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The Multi-Agent Simulation-Based Framework for Optimization of Detectors Layout in Public Crowded Places

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Abstract
In this work the framework for detectors layout optimization based on a multi-agent simulation is proposed. Its main intention is to provide a decision support team with a tool for automatic design of social threat detection systems for public crowded places. Containing a number of distributed detectors, this system performs detection and an identification of threat carriers. The generic model of detector used in the framework allows to consider detection of various types of threats, e.g. infections, explosives, drugs, radiation. The underlying agent-based models provide data on social mobility, which is used along with a probability based quality assessment model within the optimization process. The implemented multi-criteria optimization scheme is based on a genetic algorithm. For experimental study the framework has been applied in order to get the optimal detectors' layout in Pulkovo airport.

Keywords: sensors, detectors layout, evolutionary computation, multi-objective optimization, crowd simulation, crowded environment, agent-based simulation, security, genetic algorithms

1 Introduction

Today facing crowded places is an ordinary practice in urban life. This usually happens, for example, at transport hubs (airports, stations). Crowded places are connected with several types of threats that have a large effect on public safety. Because of the large number of people crowds, they often become a target for terrorist attacks. On the other hand, the complex character of crowds and inability to check everybody allows smugglers to transport illegal cargo through crowded places. And the interactive nature of crowds with many contacts inside, leads to the propagation of infections.

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In order to detect such threats, screening detectors are widely used. The main principle of functioning for such detectors is based on a sequential gathering of air samples. It takes some period of time, from tens of seconds to a half an hour (Gooding, 2006). A detector generates a signal of alert if an internal test gives a positive result. Such screening detectors usually are not as precise as individual checking. But they are less time consuming and can handle more people without causing queues. Due to economical reasons and installation limitations, it is usually impossible to cover the entire crowded place with such detectors. And there are also different types of detectors which can differ by some parameters like cost, detection precision, etc. Thereby, there is a need to choose detector types, and correct positions for detector placement. This determines a multi-objective optimization problem.

Pedestrian flows formed by people's movements have a great influence on different characteristics of the crowded place, which affects the performance of detectors layout. However, it is not enough to know only aggregated characteristics in order to find out optimal detector layout. Some goals of the detection system, which is being designed, may require more detailed information, e.g. the goal of identification of individual "threat carriers". Usually a single detector cannot solve the identification problem, as it has its latency and it is receptive to noise caused by a large group of people. In this case, an identification problem is solved on the level of a whole detection system.

This work is devoted to the detector layout optimization problem and contributes: an optimization framework architecture based on agent-based simulation; a formulation of multi objective combinatorial optimization problem based on quality assessment model which uses information about pedestrian flows and accounts the described types of detectors; a data structure optimization procedure which allows reducing time of optimization procedure spent dealing with massive simulation data; an experimental case study for Pulkovo airport (Saint-Petersburg).

2 Related works

The general problem of detector layout optimization has emerged in various fields such as gas leak detection, intruder detection, detection of threats in water, and detection of biological or chemical attacks. This problem is well known in the wireless sensor networks engineering area of research (Molina., Alba & Talbi 2008; Dhillon & Chakrabarty, 2003). Works in this area are focused on the network's topology, observable natural phenomena coverage, and don't take into account aspects connected with crowd dynamics and crowd simulation. Another related area is tracking people with a system of video cameras (Qian & Qi, 2008; Jin & Bhanu, 2012).

The most widely accepted approach to solve the task of detector layout optimization within the crowded place is based on aggregated information about such a place, and geometric principles. Particularly, Kiekintveld & Lerma (2011) consider detecting biological weapons. Their approach is based on a natural idea to place more detectors in areas with more population and fewer in areas with fewer people. They try to optimize coverage of important zones based on geometrical principles. The work assumes presence of data about population density, which may be unknown in advance. The model of detectors is not oriented to take into account features such as time of sample gathering. Also, visiting several sensors does not influence the optimization process directly, and some features like different velocity of threat spreading in different directions can be ignored. Väkevä(2007) have proposed to use risk-based analysis for detector placement which is aimed at event detection. The authors (Nie, Batta, Drury & Lin, 2007; Stolkin, Vickers & Nickerson, 2007) use similar approach to ours, which is focused on the calculation of probability of an agent interception based on several measurements performed by independent detectors. In the work (Nie, Batta, Drury & Lin, 2007) the model assumes the presence of only the one suicide bomber, and detectors work in an instant mode. Otherwise, our model is targeted to deal with the cumulative probability of detector's activation which is received from a group of participants. Also, in the last work, influence of pedestrian activity is not taken into account. Approaches which apply in gas leak detection or water threat detection areas commonly use methods based on coverage volume optimization and calculating probability from independent measurements and sources optimization (DeFriend, Dejmek, Porter, Deshotels & Natvig, 2008; Legg S. W. et al, 2012; Berry, Hart, Phillips, Uber & Watson, 2006) and are focused on an event detection, not an agent identification.

3 Problem statement

In this section the used terminology and class of problems under consideration are defined.

The detector layout optimization problem is solved within a defined spatial area. That area is structured by a certain topology, which may influence pedestrian flows inside it. The topology is determined by floors, walls, and other barriers, and may have staircases, transitions, lifts, entrances, and exits. Pedestrian flows are formed by agents, which move through the area according to their goals and environmental circumstances. Some agents are threat carriers. Threat in a general case is some feature the detection system looks for, which can be detected by some type of detectors. Depending on the use case, threat carriers can or cannot transmit threats to other participants. The detection system may be managed by a security service of the crowded place. Depending on the use case, the goal of the detection system may be defined as both: detection of threat event appearance inside the crowded place; identification of individual agents, which are threat carriers.

Individual detectors within the detection system have certain parameters and limitations such as: radius of detection zone, base detection probability, installation cost, and collect time interval. The last limitation makes detectors unable to recognize threat carriers on the fly. Detectors are able to do it only for a group of agents, whose trajectories have crossed the detection zone at different time moments. Some agents in this group can be threat carriers. The detector layout covering the whole investigating area is usually not possible due to different reasons: economical, installation limitations, precision requirements. Therefore, we need to find the optimal detector layout, which will provide us with information about threat presence and/or separate threat carriers depending on the concrete goal. If the goal of the whole system is to detect an emergence of a threat, than a layout of detectors should be optimized in order to increase the probability of the threat detection. If the goal is to identify concrete threat carriers, the system of detectors has to use measurements from different detectors in order to increase a precision of identification. In this work the both purposes are considered: the simultaneously increasing probability of threat detection and identification. However, the second task of identification is the priority. The optimization process relies on the solution's quality assessment model, which depends on the optimization goal. In the case of identification this quality assessment model has to estimate personal agents' probability of being a carrier. This assumes the use of information about pedestrian flows.

In the next sections the detector layout optimization framework is proposed.

4 Architecture of the optimization framework

The defined optimization problem operates with objects that have their own complex behavior: agents, environment, detectors, and system of detectors. These behaviors should be simulated in order to reproduce the complex system's dynamics and in order to evaluate the solution's performance. For this purpose, the optimization framework relies on the system of models: agent-based crowd dynamics model, detectors models, model of the complex detection system.

The solution obtained by the optimization process should be based on pedestrian mobility data representing the real dynamics in a concrete spatial area (crowded place). This data can be taken from both observations (e.g. pedestrian tracks caught by video cameras) or from microscopic models. A large amount of pedestrian tracks acquired from observations could serve as the best means to represent real people's behavior. But a fully data-driven approach to pedestrian mobility analysis cannot be applied in all cases due to various reasons, including absence of data because of high cost of tracking infrastructure; availability of only partial observed macro-characteristics like crowd density; the crowded place under investigation may not exist (e.g. in case of design). In these cases simulation-based data acquisition on pedestrian flows is performed. For this purpose the special *agent-based simulation engine* is utilized. And one of this engine's major requirements is support of integration of various models, which define different aspects influencing pedestrian flows: virtual society models, population mobility models, environment models, and external models.

The second important part of the framework is a *single detector model*. This model consists of a few basic parts which determine its behavior as a reaction to an environment based on the virtual society model, population mobility model, environment model, and external model. The screening process sub-model determines how to treat group of agents who have passed the area around the detector, and determines the probability of threat detection event.

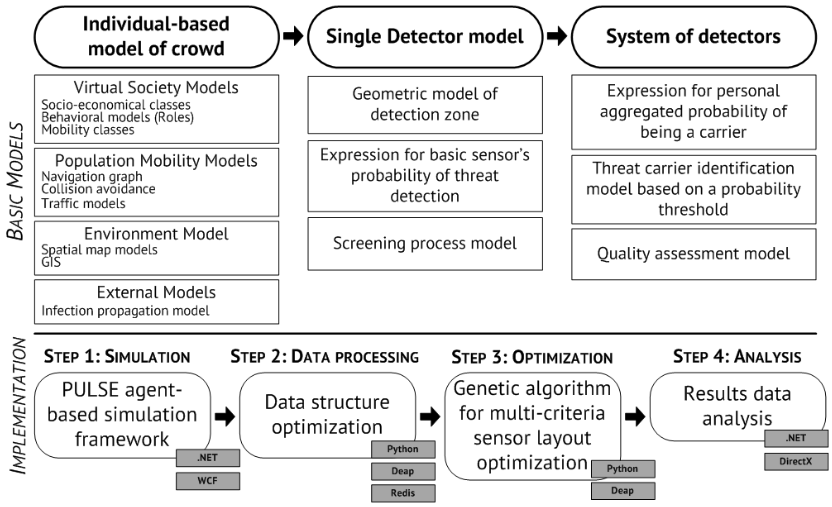

Fig. 1. Scheme of the framework's high-level architecture

System of detectors model simulates the behavior of the whole security system consisting of all detectors. It aggregates information flows from separated detectors about individual agents. Expression for *personal aggregated probability* of being a carrier is used in order to estimate the probability of individual agents to be a threat carrier. *Quality assessment model* aggregates this information to estimate performance of the overall detectors layout (whole system).

Basing on the listed models, the implementation of the framework consists of three main components: PULSE agent-based simulation engine (Karbovskii, Voloshin, Puzyreva & Zagarskikh, 2014) data structure optimization module, detector layout optimization module based on a genetic algorithm, and auxiliary optimization results' analysis module, which includes interactive visualization. It can solve the following tasks: rapid prototyping of different crowded place topologies, features of pedestrian movement and behavior of agents specific for specialization of a crowded place, data reorganization in a way efficient for investigation of settings important for the optimization and accounting pedestrian flows influence for the system performance.

Agent-based simulation. Agent-based simulation provides a large amount of data on population mobility within the spatial area under investigation. Several types of social models are incorporated into the framework in order to represent agents' behavior and interaction specific to a particular scenario. Virtual society model represents socio-economic classes, roles, and mobility classes, which determine the behavior of agents involved in the simulating scenario. Population mobility model reproduce pedestrian movement dynamics in detail by incorporating navigation and collision avoidance models. These models describe psychological, social, and physical forces which influence each agent and forms agent's behavior according to the use case for detectors layout optimization.(Fang, Qin, Lu & Zhao, 2012; Schadschneider & Seyfried, 2009; Seyfried & Schadschneider, 2008). Environmental model represents investigating threat phenomenon, and, for example, defines if the threat carrier can transmit a threat to other agents. It should be noted that the real data on pedestrian tracks can still be used by the framework instead of simulation. It can be incorporated into the models in frames of calibration in order to increase the accuracy of simulation.

Data structure optimization. The second part of the solution is the data processing module which aggregates data coming from simulation engine and reorganizes it in order to reduce the solution's quality assessment time within the optimization process. Before start of processing the set of potential locations for detectors is specified. The module consumes the raw data generated by the simulation engine, which contains information about each agent's position and state for every second of simulation. The data related to adjusted space of each detector (detector has certain detection radius) is aggregated and processed according to the model from Section 3. The first aggregation step is the partitioning of geometric space of a crowded place into a grid. Then all the static spatial objects like walls along with moving agents are distributed by their location to cells of the grid for each moment of simulation time. Information about the agents, which fall into a detecting zone of sensors, is selected depending on a detection radius. Results are merged according to collection interval of a particular detector and aggregated according to global detection model. Finally, the data structure for fast access to aggregated information by a set of values (detector id, collection interval, radius, agent id) is formed.

Genetic algorithm. The third module is an optimization module containing implementation of NSGA-2 multi objective genetic algorithm, which employs the quality assessment algorithm based on the model from Section 3 as fitness. Genome is an ordered set of detector placement positions and certain types associated with them. Mutation is a random change of one of the detectors in the set to another detector position and associated type. Single point crossover with removing of duplicates is used.

A description of the models and the framework's implementation are given in the next sections.

5 Threat carrier's detection and identification

Single Detector model. In order to get a flexible solution for the class of problems presented in the Section 3, we introduce the generic detector model which is presented below.

Let introduce several definitions. $D = \{d_i, i \in [1, n]\}$ – set of detectors, $A = \{a_i, i \in [1, m]\}$ – set of agents A^I – set of carriers, A^N- set of non carriers, X – investigated spatial area (e.g. building plan containing floors, walls, doors, lifts, stairs), T – simulation time interval, $G = X \times T$ - time-spatial coordinate, $x{:}A{\times}T{\rightarrow}G$ – operator which give a position (in space and time) of an agent at the concrete time, $u(a_i) = \big(x(a_i, t_0), \ldots, x(a_i, t_k)\big), [t_0, t_k], t_j < t_{j+1}$ – agent's trajectory in space and time.

For any particular detector d has the following characteristics. R^d– radius of the circle determining detection zone where d can detect a threat carrier. p_{base} – probability of detection in the point of d's location. The presented below function estimates probability of detection of a threat carrier a which is away from d by distance r_a:

$$p_a(r_a) = \begin{cases} 0, r_a > R^d \\ p_{base}\left(\frac{R^d - r_a}{R^d}\right), r \leq R^d \end{cases} \quad (1)$$

For the sake of simplicity it is assumed that detector has so small probability to detect false-positive agent so it can be neglected. c^d – cost of d. $CI = (t_1, \dots, t_s), t_i < t_{i+1}$ – sequence of collect intervals timestamps of d.It is assumed that each collect interval of d has the same length.

For any particular collect interval $g_j = [t_j, t_{j+1}]$ trajectories of several treat carriers can intersect detection zone of d. In that case threat detection probability is determined by contributions of all such agents. $B = \{b_i, i \in [1, k]\} \subseteq A$ - set of all agents in the interval g_j, $B^I \subseteq B$ - set of threat carriers in the interval g_j. In this case probability of threat detection or threat detection event probability for detector d and its collect interval g_j can be expressed as:

$$P^d(g_j) = 1 - \prod_{i=1}^{|B^I|}\left(1 - p_{b_i}(r_{b_i})\right). \quad (2)$$

Here $\left(1 - p_{b_i}(r_{b_i})\right)$ corresponds to the probability of not detecting a contribution from agent b_i. It should be noted that every agent can have many location points which falls into detection area of a detector. For the sake of simplicity the point with minimal distance to center of the detector will be used to determine agent's contribution to the threat detection event probability. Thus, at the end of collect interval detector d reports: its location and characteristics, timestamps for current collect interval g_j and signal of detection and data of agents which has crossed the detection zone if threat has been found. It is assumed that identification of each agent whose trajectory has crossed a detection zone during collect interval can be performed by RFID label or video cameras.

System of detectors model for identification. From the point of view of the detection system every agent in the group seems to be equally suspicious due to the system can't know exactly which agent is a threat carrier after threat detection event has happened.

There can be different considerations how to determine probability of individual from the group probability. One can be leaded by the following consideration. Let introduce the following events: H – detector d has found the threat after the end of collect interval g_j, F^i – agent a_i is a carrier. The system, which looks for threat carrier, may assign personal agent's probability by the formula:

$$P(F^i|H) = \frac{P(H|F^i)P(F^i)}{P(H)} = \frac{p_{b_i}(r_{b_i})pt(b_i)}{\sum_{j=1}^{k} p_{b_j}(r_{b_j})pt(b_j)} = \frac{R^d - r_{b_i}}{\sum_{j=1}^{k}\left(R^d - r_{b_j}\right)} = P_{b_i}(d, g_j) \quad (3)$$

$pt(b_i)$ is the probability that agent in the group is a threat carrier. It is assumed that any two agents have equal probability to be a threat carrier so $pt(b_{i_1}) = pt(b_{i_2}) \forall\, i_1 \neq i_2$ and according to (1) we get the final expression. This formula assumes that each agent in set B can be a threat carrier and estimates its conditional probability to be a carrier (this model was chosen for the sake of simplicity). Personal aggregated probability a_i which formed by personal probabilities from sequence of visited detectors $Dv^{a_i} = (vd_1, \dots, vd_s), vd_i \in D$ where threat detection event has happened are estimated by the following formula:

$$P_+^{a_i}(Dv^{a_i}) = 1 - \prod_{j=1}^{|Dv^{a_i}|}\left(1 - P_{a_i}\left(vd_j, g_{vd_j}\right)\right) \quad (4)$$

g_{vd_j} is the collect interval, during which the agent a_i resides in an active zone of the detector vd_j. The formula (4) relies on precise knowledge of the detectors that have detected the threat. One way to obtain this information is to simulate this detectors layout. This way comes with a high level of stochasticity, which may require multiple runs and an aggregation of results. Thus, this way is characterized by high computational complexity. The second way is to calculate a personal aggregated probability for each possible subsequence of the sequence Dv^{a_i} and probability the concrete subsequence to appear. Then we can calculate mathematical expectation of a personal aggregated probability. The computational complexity of this approach has an exponential growth depending on the count of visited detectors. In some situations agents can have tens of visited detectors.

We propose the following heuristic for estimation of personal aggregated probability, which has reduced computational complexity. From the point of view of the detection system there can be two outcomes: visited detector vd_j raises the detection event with the probability $P^{vd_j}(g_{vd_j})$; the detector doesn't raise an event with the probability $1 - P^{vd_j}(g_{vd_j})$. In this case mathematical expectation of personal probability of agent a_i with detector vd_j is:

$$MP_{a_i}\left(vd_j, g_{vd_j}\right) = P_{a_i}\left(vd_j, g_{vd_j}\right) * P^{vd_j}(g_{vd_j}) + 0 * (1 - P^{vd_j}(g_{vd_j})) \quad (5)$$

This mathematical expectation is the personal probability, which can be assigned to the agent a_i by the system depending on all the probable outcomes. Substituting (5) into (4) we get the expression of personal aggregated probability for the agent a_i:

$$P_+^{a_i}(Dv^{a_i}) = 1 - \prod_{j=1}^{|Dv^{a_i}|}\left(1 - MP_{a_i}\left(vd_j, g_{vd_j}\right)\right) \quad (6)$$

Depending on the value of that probability, the system can decide to intercept and check the agent or let it go. Let $C(d_i)$ is a function, which determines cost of detector d_i. So, the following formulation of a multi objective optimization problem can be set:

$$c_1 = \sum_{i=1}^{|A^I|}\left(1 - P_+^{a_i}(Dv^{a_i})\right), \ c_2 = \sum_{i=1}^{n} C(d_i), \min(c_1, c_2). \quad (7)$$

6 Experimental study

For the case study an issue of detectors layout optimization at the Pulkovo airport terminal (Saint-Petersburg, Russia) is chosen. The terminal has high security requirements. At the same time it is characterized by complex spatial topology and by complex pedestrian behavior forming flows within the airport. The case study reproduces one regular day of the airport and takes into account the real flight schedule. The simulation involves 4300 agents travelling through the 4-floor airport building. The simulator generates routes for agents depending on their goals, which are defined by agent's role. There are the following roles: arriving passengers, departing passengers, transfer passengers, receiving individual, sending individual, personal of the airport, personal in commercial zones, taxi drivers. Also, behavior of agents with the same role can vary depending on their social-economic classes and stochastic selection of minor goals (e.g. visiting toilets). Two types of threat detectors were used for the optimization. Detectors' parameters of both types are presented in the table 1. An abstract threat is considered in two experimental scenarios. In the first scenario threat can be carried only by arriving passengers from planes (Scenario I). Total amount of threat carriers is set to 10% of all agents. In the second scenario the source of threat is placed in the several places in the airport (Scenario II). As a result about 50% of the agents became threat carriers leaving the airport. In order to evaluate the proposed approach (GA) the results are correlated with an deterministic solution based on maximal density coverage heuristics (DE). This solution implies use of the spatial points with the maximum number of agents passing through it as places for detectors.

With the growth of the probability value count of such findings is decreasing. The threshold value equal to 0.7 for Scenario II (Fig 7, right) give us a chance to precisely recognize more than 35 % threat carriers. If the threshold with the value 0.45, for example, is chosen, the number of correctly recognized treat carriers will be greatly increased and become more than 50%, but in the same time the number of incorrectly recognized agents will become closer to 20%. It means, that will be 20% of incorrectly recognized normal people who will be needed to be checked by security or other appropriate service. Such a kind of tradeoff between degree of detection correctness and amount of false-positive agents can be used in different situations. For example, if the goal is to detect in a crowded place a sign of a treat presence , that can be infection, radioactive or chemical pollution, security service may prefer to use threshold in the range of 0.2 and 0.3 to cover most part of dangerous situations.

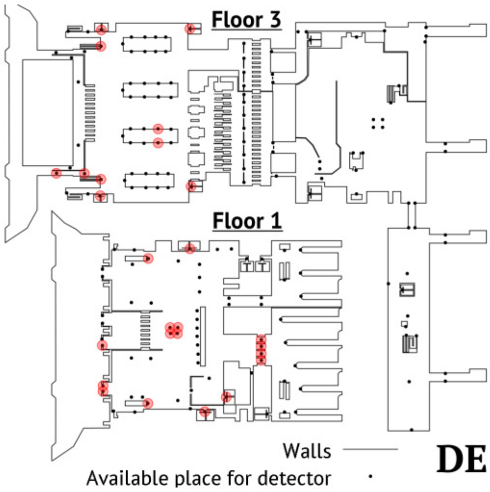

Fig 6. Detector layouts generated by density based heuristic (DE) and genetic algorithm (GA) for Scenario II

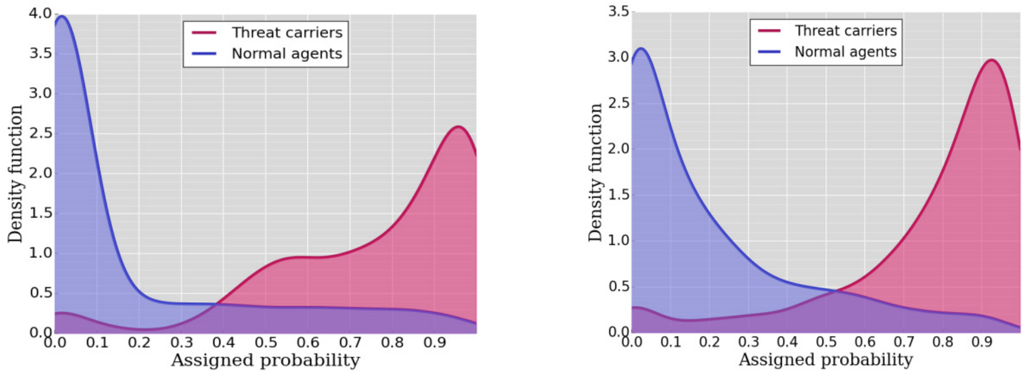

Fig 7. Distribution of agents depending on the probability assigned by the system for Scenario I (left) and Scenario II (right)

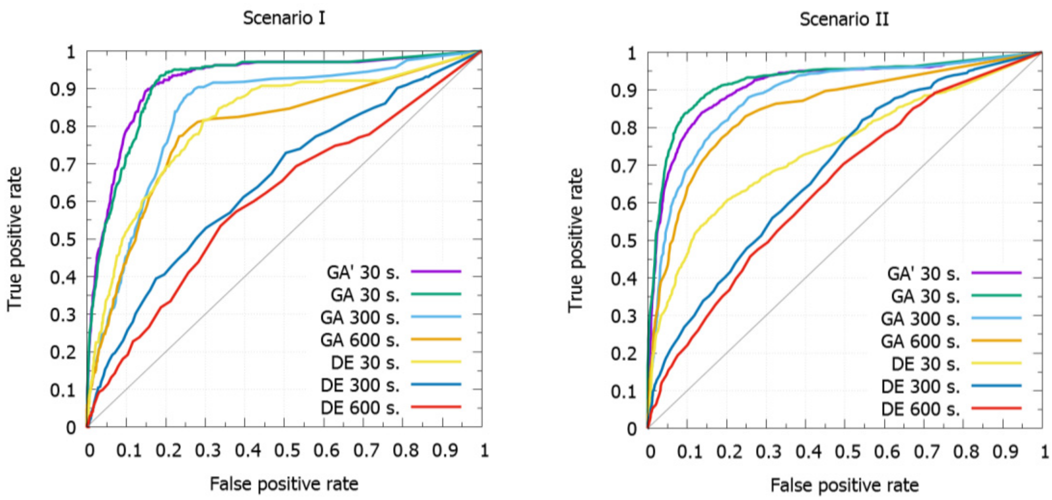

Fig 8. Receiver operating characteristics for Scenario I (left) and Scenario II (right)

Solution based on density cover heuristic generates layout with detectors placed in the most crowded points (e.g. entrances, gates). GA, in the opposite side, provides not obvious solutions depending on the simulated scenario. In the figure 6 two solutions are presented for scenario II in a case of 35 detectors limit. It should be mentioned that in Scenario I GA provides the different solution and covers the most part of arrival area (floor 2), because threat carriers have the role of arriving passengers. This shows the capability of the proposed approach to take into account behavioral patterns of simulated crowd in the modeling scenarios. As a result GA produces more efficient solutions. Performance of the two approaches can be compared with the use of receiver operating characteristic(ROC) presented in the figure 8. The receiver operating characteristic, which presented in the Fig 8, shows true positive rate against the false positive rate at various threshold settings. We can see that all the solutions provided by DE give worse results (farther away from the perfect point (0.0, 1.0)) even than GA solutions consisting of low-quality sensors with large collection time interval. The experimental study shows that the evolutionary process gain better performance (faster convergence and better fitness) with use of density-based solution within the initial population than just random generated population (Fig. 8, GA').

Relying on the obtained results (Fig. 8), it can be concluded that quality of a solution decreases with the increase of the collect interval. Higher values of collect interval lead to more agents fall into the active zone of the detector that affects . In case of threat detection it can be even preferable, as the detector with larger group of caught agents has greater probability to raise alarm. But in case of identification it would increase false positive rate and decrease true positive rate. Detectors with different values of collect interval can be composed into one layout in order to balance between identification goal and threat detection goal. For example, solutions of GA (Fig 7) use several detectors with large collect interval in order to decrease the cost of the system by covering less used passages and elevators at the third floor with the detectors.

The parameter study for detector count for Scenario II demonstrated that the best configuration consists of 35 detectors. Also, it is observed that a lack of detectors in the system leads to poor performance (e.g. in case of 15 detectors). But at the same time, too large amount of detectors increases a level of noise and negatively affects on the precision of identification.

7 Conclusion and future works

In this work the detectors layout optimization framework is presented. Experimental study for Pulkovo airport shows how it can be applied to solve such class of the detection problems. The quality assessment model proposed in this paper is based on estimation of personal aggregated probability of individual agents. It serves as a quantity measure for individual solutions during the optimization process. Despite of the simplicity of the model it allows to take into account details of pedestrian movements inside crowded place that may potentially lead to efficiency gains. Data structure optimization helps to perform broad investigation of different settings that influence on performance of detectors layout. Modularity and facilities for parallelization, which the framework provides, incline to leverage more complex cases with bigger volumes of data. Conducted experimental study shows that generated solutions can be better than ones provided by density-based heuristic. Future research includes an extension and complexification of the case study under the investigation with taking into account portable detectors. Using of such type of the detectors along with static detectors can reduce cost of the whole detection system. Also mobile detectors could be used in an urgent mode for rapid deployment of detection system in case of emergency. In this case optimization problem is more complex and is intended to find optimal patrolling strategy. Another direction is to investigate the capability of building plan correction within the optimization procedure in form of co-evolution. The model of the system of detectors can be enhanced with use of probabilistic graphical models, which are based on an interconnection of information flows about different detectors' decisions (e.g. Bayesian networks model or Markov chains). As this approach relies on an implicit information from different sources, it causes better precision of personal probability estimation. All the described above extensions can be easily integrated to the proposed framework whose modularity is greatly suitable for such cases.

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