Master Thesis
Computational model of Zebra Finch song learning and the influence of sleep on it

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Abstract

The Zebra Finches are songbirds which learn the song of their tutor. They learn it from 25 days post hatch (DPH) to 90 DPH (Liu, Gardner, & Nottebohm, 2004). Zebra finches are commonly used as a model of speech acquisition.

Derégnaucourt, Mitra, Fehér, Pytte, and Tchernichovski (2005) showed that sleep plays an important role in the learning of tutor songs. Indeed, they showed that sleeping has a negative impact on song restitution by zebra finches in the short term but a positive impact on the long run. Song restitution is less complex and less similar to the tutor song from one morning to the previous day evening, but the greater this loss in performance was overall for one bird, the better this bird was able to reproduce the tutor song at the end of its learning.

In addition to that, Dave and Margoliash (2000) have found neurons in the motor cortex which fires sequences during sleep that correspond to their activity pattern when the birds sing in adult zebra finches. This shows that motor neurons that are highly correlated with bird's own song (BOS) are activated during the night. These identified replays suggest that some learning may occur during sleep that use past experiences.

Our hypothesis is that during its sleep, the zebra finch restructures the knowledge it has acquired so far thanks to replay mechanisms. We hypothesize that this restructuring can account for the loss of performance in the short term and an improvement of performance in the long term.

The goal of this internship is to offer a model of the zebra finch song learning which can explain the correlation between the loss of performance every night and the overall performance at the end of learning.

We built a two-step learning algorithm with biological constraints that switches between two phase. The "day" phase in which the algorithm tries to improve its song production by optimizing the parameters of the motor sequence without changing the sequence itself, and a "night" phase learning algorithm where the algorithm tries to improve the sequence itself to allow the motor command to match better the dynamics of the song without changing the parameters. We think that modification of the sequence will have a negative impact on the short term performance as the fit made during the day will no longer match the new sequence, but that the new sequence will allow the day fit to match better the tutor song as the sequence is better suited to describe the tutor song.

Our preliminary results did not confirm this hypothesis. Though, several modifications of the models or little additions seems promising to reproduce the effect we target.

Contents

1. Introduction

1.1 Zebra Finch song learning

1.1.1 Characteristic of the zebra finch song learning

insert zebra finch figure

The Zebra Finches are songbirds which learn the song of their tutor. Only males sing and this behaviour is part of the courtship of the bird. They learn their tutor song from 25 days post hatch (DPH) to 90 DPH (Liu et al., 2004) and will sing the same song for the rest of their lifes. The songs have rather complex structures, composed of chains of syllables. A syllable is defined by a sound surrounded by short silences. This chain of syllable is called a “motif” (Doupe & Kuhl, 1999; Margoliash, 2002). Zebra finches are close-ended learners (Margoliash & Schmidt, 2010), they learns only one song and will retain it their whole life, in comparison of open-ended learners such as canaries which learns a new song each year.

The Zebra Finch learning development has been described in two different phases. First of all, the Zebra Finch is in a sensory phase until 65DPH. During the sensory phase, it almost does not sing and only listens to the song of its tutor, which can be sung by a real Zebra Finch or by a song playback. This is a critical period in which the bird memorizes fully the tutor song. Birds who have access to the tutor song for only ten days between 25DPH and 65 DPH sing the tutor song as good as the bird with access to the tutor song during their whole learning (Böhner, 1990; Roper & Zann, 2006). The second phase is the sensorimotor phase during which the bird sings and uses its auditory feedback to improve its performance. Starting from 25DPH to 30DPH, the bird produces a *subsong*, a process similar to babbling. Then, the bird produces a *plastic song* starting from 50DPH. The plastic song is the first attempts of the bird to imitate the tutor song it has memorized. Its song productions are highly variable and become better and better copies of the tutor song. After 90DPH, the song has reached its *crystallization*. The song is fixed and will not change throughout the Zebra Finch adulthood. The song of the Zebra Finch gets highly stereotyped (Williams, 2004). Zebra Finches needs auditory feedback to learn to sing. Deafening in juvenile has severe impact on song acquisition, even if the tutor song has already been acquired. Deafening once the song is fully learned has a much smaller impact on performance (Scharff & Nottebohm, 1991; Doupe & Kuhl, 1999). In addition to that, Zebra Finches raised in isolation will also develop abnormal songs. These two observations shows that Zebra Finches songs are acquired and not innate. Therefore, Zebra Finches need to learn how to sing. Understanding what mechanisms underlie this learning can help us understand what are the prerequisites of vocal learning in others species and especially in Humans.

1.1.2 Why is zebra finch song learning studied

Songbird and especially Zebra finches are commonly used as a comparison with human about vocal development. Indeed, the song they produce are not innate even though they have predispositions toward learning their songs. They produce song with complex structures composed of syllables.

The neuroanatomy of Zebra Finch has also been extensively studied and the different structures involved in singing has been identified (Nottebohm, 2005; Bertram, Daou, Hyson, Johnson, & Wu, 2014). Doupe and

Kuhl (1999) even proposed parrallels between the areas involved in song production with songbird and the areas involved in speech with humans.

Zebra Finches are also excellent laboratory animals. They are easily domesticated and easy to study compared to other songbirds or "speaking" animals. As they learn only one song, their vocal progress is easily trackable. The developmental trajectory can be inferred. Derégnaucourt et al. (2005) for instance tracked from the syllables trajectories by clustering syllable productions over time.

not beautiful sentence

change paragraph

* Well studied Neuroanatomy * Easy to study experimentally * Easily domesticated * Learn one song * Learn quickly (90DPH) * Easy to track song development

1.2 Neurobiology of the Zebra Finch

1.2.1 Neuroanatomy of the Zebra Finch song system

* Connection between RA, HVC, Area X, … Inhibition, excitation

1.2.2 Pattern of activation in RA and HVC

* HVC clock like, temporal structure (Ali et al.) * RA activation while singing at very precise time and sparse coding

* Motor control (Ali et al.) Ali et al. shows real two different learning: spectral and temporal

1.3 Models of song learning

Only very few models have been created. Even less are actual computational models.

1.3.1 Reinforcement learning

* Proposed but no real explanation of what could be the state space, the action space, the reward function (Dave&Margoliash). * Used in paradigm to test different hypothesis (averse reward to force change in behaviour of the bird)

1.3.2 Song preferences in selection (Marler)

* Behavioural model to explain how the bird select its template * TODO: Add more

1.3.3 Coen's model

* Clustering technique with babbling (multimodal)

* Cluster the tutor song syllables thanks to their characteristics * Babbling, create a mapping between the motor space and the identified cluster * Use of a real synthesizer but not actually built to model zf vocal apparatus * No quantitative means to see how good is the song reproduction * The learning is only babbling, nothing is driving the model in a specific direction.

1.4 Song synthesizer

1.4.1 G. B. Mindlin's song synthesizer to reproduce Zebra Finch song

G. B. Mindlin and his team built a model of the Zebra Finch vocal apparatus. They described with differential equations the behaviours of the components of this vocal apparatus (see Fig 1.1). The differential equations model the separation between the syringeal labia. Each labia is modeled as a spring and mass

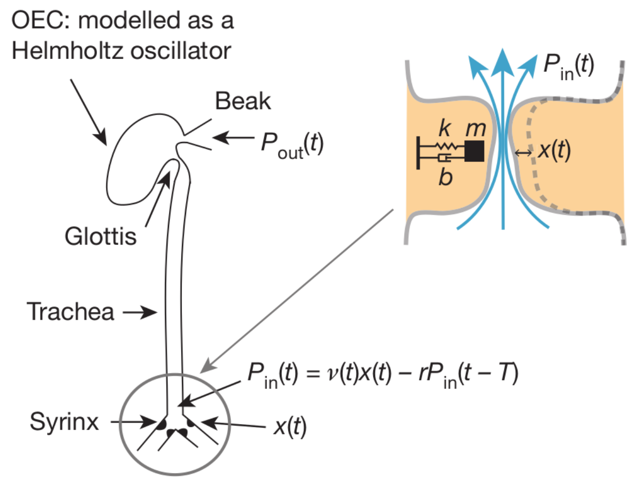


Figure 1.1: Model of the zebra finch vocal apparatus
The air ($P_{sub}(t)$) comes from the air sac below the syrinx, then goes up to the trachea, the glottis, resonate in the oro-esophageal cavity (OEC) and the beak ($P_{out}(t)$). Each component acts as a filter in G.B. Mindlin's team model of the zebra finch vocal aparatus. Figure 1b taken from Amador, Perl, Mindlin, and Margoliash (2013).

system that can produce sustainable oscillations. Depending of the parameters it receives, the synthesizer is able to produce a vast variety of sounds, either very pure or very rough, depending of the strength of the labia tension (Amador & Mindlin, 2008; Boari, Perl, Amador, Margoliash, & Mindlin, 2015). The dynamic system shown in equation 1.1 described the mathematical simplification of their model.

$$\begin{cases} \frac{\mathrm{d}x}{\mathrm{d}t} = y \\ \frac{\mathrm{d}y}{\mathrm{d}t} = -\alpha\gamma^2 - \beta\gamma^2 x - \gamma^2 x^3 - \gamma x^2 y + \gamma^2 x^2 - \gamma x y \end{cases} \tag{1.1}$$

x describes the position of the syringeal labia. γ is a constant which takes into account values specific for the Zebra Finch vocal apparatus. α and β are unit-less time-dependant parameters. α is proportional to the air sac pressure, that is how much air is coming through the syrinx, and β is proportional to the syringeal labial tension. It can be hypothesized that these two parameters can be easily modified by motor actions. Therefore, the whole singing behaviour can be described as the dynamics of muscles acting on the air sac pressure and the syringeal labial tension. Thus, this synthesizer provides a way to bridge the gap between actual motor commands and song production. Even if the model is simplified, as it assumes a symmetry in the labial tensions, it is able to produce a rich variety of sounds.

This model of birdsong production shows that low dimensional but biologically realistics parameters can describe the singing behaviour of the Zebra Finch. Simple variations in the motor space produces complex and diverse variations of the song production. This model simplifies greatly the study of song production behaviour, as it is possible to study the dynamics of song production in the motor space while keeping realistic constraints.

1.4.2 Zebra Finches are sensible to song produced by the synthesizer

The computational model of the zebra finch vocal apparatus is a real sound synthesizer. It produces sound waves which birds, as we, can listen to. As explained in 1.2, Zebra Finches have neurons which are highly selective to their BOS. When the bird is asleep and listen to their own song, these neurons fire in a very specific pattern. To assess the quality of their synthesizer, G.B. Mindlin team tested if their synthetical song, built from the BOS, will activate these neurons (Amador & Mindlin, 2014; Boari et al., 2015). They showed that even if the strenght of the activation was not as strong as the bird listening to its BOS, their synthesized song performed better than a conspecific song or the BOS played in reverse. This suggests that the synthesis is sufficiently good to trick a bird. The synthesizer is thus ablet to produce good imitation of Zebra Finch songs.

1.4.3 Gestures and song structure

The study of the parameters α and β over the time course of the song reveals interesting results. Amador, Perl, Mindlin, and Margoliash (2013) propose to describe songs by the sequence of air sac pressure (α) and syringeal labial tension (β) trajectories, called gestures. A gesture starts and stops when there is a discontinuity in the trajectory of either the air sac pressure or the tension (see Fig 1.2). If notes and syllables are the primitives of a song in the sensory space, a gesture is the primitive of a song in the motor space. Several subsequent gestures are needed to produce one syllable.

Amador and her collaborators suggested that spiking pattern observed in HVC is correlated with the onset and offset of gestures and therefore that teh HVC activity is not a clock-like pattern but the transmission of high level motor commands which defines the song structure. This has been contested by Lynch, Okubo, Hanuschkin, Hahnloser, and Fee (2016) and Picardo et al. (2016) with extensive statistical analyses. Even if HVC neurons do not actually fire on the onset and offset of gestures, the gesture framework is very interesting because it allows us to think about the song structure representation in the motor space, which is of particular interest to build a biologically plausible model of song learning.

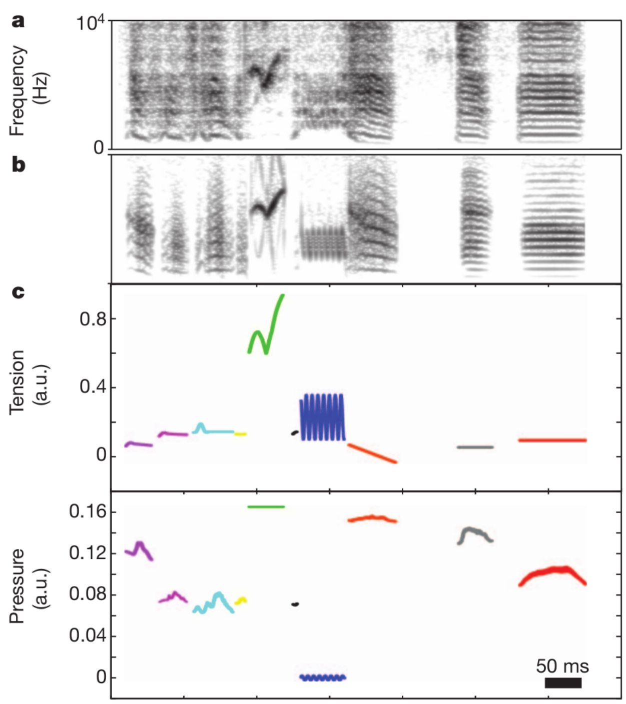


Figure 1.2: A birdsong and its associated parameters for reproduction segmented in gestures **a)** spectrograph of a bird's song. **b)** spectrograph of the synthetic song. **c)** the paramaters α and β for the song. There is several discontinuities in their trajectories. Each continuous segment forms a gesture. Figure from Amador, Perl, Mindlin, and Margoliash (2013).

1.5 Influence of Sleep in the Zebra Finch song development

Several studies showed that sleep is involved in the song learning and maintenance. Dave and Margoliash (2000) shows thanks to electrophysiology recording the . Derégnaucourt et al. (2005) showed that sleep has

complete these sentences

1.5.1 Song replays during sleep

As explained in the Section 1.2, the song system in the zebra finch brain is highly specialized. Neurons in HVC or RA have a very precise and stereotyped pattern of activation when the adult bird sings. Dave and Margoliash (2000) studied the pattern of activation of RA neurons while adult birds were asleep. They observed that neurons in RA spontaneously burst in patterns similar to their activation patterns when the bird sings. Dave & Margoliash hypothesize that this replay activity could be the product of an off-line learning mechanism. Indeed, neural replays have already been found in the rat and it has been showed that these replays influence the construction of its cognitive maps (de Lavilléon, Lacroix, Rondi-Reig, & Benchenane, 2015) or that the suppression of the replays impairs the learning (Girardeau, Benchenane, Wiener, Buzsáki, & Zugaro, 2009).

Dave & Margoliash's results were obtained on adult birds which have already learned their song. Though, we can hypothesize that RA replays also occur in the juvenile bird and impacts its learning. The actual function of the mechanism that produces these replays must still be determined.

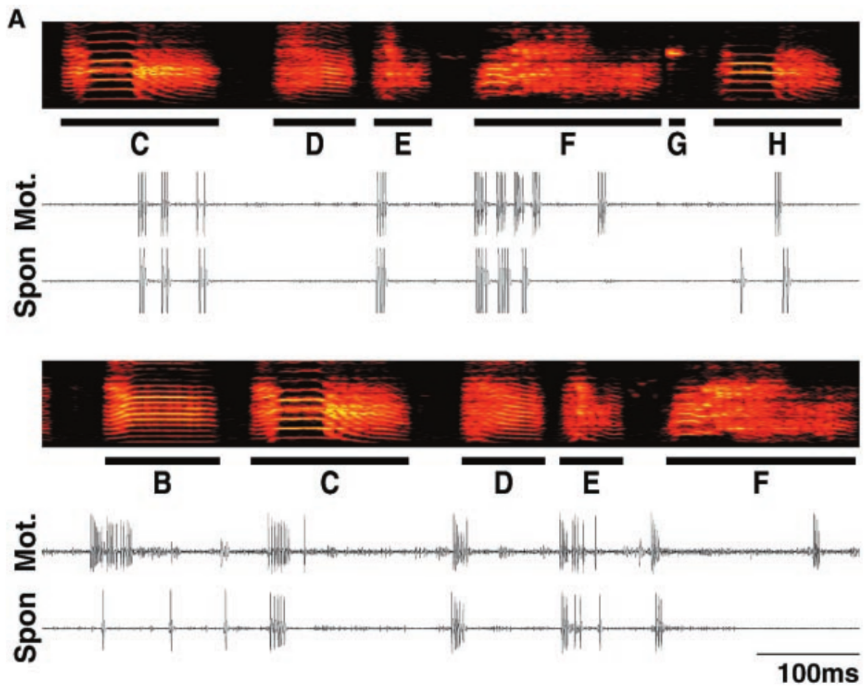


Figure 1.3: Neuronal replay during sleep

Recording of the activity of two different neurons for one bird. For each neuron, a premotor activity is shown with the spectrograph of the BOS and the raw trace of a spontaneous activity during sleep that matches the premotor pattern. Taken from Dave and Margoliash (2000).

1.5.2 The impact of sleep on the birdsong learning

Derégnaucourt et al. (2005) recorded entire song developments of Zebra Finches and studied the vocal trajectories during the whole learning process as during the cycles of sleep and wakefulness. They tracked the development of syllables and clustered them. Thanks to this database, they computed the shift in the mean of the clusters for each syllable either in the same day (2 random samples of 100 songs), from evening to the morning (last 100 songs compared to the first 100 songs of the next day) or from the middle of one day to the middle of the next day (random sample of 100 songs compared to a random sample of 100 songs of the next day). They computed the total vocal change for each of these cluster, that is the relative variation of syllable features Tchernichovski, Nottebohm, Ho, Pesaran, and Mitra (2000)[1]. They found that vocal changes were the most important with the the cluster of the evening songs compared to the next day morning song, compared to the changes that occur for one day to the next or in the same day (see Fig 1.4). This result shows that sleep has a big impact in the development of the birdsong, because it cannot be explained by the day to day vocal change.

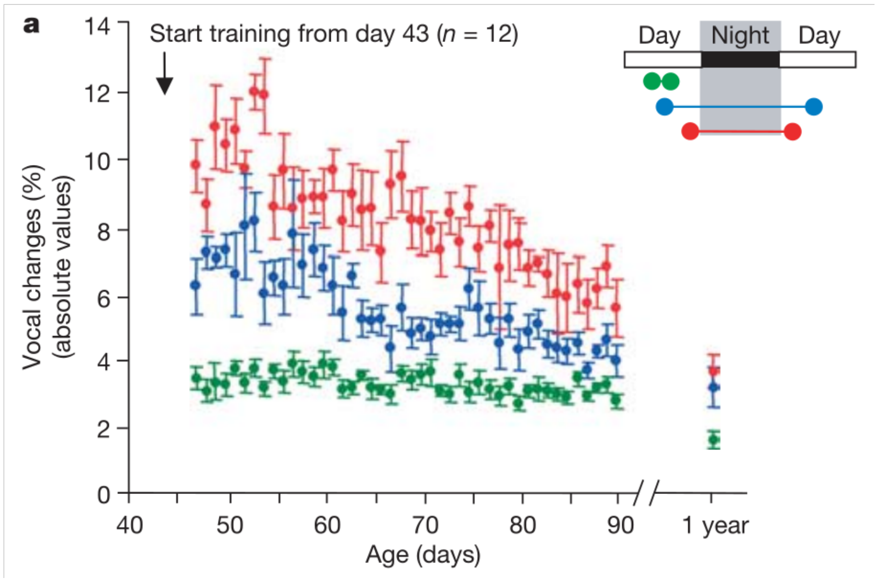


Figure 1.4: Absolute vocal change during song development

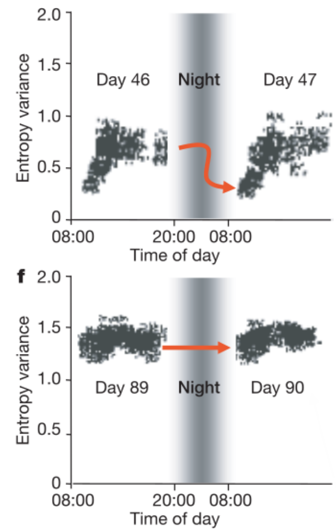
Vocal changes in absolute values (median + s.e.m). Green is the change across random sample during the same day (baseline). Blue is the change between random sample from one day to the next. Red is the vocal change from one evening to the next morning. Taken from Derégnaucourt, Mitra, Fehér, Pytte, and Tchernichovski (2005).

The vocal change measure Derégnaucourt and his team used is an absolute measure. That means that this measure cannot tell if the change goes in the same trend as the whole learning or in the opposite direction. Thus they introduce a signed measure of vocal change. If the change goes toward the value of the feature at the end of the learning, the signed vocal change is positive, otherwise, it is negative. The signed vocal change showed that sleep actually has a *negative impact* on learning. Indeed, the effect of night-sleep is almost always negative (see Fig. 1.5a). The effect cannot be explained by the fact the bird has not sung for a long time. Indeed, preventing the bird of singing for 8 hours does not yield the same effect. Thus, this unlearning is due to a mechanism which occur during sleep.

The authors computed the performance of the bird to reproduce its tutor song at the end of its development thanks to a similarity measurement (Tchernichovski et al., 2000, developped in section 2.1.2). Surprisingly, they found that the more the post-sleep deterioration was important overall, the better the bird was able to imitate the song of its tutor, as seen on Fig. 1.6. The negative impact sleep has on learning on the short term (day to day) has a positive impact in the long run. It shows that a learning mechanism is at play during sleep. This learning mechanism has a different function than the learning mechanism during the day. The authors suggest that the oscillations in vocal learning may help the bird get out of local maxima in development. Several learning algorithm can be investigated to explain these results.

[1]These measures are detailled in Section 2.1.2

(a) Vocal changes in signed values during sleep



(b) Entropy variance decreases during sleep

Figure 1.5: Sleep has a negative impact on vocal development
a) Vocal changes in signed values (median + s.e.m) during night-sleep compared to overall development trend. **b)** Entropy variance increase overall song development but decrease during night when the bird is still learning. At 90DPH, the bird has reach crystallisation of the song and sleep has little to no impact. Taken from Derégnaucourt, Mitra, Fehér, Pytte, and Tchernichovski (2005).

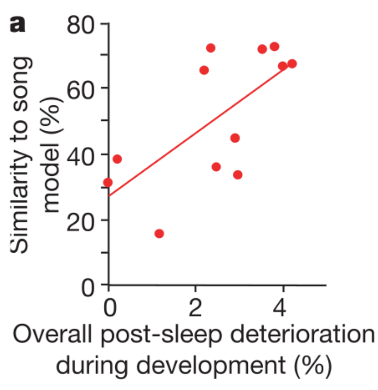


Figure 1.6: Correlation between post-sleep deterioration and similarity of the tutor song at the end of learning.
The more the sleep deteriorate the bird's learning from one day to the next, the better the bird reproduces its tutor song at the end of its learning. Taken from Derégnaucourt, Mitra, Fehér, Pytte, and Tchernichovski (2005).

1.6 A computational model of birdsong learning to explain the sleep influence

1.6.1 Interest of a computational model of birdsong learning

* Computational model helps understanding what are the *implementation constraints* of the learning mechanisms * Use of synthesizer Realistic computational budget *Easily make hypotheses that can be tested experimentally afterwards Abstracted and controlled environment

1.6.2 Goal: Build a modular two-step learning model and look for learning algorithm that can account for Derégnaucourt's results.

2. Our Model

The goal of this internship is to build a computational and behavioral model of birdsong learning with realistic constraints and try to model the impact of sleep on song development as presented in the Section 1.5.2. The model is developped from scratch in Python 3. It uses the birdsong synthesizer built by G.B. Mindlin and his team and the standard measures used to analyse birdsong.

The Model is a two-step learning model. The model alternates between two different learning algorithms. The hypothesis we make is that one of these learning algorithm correspond to the learning algorithm the bird uses during the day, and the second algorithm is the algorithm used by the bird during its sleep. We hypothesize that the algorithm used during sleep should focus on restructuration of the song models the bird has and to the diversity . We think that an algorithm targetting these yields the negative impact of sleep in the short term with a positive impact at the end of learning as Derégnaucourt et al. (2005) observed.

The source code of the model is available at https://github.com/PaulEcoffet/birdsonglearningmodel.

2.1 Global Architecture

The model is built in several modules. First of all, the model uses G.B. Mindlin's synthesizer to produce realistic song with biologically plausible parameters (see Section 1.4). Then, song features measurement and songs comparison methods have been implemented and used as the hearing system. The song feature measures were taken from the litterature (Tchernichovski et al., 2000). They are the standard measures used to describe songs and syllables in the birdsong research community.

The birdsong learning model I built is a two-step learning algorithm. One algorithm models the learning process of the bird during the day, the other models the learning during the night. These day and night models can be easily changed in the program I wrote.

2.1.1 Boari's implementation of the birdsong synthesizer

We want to use G.B. Mindlin's synthesizer because it allows us to build a computational model with realistic constraints. It bridges the gap between the motor commands and the song production thanks to a biophysical model of the Zebra Finch vocal apparatus. Our model can produce simple streams of α and β parameters and send them to the synthesizer. Then, the synthesizer produces real sound waves that can be analyzed by the hearing system.

We use the implementation of the synthesizer available for download on the Dynamical System laboratory of the University of Buenos Aires (http://www.lsd.df.uba.ar) (Boari et al., 2015). The downloaded program was actually a combination of an α and β parameters extractor from an audio file and the synthesizer which can only use the extracted parameters. I extracted the synthesizer from the source code and adapted it so that it can receive arbitrary parameters. The synthesizer had several bugs. It is supposed to generate a sound stream of the same length of the parameter stream. That is, if there is 10 000 values of *alpha* and *beta*, the synthesizer should return a sound wave composed of 10 000 values. But it actually dismiss 2 parametesr, returning only 9 998 values. As the implementation of the synthesizer was badly documented and the source code was not self explanatory at all, I decided to pad the α β streams with 2 dummy values to prevent this bug.

I have also developped a small Cython package to call Boari's C synthesizer from Python. The source code of this package is available at https://github.com/PaulEcoffet/birdsynth.

2.1.2 Characterizing and comparing songs

As we wanted to work on real audio signal, our algorithm must use relevant features of the songs to describe them. Indeed, it needs to compare its production to the tutor song so as to correct its errors and improve itself.

Measurement of the song features

Tchernichovski et al. (2000) suggested several measures to characterize Zebra Finch songs. To apply these measures, the song is first cut into several time windows, and the measures are computed for each time windows. These measures give us a fine-grained description of the song throughout time.

They are extensively used in the birdsong research community (Coen, 2007; Derégnaucourt et al., 2005; Lipkind et al., 2013; Liu et al., 2004).

The measure we use are the Amplitude, the Frequency Modulation, the Amplitude Modulation, the Pitch, the Goodness and the Wiener Entropy of the signal. Tchernikovski and his team developped a software called Sound Analysis Pro 2011 to compute these features. Though, this software runs only on Windows and its functions cannot be called by another program. I have thus ported the implementation of the song features measurement from a Matlab implementation (called Sound Analysis Toolbox) to a Python implementation. The values of the features for the same song computed by my implementation matched qualitatively the values of the Matlab implementation (see Figure **??**).

I have also reimplemented the spectral derivative plot which is extensively used in the songbird research community to represent songs.

insert graph to show the match

Comparison of two songs

Tchernichovski et al. (2000) also introduced a similarity measurement. This similarity measurement compares how a song is related to its tutor song. To do so, the algorithm looks for matches in the features for each sound window of the tutor song and the pupil song. The similarity score is the percentage of the tutor song that has been matched to the pupil song. The similarity score does not punish wrong order of syllables. For instance, if the pupil sings the syllables A-C-B instead of A-B-C, the similarity will be very high even if the syllables are sung in the wrong order.

Similarity is really long to compute and is only meaningful when comparing two complete songs. It is also almost unaffected by temporal mismatches. Others methods are used to compare syllables or notes. For simplicity, syllables are compared by the study of means and variance of every features (Pitch, Entropy, …) during the syllables. Two syllables are considered similar if they have the same mean and variance for every feature.

The Python module I wrote to compute song features and similarity scores is called *birdsonganalysis* and is available for download at https://github.com/PaulEcoffet/birdsonganalysis/.

2.1.3 Song Model

Our computational model works on the motor representations of songs. The goal of this model is to adjust these representations so that they generate an accurate imitation of the tutor song with G.B Mindlin's synthesizer. I call these motor representations *Song Models*. The representation we choose for the Song Model is highly inspired from Amador et al. (2013) works on gestures, as our algorithm has to feed the synthesizer with the revelant streams of α and β parameters. Gestures are motor primitives. They describe simple and continuous variations of the synthesizer parameters. Therefore, the Song Model is described as an *ordered sequence* of gestures of different durations. A gesture describes by two simple formulas the α

and β parameters for its duration. For instance, the sequence of a song model could be "first, gesture A for 50 ms, then gesture B for 30 ms, then gesture C for 120 ms".

Be SM a song model, it is defined by the n-uplet in equation 2.1.

$$SM = (G_i \ \forall i = 1..n) \tag{2.1}$$
$$G_i = (Start_i, P_i) \tag{2.2}$$

With G_i the i^{th} gesture of the song model. $Start_i$ is the time at which the gesture G_i starts, P_i are the parameters of the gesture that describe the α and β streams. $Start_i < Start_{i+1} \ \forall i$, therefore, the gestures are sequenced chronologically in the song model. The gesture G_i ends when the gesture G_{i+1} starts, or when the song is finished.

A gesture describes the α and β streams with two formulas parametrized by 18 values. The formulas are sums of affine and sinusoidal functions. They are described in equations 2.3 and 2.4.

$$\alpha(t) = a_\beta \times t + b_\beta + d_\beta \sin(\omega_\beta \times 2\pi \times t + \phi_\beta) + c_\beta \tag{2.3}$$
$$\beta(t) = a_\alpha \times t + b_\alpha + \sum_{i=1}^{3} [d_{i,\alpha} \sin(\omega_{i,\alpha} \times 2\pi \times t + \phi_{i,\alpha})] + c_\alpha \tag{2.4}$$

We choose these formulas because they roughly described the pattern of α and β for each gesture that we have observed using the parameters extractor built by Boari et al. (2015) while being still relatively simples. Therefore, a gesture is always described by 18 parameters, whatever its length. It greatly simplify the model as the number of parameters to describe the song reduces massively. Indeed, he synthesizer needs an α and a β value at each sound sample. It means that at 44 100 Hz, to generate a sound of 20 ms (the average duration of a gesture), the synthesizer needs 14 000 values. Our simplified formula reduces thes 14 000 values to only 18.

To simplify even more our model, we made the assumption that the song the bird will produce matches exactly the duration of the tutor song. Therefore, the gesture G_i tries to match the tutor song starting from $Start_i$ to $Start_{i+1}$. Be TS the tutor song, we can thus define the subset TS_i, the part of the tutor song that the gesture G_i targets to imitate.

$$TS_i = (TS(t) \ \forall t = Start_i..Start_{i+1}) \tag{2.5}$$

This is unrealistic as the pupil song timings do not exactly match the timings of the tutor song. This constraint is due to the comparison method we choose to assess the resemblance between the generated song and the tutor song.

All gestures at creation have the same 18 parameters (see Appendice **??**). These inital parameters were found with grid search to prevent the algorithm from getting stuck in either producing only silence or only sound. Indeed, if the initial parameters produce sound, the algorithm may not be able to find the parameters that make the synthesizer silent, and reciprocally. The initial parameters we choose are at the boundary between silence and phonation to avoid this issue.

2.1.4 A two-step learning model

Following the architecture of the Song Models, we notice that there are two tasks to be fulfilled. First of all, for each gestures G_i, the parameters P_i must be fit so as to produce the imitation of their corresponding part of the tutor song TS_i. Secondly, the gesture sequence SM must be adapted so that the gestures start and end at meaningful positions $Start_i$ and $Start_{i+1}$. Indeed, gestures represent discontinuities of trajectory in the motor space, therefore, the gesture onsets and offsets should be in relevant position to produce the discontinuities needed to match the tutor song.

graphic for sequence and for parametrization of gesture

There is therefore two algorithms that must be implemented. we can hypothesize that one of these algorithm occurs only during day and the other only during night. The optimization of each parameters gesture have only a positive impact on the bird performance, but the sequence optimization could destroy the progress of the gesture's parameters optimization by changing how the gestures are organized. Therefore, we hypothesize that the sequence optimization algorithm will have a negative impact on the bird performance on the short term, but that it is needed to find the best solution and have a positive impact on the long run. We thus think that if the parameter optimization occurs during the day and the sequence optimization occurs during the night, we can explain the results of Derégnaucourt et al. (2005).

2.2 Day learning algorithm: Parameters optimization

2.2.1 Algorithm

The goal of the day learning algorithm is to find the best parameters for each gesture of Songs Models. We hypothesize that the bird has a small population of concurrent Song Models to optimize, `nb_song_models`. Several values of population size have been tested from 1 to 15 Song Models. We also assumed that the bird has perfect representation of the tutor song features. It simplifies the model and is consistent with the results of Roper and Zann (2006) who showed that the bird needs only to be exposed to the tutor song for 10 days before the beginning of its learning to be able to reproduce it (as discussed in Section 1.1.1).

The bird optimizes gesture parameters with a *stochastic hillclimbing* algorithm. The bird picks a random song model SM_i to optimize, then picks a random gesture $G_{i,j}$ from this song model. It compares the sound production of the gesture with its actual parameters $P_{i,j}$ to the expected result from its tutor song memory. It then tries a small variation of every parameters of the gesture $P'_{i,j}$ according to a normal distribution (See equation 2.6). If $P'_{i,j}$ produces a sound matching the tutor song better than $P_{i,j}$, then the parameters $P'_{i,j}$ are the new parameters of the gesture. Otherwise, the P_{i_j} stays the gesture parameters.

$$P'_{i,j} \leftarrow P_{i,j} + \mathcal{N}(\boldsymbol{\sigma}) \tag{2.6}$$

$\boldsymbol{\sigma}$ is the covariance matrix of the parameters, and is analogeous to the learning rate of the algorithm. Several $\boldsymbol{\sigma}$ have been tested. They are described in the appendix .

The process is repeated `nb_train_per_day` times.

Hillclimbing figure

2.2.2 Comparison method

To compare the song production of the gesture with the corresponding part of the tutor song, we cannot use similarity score as it is only useful with whole songs (Tchernichovski et al., 2000) and is computationaly very expensive (computing the similarity between two songs takes approximatively 10 seconds). We cannot also use the mean and variance of each song features because it makes us lose temporal information of the production. As the gesture matches a precise segment of the tutor song, we can compare the features of the sound window by window between the tutor segment and the produced segment. We thus computed the distance between these features with the following method.

Be S_i the sound generated by the synthesizer with G_i, and $Features$ the function that takes a signal and computes the song characteristics window by window and returns it as a matrice $\mathcal{M}_{nb\_windows,nb\_features}$. The distance between the two signals is computed by the formula 2.8.

$$A = Features(S_i) - Features(TS_i) \tag{2.7}$$

$$dist = \sqrt{\sum_{i=1}^{nb\_windows} \sum_{j=1}^{nb\_features} a_{i,j}^2} \tag{2.8}$$

Note that we can do that only because we hypothesized that a Song Model tries to match exactly the tutor song timing as explained in section 2.1.3. Other methods of comparison such as Dynamic Time Warping can be investigated to allow a more flexible timing in the Song Model. We used a fixed duration distance for simplicity.

The goal of the hillclimbing algorithm is to minimize *dist* for each $G_{i,j}$.

2.2.3 Synthesizer issues

The production of the whole song by the synthesizer is rather long. It takes approximately 1 or 2 seconds of computational time to produce 1 second of song. So as to improve the performance of the program, I decided to generate only the sound of the gesture and to compare it with its corresponding tutor song part. G.B. Mindlin's synthesizer is not highly influenced by its previous state, although it seems to have a few fixed oscillatory patterns that create phase dependant problems. For instance, be $S(\alpha, \beta)$ the sound signal generated by the synthesizer, we have slightly different results in phase when we generate $S(\alpha_{whole\_song}, \beta_{whole\_song})$, extract the sound from $Start_i$ to $Start_{i+1}$ and compare it to S_i. These slightly different phases have an impact on the song feature measurements (see Figure **??**). Therefore, new gesture parameters can improve the song imitation for a partial generation of the songbut impact negatively the whole song production. Loss of performance can happen due to this issue. As the speed gain from the partial generation of the song is massive, I keep it in the model. Sadly, the loss in performance due to this bug is too common and we plan to fix it for future simulations.

figure showing the small differences in measurements

Nonetheless, our prediction with the day learning algorithm is that it will have a positive impact on performance every day. Though, as the gesture sequence may not be adapted to describe the motor commands needed to imitate the song, and as the hillclimbing algorithm always tries to locally improve the song imitation, the bird should get stuck in local optima. The bird can no longer improve its performance once in a local optima, even though it is far from reproducing a good copy of the song[1]. The bird also needs to improve the gesture sequences of its Song Models to produce accurate imitation of the tutor song.

2.3 Night learning algorithms: Sequence Optimization

We hypothesize that the sequence optimization algorithm occurs during the bird's sleep. We think that sequence optimization can explain Derégnaucourt's results showing that sleep has a negative impact on performance in the short term but a positive impact on the long term. Indeed, the bird needs to know when he must change its motor trajectory, if the sound it targets must be described in more gestures, or the gesture to produce a targeted sound must be shorter or longer. Modifying the gesture sequence without changing gesture parameters must negatively impact the performance, as the parameters were picked for a sequence which no longer correspond to their target. The presence of replays of song motor commands during sleep suggests that the bird works on the motor patterns of its song. This corroborate our hypothesis that the bird has access to the song representations when it sleeps.

Evolutionary algorithms are amongst the simplest algorithms to optimize a sequence (Eiben & Smith, 2003).Our algorithm takes the population of Song Models from the day learning algorithm. It then extends this population to a size of `nb_song_models_night` by creating new Song Models that are sequence variations of the day Song Models. The increase in population allows more diversity in the sequences and thus a better exploration of the possible sequences adapted for the reproducing the tutor song.

not really a good source

The variation of a sequence can be done with several rules. The algorithm can either insert a new gesture between two gestures, remove a gesture, change the duration of a gesture, copy the gesture parameters of a gesture to another gesture, or simply do nothing.

The new Song Models are then evaluated. The worst Song Models are replaced with variations of the best Song Models.

[1] Note that we cannot test this prediction before having corrected the issues explained above

Then, `nb_song_models` Song Models are selected to be the next day Song Models. They can be picked either by random or by selecting the best Song Models, depending on the simulation parameters.

2.3.1 Microbial Genetic Algorithm

We used a variation of the Microbial Genetic Algorithm as our night learning algorithm. The Microbial Genetic Algorithm is one of the simplest evolutionary algorithm. Two random individuals of the population are compared according to a criterion in a tournament. The winner of the tournament stays in the population, and the loser of the tournament is replaced by a variation of the winner. Therefore, the most accurate descriptions of the gesture sequence propagates in the population while poor descripitions are forgotten. The algorithm does `nb_tournaments` tournaments each time it is run. We hypothesize that the amount of tournaments should be in the same order of magnitude as the amount of replays observed during sleep. Indeed, a tournament need Song Models activations, so the patterns that represent them must be activated too.

We choose to use the same criterion as for the day learning algorithm. The Song Model that wins a match is the one that has the lowest *dist* with the tutor song. The underlying hypothesis is that the bird is able during its sleep to infer what would be the effect of the gesture sequence modification on its song production without any auditory feedback.

Even if we still select on the song reproduction quality, we hypothesize that the sequence variation generates nonetheless loss in performances. We also hypothesize that an explicit maintenance of *diversity* in the population would produce a even stronger loss in performance in the short term and improve in performance on the long term. Indeed, evolutionary algorithm can get stucked in local optima because only one kind of solution has propagated in the whole population. Small variation of the best solution are always less performant. The idea of diversity is to encourage different solutions even if they are less good than the other individuals. Diversity is a way of encouraging exploration instead of exploitation of the best solutions (Eiben & Smith, 2003). The most different individuals explore whole new sequences that have the room to be improved so as to outpass the actual best sequences. This method is a multi-objective optimisation which minimise distance and maximise diversity.

I implemented the explicit diversity maintenance by punishing the Song Models that have too much neighbours. Song Model SM_j is a neighbour of SM_i if they have a sequence of gestures close to the sequence of SM_i. I decided to measure it by the closeness of the onset of each gesture between Song Models. Be $Seqdist(SM_i, SM_j)$ the sequence distance between two song models.

$$Seqdist(SM_i, SM_j) = \sum_{k=0}^{nb\_gestures\_SM_i} \min_{l \in 0..nb\_gestures\_SM_j} (|Start_{i,k} - Start_{j,l}|) \tag{2.9}$$

SM_i and SM_j are considered neighbour if $Seqdist(SM_i, SM_j) < th$, th a fixed threshold.

For each SM_i, the algorithm compute the number of neighbours it has and then multiply the distance between the song model production and the tutor score with the number of neighbours. It is a variation of what is found in the literature for maximisation of a score with diversity where the score is divided by the number of neighbours. Here, as we try to minimize the score, we punish by multiplication. Be $score_i$ the score of SM_i.

$$neighbours_i = \sum_{j=1}^{nb\_song\_models\_night} \mathbb{1}_{Seqdist(SM_i, SM_j) < th} \tag{2.10}$$

$$score_i = dist(SM_i, TS) \times neighbours_i \tag{2.11}$$

In a tournament, the winner is the Song Model with the lowest score. `nb_tournaments` are made for each night learning algorithm run.

insert figure from poster of algorithm

We predict that the structure variations yield a loss in performance on the short term because the gestures parameters are no longer adapted to the new structure. We also hypothesize that the diversity criterion makes the effect even stronger, as it will discard more good performance in favor of more exploration of the sequence space. This exploration allows the discovery of more adapted sequences that are not fit yet. Therefore, this algorithm should reproduce Derégnaucourt et al. (2005) observations about the influence of sleep on song development.

2.4 Parameters

* Tried to be realistic * most are fit through gridsearch * Realistics: Number of days, number of syllables sung during all dev * Gridsearch optimization * Default value for gesture parameters * Learning rate * Prevent part of unlearing * Could be fit to match real song learning rate * Coefficient for score optimization * Algorithm way better in score than Boari but qualitatively very different to the ear * Look at which parameters boari's method was better than algo and put priority on them * Amplitude and entropy * Diversity threshold to maximise variance in diversity score

* Value: 5000 * Other parameters * Number of song models during day and night: Depend of runs * Boundaries for parameters values: Fixed * Number of tournaments during night: depend of runs * Correlated with replay? By how much?

3. Analyses and results

3.1 Learning method is as good Boari's method or better

* Using standard measure criteria in the birdsong community * Simple description of motor params sufficient to produce good songs * Qualitatively same amount of gestures * Can be due to luck

3.2 Too little training per model cause divergence

* maybe due to global vs local error

3.3 Derégnaucourt results not reproduced

* Syllables extracted by time of begin and end * Without or with diversity * No night deterioration * Night deterioration has no impact in overall learning

4. Discussion

4.1 The synthesizer which cannot produce every sounds

* Our score really close to boari's method (not way better or way worst), maybe we reached synthesizer limits

4.2 The parameters description we choose

* more simple/complexe possible than sum of sin and affine?

4.3 The unlearning during day due to the gesture learning

4.4 Fixed duration of songs in learning

* Dynamic Time Warping can correct that

4.5 Big artificial separation between structuration and gestures optimization

4.6 Diversity not strong enough? What if only diversity during night?

* Maybe not convergence * Maybe what we are looking for

5. Conclusion

5.1 Learning algorithm with two step learning

* Very few of them * Working with realistic synthesizer * modular architecture, easy to test new models

5.2 Restructuration didn't yield the expected effect

* More parameters search might be able to fix it

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