



#### Next-Generation Sequencing Technologies

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## Current Topics in Genome Analysis 2016

#### Elaine Mardis

## Qiagen NV Paid Member of Board

NATIONAL HUMAN GENOME RESEARCH INSTITUTE Division of Intramural Research

#### **Massively Parallel Sequencing basics**

How massively parallel sequencing works

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### NGS has transformed biomedical inquiry



E.R. Mardis, Nature (2011) 470: 198-203, Ann. Rev. Analyt. Chem. (2013)

## Massively Parallel DNA sequencing instruments

- All MPS platforms require a library obtained either by amplification or ligation with custom linkers (adapters)
- Each library fragment is amplified on a solid surface (either bead or flat Si-derived surface) with covalently attached adapters that hybridize the library adapters
- Direct step-by-step detection of the nucleotide base incorporated by each amplified library fragment set
- Hundreds of thousands to hundreds of millions of reactions detected per instrument run = "massively parallel sequencing"
- A "digital" read type that enables direct quantitative comparisons
- Shorter read lengths than capillary sequencers

## Library Construction for MPS

#### **DNA fragments**



- Shear high molecular weight DNA with sonication
- Enzymatic treatments to blunt ends
- Ligate synthetic DNA adapters (each with a DNA barcode), PCR amplify
- Quantitate library
- Proceed to WGS, or perform exome or specific gene hybrid capture

## PCR-related Problems in MPS

- PCR is an effective vehicle for amplifying DNA, however...
- In MPS library construction, PCR can introduce preferential amplification ("jackpotting") of certain fragments
  - Duplicate reads with exact start/stop alignments
  - Need to "de-duplicate" after alignment and keep only one pair
  - Low input DNA amounts favor jackpotting due to lack of complexity in the fragment population
- PCR also introduces false positive artifacts due to substitution errors by the polymerase
  - If substitution occurs in early PCR cycles, error appears as a true variant
  - If substitution occurs in later cycles, error typically is drowned out by correctly copied fragments in the cluster
- Cluster formation is a type of PCR ("bridge amplification")
  - Introduces bias in amplifying high and low G+C fragments
  - Reduced coverage at these loci is a result

## Hybrid Capture

- <u>Hybrid capture</u> fragments from a whole genome library are selected by combining with probes that correspond to most (not all) human exons or gene targets.
- The probe DNAs are biotinylated, making selection from solution with streptavidin magnetic beads an effective means of purification.
- An "exome" by definition, is the exons of all genes annotated in the reference genome.
- Custom capture reagents can be synthesized to target specific loci that may be of clinical interest.



## **Multiplex PCR Amplification of Targets**



- 1. Design amplification primer pairs for exons of genes of interest; tile primers to overlap fragments in larger exons
- 2. Group primer pairs according to G+C content, Tm and reaction condition specifics
- 3. Amplify genomic DNA to generate multiple products from each primer set; pool products from each set
- 4. Create library by ligation or tail platform adaptors on the primer ends
- 5. Sequence

## Massively Parallel Sequencing by Synthesis



### Illumina Patterned Flow Cell



## **Platforms: Illumina**

				-		
	MiSeq	NextSeq	500	н	liSeq 2500	HiSeq X*
Key applications	Small genome, amplicon, and targeted gene panel sequencing.	Everyday ger transcriptome and	nome, exome, e sequencing, more.	Production exome, sequenc	n-scale genome, transcriptome ing, and more.	Population-scale human whole-genome sequencing.
Run mode	N/A	Mid-Output	High-Output	Rapid Run	High-Output	N/A
Flow cells processed per run	1	1	1	1 or 2	1 or 2	1 or 2
Output range	0.3-15 Gb	20-39 Gb	30-120 Gb	10-180 Gb	50-1000 Gb	1.6-1.8 Tb
Run time	5-65 hours	15-26 hours	12-30 hours	7-40 hours	< 1 day - 6 days	< 3 days
Reads per flow cell†	25 Million‡	130 Million	400 Million	300 Million	2 Billion	3 Billion
Maximum read length	2 × 300 bp	2 × 150 bp	2 × 150 bp	2 × 150 bp	2 × 125 bp	2 × 150 bp

- High accuracy, range of capacity and throughput
- Longer read lengths on some platforms (MiSeq)
- Improved kits, improved software pipeline and capabilities, cloud compute









## **Platforms: Ion Torrent**



PGM

• Three sequencing chips available:

- 314 = up to 100 Mb
- 316 = up to 1 Gb
- 318 = up to 2 Gb
- 2-7 hour/run
- up to 400 bp read length
- 400kreads up to 5 Mreads



Proton

- Two human exomes (Proton 1 chip) or one genome (@20X-Proton 2 chip) per run
- Ion One Touch or Ion Chef preparatory modules
- 2-4 hour/run
- ~200 bp average read length
- Proton 1 produces 60-80 Mreads 
   <u>>50 bp</u>
- Low substitution error rate, in/dels problematic, no paired end reads
- Inexpensive and fast turn-around for data production
- Improved computational workflows for analysis

#### Post Data Generation Analyses

Bioinformatic and computational approaches to NGS

#### The Human Genome Reference enables MPS Genomics

- The human genome reference sequence is the keystone interpreting MPS sequencing read data
- <u>Alignment</u> of reads to the human reference sequence is the first step to identify variation of all types
- Mis-aligning sequences identify structural alterations
- Alignment and analysis of RNA sequence data provides information about gene expression changes



#### Short Read Alignment...

Is like a jigsaw puzzle...



...where they give you the cover on the box





## Some pieces are easier to place than others...





#### Repetitive Sequences Result in Multiple Read Alignments



## Reads are Aligned, Now What?

- Data calibration and cleanup:
  - Mark proper pairs (if applicable)
  - Mark duplicate reads!
  - Correct local misalignments
  - Recalculate quality scores
- Call SNPs
- Evaluate Coverage
  - Compare SNPs from NGS to SNPs from array data OR
  - Compare SNPs from tumor to normal (Which are shared? Number?)
  - Integrated Genome Viewer
  - RefCov and others
- Analyze the data

### Integrated Genomics Viewer (IGV)



## IGV: Somatic Single Nucleotide Variant QC



#### RefCov: Coverage Depth and Breadth from Hybrid Capture

		COVERAGE color sche	eme: 💿 analogous 🔾	complementary	alignment Algo	orithm: 💿 original 🔵 ne	w enrichment	
		<ul> <li>depth 40</li> <li>depth 30</li> <li>depth 20</li> <li>depth 15</li> <li>depth 10</li> <li>depth 5</li> </ul>	covera	ge (%)	<ul> <li>unique on target</li> <li>duplicate on target</li> <li>unique off target (wing:</li> <li>unique off target</li> <li>duplicate off target</li> <li>unaligned</li> </ul>	span 500) sequence (Gb)	<ul> <li>unique on target</li> <li>total on target</li> <li>theoretical max</li> </ul>	factor
		edepth 1	0 20 40 6	60 80 100	0.1	0.2 0.3		
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	78.5	0.08		6742.6	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	81.0	0.08		7478.4	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	82.7	0.06		6580.2	16233.0
normal	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	97.5	0.10		5490.4	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	82.2	0.12		7253.9	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	83.0	0.10		6077.6	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	81.0	0.07		5136.3	16233.0
normal	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	98.4	0.08		4481.8	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	83.5	0.09		4078.8	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	82.4	0.06		6901.0	16233.0
tumor FFPE	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	94.4	0.11		6015.6	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	81.6	0.07		5168.9	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	83.4	0.09		7181.3	16233.0
normal	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	8'7.9	0.04		5330.5	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	79.1	0.08		3839.6	16233.0
normal	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	98.6	0.12		6247.8	16233.0
normal	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	98.5	0.11		5165.4	16233.0
tumor FFPE	Komen	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	83.4	0.10		7524.1	16233.0
tumor FFPE	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	96.8	0.08		4700.9	16233.0
tumor FFPE	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	97.4	0.12		5084.5	16233.0
tumor FFPE	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	93.5	0.05		5164.5	16233.0
tumor	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	99.0	0.1	6	7059.6	16233.0
tumor FFPE	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	98.1	0.08		4990.2	16233.0
tumor	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	92.7	0.07		4592.4	16233.0
tumor FFPE	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	97.7	0.08		5560.4	16233.0
tumor FFPE	TCGA	2805113-Komen/Ellis_Late_Relapse-20 (1	IL)	97.4	0.07		5072.2	16233.0

http://gmt.genome.wustl.edu/genome-shipit/gmt-refcov/0.3/index.html



# Data and coverage characteristics

Sequencing Data							
	Exome	Whole Genome					
Data generated	6 Gbp	118 Gbp					
Target space	37 Mbp	3.2 Gbp					
Typical map rate	<b>98.5</b> %	95.0%					
Typical dup rate	8.8%	3.4%					
Avg. CDS sequence depth	65x	30x					
% of CDS covered >10x	90-95%	<b>95-99</b> %					

Variant Detection							
	Exome	Whole Genome					
SNV calling	Good	Good					
Small indel calling	Good	Good					
CNV calling	Poor	Good					
SV calling	Poor	OK					
Typical SNVs called	~50,000	~3 million					

## False Negativity/Positivity

- Most false negatives are due to lack of coverage
- False positives are due to multiple reasons, including:
  - Variant is only called on one strand
  - Variant is only called at the end of the read
  - Coverage of the matched normal at that locus is poor
  - Gene has a pseudogene/paralog and the reads are mis-mapped
  - High sensitivity variant calling algorithms have elevated false positive rates to achieve detection of subclonal variants and low false negative rates
- Data that verifies or refutes variant calls can help to define bioinformatic filters to remove them

## Integrated Systems: Qiagen GeneReader



- Modules for Sample Prep, Library Construction/Amplification, SBS sequencing
- Onboard analysis and interpretation software for mutation detection and interpretation based on Ingenuity Variant and Pathway Analysis

# **Third Generation Sequencers**

Variations on a theme

### **Real Time Sequencing of Single DNA Molecules**



ulse is produced fluorescent base the polymerase te. sphate is during ation, releasing ophore



## **Pacific Biosciences RS**



## **Considerations for PacBio WGS**

- High molecular weight genomic DNA
  - DNA must be of sufficient quality to allow for >30 kb shearing to produce PacBio Continuous Long Reads (CLR)
- Consistent shearing >30 kb
  - Shearing genomic DNA >30 kb is challenging and requires a consistent technology
  - Preferred method: Diagenode Megaruptor
  - Alternate method: Covaris g-Tube
- Sufficient DNA for PacBio sample prep
  - A single PacBio sample prep reaction requires 5 µg sheared DNA
  - One library is composed of 8-10 sample prep reactions
  - At least 2-4 libraries are required for 60x coverage

## **Read Length Comparisons**



10000

20000

30000

40000

Subread Length

60000

50000

70000

Library #1 18-50kb

- Mean Subread Length 13,720 bp •
- N50 Length 19,411 bp •

Library #3 30-80 kb

- Mean Subread Length 15,008 bp •
- N50 Length 24,136 bp ٠

## The Human Reference is a Work in Progress!

- The current reference GRCh38 is not optimal for some regions of the genome and/or some individuals/ancestries.
- GRCh38 is comprised of DNA from several individual humans.
- Allelic diversity and structural variation present major challenges when assembling a representative diploid genome.
- New technologies, methods, and resources since 2003 have allowed for substantial improvements in the reference genome.
- Additional high-quality reference sequences are needed to represent the full range of genetic diversity in humans

#### Improving the Human Reference Genome(s)



http://genome.wustl.edu/projects/detail/reference-genomes-improvement/



## First Gold Genome - NA19240

- NA19240 Yoruban sample
- Generated >70X raw PacBio data

	Initial Assembly Stats		
# Seq Contigs	3569		
Max Contig Length	20,393,869 bp		
Total Assembly Size	2,745,634,789 bp		
N50	6,003,115 bp		
N90	848,151 bp		
N95	345,457 bp		

## Alignment of NA19240 to BioNano map



## Finished BACs Resolve This Region

0001.11 🗷											
_000001.11 (Graphical S	Sequence View) [Hs_NA]	19240-1.0-GRCh38	3.p2]								
148,050 K 148,060 K	148,070 K 148,080 K	148,090 K 14	3,100 К  148,110 К	148,120 K	148,130 K	148,140 K	148,150 K	148,160 K	148,170 K	148,180 K	148,190 K 1
GRCh38			< AC239803.3 <			/ ér239889.3 /					
cks: 1 on, 9 off 8 gene models shown											
TRN-6TT9-2 tRN <del>R</del> -Asn	PDE4DIPP1 🔉 exon        exon		<b>▲</b> ++++++++<	< <b>↓                                    </b>	~ 	ABHD17AP1 > exon Luc	NBPF11 NBPF11 LOC10050 XR_4268	3824 <b>8</b> 36.2 <b>8</b>			
PB Assembly						XR	922068.1				
120/mapping/NA19240/LKPB_Wa	ashU/superclean_10302015/review	w/super_clean_alignmer	its.asnt, total 3 objects sł	hown							
lignments (GRCh38.p2<=>Hs_NA	A19240-1.0), total 2 objects shown LKPB01000562.1								LKPB01000178.		
BAC Alignment	S, 3 entries, total 2 objects sh	own	LKPB. LK.	LKPB0LKPB01	K LK						
gnment: NC_000001.11 x AC2704	453.1, 1 entry, total 1 object shown	1			10 11 01						
Duplications, Eichler Lab, total 78	features shown										
> > > > > > > > > > > > > > > > > > >	chr1120544125 chr1148965451	chr11490586 1_K1270711v1_ron_ chr1143590013 chr1120442761 chr11485722 chr1148121 chr1120844 chr11489863	95 > > > > > > > > > > > > > > > > > > >	> chr1014	3627245 ► ch chr chr ch ch	chr1146905970	chr116617335	3777 >	> >	chr114647	4417
	chr1120485199 > > chr1149019652 > >	chr1145588742 chr1145588742 chr1144420967 chr1144420967 chr1145988 chr1145888120 chr114588120	chr1: ch4133 > c64433 > 818 > 818 > 818 > chr1: > chr1:	145400309 144435842 chrl12 chrl12 chrl119638095 chrl119638095	6602822 chr16_K1 21443756 9860072 cd 119828172 c c c	27072841_r > hr16-32726390 > hr16-33148870 > chr16-32199901 > hr15-28454632 > chr15-23225652					

## Platinum/Gold Genome Status

Data Source	Origin	Level of Coverage	Status
CHM1	NA	Platinum	Assembly Improvement
CHM13	NA	Platinum	Data Generation
NA19240	Yoruban	Gold	Analysis Underway
HG00733	Puerto Rican	Gold	Assembly Assessment
HG00514	Han Chinese	Gold	Assembly QC
NA12878	European	Gold	Assembly QC
HG01352	Columbian	Gold	Assembly Underway
HG02818	Gambian	Gold	Not Started
HG02059	Kinh Vietnamese	Gold	Not Started

 $\bigcap$ 



## **10X Genomics: Linked Reads**

- Long-range information from short reads
  - Partition long input molecules into GEMs (*Gelbead-in-Emulsion*)
  - Gelbeads carry barcode oligos that are incorporated in sequencing library
  - Use barcodes to link short reads back to original long input molecules



• Resulting barcoded reads are called *Linked-Reads* 



## **Oxford Nanopore Sequencing**





Protein nanopore set in an electrically resistant polymer membrane Each nanopore is controlled and measured by a matched ASIC (Application Specific Integrated Circuit) Post-run data analysis compares pore current changes to a model of all possible multimers

- Variable read lengths
- Electrical current-based detection of multiplex nucleotides in pore
- Error rate is around 10-20% with newest pore/software

## **Nanopore Sequencing Devices**





### Genome-guided Immunotherapy Decision-making

Identifying "non-self" Neoantigen Landscapes

## NGS to identify tumor-specific antigens

- Early work from the labs of Thierry Boon and Hans Schreiber (among others) suggested that tumor <u>specific</u> mutations can sometimes function as tumor <u>specific</u> antigens
- James Allison and Bert Vogelstein predicted that many/most tumors should express mutational antigens based on their genomic repertoire of coding variants, and these might be the ideal tumor-specific targets for cancer immunotherapy
- In the past, identifying the tumor mutation landscape and its most immunogenic peptides has been hampered by technical obstacles, most of which have now been overcome by NGS and bioinformatic approaches to epitope prediction

## Genome-guided Immunotherapy

- In using genomic data to predict neoantigen load for a specific tumor, we utilize:
  - massively parallel sequencing and analysis to compare cancer and normal exomes and identify cancer-unique peptides
  - the HLA haplotypes of the individual patient
  - RNA sequencing data from the cancer cells to identify genes that are mutated <u>and</u> expressed
- These input data are considered by algorithms that model the binding of peptides to the MHC and calculate binding energies, producing a list of tumor specific mutated antigens (TSMAs) or neoantigens
- This information can describe the cancer's neoantigen load

#### pVac-Seq Pipeline: Open Source Neoantigen Prediction



Hundal et al., Genome Medicine 2016

#### Mutation/Neoantigen Load and Checkpoint Blockade Response Potential



Tumors with a high mutational (neoantigen) load tend to respond to checkpoint blockade immunotherapy

### Germline DNA Repair Defects and Checkpoint Blockade Response Potential



Dung et al., NEJM 2015

## **GBM27:** Rapid Progression in CNS



- Male patient, early 30's, prior history of colon polyps
- GBM removed by craniotomy 8 months ago
- Post surgery temozolomide (TMZ) therapy
- Spinal metastasis resected 3 months ago, FMI test indicated high mutation load/ pol E mutated germline status : treatment with Pebrolizumab
- Second spinal metastasis identified upon complications, removed 2 months ago
- All tumors studied by high coverage exome sequencing compared to PBMC normal, and by IHC

#### **GBM27:** Clonal Evolution



# GBM27: Evolving Immune Response









Metastasis2

Pembrolizumab (Keytruda) CD4Recent MRI indicated

Patient remains NED on

•

response of remaining untreated right frontal horn lesion in the brain





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Our patients and their families

