HiSeq – PCR-free	BWA	56	99	Genome
Illumina	Illumina HiSeq – PCR-free	BWA	190	99	Genome
Life Technologies	Ion Torrent	tmap	80	237	Exome
Illumina	Illumina HiSeq – PCR-free	BWA-MEM	60	250	Genome
Life Technologies	Ion Torrent	tmap	12	200	Genome

ftp://ftp-trace.ncbi.nih.gov/giab/ftp/data/NA12878

Zook, J.M. et al. (2014) Nat Biotechnol. 32(3):246-51.

Integration methods to establish benchmark variant calls



Integrating human sequence data sets provides a resource of benchmark SNP and indel genotype calls

Justin M Zook¹, Brad Chapman², Jason Wang³, David Mittelman^{3,4}, Oliver Hofmann², Winston Hide² & Marc Salit¹

Clinical adoption of human genome sequencing requires methods that output genotypes with known accuracy at millions or billions of positions across a genome. Because of substantial discordance among calls made by existing sequencing methods and algorithms, there is a need for a highly accurate set of genotypes across a genome that can be used as a benchmark. Here we present methods to make high-confidence, single-nucleotide polymorphism (SNP), indel and homozygous reference genotype calls for NA12878, the pilot genome for the Genome in a Bottle Consortium. We minimize bias toward any method by integrating and arbitrating between 14 data sets from five sequencing technologies, seven read mappers and three variant callers We identify regions for which no confident genotype call could be made, and classify them into different categories based on reasons for uncertainty. Our genotype calls are publicly available on the Genome Comparison and Analytic Testing website to enable real-time benchmarking of any method.

As whole human genome and targeted sequencing start to offer the real potential to inform clinical decisions¹⁻⁴, it is becoming critical to assess the accuracy of variant calls and understand biases and sources of error in sequencing and bioinformatics methods. Recent publications have demonstrated hundreds of thousands of differences between variant calls from different whole human genome sequencing methods or different bioinformatics methods⁵⁻¹¹. To understand these differences, we describe a high-confidence set of genome-wide genotype calls that can be used as a benchmark. We minimize biases toward any sequencing platform or data set by comparing and integrating 11 whole human genome and three exome data sets from five sequencing platforms for HapMap/1000 Genomes CEU female NA12878, which is a prospective reference material (RM) from the National Institute of Standards and Technology (NIST). The recent approval of the first next-generation sequencing instrument by the US Food and Drug

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Zook, JM et al (2014) Nat Biotechnol. 32(3):246-51.

Administration highlighted the utility of this candidate NIST reference material in approving the assay for clinical use¹².

NIST, with the Genome in a Bottle Consortium, is developing well-characterized whole-genome reference materials, which will be available to research, commercial and clinical laboratories for sequencing and assessing variant-call accuracy and understanding biases. The creation of whole-genome reference materials requires a best estimate of what is in each tube of DNA reference material, describing potential biases and estimating the confidence of the reported characteristics. To develop these data, we are developing methods to arbitrate between results from multiple sequencing and bioinformatics methods. The resulting arbitrate integrated genotypes can then be used as a benchmark to assess rates of false positives (or calling a variant at a homozygous reference site), false negatives (or calling homozygous reference at a variant site) and other genotype calling errors (e.g., calling homozygous variant at a heterozygous site).

Current methods for assessing sequencing performance are limited. False-positive rates are typically estimated by confirming a subset of variant calls with an orthogonal technology, which can be effective except in genome contexts that are also difficult for the orthogonal technology¹³. Genome-wide, false-negative rates are much more difficult to estimate because the number of true negatives in the genome is overwhelmingly large (i.e., most bases match the reference assembly). Typically, false-negative rates are estimated using microarray data from the same sample, but microarray sites are not randomly selected, as they only have genotype content with known common SNPs in regions of the genome accessible to the technology.

Therefore, we propose the use of well-characterized wholegenome reference materials to estimate both false-negative and false-positive rates of any sequencing method, as opposed to using one orthogonal method that may have correlated biases in genotyping and a more biased selection of sites. When characterizing the reference material itself, both a low false-negative rate (i.e., calling a high proportion of true variant genotypes, or high sensitivity) and a low false-positive rate (i.e., a high proportion of the called variant genotypes are correct, or high specificity) are important (Supplementary Table 1).

Low false-positive and false-negative rates cannot be reliably obtained solely by filtering out variants with low-quality scores because biases in the sequencing and bioinformatics methods are not all included in the variant auality scores. Therefore, several variant

http://www.slideshare.net/GenomeInABottle/presentations

~2.7M high confident snps are detected by multiple algorithms



Zook, J.M. et al. (2014) Nat Biotechnol. 32(3):246-51.

Systematic comparison of variant calling pipelines using GIAB



Hwang S, Kim E, Lee I, Marcotte EM. (2015) Sci Rep. 5:17875.

The mutation caller performance varies drastically, 2013



Kim, S.Y., Speed, T.P. (2013) BMC Bioinformatics. 10;14:189.

Evaluation of somatic mutation callers 2016



Krøigård AB et al (2016) PLoS One. 11(3):e0151664.





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CHALLENGES - ABOUT DREAM - OUR COMMUNITY - PUBLICATIONS



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ICGC-TCGA-DREAM Somatic Mutation Calling Challenge ICGC-TCGA-DREAM Somatic Mutation Calling Challenge DEC 12, 2013 - NOV 1, 2014 Closed



http://dreamchallenges.org

Challenge data and assessment



Combining tumor genome simulation with crowdsourcing to benchmark somatic single-nucleotide-variant detection



Ewing, A.D. et al. (2015) Nat Methods. 12(7):623-30.

nature methods

ExAc: Exome Aggregation Consortium



Gene summary

(Coverage shown for canonical transcript: ENST00000269305)

Mean coverage 61.34



http://exac.broadinstitute.org

Optimizing Cancer Genome Sequencing and Analysis

Graphical Abstract



Authors

Malachi Griffith, Christopher A. Miller, Obi L. Griffith, ..., Elaine R. Mardis, Timothy J. Ley, Richard K. Wilson

- 1) Sample and case selection
- 2) Matched normal samples
- 3) Library construction
- 4) Sequencing platform
- 5) Sequencing depth
- 6) Exome-seq
- 7) Whole genome sequecing
- 8) Targeted sequencing
- 9) Sequence alignment
- 10) Variant calling
- 11) Subclonal inference
- 12) RNA-seq

Griffith M. et al (2015) Cell Syst. 1(3):210-223.