DRONETIM:Dynamic Routing Of uNmanned-aerial and Emergency Team Incident Management

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Dispatching policies for emergency teams has been studied and implemented in order to minimize the time needed to respond to a sequence of incident requests (Park, Wadell, and Haghani, 2019). Nonetheless, an important opportunity for policy improvement is the application of Unmanned Aerial Vehicles (UAV) with emergency teams. The role of the UAV in the heterogeneous vehicle-team is to explore unknown traffic conditions, unexpected situations on roads and enhance already known information from loop detectors, automatic vehicle identification detectors, probe vehicle data, and other types of sensors. One approach to address this integration is through the constraint satisfaction framework (CSP). Though this method may be sufficient, its adoption is limited due to the requirement of satisfying the set of constraints which may pose problems in finding an optimal solution when there are numerous constraint violations. A more comprehensive and general approach would focus on maximizing or minimizing a set of cost constraints to improve the overall benefit of the assignments for the system (Modi et al., 2005; Petcu and Faltings, 2005; Yeah and Yokoo, 2012).

In this study, we present a framework for Dynamic Routing Of uNmanned-aerial and Emergency Team Incident Management (DRONETIM) for improved incident response under a distributed constraint optimization problem (DCOP). In DRONETIM, UAVs and Emergency Response Vehicles (ERVs) are modeled to coordinate their value assignments in order to maximize the total utility of a defined system that is typically subject to multiple cost constraints. In CSP, the vehicles, represented by $A = UAV_n \cup ERV_m, \forall n \in N, m \in M$ are assigned to tasks X_i subject to a set of constraints including but not limited to resource constraints for total assignment to vehicle a and deadline for a given task. In DRONETIM, UAVs hold variable X_{UAVn} where $n \in N$ is the number of UAVs. The domain $D_{X_{UAVn}}$ for the variable X_{UAVn} is the set of possible regions $r \in R$ that make up the grid network where R is the number of regions. As an example, $UAV1$ holding variable X_{UAV1} has a domain given by $D_{X_{UAVn}} = \{1, 2, \ldots . R\}$.

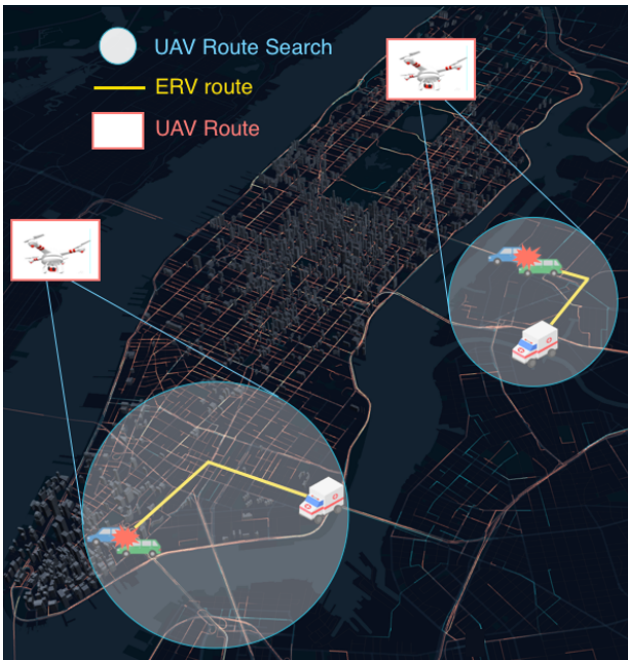


Figure 1 UAVs information sharing with ERVs for traffic incident management

The cost $c_r^n : D_{X_{UAVn}} \rightarrow \mathbb{R}$, of $UAVn$ monitoring region r is given by the resource consumed when assigned to region r as $c_r^n = k * |d_{i,r}| + K_r$, where k is power consumed per unit distance of flight, $|d_{i,r}|$ is the Euclidean distance between UAVs current location i and region r and K_r is fixed power consumed in monitoring region r. The sum of costs for value assignments of vehicle $UAVn$ cannot be more than available resource A_n given by $\sum_{r \in R} c_r^n \leq A_n$. The benefits $b_r^n : D_{X_{UAVn}} \rightarrow \mathbb{R}$ of $UAVn$ monitoring region r is defined through: 1. The type of incident β_r^h in region r., 2. The density ρ_r of routes/links in region r. The function is defined as $b_r^n(\rho_r, \beta_r^h) = \alpha * \rho_r + \sum_{h=1}^{H} \beta_r^h$, where α and β_r^h are constants describing general traffic state at given time of day, a value for severity of incident (e.g., single car, multiple car, hazardous vehicle, etc), type h. The utility $U_r^n : D_{X_{UAVn}} \rightarrow \mathbb{R}$ of $UAVn$ monitoring region r is defined as the difference between the benefit b_r^n and the cost c_r^n given by $U_r^n = b_r^n - c_r^n$. ERVs hold a variable X_{ERVm} where $m \in M$ is the number of ERVs. The domain $D_{X_{ERVm}}$ for the variable X_{ERVm} is the incident $I_r^h \in R$ in the grid network. As an example, within a given time window, ERV1 holding variable X_{ERV1} may have a domain given by $D_{X_{ERV1}} = \{I_1^1, I_1^2, I_2^3, \ldots, I_r^h\}$, with incidents $I_1^1 = 1, I_1^2 = 1, I_2^3 = 2, \ldots, I_r^h = r$. Current state of ERV is its current location j and available resource A_j at that location represented by the pair (j, A_j). The cost $c_{I_r^h}^m : D_{X_{ERVm}} \rightarrow \mathbb{R}$, of $ERVm$ to arrive at incident I_r^h in region r is given by the resource consumed to assign to region as $c_{I_r^h}^m = q * \left|d_{j,I_r^h}\right| + Q$. Where q is energy consumed per unit distance, $\left|d_{j,I_r^h}\right|$ is the Manhattan distance between the ERV's current location j and incident I_r^h and Q is extra energy consumed due to detours. The sum of cost for value assignments of vehicle $ERVm$ can not be more than the available resource A_m. This is represented by $\sum_{r \in R} c_{I_r^h}^m \leq A_m$, and can

be relaxed to assume ERVs always have energy to attend to any incident within their grid in a time window.

A UAV and ERV cannot be assigned to two regions in the same time window. This is represented by the relations below.

$$\forall A_{UAVn}, B_{UAVn} \in X_{UAVn} \times X_{UAVn}, A \neq B \Rightarrow A_{UAVn} \neq B_{UAVn}$$

$$\forall A_{ERVm}, B_{ERVm} \in X_{ERVm} \times X_{ERVm}, A \neq B \Rightarrow A_{ERVm} \neq B_{ERVm}$$

The following represents the utility constraints between any two variables: UAV provides information about region to ERV and this quantifies the cost constraint between the two vehicles

$$u\left(X_{UAVn}, X_{ERVm}\right) = \begin{cases} \alpha * \rho_r & \text{if } X_{UAVn} == X_{ERVm} \\ 0 & \text{otherwise} \end{cases}$$

To optimize the monitoring of regions by UAV's, the overlap or common surface area $\Omega\left(X_{UAVa}, X_{UAVb}\right)$ between any two regions is defined as.

$$u\left(X_{UAVa}, X_{UAVb}\right) = \begin{cases} -\Omega\left(X_{UAVa}, X_{UAVb}\right) & \text{if } X_{UAVa} \neq X_{UAVb} \\ -\infty & \text{otherwise} \end{cases}$$

To optimize the use of ERVs', the utility for value assignment of ERVs' to different incidents is defined as .

$$u\left(X_{ERVa}, X_{ERVb}\right) = \begin{cases} 0 & \text{if } X_{ERVa} \neq X_{ERVb} \\ -\infty & \text{otherwise} \end{cases}$$

The coordination of value assignment is such that UAVs' and incident region are same for ERV to utilize information from region to reach incident efficiently. If the set of variables is defined as $X = \{X_{UAVn} \cap X_{ERVm}\}$, and each variable X_i takes a value in the finite set of domain D_i then the joint domain D_X is defined as the Cartesian product of the domain of each variable $D_X = D_{X_{UAVn}} \times D_{X_{ERVm}}$. $\mathbf{X}_i$ refers to the possible assignment of X_i. $\mathbf{X}_i \in D_i$ and $\mathbf{X}$ is the possible joint assignment of variables in X, i.e. $\mathbf{X} \in D_X$. For a given sequence of variables $S \subseteq X$, a factor is a function $u : D_S \to [-\infty, \infty)$. Variables in the scope of u is referred to as X_u. The set of factors of the problem is denoted by U. The max-sum algorithm provides an approximate solution to the problem of maximizing a function that decomposes additively as a sum of functions with smaller scope.

$$\text{maximize} \sum_{u \in U} u\left(\mathbf{X}_u\right) \quad \forall i \in \{1, \ldots, N, 1, \ldots, M\}$$

subject to $\mathbf{X}_i \in D_i$. $\mathbf{X}_{\mathrm{u}}$ contains the values assigned by $\mathbf{X}$ to the variables in the scope of factor u. Messages are sent from variables to factor and vice-versa, repeated for a specified number of iterations.

$$\mu_{x \to u}(\mathbf{X}) = \sum_{u' \in \aleph(x) \setminus \{u\}} \mu_{u' \to x}(\mathbf{X})$$

$\aleph(x)$ is the factors that have variable x in its scope, and $\mu_{u' \to x}$ is the last message received by variable x, from factor u'

$$\mu_{u\to x}(\mathbf{X}) = \max_{S}\left(u(\mathbf{X},\mathbf{S}) + \sum_{s\in S}\mu_{s\to u}(\mathbf{X})\right)$$

Max-sum determines the optimal value at the next stage independently for each variable

$$\mathbf{X}^* = \arg\max_{\mathbf{X}} \sum_{u\in\aleph(x)} \mu_{u\to x}(\mathbf{X})$$

Scenarios	Assignment 1	Assignment 2	Assignment 3	Assignment 4
1	UAVs ERVs	UAVs ERVs	UAVs ERVs	UAVs ERVs
Agents: 2	0 1	1 0	1 1	1 1
Variables: 2	Optimal value: 33	Optimal value: 37	Optimal value: 50	Optimal value:50
2	UAVs ERVs	UAVs ERVs	UAVs ERVs	UAVs ERVs
Agents: 2	0 1	1 0	1 1	1 1
Variables: 3	Optimal value: 320	Optimal value: 400	Optimal value: 425	Optimal value:425
3	UAVs ERVs	UAVs ERVs	UAVs ERVs	UAVs ERVs
Agents: 3	1 1	1 2	2 1	1 2
Variables: 3	Optimal value: 345	Optimal value: 425	Optimal value:445	Optimal value:550
4	UAVs ERVs	UAVs ERVs	UAVs ERVs	UAVs ERVs
Agents: 4	0 1	1 1	2 1	2 2
Variables: 4	Optimal value: 443	Optimal value: 595	Optimal value:605	Optimal value:610
5	UAVs ERVs	UAVs ERVs	UAVs ERVs	UAVs ERVs
Agents: 7	2 2	3 4	3 4	3 4
Variables: 7	Optimal value: 610	Optimal value: 630	Optimal value: 670	Optimal value: 690
6	UAVs ERVs	UAVs ERVs	UAVs ERVs	UAVs ERVs
Agents: 8	1 3	2 3	3 4	4 4
Variables: 7	Optimal value: 1180	Optimal value: 1193	Optimal value: 1195	Optimal value: 1240
7	UAVs ERVs	UAVs ERVs	UAVs ERVs	UAVs ERVs
Agents: 12	1 2	2 4	6 7	4 6
Variables: 10	Optimal value: 1197	Optimal value: 1191	Optimal value: 1335	Optimal value:1675

Figure 2 Sample results for multiple scenarios for CSP showing the assignment process for UAVs and ERVs to optimize the value assignment

The expected results for multiple scenarios using DRONETIM will be presented with a comparative analysis of the benefit gained through our framework when compared with CSP. This research presents the first DCOP framework for coordinating UAVs and ERVs for improved response to emergencies. The proposed method is unique since it addresses communication between the heterogeneous vehicle for improved efficiency.

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