A normalization technique for next generation sequencing experiments



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ABSTRACT

Motivation: Next generation sequencing (NGS) are these days one of the key technologies in biology. NGS' cost effectiveness and capability of finding the smallest variations in the genome makes them increasingly popular. For studies aiming at genome assembly, differences in read count statistics do not affect the outcome. However, these differences bias the outcome if the goal is to identify structural DNA characteristics like copy number variations (CNVs). Thus a normalization step must removed such random read count variations subsequently read counts from different experiments are comparable. Especially after normalization the commonly used assumption of Poisson read count distribution in windows on the chromosomes is more justified. Strong deviations of read counts from the estimated mean Poisson distribution indicate CNVs.

Results: We test our normalization technique on sequencing results from three different sequencing centers with a wide range of quality levels. After normalization, regions that deviate from the estimated Poisson distribution are have been identified as sex specific or previously identified CNV regions.

MOTIVATION OF NORMALIZATION

Without normalization: assumption of Poisson read count distribution not justified

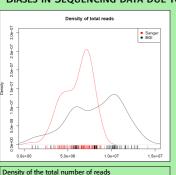
different number of total reads

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- Reads with multiple mapping positions:
 Excluding: underestimated read counts → wrongly detected deletions
 - All possible matches: overestimated read counts → wrongly detected amplifications

NORMALIZATION IS ESSENTIAL FOR NGS QUANTITATIVE DATA ANALYSIS

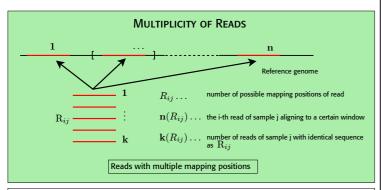
BIASES IN SEQUENCING DATA DUE TO LANE QUALITY AND OTHER EFFECTS



Genomic position	BGI_FC20C A5AAXX2	BGI_FC_20C A6AAXX1	BGI_FC20CA 6AAXX2	
Chr1:200,000- 250,000	7317	9025	9165	
Chr1:250,000- 300,000	321	442	450	
Chr1:300,000- 350,000	5504	6303	6453	
Chr1:350,000- 400,000	22949	26791	28536	
Chr1:400,000- 450,000	13954	15583	16259	
Total mapped reads	6,012,023	7,495,175	7,830,023	
Data matrix of unnormalized read counts.				

SUGGESTED NORMALIZATON PROCEDURE

NORMALIZATION STEP 1: READS WITH MULTIPLE MAPPING POSITIONS



Normalized read count:

$$\hat{x}_j = \sum_{i=1}^{l} \frac{\mathbf{k}(R_{ij})}{\mathbf{n}(R_{ij})}$$

Usually only the number of reads in the windows are just counted

NORMALIZATION STEP 2: LANE EFFECT

- Each lane shows different characteristics

 → different number of reads mapped back

 → normalization of the read counts per lane (by the number of reads which were mapped back)

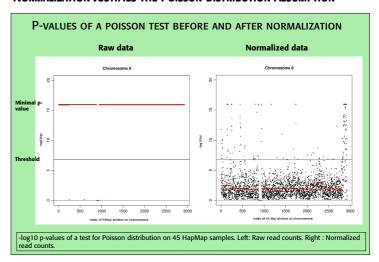
 → quality and the number of reads implicitly considered

 $\mathrm{T}_i\ldots$ number of total aligned reads of sample j

Normalized read count of sample j in window i: $\overline{x}_{ij} = x_{ij} \cdot rac{\min_j T_j}{T_i}$

EXPERIMENTS ON HAPMAP DATA

NORMALIZATION JUSTIFIES THE POISSON DISTRIBUTION ASSUMPTION



TESTING THE POISSON ASSUMPTION

Poisson test: Brown and Zhao then Bonferroni correction of the p-values.

REJECTION RATE OF THE POISSON ASSUMPTION

	Data set 1 (46 lanes of one sample)	Data set 2 (45 lanes of 45 samples)
Raw data	93,1 %	93,1 %
Multiple reads normalization	92,9%	73,6%
Lane effect normalization	84,9%	18.4%
Both normalizations	34,0%	0.1%

DATA SETS

From 1000 Genomes on HapMap samples sequenced by the Solexa Genome Analyzer

- Data set 1: lanes from single sample NA19328
- Data set 2: lanes from 45 different samples

