Context dependent variability in note sequences in Bengalese Finch songs

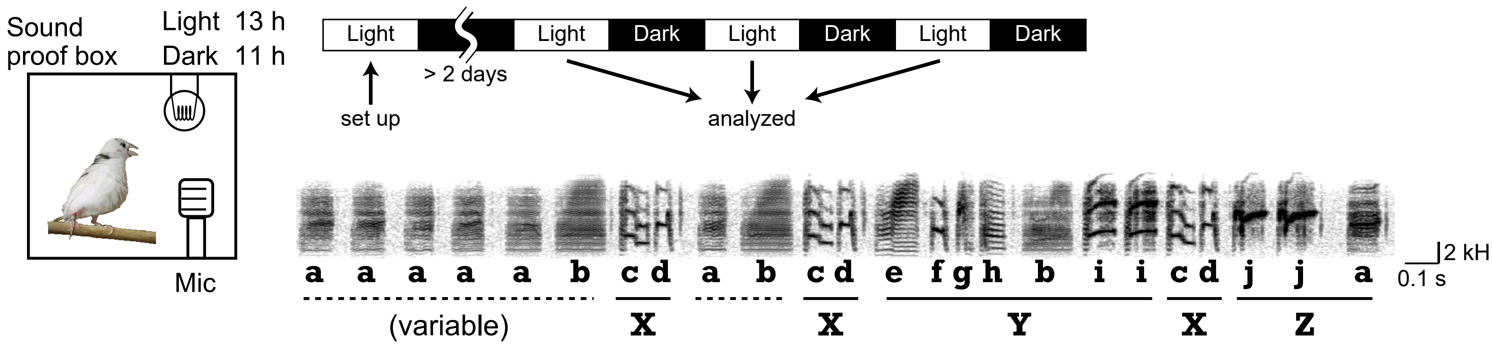
Takuya Koumura & Kazuo Okanoya (University of Tokyo)

Conclusions

Number of repeated song notes & motif transition entropy were biased

Some of the note repeats & transitions had circadian rhythms

Their trajectories were different from one another



Motifs (frequently appearing sequences)

X → c d

Y → e f g h b i^n

Z → j^n a

Repeat

Motif to motif (or note) transitions

X → a, Y, Z

Z → a, b

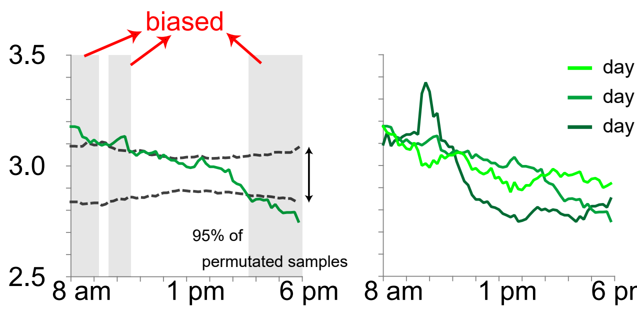
Number of repeated notes

(average over 3 hour window)

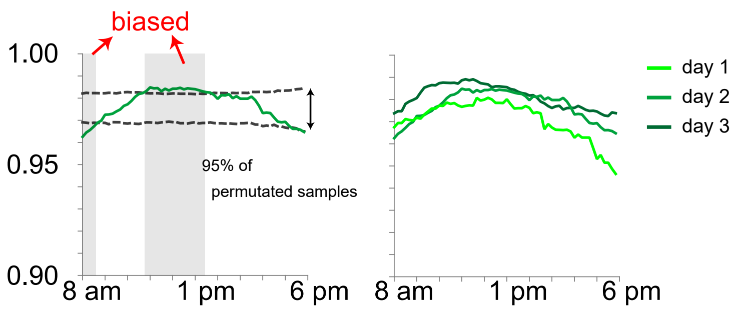
Transition entropy

$-\sum_{\mathbf{N}} P(\mathbf{M}|\mathbf{N}) \ln P(\mathbf{M}|\mathbf{N})$

in 3 hour window



Ave. correlation coefficients = 0.71 (p=0.027)



Ave. correlation coefficients = 0.78 (p=0.005)

Result summary

	Motifs	Transitions	Transitions with circadian rhythms	Repeats	Repeats with circadian rhythms
Bird A	3	2	0	2	1
Bird B	6	5	2	6	3
Bird C	5	2	1	-	-
Bird D	3	2	0	-	-

Detailed methods

Subjects

Four adult male Bengalese finches (Lonchura striata domestica), age > 120 days post hatch.

Recording

Each bird was put in a separate sound attenuation box with an LED light and a microphone. All recorded songs were undirected song.

Notes and bouts extraction

The recorded sound was band-pass filtered at 1.5-6.5 kHz. Sound envelope was calculated by full-wave rectification and low-pass filtering at 200 Hz. Intervals with the envelope larger than manually determined threshold were extracted as song notes. Short intervals (< approx. 10 ms) and short gaps (< approx. 5 ms) were removed (these length were adjusted separately in each subject). Song bouts were defined as sound intervals with length > 2 s with silences > 0.3 s at both ends. (Tachibana, et. al., 2014)

Note labeling

First, bouts were randomly chosen so that the number of total notes included in the bouts > 512. The notes in the chosen bouts were manually labeled and used as training data for the multi-layered convolutional neural network (LeCun, et. al., 1998). Half of the training data were used for parameter learning, and the super-parameters were determined so as to minimize the classification error in the other half. Then the rest notes were labeled by the trained neural network. All labels were manually checked and (if necessary) modified according to the visual inspection of the spectrogram. To validate the appropriateness of the classification with manual label modification, two fold cross validation was performed. The classification error in the cross validation was 0.1-0.5%.

Number of repeated notes & transition entropy

Motifs were extracted manually. The amount of the notes that did not belong to any motifs or introductory parts was < 1% of the total notes. Number of repeated notes in each motifs were counted separately and averaged over 3 hour time window. If a motif has more than one consecutive motifs or notes, transition entropy in 3 hour time window was calculated. The transitions with total frequency < 2% was ignored.

Detection of bias

To test if there was a bias in the number of repeated notes or transition entropy, bouts were randomly permutated. Then the number of repeated notes and transition entropy were calculated according to the permutated samples. If the actual values were outside of the 95% range in which the values calculated from permutated samples distributed, the values were considered to be biased at the time. The number of permutated samples was 2048.

Correlation analysis

To evaluate if there were circadian rhythms in the number of repeated notes or transition entropy, the average correlation coefficients between the values in pairs of days were calculated. Then bouts in each day were circular-shifted with random amount of time. The number of repeated notes or transition entropy was considered to have circadian rhythms if the average correlation coefficients were larger than 95% of those in circular-shifted samples. The number of circular-shifted samples was 2048.