Joint Mission and Communication Aware Mobility Control in Mobile Ad-Hoc Networks

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***Abstract*—In this paper, we study a mobility control problem in mobile ad-hoc networks with controllable mobility. Especially, we consider mission-critical networks in which nodes have their own specific missions whose degree of satisfaction depends on the their locations as well as want to maintain a good communication quality with their neighbor nodes that also depends on their locations. Hence, in this paper, we study a joint mission and communication aware mobility control problem. We formulate the problem as a potential game and develop a distributed algorithm that converges to the Nash equilibrium. In addition, we also show that if some minor conditions are satisfied, our algorithm provides a global optimal solution that minimizes the weighted sum of costs for mission and communication.**

I. Introduction

In general, the communication quality between two nodes depends on the channel condition of the link between them, which in turn strongly depends on the distance between them. As the distance between two nodes increases, the channel condition of the link between them gets worse, and thus the error rate increases and the achievable data rate decreases. On the other hand, in many cases in mission-critical networks, the mission of a node is location-specific. For example, consider a surveillance network for a specific area with networked robots each of whose mission is to lookout its own sub-area. In this case, each robot may have the best spot for keeping watch on its sub-area, and as it further deviates from that spot, the degree of satisfaction for its mission might get more degraded. In other words, the best location of each node varies according to the object of mobility control, i.e., communication quality and mission. Hence, it is important to control the mobility of nodes jointly considering their communication quality and mission to improve the overall performance in mission-critical networks.

In this paper, we study the problem that determines the locations of nodes in the mission-critical ad-hoc network with jointly considering their missions and communication qualities. We define two cost functions for each node that represent its degree of dissatisfaction for its communication quality and mission, respectively. We then define the overall cost function for a node as the weighted sum of its costs for communication quality and mission, and try to minimize the sum of overall costs of all nodes in the network. Since the problem is a non-convex optimization problem, which is inherently difficult to solve, we take a game-theoretic approach, in which each node tries to minimize its own cost function by controlling only its own mobility in a distributed way. We will show that our game possess an exact potential function, and thus our game is a potential game. We provide a distributed algorithm that converges to the Nash equilibrium by using theories of the potential game. In addition, we also show that if some minor conditions are satisfied, our algorithm converges to the global optimal solution that minimizes the sum of cost functions of all nodes in the network.

Recently, mobility control or node placement problems are studied in mobile ad-hoc networks [1]–[6]. However, they considered only communication aware mobility control, while in this paper, we consider joint mission and communication aware mobility control. Hence, the frameworks that are developed in [1]–[6] cannot be used to solve the problem in this paper, and thus we take a different approach from those in [1]–[6]. Recently, a similar problem to ours is studied in [7], [8], where a mobility control problem of robots jointly considering both communication (routing) and task. However, in [7], [8], a simple physical layer model for communication is used to obtain a link reliability metric and no convergence nor optimality analysis is done for the proposed algorithm. The authors propose a centralized algorithm in [7] and a distributed algorithm in [8], which is the extended work of [7].

This paper is organized as follows. In Section II, we introduce our system model and problem. We provide our mobility control algorithm in Section III. In addition, we provide numerical results in Section IV. Finally, we conclude in Section V.

II. System Model

We consider a mobile ad-hoc network that consists of set $\mathcal{N}$ of nodes. Each node has controllable mobility, i.e., the location of each node can be controlled by itself or operator to fulfil its mission and improve its communication quality.

The location of node i is denoted by (x_i, y_i). Even though a node can be mobile, we assume that its movement is constrained within a rectangle, which is defined as

$$x_i^{min} \leq x_i \leq x_i^{max} \quad \text{and} \quad y_i^{min} \leq y_i \leq y_i^{max}, \quad \forall i \in \mathcal{N}.$$

In addition, we assume that the connectivity of the network

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is not changed. In other words, a node has a fixed set of its neighbor nodes that it can communicate with. We denote the set of neighbor nodes of node i as $\mathcal{N}_N(i)$. We assume that each node i can easily obtain information on the locations of its neighbor nodes through message passings with them.

Each node has its own mission that can be fulfilled perfectly when it is at a specific location, which we call its target location (for mission). We denote the target location of node i as (x_i^M, y_i^M). Even though each node has its target location, we allow it to move around its target location, if necessary. For example, a node can deviate from its target location to maintain a good communication quality with its neighbor nodes. However, we assume that the degree of satisfaction for the mission of a node decreases as the distance between its current location and target location increases. We call the distance between current location and target location of a node its *location deviation*. Hence, the location deviation of node i is defined as

$$d_i^M(x_i, y_i) = \sqrt{(x_i - x_i^M)^2 + (y_i - y_i^M)^2}, \quad \forall i \in \mathcal{N}. \quad (1)$$

The degree of satisfaction for the mission of node i is represented as a cost function for its mission, $C_i^M(d_i^M)$, which is a function of its location deviation. We assume that function $C_i^M(d_i^M)$ is an increasing and strictly convex function of d_i^M.

With locations of node i and its neighbor node j, the distance between them is obtained as

$$\begin{aligned} d_{i,j}(x_i, y_i, x_j, y_j) =& \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, \\ & \forall i \in \mathcal{N}, \forall j \in \mathcal{N}_N(i). \end{aligned} \quad (2)$$

We assume that the path gain of a transmitting link from node i to its neighbor node j depends on the distance between them. Then, the received signal-to-noise ratio (SNR) of a link from node i to node j, $\gamma_{i,j}$ is obtained as

$$\gamma_{i,j}(d_{i,j}) = \frac{K_{i,j} d_{i,j}^{-\alpha} P_i}{N_0}, \quad \forall i \in \mathcal{N}, \forall j \in \mathcal{N}_N(i), \quad (3)$$

where $K_{i,j}$ is some constant that depends on transmitter and receiver nodes i and j, α is the path gain exponent, P_i is the transmission power of node i and N_0 is the noise power level, which are assumed to be fixed.

We assume that the underlying medium access control (MAC) protocol is given (either by scheduling or random access) such that the time fraction that node i can transmit its data to its neighbor node j successfully is given by $T_{i,j}$. In addition, we assume that each node i can transmit its data to its neighbor node j at a rate given by the Shannon capacity according to the received SNR at receiver node j. Hence, the average achieved data rate of a transmitting link from node i to its neighbor node j, $R_{i,j}(d_{i,j})$, is obtained as

$$\begin{aligned} R_{i,j}(d_{i,j}) =& T_{i,j} W \log_2(1 + \gamma_{i,j}(d_{i,j})), \\ & \forall i \in \mathcal{N}, \forall j \in \mathcal{N}_N(i), \end{aligned} \quad (4)$$

where W is the bandwidth of the system. Then, we define a cost function for the communication quality of node i as $C_{i,j}^C(-R_{i,j}(d_{i,j}))$. We assume that function $C_{i,j}^C(-R_{i,j}(d_{i,j}))$ is an increasing and convex function of $-R_{i,j}(d_{i,j})$ [1].

The objective of this paper is joint mission and communication aware mobility control of each node, i.e., to find the location of each node by jointly considering its costs for mission and communication quality with its neighbor nodes. In the next section, we study this issue in more detail.

III. Joint Mission and Communication Aware Mobility Control

We now define the optimization problem as

$$\begin{aligned} \underset{\boldsymbol{x},\boldsymbol{y}}{\text{minimize}} \quad & \sum_{i \in \mathcal{N}} w_i^M C_i^M(x_i, y_i) \\ & + \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}_N(i)} w_{i,j}^C C_{i,j}^C(x_i, y_i, x_j, y_j) \\ \text{subject to} \quad & x_i^{min} \le x_i \le x_i^{max}, y_i^{min} \le y_i \le y_i^{max}, \ \forall i \in \mathcal{N}, \end{aligned} \quad (5)$$

where $\boldsymbol{x} = (x_i)_{i \in \mathcal{N}}$, $\boldsymbol{y} = (y_i)_{i \in \mathcal{N}}$, w_i^M is the weight factor for mission of node i and $w_{i,j}^C$ is the weight factor for the communication quality of a link from node i to node j. Note that due to cost function for the communication quality, in general, the above problem is a non-convex optimization problem, which is inherently difficult to solve. Hence, in this paper, instead of taking an optimization-theoretic approach, we take a game-theoretic approach. Even though in general, the solution of the game-theoretic approach, i.e., Nash equilibrium, may not be the global optimal solution of the above problem, the game-theoretic approach has its own meaning and makes it possible to develop a distributed algorithm. In addition, we will show in this section, if some minor conditions are satisfied, the game-theoretic approach also provides the global optimal solution of the above problem.

The mobility control game is defined as $G^{MC}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$, where $\boldsymbol{I}$ is the set of players of the game, which correspond to nodes in the network, $\boldsymbol{A}$ is the strategy set, in which the strategy of each player i is given by $A_i = \{(x_i, y_i) \mid x_i^{min} \le x_i \le x_i^{max},\ y_i^{min} \le y_i \le y_i^{max}\}$, and $\boldsymbol{C}$ is the set of cost functions, in which the cost function of player i, C_i is defined as

$$\begin{aligned} C_i(\boldsymbol{x}, \boldsymbol{y}) =& C_i(x_i, y_i; \boldsymbol{x}_{-i}, \boldsymbol{y}_{-i}) \\ =& w_i^M C_i^M(x_i, y_i) \\ & + \sum_{j \in \mathcal{N}_N(i)} w_{i,j}^C C_{i,j}^C(x_i, y_i, x_j, y_j) \\ & + \sum_{j \in \mathcal{N}_N(i)} w_{j,i}^C C_{j,i}^C(x_j, y_j, x_i, y_i), \end{aligned} \quad (6)$$

where $\boldsymbol{x}_{-i} = (x_j)_{j \in \mathcal{N},\, j \ne i}$ and $\boldsymbol{y}_{-i} = (y_j)_{j \in \mathcal{N},\, j \ne i}$. The cost function for node i is defined as the weighted sum of its cost for mission and costs for the communication quality of each of its transmitting and receiving links with its neighbor nodes. As in the above equation, the cost function of each node depends on only its own location and its neighbor nodes' locations.

[1]This is equivalent to the case that we first define a concave utility function $U_{i,j}^C$, which is an increasing concave function of $R_{i,j}(d_{i,j})$, and then define a cost function $C_{i,j}^C = -U_{i,j}^C$.

Hence, each node can evaluate its cost with only its own information and its neighbor nodes' information.

We now show the mobility control game $G^{MC}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$ is a potential game with an exact potential function. To proceed it, we first provide the following definitions [9].

Definition 1: A function $P : \boldsymbol{A} \to R$ is called an exact potential function of game $G(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$, if

$$\begin{aligned} C_i(\boldsymbol{a}) - C_i(b_i, \boldsymbol{a}_{-i}) =& P(\boldsymbol{a}) - P(b_i, \boldsymbol{a}_{-i}), \\ & \forall i \in \boldsymbol{I},\ \boldsymbol{a} \in \boldsymbol{A},\ b_i \in A_i. \end{aligned}$$

Definition 2: If game $G(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$ admits an exact potential function, it is called a potential game with an exact potential function.

Proposition 1: Let us define a function $P : \boldsymbol{A} \to R$ as

$$\begin{aligned} P(\boldsymbol{x}, \boldsymbol{y}) =& \sum_{i \in \mathcal{N}} w_i^M C_i^M(x_i, y_i) \\ &+ \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}_N(i)} w_{i,j}^C C_{i,j}^C(x_i, y_i, x_j, y_j). \end{aligned} \tag{7}$$

Then, it is an exact potential function of game $G^{MC}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$.

Proof: We can show that function P satisfies the condition for the exact potential function in Definition 1 by the fact that the strategy of node i, i.e., (x_i, y_i), affects on only its own cost for mission, i.e., $C_i^M(x_i, y_i)$, and costs for its transmitting links to neighbor nodes and receiving links from its neighbor nodes, i.e., $C_{i,j}^C(x_i, y_i, x_j, y_j)$ and $C_{j,i}^C(x_j, y_j, x_i, y_i)$, $j \in \mathcal{N}_N(i)$.

Let us consider two strategies $(\boldsymbol{x}, \boldsymbol{y})$ and $(x_i', y_i', \boldsymbol{x}_{-i}, \boldsymbol{y}_{-i})$. Then,

$$\begin{aligned} & P(\boldsymbol{x}, \boldsymbol{y}) - P(x_i', y_i', \boldsymbol{x}_{-i}, \boldsymbol{y}_{-i}) \\ &= w_i^M C_i^M(x_i, y_i) - w_i^M C_i^M(x_i', y_i') \\ &\quad + \sum_{j \in \mathcal{N}_N(i)} \left\{ w_{i,j}^C C_{i,j}^C(x_i, y_i, x_j, y_j) - w_{i,j}^C C_{i,j}^C(x_i', y_i', x_j, y_j) \right\} \\ &\quad + \sum_{j \in \mathcal{N}_N(i)} \left\{ w_{j,i}^C C_{j,i}^C(x_i, y_i, x_j, y_j) - w_{j,i}^C C_{j,i}^C(x_i', y_i', x_j, y_j) \right\} \\ &= C_i(\boldsymbol{x}, \boldsymbol{y}) - C_i(x_i', y_i', \boldsymbol{x}_{-i}, \boldsymbol{y}_{-i}). \end{aligned}$$

Hence, by Definition 1, function P is an exact potential function of game $G^{MC}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$. ■

Note that the potential function in (7) is equal to the objective function of the optimization problem in (5).

We now show the existence of Nash equilibria for mobility control game $G^{MC}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$.

Proposition 2: The mobility control game $G^{MC}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$ has at least one Nash equilibrium.

Proof: Since mobility control game $G^{MC}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$ is a potential game with a compact strategy set $\boldsymbol{A}$ and a continuous potential function P, it has at least one Nash equilibrium [9]. ■

We have shown that there exist Nash equilibria for our mobility control game $G^{MC}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$. We now study the algorithms that converge to the Nash equilibrium of our mobility control game. We assume that the mobility control game is played iteratively and at each iteration of the game, only one player can change its strategy according to a decision rule. This player is chosen randomly or in a round-robin way. We provide some decision rules [10] below.

Definition 3: In the *best reply dynamic*, whenever player i has an opportunity to revise its strategy at iteration $n+1$, it will choose $\left(x_i^{(n+1)}, y_i^{(n+1)}\right)$ such that

$$\left(x_i^{(n+1)}, y_i^{(n+1)}\right) \in \underset{(x_i, y_i) \in A_i}{\operatorname{argmin}}\ C_i\left(x_i, y_i; \boldsymbol{x}_{-i}^{(n)}, \boldsymbol{y}_{-i}^{(n)}\right),$$

where $\left(x_i^{(n)}, y_i^{(n)}\right)$ is the strategy of player i at iteration n.

Then, we have the following properties for the convergence to the Nash equilibrium of our mobility control game.

Proposition 3: Mobility control game $G^{MC}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$ converges to the Nash equilibrium, if each player follows the best reply dynamic [10].

Note that since at each iteration, a single player, e.g., node i, tries to decrease its cost, i.e., $C_i(\boldsymbol{x}, \boldsymbol{y})$, according to the above decision rules, the value of the exact potential function in (7) also decreases until it converges to a certain value. Therefore, we can see that the objective value of the optimization problem in (5), which is equal to the potential function, decreases and eventually converges to a certain value in our mobility control game.

We now consider a special case in which the SNR of each link is high. In this case, we can approximate the average achieved data rate of a transmitting link from node i to its neighbor node j, $R_{i,j}(d_{i,j})$, in (4) as

$$R_{i,j}(d_{i,j}) \approx T_{i,j} W \log_2(\gamma_{i,j}(d_{i,j})), \quad \forall i \in \mathcal{N}, \forall j \in \mathcal{N}_N(i). \tag{8}$$

In addition, we consider the following conditions for the cost function for the communication quality of node i for its neighbor node j, $C_{i,j}^C(r)$:

$$\frac{dC_{i,j}^{C2}(r)}{dr^2} - \ln 2 \times \frac{dC_{i,j}^C(r)}{dr} \geq 0. \tag{9}$$

For example, if $C_{i,j}^C(r) = e^{ar}$, $a \geq \ln 2$, the above condition is satisfied. Then, we have the following proposition.

Proposition 4: If the cost function for the communication quality of node i for its neighbor node j, $C_{i,j}^C(r)$, satisfies the condition in (9) and $T_{i,j} W \alpha \geq 1$, then the best reply dynamic is guaranteed to converge to the global optimal solution of problem (5).

Proof: Consider

$$\begin{aligned} & C_{i,j}^C\left(-R_{i,j}\left(d_{i,j}(x_i, y_i, x_j, y_j)\right)\right) \\ &= C_{i,j}^C(-T_{i,j} W \log_2(\gamma_{i,j}(d_{i,j}(x_i, y_i, x_j, y_j)) \\ &= C_{i,j}^C\left(\log_2\left(\left(\frac{N_0}{K_{i,j} P_i}\right)^{T_{i,j} W} d_{i,j}(x_i, y_i, x_j, y_j)^{T_{i,j} W \alpha}\right)\right). \end{aligned}$$

Since $d_{i,j}(x_i, y_i, x_j, y_j)$ is a convex function of (x_i, y_i, x_j, y_j) and we assumed that $T_{i,j} W \alpha \geq 1$, $\left(\left(\frac{N_0}{K_{i,j} P_i}\right)^{T_{i,j} W} d_{i,j}(x_i, y_i, x_j, y_j)^{T_{i,j} W \alpha}\right)$ is also a convex function of (x_i, y_i, x_j, y_j) [11]. Hence, now, we only have to show that $C_{i,j}^C(\log_2(d))$ is an increasing and convex function of d, if the condition in (9) is satisfied [11].

Since cost function $C_{i,j}^C(r)$ is assumed to be an increasing function of r, $C_{i,j}^C(\log_2(d))$ is also an increasing function of d. We now examine the second derivative of $C_{i,j}^C(\log_2(d))$ with respect to d as

$$\frac{d^2 C_{i,j}^C(\log_2(d))}{dd^2} = \frac{1}{d^2(\ln 2)^2}\left(\frac{d^2 C_{i,j}^C(r)}{dr^2} - \ln 2 \times \frac{dC_{i,j}^C(r)}{dr}\right)\Bigg|_{r=\log(d)}. \tag{10}$$

Since cost function $C_{i,j}^C(r)$ satisfies the condition in (9), we have $\frac{d^2 C_{i,j}^C(\log_2(d))}{dd^2} \geq 0$, and thus $C_{i,j}^C(\log_2(d))$ is a convex function of d. In addition, we assume that the cost function for the mission of node i, $C_i^M(d_i^M)$, is also a convex function of d_i^M in Section II. Therefore, since potential function P in (7) is defined as the weighted sum of cost functions for mission and communication quality, potential function P is also a convex function. In this case, we can easily see that the best reply dynamic is equivalent to the Gauss-Seidel algorithm [12] for minimizing potential function P in (7), while satisfying its convergence conditions. Hence, the convergent solution in this case is not only the Nash equilibrium but also the optimal solution that minimizes potential function P in (7), which is equal to the objective function of problem (5). ■

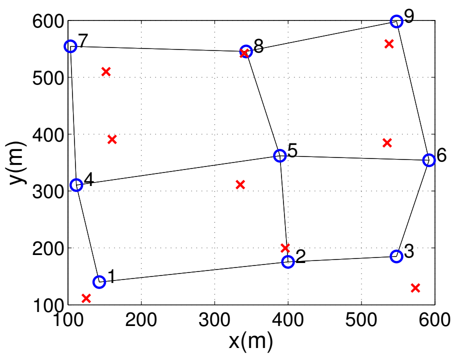
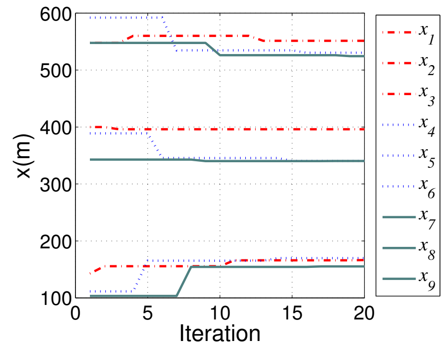


Fig. 1. Simulation topology.

IV. NUMERICAL RESULTS

In this section, we provide numerical results for our algorithm. We set cost functions and parameters as follows: $C_i^M(d_i^M) = 5(e^{10^{-2}d_i^M} - 1)$, $C_{i,j}^C(-R_{i,j}) = 100e^{-R_{i,j}}$, $K_{i,j} = 1$, $P_i = 1$, $T_{i,j} = \frac{1}{12}$, $\forall i \in \mathcal{N}$, $\forall j \in \mathcal{N}_N(i)$, $W = 10$, $N_0 = 10^{-6}$, $\alpha = 2$. We consider a network in Fig. 1, which consists of 9 nodes (i.e., $N = \{1, 2, \ldots, 9\}$), where each circle denotes the initial location of each node and the nearest X-mark to each circle denotes the target location for mission of the corresponding node. The edge between two nodes represents that two nodes are the neighbor node of each other. We set the constrained area of each node as the rectangular area, where the node is initially loacted.

We consider the case in which each node adopts best reply dynamic as its decision rule. We set $w_i^M = 0.5, \forall i \in \mathcal{N}$ and $w_{i,j}^C = 0.5, \forall i \in \mathcal{N}, \forall j \in \mathcal{N}_N(i)$. In Figs. 2(a) and 2(b),



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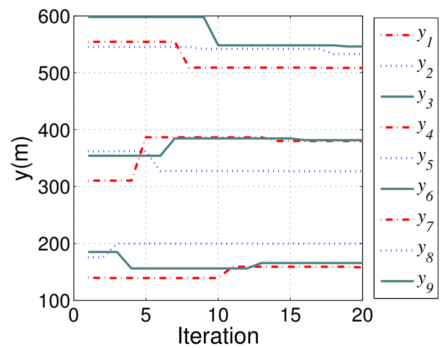
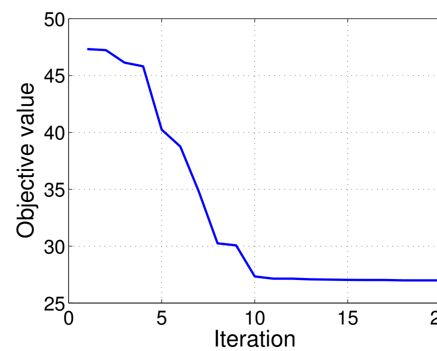
(a) $x_i, \forall i \in \mathcal{N}$.



(b) $y_i, \forall i \in \mathcal{N}$.

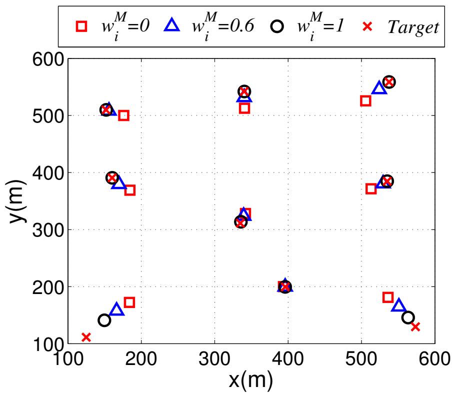


(c) Objective value.

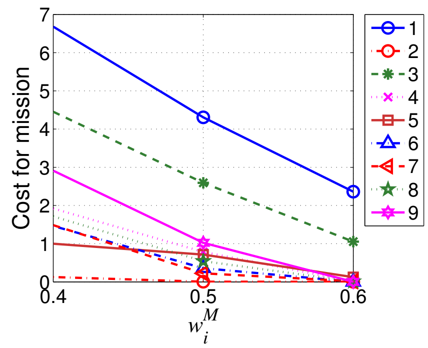
Fig. 2. Convergence of our algorithm with $w_i^M = w_{i,j}^C = 0.5, \forall j \in \mathcal{N}_N(i)$.

we plot the trajectory of the location (i.e., x_i and y_i) for each node i. From this figure, we can see that the location of each node converges to a fixed location with our algorithm. In Fig. 2(c), we plot the trajectory of the objective value of the optimization problem in (5), i.e., the weighted sum of costs for missions and communication qualities of all nodes. We can see that the objective value monotonically decreases and eventually converges to a fixed value, as mentioned in Section III.

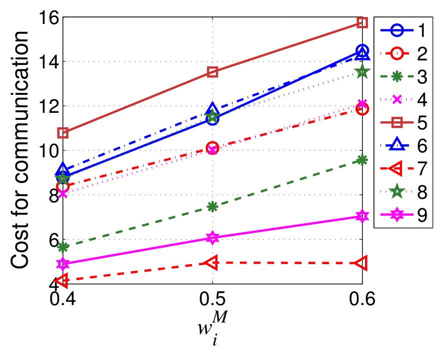
We now examine the impact of the weight factors for mission and communication quality. In Fig. 3, we set weight factors w_i^M and $w_{i,j}^C$ of each node i as $w_i^M + w_{i,j}^C = 1, \forall i \in \mathcal{N}, \forall j \in \mathcal{N}_N(i)$. Fig. 3(a) shows the converged locations of all nodes according to the weight factors. In addition, Figs.



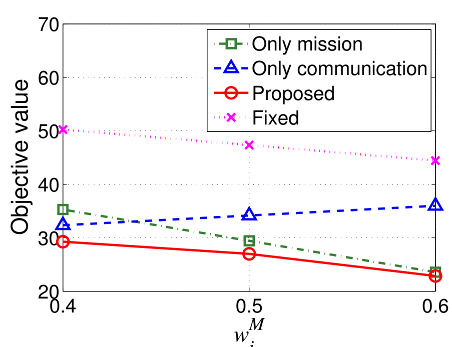
(a) Converged locations.



(b) Cost for mission.



(c) Cost for communication.



(d) Performance comparison.

Fig. 3. Numerical results with varying weight factors.

3(b) and 3(c) show the (unweighted) costs for mission and communication quality of each node at its converged location (x_i^*, y_i^*), i.e., $C_i^M(x_i^*, y_i^*)$ and $\sum_{j\in\mathcal{N}_N(i)} C_{i,j}^C(x_i^*, y_i^*, x_j^*, y_i^*)$, respectively. As shown in Figs. 3(a), 3(b), and 3(c), as the weight factor for mission gets larger, each node gets closer to its target location in order to reduce the cost for its mission, which results in the increase of the cost for its communication quality. On the other hand, as the weight factor for communication quality gets larger, each node gets closer to each other in order to reduce the cost for its communication quality, which results in increase of the cost for its mission. In Fig. 3(d), we compare the performance of our proposed algorithm with those in the following three cases: 1) the case in which each node update its location considering only its mission; 2) the case in which each node updates its location considering only its communication quality; 3) the case in which each node maintains its initial location. Fig. 3(d) clearly shows that our mobility control algorithm can provide the appropriate location of each node, while minimizing the total cost for missions and communication qualities of all nodes.

V. Conclusion

In this paper, we studied a joint mission and communication aware mobility control problem in mission-critical mobile ad-hoc networks based on a game-theoretic approach. We showed that our problem is modeled as a potential game and developed a distributed algorithm that converges to the Nash equilibrium. We also showed that with some minor conditions, the solution of our algorithm is also a global optimal solution that minimizes the sum of cost functions of all nodes. Numerical results show that our algorithm provides the appropriate location of each node jointly considering its mission and communication quality.

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References

[1] A. So and B. Liang, "Enhancing WLAN capacity by strategic placement of tetherless relay points," *IEEE Transactions on Mobile Computing*, vol. 6, no. 5, pp. 522–535, May 2007.

[2] A. Srinivas and E. Modiano, "Joint node placment and assignment for throughput optimization in mobile backbone networks," in *IEEE INFOCOM*, 2008, pp. 1804–1812.

[3] C. Dixon and E. W. Frew, "Maintaining optimal communication chains in robotic sensor networks using mobility control," *Mobile Networks and Applicaitons*, vol. 14, pp. 281–291, 2009.

[4] H.-T. Roh and J.-W. Lee, "Optimal placement of a relay node with controllable mobility in wireless networks considering fairness," in *IEEE CCNC*, 2010.

[5] ——, "Joint node scheduling and relay node placement in wireless networks with a relay node with controllable mobility," *Wireless Communications and Mobile Computing*, doi: 10.1002/wcm.1007.

[6] ——, "Communication-aware position control for mobile nodes in vehicular networks," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 1, pp. 173–186, Jan. 2011.

[7] M. M. Zavlanos, A. Ribeiro, and G. J. Pappas, "Mobility and routing control in networks of robots," in *IEEE CDC 2009*, 2009, pp. 7545–7550.
[8] ——, "Distributed control of mobility & routing in networks of robots," in *IEEE SPAWC 2011*, 2011, pp. 236–240.
[9] D. Monderer and L. S. Shapley, "Potential games," *Games and Economic Behavior*, vol. 14, no. 1, pp. 124–143, May 1996.
[10] A. MacKenzie and L. DaSilva, *Game Theory for Wireless Engineers*. Morgan & Claypool Publishers, 2006.
[11] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.
[12] D. P. Bertsekas and J. N. Tsitsiklis, *Parallel and Distributed Computation: Numerical Methods*. Athena Scientific, 1999.