Effects of Personality Distribution on Collective Behavior

Brent E. Eskridge$^1$ and Ingo Schlupp$^2$

$^1$Southern Nazarene University, Bethany, OK 73008
$^2$University of Oklahoma, Norman, OK 73019
beskridge@snu.edu

Abstract

Optimizing group success is challenging for multi-robot systems, especially for large systems such as robot swarms where even simple individual interaction rules can lead to complex group behavior. Studies of natural systems have shown that heterogeneous groups can outperform homogeneous groups, especially when individual differences lead to role or niche specialization. This happens even when the individuals are seemingly identical. Although individuals within a group may appear physically identical, they can vary widely in their personality, which significantly affects their behavior. However, determining the most effective composition of personalities in a group is particularly difficult in natural systems given the ambiguities of animal personalities and the physical challenges of repeated evaluations. Using a biologically-based collective movement model, we evaluate different personality distributions to determine their effect on the overall success of the group. Results show that although there are distributions that are clearly more effective than others, in many cases, there is a wide range of distributions that results in high group success. Furthermore, experiments using variable, or adaptive, personalities demonstrate that successful distributions are stable equilibriums as initially extreme distributions converge to these successful distributions as personalities change.

Introduction

In many robot swarms, individuals within the swarm are assumed to be heterogeneous, especially, and perhaps most importantly, with respect to their decision-making. In fact, heterogeneity is argued to be a requirement for a multi-robot system even to be considered a swarm (Şahin, 2005). Variations in either morphology or decision-making can present significant challenges given the complexities that arise as robots interact. However, such differences can also provide significant benefits (Couzin et al., 2005).

While most work involving these benefits focuses on morphological differences, of particular interest here are differences in the decision-making process, especially those that are adaptive. The ability for individuals in a group to adapt their decision-making to improve group-level performance is key to the usefulness of multi-robot systems in dynamic, real-world tasks. Recent research in animal groups has shown that such systems exist in nature. Animals are known to exhibit sets of correlated traits referred to as personalities, that in part, determine their behavior (Sih et al., 2004). Furthermore, these personalities are known to change in response to both individual experiences and the distribution of personalities in the overall group (Dall et al., 2004; Montiglio et al., 2013). As such, animal personalities can provide inspiration as a means of integrating adaptive individual differences within a group to improve performance. Furthermore, we have previously shown that using a simple mechanism to introduce personality into a collective movement model can result in a significant increase in success (Eskridge et al., 2013). However, it is not well understood how the distribution of personalities affects group performance, nor how stable effective personality distributions are.

In the work presented here, we use a biologically-based collective movement model to explore how distribution of personalities, especially as they pertain to leaders and followers, affects the overall success of the group in initiating a movement. Simulations demonstrate that, for many of the groups evaluated, there is a wide range of personality distributions that results in high group success. Furthermore, the results demonstrate that these successful distributions are stable equilibriums. This is indicated not only by the wide range of successful distributions, but also by additional experiments using variable personalities in which extreme personality distributions converge to the more successful distributions as personalities change.

Related Work

Animal personalities are the focus of much recent research effort (Sih et al., 2004; Wolf et al., 2007). Personalities refer to correlated behavioral traits in animals that are frequently found together such as an insensitivity to social information and an increased likelihood of leaving the safety of cover to forage for food. The most commonly studied personality traits lie along the bold-shy continuum and have been observed in a variety of animal species (Frost et al., 2007; Harcourt et al., 2009b). Of particular interest to the work presented here is the fact that individuals with bold person-
Personality differences between individuals can lead to differentiation in roles within a group. The combination of different personalities within a group and the associated roles assumed by different members have been found to improve the overall success of the group (Couzin et al., 2005; Dyer et al., 2009; Modlmeier and Foitzik, 2011; Modlmeier et al., 2012). Studies have shown that these personality differences can be stable and maintained over time (Dall et al., 2004; Oosten et al., 2010). One explanation for the maintenance of personality differences is through niche role specialization (Montiglio et al., 2013), with some theorizing that specialization occurs at the genetic level (Montiglio et al., 2013; Nonacs and Kapheim, 2007).

Although these personality differences are known to confer benefits to group performance, the effects of the distribution of these personalities within a group on that performance are not well understood. This is in part due to the complexity of the interactions between individual personalities, including the effects on group behavior through individual personalities (Magnhagen and Staffan, 2005; Cote et al., 2011) and the effects on individual behaviors by group personality (Cote et al., 2011). Furthermore, it is difficult to precisely measure the distribution of individual personalities in a group. In fact, few studies even report the specific distribution of personalities. Distributions that are reported consist of groups that are either randomly created in the lab (Magnhagen and Staffan, 2005), are drawn from environments that have unique fitness effects on personalities (Magnhagen, 2006), or do not classify personalities as bold and shy (David et al., 2011). While some studies have constructed groups with artificial personality distributions to evaluate the effects of different compositions (Sih and Watters, 2005; Pruitt et al., 2013), most did not systematically evaluate a range of different personality distributions to directly test the effects on overall group performance. However, Pruitt and Keiser (2014) recently observed that spider colony success in collective foraging was tied to the degree to which a leader is bold. Their results indicate that even when the number of bold and shy individuals were kept constant, groups were more successful when the difference between bold and shy personalities was large.

**Methods**

The simulations used for this work were performed using a modified version of a collective movement model developed through observations of collective movement attempts in a group of white-faced capuchin monkeys (Gautrais, 2010; Petit et al., 2009), and was later confirmed in observations of sheep (Pillot et al., 2011). The model could be classified as a probabilistic finite state machine (PF FSM) (Brambilla et al., 2013) and uses anonymous quorum-sensing to determine the rates of collective movement decisions. The anonymous quorum-sensing nature of the model means that leaders, whether successful or unsuccessful, cannot be recognized as such, and decision-making must rely on the number of participating individuals only. 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 (Pyritz et al., 2011).

**Collective Movement Model**

The collective movement model uses three rules to govern the decision-making process involved in starting collective movements (Petit et al., 2009; Gautrais, 2010). The first rule assumes that all individuals within the group can initiate a collective movement attempt with a constant rate of \(1/\tau_{o}\), with \(\tau_{o} = 1290\). While this assumption may not hold for groups with dominant leaders, studies have shown that it is a viable assumption for egalitarian animal groups, such as the capuchin monkeys used in the model’s development and robot swarms (Brambilla et al., 2013).

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:

\[
\tau_{r} = \frac{\alpha_{f} \beta_{f}}{1 + N - r} \quad (1)
\]

where \(\alpha_{f} = 162.3\) and \(\beta_{f} = 75.4\) 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 decide to 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:

\[
C_{r} = \frac{\alpha_{c}}{1 + (r/\gamma_{c})^\gamma_{c}} \quad (2)
\]

where \(\alpha_{c} = 0.009, \gamma_{c} = 2.0,\) and \(\varepsilon_{c} = 2.3\) 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
Integrating Personality

As with our previous work (Eskridge et al., 2013), personality was incorporated into the collective model using an individual-specific value referred to as a “k factor” (Gautrais, 2010). In the original model, this value was a constant and was used to investigate the effects of altering the rate at which individuals initiate, follow, and cancel. With the addition of the k factor, initiation attempts are calculated at the constant rate of \( k/\tau_o \), and the following and canceling rate calculations are calculated as follows:

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

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

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 (Harcourt et al., 2009a). Second, the magnitude with which a shy personality affects the model should be the same as a bold personality so as not to bias effects of one personality value 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 used to calculate k 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, discuss personality of the individual animals involved one can assume that the individuals could be classified as having either bold or shy personalities. Therefore, the integration of personality incorporated the concept of a moderate personality \((p = 0.5)\) which produced the same equations as the original model. Larger personality values were interpreted as bolder personalities (e.g., \( p = 0.9 \)) and smaller values were interpreted as shyer personalities (e.g., \( p = 0.1 \)). 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:

\[
k = 2 \left( 1 + \frac{e^{-\alpha p - \alpha' p'}}{m} \right)^{-1} \tag{5}
\]

where \( p' \) is \( p \) for initiating and is \( 1 - p \) for canceling and following. Although different parameter values could be chosen for each decision, the choice of a single parameter was made to avoid over-complicating the model.

Winner and loser effects are feedback mechanisms in which experience affects future success. They sometimes exist as a self-assessment mechanism that affects an individual’s perception of its own abilities to the point where it can alter behavior without any actual change in ability (Fawcett and Johnstone, 2010). This self-assessment was incorporated into the model by updating the initiator’s personality after every initiation attempt using the following standard update (or learning) rule (Bernstein et al., 1988; Katsnelson et al., 2012; Sutton and Barto, 1998):

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

where \( p_t \) was the initiator’s personality before the 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, the personality was primarily determined through long-term historical success and changes were minor. When \( \lambda \) was high, the personality was primarily determined through short-term success, namely the last initiation attempt, and changes from one attempt to the next were significant. For the simulations described here, 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.

Numerical Implementation

Numerical simulations of the collective movement model were implemented in Java using a customized version of the original algorithm (Gautrais, 2010). The time of each event was calculated as a random number drawn from an exponential distribution using the appropriate rate equation. 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 (Eskridge, 2012). To evaluate the effects of personality distributions as the number of individuals is scaled up, experiments using group sizes of 10, 20, 30, 40, 50, and

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1Simulation source code and data analysis scripts are available for download from [https://github.com/snucsne/bio-inspired-leadership](https://github.com/snucsne/bio-inspired-leadership).
Table 1 shows the details for evaluations with the highest mean success for group sizes of $N = 10, 20, 30, 40, 50,$ and $100$. Note that while the “optimal” number of bold individuals in the group increased as the group size increased, the percentages fluctuated, especially for groups sizes $N = 40, 50,$ and $100$. Since, as mentioned above, the differences between many distributions was not statistically significant, we cannot claim that these fluctuations are generalizable, but it does merit note.

**Variable Distribution**

Once the most effective fixed personality distributions of bold and shy personalities were identified, evaluations using variable personalities were performed. Figure 2 shows the percentage of bold personalities in a group at the beginning of the evaluation versus the end of the evaluation for each group size and a range of initial percentages of bold personalities. Other than a group size of $N = 10$, groups were able to support a wide range of distributions of bold and shy personalities, including many that were much larger than the “optimal” distribution previously identified.

Figure 3 shows the initial percentage of bold personalities in the group versus the mean success for leaders initiating collective movements. For group sizes of $N = 10$, 20, and 30, there was close agreement of the maximum success percentage between evaluations with variable personality and the most effective fixed personality distribution, denoted with a horizontal dashed line. However, simulations with variable personality had statistically significantly lower fitness than simulations with fixed personalities in the optimal distribution (Kolmogorov-Smirnov, $p << 0.001$). Interestingly, for larger group sizes, initial personality distributions with a greater percentage of bold individuals than the “optimal” (denoted with a vertical dashed line) performed consistently better than distributions closer to the most effective distribution found in using fixed personalities.

Figure 4 depicts representative personality histories for a group size of $N = 40$ and three different initial personality distributions. In Figure 4a, only 10% of the group was initially bold. However, within relatively few simulations, additional bold leaders emerged from within the group. Furthermore, significant variations in shy personalities were observed as individuals experienced temporary success in initiating movements, but ultimately failed to consistently succeed. In Figure 4b, 50% of the group was initially bold. Since this value was close to the “optimal” distribution (see Figure 3d), no transitions in personality from bold to shy or shy to bold were observed. Lastly, in Figure 4c, 90% of the group was initially bold. As the experiments with fixed personalities showed that groups with such extreme personality distributions are clearly suboptimal, failed bold initiators quickly adapted their personalities, and their roles, to be shy followers. Once this adaptation occurred, personality values stabilized for the remainder of the evaluation.

### Table 1: Results of simulations with fixed personalities used to identify the most effective personality distributions of bold and shy personalities are shown.

<table>
<thead>
<tr>
<th>Group Size</th>
<th>Bold Individuals</th>
<th>Bold Percentage</th>
<th>Success Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>2</td>
<td>20%</td>
<td>86.9%</td>
</tr>
<tr>
<td>20</td>
<td>7</td>
<td>35%</td>
<td>91.7%</td>
</tr>
<tr>
<td>30</td>
<td>12</td>
<td>40%</td>
<td>93.6%</td>
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<tr>
<td>40</td>
<td>18</td>
<td>45%</td>
<td>94.4%</td>
</tr>
<tr>
<td>50</td>
<td>21</td>
<td>42%</td>
<td>94.8%</td>
</tr>
<tr>
<td>100</td>
<td>44</td>
<td>44%</td>
<td>95.5%</td>
</tr>
</tbody>
</table>

100 were performed. To account for the fact that the model is probabilistic, 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 noted above were the same as those used in the original model (Gautrais, 2010; Petit et al., 2009).

### Results & Analysis

Two types of experiments were performed to evaluate the effects of the distribution of personalities on the overall group’s success in initiating collective movements: a) fixed personalities with a fixed bold/shy distribution, and b) variable personalities with a fixed initial bold/shy distribution. The first type of experiment allowed for the identification of effects on the initiation success by different personality distributions. The second type allowed for evaluations on the stability of effective distributions and the ability of groups with suboptimal distributions to adapt.

### Fixed Distribution

To find the most effective personality distribution of bold and shy personalities, referred to hereafter as the “optimal” distribution, a search of different distributions using fixed personalities was made. Figure 1 shows the percentage of bold personalities in the group versus the mean success for leaders initiating collective movements. Although the differences between many bold percentages, especially for larger group sizes, were not statistically significant, the bold percentage with the highest mean success was chosen as the “optimal” distribution. Note that evaluations using either all bold or all shy personalities performed the same. In fact, further analysis indicated that the results were identical to one another and results of previous simulations that did not use the personality modification.
Figure 1: Plots of the percentage of bold individuals in the group versus the mean percentage of successful initiations for different group sizes in simulation treatments with fixed personalities and fixed distributions are shown. Horizontal and vertical lines denote the “optimal” percentage of bold individuals and the resulting mean success, respectively.

Figure 2: The mean percentage of bold personalities at the end of $2000 \times N$ simulations with variable personalities and fixed initial distributions are shown (mean/SD). Error bars representing the standard deviation are also plotted, but are often too small to see. Horizontal lines denote the most effective bold personality percentage found during fixed personality evaluations.
Figure 3: Plots of the percentage of bold individuals in the group versus the mean percentage of successful initiations for different group sizes in simulation treatments with variable personalities and fixed initial distributions are shown (mean/SD). Error bars representing the standard deviation are also plotted, but are often too small to see. Horizontal and vertical lines denote the “optimal” percentage of bold individuals and the resulting mean success, respectively.

Figure 4: Representative histories of individual variable personalities and the resulting distribution of personalities are shown for a group size of $N = 40$ and three different initial personality distributions.

**Discussion**

These results allow us to identify three significant contributions. First, as has been observed both in natural systems (Sih and Watters, 2005; Modlmeier and Foitzik, 2011) and in previous research using artificial systems (Pinter-Wollman, 2012), groups containing a combination of bold and shy personalities performed statistically significantly better than groups consisting of a single personality type (see Figure 1). Although the success rate of movement initiations varied with group composition, with some distributions having significantly higher success than others, these results indicate that there is a broad range of effective distributions of bold and shy personalities that have comparably high performance. However, note that these effective distributions do not include moderate personalities, as all individuals were either bold or shy. While this is consistent with observations in nature which indicate that larger differences between bold and shy personalities result in increased success (Pruitt and Keiser, 2014), the lack of moderate personalities is most likely the result of the personality update rule. For a moderate personality to be stable, it must succeed
as often as it fails. However, this is unlikely since a bolder than average personality is more likely to succeed and become bolder, while a shyer than average personality is more likely to fail and become shyer.

Second, as a result of this broad range of effective distributions, we conclude that the high performing personality distributions are stable equilibriums between bold and shy personalities, much like other stable distributions observed in nature (Mottley and Giraldeau, 2000). This conclusion is further reinforced by simulations using variable personality in which initially extreme personality distributions (e.g., 10% or 90% bold personalities) converged to higher performing distributions (see Figure 2).

One particularly interesting result is that the final distribution of personalities was dependent on the initial distribution. If the final distribution of bold and shy personalities was independent of the initial distribution, one would expect the plots in Figure 2 to be relatively horizontal lines. This is most likely due to the broad range of effective distributions shown in Figure 1 and the lack of sufficient pressure to reach the optimal distribution. Furthermore, when one considers that either consistent initiation success or failure is required to transition a personality from shy to bold or bold to shy, achieving the optimal distribution of personalities appears even less likely.

Lastly, it was surprising that a relatively large percentage of bold leaders (approximately 70%) was supported in many groups. At first glance, this result is counterintuitive given the effects of bold and shy personalities on the collective movement model and the general perception that such a percentage is “too high.” However, these results indicate that a bold leader only needs to recruit a sufficient number of shy followers to prevent a quick cancellation of the movement. Once a critical number of followers had joined the movement, other bold individuals joined the movement before the initiator canceled. In the bigger picture, a large percentage of bold leaders can promote higher group success. With more bold leaders, it is more likely that a bold individual initiates first, thus increasing the chances of a successful movement. Given that there are observations of animal groups with both lower (Harcourt et al., 2009b) and higher (Magnhagen, 2006; Sinn et al., 2008) percentages of bold individuals, no general conclusions regarding the relative frequencies of each personality type can be drawn. Current simulations allow for multiple initiations in a group, which may affect the percentage of bold leaders supported in a group.

Conclusions and Future Work

As discussed above, there are three significant conclusions that can be drawn from this work. First, these results show that groups with personality distributions containing a combination of bold and shy personalities perform at a higher level than those having a single personality type. In many cases, groups with a combination of personalities had almost twice the success in initiating collective movements as single personality groups. Second, these high performing personality distributions were stable equilibriums, as is seen in the simulations with variable personality when initially extreme distributions converge towards the higher performing personality distributions after relatively few simulations. Finally, these results show there is a wide range of effective personality distributions, with some groups supporting up to 70% of the group being bold leaders.

This work represents but one aspect of a larger research effort. The most significant opportunity for future work is to incorporate these results into simulations involving actual movement. Such simulations would provide a number of real-world constraints that may affect the personality distributions discussed in this work, including such things as local communication, dynamic communication networks, and conflicts of interest. Another avenue of investigation would be into the lack of moderate personalities in the results. Stable, moderate personalities are observed in natural systems, but in these simulations, personalities diverge into distinctly extreme bold and shy personalities. Possible reasons for this include the personality function used (see Equation 5) or the collective movement model itself.

Acknowledgments

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References


