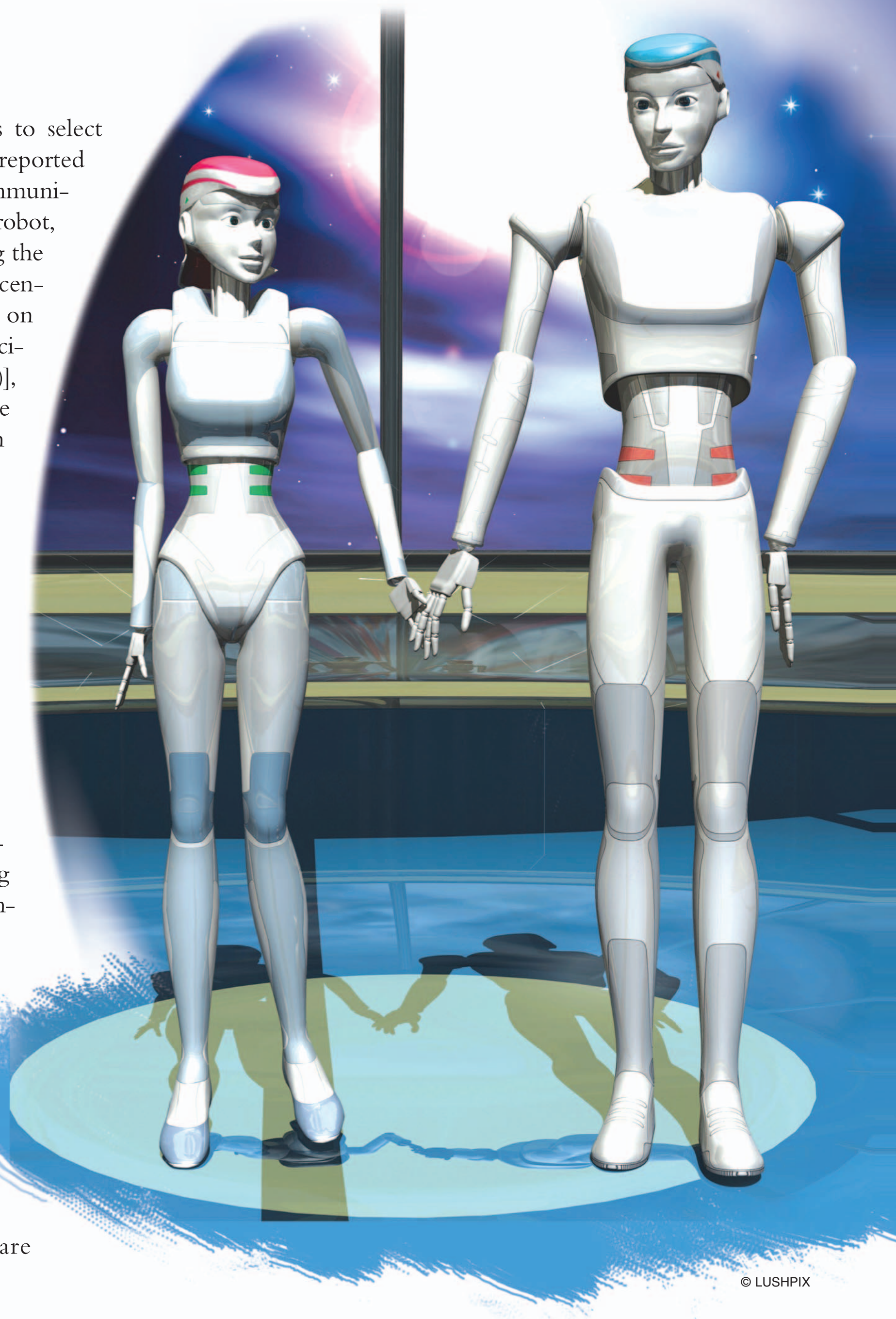
Robot to Robot

Communication Aspects of Coordination in Robot Wireless Networks

BY IVAN MEZEI, VELJKO MALBASA, AND IVAN STOJMENOVIC

Robots coordinate among themselves to select one of them to respond to an event reported to one of the robots so that the communication cost of selecting the best robot, response time, and cost of performing the task are minimized. Existing solutions are either centralized, assuming a complete graph, or based on flooding with individual responses to a robot decision maker [simple auction protocol (SAP)], ignoring communication cost and response time bound. This article proposes auction aggregation protocols (AAPs) for task assignment in multihop wireless robot networks. A robot collector leads an auction and initiates a response tree construction by transmitting the search message. After receiving the message, each robot makes a decision on whether to retransmit a search message, based on the estimated response cost of its robots, up to *k*-hops away. Robots wait to receive the bids from its children in the search tree. Then, robots aggregate responses by selecting the best bid and forward it back toward the robot collector (auctioning robot). When distance is used as the sole cost metrics, the traversal aggregation algorithm [routing with face traversal (RFT)—routing toward the event with the traversal of the face containing the event] can be applied and is an optimal solution. Several other protocols and their enhancements are also described here.

Multirobot systems (MRSs) are well studied in literature [1], and the focal point of the majority of MRS-related articles is on coordination and cooperation. The term networked robotics emerged recently emphasizing that robots can be connected by a wireless medium forming a communication network. There are



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Networked robotics emphasized that robots can be connected by a wireless medium, forming a communication network.

various applications of networked robots. They can coordinate to perform exploration, mapping, search, reconnaissance, fire prevention tasks, or gaming (e.g., robot soccer). According to a recent review article on the status of robotics [2], communication between entities is fundamental to both cooperation and coordination and is hence the central role of the network. Communication cost for coordination among robots should be minimized for several reasons. Wireless medium is shared, and so multiple synchronous messages cause collisions. Mobile robots are energy constrained. Large robot multihop networks may pose scalability issues and significant delay in making action decisions unless coordination protocols are tailored to the application, energy, and time constraints.

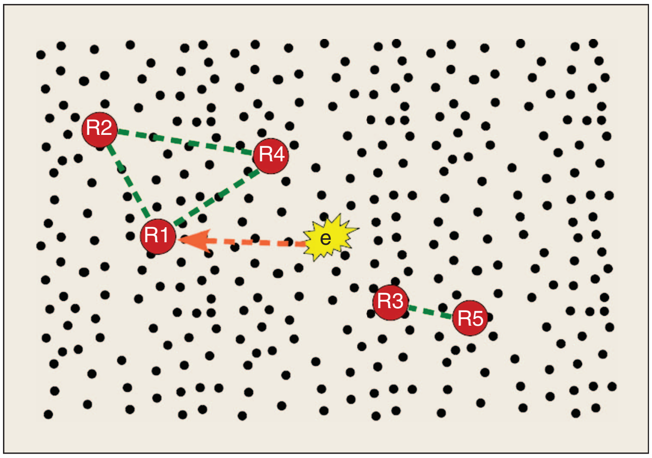

Figure 1. *An area with one event being monitored by sensors and five robots.*

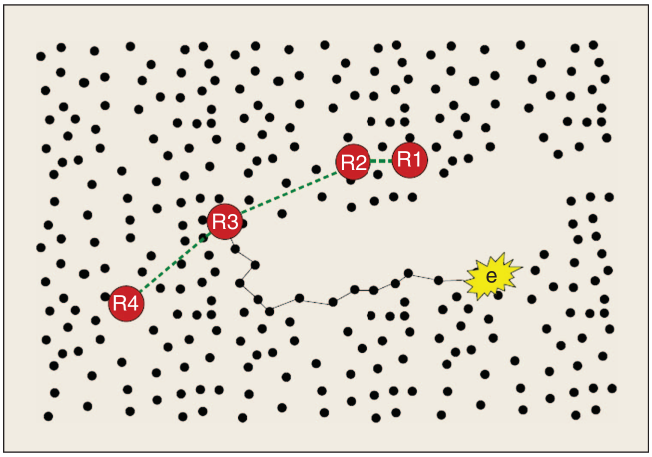

Figure 2. *Sensors not deployed uniformly (or malfunctioning).*

Two major topics of robot–robot coordination are communication and task assignment, which are closely interrelated. In this article, we only consider a simple task assignment formulation. We assume that an event was reported to one of the robots, and a response by one robot is required. Thus, the task assignment problem is to find the best robot to respond to an event and assign a task to it. The input of the problem is information about an event (location, response time, etc.), and the output is an assigned task to the best robot.

Robots are organized into a network that is modeled as the unit disk graph (UDG) [3]. All robots have the same transmission radius R, and a message sent by one robot is received by all neighboring robots located at a distance up to R. The robot receiving the event information needs to decide which robot is the best to respond. To make a decision, it initiates a message exchange (sending and receiving messages) among robots, following UDG. Normally, messages originate from and converge toward the robot decision maker.

Solutions described in this article do not depend on the particular environment served by networked robots. One such environment of interest to us is wireless sensor and robot networks (WSRN), as an extension of MRS. WSRN consist of sensors and robots linked by wireless medium to perform distributed sensing of the physical world, processing of sensed data, making decisions, and acting upon sensed events (see Figures 1 and 2). We will illustrate our problem statement using this scenario. Upon event occurrence (e.g., a fire or the failure of a sensor), sensors detect the event and route information to one of the robots in the vicinity, which may not be the closest one. The robot that receives the report may itself be the best candidate for responding. However, a remote, busy, or energy-limited robot could receive the report.

In Figure 1, robot R3 is the closest, but the event was reported to R1. R1 is the decision maker and consults other robots in its vicinity to find the best responder, which would be the robot closest to the event. In Figure 1, R1 consults R4 and R2 and decides that R4 is the best robot to respond. In this example, two more robots exist, R3 and R5, which are disconnected from R1. Robot R3 is really the closest but was not involved in the process of selecting the best responder. In example in Figure 2, R3 received the report, because there is a sensor void area between the event and the closest robot R1. R1 is able to act but the sensors were not able to report the event directly to it. R3 initiates the bidding process and discovers the nearest robot R1 that is then assigned to the task.

Most of the existing solutions referring to multirobot coordination for single or multiple events, single or multiple robots, single or multiple tasks to each robot etc. are centralized. One of the robots, or a central entity, gathers all the information from the other robots and makes a decision. The communication cost for gathering information in case of multihop robot networks is rarely considered. Indirectly (since no details of the communication protocols used are given), a complete graph (where each robot is within communication distance to any other robot) is assumed. Centralized solutions usually define the coordination problem as an integer linear programming problem. The main advantage of a centralized solution is that, theoretically, the optimal solution can be found. However, the centralized solution features a high computation and communication overhead, lack of scalability, and slow responsiveness. Moreover, the actual cost for communicating is ignored, especially for large robot networks. It is further not clear how robots communicate if the graph is not a complete one. Centralized solutions also have low fault tolerance if the leader is malfunctioning in any way.

Localized and distributed solutions utilize spreading all decision making and planning responsibility among robots. Here, we consider the multihop UDG scenarios, where the communication graph is not complete. Robots only use the locally available information to make their decision. Good scalability and fault tolerance are the main advantages. Proposed solutions are normally close to the optimal one. However, decisions made based on the local information can sometimes be highly suboptimal. We only identified one distributed solution designed for the multihop scenario, SAP [4], which considers the multihop UDG model of robot communication. It is flooding based; each robot retransmits the received search request exactly once and responds to the auctioneer by a separate routing task. For large robot networks, it incurs an unacceptable delay in selecting the best robot, although the best responding robot is expected to be near the event.

In this article, we first propose to limit the robot selection to a certain local neighborhood, even for SAP. We then propose a localized solution, based on the market paradigm, called AAP. The bidding process is spreading to neighboring robots until no improvement can be envisioned within a k-hop neighborhood of a robot that analyzes if any more remote robots could provide better a service than the best service it is already aware of. If not, it stops the search process and responds back to its parent robot with the best possible recommendation it has. During the contraction process of bid gathering, best bids are forwarded back to the auctioneer robot by intermediate robots. The main advantage is that the search is limited to some neighborhood and flooding potentially huge robot network is avoided. When the best robot is selected based solely on its distance to the event, the search can be very efficient by simply routing toward the event location, with the traversal of the face of Gabriel graph containing the event discovering the nearest robot (RFT—routing with face traversal algorithm). Simulation data confirm findings and show the performance of our protocol in some scenarios.

Literature Review

Multirobot Task Assignment

Taxonomy of multirobot task allocation (MRTA) problems is presented in [5]. In most of the papers, the task assignment problem is formulated as a variant of the integer linear programming problem (e.g., [4] and [6]). Mobility is usually not considered (an exception is [6]). In those centralized formulations, the optimization objective is any of energy consumption minimization, maximization of processing time, utility maximization, total travel distance minimization, or residual energy maximization. Although these centralized solutions can be formulated to target our scenario (single event), they either ignore communication cost or assume a complete graph.

Normally, messages originate from and converge toward the robot decision maker.

The communication aspects of task assignment are rarely taken into account. In centralized MRTA [7], communication aspects are modeled by including one term in the optimization objective function, which represents the number of robot pairs that can communicate (and that should be maximized). The communication protocol is not specified and only single-hop (direct) communication is considered. In [8], robots are likely to win tasks that have a low cost for themselves but a high average cost for the rest of the team. When there is only one task to assign, the closest robot is selected. This article does not discuss any communication protocol among sensors or robots. Thus, the complete graph is assumed in the coordination process.

A communication-efficient multirobot (CEMR) task scheduling algorithm for heterogeneous MRS is given in [9]. CEMR assumes direct communication between each robot and a central unit, and direct communication among some robot pairs. Each robot reports its status and detected tasks to a central unit, which allocates tasks using an auction-based method with a fitness function (including capability, distance from task, and availability). Robots receive the status, including the position, of all other robots from the central unit and can also ask directly for help from other nearby robots. The article does not discuss any multihop communication protocols. A simulation is made with six robots, and the alternative approach is broadcasting, which is a direct request to all other robots instead of to a few of them who might be available based on a priori knowledge.

Three decentralized task allocation schemes among unmanned aerial vehicles (UAVs) in a destroy targets scenario using negotiation concepts from team theory and game theory are given in [10]. It is acknowledged that full communication between all UAVs poses high communication costs, and the idea of localized communication (communication among neighbors only) is given as well as the necessity for multihop communication if agents are out of the communication range. However, only a complete graph is simulated. Multihop communication was stated in some scenarios, but there is no discussion of any communication protocol actually applied.

In summary, finding solutions to concrete task assignment scenarios in the presence of robot mobility (when communication cost is not negligible, and communication protocols need to be specified) still remains a research challenge.

Market-Based Task Assignment and Auctions

For robot–robot coordination, a market-based approach [11] is considered. It is based on auctions organized by a robot or

Centralized solutions usually define the coordination problem as an integer linear programming problem, ignoring communication costs.

sink (central unit) collecting the task, the cost of performing tasks by each robot, and potential benefit to the team. Robots positioned in local neighborhoods participate, but the locality is not predetermined; it is rather task-dependent. Robots participating in the auction decide on whether or not to invite more robots to the auction, as the invitations themselves cause communication overhead. One of the well-known auction protocols is MURDOCH [12]. It uses anonymous broadcasting as a means to communicate and has the following five distinct steps: task announcement, metric evaluation, bid submission, auction closing, and progress monitoring/contract renewal. However, MURDOCH assumes a complete graph among robots, while we use UDG. Similarly, in [13] and [14], local auctions are used as a distributed solution to dynamic MRTA. However, all robots participating in an auction can communicate directly to the auctioneer.

Article [15] considers the problem of selecting one mobile sensor for each of the positions to be covered so that the total distance traveled by the selected sensors to their allocated positions is minimized. The market-based algorithm described gives the same results as the matrix scan algorithm (where each element in the matrix is the cost associated with the respective worker and job), which selects the smallest element in the whole matrix as part of the solution, deletes the selected row and column, and continues the scan in the same way for the smaller matrix. When only one task exists, the closest robot is assigned to it, and the communication aspects of finding it are not discussed.

Survey article [16] summarizes research work done in the field of robot coordination using the market-based approach. Auction can be either centralized (for all robots) or localized, where only nearby robots will respond. Market-based approaches have yet to be implemented on teams of more than a few robots [16]. There is no discussion of communication cost for large robot teams, except a simple statement [16, Table 3] that communication cost is proportional to the number of robots.

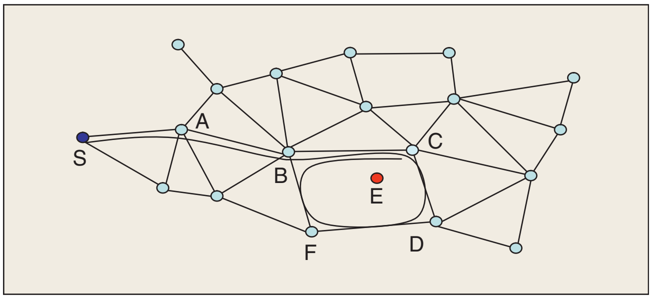

Figure 3. The face traversal algorithm over the Gabriel graph of UDG.

To the best of our knowledge, bid aggregation in the task assignment problem in robot–robot coordination was not considered in literature. We refer here to the aggregation of responses of several robots by an intermediate robot, which then selects the best of them and forwards only that bid to the auctioneer.

Simple Auction Protocol

We identified only one protocol [4] for a single-task, single-robot (called actor in [4]) assignment, which explicitly considers multihop scenarios (UDG). It is a localized solution for actor–actor coordination based on auction protocol [4] and is called here a SAP. The request for service is flooded from the actor node that collected the report, and each actor responds back (with the offer to provide service and the cost of doing it) to it by a separate routing task. If blind flooding is used for actor search, each robot retransmits the request upon receiving it for the first time and ignores it afterward. This protocol can always find the closest robot to the event, since all robots are consulted. However, the response time can be large even in the cases where the best robot is near the event, since the response from all robots is gathered before a decision is made.

Face Traversal

Stateless position-based routing with guaranteed delivery was first described in [17]. It was applied in [18] for the data storage problem as follows. A geographic hash table is used to find the location for storing data based on its hashed table. Data is then routed toward home, as decided by the hash table, and stored there; in Figure 3, Point E is the home. However, E is not an existing node in the network. Routing proceeds with the greedy-face-greedy (GFG) algorithm [17] from the source S toward destination E. It will create a loop in the face containing E. In Figure 3, the whole path is SABCDFC, and loop CDFC is detected. The closest node in the network to node E is the one from the loop. In Figure 3, it is node D, and node F can decide it since the closest node to E travels together with the message. Face traversal is done using Gabriel graph of UDG. An edge *uv* belongs to Gabriel graph if and only if no other edges are located inside the circle with diameter *uv*. Thus, its construction is easy. Figure 3 shows only the Gabriel graph of UDG for clarity. A readable and correct explanation of the GFG algorithm can be found in [19].

Improved Simple Auction and Auction Aggregation Protocols

For simplicity, in the following sections, we assume that the robot network is connected, and the event location is known to the bidding robot (robot collector). Note that in WSRN, sensor nodes may be used to connect some robots; however, this scenario is not considered here.

In this section, we describe five new protocols: *k*-SAP, SAAP, *k*-SAAP, *k*-AAP, and RFT. The first one is an improvement of the SAP. Instead of flooding the whole network, one can search for bids only among robots located up to k-hops away from bidding robot. This protocol applies limited flooding (only up to k-hop neighbors), and it will be designated as k-SAP. In example in Figure 4, 1-SAP will gather bids only from R2 and R3, and thus, the best bid from R4 is not considered; 2-SAP will flood from R1, R2, R4, R3, R8, and R5 robots; 3-SAP will consult all the robots.

Another improvement of SAP in terms of communication overhead reduction is the use of the AAP. Instead of using separate routing tasks, the constructed tree can be used for reporting back. The protocol has tree expansion and tree contraction phases. Tree expansion starts from collecting robot R1 by creating a tree rooted at R1 (see Figure 4). Retransmissions create a response tree. Each node, with retransmission, includes identification number of its parent robot in the message so that robots can locally decide whether or not they are leaves in the created tree. Note that each node selects only one parent in case of multiple received bids (e.g., R9 is joined only to R4). They become leaves if they do not retransmit the bid or do not hear any other robot listing them as their parent.

Leaf nodes start responding back to parent robots, with the best cost they are aware of. This is in fact auction aggregation and, thus, reduces the number of messages in the bidding phase. Each intermediate node waits to hear from all its neighbors, which declared it as a parent, thus becoming a local collector. After hearing, they select the best cost and report further toward the collector. At the end, the collector decides which robot is the best to perform the required action and routes the decision to that robot. In the example in Figure 4, robots R5, R6, R7, R8, and R9 are leaves in the created tree and return their bids to their parent nodes. R4 returns to its parent R2, its own bid as the best it is aware off; similarly, R3 also returns its own bid. R2 returns to R4 as the best bidder. The root node (R1) then selects the best bid (in this case, from R4) from the two received offers and delivers the task to R4 along the created path of R1–R2–R4. This version of AAP will be designated as simple AAP (SAAP). In the case of limited flooding (only up to k-hop neighbors from the collector), it is called k-SAAP. The difference between k-SAAP and k-SAP (and similarly between SAP and SAAP) is that individual bids are aggregated at intermediate nodes, instead of routing all of them back to the collector robot.

Providing autonomy in retransmitting decisions to individual robots can further refine the algorithm. In k-SAAP, the receiving robot will retransmit only if it is at a distance $<k$ hops from the collector. The new k-AAP protocol applies k-hop neighborhood around the current robot. Each robot is assumed to already know the position, cost, and availability of all its neighboring robots up to k-hops away. One simple way is periodic diffusion of its local information [including the status of its (k-1)-hop neighbors] to its neighbors (hello message) or piggybacking it to data messages.

In our k-hop AAP (k-AAP), the robot that received the bid (and the best learned cost C associated with previous senders on the path from the bidding robot to it) will compare C and

All robots participating in an auction can communicate directly or in k-hops to the auctioneer.

the cost of providing service with all of its k-hop neighbors. It will retransmit the message only if at least one of its own k-hop neighbors has cost $<C$. Otherwise, it will not retransmit and will start auction aggregation by returning a response message to its parent node on the search path.

k-AAP is a localized algorithm, where each robot makes a decision on whether or not to retransmit based on k-hop knowledge. In the simplest version, 0-AAP protocol (for $k = 0$), the receiving robot declares itself as the selected one corresponding to the use of 0-hop knowledge (no knowledge at all). In the 1-AAP protocol, the collecting robot R1 will retransmit if any of its first neighbors has a lower cost. In the example in Figure 4, this still results in no transmission from R1. In the k-AAP, R1 will retransmit if any of its k-hop neighbors has a lower cost. In Figure 4, R4 is 2-hop neighbor of R1 with a lower cost, and R1 then retransmits in 2-AAP version. R3 will not retransmit, while R2 will, because R4 is its 1-hop neighbor. Every retransmitting node will include with the message the lowest cost it is aware of. R4 will not retransmit.

In the special case, when cost metrics equals distance (from given robot to the event), another specialized algorithm may be used. We formalize it as the RFT algorithm (routing toward the event with face traversal encircling the event). It is in fact algorithmically equivalent to the face traversal algorithm described in the literature review. In the example in Figure 4, the RTF algorithm starts after the collecting robot R1 receives the task. RTF routes from R1, using robot networks, toward the event location e. Routing will end by traversing a face containing e. In Figure 4, the face is e→R1→R2→R4→R9→R5→R3→R1→e. Upon completing the face traversal, the first node on the face (R1 in Figure 4) decides the best (closest) robot (R4 in this example).

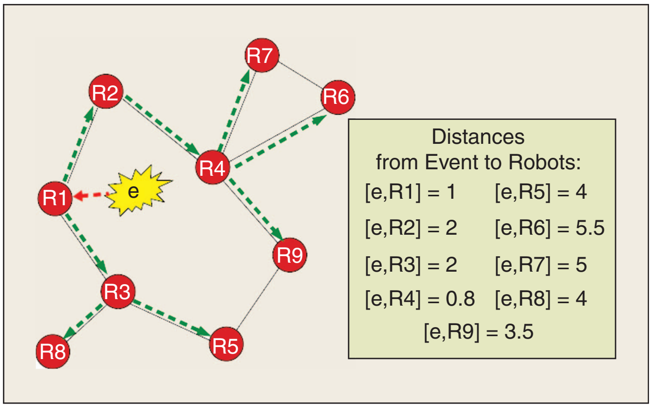

Figure 4. AAP for selecting the best robot.

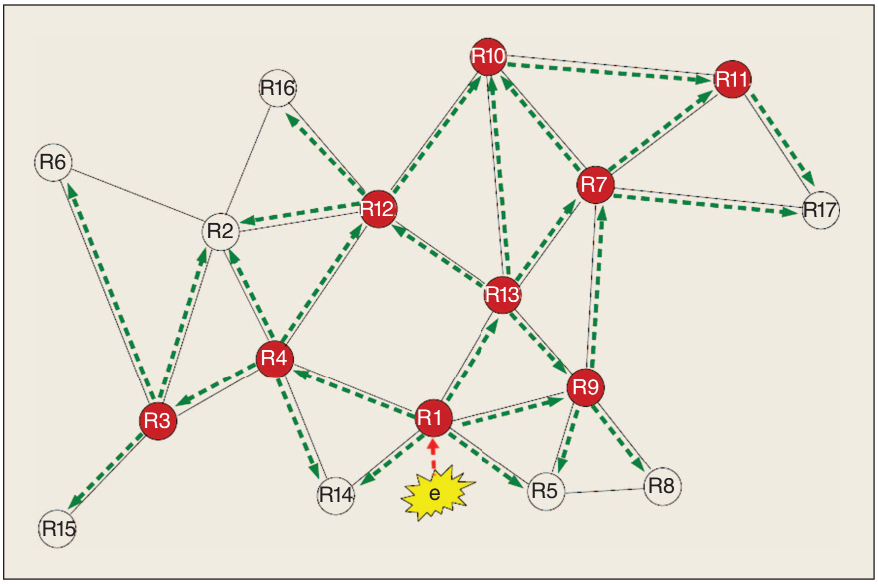

Figure 5. *Auction aggregation with a backbone.*

Further Enhancements

In this article, we do not discuss particular cost metrics and particular task assignments. Instead, we concentrate on the communication aspects only, because they were largely ignored in the literature. The designed protocols are intended to be an integral part of the task assignment process in concrete scenarios.

Applying intelligent flooding schemes can further enhance AAPs. In addition to the criteria for retransmitting a search message, in particular protocols, efficient broadcasting can be applied to stop retransmission at a node B if B should not retransmit by neighbor elimination and backbone-based broadcasting [20]. In Figure 5, gray nodes belong to a backbone, and only they expand a search tree and aggregate responses. Suppose an event is reported to node 1. The aggregation tree is shown. Nodes that are not in backbone may report their service offer if desirable but do not expand the tree.

Another improvement of aggregation protocols is the development of versions that look for the best response within time limits. During flooding, each node adds the best-known cost to its message. Whenever a child node retransmits this search message with a better cost than the present one, a parent node routes such a response toward the auctioneer. The response will be blocked along the route by a node that already knows about a better offer. Nodes on the route will also update their best offer information for future service offers. Versions with k-hop local knowledge in the search phase can be distinguished.

To improve the suboptimality of localized decisions of k-SAP and k-SAAP, especially for a higher number of robots and low values of k, 1-hop greedy search for better robot could be added after the original assignment is proposed. That is, the selected robot, after getting the task, will check if any of its neighbors has a lower cost. If so, it can reassign the task, and such a search can be repeated by the selected neighbor, until no improvement is possible. k-simple auction protocol with greedy extension (k-SAPG) and k-simple auction aggregation protocol with greedy extension (k-SAAPG) will be simulated to find if the 1-hop greedy search for a better robot will gain better assignments at the cost of a small increase of communication overhead.

Conclusion

Simulations of all new protocols are underway to show various trade-offs among newly proposed solutions and confirm their advantage over existing flooding based solutions. Main trade-offs are between the amount of messages sent by the system and the ability to select the nearest or nearby robot. These initial simulations will assume distance to be a single cost metric. Further evaluations could be carried later by considering other cost metrics and combining them with the distance. One option for the goodness metric for the performance of each protocol is the ratio of the cost of the selected robot over the minimal possible cost of any robot, which depends on the message overhead of a particular solution, and other parameters such as the number of robots, their network density, presence of void areas, or communication obstacles, and others. This article assumes a fault-free environment. For instance, there are no communication failures (more precisely, acknowledgments can be used to confirm message receipt, and resend otherwise). However, typical implementations of transmissions with all neighbors as recipients do not rely on acknowledgments. Therefore, protocols should be revisited to add fault-tolerant features.

The ultimate test for the proposed algorithms is their use as part of robot team coordination in various applications. We envision their application to address single-task, single-robot demands with simple and efficient solutions. However, we also believe that they can find application in MRS, where robot network does not form a complete or connected graph. For example, robots playing soccer may receive messages from nearby teammates about their passing or movement intentions to adjust their own behavior. In summary, we believe that we have addressed an important issue in robot task assignments that has been neglected so far in open literature.

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Keywords

Robot–robot coordination, wireless sensor and robot networks, auction aggregation protocols.

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