Connecting trapped civilians to a wireless ad hoc network of emergency response robots

Georgios Loukas and Stelios Timotheou
Intelligent Systems and Networks Group
Imperial College London
Exhibition Road, SW7 2BT
{gl1, stelios.timotheou05}@imperial.ac.uk

***Abstract*—During a disaster, communications are usually impaired. In order for the rescuers and endangered civilians to communicate, we suggest the use of mobile robots that can act as wireless routers. We describe how they can locate trapped civilians and initiate an ad hoc network connection between them and the rescuers, so that the latter can better assess the situation and plan the rescue operation accordingly. The novel problem that arises is the optimal allocation of these robots so that they connect as many civilians as possible, while maintaining their multi-hop connection with a static wireless sink that represents the group of rescuers. We present a centralised formulation, which stems from a combination of characteristics typically found in assignment and network flow optimisation problems. We consider both exact locations for the civilians and uncertain locations with a probabilistic representation. We also present a distributed heuristic with which the robots start from the location of the sink and move autonomously trying to connect the civilians while maintaining connectivity. We evaluate our distributed heuristics in a building evacuation simulator and compare them with the centralised approach.**

I. Introduction

During an emergency, it would be particularly desirable to establish some sort of continuous communication between the rescuers and the victims. For this reason, we have investigated the use of robots equipped with wireless devices that form a network to connect civilians with rescuers. In recent years, mobile robots have been routinely used in emergency response operations to reach areas that are inaccessible to humans. Usually, they are designed to search for victims, inspect structural integrity, or detect hazardous materials, but with recent advances in small-size robotics and wireless communications, emergency response robots can also be designed to form ad hoc networks. For example, the first priority during a disaster may be to establish network communication with immobilised civilians, so that the rescuers better assess their condition and plan their course of action accordingly. Our aim is to provide mobility mechanisms and strategies with which emergency response robots will establish two-way network connection between the rescuers and as many civilians as possible. We assume that the civilians carry some wireless device that can be used to transmit video or initiate a VoIP connection over a short range. The goal of the mobile robots is to get in range of these devices, so as to route their network traffic to the rescuers, which we represent as a static wireless sink. Examples of robots, where this ad hoc networking paradigm applies include the Soryu III [1], which provides live video streaming and two-way voice connection with trapped civilians, and Packbot that is designed for military operations [2].

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Ad hoc networking for the collaboration of search and rescue robotic operations was first suggested in [3] and further investigated in [4], [5], but their authors assumed star topology with a control station in the centre of the search area, which is usually impractical during a disaster. Here, we tackle the fundamental problem of the optimal allocation of such robots that need to form an ad hoc network with all or as many static civilians as possible while at the same time being connected to a wireless sink over multiple hops. Commonly, robotic networks are formed so that they optimise network criteria, such as fault tolerance via bi-connectivity [6], area coverage [7] and power-efficiency [8], [9]. Related problems can also be found in the field of network design, but they usually refer to wired networks and their goal is to select or add links to achieve some network objectives [10], [11]. Finally, mobility-assisted relocation has also been explored in sensor networks, but the focus in such networks is either the area coverage or the degree of connectivity, and not the connection of specific targets [12].

II. Assumptions

Emergency response operations are usually carried out in constrained environments. For this reason, we choose a graph $G = (V, E)$ representation of the physical world, which is preferable for environments where there are limited movement options for the robots. Let us assume that R_{civ} is the range of the device carried by each civilian and R_{rob} is the range of the wireless robots. Let us also assume that two-way connection between two wireless devices is guaranteed when their euclidian distance is smaller than the minimum of their respective ranges. The robots need to maintain multi-hop connectivity with a static wireless sink s, which may represent a command centre or a group of rescuers. A civilian is successfully connected to the network if he/she is connected to a robot that is in turn connected to the sink. Also, we assume that the physical world graph G is known to the robots.

III. A CENTRALISED APPROACH

A. A centralised formulation

Our goal is to find appropriate positions for the robots so that the number of connected civilians is maximised and the connectivity of the formed network is maintained. The robots have identical characteristics and hence do not need to be explicitly distinguished; we only need to find optimal locations for them. The binary decision variables $\mathbf{x} = \{x_u : u \in V\}$ denote whether a robot should be allocated to vertex u.

To capture connectivity relationships, we use the binary matrices A and B to represent robot-to-robot and robot-to-civilian connectivity respectively. A is a $|V| \times |V|$ matrix with its $A_{u,v}$ element representing whether vertex $v \in V$ is in range R_{rob} of vertex $u \in V$. The $M \times |V|$ matrix B has elements $B_{c,u}$ equal to 1 if a robot at vertex u would be connected with civilian c.

To formulate the problem, we also need to introduce the binary variables $y_c, c = 1, ..., M$, where M is the number of civilians. Variable y_c shows whether civilian c has been connected by at least one robot. The problem can be formulated as follows:

$$\text{maximize} \sum_c y_c \tag{1a}$$

$$\sum_u x_u <= N, \tag{1b}$$

$$y_c = \min\{1, \sum_u x_u B_{c,u}\}, \forall c \tag{1c}$$

$$c_{u,v} = \max\{0, A_{u,v}x_u + A_{v,u}x_v - 1\}, \forall u < v \tag{1d}$$

$$c_{v,u} = c_{u,v}, \forall u < v \tag{1e}$$

$$c_{u,u} = 0, \forall u \tag{1f}$$

$$-\frac{1}{N}x_u + \sum_v f_{v,u} = \sum_v f_{u,v}, u \neq s \tag{1g}$$

$$\frac{1}{N}\sum_{u \neq s} x_u + \sum_v f_{v,u} = \sum_v f_{u,v}, u = s \tag{1h}$$

$$0 \leq f_{u,v} \leq c_{u,v}, \forall u, v \tag{1i}$$

$$x_u \in \{0, 1\}, \forall u \tag{1j}$$

where N is the number of robots, whereas $f_{u,v}$ and $c_{u,v}$ are continuous variables that denote the amount of traffic flow and the capacity of link (u, v). A link capacity is nonzero if there are robots at vertices u and v and they are connected. The auxiliary variables $f_{u,v}$ and $c_{u,v}$ have been employed to deal with the multi-hop connectivity constraint.

In the above formulation, Eq. (1b) indicates that we cannot use more than N robots, while Eq. (1c) represents whether civilian c is connected to the network. To formulate the connectivity matrix of the robots for given robot positions $\mathbf{x}$, we have employed a network flow formulation. If two robots at u and v are connected, then according to Eq. (1d) - (1f) the capacities $c_{u,v}$ and $c_{v,u}$ are equal to 1; otherwise they are equal to zero. Hence, the actual links of the formed network for specific robot locations are represented by the nonzero capacities. Connectivity is ensured if small hypothetical traffic flows from the sink s can reach all robot nodes. Transmission of traffic flows in the network implies that the flow conservation equations (1g)-(1i) are satisfied so that the total incoming traffic to any vertex is equal to its total outgoing traffic.

In Eq. (1g) and (1h), the first term represents the supply b_u of vertex u which accounts for the amount of flow that enters the network from the outside. Note that a source vertex has positive supply $b_u > 0$, a sink vertex negative supply $b_u < 0$, and transshipment vertices have $b_u = 0$ [13]. If the amount of traffic sent from the sink vertex to each of the robots is equal to $1/N$, the total amount of traffic received by a link never exceeds 1 and the capacity constraint (1i) is never violated. Consequently, the set of Eq. (1g), (1h) is feasible only when all robots are connected to the sink. Also, the sink's supply must be equal to the robots' total demand so that $\sum_u b_u = 0$.

Due to the presence of the *min* and *max* terms in Eq. (1c) and (1d) respectively, the above formulation is not linear. However, both expressions can be transformed into equivalent linear ones. In our case, Eq. (1c) is equivalent to the combination of Eq. (2b), (2c) and the goal function (2a). This is because when $\sum_u x_u B_{c,u} = 0$, then Eq. (2b) and (2c) force y_c to zero. Additionally, when $\sum_u x_u B_{c,u} \geq 1$, then $0 \leq y_c \leq 1$ and expression (2a) ensure that y_c will take the maximum value in that interval, i.e. $y_c = 1$.

$$\text{maximize} \sum_c y_c \tag{2a}$$

$$\sum_u x_u B_{c,u} \geq y_c, \forall c \tag{2b}$$

$$0 \leq y_c \leq 1, \forall c \tag{2c}$$

Furthermore, constraint (1d) is equivalent to constraints (3a)-(3d). Eq. (3b) - (3d) force $c_{u,v}$ to zero when not both terms $A_{u,v}x_u$ and $A_{v,u}x_v$ are equal to 1. In addition, when both terms are equal to 1 then from Eq. (3a) $c_{u,v} \geq 1$ and from Eq. (3b) and (3c) $c_{u,v} \leq 1$, implying that $c_{u,v} = 1$.

$$A_{u,v}x_u + A_{v,u}x_v - 1 \leq c_{u,v}, \forall u < v \tag{3a}$$

$$A_{u,v}x_u \geq c_{u,v}, \forall u < v \tag{3b}$$

$$A_{v,u}x_v \geq c_{u,v}, \forall u < v \tag{3c}$$

$$0 \leq c_{u,v} \leq 1, \forall u, v \tag{3d}$$

The described centralised formulation provides an optimal solution to the problem when the civilian positions are known. However, a slightly modified formulation can provide an optimal solution also in the case of uncertain locations.

Let $E[Z_u]$ represent the expected number of civilians at vertex u and y_u show if the civilians at vertex u are connected. Let also the $|V| \times |V|$ binary matrix D represent the connectivity of robots with possible locations of civilians, where element $D(u, v)$ shows whether a robot at location u can

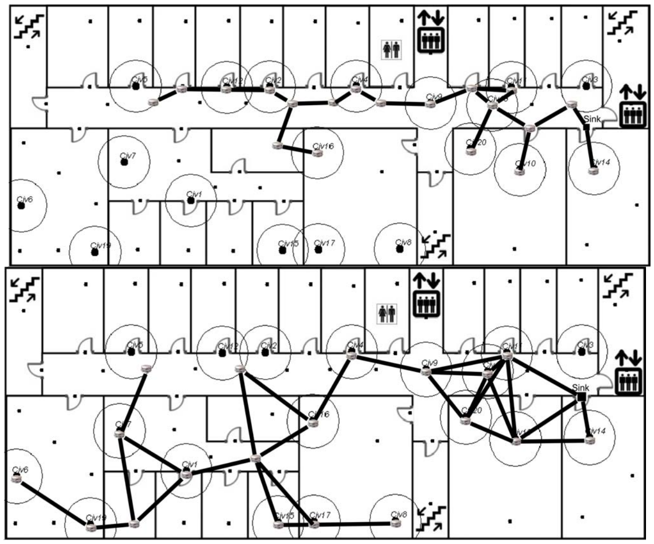

Fig. 1. Robot allocations according to the centralised solutions for (i)$R_{rob} = 8m$ and $R_{civ} = 4m$, (ii)$R_{rob} = 14m$ and $R_{civ} = 4m$

connect civilians at location v. To obtain a formulation for the uncertain locations case we need only to replace expressions (1a) and (1c) in formulation (1) by expressions (4a) and (4b) respectively.

$$\text{maximize} \sum_u E[Z_u] y_u \tag{4a}$$

$$y_u = \min\{1, \sum_v x_v D_{v,u}\}, \forall u \tag{4b}$$

B. Numerical results using the general centralised approach

We have performed numerical evaluation of our approach for varying number of robots. In the case of known locations of civilians, we have constant number of civilians $M = 20$. For the solution of problem (1), a standard mixed integer programming solver was employed. Fig. 1 shows two instances of optimally allocated robots for combinations of robot and civilian ranges. In Fig. 2, the effect of the number of robots was examined for different combinations of civilian and robot ranges. Interestingly, the civilian connectivity increases linearly with the number of robots. Similar behaviour is observed for the case of uncertain locations of civilians (Fig. 3), when employing the corresponding formulation. For the latter, we have used a truncated exponential distribution of civilians with mean 0.25 civilians per vertex and created 20 different sets of civilian locations.

IV. A DISTRIBUTED APPROACH

The centralised approach presented in Section III provides an exact solution to the problem of allocating robots to locations, but may be considerably demanding in terms of processing. For this reason, a more practical approach is to use a distributed algorithm that can be run on each robot and make use of the ad hoc network that the robots are forming for their cooperation.

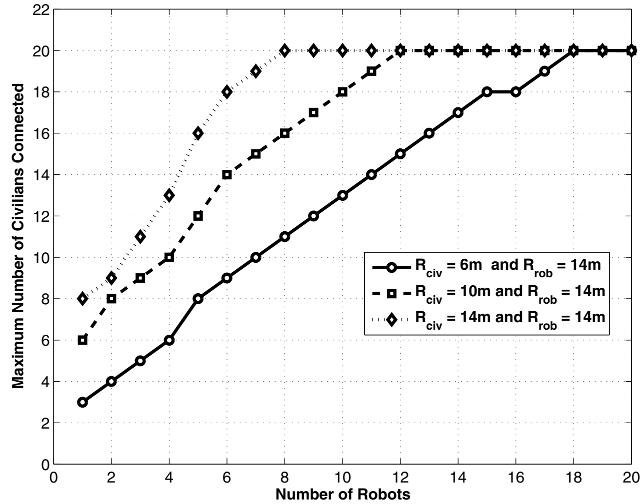

Fig. 2. Maximum number of connected civilians for varying number of robots and different combinations of ranges, for known locations of civilians

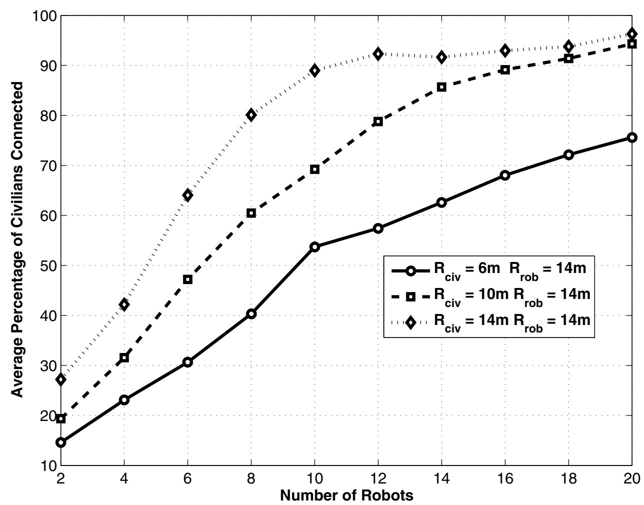

Fig. 3. Average percentage of connected civilians for varying number of robots and different combinations of ranges, for uncertain locations of civilians

A. The distributed algorithm

We address the challenge of retaining connectivity between the robots with the use of a clustering scheme. If we assume the maximum radius of each cluster to be smaller than $R_{rob} + R_{civ}$ and the graph G to be sufficiently dense, then when inside a cluster the connectivity constraint is always satisfied. Within the cluster, the robots can simply be allocated according to the number of civilians they will connect. This clustering approach is realistic in the context of emergency response, because the civilians in a disaster area are naturally clustered in groups, either because they were together when the disaster happened or because they grouped in their effort to survive. In practice, the wireless sink or one of the robots is responsible to group the locations of the civilians into clusters according to the k-means clustering algorithm and inform all robots about this grouping. Connectivity between clusters is maintained by forming chains of robots with maximum distance R_{rob} between them. Essentially, the heuristic approach is composed of two stages:

- *Find the most attractive cluster*. The metric for the attractiveness of a cluster is the number of civilians that it contains divided by the distance to the cluster
- *Allocate robots inside this cluster and the rest move on to the next cluster*. When on a cluster centre, each robot moves to a location that maximises the number of connected civilians of this cluster, until all are connected.

This is presented in more detail in Algorithm 1.

Algorithm 1 Heuristic distributed algorithm

Run on the sink or one of the robots before they start moving
Partition the vertices of the civilians into clusters of maximum distance $R_{rob} + R_{civ}$ from the cluster's centre using the k-means algorithm, and inform all robots.
Run on all robots before they start moving
Identify most attractive cluster centre, set it as objective and move towards it. The metric is the number of civilians that belong to the cluster divided by the distance.
Run on each robot every time they arrive at a vertex

```
if Current vertex is the objective then
  if Current vertex is a cluster's centre then
    if Some other robot already settled on this vertex then
      if There exists at least one civilian of this cluster
      that is not yet connected to the network then
        Find vertex from where the maximum number
        of unconnected civilians of this cluster are con-
        nected, set it as objective and move towards it
      else
        Identify next most attractive cluster centre, set it
        as objective and move towards it.
      end if
    else
      Stay on this vertex and inform all other robots
    end if
  else
    Stay on this vertex to ensure connectivity and inform
    all other robots
  end if
else
  if Connectivity will be lost if this robot continues towards
  its objective then
    Stay on this vertex to ensure connectivity and inform
    other all robots
  else
    Continue towards objective.
  end if
end if
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B. Simulation results for the distributed algorithm

In order to evaluate our distributed algorithm, we implemented it as the movement decision model of robot agents in the Building Evacuation Simulator [14]. Figure 4 shows the final allocation of the robots for the given civilian clustering,

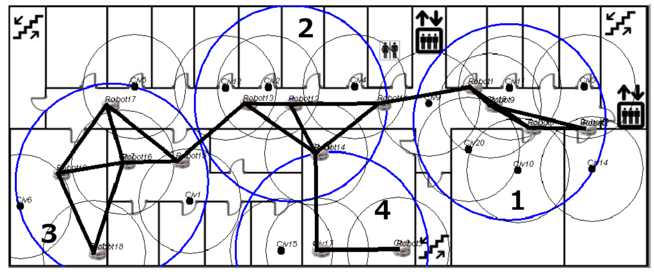

Fig. 4. Solution of the distributed algorithm for the given clustering of civilians

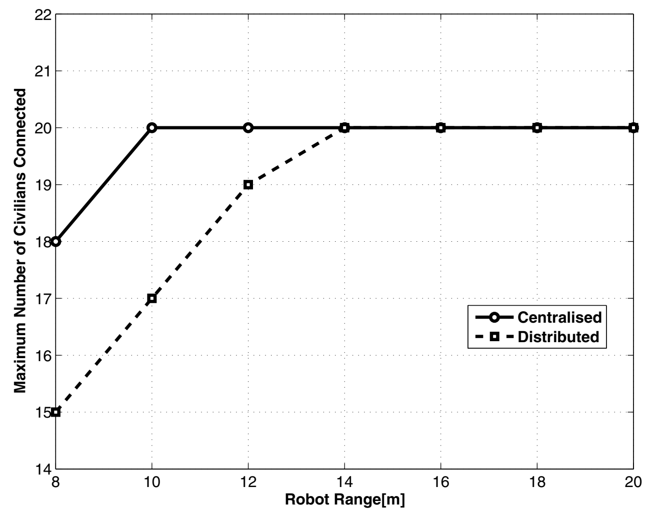

Fig. 5. Comparison between the distributed and centralised approach in terms of number of connected civilians against the wireless range of the robots

where the larger circles represent the clusters and the smaller circles are the ranges of the civilians. The robots moved first to cluster 1, which was closer and had the most civilians, connected all its civilians, and the remaining robots moved to clusters 2, 3 and 4 according to the attractiveness metric. The distributed heuristic reached comparable results with the centralised solution (Fig. 5), but with an average increase of approximately 40% for the distance travelled by the robots. With the centralised approach the robots know their destination before they start moving and go there directly, while in the distributed case the robots need to move around the area and gradually identify their final positions.

C. Introducing uncertainty

In this section we do not any more consider a priori known locations of civilians. Let $Prob(Z_u = m)$ be the probability mass function associated with the number of civilians on vertex u. Since the robots are aware only of the probability distribution of the civilians in the area and there is a limited number of robots, they need to move so that they maximise the number of civilians that they will connect with low risk. For this reason, we employ a risk measure, the Expected Shortfall $ES_q(u)$, borrowed from the field of financial risk management, which shows the expected number of civilians on location u in the worst $q\%$ cases [15]: $ES_q = \mathbf{E}(Z_u | Z_u < m)$ where

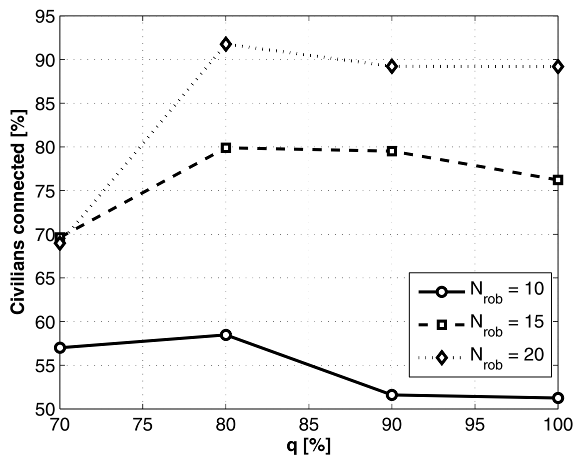

Fig. 6. Evaluation of the distributed heuristic for different numbers of robots N_{rob} and varying risk parameter q

m is determined by $Prob(Z_u < m) = q$ and q is the given threshold. Note that for $q = 100\%$, the expected shortfall is equal to the expected number of civilians.

The distributed heuristic now changes in the following aspects:

- The robots resolve the uncertainty for each vertex that they visit, and the rest of the robots are informed through the network they form.
- Each vertex is described by a value for the expected shortfall, ES_q. A vertex is included in the set of vertices to be clustered only if $ES_q > ES_{th}$, where ES_{th} is an appropriately selected threshold for the expected shortfall. Thus, clustering is perform for that set of vertices only.
- The attractiveness of the clusters is associated with the sum of the expected shortfall of the clustered vertices of the particular cluster and the distance between the robots and the cluster considered.
- When all vertices of a cluster are covered, a robot reduces the ES_{th} threshold, computes new clusters for the remaining vertices and informs the rest of the robots. With this scheme, the robots move gradually from locations of high to locations of low ES_q.

We have evaluated our heuristic for varying risk parameter q for truncated exponential distribution of civilians with mean 0.25 civilians per vertex (Fig. 6).

Moderate-risk strategies ($q = 80 - 90\%$) yielded better results than the high-risk ($q = 100\%$) and low-risk strategies ($q = 70\%$). The latter on several occasions missed distant high-reward clusters, while the former allocated robots to locations where their expectations were not met.

V. Conclusions and Future Work

We have proposed the use of mobile robots with wireless capabilities for the establishment of communication between rescuers and endangered civilians in a disaster. We addressed the problem of optimal allocation of these robots in a disaster area with the goal of maximising the number of civilians that are connected to an ad hoc network formed by the mobile robots. We developed both a centralised formulation and distributed heuristic to achieve this goal. The centralised formulation allows us to examine the effect of the different parameters of the problem, as well as provide a comparison basis to evaluate any non-optimal approaches, such as our heuristic. In both approaches, we considered a priori known, as well as uncertain locations of civilians.

In the future we intend to improve the current distributed heuristic with an additional level of optimisation in terms of the selection of clusters and the parallel choice of different clusters by groups of robots, so that the necessary number of robots and the average energy consumption are minimised.

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