The Hero's Dilemma: Survival Advantages of Intention Perception in Virtual Agent Games

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***Abstract*—Conjecturing that an agent's ability to perceive the intentions of others can increase its chances of survival, we introduce a simple game, the Hero's Dilemma, which simulates interactions between two virtual agents to investigate whether an agent's ability to detect the intentional stance of a second agent provides a measurable survival advantage. We test whether agents able to make decisions based on the perceived intention of an adversarial agent have advantages over agents without such perception, but who instead rely on a variety of different game-playing strategies. In the game, an agent must decide whether to remain hidden or attack an often more powerful agent based on the perceived intention of the other agent. We compare the survival rates of agents with and without intention perception, and find that intention perception provides significant survival advantages and is the most successful strategy in the majority of situations tested.**

***Index Terms*—awareness, intention perception, non-cooperative game theory, simulation, intention trilogy**

I. Introduction

In a bleak world short on food and supplies, you find yourself a part of the only small community left dedicated to preserving knowledge and hope among the ruins of pandemic war. A former lieutenant, you lead a group of survivors on a predawn supply run. As you scour barren store shelves and rummage through debris and trash, your team is able to find just enough remnants to bring back to camp. Unfortunately, you and your companions are not the only survivors searching for food that morning.

One of your lookouts spots a band of scavengers from an enemy camp making their way toward your location. You have no reason to believe that they're aware of your presence; with stealth a direct confrontation might be avoided. The enemies are heavily armed, so any confrontation could prove fatal. Quickly, you motion for your team to hide and wait.

To your dismay, the enemies reach your location and decide to explore. They are set on finding supplies themselves but instead find nothing. Lying in wait, your stomach sickens as you watch their frustrations rise and their suspicions mount that they might not be alone.

You are left with few options. You can order your team to remain hidden and risk being discovered, or you can initiate an ambush, which would at least give you the advantage of a surprise attack. If discovered, you would lose your supplies and perhaps your lives, but fighting also carries with it the risk of death. Should you hide in hope of escaping detection, or fight, launching your own surprise attack? Neither choice offers much hope. Desperate, you signal to prepare an attack, but determine that you will only open fire once it becomes clear you have been discovered. Hand poised in the air, trembling but ready to signal, you ask yourself: *have I made the right choice*?

In this study, we test the outcomes of a simple two-player game in which one agent must decide whether to fight an adversarial agent, based on the perceived intentional stance of the adversarial agent. For each altercation there is a chance of death, but there is an advantage to striking first if currently undetected by the adversarial agent. In one scenario, the agent can perceive that the adversarial agent intends to attack, and in the other scenario, the agent cannot. For agents that lack perception, we test a variety of strategies such as attacking at random, attacking only in retaliation, and always attacking. For those that are perceptive, the employed strategy is to attack once the adversarial agent has detected them and intends to attack, forfeiting the advantage of surprise but nevertheless striking first. Similar to simulation studies of the famous Prisoner's Dilemma [1], [2], we use our simulated agent experiments to analyze statistical outcomes, measuring differences in survival rates for various strategies and parameter settings.

We ask the question, *"Is the perceptive agent strategy the best option when considering the trade-offs and interactions of many independent factors?"* Compared against an aggressive always-attack strategy and a retaliatory tit-for-tat strategy (with

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shown success in iterated Prisoner's Dilemma games [1]), it is not obvious whether the perceptive agent strategy would be the most advantageous. However, we find that this strategy prevails in nearly all situations tested.

II. Related Work

Several studies have used virtual agents to understand the role of intention perception in situations similar to the Prisoner's Dilemma [1]–[13]. Especially relevant to our work presented here, Anh et al. implemented an intention-recognition algorithm in an iterated Prisoner's Dilemma tournament, and found that the intention-recognition algorithm outperformed several other well-known algorithms [2]. One such algorithm was *tit-for-tat*, an algorithm which Axelrod and Hamilton investigated in their well-known iterated Prisoner's Dilemma tournaments [1]. Although researchers have established that tit-for-tat does not work as well in random situations and thus may not be as successful as first thought, the success of Anh et al.'s intention recognition algorithm suggests that intention-recognition may be favorable in Prisoner's Dilemma-like survival situations.

Many studies of intention perception have focused on psychological aspects, such as the mechanism by which people and animals discern the intentions of others [14], [15]. Blakemore and Decety analyzed people's ability to correctly identify the intentions of intelligent virtual agents [16], in contrast to the fully virtual agent-based simulations considered here. Heinze explored the use of virtual agents in intention-perception studies, proposing various methods for modeling intention recognition as a software engineering problem [17]. Relevant to the adversarial scenarios based on intention perception studied in this paper, Heinze notes that *"when intention recognition is successful the element of surprise is removed and the enemy successfully anticipated; when intention recognition fails the results are often catastrophic."* [17].

Balancing the adversarial perspective, intention-recognition algorithms can also be viewed as cooperative [2]. It has been speculated that competition-repressors, such as unfavorable payoffs in Prisoner-Dilemma type scenarios, may contribute to cooperation [18]. Studying cooperation in the biological sense provides a new perspective on evolution, as cooperation is seemingly at odds with the fundamental aspect of competition inherent in natural selection [19]. A key aspect of social evolution, cooperation can be approached from the mathematical standpoint of game theory. The conundrum posed by cooperation can be defined by two aspects: (i) when two cooperators get a higher payoff than two defectors, (ii) yet there is an incentive to defect. Our study evaluates the performance of various strategies with respect to survival rate, and provides insight on how intention perception may lead to more "cooperative" outcomes where both parties survive.

III. Methods

We simulate interactions between two agents, a "hero" and "adversary," to investigate whether a strategy leveraging the

Fig. 1. A possible progression for the Hero's Dilemma with the INTENTION strategy employed. The adversary searches for and discovers the hero; the hero attacks and defeats the adversary.

ability to detect the intention of the adversary provides a measurable survival advantage over intention-blind strategies. In this scenario, the presence of the hero is initially unknown to the adversary, but with some probability the adversary may eventually discover the hero. If the hero is found, the adversary will soon engage in battle. The hero is typically weaker than the adversary, so avoiding conflict is in its interest, but attacking first gives the hero an element of surprise which improves its chances of survival. The hero has two paths out of this situation: (i) hide until the adversary leaves or (ii) attack and hope to defeat it. Should the hero stay hidden or attack? We test several strategies for the hero: never attack, always attack, randomly decide to attack, attack only when the adversary strikes first, and attack once found but before the adversary strikes. The lattermost strategy involves intention awareness, as the hero first determines whether the adversary plans to strike. We find that this intention aware strategy provides the greatest survival advantage for the hero in almost all of our tested cases (Section IV), and notably maintains a high adversary survival rate as well. To test whether the survival advantages gained are simply the result of increased hesitancy to attack, we further implement a cautious hero which attacks with the same probability, and thus the same hesitancy, as intention-perception heroes. However, unlike the intention-perception hero's attacks, the cautious hero's attacks are uncorrelated to the intentional stance of the adversary, isolating the benefits of intention perception from those of mere caution.

Fig. 2. A possible progression for the Hero's Dilemma with the ALWAYS strategy employed. The hero attacks the adversary immediately; the adversary attacks back and defeats the hero. Note that the intention of the adversary is unaware to the hero, hence the question mark on its face.

A. Experimental Setup

The interactions between hero and adversary are modeled after a first-person dungeon crawl video game [20], where discrete time steps are used to trigger the two agents' actions. All hero and adversary encounters last a total of ten time steps, where at any given time step each agent is either idle, in its attack cycle, or dead. The attack cycle length C is the number of time steps between attacks for both hero and adversary agents. That is, after an agent's first attack, the agent will attack every C time steps until either an agent is killed or ten time steps elapse.

Beginning the encounter, the adversary has a chance P_d to discover the hero on each time step. If the adversary discovers the hero, it starts its attack cycle which lasts C time steps. The adversary then strikes at the end of its cycle with a $P_{k,a}$ chance of killing the hero and starts its next attack cycle. If the hero decides to attack, it begins its attack cycle, of same length C, but attacks at the beginning of its cycle and has a $P_{k,h}$ chance of killing the adversary. Since the adversary strikes at the end of its cycle while the hero strikes at the start, most cycle values leave a window in which a hero employing the INTENTION strategy can attack after having been detected. However, if the hero has not yet been detected, the probability of the hero killing the adversary on a given attack is $P_{k,h} + P_{k,s}$ instead of $P_{k,h}$. The default values for all of these parameters are in Table I, which vary by experiment, as noted for each. Note that while the default value for $P_{k,h}$ is less than that of $P_{k,a}$, we vary both parameters in our experiments and thus also test scenarios where $P_{k,h}$ is greater than $P_{k,a}$.

TABLE I
DEFAULT VALUES.

Agent	Description	Notation	Value
Hero	Prob rand attack	P_r	0.2
Hero	Prob of kill	$P_{k,h}$	0.5
Hero	Surprise boost	$P_{k,s}$	0.2
Adv.	Prob of kill	$P_{k,a}$	0.7
Adv.	Prob discover hero	P_d	0.1
Both	Cycle length	C	3

TABLE II
HERO STRATEGIES.

Strategy	When to enter attack cycle
NEVER	Never enter
ALWAYS	Enter on first step
RANDOM	Enter at each step with chance P_r
RETALIATE	Enter after adversary attacks
INTENTION	Enter after adversary starts cycle
CAUTIOUS	Enter at each step with chance P_I

TABLE III
P_I, THE EMPIRICAL PROBABILITY ESTIMATE OF AN INTENTION AGENT BEGINNING AN ATTACK, FOR VARYING P_d VALUES.

P_d	P_I
0.05	0.047
0.10	0.093
0.15	0.137
0.20	0.179

Table II lists the possible strategies for the hero agent, and includes the added CAUTIOUS strategy. Note that the CAUTIOUS strategy is effectively the same as the RANDOM strategy, except P_r, the usual probability of attacking, is replaced with P_I, the empirical probability of the INTENTION strategy attacking on a given step as estimated from observed frequencies. The values of P_I vary with P_d and are displayed in Table III, where each value is averaged from 10,000 simulations. We found the P_I values by dividing the total number of simulations in which the intention hero attacked the adversary by the sum of the step numbers at which the first attack occurred. We are only concerned with the step number of the first strike because agents always continue attacking after their first strike. Note that intention heroes always attack the adversary immediately after realizing that the adversary has started its attack cycle. Thus, the observed P_I closely trails P_d, the probability of the adversary detecting the hero.

IV. Results

Our experiments demonstrate that the intention-aware strategy significantly increases the probability of a hero agent surviving an encounter in most cases tested.

We show the effects of varying the parameters of our simulation, measuring the resulting survival rates for hero and adversary agents. Each of these graphs were generated from 50,000 simulations per set of parameters and include 95%

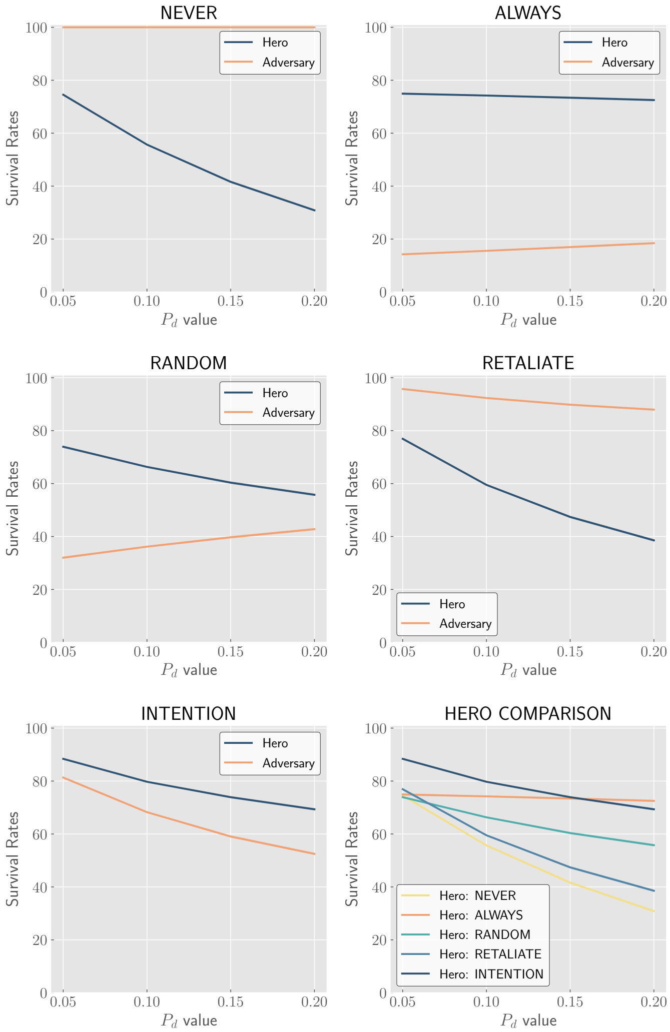

Fig. 3. The effect of the P_d on hero and adversary survival rates in regards to indicated strategies.

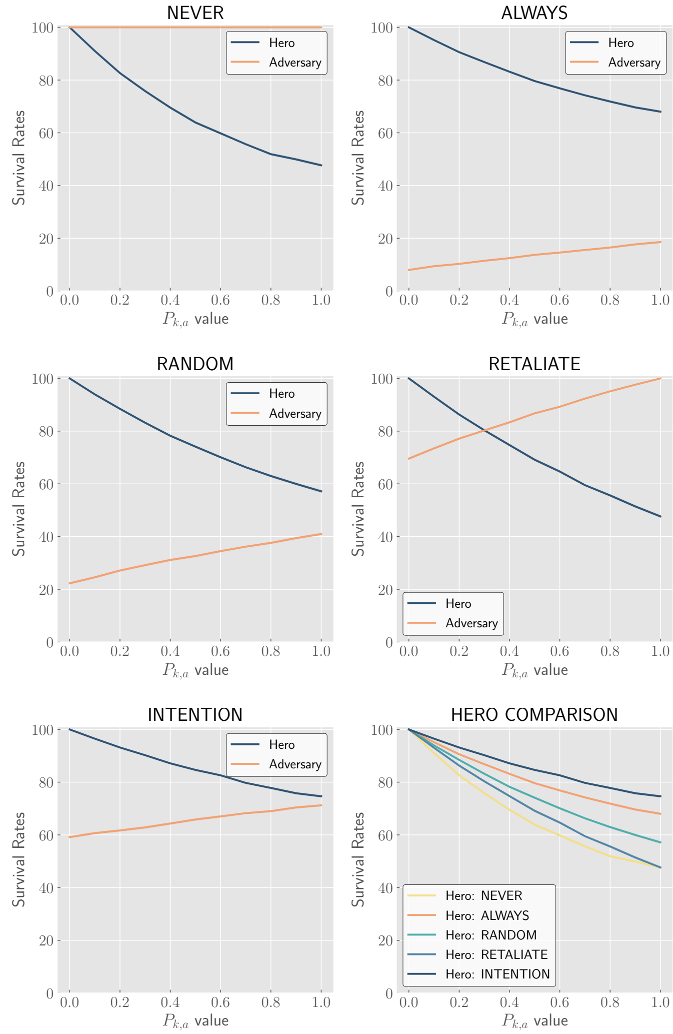

Fig. 5. The effect of $P_{k,a}$ on hero and adversary survival rates in regards to indicated strategies.

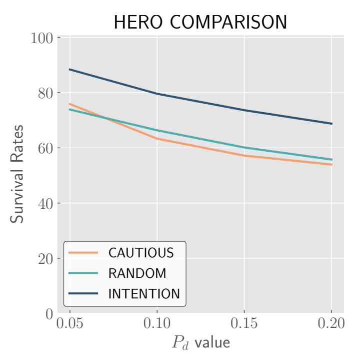

Fig. 4. Comparison of the INTENTION, RANDOM, and CAUTIOUS strategies.

confidence intervals (which in all cases do not exceed the line width, given the number of trials and low variance).

Figure 3 shows the effect of varying the probability of detection, P_d. We see that P_d is negatively associated with hero survival rate for all strategies (see Figure 3), yet this negative association varies in strength across different strategies. In particular, the ALWAYS strategy has the weakest association. We also see that the INTENTION strategy starts out with the highest survival rate but is eventually overtaken by the ALWAYS strategy when the hero is detected very often. When detection probability is high, an early attack by the adversary becomes overwhelmingly likely, giving an agent that attacks immediately (as the ALWAYS strategy does) a clear advantage. When undetected escape is not an option, it makes little sense to delay attacking in hopes of remaining undetected.

In Figure 4, we see that the CAUTIOUS strategy does not perform as well as the INTENTION strategy nor the usual RANDOM strategy, showing that the survival advantages of intention perception are not simply due to an increase in caution. Figure 5 reveals that INTENTION has the highest hero survival rate with respect to high values of $P_{k,a}$, which is the chance that the adversary kills the hero during an attack. INTENTION also consistently has the highest hero survival when varying $P_{k,a}$.

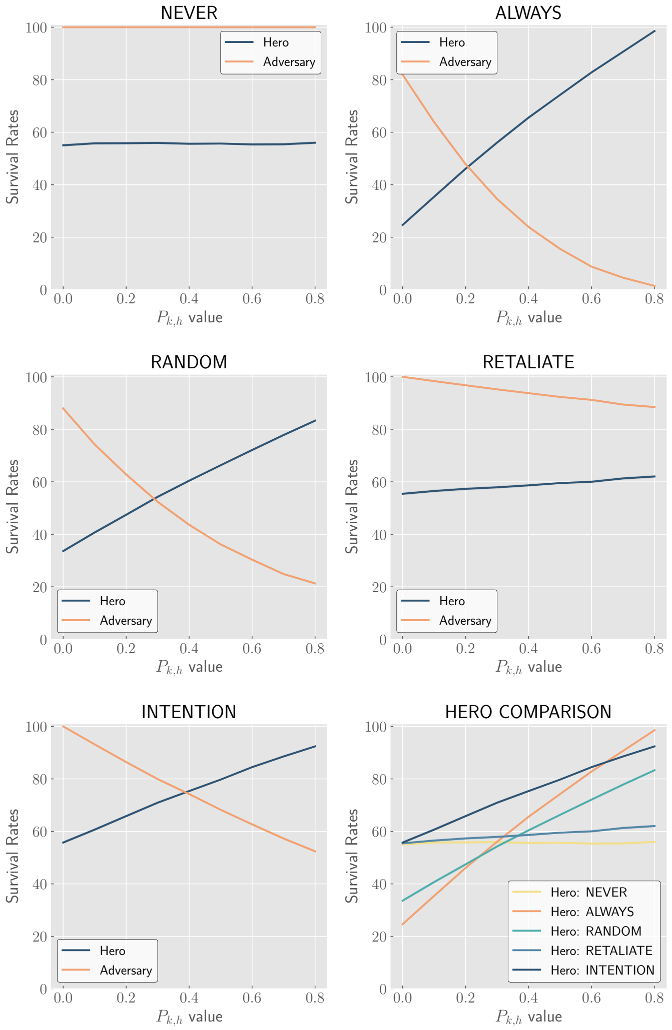

Fig. 6. The effect of $P_{k,h}$ on hero and adversary survival rates in regards to indicated strategies.

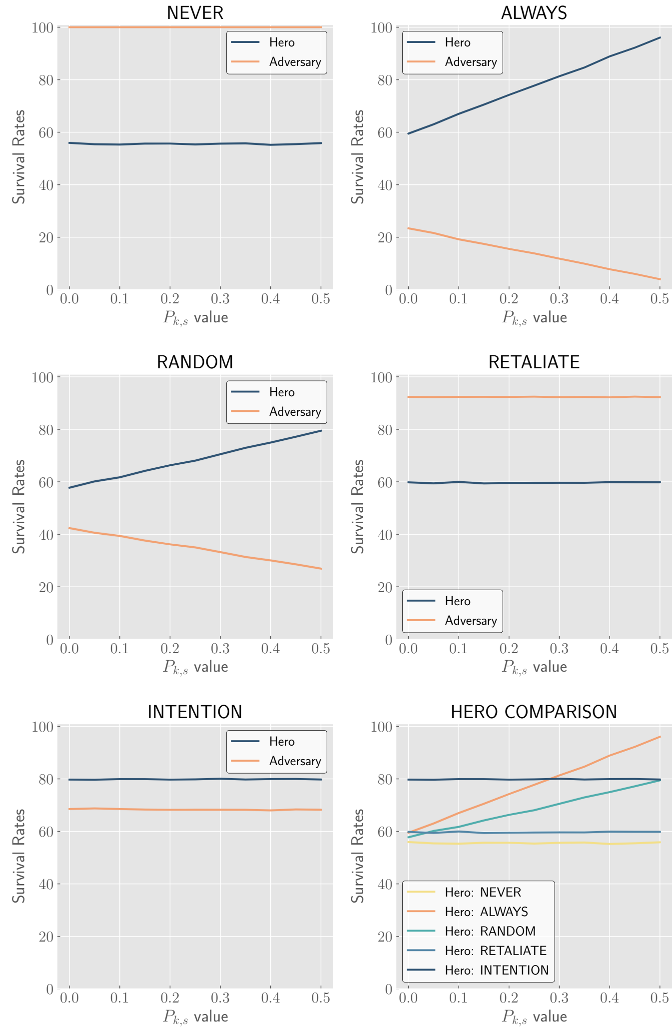

Fig. 7. The effect of $P_{k,s}$ on hero and adversary survival rates in regards to indicated strategies.

Figure 6 shows that hero survival rates increase with respect to high $P_{k,h}$ values for all strategies except NEVER. The strategy that benefits the most is ALWAYS, which eventually overtakes INTENTION as the best strategy at very high $P_{k,h}$ values. This makes sense, as a strong hero agent (with large $P_{k,h}$) can initiate attacks with less chance of defeat, since they are more likely to deliver initial critical hits.

Figure 7 reveals that only the hero survival rates of the ALWAYS and RANDOM strategies increase with respect to $P_{k,s}$, the boost given to hero attacks when the adversary is surprised. While NEVER and RETALIATE never gain the boost because they do not initiate attacks, it is also important to note that INTENTION waits until being detected before attacking and therefore does not gain the surprise boost either. Although the INTENTION strategy's hero survival rate is constant, it starts at 80% while the others' start at about 60%. Ultimately, as $P_{k,s}$ increases, the hero survival rate of the ALWAYS strategy surpasses that of INTENTION.

Figure 8 demonstrates a positive association between attack cycle length and hero survival rate for all strategies; however, this association is weakest for the ALWAYS strategy.

Figure 9 shows that the hero survival rate for the NEVER and RETALIATE strategies are more dependent on $P_{k,a}$ than $P_{k,h}$ because the NEVER agent does not attack, so changing $P_{k,h}$ has no effect, and the RETALIATE agent can only attack once it has already been hit by an adversary, making its survival more dependent on the strength of the adversary's attacks. In contrast, the adversary survival rate for the INTENTION strategy is more dependent on $P_{k,h}$ than $P_{k,a}$. ALWAYS, RANDOM, and INTENTION are clearly dependent on both values and look very similar when it comes to high $P_{k,h}$ and low $P_{k,a}$. However, when the reverse is true (i.e., high $P_{k,a}$ and low $P_{k,h}$) INTENTION fares much better, as it avoids starting fights it cannot win.

Figure 10 reveals that defensive strategies (namely, INTENTION, RETALIATE, NEVER) fare worse with high P_k values while offensive strategies (ALWAYS, RANDOM) fare worse with low P_k values. All strategies do better with

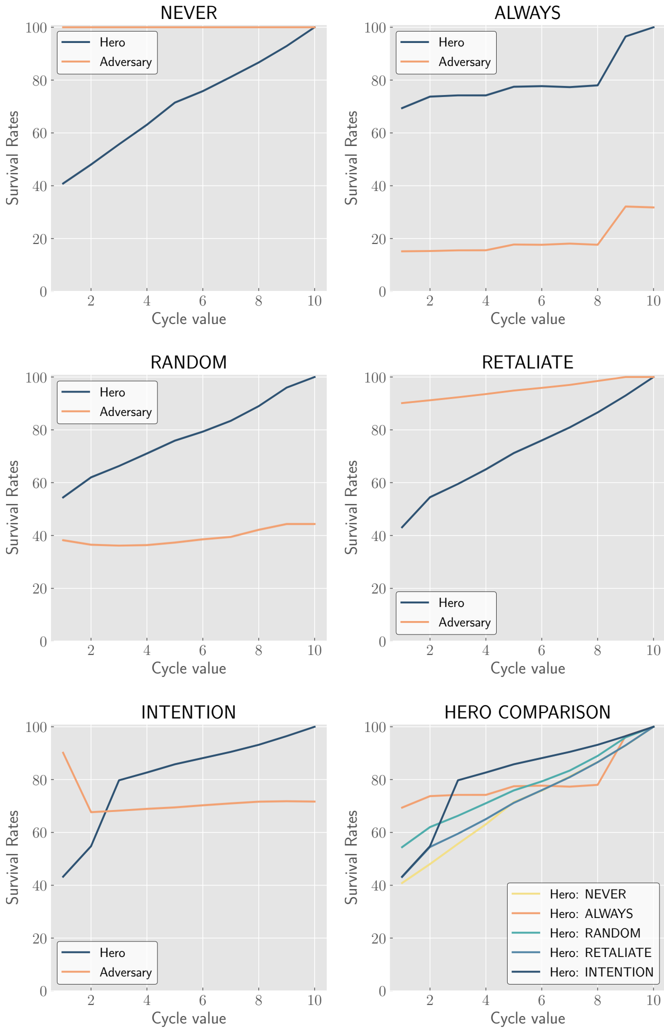

Fig. 8. The effect of attack cycle length on hero and adversary survival rates in regards to indicated strategies.

larger cycles, but vary in the nature of the relationship.

V. Discussion

Overall, the INTENTION strategy provides the strongest survival advantage across the tested parameters. However, the ALWAYS strategy can provide a greater survival advantage in specific cases where there is either an increased advantage in surprising the adversary, or a decreased advantage in staying hidden. Furthermore, the performance of the CAUTIOUS strategy indicates that the survival advantage of INTENTION is not due to increased cautiousness, but rather the knowledge of intention. As seen in Figure 4, the CAUTIOUS strategy results in a lower survival rate than INTENTION and even RANDOM in most cases.

As the probability of detection increases, hero survival rate decreases for all strategies, since all heroes suffer from being quickly discovered. Additionally, the survival advantage of INTENTION over ALWAYS decreases, since there is a decreased advantage in staying hidden. Heroes using the ALWAYS strategy always attack and reveal their locations on the first step, such that increasing the probability of detection has little impact on their survival. In contrast, heroes using INTENTION always refrain from attacking until they have already been detected, such that increasing the probability of detection means that they are often detected sooner.

When the cycle count is one or two, it is impossible for the INTENTION strategy to attack before the adversary attacks, which makes it roughly equivalent to the RETALIATE strategy, as seen in Figures 8 and 10. Thus, heroes using the ALWAYS and RANDOM strategies perform better with low cycle counts, as they can attack first. But once the cycle count is greater than or equal to 3, the INTENTION strategy has the highest performance. This is partly because INTENTION benefits from long step counts, which means the adversary must wait longer to attack once they discover the hero. In addition, the ALWAYS strategy does not benefit as greatly because it attacks and alerts the adversary on the first step, so adversaries still have time to launch attacks until the cycle length nears the total step count.

The INTENTION strategy is preferable when the probability of the adversary killing the hero is high, since as that value increases, detection becomes more undesirable.

Not only does the ALWAYS strategy benefit more than the INTENTION strategy from increasing the probability of the hero killing the adversary because they attack more often, but ALWAYS also typically gains a probability boost on the first hit because the hero has not been detected. As this probability boost increases, the survival rates of heroes using the ALWAYS strategy start to surpass those using INTENTION. This is because the ALWAYS strategy typically attacks while undetected by the adversary while the INTENTION strategy always waits until being discovered. Heroes using the RETALIATE or NEVER strategies are also unaffected by increasing the probability boost granted from a surprise attack, since they do not ever attack prior to being detected. Those using the RANDOM strategy experience increased survival rates but to a lesser degree than ALWAYS because they do not consistently surprise attack. Overall, we see that the ALWAYS strategy begins to provide a greater survival advantage over INTENTION when either the probability of the hero killing the adversary or the surprise probability boost is high. Furthermore, ALWAYS and INTENTION are the two best performing strategies.

Both the hero and adversary gain a significant survival advantage by attacking first. Figure 9 suggests that the survival of heroes using NEVER and RETALIATE is more dependent upon the probability of the adversary killing the hero, while adversary survival when heroes use ALWAYS and INTENTION depends more on the probability of the hero killing the adversary. Since the adversary always strikes first for NEVER and RETALIATE while the hero always strikes first for ALWAYS and INTENTION, this suggests that if an agent is attacked first, its survival depends mainly upon its opponent's attack strength.

The advantage of attacking first explains why the hero survival rates of NEVER and RETALIATE were consistently

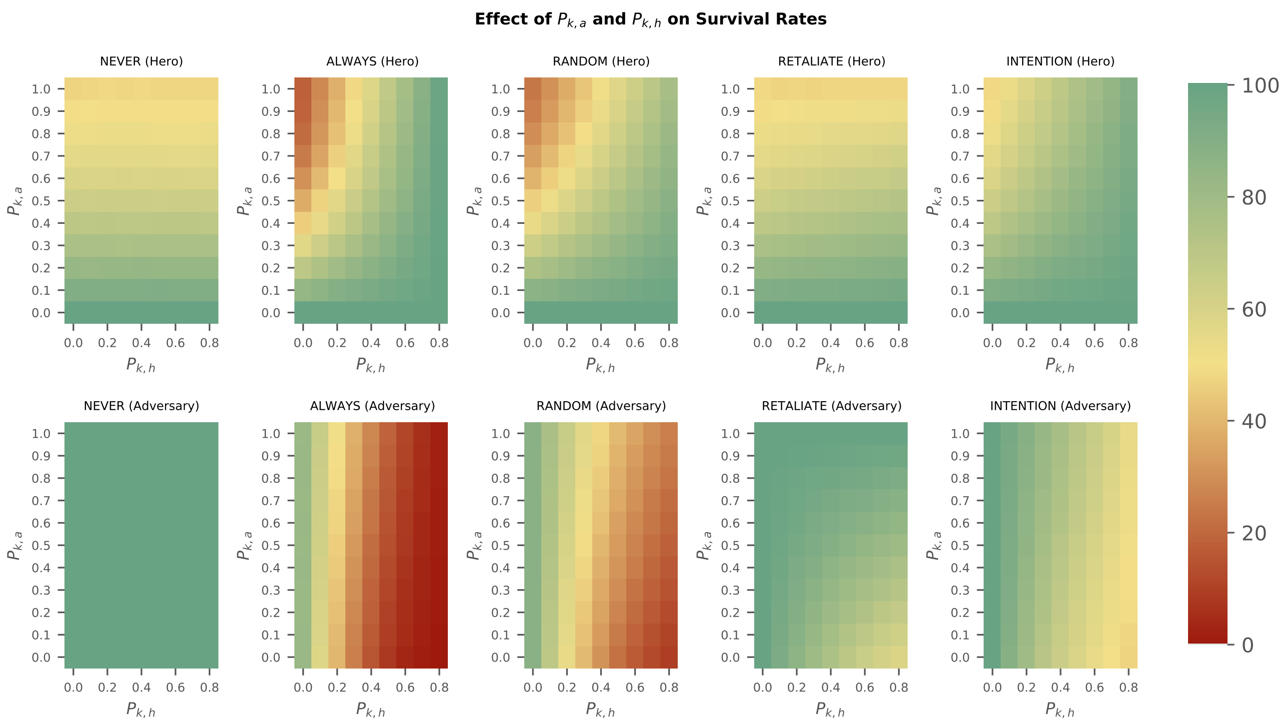

Fig. 9. The joint effect of $P_{k,a}$ and $P_{k,h}$ on hero and adversary survival rates in regards to indicated strategies.

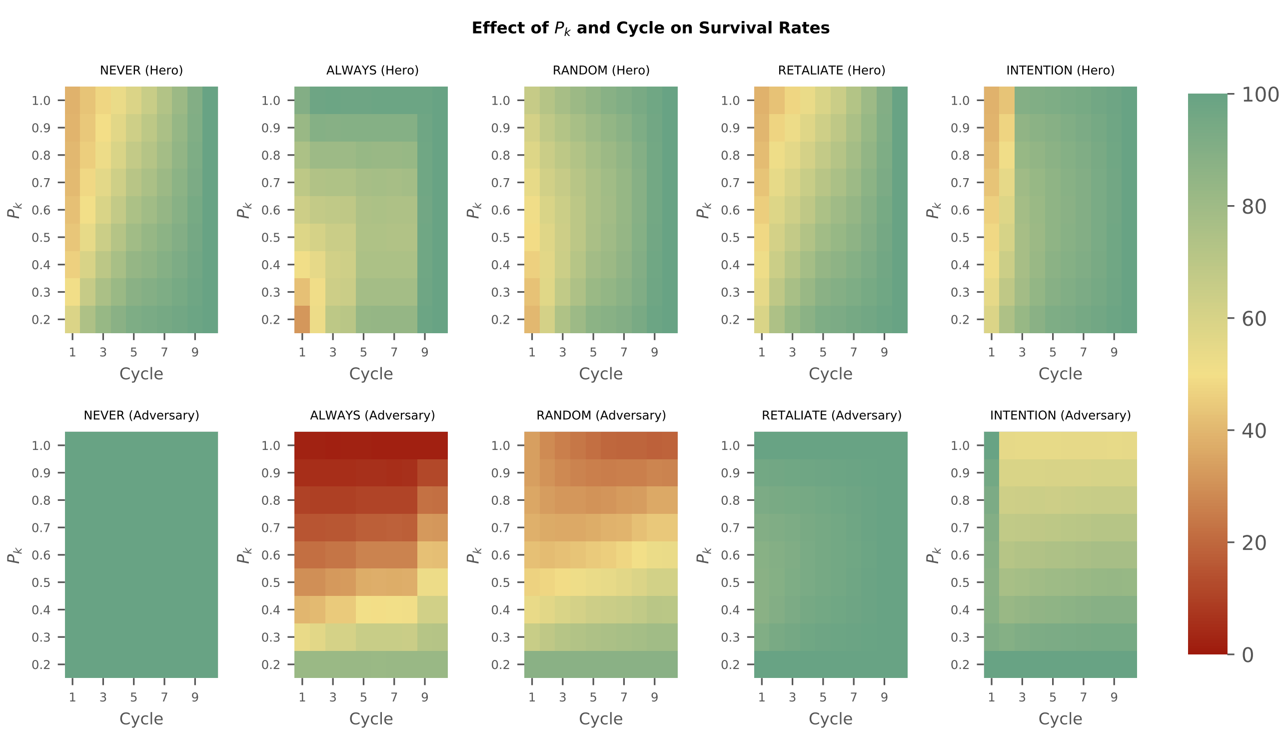

Fig. 10. The joint effect of P_k and attack cycle length on hero and adversary survival rates in regards to indicated strategies, where $P_k = P_{k,a} = P_{k,h} + 0.2$.

lower than those of INTENTION and ALWAYS. However, unlike ALWAYS, INTENTION heroes attack only when detected, thus providing the greatest survival advantage in most cases—when the hero's first attack is weaker than that of the adversary, the attack cycle length is long enough for the INTENTION hero to attack first, and the probability of detection is low. Moreover, INTENTION provides a higher overall *adversary* survival rate compared to ALWAYS. Thus, intention perception may be a useful strategy for promoting cooperation and optimizing universal survival, trying to minimize the loss of life for all involved while still providing strong protective benefits for agents employing that strategy.

VI. Conclusion

"Strike First" is not always a winning strategy, at least when it implies attacking while unprovoked. This is especially true for outmatched agents. A wiser strategy would be to attack only when no other options remain; knowing *when* to strike depends crucially on perceiving the intentions of a potential adversary. Introducing the Hero's Dilemma as a simple, two-agent adversarial game, we demonstrate that agents possessing intention perception gain statistically meaningful survival advantages. We find that agents using the INTENTION strategy have the highest survival rate in almost all cases—when (a) the hero's first attack is weaker than the adversary's, (b) when it is possible to detect the adversary's intentions and strike before being struck, and (c) when it is relatively unlikely for the adversary to discover the hero.

Additionally, we find that attacking first provides a significant survival advantage to both heroes and adversaries, as the survival of agents who are attacked first depends primarily on their opponents' strength. This explains why INTENTION is the best strategy overall, as it allows the hero to attack first, but only when necessary. Furthermore, this means that RETALIATE, a strategy that always attacks second, is most beneficial when adversary strength is low, while ALWAYS, a strategy that attacks first, is most beneficial when hero strength is high. Overall, the best strategy strongly depends on the agents' probability of being detected and the relative strength of the competing agents.

Not only does INTENTION give the hero agent the best survival rate, but it is also the best strategy to minimize overall damage. By limiting unnecessary attacks on both the adversary and the hero, an INTENTION strategy could be seen as an important component of strong, yet cooperative, diplomacy.

Although the game is simple and does not encompass all possible factors, like the Prisoner's Dilemma it allows one to draw insights concerning the benefits and risks of cooperation and aggression. When your opponent is strong, likely to inflict major damage, and intends to strike, it is best to attack first—but only when forced to. If you are strong, always attacking becomes a viable option, but likely entails other negative consequences. These lessons can be drawn from the study of a relatively simple game, and our results provide evidence of the usefulness of intention perception in agents. Having a model of the minds of other agents, being able to attribute intentions to them and act accordingly, would seem to be as useful in virtual worlds as it is in our own.

Acknowledgment

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