

# Peer Designed Agents: Just Reflect or Also Affect?

## (Extended Abstract)

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### ABSTRACT

Peer Designed Agent (PDA), computer agents developed by non-experts, is an emerging technology, widely advocated in recent literature for the purpose of replacing people in simulations and investigating human behavior. Its main premise is that the strategy programmed into these agents reliably reflect, to some extent, the behavior used by the programmer in real life. In this paper we show that PDA development has an important side effect that has not been addressed to date — the process, that merely attempts to capture one’s strategy, is also likely to affect the developer’s strategy. The phenomenon is demonstrated experimentally via the penetration detection game, using different setting variations. This result has many implications concerning the appropriate design of PDA-based simulations, and the validness of using PDAs for studying individual decision making.

### Keywords

PDAs, decision making, simulation design

## 1. INTRODUCTION

Peer designed agent (PDA) technology has been gaining much interest in recent years, mostly due to its potential of reducing much of the complexities and overheads of using people in laboratory experiments. Unlike expert-designed agents, PDAs are developed by non-domain experts, where the goal is exhibiting a human-like behavior rather than an optimal one. As such, PDA technology has been increasingly used in recent years for replacing people in system evaluation in various domain such as negotiation, costly information gathering [2], security systems and parking allocation. Another common use of PDAs is in studying individual decision making. The main premise in all these works is that the developed PDAs adequately represent the strategy of their developers. Despite the great interest in PDA technologies, all prior research in this field has focused on measuring the similarity between the behaviors exhibited by PDAs and their developers, either in the macro level, i.e., comparing the collective or “average” behavior, or in the micro level, i.e., comparing individual behaviors in similar decision situations [2]. None of prior research (to our knowledge) has

**Appears in:** *Alessio Lomuscio, Paul Scerri, Ana Bazzan, and Michael Huhns (eds.), Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014), May 5-9, 2014, Paris, France.*  
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attempted to investigate whether developers’ strategy goes through some kind of transformation throughout the process. If indeed the process of developing a PDA has some effect on developers’ strategies, then a great caution should be used with this technology. In particular, one needs to keep in mind that the change in the developers strategies preclude the consideration of this group of strategies as a reliable representative sample of the general population strategies. Therefore, even if PDAs reliably represent their developers, the results obtained by using them apply to a population which is somehow different than the original one. In this paper we attempt to answer the question of whether indeed the development of a PDA changes one’s strategy. For this purpose, we present the experimental methodology and results of several experiments that compare people’s strategies before and after developing PDAs, and the strategies used by the PDAs they developed. The analysis of the results suggests that indeed people’s strategies change through the development of a PDA. Furthermore, we show that for most settings, the development of PDAs results in a positive change in the developers’ strategies. This result has an important implication in the form of using PDA technology as a means for improving people’s problem solving skills.

## 2. PENETRATION DETECTION GAME

The game used to test our hypothesis is from the security domain. Here, we consider the problem of perimeter patrol by a team of robots, similar to the work by Agmon et al. [1]. In this problem, a team of  $k$  robots is required to repeatedly travel along a cyclic path of  $N$  segments in order to detect penetrations that are controlled by an adversary. In our version of the game, the user plays the role of the adversary, and acts against simulated robots. The robots execute a specific random-based patrolling strategy, and the human player/PDA is asked to choose a segment through which it attempts to penetrate. The optimal strategy for the adversary is to choose the segment associated with the lowest probability of penetration detection. This strategy is believed to be deduced from the amount of knowledge the player has on the patrolling strategy. The optimal strategy for the patrolling robots is the one associated with the highest probability of penetration detection. This strategy can be efficiently computed when the robots face a full knowledge adversary, a random adversary, zero-knowledge, adversary or an adversary that may analytically estimate (to some extent) the weakest spot of the patrol [1]. However, it is unclear when to use which strategy, as the adversarial knowledge level is unknown.

### 3. EXPERIMENTAL DESIGN

The game was developed in a way that it could be played either using an interactive GUI client or through the use of a PDA. For the PDA development task, we followed the common practice from prior work [3], i.e., provided a skeleton of a functional PDA that lacked only its strategy layer. Strategy developers thus had to develop only that last component, using a rich API that was supported by the agent. 36 senior undergraduate or graduate computer science students were recruited for the experiments. Each participant received thorough instructions of the game rules, her goal in the game and the compensation method, which essentially was linear in her score in the game. This was followed by taking part in several practice games. Participants could practice until stating that they understand the game rules and they have a good sense of what their game strategy is like. Then participants were requested to play the web-based version of the game (Figure 1). After participating in the web-based version, participants were asked to design a PDA which will play this game on their behalf. After submitting the PDAs, participants were asked once again to play the web-based version of the game. In order to avoid any bias in their game playing, participants were told they were about to program a PDA only after collecting the data from the games they played. In addition to analyzing the behavior of participants in the game played, we also measured the performance of the PDAs developed.

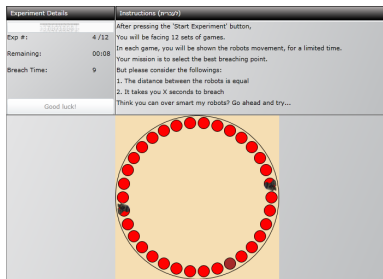


Figure 1: The penetration detection web-based game.

The evaluation was carried over with 12 different variants of the game, each differing in the patrolling strategy used by the robots and the initial problem setting. The measure used to evaluate the performance of the patrol strategy, thus also the performance of the adversary working against this strategy, is the expected probability of penetration detection (ppd): higher expected values of ppd means better performance of the strategy. Equivalently, from the adversary's perspective (the human subjects and the PDAs), lower expected values of ppd are better. Four patrolling strategies were used (v-Neighbor, v-Min, MaxiMin and MidAvg), all random-based, and all follow the patrolling framework described in [1]. According to this framework, the  $k$  given robots are spread uniformly (in time) along the perimeter with distance  $d$  between every two consecutive robots, and maintain this uniform inter-robot distance along the execution. At each time step all robots either continue straight with probability  $p$ , or turn around with probability  $1 - p$  (and if so, they stay in place for one time unit). Therefore, the probability  $p$  characterizes the patrol strategy, and this value depends on the adversarial model. It is assumed that the adversary—after choosing a penetration spot—remains

in its position for  $t$  time units (known as *penetration time*), during which it might be detected by a robot that passes through its chosen penetration spot.

### 4. RESULTS AND ANALYSIS

Figure 2 describes the expected ppd values achieved with all 12 game variants in the penetration detection game for the three groups (pre-PDA, PDAs and post-PDA). The difference in performance between the pre-PDA and the post-PDA groups is statistically significant ( $p$ -value  $< 0.03$ ) for ten out of twelve variants of the game, indicating that indeed different strategies have been used. In particular, we observe that in the latter group, except for two cases ( $v = 9$  and MidAvg, both for  $d = 16, t = 9$ ), the expected ppd values of the post-PDA group has dropped considerably supporting the hypothesis that the process of PDA-development improves one's strategy.<sup>1</sup>

As for the PDAs themselves, these performed generally better than the pre-PDA group. Compared to the post-PDA group, no specific pattern is observed — in some cases they did substantially better, in some substantially worse and in others the same. We note that in this domain the comparison between the PDAs performance and people's performance suffers from the complexity of the decision problem associated with this domain — while it is possible that the PDA uses a strategy that is similar to its developer's, the PDA manages to execute it more effectively, primarily due to its preferred computational and storage capabilities. Therefore, we do not attempt to attribute the process of change in one's strategy to any specific phase in the PDA development.

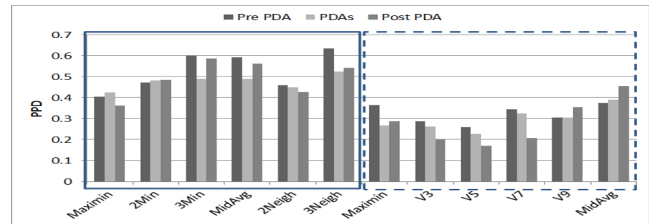


Figure 2: The probability of penetration detection before and after designing the PDAs, and when played by PDAs. In the solid box on the left,  $d = 8, t = 6$  and in the dashed box on the right  $d = 16, t = 9$ .

### 5. REFERENCES

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<sup>1</sup>Note that better performance of the adversary (the human players) infers worse performance of the patrolling strategy.