The Transmission of Migratory Behaviors

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Extended Abstract

In nature, animals rely upon migratory behaviors in order to adapt to seasonal variations in their environment. However, the transmission of migratory behaviors within populations (either during lifetimes or throughout successive generations) is not well understood (Bauer et al., 2011). In *Artificial Life* research, *Agent Based Modeling* (ABM) is a bottom-up approach to study evolutionary conditions under which adaptive group behavior emerges. ABM is characterized by synthetic methods (understanding via building), and is becoming increasingly popular in animal behavior research (Sumida et al., 1990). Combining an *Artificial Neural Network* (ANN) and *Evolutionary Algorithm* (EA) for adapting agent behavior (Yao, 1993) has received significant research attention (Phelps and Ryan, 2001), (Lee, 2003).

ABM is an analogical system that aids ethologists in constructing novel hypotheses, and allow the investigation of emergent phenomena in experiments that could not be conducted in nature (Webb, 2009). Numerous studies in ethology have formalized mathematical models of migratory patterns in various species (Bauer et al., 2011). However, there have been few studies that examine ontological and phylogenetic conditions requisite for emergent migratory behavior. ABM is advantageous (compared to formal mathematical models of migratory behavior), since various evolutionary processes can be simulated, and variations in resultant migratory behaviors examined. For example, ABM has been used to predict the consequences of forced human migrations (Edwards, 2009), and migratory behavior between groups of Macaque monkeys (Hemelrijk, 2004).

In this research, ABM is used to investigate a hypothesis posited in ethological literature: that migratory behavior is adopted as an adaptive foraging behavior, where such behavior is either genetically or culturally determined (Huse and Giske, 1998). This study aims to investigate the evolutionary and cultural conditions that give rise to migratory behaviors and thus adaptive foraging. In cultural behavioral transmission, ontogenetic transfer occurs between agents during their lifetime. Alternatively, migratory behavior is phylogenetically transmitted through successive generations (Bauer et al., 2011). A minimalist simulation model (distribution of four food patches and 200 agents on a grid) demonstrates the impact of ontogenetic versus phylogenetic transmission of migratory behavior and thus agent group adaptivity.

Agents use an ANN controller (figure 1, left). ANN connection weights are adapted with an EA. Agent fitness is the food amount consumed during a lifetime (200 iterations). The EA selects for effective foraging behaviors, which depends upon agents periodically migrating to where food is plentiful. Stimuli for migratory behavior take the form of cyclic *seasons* in the environment and agents signaling their movement direction to neighbors. When it is *winter* (food is scarce) in one half of the environment, it is *summer* (food is plentiful) in the other half, where each seasonal cycle (50 iterations) the winter and summer zones are switched.

Each iteration, agents receive the sensory inputs: *signal* from the closest agent, their current *fitness* and *recurrent* connections (activation value of the hidden layer in the previous iteration). Agent behavior is: *move* to an adjacent grid square, *mimic* or *mate* with a neighboring agent. The output with the highest activation is selected (figure 1, left). Each iteration, agents also emits a signal (output not depicted in figure 1), conveying the sender's current direction of movement and thus indicating migratory behavior.

Via choosing to *mimic* or *mate*, agents either imitate their neighbor's migratory behaviors or pass genetically encoded migratory behaviors onto their offspring. If an agent mimics, it copies the ANN connection weights of its closest neighbor, thus mimicking its neighbors behavior, which includes the *direction* signal sent each iteration. If an agent mates, fitness proportionate selection (Eiben and Smith, 2003) is used to select a mate from the agent population. Genotypes (floating-point value strings) encoding the ANNs are recombined using 2-point crossover (Eiben and Smith, 2003). Two child ANNs are produced and replace the parents to keep the population size constant. If an agent moves, then it moves one grid cell *north*, *south*, *east*, or *west* (figure 1, left).

Figure 1 (center and right) illustrates agent adaptation occurring over evolutionary time. Agents become effective gatherers via learning a migration behavior allowing them

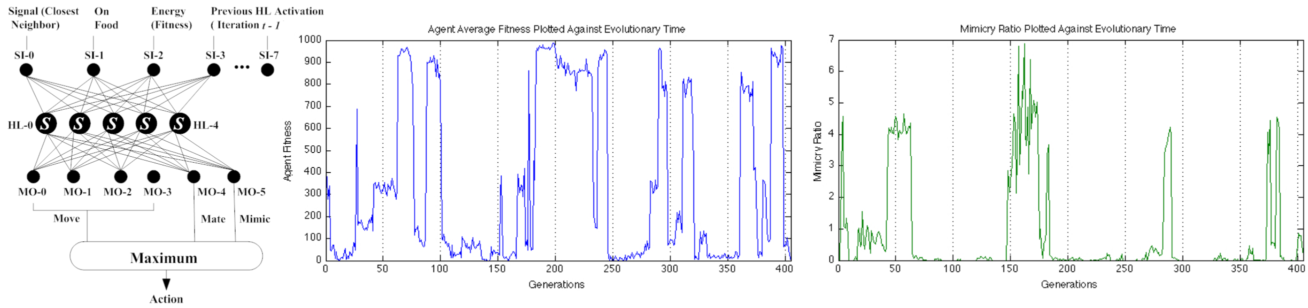

Figure 1: *Left:* Each agent is a recurrent feed-forward ANN. *SI:* Sensory Input. *MO:* Motor Output. *HL:* Hidden Layer. *Center:* Average agent group fitness over 400 generations of neuro-evolution. *Right:* Average mimicry ratio over 400 generations.

to move about the environment in synchronization with the seasons (moving to where food is plentiful). Figure 1 also delineates a cyclic process in agent adaptive behavior, and the relationship between fitness and behavioral mimicry. *Mimicry ratio* indicates the average preference of an agent to mimic over another behavior. Figure 1 (center) also indicates agents periodically adapt to effective foraging behavior (indicated by fitness spikes). Fitness increases result from agents adopting migratory behaviors to adapt to the environment's seasonal variation, where such increases are enhanced by behavioral mimicking in preceding generations.

We hypothesize that subsequent periodic fitness drops, and preceding mimicry ratio decreases (figure 1, right), result from the selection and propagation of fit yet non-robust behaviors. Periodic fitness increases (figure 1, center) indicate the agents converge towards an effective gathering behavior. However, concurrently, behavioral heterogeneity is bred out of the population. Convergence results in a homogenous agent group that is unable to cope with seasonal variation in the environment. This in turn causes the periodic fitness crashes (figure 1, center), where most of the population dies off, and only those agents with robust behaviors (suited to seasonal variation) survive and are selected for.

Thus, behavioral takeover in the population (accelerated by behavioral mimicry and fitness proportionate selection) results in a largely homogenous population with low genotype and fitness diversity (Wineberg and Oppacher, 2003) and non-robust behaviors. Subsequent fitness decreases reintroduce behavioral heterogeneity (and fitness diversity) into the population and allow agents to re-adapt to the environment's seasonal variation via adopting a migratory behavior. Figure 1 (center and right) also indicates that variations in the mimicry rate impact the rate of agent adaptation and re-adaptation, as well as the duration of fitness spikes. That is, fitness increases are correlated with high mimicry ratios and fitness crashes cause behaviors containing the propensity to mimic to be periodically lost, and then rediscovered in the subsequent re-adaptation phase.

Whilst preliminary results indicate the importance of behavioral mimicry and genetic transmission of migratory behaviors to a population's overall adaptivity (supporting ethological research), their contribution to adaptive behavior is subject to ongoing research. Current investigation is of conditions under which cultural versus genetic transmission of migratory behaviors prevail, and the impact of lifetime duration on cultural and genetic transmission of behaviors.

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