Evolution of Cooperation in Packet Forwarding with the Random Waypoint Model

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Abstract: In multi-agent systems with self-interested individuals interacting locally, it can be difficult to determine if cooperative behavior will emerge. Evolutionary Game Theory provides some valuable tools to this end, but is not suited to systems with dynamic models of interaction. Mobile ad hoc networks provide a compelling application for evolutionary game theory, but there are still significant gaps between the theoretical results and the practical challenges. We discuss and provide some of the assumptions necessary to apply previous work in evolutionary game theory to the ad hoc network packet routing domain. We then analyze the similarities and differences between Brownian mobility and Random Waypoint mobility and show that convergence to cooperation requires a significant reduction in velocity for the Random Waypoint model. Our contribution is to provide evidence that more realistic mobility models can make convergence to cooperation more difficult than previously shown using random methods.

1 INTRODUCTION

Evolutionary game theory has emerged as a useful framework for understanding the emergence of cooperation in populations of inherently selfish individuals. These abstract models and metaphors have been combined with a consistent methodology to analyze problems that are common across a wide range of applications including biology, sociology, physics, and computer science. In general, evolutionary games provide a means to model complex adaptive systems with evolving individual and collective behavior.

One of the most well-known and studied games is the Prisoners' Dilemma, (PD) (Axelrod, 1992) a symmetric, two-player game in which individuals must choose between cooperation (C) and defection (D). In this game, cooperation is at a disadvantage and a rational player will always defect in one-shot play. In fact, defection has been shown to be the Nash equilibrium pure strategy (Axelrod, 1992). This game structure is a metaphor for many types of interactions, including ad hoc network packet forwarding. (Nisan, 2007)

Mobile ad hoc networks (MANETs) are multi-hop, wireless networks where each node is both a client and a router, and direct communication is limited by geographic distance. MANETs are characterized by a population of agents with a series of pair-wise interactions, making it an ideal application for evolutionary game theory. The performance of these networks is dependent on both the level of activity and the components' ability to adapt to changes in the network. Simple and lightweight approaches to local decision making can reduce the effects of mobility on the routing overhead (Viennot et al., 2004). We show the properties of the Random Waypoint Model with respect to Brownian motion and then explore effects of mobility on the evolution of cooperation.

For a population of individuals playing a PD game, cooperative behavior has been shown to evolve based on the graph structure, interaction models, and strategy evolution mechanisms. Certain properties of the graph promote cooperation, such as scale-free networks (Boccaletti et al., 2006) and a high clustering coefficient (Assenza, 2008). Additionally, other works such as (Poncela et al., 2008) and (Szolnoki et al., 2008) have explored preferential attachment models and (Helbing and Yu, 2009) uses graph rewiring mechanisms to promote cooperation. Recent work has shifted to more realistic models of rewiring based on dynamic spatial models (Meloni et al., 2009). In these models individuals interact based on their locality and move through the environment and, as a result, the partners that an agent in-

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teracts with is often repeated for some length of time before changing.

Prior work showing the effects of interaction models used random selection (Oliphant, 1994), random initial selection with fixed neighbors (Cohen et al., 1999), or grid-based environments where agents are limited to interaction in a finite set of locations in the space, as found in (Poncela et al., 2008), (Szolnoki et al., 2008) and (Helbing and Yu, 2009). While these discrete representations are convenient for reducing the complexity of the simulation they do not often model practical scenarios. More recent work has explored simple mobility models for changing interactions, such as Brownian motion, that do not emulate the motion that would be expected from individuals moving in the real world (Johnson and Maltz, 1996).

The main contribution of this work is the application of random waypoint (RWP) mobility to evolutionary game theory with a graph-based interaction model. This extends prior work with a more realistic representation of agent movement that better reflects the expected behavior of a mobile ad hoc network. We show that the RWP model has significant effects on the evolution of cooperation among a population of mobile, self-interested agents.

In Section 2 we will discuss how the Prisoners' Dilemma can be used as a packet forwarding interaction model between pairs of agents. In Section 3.1 we will discuss the process for choosing pairs of agents to interact as a function of communication distance. In Section 3.2 the method and justification for evolution of individual agent strategies will be provided. Section 4 discusses the mobility model that motivates the primary contribution of this work. Finally, we will provide our simulation parameters and results in Section 5 and discuss the implications of our findings in Section 6.

2 PACKET FORWARDING GAME

A wireless ad hoc network is a decentralized network without a fixed infrastructure to facilitate routing of packets. Every node is both a client and a router and the functionality of the network relies on each node to cooperate. In scenarios where the nodes are self-interested, each node in the network participates (or chooses not to participate) in forwarding packets across the network to allow for communication between end points. In this environment, network nodes must choose between forwarding (C) and not forwarding (D) packets that are being routed through them.

Due to a lack of a routing infrastructure, flooding in mobile ad hoc networks (MANETs) has been shown to be an effective method of communication (Ho et al., 1999). Flooding is defined as a mechanism where each node rebroadcasts a message m once when it is received, then ignores m if it received again. As a result, messages are diffused across the network and result in many pairwise interactions between neighboring nodes. We model this interaction using a game theoretic framework.

	C	D
C	1, 1	0, b
D	b, 0	0, 0

Figure 1: Normal form reduced Prisoners' Dilemma game with single parameter b as the benefit of defection.

The Prisoners' Dilemma is a nonzero-sum, noncooperative, two-player game. In this game R is the payoff for mutual cooperation, T is the temptation to defect, S is the "suckers" payoff, and P is the payoff for mutual defection. We use the reduced form as defined in (Nowak, 1992) with the payoff values $R = 1, T = b(b > 1), S = P = 0$, shown in Figure 1. This simple model allows us to analyze the effects of the mobility model with respect to a single parameter b representing the benefit of defection. More complex models of interaction for packet forwarding in ad hoc networks exist (Kamhoua et al., 2010), but the additional parameters required would make it difficult to focus solely on the effects of mobility.

When both neighbors cooperate all packets are forwarded. Defection can be attractive when neighbors cooperate for a number of reasons. A selfish agent can conserve battery life, CPU cycles, or available network bandwidth while relying on its own packets to be forwarded. This type of selfish behavior by a small percentage of nodes in the network has been shown to have significant negative impact on network communication (Tanachaiwiwat et al., 2004). More importantly, when an agent is interacting with many defectors there should be a mechanism to cease cooperation so not to be taken advantage of.

Each node would benefit to have its own packets forwarded and relies on its neighbors to do so. However, there are complications that arise when the packets are not originating from the neighboring agent but rather being forwarded from another agent. Assuming agents are able to monitor the behavior of their neighbors, an agent considering defection runs the risk of having a neighbor witness this non-cooperation and retaliate in the future. However, if a packet originates from a non-neighbor source then the forwarding agent has no motivation to retaliate against a neighboring defector. In order to bound our analysis to pairwise interactions between nodes we must address this disparity.

One method for handling a mixture of direct and indirect packets is a stochastic game in which the cost of defection is different for each packet type. Fortunately, we can use the probability distribution of direct and indirect packets, along with their respective costs for defection, to form a single normal form game that will yield the same behavior over a large number of interactions. A simpler model for dealing with indirect packets is to assume that there is a community enforcement mechanism that requires nodes place as much value on forwarding others' packets as it does its own (Kamhoua et al., 2010). Using this mechanism, a defecting agent can expect to be punished equally for failing to forward any packet, regardless of where it originated. Both methods yield a normal form game that is sufficient for capturing the nature of the packet forwarding interactions.

3 EVOLUTIONARY GAMES

Evolutionary game theory (EGT) is the application of game theory to populations of individuals. These individuals can be biological life forms in an ecosystem, particles interacting to form compounds, or automated systems that exhibit an emergent behavior. While game theory focuses on the interactions between a specific pair of individuals, EGT provides a set of mechanisms for repeated interactions among members of a population. As a result, complex patterns and behaviors can emerge from relatively simple individual strategies.

Evolutionary games can be characterized by three components: a game, an interaction model, and strategy evolution mechanisms. We have already discussed the packet forwarding game in the previous section, which will be our focus in this work. The interaction model determines how agents are paired to play an instance of the game at each time step, and is discussed in the next section. Then, we will describe the strategy evolution mechanism, which is used by individuals to change their strategy based on the outcomes of the interactions in a time step.

3.1 Interaction Model

We model interactions between agents as a graph with vertices representing individuals and edges indicating pairwise interaction at each time step. Unlike Erdös-Renyi graphs, where agents are paired randomly with some probability, the agents are given a random location in the space and an edge is formed based on their locality.

Consider a graph where nodes are placed in a d-dimensional space $\mathbb{R}^d$, with edges existing only between nodes that are close to each other. A geometric graph $G(V,r)$ is an undirected graph with $V \subset \mathbb{R}^d$ as the set of vertices.For this work we consider point in 2 dimensional space with $V \subset \mathbb{R}^2$. The set of edges is defined as $E = \{(u,v)|(u,v \in V) \wedge (0 < \| u - v \| \leq r)\}$, where $\| \cdot \|$ is the distance norm on two points (x_1,y_1) and (x_2,y_2). We use the ℓ_2-*norm*, or Euclidean distance, defined as $\sqrt{(x_1-x_2)^2+(y_1-y_2)^2}$.

To simplify analysis, we will assume that all vertices are normalized to have the same radius $r = 1$ and are in a toroidal space. A toroidal model is chosen to remove the border effects on the degree of vertices. The initial configuration corresponds to a random geometric graph (Penrose, 2003) with the topology depending on the number of agents N and the length of the space L. The density of the agents $\rho = N/L^2$ has a direct effect on the connectivity of the graph and the component size. We represent the degree of node i at time t as $k_i(t)$.

There is a very large body of work in evolutionary Prisoners Dilemma that makes use of round-robin interaction in a population (Kendall et al., 2007). While the round-robin approach is ideal for generating randomized, well-mixed interactions, it does not consider the types of spatial interactions that are observed in ad hoc networks. The spatial model has a significant effect on game play because of the dependence of edges. For example, assume a population of 1000 nodes where a pair of nodes A and B are neighbors and C is also a neighbor to B. Because A and B, and B and C, are related based on distance there is a higher likelihood that C will be a neighbor of A as opposed to another arbitrary node being a neighbor of A. This dependency on interactions can contribute to the formation of clusters of cooperation, as discussed in Section 4.

At each simulation time step agents interact with all of their neighbors and keep track of the payoffs received. In the context of mobile ad hoc networks, this behavior is analogous to multicast communication. While there exist routing protocols for ad hoc networks that allow direct addressing of packets, it has been shown that there is a threshold of mobility at which maintaining the routing paths is difficult and multicast flooding is the most reliable method of delivery (Ho et al., 1999). Knowledge of the forwarding behavior of a neighbor is made possible by watchdog mechanisms (Marti et al., 2000) and observation of transmissions made by neighboring nodes.

3.2 Evolution of Strategies

As agents interact with their neighbors they may determine that it is in their best interest to change their behavior to increase their individual payoff in future interactions. One methodology for adjusting behavior is to adopt a method of replication by imitation (Weibull, 1997). Using this method agents observe the payouts received by other agents and decide if they wish to adopt that strategy as their own in the future. For mobile ad hoc networks it makes sense to limit any observations to neighboring agents, although in some environments it could be argued that no information is available regarding the payouts received by other agents.

In the interest of being consistent with prior work in the evolution of cooperation on mobile networks we adopt the payoff monotone replication function described in (Poncela et al., 2009). At each time step an agent i, with degree $k_i(t)$ at time t, chooses an agent j, with degree $k_j(t)$ at time t, at random from its neighbors. Let the total payoffs received by these agents in the current time step t be $f_i(t)$ and $f_j(t)$, respectively. If $f_i(t) \geq f_j(t)$ then agent i keeps its current strategy. If $f_i(t) < f_j(t)$ then agent i adopts agent j's strategy with probability

$$P_i = \frac{f_j(t) - f_i(t)}{b \cdot max\{k_i(t), k_j(t)\}} \quad (1)$$

This update is done synchronously for all agents at the end of each time step, after they have completed their interactions with their neighbors and received the associated payoffs. After all of the agents have completed their strategy update the total payoffs are reset to zero.

4 MOBILITY MODEL

Much of the previous work analyzing the effects of mobility models on the evolution of cooperation uses lattice or grid-based models, such as (Perc and Szolnoki, 2008) and (Helbing and Yu, 2009). While this approach provides a useful simplification of the space of interaction, it constrains interaction to adjacent grid locations and limits the opportunities for movement. Some recent work explores a continuous 2D space with a Brownian motion model (Meloni et al., 2009), which is well-suited to modeling the random motion of particles in physics. However, because we seek to model mobile devices held by persons with intentional movement our analysis requires a more appropriate mobility model.

Random Waypoint (RWP) (Johnson and Maltz, 1996) mobility is a widely used model for simulating mobility in ad hoc networks. It was designed to emulate the movement patterns of mobile users and devices and includes parameters for location, direction, velocity. At the initial time step each node is assigned a random location in the space and a random waypoint representing the destination. Given a velocity v, at each time step the mobile nodes move a distance v directly towards their destination waypoint. Upon reaching the destination the node will pause for p time steps, randomly generate a new waypoint, and then continue movement towards the new destination. In this work we set $p = 0$.

Unlike the Brownian motion model, the groupings of nodes are much more 'volatile', meaning that nodes that are near each other are highly likely to seperate as time passes. The implications of this model on the evolution of cooperation are significant. Because individual cooperation relies on neighbors also cooperating, the population will often form regions of cooperation that can withstand defection (Nowak, 1992), as shown in Figure 2. With a Brownian motion model these pockets are relatively stable and nodes will remain within relatively close distance of each other. When using RWP nodes are often moving along a vector and will move in and out of cooperation regions, adapting to their current neighbors as they pass. As a result, regions of cooperation are often unstable because the cooperating neighbors are unlikely to be nearby for very long. This requires regions of cooperation that are large enough to withstand the constant churn of individuals passing through them.

Even though the RWP mobility paints a grim picture of the potential for cooperation there are still conditions under which cooperation can flourish and the population will converge. In the next section we present the details of our simulation and provide the parameters that will encourage cooperation in a large population of mobile devices.

5 SIMULATION AND RESULTS

Simulations were created using the MASON multi-agent simulation developed at George Mason University (Luke et al., 2005) and using the included libraries for 2D continuous toroidal space. MASON was chosen because it is a lightweight environment that allowed for rapid development of simulations

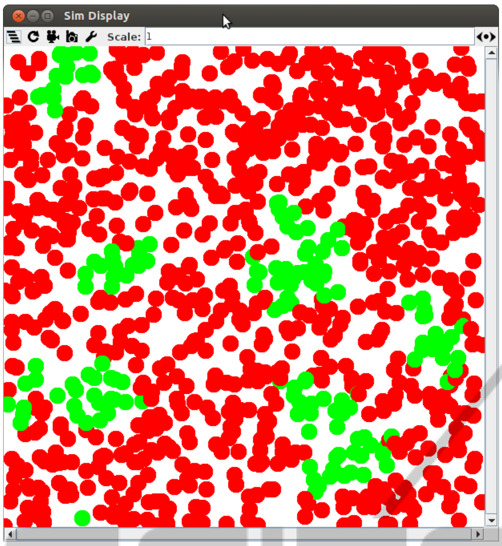

Figure 2: A snapshot of a simulation run exhibiting clusters of cooperation. Cooperators (green) rely on cooperating neighbors to receive sufficient payouts that discourage changing their strategy to defection (red).

with 10^3 agents over many runs.

We make some assumptions for simulation that may or may not be an accurate depiction of real world conditions. We model the mobile agents as point objects in a 2 dimensional toroidal space and have them interact whenever they are within radius $r = 1$ of each other. The toroidal space removes edge conditions and is meant to represent a sampling of a larger space. While the interactions wrap around the edge, we feel the number of agents is sufficient to avoid agents experiencing feedback effects from their own actions. Finally, the strategy evolution relies on an agent having information about the payoffs received by its neighbors. While it's feasible that an agent may have this information, it is not necessarily true in all situations.

We first compare the dynamic properties of RWP and Brownian mobility using two standard metrics: link change rate (LCR) and link density (LD) (Cho and Hayes, 2005). LCR (Equation 2) is the average rate of change of edges on the graph and is computed as the sum of edges added and removed per time step. LD (Equation 3) is measured as the average number of time steps a link is maintained and measures the average time agents spend linked with the same neighbors. For the set of agents A, velocity v, and time of simulation $t < T$, let $E_A(t)$ and $E_R(t)$ be the edges added and removed at time t, respectively, with $E_A^i(t)$ and $E_R^i(t)$ returning only those edges for agent i. E_T is the set of all edges in the simulation and $D(e)$ is the duration of one instance of a specific edge. We set a density value of $\rho = 1.3$ to remain consistent with

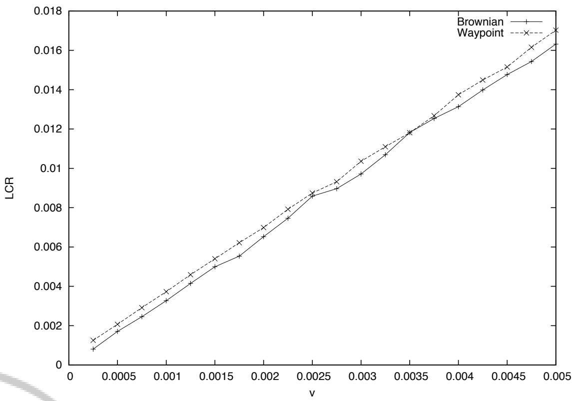

Figure 3: Link change rate (LCR) for the Brownian and RWP mobility models with respect to velocity for $N = 10^3$, $\rho = 1.3$. In general, the RWP mobility has a slightly larger rate of change, but both models remain similar regardless of velocity.

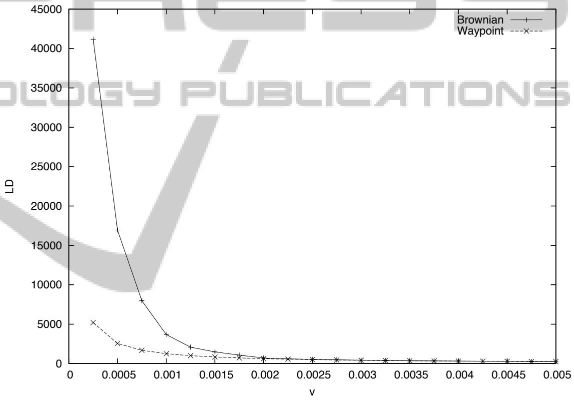

Figure 4: Link duration (LD) for the Brownian and RWP mobility models with respect to velocity for $N = 10^3$, $\rho = 1.3$. At low velocities the Brownian model has a significantly larger duration, but both mobility models converge as velocity increases.

previous work (Meloni et al., 2009), which requires $L = 27.735$ for 10^3 nodes.

$$LCR = \frac{\sum_{i \in A} \sum_t^T E_A^i(t) + E_R^i(t)}{|A| \times T} \tag{2}$$

$$LD = \frac{\sum_{i \in A} \sum_t^T \sum_{e \in E_R^i(t)} D(e)}{E_T} \tag{3}$$

In Figure 3 we compare the LCR for the Brownian and RWP mobility models with respect to velocity. RWP exhibits a slightly higher LCR than the Brownian mobility in all cases, but they do not show any indication of divergence up to $v = 0.02$. This indicates that the RWP mobility model is not introducing additional volatility with respect to the addition and removal of edges.

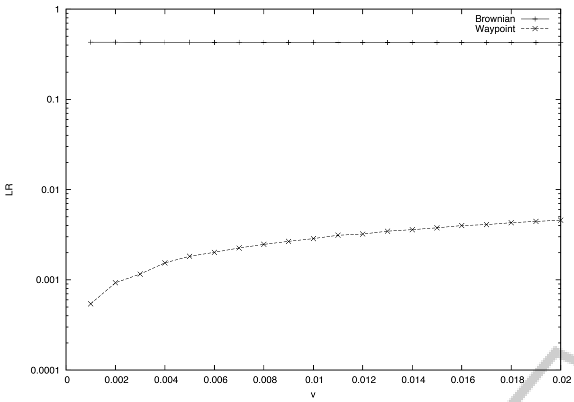

Figure 5: Link repetition (LR) for the Brownian and RWP mobility models with respect to velocity for $N = 10^3$, $\rho = 1.3$. The Brownian model has relatively fixed LR regardless of velocity while RWP has a vastly different LR value that changes with respect to velocity.

In Figure 4 we show the LD for Brownian and RWP mobility with respect to velocity. At very low velocities these models exhibit significantly different link durations, with Brownian motion maintaining links orders of magnitude longer than RWP at $v = 0.005$. However, as the velocity increases both mobility models converge to similar link durations. Because the Brownian mobility randomly chooses a new direction at each time step there is an increased likelihood of remaining in range of a neighbor until the random walk leads the agent away. On the other hand, because RWP uses time-dependent movement, an agent within range that moves away in a given time step is likely to continue on that path.

Intuitively, these mobility models should differ significantly with respect to the diversity of the edges that are formed. Two arbitrary nodes in the Brownian mobility model are more likely reform the same edge within a short period of time than the same pair of nodes in the RWP mobility model. To capture this behavior we define the *link repetition* (LR) of a dynamic graph in Equation 4, with $L(e)$ being the last time step that edge e existed and E_A being the set of all edges added over all time steps.

$$LR = \frac{\sum_t^T \sum_{e \in E_A(t)} (t - L(e))^{-1}}{|A| \times |E_A|} \tag{4}$$

This metric measures the likelihood of newly formed edges being between vertices that were recently connected. By accumulating the inverse of the time between link disconnect and reconnection we can identify conditions under which neighbors are interacting with the same neighbors, regardless of link change rate. A high LR value indicates that agents are reforming edges with neighbors within a relatively short period of time after the edge is removed. A low value indicates that agents are interacting with a wide range of other agents and not often reforming edges with the same neighbors.

In Figure 5 we show the LR value for both mobility models. Brownian motion maintains a fixed link repetition ($LR \approx .43$) value regardless of velocity, while the RWP mobility has an LR value that is consistently much smaller and increases with respect to velocity. These values reflect the stepwise random behavior of Brownian motion that leads to edge reconnection at a fixed rate, while the time-dependent behavior of RWP mobility leads to a low reconnection rate. As velocity increases, the RWP mobility moves agents at a faster rate, leading to more opportunities for reconnection as they cover more of the space in less time.

While link retention is not the singular measure to differentiate between Brownian and RWP mobility, it does provide some insight into why these models should behave differently with respect to the emergence of cooperation. Clusters of cooperators thrive on repeated interaction with other cooperators (Oliphant, 1994), so repeated interaction (even with a small number of time steps disconnected) can be a powerful influencer of the convergence to cooperation in the whole population . When repeated interaction is limited, the pockets of cooperation are no longer characterized primarily by the agents that are members of the clusters, but rather the inherent structure of these clusters. In the RWP mobility model the clusters of cooperation must be stabilized by reduced movement to allow cooperation to stabilize and convert the constant stream of new agents to cooperation.

5.1 Node Density

In Figure 6 we show the effect of density on how often the population converges to full cooperation. These results are very similar to those found in (Meloni et al., 2009), shown in Figure 7 but are at a velocity of $v = 0.001$ rather than $v = 0.01$, an order of magnitude reduction. Simulations run at $v = 0.01$ using RWP movement always converged to defection, regardless of density. This significant difference further reinforces that RWP mobility has a strong effect on the stability of cooperative 'communities' that can be remedied by decreasing the relative velocity of the agents.

As show in Figure 6, at low values of density ($\rho \lesssim 1$) the agents are sparsely distributed and cooperators are unable to form regions of cooperation. Conversely, at high densities ($\rho \gtrsim 7$) agents are well-mixed and interact with a large number of other

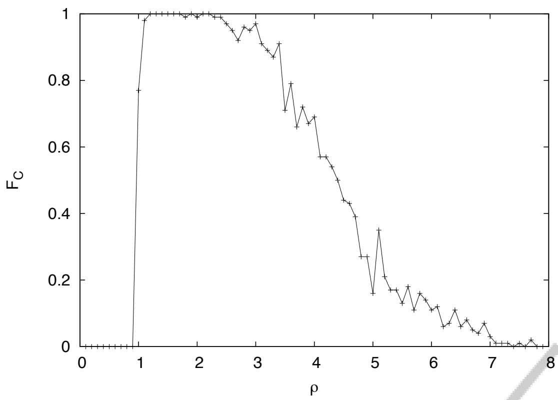

Figure 6: Fraction of simulations F_C using Random Waypoint mobility that converge to full cooperation as a function of density ρ with fixed value of $N = 10^3$, $b = 1.1$, and $v = 0.001$. Results are given as a fraction of 100 simulation runs.

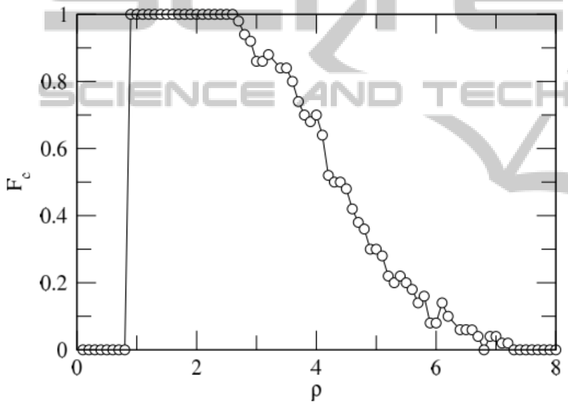

Figure 7: Fraction of simulations F_C using Brownian mobility that converge to full cooperation using Brownian mobility as a function of density ρ with fixed value of $N = 10^3$, $b = 1.1$, and $v = 0.01$, as reported in (Meloni et al., 2009). Results are given as a fraction of 100 simulation runs.

agents. In this case there are many opportunities for defectors to get a high payout and encourage cooperators to defect. Finally, there is a region of density ($1.2 \lesssim \rho \lesssim 2.4$) where the population will almost always converge to cooperation and we observe a steady decrease in convergence to cooperation as ρ approaches 7.

5.2 Velocity vs. Benefit of Defection

We now seek to determine the parameter values that encourage cooperation in mobile ad hoc network packet forwarding. Due to the complexity and overlap of the models of interaction and mobility, a purely analytical solution to this problem is difficult to derive. Therefore, we seek an empirical solution based

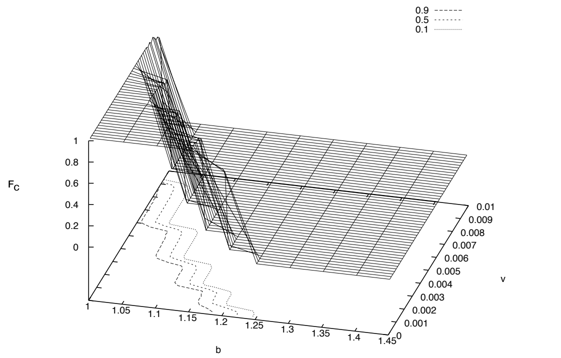

Figure 8: Fraction of simulations F_C out of 100 that converge to cooperation with respect to velocity (v) and the temptation to defect (b) with fixed values of $N = 10^3$ and $\rho = 1.3$.

on modeling and simulation of a set of random instances. Of particular interest are the effects of node density on cooperation and the relationship between velocity and the benefit of defection. Because r is fixed at $r = 1$, to adjust the density we must change the size of the $L \times L$ space. This will alter the set of possible agents chosen as neighbors while keeping the velocity relative to the fixed communication radius. Agents play a pure strategy and are initialized with a random strategy with 50% probability of being a cooperator or defector.

In order to show a wide range of behavior we have run simulations for different values of velocity and temptation to defect. In Figure 8 the effects of these parameters on the convergence to cooperation is shown. For very small values of b cooperation is more likely, even as the velocity is increased. This can be attributed to the relatively low payoffs that selfish agents will receive, reducing the likelihood of neighbor nodes choosing to adopt the same strategy. Likewise, an increase in velocity also diminishes the chances of the simulation converging to cooperation.

As clusters of cooperators form, the agents rely on their neighborhood to boost their own payoffs as well as help to influence other agents to also engage in cooperation. Additionally, it's important that agents moving through the region of cooperation have ample opportunity to observe the benefits and adopt the strategy before they move out of the cluster. As velocity increase there is a corresponding increase in the frequency and number of intruding defectors that can exploit cooperators for higher payoffs and provide neighboring agents with incentive to also defect. Additionally, an increased velocity reduces the time that and agent passing through the cluster will have to interact with cooperators and adopt their strategy for itself. These challenges, while not unique to the RWP mobility model, are significantly more pronounced in their effects.

6 DISCUSSION

We show that more realistic mobility models, as opposed to fully random models, can make it more difficult for cooperation to evolve in a population of individuals. We also provide a set of assumptions that begin to bridge the gap between theoretical agent interaction models and distributed packet forwarding using local decision processes. The main contribution of this work is to show that the random waypoint mobility model, a more realistic representation of agent movement for mobile ad hoc networks, has a significant effect on the emergence of cooperation.

Full convergence to cooperation was realized in the RWP model, but only by significantly reducing the velocity of the agents to counteract the resulting volatility due to a lack a stability in cooperation clusters. Unlike random walk models, where agents are likely to remain near each other for many time steps, the RWP model define vectors of movement that will often result in agents following divergent paths. In the Brownian mobility model, regions of cooperation are composed of a community of agents that are likely to remain together. The RWP model, on the other hand, yields cooperation regions in which the member agents are fleeting and the stability is influenced by the interaction structure and its ability to convert defectors to cooperators as they enter the region.

These results can be used to design internal mechanisms for individual networked devices as well as provide insight into the effect of mobility on collections of ad hoc networked devices. Significant work is still needed to show the applications of these results to real networks, but they provide a foundation to support the applicability of evolutionary game theory to the design and analysis of mobile ad hoc networks.

6.1 Future Work

There is a wealth of movement models, surveyed in (Bai and Helmy, 2004), that are intended to model specific real-world phenomenon. Temporal dependency models generate motion that is dependent on prior time steps and model gradual turning and acceleration. Spatial dependency models provide mechanisms for squad-based movement that would more accurately model devices being carried by groups of people. Geographic restriction models consider environments where movement and communication is restricted by the existence of impassable objects, such as buildings. Each of these models and their unions have unique properties that will no doubt have an effect on the evolution of cooperation.

We plan to explore other types of games that capture ad hoc network behavior, such as those discussed in (Kamhoua et al., 2010). The pure strategies used in our simulations assumes that an agent does not discern between the identities of neighboring nodes. While this provides an efficient, memoryless operating methodology, there is the potential to include identification of neighbors and recall of historical interactions. This additional bookkeeping would allow for iterated play and, as a result, more sophisticated strategies such as Tit for Tat or Grim Trigger (Axelrod, 2000).

The replicator dynamics used for adopting the strategy of a neighbor relies on the communication of reward or the ability to observe the action and payoff that neighboring agents receive. While this is a common mechanism for evolutionary games it not a realistic assumption in physical environments with selfish agents that see no benefit in making this information available. In these cases a new method for updating an agent's strategy will be necessary.

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