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An Evolutionary Game Theory Approach for Intelligent Patrolling

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Abstract

In order to achieve a secure country, many security policies and strategies have been implemented and numerous security forces have been enlisted such as regular police forces, Army, and Navy, among others. Each security force has different roles and responsibilities. One important area of concern related to national security is border security. Border protection is a challenging problem due to the different types of illegal activity that must to be controlled such as drug smuggling, terrorist attacks, illegal immigration, etc. One common approach to achieve border security is patrolling. Patrolling can be defined as the act of traveling an area in regular intervals in order to secure it against different threats. This paper presents a hybrid method that combines an evolutionary approach and game theory concepts in order to define the multi-agent patrolling strategy that simultaneously optimizes maximum idleness, infiltration ratio, and total patrolling cost.

Keywords: Desicion Making, Multi-Objective Optimization, Game Theory

1. Introduction & Background

Provide security to people is one of the most important concerns for all governments or security agents around the world. However, provide protection for airports, historical landmarks, or national borders are a very challenging task for any police force or security agencies [1]. The protection of these important locations includes tasks such as monitoring all entrances or inbound roads and checking inbound traffic. National borders represents a critical area to be protected because is through border where arms drug, or money can be introduced into the country illegally.

The patrolling problem has been addressed in the past in different ways. For instance Machado *et al*. (2002) [2] presents an empirical approach to the multi-agent patrolling problem, Chevaleyre (2004) [3] describes a theoretical approach to the problem. The problem is considered a NP-Hard (Non deterministic polynomial time hard) problem. Several methods have been developed in order to solve this challenging problem. Glad *et al.* (2008) [4] presents a theoretical study that addresses the problem of patrolling an unknown environment using ant colony optimization. Another similar work that applies ant colony optimization was presented by Lauri *et al,* (2008) [5] His work combines an evolutionary approach to ant colony optimization. The patrolling problem is analog to the network interdiction problem where the objective is to stop or reduce the flow of the network (stop the flow of illegal infiltration). There is also several works related to this topic applied in security applications. For instance, Wood [6] proposed an integer programming model to reduce the flow of drugs in a river network. Another similar work in network interdiction was presented by Cormican *et al*, [7].They presents the network interdiction problem as

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stochastic problem. A novel research presented by Israeli and Wood [8] revise the problem of cutting the arcs in a network in order to maximize the shortest path length.

The Patrolling problem is considered as a NP-Hard (Non deterministic polynomial time hard) problem that is very difficult to solve as the size of the area to be covered grows using mathematical o exacts methods. Some of the methodologies that have been proposed in literature include heuristic methods. For instance, Glad *et al,* [9] address the problem of patrolling an unknown environment using ant colony optimization. Lauri and Koukam [10] implements also a ant colony optimization including some evolutionary concepts to their work

One of the most important challenges that Border Patrol agency faces is predictability. Adversaries can observe security strategies over time and exploit any predictable behavior to their advantage. One option to deal with this fact is to introduce randomization to the patrolling task. Applying game theory strategies in order to obtain best suitable patrolling strategies is another approach that has been used for several researchers in the past. For instance Wang [11] proposes an Evolutionary Game theory approach that focus in the fact that in multi-agent systems the actions of one agent affects the action for other agents and focusing in investigate an optimal coordination approach for multi-agent systems. Paruchuri and Pearce [12] develop a Heuristic approach for security against multiple adversaries in Stackelberg games in their work they consider domains where treats come from unknown adversaries and model those domains as Bayesian games in they approach the agent can maximize reward by finding an optimal strategy without requiring equilibrium. Considering unknown adversaries is very important in the Patrolling problem because the variety of treats such as illegal infiltration, drug smuggling, terrorism, etc. Luo *et al*, [13] addresses a network security problem also using a game theory based approach. Luos's work the interactions between attackers and defenders are modeled as a non-cooperative non-zero-sum game dynamic game with incomplete information and uncertainty of multi-state attacks.

The learning process in a game is one of the most important aspects in game theory how both players learn from each other during time. Santana *et al.* [14] address the multi-agent patrolling problem with reinforcement learning. In their work they investigate the creation of adaptive agents that can learn to patrol using reinforcement learning techniques. In order to apply these techniques the task was modeled as a Markov Decision Process (MDP). Another approach the explore the cooperation between agents is the work proposed by Pasqueletti *et al* [15] in their work they consider the problem of find an optimal multi-agent trajectories to patrol a certain area and present a heuristic with performance guarantees, and 8-approximation algorithm to solve the NP-hard patrolling problem.

This work considers the patrolling problem as a multiple objective optimization problem. Were three different objective will be optimized simultaneously. The method used in this work to solve the proposed multiple-objective patrolling problem is a hybrid algorithm that combines evolutionary approach an game theory concepts in order to select an optimal multi-agent patrolling strategy. The next section will be focused in the description of the problem and the objectives that will be considered to be optimized.

2. Problem Description

The objective of the patrolling task is to secure a specific location. This location or area can be modelled as a network $G(V,E)$. Where V represents the set of point in the area that will be secure by agents and E represents the set of possible routes that an agent uses to travel from one point to another. In order to build the network to be patrolled the locations or positions for each node in the network are needed. The task of patrolling consists in an agent or group of agents traveling through the network in order to secure all the nodes. The objective of this paper is to develop a model in order to find the optimal way that each agent has to patrol the network in order to optimize specific objective functions.

2.1 Patrolling Model.

To patrol is literally "the act of walking or travelling around an area (network), at regular intervals, in order to protect or supervise it" [3]. Let's considers strategy $s_j(i)$ for a patrolling strategy j performed by single agent i. A patrolling strategy consists in a cyclic route through the network. Therefore a multi-agent strategy is given by Equation 1

$$\mathbf{x} = \{s_1(i), s_2(i), \ldots, s_j(i), \ldots, s_p(i)\} \tag{1}$$

Where:

x	multi-agent patrolling strategy
$s_j(i)$	patrolling strategy (route) j performed by agent type i
j	Index for the number of single agent strategy j=1,2,…, p
i	Agent index $i=1,2,3,\ldots, K$
K	Total number of different type of agents

Each agent i will be assigned to perform a specific patrolling strategy j. However, not all agents are the same. In this work the patrolling problem is modelled as a multi-agent patrolling problem where each agent has different characteristics that affect the quality of the patrolling. These characteristics are: velocity of patrolling and agent's cost. Vector **a** allocate the type of agent that will be performed specific route $s_j(i)$ For instance **a**= {1,2,1} means that strategy 1 $s_1(1)$ is performed by an agent type one, strategy two $s_2(2)$ by agent type 2, and strategy 3 $s_3(1)$ is performed again by agent type 1. The objective of the proposed problem is to select the agents and assign to each agent a route (patrolling strategy) that optimizes specific performance measure value. Three different measures or objectives are used to define the quality of the patrolling strategy. All the objectives will be explained in next sections

- Minimization of the delay between two consecutives visits of a specific place(WI(**x**))
- Minimization of infiltration ratio that is defined as the success of the defender to caught the attacker (*IR*(**x**))
- Minimization of total cost of a specific patrolling strategy. *TC*(**x**)

2.1.1 Worst Idleness WI(x).

Max idleness can be defined as the biggest idleness (amount time that a node is not visited) value that occurred during the entire patrolling process for all the nodes for all the agents [16]. The vector $\boldsymbol{\psi} = \{ \mathcal{T}(\tau_1), \mathcal{T}(\tau_2), \ldots, \mathcal{T}(\tau_V)\}$ represents all the idle times for all the nodes for a specific multi-agent strategy **x.** Therefore the worst idleness is given by Equation 2.

$$\mathrm{WI}(\mathbf{x}) = \mathrm{Max}\ [\boldsymbol{\psi} = \{ \mathcal{T}(\tau_1), \mathcal{T}(\tau_2), \ldots, \mathcal{T}(\tau_V)\}] \tag{2}$$

In real life the attacker has the advantage to learn from the defender and ovoid to be caught by the defender. Therefore another objective has to be considered in order to improve the quality of the patrolling strategy.

2.1.2 Infiltration Ratio (IR(x))

It is important to remember that the main objective for the attacker is to cross the border if the attacker achieves specific point in the network the attacker had been succeeded. The attacker strategy is defined by vector **r.** Each element of vector **r** represents the point that the attacker travel in order to cross the border**.**

The infiltration ratio IR (**x**) is evaluated using a simulation that generates several attackers at different times and then checking is performed. The checking consist in compare both strategies (attacker and defender) and check if the attacker achieve target point without being computed by the defender. If the defender fails to catch the attacker the attacker succeeds. Each agent strategy will be compared against each attacker strategy. The IR(**x**) will be given for the average of the IR of specific agent strategy against all the attackers' strategies.

2.1.3 Total Patrolling Cost (TC(x)).

The third objective to be considered is the total cost of the patrolling task. Even though security is a very important aspect having high security at a lowest cost is also a very important aspect in any optimization problem. The evaluation of this objective consists in adding the cost of each agent involved in the patrolling task. The evaluation of the total is basically the summation of the cost involved to use specific agent. The total cost is evaluated by Equation 3.

$$TC(\mathrm{x}) = \sum_{n=1}^{p} c[a(n)] \tag{3}$$

Where:

c = Set of costs for each agent

a = Vector that defines which agent will be selected for a specific patrolling task

Therefore, the patrolling problem considered was become into a multiple objective optimization problem where 3 different objectives want to be optimized simultaneously. The multiple-objective optimization problem to be solved is presented in Equation 4.

$$\text{Min WI}(\mathrm{x}) \quad , \quad \text{Max } CR(\mathrm{x}) \quad , \quad \mathrm{T}C(\mathrm{x}) \tag{4}$$
$$s.t.$$
$$\mathrm{x} \epsilon \mathrm{X}$$

3. Evolutionary Game Theory Algorithm

In order to solve the multiple objectives patrolling problem presented in section 3. An evolutionary game theory algorithm was developed. Evolutionary algorithms have proven to be able to perform well when solving complex NP-Hard problems. Even though there are countless alternatives to solve these types of problems, a hybrid approach that combines evolutionary algorithms and game theory techniques was selected to solve the presented problem. However, a comparison between different solution methods will be considered as part of future research. The details of the algorithm proposed are presented next.

3.1 Initialization and evaluation.

The first step of the algorithm is to generate an initial population for both players: the defender and the attacker. Both populations were generated randomly in order to have a variety of genetic material in the first generation. Then the three objectives considered to be optimized are evaluated for each patrolling strategy generated. Once the three objectives were evaluated nondominated patrolling strategies and all attacker strategies are selected to next stage for the algorithm.

3.2 Selection.

The objective of this stage of the algorithm is to select the best solutions of each population (defender and attacker) to undergo crossover and generate the individual for next generation. The selection is different for each population and both procedures are explained next:

- <u>Attacker Selection:</u> In order to select which attacker strategies will undergo crossover. A game between attacker and defender is performed. In order to solve the game, iterated elimination of dominated solutions is used. The main idea of this technique is to eliminate all the strategies are dominated for other strategies. In game theory, strategic dominance occurs when one strategy is better than another strategy for one player, no matter how that player's opponents may play. Therefore it not make sense to select a strategy that is worse than other strategy regardless the decision of the other player.

- <u>Defender Selection:</u> Two fitness functions are considered as shown in [17]. The main idea for a fitness function in evolutionary algorithms is to measure the quality of the represented solutions. The first fitness metric, $f_1(\mathbf{x})$, is a dominance count-based metric. It aims to select individuals which are more dominating (intended to achieve proximity). While the second fitness metric, $f_2(\mathbf{x})$, is distance-based. This metric is intended to maintain population diversity. Solutions that are farther away respecting to other solutions (Euclidian distance) will have better fitness values. Finally, the third fitness metric used is the aggregated fitness metric, $f\mathrm{a}(\mathbf{x})$. The aggregated fitness metric is the result of the sum of fitness metric 1 plus fitness metric 2; $f\mathrm{a}(\mathbf{x}) = f_1(\mathrm{x}) + f_2(\mathrm{x})$. It aims to weigh both metrics equally. Then, the nondominated solutions are ranked based on this aggregated fitness metric and selected to the reproduction step.

3.3Reproduction.

In this section the current ranked solutions for the previous step (defender and attacker strategies) will generate the new individuals that will be part of the next generation. The recombination method used is called sub-system rotation crossover (SURC). All the details of the SURC can be consulted in [17]. The crossover operator used was 75% and the mutation operator was 1%. In order to prevent losing good solutions a elitism of 25% was considered. All the details of these parameters can be consulted in [20]. The new generation is formed by elite parents and new children. Once the next generation is completed, the algorithm returns to the evaluation stage and repeat the procedure until the specified number of generations is reached. At the end the last generation will be evaluated and the nondominated solution will be selected as a solution of the problem.

4. Numerical example

In order to show the performance of the developed algorithm a test network is modeled in order to be patrolled by different agents. This example considers a network with 10 nodes, 5 strategies, and 5 different type agents to choose from. The data used to model the network and the characteristics for each agent are presented in Table 1. The algorithm was coded in MATLAB and parameters used in the algorithm are: Population size =100, Elitism= 25%,Crossover =75%, Mutation =1%, and Generations =50

Table 1: Example Data.

Coordinates of Nodes

NODE #	X	Y
1	1	3
2	3	6
3	2	5
4	9	6
5	4	5
6	6	2
7	8	4
8	4	2
9	6	4
10	8	1

Agent’s Characteristics

Agent #	Cost	Vel.
1	10	6
2	17	8
3	23	11
4	35	12
5	40	13

After run the program for 50 generation a Pareto set of 24 solutions was obtained. (See Figure 1)

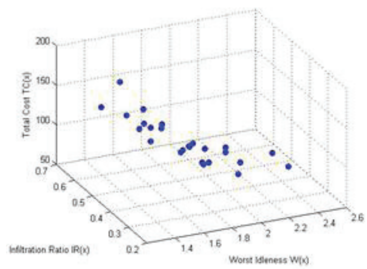

Figure 1: Pareto set of solutions

Each point in Figure 1 represents a multi-agent patrolling strategy or a possible solution to the problem. In order to show one solution the closest solution to the ideal point [0,0,1) in a normalized space was selected. The objectives for the selected solution are the following: WI(**x**) =1.854 seg, IR(x)=40%, TC(**x**) =89. Figure 2 shows the routes for all the 5 agents considered in the problem.

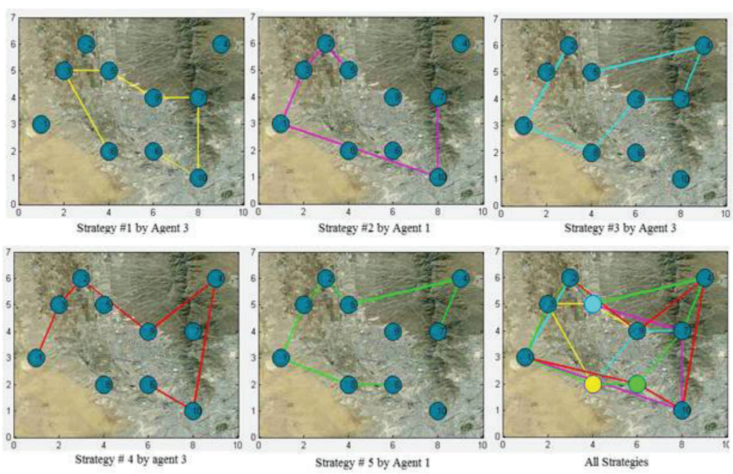

Figure 2: Patrolling strategies

Each picture represents the route that specific agent *i* will follow through the network. For instance strategy (route) 1 will be performed by agent type 3 and this agent will visit nodes 8-3-5-9-7-10-6. The last picture represents all the strategies performed at the same time.

5. Conclusions

The present work considers protecting a specific geographic area between two countries (National Border) allocating different type of agents with different characteristic. These agents will perform specific patrolling strategies (routes) in order to secure a specific location. This paper proposes an evolutionary game theory algorithm used to specify which route or patrolling strategies each agent will follow. The quality of the multi-agent patrolling strategy is defined by the optimization of three different conflictive objectives (WI($\mathbf{x}$), IR($\mathbf{x}$), and TC($\mathbf{x}$)). The solution of the problem is presented as a set of nondominated Pareto solutions. This set of solutions contains a variety of solutions with different objectives that provide multiple options to the decision maker. However this variety could be a problem. Therefore a post-Pareto analysis will be considered as a future research in order to help the decision maker to select a solution among the set. There is still several points that have to be addressed in future research in order to make model more robust. These points include the comparison among other methods and testing of the scalability of the model to solve larger problems. Additionally, more characteristics will be added to the defender and attacker in order to make the model more realistic.

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