# Effects of Personality Decay on Collective Movements

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## ABSTRACT

In natural systems, many animals organize into groups without a designated leader and still perform complex collective behaviors. Although individuals in the group may be considered equal, all the individuals differ in the traits each of them possess. Of particular interest is the idea of an individual's personality as it often plays a role in determining which individuals lead collective behaviors. Personality is, in part, developed and maintained by an individual's experiences. However, neither an individual, nor its environment remains unchanged. Therefore, there is a need for an individual to continue to gain new experiences to ensure that its information about itself and its environment are current. Since observations have shown that the effects of experience on personality can decay over time, we investigate the effects of this decay on the emergence of leaders and followers and the resulting success of a group's collective movement attempts. Results show that personality decay has a negative effect on the overall success of the group in collective movements as it prevents the emergence of distinct personalities, a necessary requirement for individuals to assume distinct leader and follower roles.

## Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*coherence and coordination,multiagent systems*

## Keywords

collective movement, coordination, leadership, adaptation

## 1. INTRODUCTION

There are many examples in the natural world where animals form large groups and engage in collective behavior. While there is not a consistent leader in many situations, there are leaders for each individual movement. An individual's personality has been shown to be a factor in determining which individuals will be leaders and which will be followers. Bold individuals are generally leaders, while shy individuals are generally followers [6]. However, personalities are not fixed and are known to sometimes change in response to positive and negative experiences [3]. Furthermore, the effects of experience on personality decay over time and are eventually lost. In this work, we investigate the effects of such personality decay on the emergence of leaders and followers in a collective movement. Results show that the rapid decay of personalities to an initial value, regardless of the type of decay, prevents the emergence of distinct personality types, and, therefore, the emergence of distinct leaders and followers.


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## 2. METHODS

The simulations used for this work used a modified version of a collective movement model developed through observations of collective movement attempts in a group of white-faced capuchin monkeys [4, 10]. Its generality was later verified in observations of sheep [11]. Despite being a collective movement model, actual movement through an environment is not a part of the model. Rather, the focus of the model is on the decision-making process that precedes a movement. Examples of such situations are found in nature where individuals exhibit notifying behaviors indicating a preferred direction of movement during a predeparture period [12].

## 2.1 Collective Movement Model

The collective movement model uses three rules to govern the decision-making process involved in starting collective movements [4, 10]. The first rule assumes that all individuals within the group can initiate a collective movement attempt with a constant rate of $1/\tau_o$.

The second rule describes the rate at which followers join the collective movement attempt and is calculated by $1/\tau_r$. The time constant $\tau_r$ for the following rate is calculated using the following:

$$\tau_r = \alpha_f + \beta_f \frac{N-r}{r} \tag{1}$$

where $\alpha_f$ and $\beta_f$ are constants determined through direct observation, $N$ is the number of individuals in the group, and $r$ is the number of individuals following the initiator. As the number of individuals following the initiator increases, the rate at which individuals join the movement also increases.

Not all initiation attempts are successful as initiators often cancel and return to the group. The third rule calculates this cancellation rate using the following:

$$C_r = \frac{\alpha_c}{1 + (r/\gamma_c)^{\varepsilon_c}} \tag{2}$$

where $\alpha_c$, $\gamma_c$, and $\varepsilon_c$ are constants determined through direct observation, and $r$ is the number of individuals following the initiator. Simulations of the model include the implicit assumption that a successful collective movement requires all of the members of the group to participate, since there is a non-zero probability of canceling even if all but one member participates. While this is not necessarily the case in nature, cohesive collective movements are the primary focus of this work and, as such, incomplete movements are considered failures.

## 2.2 Integrating Personality

To investigate the effects of altering the rate at which individuals initiate, follow an initiator, and cancel a movement, Gautrais added an individual-specific constant, referred to as a "$k$ factor," to the rate calculations of the collective movement model [4]. Initiation attempts were now calculated at the constant rate of $k/\tau_o$, and the following and canceling rate calculations were modified as follows:

$$\tau_r = \frac{1}{k}\left(\alpha_f + \beta_f \frac{N-r}{r}\right) \tag{3}$$

$$C_r = k\left(\frac{\alpha_c}{1 + (r/\gamma_c)^{\varepsilon_c}}\right) \tag{4}$$

where the variables are defined as before. Since this $k$ factor can either increase or decrease the three decision-making rates, it was an ideal means of incorporating the effects of personality into the model.

Three important points were considered in integrating personality with the collective movement model. First, personality has been observed in natural systems to affect the events used in this model in different ways. For example, a bold personality should result in a higher initiation rate and lower following and canceling rates, while a shy personality should result in a lower initiation rate and higher following and canceling rates [5]. Second, the magnitude with which a shy personality affects the model should be the same as a bold personality so as not to bias the model towards one personality over another. Since $k$ had a non-inclusive lower limit of zero, the non-inclusive upper limit of two was chosen to ensure balance. In the simulations described below, personalities were limited to the range $[0.1 : 0.9]$ to ensure these limits were satisfied. Lastly, although neither the original model, nor the observations on which the model was based, discussed the personality of the individual animals involved, it was assumed that the observed group members could be classified as having either bold or shy personalities. However, since the personalities of the observed individuals were unknown, all individuals were assumed to have had a default moderate personality ($p_i = 0.5$), which produced the same results as the original model. To accentuate the effects of even minor differences in personality in values close to a moderate personality and minimize the effects of differences in extreme personalities, a personality $p$ was converted to a corresponding $k$ value using the following sigmoid function:

$$k = 2\left(1 + \mathrm{e}^{\frac{0.5-p'}{10}}\right)^{-1} \tag{5}$$

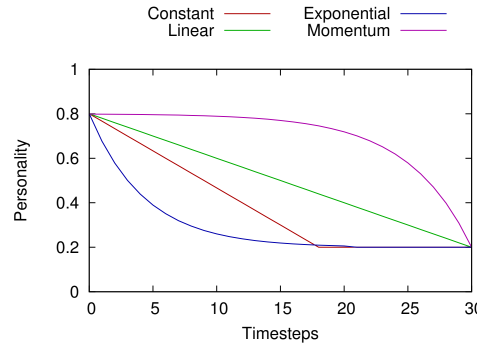


**Figure 1: The four different personality decay equations evaluated are shown for a bold personality value ($p = 0.8$) that decays to the initial, shy personality value ($p = 0.2$).**

where $p'$ is $p$ for initiating decisions and is $1-p$ for canceling and following decisions.

The initiator's personality was updated after every collective movement initiation attempt using the following standard update (or learning) rule [1, 7, 13]:

$$p_{t+1} = p_t(1-\lambda) + \lambda r \tag{6}$$

where $p_t$ was the initiator's personality for the current movement, $p_{t+1}$ was the personality after the movement, $\lambda$ was the rate at which updates changed the personality, and $r$ was the reinforcement value used to update the personality. When $\lambda$ was low, personality was primarily determined through long-term historical success and changes were minor. When $\lambda$ was high, personality was primarily determined through short-term success, and changes from one attempt to the next were significant. For the simulations described in this work, a low value of lambda was chosen ($\lambda = 0.02$) to emphasize long-term initiation success. For successful initiations, the reinforcement was $r = 1$, while it was $r = 0$ for unsuccessful initiations.

## 2.3 Personality Decay

Personalities were decayed using four different decay equations. They were:

1. Constant decay:

$$p_{t+1} = \begin{cases} p_l - \Delta t d_t & \text{if } p > p_i, \\ p_l + \Delta t d_t & \text{if } p < p_i. \end{cases} \tag{7}$$

2. Linear decay:

$$p_{t+1} = p_l + \Delta t \frac{p_i - p_l}{d_t} \tag{8}$$

3. Exponential decay:

$$p_{t+1} = (p_l - p_i)\left(\mathrm{e}^{(\Delta t - d_t)/5}\right) + p_i \tag{9}$$

4. Momentum decay:

$$p_{t+1} = (p_l - p_i)\left(1 - \mathrm{e}^{(\Delta t - d_t)/5}\right) + p_i \tag{10}$$

where $p_{t+1}$ was the decayed personality for the next simulation, $p_l$ was the personality after the last initiation attempt,

$p_i$ was the initial personality, $d_t$ was the treatment's decay time, and $\Delta t$ was the number of simulations since the individual's last initiation attempt. The first two decay equations model simple decay approaches, while the exponential decay equation is more biologically relevant. Although the momentum decay is not biologically based, a preliminary analysis of the other three decay equations indicated the need for an approach that initially yielded minimal decay, but still allowed for decay within a reasonable amount of time. Figure 1 illustrates the differences between each of these decay equations.

Since the group size affects the number of initiations an individual may make, different decay times ranging from $10 \times N$ to $2000 \times N$ were evaluated where $N$ was the size of the group. Although many of these decay times were either too short or too long, their use allowed for a better analysis of the difference between the decay equations.

## 2.4 Numerical Implementation

Numerical simulations of the collective movement model were implemented in Java using a customized version[1] of the original algorithm [4]. The time of each event was calculated as a random number drawn from an exponential distribution using the appropriate rate. As such, the simulations used continuous time events, and not discrete time.

The original model was only evaluated with a group size of 10, but other work has shown that the success of collective movement initiations increases as the group size is increased, with most success differences present in group sizes of 50 or less and diminishing effects beyond a group size of 100 [2]. As such, evaluating different group sizes presents an opportunity to evaluate the effects of personality with different group dynamics. To evaluate the impact of the initial personality value, treatments were performed using the following personality values for all individuals within a group: shy ($p_v = 0.2$), moderate ($p_v = 0.5$), and bold ($p_v = 0.8$). Within each treatment, group sizes from 20 to 50 were used. Fifty evaluations were performed for each group size, each with a different random seed. A single evaluation consisted of $2,000 \times N$ simulations, where $N$ was the group size. Each simulation constituted a single attempt at a collective movement and ended in either success (all individuals participating in the movement) or the initiator canceling. Individual personality values were reset at the beginning of each evaluation and persisted from one simulation to the next. The model parameters used were the same as those used in the original model [4, 10].

The R `changepoint` package was used to analyze trends in personality values of successive attempts in an evaluation [8]. This software package allowed for the identification of shifts in the mean personality value for a particular individual. In our simulations, these shifts, referred to as changepoints, represented a potential personality transition. Since personalities were not constant and the analysis produced a linear approximation of a portion of a personality value time series, we defined a personality to be bold if a segment of the personality had a mean value greater than or equal to 0.85. The high threshold was needed to differentiate truly bold individuals from individuals with an initial personality of 0.8 that had not yet had an opportunity to gain experience.

[1]Simulation source code and data analysis scripts are available for download from `https://github.com/snucsne/bio-inspired-leadership`.

# 3. RESULTS & ANALYSIS

Figure 2 shows the mean initiation success percentages for each decay rate equation and group size combination for a decay time of $t = 100 \times N$. Simulations using the linear and momentum decay rates had significantly higher leadership success than simulations using the constant and exponential decay rates. Previous work using baseline simulations without personality had leadership success percentages ranging from 30% to 50% and simulations with personality that did not decay had success percentages ranging from 60% to 85%. When these previous results are compared to the results of simulations with personality decay, it is evident that simulations using the exponential decay rate performed only marginally better than the baseline simulations, indicating that personality decay has a negative impact on leadership success, namely due to its role in inhibiting the emergence of distinct personalities.

For decay times shorter than $t = 100 \times N$, the constant and exponential decay equations resulted in success percentages that were marginally better than the default model implementation without personality. Simulations using the linear rate equation had higher success, but simulations using the momentum decay equation performed statistically significantly better. Even with a decay time of $t = 10 \times N$, simulations using the momentum decay equation had higher success than non-personality simulations.

For decay times longer than $t = 100 \times N$, all decay equations had higher leadership success. Since simulations using the momentum decay equation already had high success, the effects were less pronounced. Simulations using the other decay equations, however, exhibited marked improvements in leadership success. Despite this improvement, simulations using personality decay performed worse than simulations using personality, but no personality decay.

# 4. DISCUSSION

The addition of personality decay to the collective movement model was far more destructive than originally anticipated. Given the biologically inspired nature of the exponential decay equation, it was anticipated that it would provide the best performance. However, its performance, along with the performance of simulations using the constant and linear decay equations, was so poor that the momentum decay equation was developed.

A closer analysis of the results indicates that the primary reason for the loss in leadership success after the addition of personality decay is that personalities decayed too rapidly to maintain distinct personality types, and, therefore, distinct roles of leader and follower within the group. There were too few opportunities for individuals to gain recent experience and minimize the effects of personality decay.

Although the results presented here indicate that personality decay is destructive to the success of collective movements, it may still prove to be a useful concept as it has been observed in natural systems and provides an opportunity for the group to quickly adapt to environmental changes. There are a number of approaches using evolutionary computation that could be used to continue this line of investigation. One line of investigation would be to use genetic programming to evolve alternative decay equations that allow for the emergence of distinct personality types. Another approach would be to use grammatical evolution to evolve a ruleset to adapt personalities both with and without current experiences [9].


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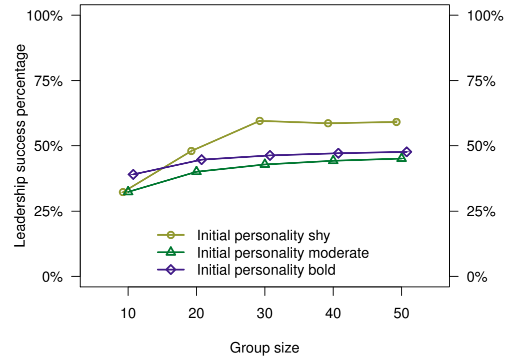
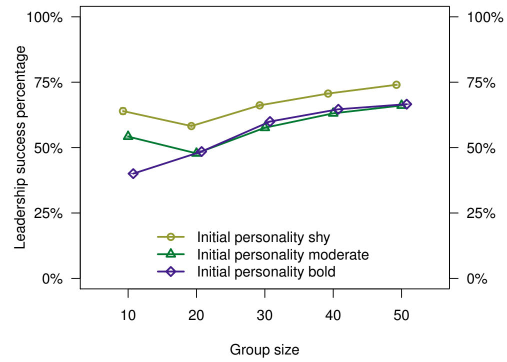
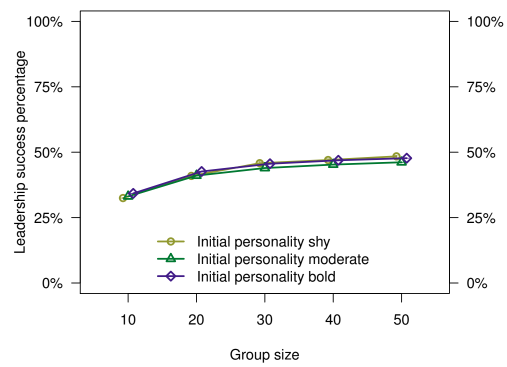


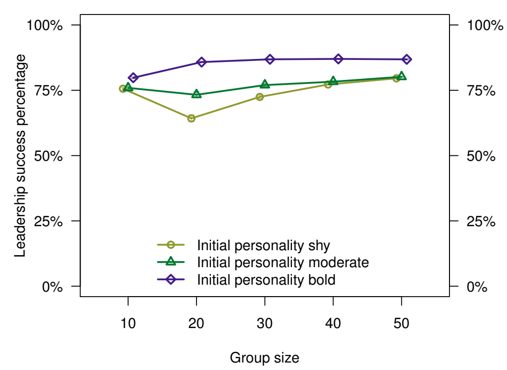

(a) Constant Decay




(b) Linear Decay




(c) Exponential Decay




(d) Momentum Decay

**Figure 2: The mean initiation success percentages for each decay rate equation and group size combination are shown for a decay time of $t = 100 \times N$.**