

# melody: Statistical Methods for the Quantitative Analysis of Song Spectrograms (Version 0.4.3)

David M. Schruth  
dschruth@u.washington.edu

December 29, 2012

## 1 Licensing

This package is licensed under the Artistic License v2.0: it is therefore free to use and redistribute, however, we, the copyright holders, wish to maintain primary artistic control over any further development. Please be sure to cite us if you use this package in work leading to publication.

## 2 Installation

Building the *melody* package from source requires that you have the proper dependency packages, *caroline*, *network*, and *sna*, installed from CRAN. This can typically be accomplished via the following commands from within the R command line environment:

```
install.packages(c('caroline','network','sna'))
```

After a successful installation the *melody* package can be loaded in the normal way: by starting R and invoking the following `library` command:

```
> library(melody)
```

## 3 Introduction

The melody package is a suite of computer vision tools for processing vocal spectrograms. In addition to temporal partitioning, unit filtering, harmonic splitting, and background noise removal functionality, the package provides a collection of methods for assessing the higher order melodic content of vocalization spectrograms. Both unit level (tone and interval) as well as inter-unit measures (syllabic variation and repetition clustering) are also currently available.

## 4 Data Input

The basic unit of analysis in the *melody* package is the spectrogram: an image representing the variation in spectral density of a (sound) signal over time. This can be represented as a two dimensional matrix of signal intensity values with rows corresponding to different frequency ranges and columns corresponding to different slices of time. One easy way to import a spectrographic image a matrix in R is to first convert the image into Portable Greymap [PGM] format, where each spectrographic intensity is coded as a greyscale value typically between 0 and 255 (the minimum and maximum values for each pixel). For an example: we read in an image in the PGM format below:

```
> pgm <- readPGM(system.file('extdata', 'calls', 'Tarsius-spectrum-Duet.female-Nietsch1998-2b2
> dim(pgm)

[1]    81 1106

>
```

## 5 The Spectrogram Object

The spectrogram object is essentially just a list composed of at least one element: our spectrogram matrix we just read in via `readPGM`. Additionally, after processing, this list also stores a list of matrices of the partitioned spectrogram units, vectors of various statistics on each of these units, and eventually, after clustering, a similarity matrix between different units. The object is instantiated using the `sg` function and requires only a single matrix as input. For an example, instantiate a spectrogram object and demonstrate the object structure and basic plotting functionality.

```
> s <- spectrogram.object <- sg(pgm)
> str(spectrogram.object)

Formal class 'sg' [package "melody"] with 1 slots
  ..@ .Data:List of 3
  .. ..$ : num [1:81, 1:1106] 255 255 255 255 255 255 255 255 255 255 ...
  .. ..$ : int 1106
  .. ..$ : int 81

>

> plot(spectrogram.object)
```

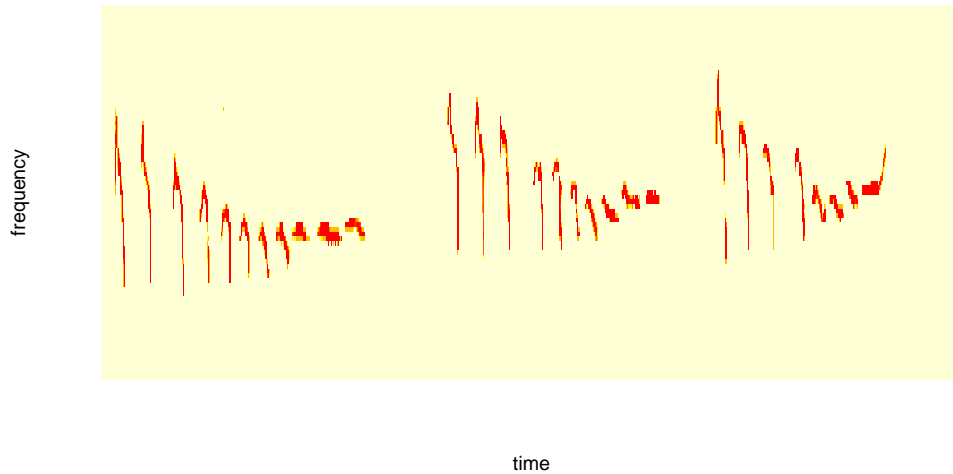


Figure 1: A spectrogram of the female component of a Tarsius spectrum duet (via the 'plot' S3 method)

## 5.1 Background vs Foreground Threshold Determination

The first somewhat trivial (but important) order of business when creating a spectrogram object is determining an absolute background/foreground threshold greyscale value. This is accomplished using the `threshold` function. In this example we use a 89 percent of the highest greyscale value as our threshold.

```
> s <- threshold(s, pct.max = 0.89)
> print(names(s))

[1] "x"           "width"       "height"
[4] "gray.dev"    "gray.mean"   "gray.max"
[7] "bg.threshold"

> s$bg.threshold

[1] 226.95
```

## 5.2 Partitioning

The first substantial step in processing a spectrogram is actually breaking it up into separate units for downstream analysis and clustering. This is accomplished by looking for relatively quiet breakpoints in the spectrogram along

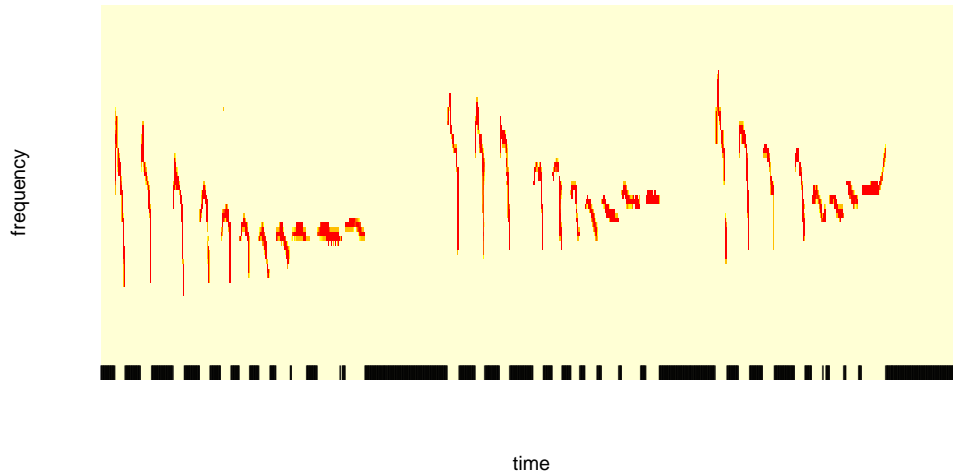


Figure 2: A partitioned spectrogram (black bands represent quiet breaks)

the time axis. Two variables (in addition to the threshold value) are used to guide this relativistic splitting process: the first is the average row value and the other is the variance in row values. The logic is that background noise will often appear as a light horizontal band punctuated by actual (higher amplitude) signal. A lambda weighting factor can additionally be used to determine how far down-biased (into the lower frequencies) this additional splitting equation carries.

```
> s <- partition(s, lambda=5)
> s$n

[1] 31

> length(s$units)

[1] 31

> plot(s)
```

### 5.3 Unit Statistics

The next important step in processing a spectrogram is calculating the simple statistics on the dimensions of each partitioned unit. By default the following

statistics are collected: height (frequency difference), width (time difference), mean y-value (weighted mean frequency), mid x-value (median time value), mid y-value (median frequency).

```
> s <- unitstats(s)
> unit.param.names <- grep('^u.*[~sl]$', names(s), value=TRUE)
> print(sapply(unit.param.names, function(x) s[[x]]))
```

	u.width	u.xavg	u.ymin	u.ymax	u.ymid	u.ylen	u.ymean
31	13	24.5	21	59	40.0	38	42.56846
65	14	58.0	22	56	39.0	34	43.16582
107	14	100.0	19	49	34.0	30	39.50602
140	13	133.5	22	43	32.5	21	36.07063
167	13	160.5	22	59	40.5	37	34.43226
191	13	184.5	23	36	29.5	13	32.13547
217	14	210.0	23	34	28.5	11	29.23475
243	18	234.0	25	34	29.5	9	30.47070
264	19	254.5	31	34	32.5	3	32.23043
307	29	292.5	30	34	32.0	4	32.06903
339	25	326.5	31	35	33.0	4	33.50951
460	15	452.5	28	62	45.0	34	51.01239
493	12	487.0	27	61	44.0	34	51.18855
525	13	518.5	29	57	43.0	28	48.87490
568	13	561.5	29	47	38.0	18	43.28964
592	12	586.0	29	48	38.5	19	43.66228
615	11	609.5	31	43	37.0	12	38.44107
637	15	629.5	31	40	35.5	9	36.45987
665	22	654.0	35	40	37.5	5	36.84981
693	24	681.0	38	43	40.5	5	39.60416
717	17	708.5	39	41	40.0	2	39.81058
804	15	796.5	26	67	46.5	41	50.86948
833	14	826.0	29	56	42.5	27	49.12722
865	15	857.5	29	51	40.0	22	46.12646
904	13	897.5	31	50	40.5	19	44.04279
927	14	920.0	35	42	38.5	7	39.29629
931	3	929.5	35	38	36.5	3	35.96113
954	18	945.0	35	40	37.5	5	37.99889
973	16	965.0	38	43	40.5	5	40.60740
1008	31	992.5	41	51	46.0	10	42.74411

	u.intensity
31	27711
65	23975
107	20514
140	16488
167	15823
191	10111

217	11370
243	14155
264	12353
307	21776
339	13371
460	23870
493	20535
525	21134
568	14079
592	13338
615	9530
637	10172
665	13548
693	15022
717	11337
804	26988
833	20902
865	14305
904	15245
927	10334
931	2205
954	11027
973	10170
1008	18524

```
>
```

## 5.4 Spectrogram Cleaning via Unit Filtering

Next we demonstrate how the `clean` function removes units depending on if it is too long or too brief temporally, too high or low frequency, or too small of a frequency difference (each unit must be at least 3 pixels high), or if it is too weak (each unit must be at least 1% of the total amplitude of the entire spectrogram).

```
> s <- clean(s)
```

## 6 Unit Level Scoring

Next we perform unit level melodic scoring for tone and interval. Tone is currently best calculated using the percentage of pixels below the background threshold [`pctbg`] or how 'white' the unit is: the whiter the unit the less noisy and the more tonal. Interval currently uses the ratio of the absolute change in per column mean-frequency over the difference between the max and min above-threshold frequencies [`ymRpuH`] (thus thick bands will not score higher interval scores than thin bands with the same slope). Each of these scores are

averaged over the whole spectrogram and unit-level scores can optionally be weighted by unit-intensity.

```
> s <- tone(s)
> s$tone
```

```
[1] 0.9307188
```

```
> s <- interval(s)
> s$interval
```

```
[1] 0.7054849
```

## 7 Unit Clustering

The final processing step is to use all of our new unit level statistics to cluster the units into a mathematical graph where each unit is a node and a match between nodes is an edge. There are currently two ways to match nodes and both involve creating a list of distance matrices for the differences in each statistic between each of the units. The first method averages all of these difference matrices and has a single cut-off value to convert the single valued matrix into a binary adjacency matrix. The second method performs the binary (TRUE/FALSE value) determination first, using an array of limits (one limit per statistic), and then collapsing these binary matrices, using boolean logic, into a single binary adjacency matrix. The resulting matrix, from either method, forms the final clustering graph. Currently syllable count is merely a count of the different clusters (isolates are also syllables) and repetition is the average degree per cluster (isolates get a score of zero repetition).

```
> s <- cluster(s, method='limits', intensity.weighted=FALSE)
> s$syllable_ct
```

```
[1] 9
```

```
> s$repetition
```

```
[1] 0.8571429
```

```
> ## weighted by intensity
> s <- cluster(s, method='limits', intensity.weighted=TRUE)
> s$syllable_ct
```

```
[1] 5.358455
```

```
> s$repetition
```

```
[1] 0.8815676
```

## 8 Plotting and Graphing Units

The *melody* package also has two convenience functions to plot and graph the processed spectrogram and clustering graph (respectively). The `plot` function simply plots the spectrogram and adds annotations appropriately as the spectrogram object is modified. The `graph` function plots a mathematical graph showing the clustering patterns of the units and grouping different syllable types. Colored unit labels along the bottom of the spectrogram correspond to the colored labels in the clustering/repetition graph.

```
> par(mfrow=c(2,1))
> plot(s)
> graph(s)
```

## References

- Nietsch A, Niemitz A (1987) The Vocal-Acoustical Repertoire of Free-Ranging Tarsius-Spectrum. *International Journal of Primatology* 8, p 483.
- Butts, Carter T. (2008). “network: a Package for Managing Relational Data in R.” *Journal of Statistical Software*, 24(2).
- Carter T. Butts (2010). *sna: Tools for Social Network Analysis*. R package version 2.2-0. <http://CRAN.R-project.org/package=sna>



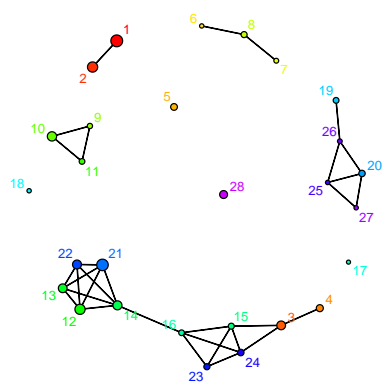
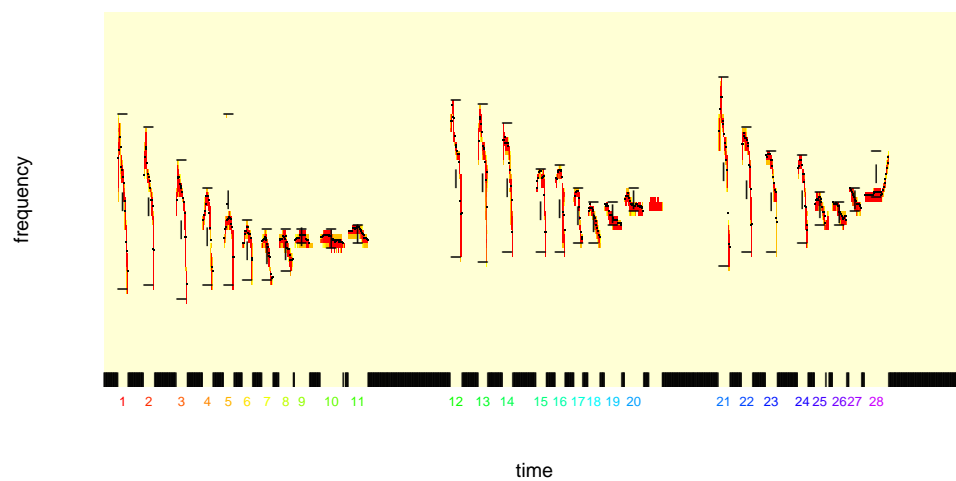


Figure 3: spectrogram and graph