ADAPTING A COMPUTATIONAL MULTI AGENT MODEL FOR HUMPBACK WHALE SONG RESEARCH FOR USE AS A TOOL FOR ALGORITHMIC COMPOSITION

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ABSTRACT

Humpback whales (*Megaptera Novaengliae)* present one of the most complex displays of cultural transmission amongst non-humans. During breeding seasons, male humpback whales create long, hierarchical songs, which are shared amongst a population. Every male in the population conforms to the same song in a population. During the breeding season these songs slowly change and the song at the end of the breeding season is significantly different from the song heard at the start of the breeding season. The song of a population can also be replaced, if a new song from a different population is introduced. This is known as song revolution. Our research focuses on building computational multi agent models, which seek to recreate these phenomena observed in the wild. Our research relies on methods inspired by computational multi agent models for the evolution of music. This interdisciplinary approach has allowed us to adapt our model so that it may be used not only as a scientific tool, but also a creative tool for algorithmic composition. This paper discusses the model in detail, and then demonstrates how it may be adapted for use as an algorithmic composition tool.

1. INTRODUCTION

Multi agent modelling is a powerful tool where autonomous artificial intelligences (agents), interact with each other and their environment. As they interact, they can produce emergent behaviour, and create phenomena that are not built directly into the system. This has made it a powerful tool in scientific research where it has been used to study the emergence of grammar in linguistics [1], genetic diversity in humans [2], and flocking behaviour in birds and fish [3].

Due to the emergent phenomena produced by multi agent models, they have found use in several different areas of sound and music computing. From a musicology perspective, research shows that they may be used to explain a variety of phenomena, from songs emerging from sexual selection pressure [4] to the evolution of intonation systems [5]. Aside from musicological research, multi agent modelling is used as a tool for algorithmic composition [6]. In this paper, we seek to demonstrate that the gap between multi agent modelling for scientific purposes and for creative purposes is often quite narrow.

The model presented here was originally designed to investigate the mechanisms underlying cultural transmission in humpback whales. We show it is possible to adapt this model and use it as a tool for algorithmic composition. First, an overview of the structure of humpback whale song is introduced, followed by a description of our model and its aims. Then, an in depth analysis of the model is presented, outside of the context of algorithmic composition. Finally, we describe the method used to adapt the model as a tool for composition and give an example of user interaction with the model.

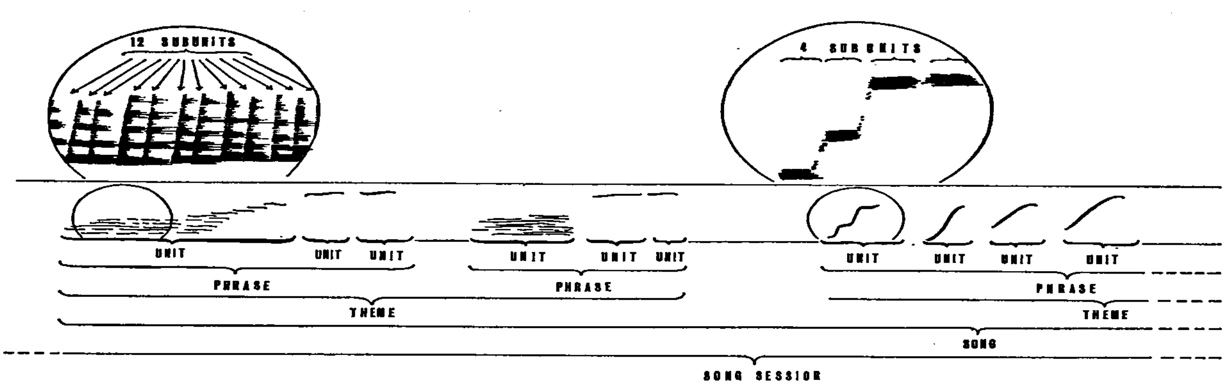

Figure 1: The structure of humpback whale song. Taken from [7]. Time on the X-axis and frequency on Y-axis.

2. HUMPBACK WHALE SONG

Before investigating the model in detail, it is necessary to first describe the natural phenomena that the model seeks to recreate. Humpback whales are a species of baleen (Mysticeti) whale. During the summer months (feeding season), humpback whales are usually found in polar Regions where the plankton that the whales feed on is abundant. During the winter months (breeding season), they migrate to warmer, tropical waters. Here they mate and give birth to calves. During migration and on the breeding grounds, male humpbacks produce long, hierarchical vocal sequences termed 'songs' [7]. Males produce individual sounds called units, which are combined to create phrases. Phrases are then combined to create themes and themes are stringed together to create songs. Songs are then repeated to create song sessions. During the mating season, all males conform to the same song. The song gradually changes throughout the season. This slow change is known as 'song evolution' [8]. It is also possible for the song of a population to be replaced by the song of another population. This is known as song revolution [9]. This was first observed when the song of the western Australian population replaced the song of the eastern Australian population. Further research into the population east of Australia revealed that this revolutionary behaviour was not an isolated incident, as the song of the eastern Australian population took over the song of the New Caledonia population. This song continued to move eastward until it eventually took over the song of the French Polynesian population [10].

Understanding these phenomena is vital, as it is what we seek to recreate using our model. Specifically, our goals are to create a spatially explicit multi agent models, where populations evolve shared repertoires, but also present the possibility for new songs to be introduced and replace the existing songs of a population.

3. THE MODEL

The model is cyclic in nature, and is segmented into three sequential sections; movement rules, song production rules, and song learning rules. These rules describe the behavior of a single agent and are carried out for every agent. Our model is created in Python using the SciPy package [11]. This model was inspired by [12] and extends on research done in [13].

3.1 Movement Rules

When our model is initialized, agents are assigned random Cartesian co-ordinates within a certain area. This area is known as the feeding grounds. While on the feeding grounds they carry out random walks to navigate the plane. After a certain number of iterations specified by the user, the agents will migrate to the 'breeding grounds', the location of which are also specified by the user. The movement behaviour to and on the feeding grounds is controlled by a variety of rules inspired by flocking algorithms. To explain these rules, we examine them from the perspective of a single agent. Our focal agent has two areas around it, a Zone of Repulsion (ZOR) and a Zone of Attraction (ZOA), as shown in Figure 2.

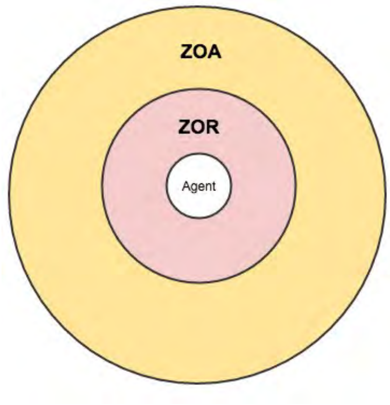

Figure 2: The two different zones around an agent. When other agents enter these zones, certain movement rules are carried out.

The ZOR rule is enacted whenever an agent has other agents within its ZOR. When this happens, an agent calculates a new trajectory based on the position of the other agents within its ZOR. This is demonstrated in Figure 3. This rule is carried out each iteration of the model.

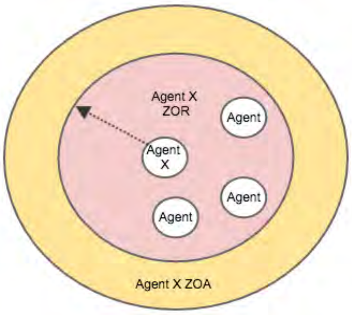

Figure 3: The ZOR rule. Agent x has other agents within its Zone of Repulsion. It calculates a new trajectory in order to avoid these agents.

The ZOA rule is enacted only when an agent is within a certain distance of the breeding grounds. This rule causes an agent to approach whatever agent within its ZOA that has the song most similar to its own. This is achieved using Levenshtein Distance. This algorithm calculates the number of insertions, substitutions and deletions required to transform one string of symbols into another string of symbols. Using these values, we calculate a ratio of similarity between two sequences of symbols produced by our agents. This rule is inspired by interactions between male humpback whales on the breeding ground [14].

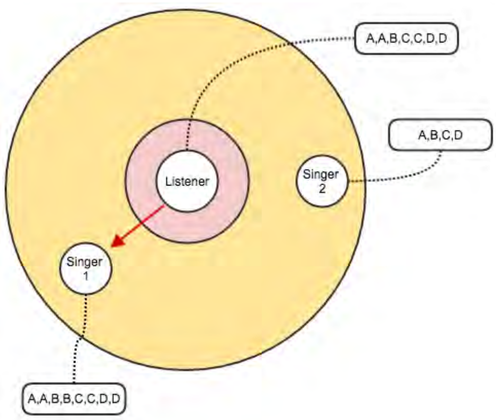

Figure 4: The attraction rule. The listening agent moves towards the singer with most similar song to its own.

3.2 Song Production Rules

Agents in the model are equipped with a first order transition matrix that is used to generate new songs. In our model, songs are represented using integers. Each integer corresponds with a unit that is associated with humpback whale song. Songs are generated from this transition matrix using equation 1.

$$x = \sum c \leq U \tag{1}$$

Where x is the output unit, c is the cumulative summation of the probability vector (the row of our transition matrix we are currently sampling from), and U is a uniformly distributed random number between 0 and 1. We use this algorithm in a recursive function to generate songs of varying length.

3.3 Song Learning Rules

In our initial model, song learning is affected only by the distance between agents. At every model run, an agent will calculate its distance from every other agent in population using the Cartesian distance formula, in equation 2.

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{2}$$

Where x_1 and y_1 are our focal agents Cartesian coordinates and x_2 and y_2 are the co-ordinates of the agent we wish to calculate the distance for, and d is distance. We use d to calculate what we call the intensity factor, which represents the energy decay in the water. It is calculated in equation 3.

$$I = \frac{1}{d^2} \tag{3}$$

Where I represents the intensity factor, and d is the distance between the two agents we are calculating I for. We can now go about the song learning stage. First, an agent estimates a transition matrix for an input sequence. This input sequence is simply the song produced by another agent in our population. To update the listening agents new transition matrix, we carry out the following matrix weighted averaging function in equation 4.

$$T_A = \big(A * (1 - I)\big) + (B * I) \tag{4}$$

Where T_A is the updated transition matrix for the listening agent, A is the original transition matrix for the listening agent, B is the estimated transition matrix for the sequence produced by a singing agent, and I is the intensity factor.

4. MODEL RESULTS

For a quick qualitative analysis, we plot our agent's Cartesian tracks and the distance between the songs of each agent using a Levenshtein distance dendrogram. This is shown in Figure 5 and Figure 6. This shows two possible scenarios that may emerge after running the model. In figure 5, we can see that the agents have clustered and have begun moving together throughout the breeding grounds. Due to the distance bias, every agent has converged on the same song. Figure 6 presents a similar situation, except the agents have formed into three distinct clusters, with three different songs emerging. This echoes results observed in the wild, where distinct populations converge on distinct songs.

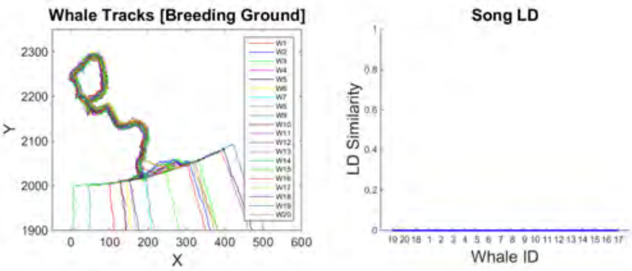

Figure 5: An example of all agents moving together and converging on the same song. The diagram on the left are the Cartesian co-ordinates of the agents over the run of the model. The diagram on the left is a dendrogram showing the level of dissimilarity between the songs of every agent.

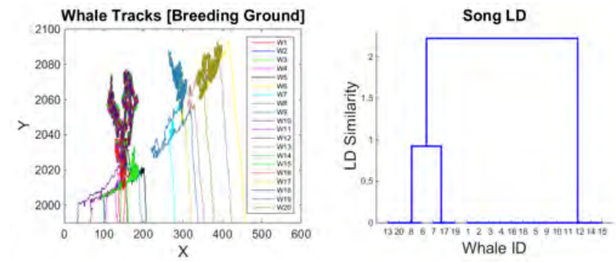

Figure 6: An example of the agents forming separate groups, each with their own song, as can be seen by the dendrogram.

While this result is interesting, it is necessary to understand how varying the parameters in the model will affect the songs produced by the population. To achieve this, we created a series of 500 experiments, in which we used linear descent to vary the size of the ZOR, ZOA, breeding grounds, and feeding grounds. We then carry out a pairwise subtraction of every agent's transition matrix from each other. This allows us to see whether the agents have converged on the same transition matrix or if there is a large amount of variety in them. These results were then stored in a 100x5 matrix. Each column corresponded with the size of the ZOA, and every 25 rows corresponded with an increase in the ZOR. Within those 25 rows and column is every combination of feeding and breeding ground size. We then took the mode of every group of these cells. This resulted in the matrix seen in Figure 7.

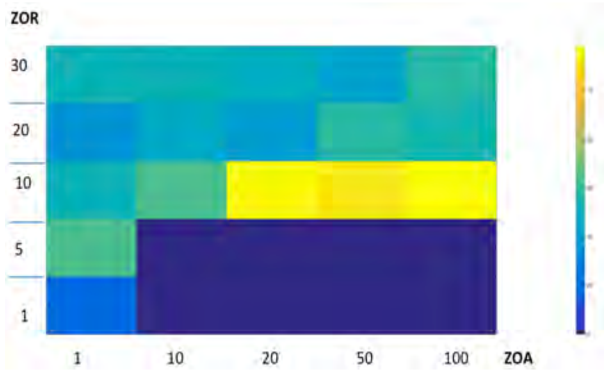

Figure 7: This graph shows how varying the parameters of the ZOR and the ZOA affects the behaviour of the model. The darker colours correspond to model runs that converged on similar songs. The bright colours represent experiments where the population had dis-similar songs.

5. ADAPTING THE MODEL

As it stands, the model does not capture the full complexity observed in humpback whale song. While agents in our model do converge on a shared song in certain situations, it does not present any change once every agent in the population has learned the song. Furthermore, first order transition matrices are not capable of capturing the hierarchical structure of humpback whale song. Despite this, our model is at a stage where it can be adapted for algorithmic composition. In this section, we describe the technical aspects of adapting our model. Following this, we move on to discuss adding a novelty method inspired by computational musicology.

5.1 Technical Considerations

Open Sound Control (OSC) [15] is a protocol used to transmit data between different audio software programs. This allows for the quick adaptation of our model to be used as a tool for composition. Using OSC, we can send data to and from our model in order to generate new musical sequences in real time. This is achieved using the Max4Live API in Ableton Live[16,17], so that the composer may introduce new songs sequences to the population, and play them back in order to generate new musical variations, based on this input and other parameter settings. This is illustrated in Figure 8.

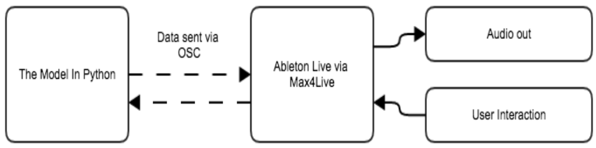

Figure 8: Signal flow from Ableton to the model.

In order to interact with the model, the user uses the ComposerIn device with a MIDI keyboard to create a sequence of notes and rhythms to be learned by a selected agent in the model. These notes are appended to a list in Max/MSP, where they are then formatted so that they can be used as an input to the model. The sequence is then sent via OSC to the selected agent, who estimates a first order transition matrix so that it may create variations on this theme. This interaction flow is demonstrated in figure 9.

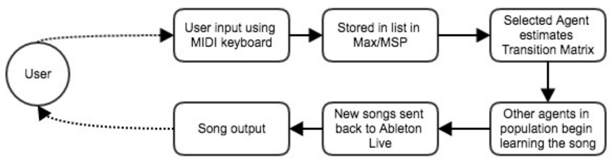

Figure 9: This shows how a composer interacts with the model.

At each iteration of our model, the song produced by each agent is sent back to Ableton Live using the modelOut device, where they are transposed in order for them to be formatted into MIDI notes. These are then stored in a message box and sequenced using a metro object. This allows the MIDI notes to be sent to any Live or Max4Live device that the composer wishes to use.

5.2 The Need for Novelty

Since the model relies on the distance between agents to influence the transmission of the song, it is possible for the song input by the composer to be overpowered by the other songs in the population of agents. This leads us to add a new dimension to the model, which will allow the user to interact with the model and actually observe the impact of their input. To achieve this, the model is extended to have a new bias added; novelty. Chosen due to theories that is a factor in humpback song evolution. [9]

Originally, we took inspiration from the work of Todd, [18] where novelty is determined by the built in expectations of the agents. This was used to develop in equation 5.

$$\alpha = \sum_{n}^{N} \frac{|\max(T(S(n))) - T(S(n),S(n+1))|}{N} \qquad (5)$$

Given a sequence, *S,* which is indexed using the value *n,* an agent calculates novelty, α, based on its transition matrix, *T. N,* the number of elements in the sequence *S,* is used as a weighting. This is defined by equation 5. The square brackets indicate that an absolute value should be taken for the top term of the equation. This novelty value, α, is used to update our learning algorithm, as shown in equation 6.

$$T_A = (A * (1 - I * \alpha)) + (B * (I * \alpha)) \qquad (6)$$

The novelty bias has a significant impact on what songs our agents choose to learn from. Low novelty will result in a song having no impact on the transition matrix of a listening agent, while a high novelty value will lead to that songs estimated transition matrix almost completely taking over the listening agent's transition matrix (Figure 10).

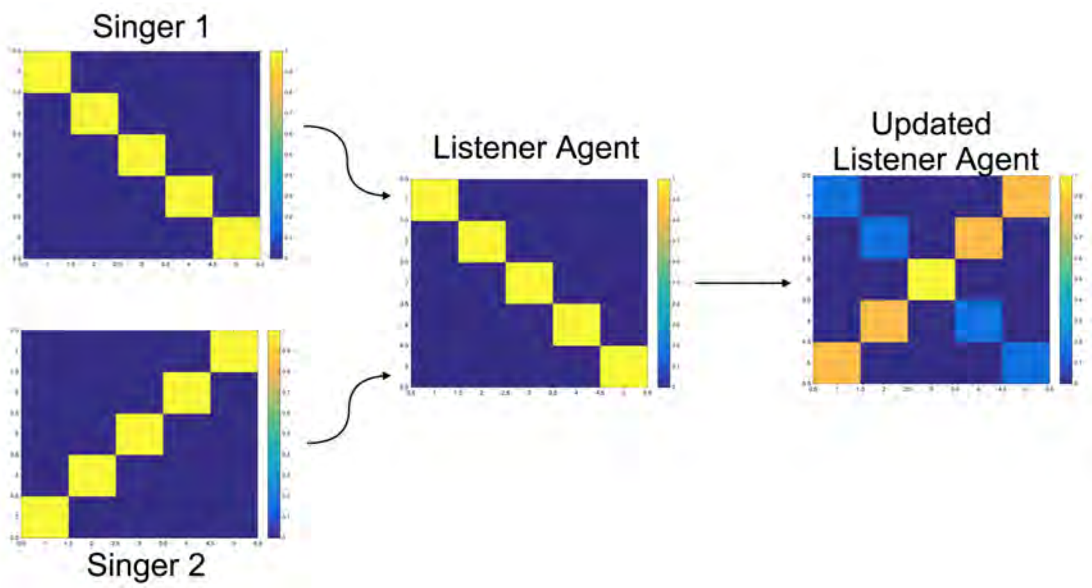

Figure 10: How the novelty algorithm affects a listener agent's transition matrix. Singer 1 and 2 are both equidistant from the listener agent. The listener learns more of singers 2 song since it is more novel in comparison to its own transition matrix.

The results returned from this method are interesting, but we found that the transition matrices in a population would converge to uniform distribution. Rather than our novelty value being weighted by the number of elements in a sequence, we have our novelty value weighted by the agent that has the highest novelty value.

$$\text{nov}[\text{m}] = \sum_{n}^{N} |\max\left(T(S(n)) - T(S(n), S(n+1))\right)| \quad (7)$$

$$\alpha = \frac{\text{nov(m)}}{\max(nov)} \quad (8)$$

We also introduce a learning rate with this algorithm, which is scaled between 0 and 1. This updates our agents learning algorithm to the following, seen in equation 13.

$$T_A = (A * (1 - I * (\alpha * \text{LR})) + (B * (I * (\alpha * \text{LR})) \quad (9)$$

The dynamic weighting algorithm produces an oscillating effect on the probability of transitioning from one unit to another, as demonstrated in Figure 11. This shows the probability of an agent moving from unit A to unit B (the red line), and the probability of moving from unit A to unit C (the blue line). At the start of the model, the probability of going from unit A to B is 100%. Another agent in the population is trained with a probability of transferring from unit A to C 100% of the time. As our agents meet on the breeding grounds they hear the song, they hear this new song and deem it to be more novel than their own, thus applying more emphasis to learning it.

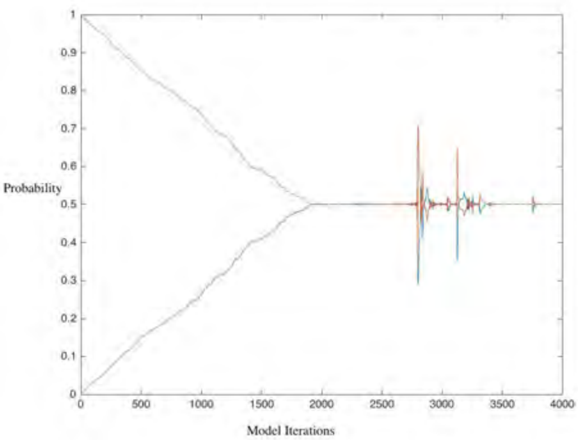

Figure 11: The figure demonstrates how the dynamic novelty algorithm creates an oscillation in the probability of transitioning from one unit to the other. (Transitioning from unit 1 to 2 in blue, transitioning from unit 1 to 3 in red).

6. MUSICAL DEMO

In order to test the model, we approached it from a compositional point of view. First, four different musical themes were chosen to form the structure of the composition. These themes were chosen specifically because they have a high novelty value when compared to each other. They are also easily recognisable rudimentary musical features. They consist of an ascending C major arpeggio (Theme A), a descending chromatic scale (Theme B), an ascending D minor arpeggio (Theme C), and a repeating G# (Theme D). These themes can be seen in figure 12. At the start of our composition, every agent's transition matrix is trained by theme A. We then presented all subsequent themes to only a single agent (agent 2). We then recorded the songs being produced by agent 1 via MIDI.

Figure 12: The four themes used in the composition.

The resulting composition is interesting, as the oscillatory nature described in section 5.2 of this document emerged not only for simple transitions as was originally observed, but also for the structured themes presented to our population. Whenever a new theme was introduced, the agent would move between the two themes, before the entire population would settle on some form of hybrid theme. We called this theme oscillation (figure 14). The corresponding hybrid theme is shown in figure 13. This is demonstrated at the point where each transition is introduced.

Figure 13: An example of a hybrid theme.

Figure 14: An example of theme oscillation.

7. CONCLUSION AND FUTURE WORK

From this paper, we have seen that scientific methods for the analysis of animal vocalisations may easily be adapted for algorithmic composition. Here, we demonstrated the model as a stand alone scientific tool, explained the technical considerations necessary for user interaction, and developed a novelty method that allows a user to have a direct impact on the songs in the population. Emergent properties, such as theme oscillation and hybrid themes were also demonstrated through a compositional demo. Future work will involve exploring the parameter space described in section 4, to investigate how it may be used as a tool to influence the emergence of hybrid themes seen in this model. It is also necessary to carry out a full investigation of the impact that the novelty metric has on the evolution of songs in the population. Finally, a method of song innovation must be produced. Although our agents develop interesting hybrid songs, they do not have any in built mechanism for song evolution. The use of the model to develop rhythmic themes is also an area that would warrant further investigation.

Acknowledgments

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