

# QUASI: A Pipeline for the Quality Assessment and Statistical Inference on Next Generation Sequencing Data from Pooled shRNA Library Screens

Mark Onyango<sup>1</sup>, Carsten Ade<sup>2</sup>, Franz Cemič<sup>1</sup> and Jürgen Hemberger<sup>1</sup>

<sup>1</sup>*Institute of Biochemical Engineering and Analytics, University of Applied Sciences Giessen, Wiesenstrasse 14, Giessen, Germany*

<sup>2</sup>*Theodor-Boveri Institute, University of Würzburg, Am Hubland, Würzburg, Germany*

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**Abstract:** With the development of next generation high-throughput sequencing solutions to expression profiling, the efficient and effortless handling of such profiling data became a key challenge for bioinformaticians and biologists alike. We therefore present a "fire and forget" style pipeline implemented in C and R, named QUASI. It is capable of quality assessments, sequence alignments, shRNA quantification and statistically inferring significant differential sequence abundance from datasets presented to it. Through blackboxing the often complex and laborious steps, QUASI presents itself as a user-friendly and time-efficient solution to handle pooled shRNA library screening data.

## 1 INTRODUCTION

The discovery of RNA interference (RNAi) in *Caenorhabditis elegans* (Fire et al., 1998) introduced new possibilities for the analysis of genes and the identification of their biological functions in cellular pathways. Introduction of double stranded RNA into its cells led to the degradation of complementary mRNA, thus silencing the corresponding gene. It was later shown that these so-called loss-of-function screens could also be applied to mammalian organisms (Elbashir et al., 2001).

Such synthetic small interfering RNAs (siRNA) were successfully employed, but the fast and transient-only gene silencing in addition to the inability to transfect otherwise hard-to-transfect cells make them inferior to small hairpin RNAs (shRNA). To overcome these downsides, new RNAi approaches were developed, using viral-vector based shRNA/shRNAmir (henceforth abbreviated shRNA) based libraries (Fewell and Schmitt, 2006) avoiding the shortcomings of siRNAs as a silencing agent, mentioned by Fewell and Schmitt.

With the development of next generation sequencing (NGS) technologies and the commercial availability of whole genome shRNA libraries, large scale RNAi screens, using barcode sequencing

protocols, have become more feasible. Features such as the high dynamic range and the vast output of DNA reads make it ideally suited for large genome-wide screenings.

One conceivable application is the search for new cancer therapeutics. The uncontrolled proliferation of many tumors results from mutations of one or several genes causing the over-expression of oncogenes or the loss of tumor suppressors. In addition, tumor cells often develop a dependency on the activity of further genes and their products. These dependencies can be exploited by suppressing the expression of these genes via shRNA mediated knockdown of the corresponding mRNA, inducing synthetic lethality. Genes whose knockdown is synthetic lethal selectively only for treated cells (with for example an induced over-expression of an oncogene) but not for untreated control cells may be promising targets for tumor therapy. Comparing untreated to treated tumor cells, significant differences in the abundance of individual shRNAs due to increased apoptosis or cell division may be observed. The genes targeted by those shRNAs can then be subjected to further validation experiments and the positive hits may then be screened for potential druggability.

Next generation sequencing technology is increasingly used to enable the analysis of pooled

RNAi screens in a high-throughput format. As a consequence, new methodologies had to be developed to analyze both RNA-Seq and shRNA sequencing (shRNA-Seq) data.

As our contribution to the topic, we developed QUASI, a pipeline supporting the handling of shRNA-Seq data by performing quality assessments, alignments and the analysis of differential shRNA abundances in cell populations infected with the same pooled lentiviral shRNA libraries.

## 2 IMPLEMENTATION

The pipeline consists of three tools, handling the quality assessment, quantification and alignment. Each tool can be called individually from the command-line.

### 2.1 Quality Assessment

The quality assessment tool takes as input a standard FASTQ file, and reads out the information contained in every read block.

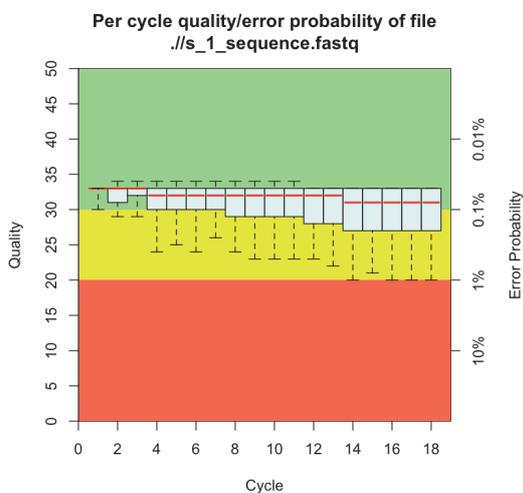


Figure 1: Box-and-Whiskers plot displaying the quality score (Phred score) distribution per cycle.

The Phred quality scores (Ewing et al., 1998) are processed to be visualized in a "Box-and-Whiskers Plot" (Figure 1), providing a powerful display of the overall quality at a single glance.

The plot presents the distributions' five-number summary in a convenient and intelligible way. The upper and lower whiskers represent the 90th and 10th percentile, respectively. The upper and lower

edge of the box represent the 75th and 25th percentile whereas the median, i.e. 50th percentile, is shown as a red line located somewhere inside the box.

The frequently observed deterioration of the read quality towards the 3' end is caused by an effect called "phasing" (Kircher et al., 2009). As the sequencing errors begin to accumulate, the distribution of quality scores, assigned to the incorporated nucleotides, broadens, thus making the boxes and whiskers longer.

Another measure of quality is the *quality-per-base* distribution (Figure 2). The quality scores for each incorporated base are individually saved for Adenine, Thymine, Cytosine and Guanine, respectively. Presenting the plot in this manner provides more insight, as base-specific sequencing errors or bias can be visualized.

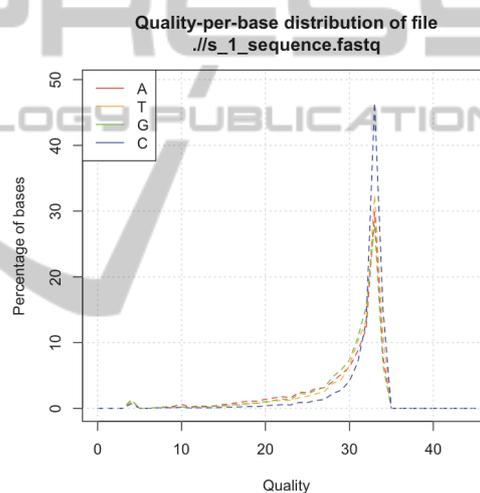


Figure 2: Distribution of quality scores for each base.

The tool saves all the relevant information, discussed above, in plain text files which are then later processed by an R script.

#### 2.1.1 Benchmark

We tested our quality assessment tool and compared the results and consumption of computational resources to the freely available tools *fastx* (Hannon, 2012) and the well known tool *FastQC* (Andrews, 2010).

In Table 1 *FastQC* is shown to have the longest run time but at the same time also offers the most detailed quality report. In omitting analysis modules, which are not relevant for shRNA-Seq (that is k-mer analysis), we are able to focus on the relevant details and save valuable time.

*FastX* seems to be slightly faster than *quasi-qa*,

but this originates from the difference in analyses performed. *FastX* only saves information concerning the nucleotidic composition and the quality distribution per cycle, whereas *quasi-qa* also analyzes the read length distribution, nucleotidic composition, quality distribution per cycle and the quality distribution per base.

Table 1: Performance benchmark of the quality assessment. All calculations were performed on an Apple MacBook Pro (late 2011) equipped with 8 GB of RAM, 2.3 GHz Intel Core i5 and a SSD harddrive. The measurements were derived from the GNU *time* command which is available on all Unix systems. It should be noted that the tools do not possess the same range of functions.

Filesize	Tool	Wall time (hh:mm:ss)	Total RAM
1.1 GB	fastqc 0.10	00:01:05	568 MB
	fastx 0.0.13	00:00:09	21 MB
	quasi-qa	00:00:10	2 MB

## 2.2 Alignment

The proper alignment tool must be chosen according to the nature of the experiment. If total mRNA was used for sequencing (i.e. RNA-Seq), TopHat, SOAPsplice or other splice-junction-aware aligners need to be chosen over splice-junction-unaware aligners, as the latter are only able to align intra-exonic reads back to the reference. Using splice-junction-unaware aligners would result in the incorrect dropping of all junction spanning reads as unmappable and therefore losing many counts.

If specific tags are sequenced, as is the case in shRNA-Seq, splice-junction-unaware aligners such as Bowtie (Langmead et al., 2009), BWA (Li and Durbin, 2009) or SOAP3 (Liu et al., 2012), are more than sufficient.

The alignment script adheres to common standards, thus only accepting FASTQ formatted files as input and writing alignments in the well known SAM format

The reads of a sample-specific FASTQ file are aligned to a predefined reference data set containing the relevant sequences of all shRNAs used in the RNAi screening experiment.

Multiple cores in a CPU are automatically detected and are assumed to be available. Using multiple cores during the alignment, drastically reduces the total runtime on a near linear scale.

A pre-defined set of parameters has been chosen for the alignment tools. However, the set of parameters can be adjusted by the user if necessary.

## 2.3 Quantification

The tool *quasi-count* must be presented with one or multiple SAM files, which will be analyzed sequentially. This tool counts the number of allocated reads to each reference sequence during the alignment step. The resulting counts will be saved in a matrix style textfile, which will later be used for the inference of statistically significant changes in shRNA frequencies.

The only other requirement, when using *quasi-count*, is that the header section of the SAM file is intact as the tool uses the information given therein to identify the sequenced shRNAs.

## 2.4 Statistical Inference

This part of the pipeline is implemented in the programming language R. The R script contains functions to read in the quality assessment data and print them out in a single PDF file, read in the count matrix textfile to start differential abundance analysis or visualize the Pearson correlation between samples.

Differential abundance analysis is done by the freely available R packages DESeq (Anders and Huber, 2010), edgeR (Robinson et al., 2010) or baySeq (Hardcastle and Kelly, 2010). The statistical assumptions, made in all three packages, are based on a negative-binomial rather than a Poisson distribution of the counts. The assumption of a Poisson distribution is not applicable in this case, due to the additional sources of variance (overdispersion), when including biological replicate samples, that cannot be accounted for as has been shown by Lu et al., (2005). This underestimation of the variance leads to an increased number of type-I errors, that is false positive discoveries of differential abundance.

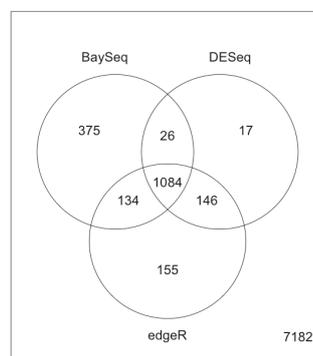


Figure 3: Example Venn diagram of significantly differentially abundant shRNAs inferred by baySeq, edgeR and DESeq.

After completing the differential abundance analysis, the shRNAs that have shown statistically significant changes in frequencies between analyzed samples are saved in a plain text file for possible further downstream analysis (e.g. GSEA, GO term enrichment, etc.).

We recommend executing all three packages to create a list containing only the overlap of shRNAs, presumed to be differentially abundant (Figure 3). This list is the most conservative estimate of relevant shRNAs.

### 3 CONCLUSIONS

QUASI presents itself as a user-friendly and time-efficient pipeline. Streamlining the analysis of pooled shRNA library screens was achieved through blackboxing the complex configurations, thus decreasing the time span from raw to evaluated data.

### 4 AVAILABILITY

The software is freely available under the GPL license from <http://sourceforge.net/projects/quade>. Also, a detailed tutorial can be found at the URL mentioned above, presenting the user a step-by-step guide.

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