STRENGTHENING SECURITY DURING SPORTING EVENTS BY UNMANNED AERIAL VEHICLES

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ABSTRACT

This paper shows how Unmanned Aerial Vehicles (UAVs) can improve security in major sporting events. Given the increase in violence among sports fans it is important to timely monitor possible conflict locations. A UAV can patrol and remotely monitor the activity at these locations. Such a patrol tour should be repeatedly executed in order to constantly update the available information about the different locations. Besides aiming to find a short tour to efficiently monitor all locations, it is important to take into consideration that the UAV might be redirected from its tour to another location where some abnormal activity is taking place. In this paper we introduce a general binary fractional program which provides a method to find a balance between the tour duration and the ability of the UAV to fly to locations of new conflicts as soon as possible. Using a case study we illustrate the purpose of our model.

KEYWORDS. Security, Sport, UAV tour planning, uncertainty

Main area: OA - Other applications in OR, MP- Mathematical Programming

1. Introduction

Violence among sports fans is an ongoing concern in many nations (Russell, 2004). Small conflicts can evolve into riots spreading out over different areas in the city, with fans acting violently and dangerously. An example of such an escalated riot is the 2011 Vancouver Stanly Cup riot, where at least 140 people were reported as injured. Two big screen TVs were set up for fans to watch the game, and at one of these locations a riot started when some spectators started throwing bottles and other objects at the large screens in the viewing area. Later, other disturbances broke out at different locations in the downtown of Vancouver. Boston Bruins flags, Canuck jerseys and even vehicles were set on fire in front of the main Canada Post headquarters. In a nearby parking lot, two Vancouver Police squad cars were later also set on fire. Windows were smashed in a bank and various businesses along the West Georgia corridor, some of which were also looted (Internet: Vancouver Stanley Cup riot).

Prevention and control of riots induces a major cost to society (Russell, 2004). Certain choices, like the means of security to deploy in prevention and control of riots may reduce these costs and improve security at the same time. Given the locations where conflicts between fans may arise, monitoring and providing real-time footage of these locations will improve situational awareness, and as such lead to a more efficient deployment (and thus reduce cost) of other means of security. To this end, we explore how Unmanned Aerial Vehicles (UAVs) could be used as means of security during major sporting events.

UAVs are aircrafts without a human pilot onboard. They are remotely operated from a control station on the ground. They can be used to record pictures or full motion video in order to obtain information about certain activity in an area. Examples of UAV use are protection of wild parks against poachers or wild fires, and obtaining intelligence information in military reconnaissance and surveillance missions (e.g. Evers et al., 2012 and Royset and Reber, 2010). For sporting events, the mobility of UAVs provides an advantage over the use of street cameras. UAVs can be directed to locations where no cameras are installed and they can record footage from different directions. They can therefore be used both to timely identify conflicts that may escalate and to provide more insight into the characteristics of a conflict which will enable a more efficient police use.

To efficiently monitor all predefined locations where conflicts may potentially arise, it is important that the UAV repeatedly patrols all these locations. When the UAV finishes a tour, it will continue flying the same tour again in order to constantly update the information on all locations. Thus, the goal is to find a route with minimal distances between the possible conflict locations to maximize the amount of data collected. At the same time, the UAV could be redirected from its planned tour to another location, based on new information about abnormal activity taking place at a given location. After arriving at this location, the UAV can provide real-time footage to improve the efficiency of deployment of other means of security. For example, the information provided by the UAV can be used to indicate the size of the police force that should be sent to the conflict and the location from where police forces could best approach the conflict.

In this paper we introduce a model in which tour duration is balanced against response time to reach locations that need immediate inspection: the UAV Patrol Planning Problem (UAV-PPP). The first objective is to obtain as much information as possible from observing the predefined conflict locations. As just mentioned, this is influenced by the length of the tour. Finding the shortest possible tour can be modeled by the well-known Traveling Salesman Problem (TSP) of which the resulting tour should then be repeatedly executed. However, our problem differs from the TSP in the sense that we take into account that the UAV has to be redirected from its tour when some abnormal activity is taking place at another location. As such, our second objective is to be able to send the UAV to such a location as soon as possible. In order to achieve this second objective, we aim to minimize the average Weighted Location Reaching Time (WLRT) over the entire tour. This can be modeled by assigning a weight to each location representing the importance of the location. We then define the WLRT of the UAV at its current location as the weighted average time it would take the UAV to reach any other location from its current location. Hence, the resulting model has some similarities to the well known warehouse allocation problem, the p-median problem: finding the *p* warehouses to open that, given a set of customers with known amounts of demand, a set of candidate locations for warehouses, and the distance between each pair of customer-warehouse, minimizes the demand-weighted distance of serving all customers from those *p* warehouses. However, in the p-median problem the goal would be to find the location(s) with the minimum WLRT in a static situation, while in the UAV-PPP the location of the UAV is constantly changing since the UAV performs a patrol tour. Concluding, our model provides a method to find a balance between the performance of patrolling potential conflict locations and the average response time required for the UAV to fly to new conflict locations.

This paper is structured as follows. In the following section we will provide some background on planning problems that are related to the UAV-PPP. In Section 3 we present our model of designing a patrol tour by balancing our two objectives. In Section 4 we present the results of a case study and in Section 5 we conclude and give recommendations for further research.

2. Literature review

The TSP is a well-known, widely researched optimization problem. In the standard TSP the aim is to find a minimum length tour such that all specified locations are visited. The locations may for example represent customer locations and the length of the tour may for example represent travel time, travel cost or fuel consumption. For a survey of the TSP we refer to Gutin and Punnen (2002).

The standard TSP does not take into account adjustments to the tour based on new requests appearing at a certain location during the execution of the tour. Problems that do take real-time information on such new requests into account are generally referred to as 'on-line' planning problems. For the TSP several on-line planning methods have been developed. The Plan-At-Home (PAH) algorithm (Ausiello et al., 2001) for example, describes a rule on how to continue the tour depending on the location of a new request. If the distance between the depot and the new location does not exceed the distance between the depot and the current location, the tour is continued and the new location is considered when reaching the depot next. Otherwise, the tour is aborted and a newly optimized tour, including the new location(s), is started again at the depot. An algorithm based on a decision rule such as the PAH, does not take into account the probability that new a request occurs at a certain location and/or its associated weight, nor does it take into account the time it takes to reach a new request from the current location.

One research that does take these issues into account is related to routing a number of mobile resources (vehicles) to serve foreseen and unforeseen tasks (Larco et al., 2012). Since the tours must satisfy the maximum shift duration, it may happen that not all customer tasks can be fulfilled within the shift. As such, the part of the problem of servicing the foreseen tasks is modeled by the Team Orienteering Problem (TOP). The Orienteering Problem (OP) is a generalization of the TSP where not all (customer) locations have to be visited. The TOP is the multi-vehicle variant of the OP. For unforeseen tasks they consider a so-called 'Time-averaged Maximum Coverage Location Problem' (TAMCLP). An unforeseen task appears at one location out of the set of known customer locations. In the TAMCLP a location is considered to be 'covered' when it can be reached within a predefined time limit. The objective of the TAMCLP is to maximize the average weighted coverage over the entire tour. Like in the UAV-PPP, weights are associated to the locations where potentially new requests could appear.

Our problem is similar to the problem addressed by Larco et al. (2012) but it differs in two aspects. While Larco et al. use a shift length that restricts the total number of locations that can be visited, we assume that the UAV has enough capacity to perform several patrol tours during a desired time period (for instance before the start of a big game and ending some time after the game has finished). Hence, we model this part of our problem as a TSP instead of a (T)OP. The second difference lies in the modeling of the new (unforeseen) tasks. The coverage in the TAMCLP indicates whether or not a certain predefined service level agreement is met with respect to the maximum time it should take to serve unforeseen customer requests. When exceeding the predefined time limit, the new request is considered not to be covered. In our problem however, we consider a gradual decrease in the 'reachability' of a location, since we aim to minimize the *average* time it takes to reach the locations.

3. The UAV Patrol Planning Problem

In this section we introduce the UAV Patrol Planning Problem (UAV-PPP) based on a mathematical problem formulation. The aim of the UAV-PPP is to determine an efficient patrol tour that covers all potential conflict locations, and at the same time to achieve an average small response time in case the UAV is be redirected to a location of a new conflict. We assume that the new conflicts occur at any of the locations from the set of predefined conflict locations that will be patrolled.

In constructing the tour we focus on the response time of handling one specific new request at a time. Note that the patrol tour is designed based on initial knowledge about the different potential conflict locations. When implementing this patrol tour in practice, a strategy would have to be developed on how to act during and after the moment that the UAV is redirected to a location which requires immediate inspection. In Section 5 we give some directions on how this could be done.

Since we are looking at patrolling during a desired time period, the endurance of the UAV is expected to cover this period as well as the time required for the UAV to return to the depot. Therefore, no extra assumption on maximal flight time is necessary. Since there is no constraint on total flight time or fuel usage, the flight times between locations to be patrolled are modeled as estimated flight times. During the patrol tour, we assume that no additional time is required for recording footage at the individual locations and that this information is immediately available to the control room. That is, in case no abnormal activity is observed, the UAV will immediately fly to the next location of its tour. Adjustments to our model to incorporate additional recording time in the observation tour could however be made rather easily.

Since the patrol tour will be repeatedly executed, the location of the depot from which the UAV will start and end its flight will not be taken into account in the modeling. Notice that, during patrolling there is no need to visit the depot location. In practice the UAV patrol tour should start at the location closest to the depot.

3.1 General Fractional 0-1 Programming formulation

We model the UAV-PPP by a General Fractional Program (G-FP). The objective in a G-FP is the summation of several quotient terms composed of linear functions (Li, 1994). Consider a complete graph *G(N,A)*, wherein *N* represents the set of possible conflict locations and *A* represents the set of flight paths between each two locations. Note that we have assumed that all of the locations require observation and at each of them a conflict may potentially occur. To each arc $(i,j) \epsilon A$ we associate a parameter t_{ij} to represent the expected flight time from location i to location j. Secondly, to each arc $(i,j) \epsilon A$ we associate a parameter r_{ij} to represent the average Weighted Location Reaching Time ($\mathrm{WLRT}_{\mathrm{ij}}$) to reach all other possible locations when flying from i to j. As the name suggests, $\mathrm{WLRT}_{\mathrm{ij}}$ includes the importance of all possible conflict locations, which is modeled as a weight w_k to each node $k \epsilon N$. In order to illustrate how r_{ij} can be calculated we use a small example given in Figure 1: the UAV is on its way from location i to monitor location j. Suppose a conflict starts at location k, while the UAV has been flying from i to j for x time units. In calculating r_{ij}, flight time is assumed to be proportional to distance. Then, the time to reach k from the current location is proportional to the distance expressed by:

$$g(x) = \sqrt{x^2 + b^2 - 2xb\cos(\varphi)}.$$

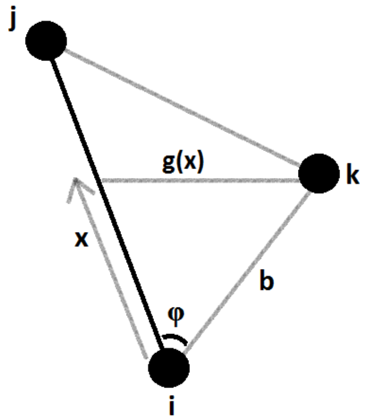


Figure 1: The UAV is on its way from location i to j. At x time units away from i, the function g(x) represents the time it would take the UAV to reach location k from its current location.

To calculate the average time to reach location *k* over all possible locations on arc *(i,j)*, which we will denote by r_{ijk} , the hypograph of *g(x)* between *x=0* and $x=t_{ij}$ should be divided by t_{ij}. The function *g(x)* can be integrated by an analytical expression. Next, by considering not only location *k*, but all possible conflict locations, we obtain the average WLRT_{ij} for arc *(i,j)* by

$$r_{ij} = \frac{\sum_{k\in N} w_k r_{ijk}}{\sum_{k\in N} w_k}.$$

Note that the values r_{ij} are scalar values which can be calculated beforehand for all arcs $(i,j) \in A$. To formulate the UAV-PPP we introduce the decision variables x_{ij}, which are assigned the value 1 in case arc *(i,j)* is selected in the tour and 0 otherwise. The G-FP formulation of the UAV-PPP is the following:

(UAV-PPP)
$$\min \alpha \sum_{(i,j)\in A} t_{ij} x_{ij} + \beta \frac{\sum_{(i,j)\in A} t_{ij} r_{ij} x_{ij}}{\sum_{(i,j)\in A} t_{ij} x_{ij}}, \quad (1)$$

Subject to
$$\sum_{i\in N} x_{ij} = 1 \qquad \forall j \in N, \quad (2)$$
$$\sum_{j\in N} x_{ij} = 1 \qquad \forall i \in N, \quad (3)$$
$$\sum_{i,j\in S} x_{ij} \le |S| - 1 \qquad \forall S \subset N,\ 1 < |S| < |N|, \quad (4)$$
$$x_{ij} \in \{0,1\} \qquad \forall i,j \in N. \quad (5)$$

The difference between this model and the standard TSP formulation is given by the Objective Function (1). In the objective function of the standard TSP formulation, only the first term of (1) is taken into consideration. In our case this term represents our first objective: finding a tour such that the total time required to carry out observation over all locations is minimized. The ratio in the second term of (1) represents the Weighted Location Reaching Time (WLRT), averaged over all possible moments during the entire tour. Minimization of this performance measure is our second objective. Recall that we previously defined WLRT_{ij}, which represents the time it would take to reach any of the predefined potential conflict locations, weighted by their importance, averaged over all possible moments when flying from location *i* to *j*. To calculate the WLRT averaged over all possible moments during the entire tour, the $WLRT_{ij}$ of each arc *(i,j)* selected in the tour should first be weighted by the time the UAV spends travelling the arc. This is expressed by the nominator of the ratio in the second term of Objective Function (1). Then, this term should be divided by the total the total tour length (expressed by the denominator) to obtain the WLRT averaged over all possible moments during the entire tour. Note that selecting an arc with a large flight time t_{ij} on one hand increases the average WLRT of the entire tour by increasing the value of the nominator. On the other hand a shorter total tour length increases the WLRT of the entire tour via the denominator. The parameters α and β are nonnegative scaling parameters of the model to adjust the emphasis on either of the two objectives. Constraints (2) to (5) are the standard connectivity, sub tour elimination and integrality constraints that any feasible TSP tour should satisfy.

3.2 Linearization

Linear fractional programming is a special field of nonlinear programming dealing with optimization problems where the objective is a ratio of two linear functions. Linearizations and solution procedures for linear fractional programming were developed among others by Isbell and Marlow (1956), Charnes and Cooper (1962) and Wolf (1985). Barros (1995) developed solution techniques and theoretical results for linear fractional programs applied to specific operations research problems.

The UAV-PPP contains not only a ratio of two linear functions, but also a linear term. Therefore, our problem can be classified as a General Fractional Program (G-FP). As mentioned before, the objective in a G-FP is the summation of several quotient terms composed of linear functions. Note that the objective function of the UAV-PPP contains two quotient terms, since the linear term can be expressed as a quotient term as well, by dividing it by one. For the special case where the decision variables are binary, which is the case in our problem, a linearization method for G-FPs was developed by Li (1994). We will apply this linearization to the UAV-PPP. First, consider the following transformation:

$$y = \frac{1}{\sum_{(i,j)\in A} t_{ij} x_{ij}}.$$

Using this transformation, program (1) - (5) can be rewritten as:

$$\min \alpha \sum_{(i,j)\in A} t_{ij} x_{ij} + \beta \sum_{(i,j)\in A} t_{ij} r_{ij} x_{ij} y \qquad (6)$$

Subject to

Constraints (2) – (5)

$$\sum_{(i,j)\in A} t_{ij} x_{ij} y = 1, \qquad (7)$$

$$y \geq 0. \qquad (8)$$

The above program still contains nonlinear terms in (6) and (7). To resolve this issue, Li (1994) derived the following theorem: *A polynomial mixed 0-1 term z =xy where x is a 0-1 variable, and y is a continuous variable less than 1, can be represented by the following linear inequalities: (1) y-z ≤ 1-x; (2) z < y; (3) z < x; (4) z ≥ 0*. In the UAV-PPP the condition on *y* to be less than 1 is always satisfied when distances are expressed in units greater than or equal to 1. Applying this theorem, program (1)-(5) can be transformed into the following linear program:

$$\min \alpha \sum_{(i,j)\in A} t_{ij} x_{ij} + \beta \sum_{(i,j)\in A} t_{ij} r_{ij} z_{ij} \;, \tag{9}$$

Subject to Constraints (2)-(5) and (8)

$$\sum_{(i,j)\in A} t_{ij} z_{ij} = 1, \tag{10}$$

$$y - z_{ij} \leq 1 - x_{ij} \qquad \forall (i,j) \in A, \tag{11}$$

$$z_{ij} \leq y \qquad \forall (i,j) \in A, \tag{12}$$

$$z_{ij} \leq x_{ij} \qquad \forall (i,j) \in A, \tag{13}$$

$$z_{ij} \geq 0 \qquad \forall (i,j) \in A. \tag{14}$$

4. Case study

4.1 Data

To illustrate the purpose of our model, we designed an artificial problem instance. Figure 2 shows a map of a city where the football stadium is located in the center at the coordinates (5,5). We have identified four potential conflict locations close to the stadium, as well as eight locations further away. We rate the locations close to the stadium to be five times as important as the locations further away from the stadium.

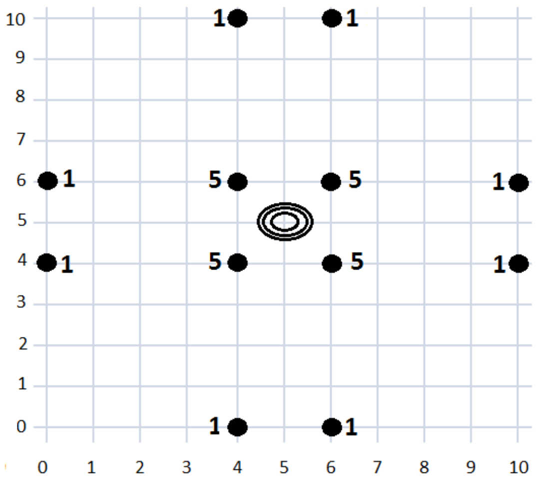


Figure 2: Map of city with football stadium located in the center and conflict locations at different locations in the city. The values (weights) at the locations denote their relative importance.

4.2 Experiments

To illustrate the design and the features of the tours resulting from different settings of our model, we implemented program (9)-(14), combined with the previously defined Constraints (2) to (5) and (8) in Java and performed the optimization with CPLEX 12.1. We will report the results of the following three settings: (α=*1*, β=*0*), (α=*0.8*, β=*0.2*) and (α=*0*, β=*1*). The second setting was chosen after observing the resulting tour durations and average WLRT for the other two settings. We chose this setting to illustrate how this model allows the decision-maker to tune the parameters alpha and beta to observe the trade-off between tour duration and the average time it would take to reach any of the conflict locations at any time during the tour.

4.3 Results

Figures 3 to 5 show the design of the resulting tours for the different settings of α and β, as well as their associated tour duration and the WLRT over the entire tour. The tour depicted in Figure 3 is a result of only minimizing the tour duration, while the tour in Figure 5 is the tour resulting from only minimizing the WLRT. The tour in Figure 4 on the other hand results from one possible setting of taking both objectives into account at the same time.

The tour depicted in Figure 5 has a somewhat remarkable pattern. This pattern is the result of constructing a tour by selecting the arcs such that average time it would take to reach any of the other locations, weighted by the importance of the locations, is minimized. Since the locations around the stadium have a high importance, selecting arcs located close to the stadium contributes to the objective ($\alpha=0, \beta=1$). Since the contribution of an arc to the WLRT of the entire tour does not only depend on its Euclidian distance, it may happen that the tour consists of arcs which cross each other, as is the case for the tour in Figure 5. Note that such a solution would never be optimal in a pure TSP.

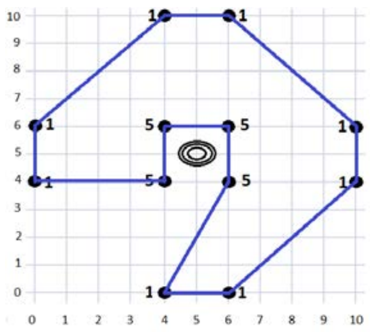
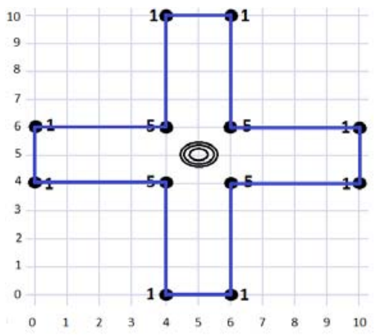
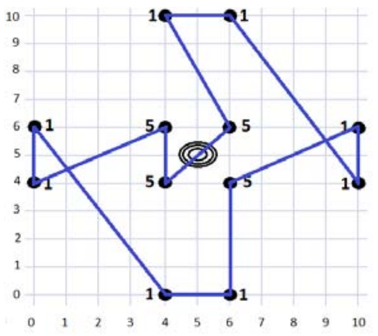
$\alpha=1, \beta=0$	$\alpha=0.2, \beta=0.8$	$\alpha=0, \beta=1$
 Figure 3	 Figure 4	 Figure 5
Tour duration: 39.44	Tour duration: 40.0	Tour duration: 44.66
WLRT: 5.49	WLRT: 5.14	WLRT: 4.82

Figure 3-5: Design of the observation tours and their associated tour duration and WLRT resulting from our model with the settings of ($\alpha=1, \beta=0$), ($\alpha=0.2, \beta=0.8$) and ($\alpha=0, \beta=1$) respectively.

These results illustrate how our model can be used to find a balance between the tour duration of the patrol tour on one hand and the average time it would take to reach a conflict that starts at any of the predefined locations on the other hand.

5. Conclusions and further research

In this paper we investigated the benefits of different tour strategies when using Unmanned Aerial Vehicles (UAVs) as a means of security in major sporting events. We developed a model to find a balance between two objectives. The first objective is to maximize the efficiency of monitoring all locations where potentially conflicts could start. Secondly, in case a conflict starts at another location than the current location of the UAV, it is important that the UAV is able to reach that location as soon as possible, so that it can provide real-time footage of the conflict to the police forces and/or other means of security. Using a case study we illustrated how the design of the patrol tour changes, as we change the emphasis on either one of the objectives.

This model can be extended to the use of multiple UAVs. In that case, the second objective could be to minimize the time it would take the closest UAV to reach the location. Consequently, it would be beneficial to spread the UAVs as 'evenly' as possible over the area at any point in time. Another extension of this model would be to incorporate new conflict locations outside of the set of predefined locations.

In this paper we focused on constructing a tour based on tour duration and response time to reach locations that need immediate monitoring. In order to further operationalize this model and provide guidelines on how the UAVs should be deployed during and after monitoring of such a location, several additional assumptions are required. For example, the time that the UAV remains at the location for monitoring (and possibly to perform support during a conflict) would have to be specified. Secondly, after finishing its task at that location, a decision would have to be made on how to continue the patrol tour again. For short inspections for example, it might be a good strategy to continue at the location where the UAV was situated before it got redirected. On the other hand, if the UAV spent a long time at the location, it might me more convenient to proceed to next location in the patrol tour or to the location closest to the current location.

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