

Towards the Integration of Multi-Attribute Optimization and Game Theory for Border Security Patrolling Strategies

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Introduction

Border security is a key element of national security policy for any sovereign nation. In the United States, the Border Patrol deploys thousands of agents integrated with technology (e.g., vehicles, cameras, sensors) and infrastructure (e.g., fences, checkpoints) to prevent illegal entry of people and goods into the country along vast land borders with Canada and Mexico. The problem of border security is incredibly complex, due to the diversity and volume of illegal activity that must be controlled, the variety of resources that can be deployed to secure the border, and the differences in circumstances, strategies, and tactics in different sections of the border.

Our goal is to develop decision support tools to assist with intelligent allocation of resource in border security. Several recent lines of work have applied game-theoretic and adversarial reasoning to security domains, including deployed transportation security systems (Jain et al. 2010) and robot patrolling strategies (Gatti 2008; Elmaliach, Agmon, and Kaminka 2009). Our approach takes this adversarial reasoning framework and incorporates elements of multi-objective optimization. Game theory and other adversarial reasoning methods typically assume a single, well-known objective function for each player. However, in complex domains like border security decision-makers must carefully weigh the impact of decisions on different objectives. For example, should the defensive posture emphasize narcotics smuggling, illegal immigration, or terrorist threats? How should the impact of patrolling activities on the community and other costs be balanced against the benefits of law enforcement? By developing solution techniques that integrate multi-objective optimization and game-theoretic analysis we hope to provide more powerful tools to decision makers to explore the space of alternative solutions and their impact on various objectives.

Patrolling Model

We study a simple patrolling scenario intended to model the problem of patrolling a remote border region. The physical domain is modeled as a weighted graph $G = (V, E)$ consisting of vertices V and edges E , as shown in Figure 1. There

are two types of agents: attackers and defenders. The goal for attackers is to move from one side of the graph to the other (represented by sets of source and target nodes); this represents a typical scenario of crossing an open region from one side of the border to destination points in the interior of the county. The paths between the source and target nodes may represent major or minor roads, or paths suitable for travel on foot. We use weights on the edges to represent the relative speed/cost of transit on the different paths (for example, it may be much slower and more difficult to use a foot path than a major highway). Nodes may represent intersections, checkpoints, or other important waypoints.

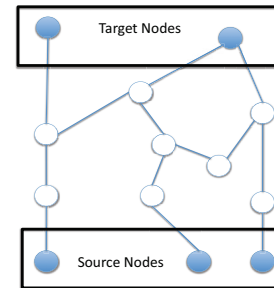


Figure 1: An example graph representing a border crossing region.

The defender agents also move through the graph to patrol the area and interdict attacker agents trying to cross the region. In our initial model each defender agent follows some fixed path through the graph representing a patrolling strategy (we plan to extend the model to randomized strategies in future work). The game proceeds in a series of discrete time steps. The progress of each agent toward the next node in their path is determined by the weight on the edge they are currently traversing. Attackers are said to be captured if they are ever in the same nodes as a defender agent on any time step before they arrive at a target node. We use multiple objectives to evaluate the performance of defender patrolling strategies. The three we consider in this work are:

- Minimize the maximum idleness, defined by the time between visits for any node.

- Minimize the patrolling cost, defined by summing a cost function over each individual edge included in the patrolling strategy.
- Minimize the infiltration ratio, defined by the probability that the attacker succeeds in moving from the source to the target node without being captured.

We assume that the only objective of the attackers is to maximize the infiltration ratio. We adopt the Stackelberg game framework commonly used in the literature on security games to represent surveillance by attacking agents. In our domain, this means that we assume attackers will be able to learn and optimize their strategy based on the patrol routes used by the defender. Our solution methods are based on the idea of identifying multiple Pareto-optimal patrolling strategies for the defender, which can be presented to human analysts for decision making.

Solution Methods

Our goal is to develop efficient methods for finding Pareto-optimal solutions to Stackelberg patrolling games defined on graphs (as defined above), with multiple objectives for the defender agent. Since these are Stackelberg games, the problem can generally be formulated as a bilevel optimization problem in which the first level optimizes the defender's objective and the second level optimizes the attackers objective. Many algorithms have been developed for solving different classes of Stackelberg security games, including some with graph-based representations (Tsai et al. 2010). However, exact optimization techniques are unlikely to scale to large graph instances because the number of possible paths in the graph grows exponentially as the size of the graph increases. Our approach instead focuses on approximate optimization using genetic algorithms, a very common approach for multi-objective optimization (Deb 2001). In addition to improving scalability, evolutionary approaches are often used in multi-attribute settings because they are well-suited to generating multiple different candidate solutions which represent qualitatively different options for the decision-makers.

Our solution method iterates between two stages of optimization; the first stage represents the decision for the defender, and the second stage represents the decision for the attacker. In the first stage, different defender patrolling strategies are represented as vectors of elements representing nodes in the network, in order of visitation. The top 75% of solutions ranked by fitness are mixed using crossover to generate new candidate strategies with a 1% random mutation rate. The top 25% of solutions are copied directly into the next generation to ensure that the best candidate so far will not be lost. Fitness is evaluated using two metrics. The first is distance-based and used to encourage population diversity. The second is a count-based metric that gives a higher value to solutions that dominate other solutions on the three different objectives defined above.

Only one of the three objectives in our simplified model (infiltration ratio) depends on the behavior of the attackers. We have experimented with two different models. The first model assumes a static attacker that appears in each graph

node with a given probability. The advantage of this method is that it is fast and can be used to find good responses to known observations of attacker behavior. However, it does not account for the ability of attackers to adapt to the defenders strategy. To account for this, we are currently in the process of developing a search-based method that uses a heuristic search approach to allow attackers to find the best-response path based on the defender's patrolling strategy.

Preliminary Results

We have developed an initial implementation of the algorithm described above for the border security domain. This algorithm has also been incorporated into the first version of a decision support tool eventually targeted at border security patrolling. An example of the results of this algorithm can be seen in Figure 2. The graph shows a set of non-dominated solutions. Each point in the graph represents the utilities for a particular solution (i.e., patrolling strategy) on each of the three metrics described above. We can see that the evolutionary approach is able to generate a diverse set of solutions approximating the Pareto-frontier.

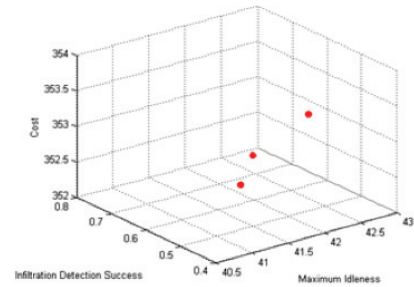


Figure 2: An example set of non-dominated solutions generated on a sample run of the algorithm.

References

- Deb, K. 2001. *Multi-Objective Optimization Using Evolutionary Algorithms*. Interscience series in systems and optimization. Wiley.
- Elmaliach, Y.; Agmon, N.; and Kaminka, G. A. 2009. Multi-robot area patrol under frequency constraints. *Annals of Math and Artificial Intelligence journal (AMAI)* 57(3-4):293–320.
- Gatti, N. 2008. Game theoretical insights in strategic patrolling: Model and algorithm in normal-form. In *ECAI-08*, 403–407.
- Jain, M.; Pita, J.; Tsai, J.; Kiekintveld, C.; Rathi, S.; Ordonez, F.; and Tambe, M. 2010. Software assistants for patrol planning at LAX and Federal Air Marshals Service. *Interfaces* 40(4):267–290.
- Tsai, J.; Yin, Z.; young Kwak, J.; Kempe, D.; Kiekintveld, C.; and Tambe, M. 2010. Urban security: Game-theoretic resource allocation in networked physical domains. In *National Conference on Artificial Intelligence (AAAI)*.