

segmentSeq: methods for identifying small RNA loci from high-throughput sequencing data

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1 Introduction

High-throughput sequencing technologies allow the production of large volumes of short sequences, which can be aligned to the genome to create a set of *matches* to the genome. By looking for regions of the genome which to which there are high densities of matches, we can infer a segmentation of the genome into regions of biological significance. The methods we propose allows the simultaneous segmentation of data from multiple samples, taking into account replicate data, in order to create a consensus segmentation. This has obvious applications in a number of classes of sequencing experiments, particularly in the discovery of small RNA loci and novel mRNA transcriptome discovery.

We approach the problem by considering a large set of potential *segments* upon the genome and counting the number of tags that match to that segment in multiple sequencing experiments (that may or may not contain replication). We then adapt the empirical Bayesian methods implemented in the baySeq package [1] to establish, for a given segment, the likelihood that the count data in that segment is similar to background levels, or that it is similar to the regions to the left or right of that segment. We then rank all the potential segments in order of increasing likelihood of similarity and reject those segments for which there is a high likelihood of similarity with the background or the regions to the left or right of the segment. This gives us a large list of overlapping segments. We reduce this list to identify non-overlapping loci by choosing, for a set of overlapping segments, the segment which has the lowest likelihood of similarity with either background or the regions to the left or right of that segment and rejecting all other segments that overlap with this segment. For fuller details of the method, see Hardcastle *et al.* [2].

2 Preparation

We begin by loading the segmentSeq package.

```
> library(segmentSeq)
```

Note that because the experiments that segmentSeq is designed to analyse are usually massive, we should use (if possible) parallel processing as implemented by the parallel package. If using this approach, we need to begin by define a *cluster*. The following command will use eight processors on a single machine; see the help page for 'makeCluster' for more information. If we don't want to parallelise, we can proceed anyway with a NULL cluster.

```

> if(require("parallel"))
+ {
+   numCores <- min(8, detectCores())
+   cl <- makeCluster(numCores)
+ } else {
+   cl <- NULL
+ }

```

The `readGeneric` function is able to read in tab-delimited files which have appropriate column names, and create an `alignmentData` object. Alternatively, if the appropriate column names are not present, we can specify which columns to use for the data. In either case, to use this function we pass a character vector of files, together with information on which data are to be treated as replicates to the function. We also need to define the lengths of the chromosome and specify the chromosome names as a character. The data here, drawn from text files in the 'data' directory of the `segmentSeq` package are taken from the first million bases of an alignment to chromosome 1 and the first five hundred thousand bases of an alignment to chromosome 2 of *Arabidopsis thaliana* in a sequencing experiment where libraries 'SL9' and 'SL10' are replicates, as are 'SL26' and 'SL32'. Libraries 'SL9' and 'SL10' are sequenced from an Argonaute 6 IP, while 'SL26' and 'SL32' are an Argonaute 4 IP.

A similar function, `readBAM` performs the same operation on files in the BAM format. Please consult the help page for further details.

```

> datadir <- system.file("extdata", package = "segmentSeq")
> libfiles <- c("SL9.txt", "SL10.txt", "SL26.txt", "SL32.txt")
> libnames <- c("SL9", "SL10", "SL26", "SL32")
> replicates <- c("AG06", "AG06", "AG04", "AG04")
> aD <- readGeneric(files = libfiles, dir = datadir,
+                   replicates = replicates, libnames = libnames,
+                   polyLength = 10, header = TRUE, gap = 200)
> aD

```

An object of class "alignmentData"
3149 rows and 4 columns

Slot "libnames":
[1] "SL9" "SL10" "SL26" "SL32"

Slot "replicates":
[1] AG06 AG06 AG04 AG04
Levels: AG04 AG06

Slot "alignments":
GRanges object with 3149 ranges and 2 metadata columns:

	seqnames	ranges	strand	tag	multireads
	<Rle>	<IRanges>	<Rle>	<character>	<numeric>
[1]	>Chr1	265-284	-	AAATGAAGATAAACCATCCA	1
[2]	>Chr1	405-427	-	AAGGAGTAAGAATGACAATAAAT	1
[3]	>Chr1	406-420	-	AAGAATGACAATAAA	1
[4]	>Chr1	600-623	+	AAGGATTGGTGGTTTGAAGACACA	1
[5]	>Chr1	665-688	+	ATCCTTGTAGCACACATTTTGGCA	1
...

```

[3145] >Chr1 991569-991589 - | CCGATAAACGCATACTTCCCT 1
[3146] >Chr1 992039-992054 - | AAGGAAATTAGAAAAT 1
[3147] >Chr1 995357-995372 + | AGAGACATGGGCGACA 1
[3148] >Chr1 995493-995507 + | AAAC TCGTGAAGAAG 1
[3149] >Chr1 995817-995840 - | AGAGATCAAGTATATAGAATTAAG 1
-----
seqinfo: 1 sequence from an unspecified genome; no seqlengths

Slot "data":
Matrix with 3149 rows.
      SL9 SL10 SL26 SL32
1      1    0    0    0
2      0    0    0    2
3      0    1    0    0
4      0    1    0    0
5      7    1    0    0
...    ...    ...    ...
3145    1    0    0    0
3146    0    1    0    0
3147    0    1    0    0
3148    0    1    0    0
3149    1    0    0    0

Slot "libsizes":
[1] 1193 1598 1818 1417

```

Next, we process this alignmentData object to produce a segData object. This segData object contains a set of potential segments on the genome defined by the start and end points of regions of overlapping alignments in the alignmentData object. It then evaluates the number of tags that hit in each of these segments.

```

> sD <- processAD(aD, cl = cl)
> sD

GRanges object with 1452 ranges and 1 metadata column:
      seqnames      ranges strand | chunk
      <Rle>      <IRanges> <Rle> | <Rle>
[1] >Chr1      265-284      * | 1
[2] >Chr1      265-420      * | 1
[3] >Chr1      265-623      * | 1
[4] >Chr1      265-688      * | 1
[5] >Chr1      265-830      * | 1
...    ...    ...    ...
[1448] >Chr1 992039-992054      * | 171
[1449] >Chr1 995357-995372      * | 172
[1450] >Chr1 995357-995507      * | 172
[1451] >Chr1 995493-995507      * | 172
[1452] >Chr1 995817-995840      * | 173
-----
seqinfo: 1 sequence from an unspecified genome; no seqlengths
An object of class "lociData"
1452 rows and 4 columns

```

```

Slot "replicates"
AG06 AG06 AG04 AG04
Slot "groups":
list()

Slot "data":
  SL9 SL10 SL26 SL32

Slot "annotation":
data frame with 0 columns and 0 rows

Slot "locLikelihoods" (stored on log scale):
Matrix with 0 rows.
<0 x 0 matrix>

```

We can now construct a segment map from these potential segments.

Segmentation by heuristic methods

A fast method of segmentation can be achieved by exploiting the bimodality of the densities of small RNAs in the potential segments. In this approach, we assign each potential segment to one of two clusters for each replicate group, either as a segment or a null based on the density of sequence tags within that segment. We then combine these clusterings for each replicate group to gain a consensus segmentation map.

```

> hS <- heuristicSeg(sD = sD, aD = aD, RKPM = 1000, largeness = 1e8, getLikes = TRUE, cl = cl)
.....

```

Segmentation by empirical Bayesian methods

A more refined approach to the problem uses an existing segment map (or, if not provided, a segment map defined by the hS function) to acquire empirical distributions on the density of sequence tags within a segment. We can then estimate posterior likelihoods for each potential segment as being either a true segment or a null. We then identify all potential segments in the with a posterior likelihood of being a segment greater than some value 'lociCutoff' and containing no subregion with a posterior likelihood of being a null greater than 'nullCutoff'. We then greedily select the longest segments satisfying these criteria that do not overlap with any other such segments in defining our segmentation map.

```

> cS <- classifySeg(sD = sD, aD = aD, cD = hS, cl = cl)
.....
> cS

GRanges object with 65 ranges and 0 metadata columns:
      seqnames      ranges strand
   <Rle>      <IRanges>  <Rle>
[1]   >Chr1         1-264      *
[2]   >Chr1        265-839      *
[3]   >Chr1        840-967      *

```

```

[4]    >Chr1      968-17054      *
[5]    >Chr1    17055-17738      *
...      ...      ...      ...
[61]   >Chr1 789508-789548      *
[62]   >Chr1 789549-944194      *
[63]   >Chr1 944195-944222      *
[64]   >Chr1 944223-958610      *
[65]   >Chr1 958611-959152      *
-----
seqinfo: 1 sequence from an unspecified genome; no seqlengths
An object of class "lociData"
65 rows and 4 columns

Slot "replicates"
AG06 AG06 AG04 AG04
Slot "groups":
list()

Slot "data":
      AG06.1 AG06.2 AG04.1 AG04.2
[1,]      0      0      0      0
[2,]     31     29     51     85
[3,]     24     18     14      0
[4,]      2      3      0      0
[5,]    121    120    147    560
60 more rows...

Slot "annotation":
data frame with 0 columns and 65 rows

Slot "locLikelihoods" (stored on log scale):
Matrix with 65 rows.
      AG04      AG06
1  0.031548 0.034761
2  0.8338   0.9883
3  0.61923  0.85384
4  0.014835 0.019089
5  0.95559  0.84837
...      ...      ...
61 0.66692  0.93945
62 0.0076827 0.024958
63 0.98159   0.86769
64 0.12483   0.018825
65 0.32536   0.99319

Expected number of loci in each replicate group
      AG04      AG06
29.40546 36.18992

```

By one of these methods, we finally acquire an annotated lociData object, with the annotations describing the co-ordinates of each segment.

We can use this `lociData` object, in combination with the `alignmentData` object, to plot the segmented genome.

```
> par(mfrow = c(2,1), mar = c(2,6,2,2))
> plotGenome(aD, hS, chr = ">Chr1", limits = c(1, 1e5),
+           showNumber = FALSE, cap = 50)
> plotGenome(aD, cS, chr = ">Chr1", limits = c(1, 1e5),
+           showNumber = FALSE, cap = 50)
```

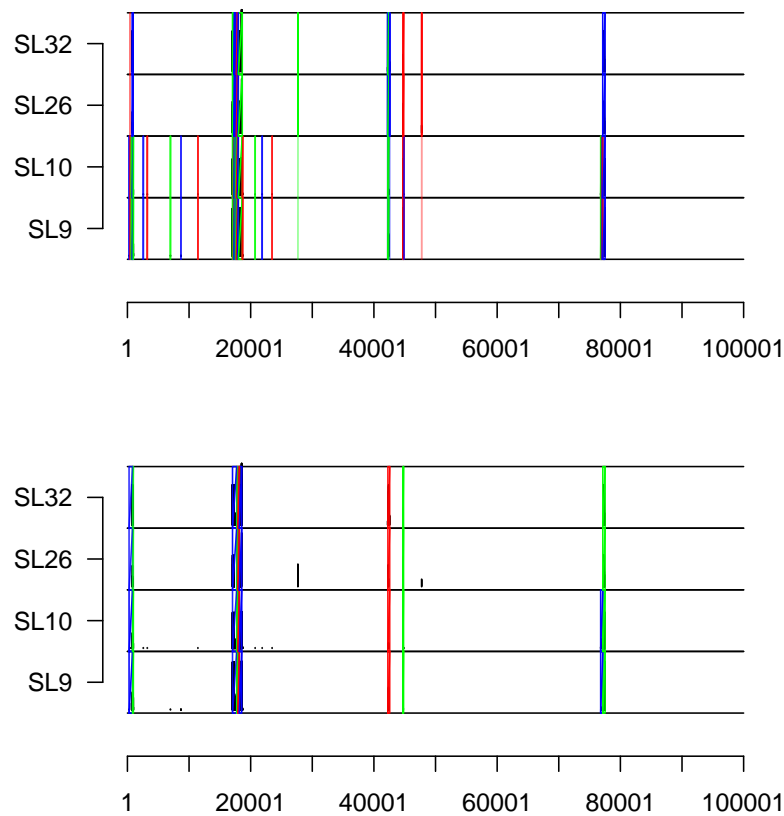


Figure 1: The segmented genome (first 10^5 bases of chromosome 1

Given the calculated likelihoods, we can filter the segmented genome by controlling on likelihood, false discovery rate, or familywise error rate

```
> loci <- selectLoci(cS, FDR = 0.05)
> loci
```

GRanges object with 34 ranges and 0 metadata columns:

	seqnames	ranges	strand
	<Rle>	<IRanges>	<Rle>
[1]	>Chr1	265-839	*
[2]	>Chr1	840-967	*
[3]	>Chr1	17739-17909	*

```

[4]    >Chr1    17910-18157    *
[5]    >Chr1    18158-18553    *
...      ...      ...      ...
[30]   >Chr1 758302-758848    *
[31]   >Chr1 758849-759196    *
[32]   >Chr1 789508-789548    *
[33]   >Chr1 944195-944222    *
[34]   >Chr1 958611-959152    *
-----
seqinfo: 1 sequence from an unspecified genome; no seqlengths
An object of class "lociData"
34 rows and 4 columns

Slot "replicates"
AG06 AG06 AG04 AG04
Slot "groups":
list()

Slot "data":
      AG06.1 AG06.2 AG04.1 AG04.2
[1,]      31      29      51      85
[2,]      24      18      14       0
[3,]      16      21       0      17
[4,]     239     173     162     177
[5,]     301     302    1096     349
29 more rows...

Slot "annotation":
data frame with 0 columns and 34 rows

Slot "locLikelihoods" (stored on log scale):
Matrix with 34 rows.
      AG04      AG06
1    0.8338  0.9883
2    0.61923 0.85384
3    0.6483  0.88199
4    0.98546 0.99732
5    0.98467 0.99843
...      ...      ...
30   0.98027 0.96982
31   0.56102 0.98788
32   0.66692 0.93945
33   0.98159 0.86769
34   0.32536 0.99319

Expected number of loci in each replicate group
      AG04      AG06
25.33357 32.75701

```

The lociData objects can now be examined for differential expression with the baySeq package.

First we define the possible models of differential expression on the data. In this case, the models are of non-differential expression and pairwise differential expression.

```
> groups(cS) <- list(NDE = c(1,1,1,1), DE = c("AG06", "AG06", "AG04", "AG04"))
```

Then we get empirical distributions on the parameter space of the data.

```
> cS <- getPriors(cS, cl = cl)
```

Then we get the posterior likelihoods of the data conforming to each model. Since the 'cS' object contains null regions as well as true loci, we will use the 'nullData = TRUE' option to distinguish between non-differentially expressed loci and non-expressed regions. By default, the loci likelihoods calculated earlier will be used to weight the initial parameter fit in order to detect null data.

```
> cS <- getLikelihoods(cS, nullData = TRUE, cl = cl)
```

We can examine the highest likelihood non-expressed ('null') regions

```
> topCounts(cS, NULL, number = 3)
```

	seqnames	start	end	width	strand	AG06.1	AG06.2	AG04.1	AG04.2
NA.61	>Chr1	789549	944194	154646	*	13	37	29	29
NA.28	>Chr1	372735	423138	50404	*	0	0	0	0
NA.45	>Chr1	552693	587497	34805	*	0	0	0	0
	likes		FDR.		FWER.				
NA.61	0.9781566	0.02184336	0.02184336						
NA.28	0.9754303	0.02320653	0.04587638						
NA.45	0.9753956	0.02367247	0.06935197						

The highest likelihood expressed but non-differentially expressed regions

```
> topCounts(cS, "NDE", number = 3)
```

	seqnames	start	end	width	strand	AG06.1	AG06.2	AG04.1	AG04.2	likes
NA.14	>Chr1	77151	77519	369	*	176	147	275	131	0.9307905
NA.56	>Chr1	758302	758848	547	*	167	166	269	134	0.8751151
NA.42	>Chr1	550077	550655	579	*	5	11	0	19	0.8663408
	FDR.NDE		FWER.NDE							
NA.14	0.06920947	0.06920947								
NA.56	0.09704717	0.18545113								
NA.42	0.10925117	0.29432304								

And the highest likelihood differentially expressed regions

```
> topCounts(cS, "DE", number = 3)
```

	seqnames	start	end	width	strand	AG06.1	AG06.2	AG04.1	AG04.2	likes
NA.48	>Chr1	634297	634350	54	*	65	90	12	17	0.9950597
NA.16	>Chr1	238359	238417	59	*	9	9	0	0	0.9914359
NA.13	>Chr1	76799	77150	352	*	6	21	0	0	0.9784148
	DE		FDR.DE		FWER.DE					
NA.48	AG06>AG04	0.004940330	0.00494033							
NA.16	AG06>AG04	0.006752209	0.01346211							


```
NA.13 AG06>AG04 0.011696524 0.03475668
```

Finally, to be a good citizen, we stop the cluster we started earlier:

```
> if(!is.null(cl))  
+   stopCluster(cl)
```

Session Info

```
> sessionInfo()  
  
R version 4.0.0 (2020-04-24)  
Platform: x86_64-apple-darwin17.0 (64-bit)  
Running under: macOS Mojave 10.14.6  
  
Matrix products: default  
BLAS:   /Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRblas.dylib  
LAPACK: /Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRlapack.dylib  
  
locale:  
[1] C/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8  
  
attached base packages:  
[1] parallel stats4 stats graphics grDevices utils datasets  
[8] methods base  
  
other attached packages:  
[1] segmentSeq_2.22.0      ShortRead_1.46.0  
[3] GenomicAlignments_1.24.0 SummarizedExperiment_1.18.0  
[5] DelayedArray_0.14.0    matrixStats_0.56.0  
[7] Biobase_2.48.0         Rsamtools_2.4.0  
[9] Biostrings_2.56.0      XVector_0.28.0  
[11] BiocParallel_1.22.0     baySeq_2.22.0  
[13] abind_1.4-5            GenomicRanges_1.40.0  
[15] GenomeInfoDb_1.24.0    IRanges_2.22.0  
[17] S4Vectors_0.26.0       BiocGenerics_0.34.0  
  
loaded via a namespace (and not attached):  
[1] Rcpp_1.0.4.6           RColorBrewer_1.1-2     compiler_4.0.0  
[4] BiocManager_1.30.10    bitops_1.0-6           tools_4.0.0  
[7] zlibbioc_1.34.0        digest_0.6.25          evaluate_0.14  
[10] lattice_0.20-41        png_0.1-7              rlang_0.4.5  
[13] Matrix_1.2-18          yaml_2.2.1             xfun_0.13  
[16] GenomeInfoDbData_1.2.3 hwriter_1.3.2          knitr_1.28  
[19] locfit_1.5-9.4         grid_4.0.0            jpeg_0.1-8.1  
[22] rmarkdown_2.1          latticeExtra_0.6-29    limma_3.44.0  
[25] edgeR_3.30.0           htmltools_0.4.0       BiocStyle_2.16.0  
[28] RCurl_1.98-1.2         crayon_1.3.4
```

References

- [1] Thomas J. Hardcastle and Krystyna A. Kelly. *baySeq: Empirical Bayesian Methods For Identifying Differential Expression In Sequence Count Data*. BMC Bioinformatics (2010).
- [2] Thomas J. Hardcastle and Krystyna A. Kelly and David C. Baulcombe. *Identifying small RNA loci from high-throughput sequencing data*. Bioinformatics (2012).