Emotion, Trustworthiness and Altruistic Punishment in a Tragedy of the Commons Social Dilemma

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Abstract. Social dilemmas require individuals to tradeoff self interests against group interests. Considerable research effort has attempted to identify conditions that promote cooperation in these social dilemmas. It has previously been shown altruistic punishment can help promote cooperation but the mechanisms that make it work are not well understood. We have designed a multi-agent system to investigate altruistic punishment in tragedy of the commons social dilemmas. Players develop emotional responses as they interact with others. A zero order Seguno fuzzy system is used to model the player emotional responses. Players change strategies when their emotional level exceeds a personal emotional threshold. Trustworthiness of how other players will act in the future helps choose the new strategy. Our results show how strategies evolve in a finite population match predictions made using discrete replicator equations.

1 Introduction

Social dilemmas are situations where individuals must choose between self interests and group interests. Typically individuals must decide whether to "cooperate" for the benefit of the group or to "defect" for their own benefit. Many challenging problems such as public land usage, pollution control, and overpopulation are examples of social dilemmas. Such dilemmas have two conflicting properties: (1) individuals benefit the most by defecting, regardless of what others do, and (2) everyone does better with mutual cooperation than with mutual defection. Unfortunately, most social dilemmas end with everyone defecting.

Mathematical games are well-suited for studying social dilemmas. In each round of these N-player games ($N > 2$), a population of individuals chooses whether to cooperate or defect. Players receive a payoff based on their own

M. Wagner et al. (Eds.): ACALCI 2017, LNAI 10142, pp. 12–24, 2017.
DOI: 10.1007/978-3-319-51691-2_2

choices and the choices others make. The goal is to gain insight into the human decision making process by observing how cooperation levels evolve over time. The most extensively investigated social dilemma game is the *public goods game*. Recently investigators have started to look at the *tragedy of the commons* (ToC) game [1] which some argue is a better model of real-world problems.

In a ToC game individuals consume a finite resource which is called public good. Cooperators limit their consumption rate to help preserve the public good while defectors consume at a higher rate. Some percentage of the public good is periodically renewed but overconsumption will eventually deplete it. Cooperators act in the best interests of the group; defectors act in their own self-interest. The social dilemma is "resolved" if all individuals cooperate—i.e., the defectors all become cooperators. The inevitable outcome, regrettably, is everyone defects and the public good is depleted.

Researchers have proposed several methods of preventing the inevitable outcome. One of the most promising is introducing a third strategy: altruistic punishment [2]. Defectors are free riders who exploit the actions of cooperators. Punishers impose a penalty on defectors to coerce them to switch strategies. This punishment is altruistic in the sense that the punisher pays a cost for penalizing those defectors.

In some of our previous work [3] we used discrete replicator equations to see how altruistic punishment can help resolve a ToC in a finite population. These coupled, first order differential equations predict how the frequency of cooperation (C), defection (D) and altruistic punishment (P) evolve. Our results showed the ToC can be resolved if the penalty imposed by the punishers is high enough. Unfortunately, despite the power of these replicator equations, they do have one limitation. The strategy frequencies evolve via Darwinian evolution. This means the evolution is determined strictly by fitness. (The amount consumed is a measure of fitness.) Strategies that have fitness greater than the average population fitness grow, while strategies with fitness less than the population average decrease. Consequently, there is no way of determining how individuals respond to other player's choices so there is no way of gaining insight into the decision making process.

That previous work showed two ways of increasing the punishment: keep the penalty β fixed and increase the number of punishers or keep the frequency of punishers x_2 fixed and increase β. (The punishment equals $x_2\beta$.) Altruistic punishment can effectively help resolve a ToC so long as the punishment level is high enough.

In our current work we take a different approach. We formulated a multi-agent system where each player (agent) makes their strategy choice independently. Each player has an emotional response to the actions of others. A strategy change is made if the emotional level breaches some threshold. The new strategy picked is based on trustworthiness—i.e., the expectation of how other players will choose in future rounds. These emotional levels grow according to a set of fuzzy rules. Specifically, each player's emotional state is modelled by a zero order Seguno fuzzy system. Our results are remarkably similar to the results predicted by the discrete replication equations. The difference now is, since player's actions are independently decided, our new approach provides a much more effective framework for studying how emotions and trustworthiness affect the human decision making process in social dilemmas.

2 Background

Humans naturally develop emotions as they interact with others. These emotions could be satisfaction, joy, annoyance, anger, sadness, or guilt. If these emotions grow strong enough they can cause individuals to change how they act in the future. In part this choice depends on trustworthiness—i.e., it depends on how they expect others to act in the future based on their prior actions.

The interplay of emotion, trust and judgement has been investigated in many studies in the literature. Research on the field of social neuroeconomics discusses the connection between emotion and decision making. Sanfey [4] suggests decisions of trust are dependent on altruism and reciprocation for the trust game to work. A link has been identified between affective states, such as positive and negative feelings on unrelated judgements [5,6]. Emotions affect a variety of decision making processes, including decisions such as whether to trust a stranger, a politician, or a potential competitor [6]. Moreover, emotion has been shown to affect related concepts like altruism, risk preferences, and the perceived likelihood of future events [7–9].

An extensive literature on Emotion exists in the field of social psychology. The majority of this literature explain how emotions get produced and how emotional states may impact decisions, including trusting decisions.

For example, Dunn and Sweitzer [10] point out that moods influence judgement in that people engage in specific behaviours because they are motivated to maintain or repair a current mood state. The authors however suggest that positive and negative feelings-valence, as observed in mood models are not the only determinants of trust judgments. They distinguish between emotion and mood and claim that emotion is a much more complex state than mood. Emotional states are shorter in duration, more intense and incorporate varied cognitive appraisals, which include individual perceptions of certainty, control over the outcome, appraisal of the situation and attribution of the cause of the emotion. Emotions with the same valence but different control appraisals (self or other) have been found to have differential impact on trust and decision making.

Mood and emotion are complex concepts and have been discussed here to provide a general context for this research. The causes for emotional change or emotional production per se are beyond the scope of this paper. Instead, we chose a level of abstraction to enable us to focus on the impact of emotion on game dynamics.

3 System Description

A ToC is an N player game ($N > 2$). Each round players will consume a fixed portion of a fixed resource. The amount consumed depends on the strategy.

C players are interested in preserving the resource so they voluntarily limit the amount consumed. On the other hand, D players are self-interested so they consume a higher amount of the resource. Periodically a fraction of the resource is renewed. However, if the overall consumption rate is too high the renewal amount is insufficient and the resource is ultimately depleted. Too many D players will eventually deplete the resource. Hence, the only way to "resolve" the ToC game is to have the player population contain only C players because then the consumption rate is less than the renewal rate so the resource is always available.

D players are free riders because they exploit cooperators. The best individual outcome is to defect, regardless of what other players do. Unfortunately this leads to the inevitable outcome of everyone defecting and the fixed resource being depleted. One way of convincing D players to change strategy is to introduce a third type of player who is an altruistic punisher.

Definition 1. *Altruistic punishment is punishment inflicted on free riders even if costly to the punisher and even if the punisher receives no material benefits from it.*

P players consume the same amount as a C player but they also penalize D players. This reduces the D player's return hopefully making defection less desirable. The punishment is altruistic in the sense the P player pays a small cost to inflict this punishment. Thus the payoff to a P player is less than a C player.

But there is another problem. C players exploit P players because they benefit from punishing D players but they don't pay any cost for punishing them. This is referred to as the *2nd order free riding problem.* (D players are 1st order free riders.) To address the 2nd order free riding problem punishers will also penalize C players who won't punish. The P player pays an additional cost for this punishment as well. Previous work has shown altruistic punishment, properly applied, can help resolve social dilemmas [11,12].

The proposed method is summarized in Algorithm 1 and is explained in more details below.

Let N be the population size and let k_1, k_2, k_3 be the number of C, P and D players respectively where $\sum_i k_i = N$. Then the frequency of a strategy i in the population is $x_i = k_i/N$. Let CR_1 be the consumption rate for a D player and CR_2 the consumption rate for C or P players where $CR_1 > CR_2$. Then the payoff to a player ℓ is

$$\pi(\ell) = \begin{cases} CR_1 - k_2\beta & \text{defectors} \\ CR_2 - ck_2\gamma & \text{cooperators} \\ CR_2 - c[(k_3\alpha) + (k_1\eta)] & \text{punishers} \end{cases} \tag{1}$$

```
Input  : Players_List(Emotion_threshold,Emotion_level,Strategy,Payoff)
Output: Players_List(Emotion_threshold,Emotion_level,Strategy,Payoff)
if First Generation then
    Emotion_level ← 0
    Emotion_threshold ← rand(5,10)
end
for Each Player do
    Play Strategy
end
for Each Player do
    Update Payoff
    Observe Actions of Other Players
    Calculate Delta_change in Emotion Using the Fuzzy Rules
    Emotion_level ← Emotion_level + Delta_change
    if Emotion_level ≥ Emotion_threshold then
        Update strategy
        Emotion_level ← 0
    end
end
```

Algorithm 1. The logic for updating agents' emotion levels and strategies.

The punishments and costs are summarized as follows:

1. $\beta > 1$ is the punishment each punisher inflicts on a defector
2. $\gamma > 1$ is the punishment each punisher inflicts on a cooperator
3. punishers pay a cost $\alpha > 1$ for each defector punished
4. punishers pay a cost $\eta > 1$ for each cooperator punished.
5. $c = 0$ if there are no D players to remove all costs and punishments. Otherwise $c = 1$

In the simulations we used $N = 20, CR_1 = 82, CR_2 = 39, \alpha = 1.0, \gamma = 0.2$ and $\eta = 0.1$. β varied depending on the investigation. The initial public goods capacity was 5000 units and decreased each round (82 units for each D player and 39 units for each C or P player). After each round, the remaining capacity was increased by 25%.

Each player has an emotional level (initialized to 0) and an emotional threshold randomly assigned between 5.0 and 10.0. During each round the emotional levels can change in response to actions taken by the other players. Players change to a new strategy when their emotional level exceeds their personal emotional threshold. The thresholds were different for each player because individuals react differently to situations. For instance, the actions of other players may anger some players while others may be merely irritated.

We designed a zero order Seguno fuzzy system to model the emotional state of the players. The emotional levels of each player changes based on the fuzzy rules (see Table 1). Players know the strategies of other players by observing their consumption rates. The antecedents for most rules use strategy frequencies but two rules use assessed penalties. For instance, a C player is "satisfied" if the frequency of cooperators is high so there is little or no change in the emotional level. On the other hand they are "annoyed" if they are paying a high penalty for free riding (moderate change) and "angry" if the frequency of defectors is high and the frequency of punishers is low (large change). The rationale for these rules is given in the table.

Trapezoidal membership functions were used for all of the antecedents based on strategy frequencies. These are shown in Fig. 1. A Heavyside function was used for the antecedents using penalties. Specifically, the membership function for Rule # 2 is

$$\mu(k_2\gamma) = \begin{cases} 0 & k_2\gamma \leq CR_2/2 \\ 1 & \text{otherwise} \end{cases} \tag{2}$$

and the membership function for Rule # 5 is

$$\mu(k_2\beta) = \begin{cases} 0 & k_2\beta \leq CR_1/2 \\ 1 & \text{otherwise} \end{cases} \tag{3}$$

The reasoning behind this type of membership function is penalties are tolerable so long as they are not too heavy. A penalty is considered intolerable if it reduces the payoff by more than 50%.

Output membership functions in a zero order Seguno fuzzy system are constants. The function will output the values 0, 1 and 5 corresponding to the three emotional states, satisfied, annoyed and angry, respectively. The constants were chosen to produce no emotional change (satisfaction), a moderate change (annoyed) or a large change (angry). A weighted average defuzzification method was used. Defuzzification determines the change in a player's emotional state by adding the crisp output value to the current emotional level of a player. A strategy is changed when a player's emotional state exceeds their personal threshold. The underlying idea is that if a threshold has been breached, then

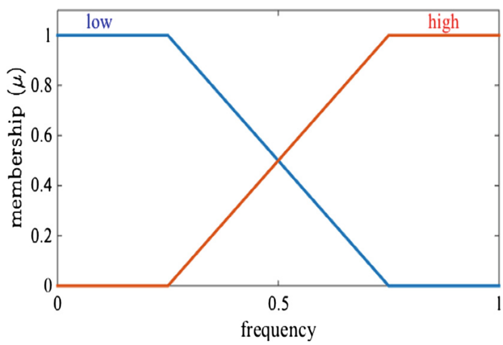

Fig. 1. Membership functions used to determine emotional state. The domain of discourse is the strategy frequency for all rules except for one C and one D rule (see text).

staying with the current strategy is no longer acceptable—i.e., a strategy change is necessary. Even though all players with a given strategy have their emotional levels increased by the same crisp output value, they do not necessarily change strategies at the same time. That's because each player has a different emotional threshold. The emotional level of a player is reset to zero when a strategy change occurs.

Table 1. Fuzzy rulebase

No	Player	Rule	Rationale
1	C	**IF** x_1 is high **THEN** y is satisfied	Public good being maintained
2	C	**IF** $k_2\gamma$ is high **THEN** y is annoyed	Paying high penalty for free riding
3	C	**IF** x_3 is high **AND** x_2 is low **THEN** y is angry	Little effort to stop defection
4	D	**IF** x_1 is high **THEN** y is satisfied	Small penalty paid for defecting
5	D	**IF** $k_2\beta$ is high **THEN** y is angry	Paying high penalty for free riding
6	P	**IF** x_3 is low **AND** x_1 is low **THEN** y is satisfied	Few free riders
7	P	**IF** x_3 is low **AND** x_1 is high **THEN** y is annoyed	Many 2nd order free riders
8	P	**IF** x_3 is high **THEN** y is angry	Many 1st order free riders

NOTE: All antecedents use strategy frequencies except Rules 2 and 5. $x_i^t = k_i/N$ is the frequency of strategy i at time t, where N is the population size and $\sum_i k_i = N$.

Figure 2 summarizes the conditions used by players to switch strategies. The rationale for these conditions is provided below.

D players switch to either a cooperator or a punisher depending on the number of P players in the population. The probability a defector will switch to a punisher is given by

$$\mathrm{prob}_{\mathrm{DP}}(k_2) = \begin{cases} 0 & k_2 < N/2 \\ 1 & \text{otherwise} \end{cases} \tag{4}$$

If more than half the population consists of punishers, then the penalty for defecting is quite high. Switching to a cooperator may not make sense because with that many punishers the penalty for being a 2nd order free rider is also likely to be high. These high penalties can be avoided by becoming a punisher. Moreover, by switching to a punisher, the defector can retaliate against those other defectors who didn't switch. If less than half of the population are punishers, then it may make more sense to become a cooperator since the 2nd order free riding penalty is relatively low. This strategy change is modelled as a probability to reflect the uncertainty in how individual defectors will choose a new strategy.

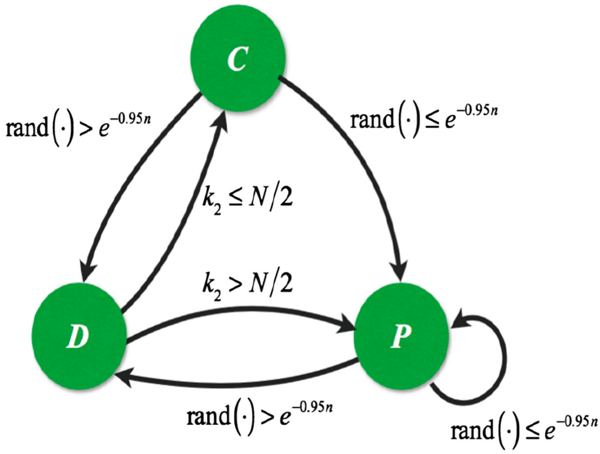

Fig. 2. Conditions to switch strategies. See text for variable definitions.

C and P players also choose their next strategy probabilistically. However, this probability is interpreted as a level of trustworthiness and other players will change their strategies as well to help resolve the ToC. This gives rise to a much more subtle and complex reasoning process.

There is little point in switching from C to P, since doing so, would do little to prevent the public good from becoming depleted. On the other hand, it would be beneficial to become a punisher if the increased penalty might induce defector strategy changes. Thus, the decision whether a cooperator switches to a punisher or a defector depends on the current status of the public good.

An example will help to clarify the idea. Suppose the public good capacity is 5000 units and player consumption rates are the same as their payoffs (minus any costs or penalties). Then by Eq. (1) each defector consumes 82 units and each cooperator or defector consumes 39 units. Table 2 shows the public good status for various population mixtures after one round with a 25% replenishment of the public good. The public good is preserved only if $k_3 \leq 5$ because the 25% replenishment restores at least the amount that was consumed. When $k_3 > 5$ the replenishment cannot compensate for the consumption so eventually the public good will be depleted.

To further illustrate the problem consider the specific case where $k_3 = 6$ and $k_1 + k_2 = 14$ with an initial public goods capacity of 5000 units. That mixture consumes 1038 units per round reducing the public good capacity to 3962 units after the first round. A 25% replenishment only raises the capacity to 4953 units, short of the 5000 unit initial capacity. The consumption rate exceeds the replenishment rate with this population mixture. One D player must switch to maintain the public good. Suppose no D player switched and one more round is played. Table 2 shows that the replenishment exceeds the consumption only if $k_3 \leq 4$. In other words, to grow the public good now requires at least two D

Table 2. consumption vs replenishment for various population mixtures. Initial public good capacity (IPGC) = 5000 and 4953 units, respectively.

k_3	$k_1 + k_2$	IPGC = 5000		IPGC = 4953	
		Consumption	Replenishment[a]	Consumption	Replenishment*
0	20	780	1055	780	1043
1	19	823	1044	823	1033
2	18	866	1034	866	1022
3	17	909	1023	909	1011
4	16	952	1012	952	1000
5	15	995	1001	995	**990**
6	14	1038	**991**	1038	**979**
7	13	1081	**980**	1081	**968**

[a]Bold indicates mixtures where consumption exceeds replenishment

players to switch strategy. Thus the status of the public goods determines how many D players must switch.

Cooperators can breach their emotional threshold if they are annoyed for a sufficiently long enough period or quickly if they are angry. C switches to P with probability

$$\text{prob}_{\text{CP}}(n) = e^{-0.95n} \tag{5}$$

where n is the number of defectors that must switch to preserve the public good. This probability, shown in Fig. 3, is actually a measure of trustworthiness that the required number of D players will switch. If the consumption rate is less than the replenishment rate then $n = 0$ because even with the D players present the public good remains viable. The C player then switches to a punisher with probability 1.0 believing the additional penalty on the defectors will cause some of them to switch. *However, if the C player does not trust a sufficient number will switch, then the C player defects.* It is important to note each C player independently decides whether to switch to P or D. P players also switch strategies if they are annoyed or angry. They use the same trustworthiness function Eq. (5) to make decisions. If the P player trusts that a sufficient number of D players can be coerced to switch with a higher penalty, then β increases by 20%. *Conversely, if a P player does not trust a sufficient number of D players will switch, then the P player defects instead.* In both instances the switch to defector is because the player does not trust a sufficient number of defectors will switch and so the public good cannot be saved. The players thus decide to act in their own self interest and consume as much as they can while some public good still remains.

The ToC game was run for 500 iterations but could be terminated early for three reasons: (1) the public good is completely depleted, (2) some public good remains but the population consists entirely of defectors—i.e., $k_3 = N$, or

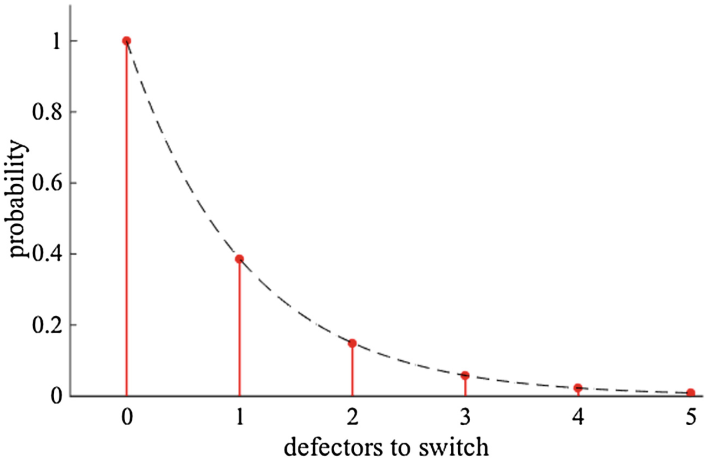

Fig. 3. Probability mass function interpreted as a level of trustworthiness the number of defectors will switch $D \to C, P$ if $C \to P$ or if $\beta \uparrow$ for punishers. Dashed line is the equation $\exp(-0.95n)$.

(3) the ToC is resolved—i.e., $k_3 = 0$. This latter condition is a fixed point in the 2-D simplex as shown by the following theorem:

Theorem. Every point on the $x_1 - x_2$ boundary is a fixed point.

Proof. $k_3 = 0$ on every point of the $x_1 - x_2$ boundary. Consequently, all players get the same payoff because no costs or penalties are imposed. There is therefore no incentive to change strategies in the future.

4 Results

The first investigation was designed to see how β affects the evolution of strategies within the population. Recall there are two ways of increasing defector punishment: fix k_2 and increase β or fix β and increase k_2. The first way is intuitively obvious; let β grow without bound and eventually defectors see no payoff whatsoever; at that point there is no reason to continue defecting. But practically speaking β is bounded—punishers are limited in how much punishment they can impose—so the only realistic way of increasing punishment is to increase the number of punishers. To test this idea we conducted a series of simulations fixing β at 4.0 and k_3 at 6 ($x_3 = 0.3$). We then increased the number of k_2 players and decreased the number of k_1 players accordingly to keep $\sum_i k_i = N$. Figure 4 shows that, if less than half the population are punishers, there simply isn't enough punishment to cause defector strategy changes. In other words, $k_2\beta$ is not a high price to pay for defecting. However, once more than half of the population contains punishers, the ToC is resolved (red trajectory). More importantly, the slope of the trajectory shows both cooperators and defectors

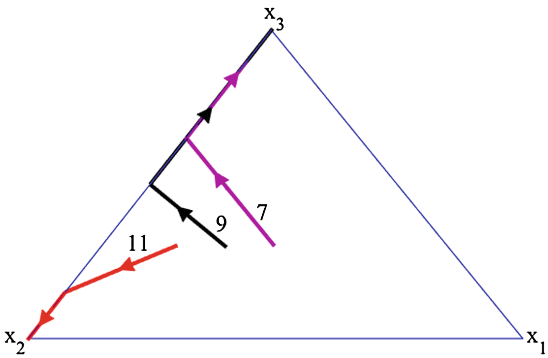

Fig. 4. Evolution of a finite population with $\beta = 4.0$ and various number of punishers. (Color figure online)

are switching to punishers. Eventually punishers completely take over the population. These results match well with the replicator equation predictions despite that in this study β was considerably lower.

The second investigation was designed to see how different player mixtures affected the population evolution. β was initialized at 7.0 in all runs. First consider the red trajectory in Fig. 5. The population was initialized at $k_i = [7\ 7\ 6]$ (equivalently $x_i = [0.35\ 0.35\ 0.3]$). The population quickly reaches a fixed point with some cooperators but mostly punishers which resolved the ToC. The brown trajectory was initialized at $k_i = [3\ 3\ 14]$ (equivalently $x_i = [0.15\ 0.15\ 0.7]$). There were not enough punishers present. All of the cooperators switched to defectors and shortly thereafter the punishers switched to defectors as well. Eventually defectors take over the population.

The black trajectory is more interesting. The population started with $k_i = [14\ 3\ 3]$ (equivalently $x_i = [0.70\ 0.15\ 0.15]$). Initially, the vast majority of players

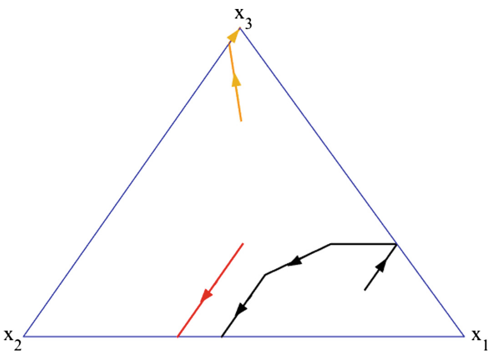

Fig. 5. Evolution of a finite populations for various β values. red: initial $[7\ 7\ 6]$ $\beta = 7$; brown: initial $[3\ 3\ 14]$ $\beta = 7$; black: initial $[14\ 3\ 3]$ $\beta = 7$. (Color figure online)

are cooperators. Following the trajectory, all of the punishers quickly decided to become defectors leaving only defectors and cooperators in the population. Cooperators don't punish defectors; thus, under normal circumstances one would expect defectors to prevail. But surprisingly some cooperators decided to become punishers. It is noticeable that the slope of the trajectory at this time is parallel to the $x_1 - x_2$ boundary which means the number of defectors isn't changing. However, the increased punishment from the growing number of P players starts to take effect. Eventually all defectors switch and the ToC is resolved.

5 Conclusion

Despite the widespread usage of replicator equations, they do suffer from one limitation: a lack of ability to provide insight into the human decision making process. Under replicator dynamics, strategies evolve strictly via Neo-Darwinistic principles. There is neither reproduction nor mutation. Strategies that produce payoffs higher than the population average grow while those less than the population average decline. Replicator equations can predict *what* strategy changes might occur, but they cannot explain is *why* they occur. Replicator equations only suggest proximate causes.

In this investigation, we considered a more realistic model that reflects human behavior. It takes into account that humans have emotions and rely on their experience to evaluate the trustworthiness of opponents. We have demonstrated a more practical and realistic approach to the modelling of strategies and strategy-change.

However, we only considered three emotions. Most notably guilt was not included. Guilt has been shown to be a motivating force in social dilemmas especially when inter-group competition is involved [13]. In the current model defectors change strategies only when the penalty for defecting is excessive. An obvious extension is to see how guilt might convince a player to switch from defection to cooperation.

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http://www.springer.com/978-3-319-51690-5

Artificial Life and Computational Intelligence
Third Australasian Conference, ACALCI 2017, Geelong, VIC, Australia, January 31 – February 2, 2017, Proceedings
Wagner, M.; Li, X.; Hendtlass, T. (Eds.)
2017, XIII, 392 p. 122 illus., Softcover
ISBN: 978-3-319-51690-5