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Supplemental Data

Detecting Expansions of Tandem Repeats in Cohorts Sequenced

with Short-Read Sequencing Data

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Figure S1 Normalised sequencing coverage comparison between the four sequencing cohorts, split by repeat expansion type.

Figure S2 Insert sizes by sample. Samples are in decreasing order of the median insert size that is indicated by a circle. Bars extend to cover 90% of insert sizes, at the 5th and 95th percentile. The interquartile range (IQR), covering 50% of the data, is indicated by small vertical bars. The dotted and dashed vertical lines indicates the threshold at which our WES and WGS samples respectively will usually have overlapping bases, between the two ends of the read.

Figure S3 exSTRa eCDF plots for simulated data labeled by size of repeat expansion. Each panel depicts one STR with 210 controls (black) and 20 intermediate size tandem repeat alleles and 20 expanded repeat alleles, with intermediates and expansions coloured in red, with smallest repeat alleles in yellow and largest in red.

Figure S4 exSTRa p-value behavior with varying repeat length. Regions in light blue are normal ranges, regions in green the intermediate range, which usually means not pathogenic, or leads to a different phenotype, possibly with lower penetrance. The region in red is the pathogenic range. True expansions are red, intermediate expansions green and unexpanded blue. Controls are not shown, as they were not tested for expansions.

Figure S5 exSTRa p-value behavior with varying control cohort size.

Figure S6. ECDFs for the 13 STR loci with coverage for the WES cohort (WES_PCR).

Figure S7. ECDFs for all 21 STR loci for the WGS with PCR cohort (WGS_PCR_1).

Figure S8. ECDFs for all 21 STR loci for the WGS with PCR cohort (WGS_PCR_2).

Figure S9. ECDFs for all 21 STR loci for the WGS without PCR cohort (WGS_PF).

Figure S10. ECDFs for all 21 STR loci for the WGS with PCR 30X sub-cohort (WGS_PCR_2_30X_1).

Figure S11. ECDFs for all 21 STR loci for the WGS with PCR 30X sub-cohort (WGS_PCR_2_30X_2).

Figure S12. Histograms of the frequency density for the empirically derived p-values for all STR loci for all four cohorts, as well as the two 30X subsets for WGS_PCR_2 (top left panel = WES, top right panel = WGS_PCR_1, middle left = WGS_PCR_2, middle right = WGS_PF_3, bottom left = WGS_PCR_2_30X_1, bottom right = WGS_PCR_30X_2). The bins on the far left, where p<0.05, are plotted at smaller bin sizes of 0.01 whilst other bins were plotted with bin size 0.05 to show greater detail.

Figure S13. Q-Q plots for the empirically derived p-values for all STR loci for all four cohorts, as well as the two 30X subsets for WGS_PCR_2 (top left panel = WES, top right panel = WGS_PCR_1, middle left = WGS_PCR_2, middle right = WGS_PF_3, bottom left = WGS_PCR_2_30X_1, bottom right = WGS_PCR_30X_2). X-axis has –log10 transformed uniform distribution quantiles, which are plotted against the empirically derived –log10 transformed p-value.

Table S1. Summary of computational methods, evaluation framework and limitations for ExpansionHunter, exSTRa, STRetch and TREDPARSE. #=Computational Burden has been split into two components: known loci (a small subset of all STR loci) and genomewide, representing thousands of STR loci. P=requires prior information for STR in terms of allele size to aid statistical test. ^=The C9orf72 repeat expansion is a hexamer repeat. $&SCA6$ is the smallest repeat expansion currently known, *IRR = in read repeat. Updated and adapted from Bahlo et al, F1000Research, 2018,+STRetch is inherently different to the other three methods in runtime since it

requires a realignment of all reads to its augmented reference, hence the "High" computational cost for the known loci. Computational costs for the statistical tests should rise linearly for additional STRs tested, with STRetch and exSTRa more computationally expensive than ExpansionHunter and TREDPARSE because they perform permutation tests to estimate p-values.

WGS_PCR_2 WGS_{TPL}21 WGS_{TPL}21 654,118,132 30.35 31 31 30.2% 30.2% **Table S2:** Coverage and alignment statistics for samples from cohorts WES, WGS_PCR_1 and WGS_PCR_2.

Table S3: Literature sources for expansion distributions for all 21 STR loci

Table S4: Bait Capture information for WES data, generated using the Agilent V5+UTR capture platform. Model refers to the genetic model, with AD = autosomal dominant, $X = X$ -linked, $AR =$ autosomal recessive. Bait information is given in the Agilent SS V5+UTR column with "Yes" indicating presence of a pair of baits, with on each side of the STR locus, "No" no baits, and "Single" indicating a single bait, only on one side. The ability to capture sequence is determined by whether sequencing 'baits' are in the vicinity (within ~50 bps) of the STR. Strcat gives the location to the STR catalogue generated by Willems et al. Chrom, start and end refer to physical map co-ordinates according to hg19.

Table S5: Individual level expansion call results for cohorts WES, WGS_PCR_1, WGS_PCR_2, and split WGS_PCR_2 cohorts for exSTRa, ExpansionHunter. BF, Bonferroni correction, performed correcting for 21 STR loci tested; mismatch calls are shown in bold; NC, Not Called, meaning no expanded STR was detected; TREDPARSE –L, TREDPARSE expansion calls based on likelihood; TREDPARSE-T, TREDPARSE expansion calls based on threshold. Available as an Excel spreadsheet (SupplementaryTable_S4.xlsx).

Table S6: WGS_Pf_3 analysis results comparing exSTRa, ExpansionHunter, STRetch, TREDPARSE. Per sample expansion calls for 118 WGS samples. Available as an Excel spreadsheet (SupplementaryTable_S5.xlsx).

Alignment

Alignment of each pair of FASTQ files was performed with Bowtie2¹ to the hg19 human genome reference build in very sensitive local mode, with maximum insert sizes of 800 bp for WES samples and 1000 bp for WGS samples. BAM files were sorted and merged with the Novosort tool. Duplicate marking was performed with Picard. Local realignment and base score recalibration was performed with the GATK IndelAligner tool and the Base Quality Score Recalibration tool² to produce input ready BAM files.

Software

The first step of the analysis is performed with a Perl module, called Bio::STR::exSTRa, which carries out a heuristic procedure to extract repeat content. In summary, this procedure uses the data from the reference database for the 21 loci presented in Table 1 to identify all reads that map to each of the STR loci, for each individual to be examined. The number of repeat motifs contained by each read are determined by the heuristic procedure, which examines each read for the repeat units that that STR is known to contain. This allows for some mismatches due to impure repeats and sequencing errors. Additionally, this is more computationally efficient than determining the exact repeat start and end and is more robust as determining the edge of the repeat can be difficult near the end of a read in the presence of mismatches.

Bio::STR::exSTRa : A heuristic procedure to extract repeat units per read

For simplicity, the following description of the data and analysis methods is only for a single locus. The algorithm is repeated independently at each locus.

Read information is extracted from a database of STR locations, such as 2–6bp repeat unit features generated using the Tandem Repeats Finder³, which is also available as the Simple Repeats track of UCSC Genome Browser. Information is extracted for one STR at a time, with the following algorithm repeated for each STR:

1. The method identifies 'anchor' reads that facilitates identifying reads within or overlapping the STR. To qualify as an anchor, the reads are required to map within 800 bp of the STR, with the anchor orientated towards the STR. An anchor may overlap the STR.

2. The anchor-mate mapping is checked. If the anchor-mate is mapped near the STR and is not overlapping or adjacent, then the read is discarded, while those reads overlapping the STR are taken forward to the next analysis step. Sometimes the read is unmapped, or mapped to another locus, which is then recovered for further interrogation in the next step.

3. Remaining anchor-mates have their sequence content matched for the presence of the repeat unit in the correct direction, allowing for the repeat to start at any base, or phase, of the repeat unit. For example, if the repeat unit is CAG, the method can also match AGC and GCA. The number of bases found to be part of the repeat unit is counted to derive a repeat-score for that read, that is designated at a given locus as x_{ij} for sample i and read j (note that the maximum defined j depends on the sample). If both ends of a read-pair overlap within an STR, both reads undergo this procedure and each end is given a score that can be resolved during the statistical analysis of the data

(the implementation in this paper did not investigate resolving these further, with both ends left in the analysis if any). An example of matching (lower case) a CAG on the opposite strand, thus matching CTG at any starting base, or phase, of the motif, i.e. CTG, TGC and GCT:

CGTTCAC**ctg**GATGTGAACT**ctg**TC**ctg**ATAGGTCCCC**ctgctgctgctgctgctgctgctg**Tt **gctgc**TTTt**gctgc**TGT**ctg**AAA

This 87 bp sequence has 48 bp marked (bold and lower case) as part of the repeat.

4. The method filters out reads where the score is lower than expected in random nucleotide sequences. While not precisely true, the assumption applied is that the four nucleotides are uniformly distributed and independent with respect to other positions. Short motifs are more likely to appear by chance. The method filters out scores where x_{ij} <lk/4^k, where l is the read length and k is the motif length. 800 bp has been chosen to avoid discarding reads overlapping the STR, with the insert size of read pairs having median ~360 bp. Some protocols may need to analyse reads further than 800 bp. This can be adjusted when calling the Perl module.

The output of this Perl module consists of a tab-delimited file consisting of a table where each row in the table is the repeat content of any read from a particular individual that has been identified as mapping to an STR locus that was to be investigated.

Note that these data do not represent the true size of the allele that the read has captured but where the method predicts an individual with repeat expansion allele at a particular STR locus to show an excess of reads and read content mapping to that STR.

R package exSTRa : detecting outlier distributions of repeat content in reads

Analysis methods for the second part of the analysis method are embedded in an R package, called exSTRa (expanded STR algorithm). The output data from step 1 can be loaded and the data visualized. In particular visualizations of the data are performed with empirical cumulative distribution functions, or ECDFs.

The analysis of the samples is treated as an outlier detection problem. For the N individuals in the cohort the method compares each individual in turn to all others, including itself for robustness, for all STR loci that will be tested for repeat expansions. Since more reads with greater numbers of the repeat motif will be visible in an individual with a repeat expansion at a particular locus, the data at the repeat locus being interrogated is used in a statistical test of a difference of distribution in number of repeats that are observed for a particular individual in comparison to the set of controls. Individuals with an expanded repeat demonstrate a shift in the distribution in comparison to individuals with normal size alleles comprising their genotype for the STR locus being examined. To visualize the results, the output is plotted as empirical cumulative distribution functions (ECDFs) in R.

Statistical Test

We developed a statistical test to detect outlier samples in comparison to a background set of samples. These outlier samples are likely to be individuals harbouring repeat expansions. To apply this test the method utilizes an empirical quantile imputation procedure, implemented in the R function quantile(). This function calculates empirical quantiles for any desired probability, for example probability $= 0.5$ generates the median observation in a dataset, but it is also capable of generating quantiles at probability points that have not been observed, by interpolating the probability distribution function based on the empirical observations. We make use of this function to firstly generate the same number of 'observations' for all samples to be tested, defined as M. In general, n is defined so that it is the largest number of observations for all of the samples, but other values could also be chosen, such as the median number of observations. The R function quantile() is applied to generate this dataset which consists of N samples, with M observations/quantiles, leading to a dataset with N by M datapoints, or quantiles. This dataset is defined as $Y=(y_{ii})$, where y_{ii} is the repeat content of the j^{th} quantile from the i^{th} individual.

The test statistic, which we call T_i , is defined as the average of multiple t-statistics generated at each quantile j, above a preset threshold $0 \le h < 1$, which we usually define $h = 0.5$.

$$
T_i = \frac{1}{D} \sum_{j:Pr(y_{ij}) \ge h}^{M} t_{ij}
$$

$$
D = |\{j: Pr(y_{ij}) \geq h\}|
$$

Sixteen of the 21 STR repeat expansion loci to be examined have a dominant mode of inheritance, with only one copy of the expanded allele. This can be observed with the ECDF plots for the autosomal dominant STR loci, where deviations in the repeat composition of reads are only noticeable after the median quantile, when the y-axis (which is the probability) exceeds 0.5. Observations below this threshold are likely to carry no signal, and are thus would not contribute to any test statistic attempting to discriminate between expansions and normal sized alleles.

Each quantile test statistic, t_{ii} is calculated similarly to a two-sample T-test like test statistic, but using a trimmed mean and variance, to robustly allow for the occurrence of more than one expansion in the background distribution, which is the case in the cohorts we tested but which will also likely be the case in other cohorts. The trimming percentage, or percentage of samples that are used is a parameter that can be set by the user in exSTRa, but the default is set at 0.15. Trimming is performed bilaterally, for both the lower and upper tails of the distributions, resulting in at least 30% of the samples being trimmed.

$$
t_{ij} = \frac{y_{ij} - m_j}{S_j}
$$

\n
$$
m_j = \frac{1}{n_j} \sum_{j:l_j \le y_{ij} \le u_j} y_{ij}
$$

\n
$$
n_j = |\{j : l_j \le y_{ij} \le u_j\}|
$$

\n
$$
S_j = s_j \sqrt{1 + \frac{1}{n_j}}
$$

where l_i is the first observation included from the lower tail of the distribution after the trimmed observations and ui the last observation included from the upper tail of the distribution, with all observations beyond this trimmed. s_i is the sample standard deviation of the trimmed samples.

We derive p-values for these test statistics using a simulation procedure.

Since the number of individuals in our simulations is not large and only test a single individual, standard permutation tests will not result in sufficient sampling of the empirical distribution thus resulting in a very coarse-grained empirical distribution. Instead we take advantage of the well-described empirical distributions of the samples by directly simulating from the background distribution, which represents the distribution of normal, or non-expanded alleles. We perform this using robust methods to ensure that samples with expanded alleles do not influence the simulation in the simulation study.

For simulation s we simulate M quantiles for N samples, by assuming that the distributions at each quantile follow large sample theory and are thus approximately normally distributed with mean m_i and standard deviation d_i , where j denotes the quantile. The method then tests this assumption by performing visual inspections of the distribution of quantiles after standardization with the R function qqnorm() and the approximation was reasonable.

The method then uses the median as our estimator for the mean, and the median absolute deviation (MAD) as our robust estimator for the standard deviation. Thus,

 \hat{m}_i = median{ $\mathbf{y}_{.i}$ }

$$
\hat{d}_{j} \hspace{2mm} = \hspace{2mm} \frac{1}{(\Phi^{-1}(3/4))} MAD\{{\bf y}_{. {\bf j}}\}
$$

 $MAD{y_{.i}}$ = median ${ |y_{ii} - median{y_{.i}}| }$

Where $y_{i} = \{y_{1i}, ..., y_{Ni}\}$, and $\Phi^{-1}(.)$ is the inverse of the cumulative distribution function of the standard normal distribution. The R function mad() incorporates the scaling factor that ensures consistency with the standard deviation when observations are normally distributed.

The method then uses the rnorm() function in R to randomly generate the N new observations for each quantile, using the STR locus and quantile specific estimators for the mean and standard deviation. The data is then sorted for each sample, as some of the new observations are no longer monotonically increasing as per definition of quantiles.

Finally, the test statistic T_s is calculated as defined above, but using the new data set generated from the simulation, where the first sample in the simulated data set is arbitrarily chosen to be the sample to be tested as an outlier. The method then repeat this for a desired number of simulations, say B, and then calculates the empirical pvalue for our test statistic pT_i using standard methods, where:

$$
p_{T_i} = \frac{\sum_{s=1}^{B} I([T_i > T_1^s]) + 1}{B + 1}
$$

Here $I(.)$ is the indicator function. T_i is the test statistic for the dataset. The method calls individuals as expanded or not for each STR locus examined based on a Bonferroni corrected threshold at the 0.05 significance level, based on the number of STR tested for each sample.

Standard deviations for the empirical p-value estimator were also calculated as follows.

$$
SD(\hat{p}) = \sqrt{\frac{\frac{1+\sum_{i=1}^{B} x_i}{B+1} (1 - \frac{\sum_{i=1}^{B} x_i}{B+1})}{B}}
$$

$$
x_i = I([T_i > T_1^S])
$$

Calling expansions with ExpansionHunter, STRetch and TREDPARSE

We performed analysis with ExpansionHunter (version 2.5.3)⁴, STRetch (GitHub commit $94d0516$) and TREDPARSE (GitHub commit 83881b4) ϵ , on the cohorts at the 21 repeat expansion loci listed in Table 1. The input data was the same BAM files generated as described above. Only specification files (in JSON format) for the DM1, DRPLA, FRAXA, FRDA, FTDALS1, HD, SBMA, SCA1 and SCA3 loci were provided with ExpansionHunter. The JSON files for the remaining loci were obtained by personal communication with Egor Dolzhenko (Illumina, Inc. San Diego, CA, USA). For data aligned with bowtie2, the --min-anchor-mapq parameter was set to 44, while for the original alignments of the Coriell samples this parameter was set to 60. The --read-depth parameter was set the median coverage for each sample in the WES_PCR cohort, otherwise this was computed by ExpansionHunter for the WGS samples. The list of STR loci provided with STRetch does not include FRDA, which was added manually. The EPM1 repeat motif is 12 bp and is not assessed using STRetch, which aligns to an augmented reference genome containing a decoy chromosome for each STR repeat motif up to 6 bp in size.

ExpansionHunter and TREDPARSE-T call allele lengths and genotypes. To call individuals as having expansions requires the user to define thresholds on allele sizes as to what constitutes an appropriate threshold. For FRAXA, we additionally tested using the premutation threshold (labelled FRAXA_pre), in addition to testing for full expansions. To call an expansion, we used the same thresholds as Dolzhenko et al⁴

(based on McMurray⁷) or the largest reported normal allele size at other loci. Other thresholds will change the sensitivity and specificity. TREDPARSE-L expansions calls were recorded for all samples labelled as "risk". exSTRa p-values were Bonferroni corrected over the number of STRs tested. STRetch reports p-values adjusted for multiple testing over all STRs genome wide, however unadjusted p-values were extracted and Bonferroni corrected over just the number of STRs tested. A threshold of $p < 0.05$ was used for significance.

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