A Hierarchical Auction-Based Mechanism for Real-Time Resource Allocation in Cloud Robotic Systems

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***Abstract*—Cloud computing enables users to share computing resources on-demand. The cloud computing framework cannot be directly mapped to cloud robotic systems with ad hoc networks since cloud robotic systems have additional constraints such as limited bandwidth and dynamic structure. However, most multirobotic applications with cooperative control adopt this decentralized approach to avoid a single point of failure. Robots need to continuously update intensive data to execute tasks in a coordinated manner, which implies real-time requirements. Thus, a resource allocation strategy is required, especially in such resource-constrained environments. This paper proposes a hierarchical auction-based mechanism, namely link quality matrix (LQM) auction, which is suitable for ad hoc networks by introducing a link quality indicator. The proposed algorithm produces a fast and robust method that is accurate and scalable. It reduces both global communication and unnecessary repeated computation. The proposed method is designed for firm real-time resource retrieval for physical multirobot systems. A joint surveillance scenario empirically validates the proposed mechanism by assessing several practical metrics. The results show that the proposed LQM auction outperforms state-of-the-art algorithms for resource allocation.**

***Index Terms*—Cloud robotics, hierarchical auction, real-time resource allocation.**

I. Introduction

NOWADAYS, mobile robotics provides heterogeneous services for humans [1]. Not surprisingly, robotic services are more complicated than ever before. Despite the diversity of robotic services, it is impossible to develop a universal robot that can perform all expected services, especially considering various constraints, such as power consumption, payload, sensory, and kinematic constraints. Besides, for traditional robotic systems, a mobile robot equipped with various sensors is usually expensive and power consuming. Instead of using a universal robot, all primary information can be efficiently retrieved from online data centers, such as a cloud, benefiting from the greatly developed network facilities.

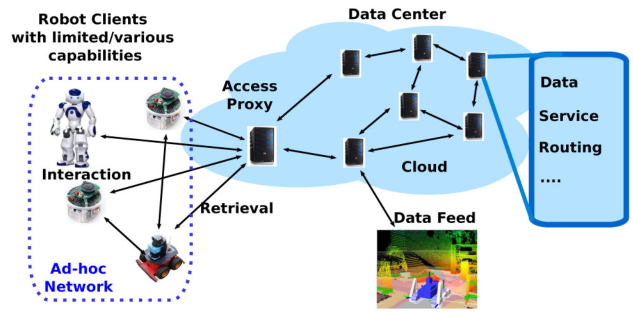

Fig. 1. Typical architecture of cloud robotic systems.

A typical cloud robotic system is shown in Fig. 1, which includes a robot-to-cloud (R2C) network and a robot-to-robot (R2R) network. In the R2C network, an Internet-based cloud infrastructure provides a data center sharing heterogeneous sensor data resources. In the R2R network, a team of robots communicates via wireless channels such as local area network (LAN), or mobile ad hoc networks (MANETs) which are implemented in this paper.

Although the cloud can alleviate the requirements of robotic tasks on local infrastructures, there are still drawbacks and challenges to be further addressed. For example, the primary hold-backs in robotics system are the limited network bandwidth and communication range. Ad hoc networks support the best-effort traffic. Different from traditional MANETs networks, cloud robotic networks require real-time responses for a range of applications, such as rescue tasks in hostile environments involving cooperative robot teams. It is because most of the robotic applications need real-time data transmission. For example, robotic mapping and localization require a large bandwidth to transmit the raw sensor measurements, when the mapping is provided as a centralized service to the robots. Besides, some applications such as cooperative control of a robot team have requirement in real-time communication. Assuming the resource is not constrained, most existing works proposed infrastructures, algorithms in various applications based on the R2C network. Very few works take serious consideration of limited access of cloud for robots.

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This paper aims at efficient access and resource retrieval of an R2C network under the constrained bandwidth. Recently, the real-time wireless multihop protocol (RT-WMP) [2] has been proposed on top of IEEE 802.11, which provides firm real-time (FRT) communication among multiple robots. RT-WMP is capable of managing the message priority and mobility for both outdoor and indoor environments. Adopting this protocol, we propose a hierarchical auction mechanism based on link quality for real-time resource retrieval in the cloud robotic system. Specifically, we stress the following contributions in this paper.

1) A generic hierarchical framework for FRT communication among multiple robots is proposed for efficient resource retrieval.
2) A resource allocation mechanism called LQM auction is proposed for the local optimization of bandwidth allocation.
3) Simulations and a joint surveillance scenario are used to evaluate the proposed mechanism in a typical cloud robotic system.

The remainder of this paper is organized as follows. In the next section, the related work in the area of resource allocation mechanisms is reviewed. Section III introduces the routing protocol RT-WMP implemented in this paper, and its corresponding ad hoc network topology. In Section IV, the hierarchical LQM auction mechanism is proposed, and its optimality is proved by theoretical analysis. After that, simulations and a joint surveillance experiment are presented in Section VI with analysis and discussion. Some concluding remarks are given at the end.

II. Related Work

Resource allocation is not a new problem. Many works have been done on various aspects such as power scheduling [3], social networked multiagent system [4], multirobot cooperation [5], and wireless sensor network topology control [6]. One popular kind of solutions is the primal-dual method. Well-known examples include the Hungarian algorithm [7], which was a combinatorial optimization method that solved the assignment problem by manipulating a matching bipartite graph. The time complexity is $O(n^3)$ after modifications by effective searching techniques. However, they are difficult to apply in decentralized structures. Meanwhile, greedy algorithm [8] mostly is not able to find the global optimal solution when solving the combinatorial problems. Local optimal is chosen at each iteration in a heuristic manner, which may yield an approximately global optimal solution within a reasonable time.

Another important approach is the market-based approach such as Stackelberg model [9], [10] and bargaining model [11], which relies on local information and self-preference of agents to arrive efficient solutions for complex and large-scale problems. Auction is one of the most effective market-based solutions to resource allocation problems. The flexibility of the auction model allows agents to necessarily cooperate and compete, to accomplish resource allocation efficiently. Researchers in various areas adopted auction-based approaches. Duan *et al.* [12] proposed a set of auction-based algorithms for the spectrum sharing. Zhang *et al.* [13] developed an auction mechanism to select transmission paths in multihop networks, which optimizes the total costs for data messages routing from sources to destinations. Apart from auctions for optimal paths, Kao *et al.* [14] presented an auction-based bandwidth allocation algorithm with a multihop flow coordination mechanism to enhance the various quality of services.

Besides, auction-based mechanisms are widely applied in multiagent systems, such as multirobot systems. Korsah *et al.* [15] proposed an auction-based multirobot task allocation method, where tasks were treated as commodities, which were auctioned to agents, so that the agents can bid for a particular task regarding their specific requirements. Many related works have been reported in this direction: e.g., auction-based algorithms are proposed for loosely-coupled tasks like exploration [16] and surveillance [17]. Auction mechanisms proposed for multirobot task allocation mainly focus on coordinated robots for completing tasks [18] and the overall cost minimization of task performance [19]. Bidding strategies [20] were proposed for various optimization problems, which were reported in [21].

Regarding auction strategies, multirobot task allocation algorithms can be classified as sequential single item auction (SSIA) [20], repeated SSIA (RSSIA) [22] and parallel single item auction (PSIA) [23]. The MURDOCH [24] algorithm is the first price-oriented single-round SSIA. Nanjanath and Gini [25] proposed an RSSIA, by which the robots repeated the auctions till all the tasks are completed. Zavlanos *et al.* [26] proposed a parallel auction algorithm for the use in a distributed auction, in which only local information was available. The results revealed that they always converged to an optimal solution, which maximized the total benefit using a linear approximation. Simulations were used to evaluate the effectiveness of auctions among a large number of agents. It was yet to be seen, however, how well this algorithm can perform under environmental disturbance, as well as that under the constraints of real-time requirements.

However, most mechanisms mentioned above are validated among a large number of virtual agents or only via simulations. Just a few of them had been evaluated on physical systems. For instance, the first-price SSIA MURDOCH [24] and the RSSIA TraderBot [22] had implemented experiments in real life. They focused on the coordination among robot teams with an assumption that there was no communication competition, which indicated that each robot can perform an allocated task by itself. Unlike their work, this paper aims at solving the resource competition among robots for offering services in practical cloud robotic systems. Besides, for distributed systems, hierarchical structures have been extensively studied in the domains of artificial intelligence [27] and robotics [28]. The reason is that hierarchical methods usually decrease the undetermined complexity for some NP-hard problems such as traveling salesman problem [29] and single task, single robot, task allocation problem [15].

There are few works on the resource allocation in the *ad hoc* mobile cloud, as per the state-of-the-art. Malhotra *et al.* [30]

outlined the significant challenges in the implementation of MANET cloud and proposed a "multihop mobile *ad hoc* cloud," by which a cloud was comprised of local resources in MANETs. Wang *et al.* [31], [32] proposed a asynchronous cloud robotic architecture combinations of an *ad hoc* cloud formed by R2R communications among participating robots and an infrastructure cloud enabled by machine-to-cloud (R2C) communications. Kamei *et al.* [33] examined the requirements and discussed the key research issues for cloud robotics in typical services for elderly care tasks.

Although many approaches have been developed for resource allocation problems, the fundamental problem of resource allocation in the cloud-based robotic system has not been fully solved. We presented an incremental auction strategy for both fair and biased cases in resource allocation [4]. In this paper, we extendedly propose a hierarchical auction-based algorithm for a real-time distributed network within multirobot systems.

III. Real-Time Wireless Multihop Protocol and Topology

This section introduces the routing protocol that is implemented in this paper and formulates the corresponding network topology.

A. Overview of RT-WMP

The RT-WMP is a token-based routing protocol that works with existing IEEE 802.11 b/g/n protocols. It is chosen as the routing protocol in the ad hoc networks of the experiments because of its robust multihop capability. Additionally, data flows in the network could be dynamically prioritized, allowing the user to determine which node is permitted to transmit.

The notable features of RT-WMP that contributed to its selection are highlighted as follows.

1) Easy implementation in the user space of a Linux system.
2) Comparability with existing WiFi equipment.
3) Storage of incoming messages in the transmission queue of the same priority done in first-in-first-out (FIFO) order.
4) Ability to fulfill real-time requirements.

The interested reader may refer to [2] and [34] to get more details on the protocol.

B. Benchmarking of RT-WMP

Tan *et al.* [34] conducted the benchmarking experiments of RT-WMP in two different indoor environments: one in an area with minimal WiFi interference, and the other in an area with significant WiFi interference. The results show that the congestion in the wireless channel greatly affects the transmission quality.

C. Ad Hoc Network Topology

The aforementioned protocol RT-WMP is used as the routing protocol that is on top of the IEEE 802.11, and to manage the message priority in a cloud robotic system. An example is shown in Fig. 2. A connected dynamic network graph $\mathcal{G}(V, E, t)$ consists of a set of n nodes $V = \{v_1, v_2, \ldots, v_n\}$, where each node has a hop number h_i, and edges, which indicate the link quality among nodes by $E = \{\boldsymbol{e}_i^j(t) | v_i, v_j \in V\}$. The distributed network topology is a hierarchy at time t, which is determined by the inherent multihop mechanism.

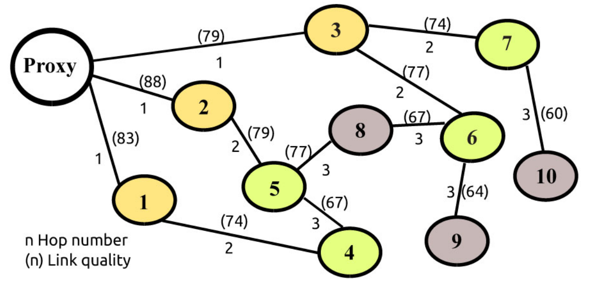


Fig. 2. Hierarchical network graph of the proposed robotic multihop architecture and the corresponding link quality. Nodes in the same layer (see Section III-C) are drawn in the same color, e.g., v_1, v_2, and v_3 are in layer $l = 1$.

Definition 1 (Layers): In a dynamic network graph $\mathcal{G}$, all the nodes in set V_l that have the same hops h_l to the proxy lie in the same layer l, where $V_l := \{v_i | h_i = l, l \in (1, L)\}$.

Definition 2 (Link Quality Matrix): The link quality matrix (LQM) of the graph is denoted by an $E := [\boldsymbol{e}_i^j(t) | v_i, v_j \in V]$ at time t. The entry $\boldsymbol{e}_i^j$ is the received signal strength between pairs of nodes. All the nodes update their LQM whenever a new frame is received. Each $\boldsymbol{e}_i^j$ is given by

$$\boldsymbol{e}_i^j = k \cdot P_i \cdot \left(d_{ij}\right)^{-\iota} \tag{1}$$

where k is a system coefficient related to the wavelength of signal, transmitter, and receiver antenna gains, etc.; P_i is the transmission power at v_i; d_{ij} is the distance between v_i and v_j; and ι is an attenuation factor of the wireless channel.[1]

To reach the optimal data transmission in a typical cloud robotic system, we present a novel resource allocation mechanism in the next section.

IV. Hierarchical Auction-Based Mechanism for Resource Allocation

Using the RT-WMP protocol, a resource retrieval system without management can easily overload the limited communication capability [34] in an *ad hoc* R2R network. Thereafter, the overload can affect the data retrieval of each robot from the cloud where the data are stored on all other clients. In this section, the problem and mechanism of resource allocation for cloud robotic systems are formulated.

A. Definitions and Assumptions

The related topological breakdown of the proposed algorithm is illustrated in Fig. 3. Several roles of topological nodes in a multihop network are defined as follows.

1) *Proxy:* A proxy refers to the node that distributes the resources in the cloud according to the final results of auctions.

[1]For a typical environment in our test, $\iota = 2$.

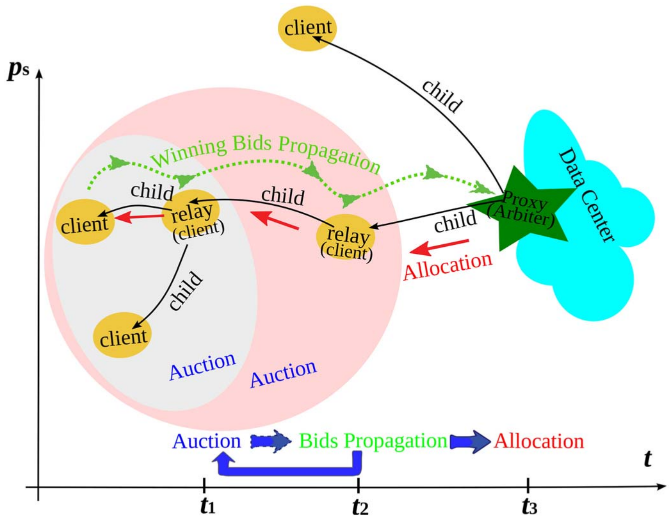


Fig. 3. Bidding information propagation in the topology of a typical network that conducts the proposed auction mechanism. Yellow eclipses represent clients. The green star represents the proxy that connects the data center, which manages the data retrieval for this local network. The region in the same color highlights the nodes in the communication range, within which the resource competition (auction) among clients is conducted (which means the auction is conducted among client nodes for each colored region).

2) *Client:* The node that being part of the system, which potentially has the needs for resources.
3) *Relay Node:* The clients that help maintain the connectivity of the network.
4) *Parent/Child:* The children of a relay node are the clients that rely on the relay node to establish connectivity to the rest of the network. Conversely, the relay node is the parent of the child nodes.

Considering the multihop network characteristics, we emphasize the following assumptions for the hierarchical auction mechanism.

1) The relay nodes help maintain the connectivity by passing the data packages of its children. The relay node after that selects the client which won the latest auction round.
2) All children compete for the transmission opportunity through relay nodes. They are not supposed to bid with nodes that are connected to other relay nodes, even for those with the same layer depth do not bid.
3) The connectivity cost is related to the requested bandwidth for transmission of each node. The less the bandwidth is queried, the lower the cost it pays.

B. Objective

The aim of the resource allocation strategy is twofold.

1) To allocate the network resources by the priorities of nodes in a network. For instance, some of the nodes with higher priorities are allocated with a lot of network resources while ensuring that all other nodes can still reasonably transmit by using the remaining network resources.
2) To maximize the total transmission rate for FRT in the above mentioned multihop network, management of the requests from nodes should be implemented.

Definition 3 (Firm Real-Time): FRT means some infrequent deadlines can be miss during the data transmission, which may degrade the system's quality of service.

Due to the lack of global information in the defined multihop network topology, the objective is to maximize the sum of the transmission rate at each relay node, such that

$$\max \quad \sum_{i}^{n_r}\left(\gamma_i^r - c_i^r\right) \tag{2}$$

$$\text{s.t.} \quad \gamma_i^r = \frac{\mathrm{Bw}_i}{2}\ln\left(1+\Gamma_i^r\right) \tag{3}$$

$$\sum_{i}^{n_r}\mathrm{Bw}_i \le \mathrm{Bw} \tag{4}$$

where n_r is the number of children of relay node v_r, c_i is the connectivity cost of the child v_i to the relay node v_r; γ_i^r is the achieved rate of data from node v_i to the relay node v_r; and Bw_i is the allocated bandwidth for v_i. The signal-to-noise ratio obtained at relay v_r is

$$\Gamma_i^r = \frac{\boldsymbol{e}_i^r}{\sigma^2 d_{ij}^2} \tag{5}$$

where d_{ij} is the physical distance for node v_i that hops to the relay node v_r. We assume that the additive noise is Gaussian distributed with zero mean and fixed concentration σ^2 for each channel.

Note that the local optimization of the transmission rate at each relay node may not necessarily guarantee the max–min fairness. For instance, some of them may use the majority of the network resource, while others cannot transmit due to the lack of resource. Therefore, an auction mechanism is proposed to ensure the rate for any node cannot be further increased without decreasing the rate of others.

C. LQM Auction Strategy

The key concepts of the proposed auction rules in a hierarchical network are described as follows.

1) *Known Information:* The LQM of a network graph $\mathcal{G}(V, E, t)$, and a set of price $\Pi = \{\pi_1, \ldots, \pi_{n_r}\}$ ($\Pi > 0$) of a unit bandwidth are announced by each relay node to its children before the bidding start.
2) *Bids:* b_i is the bid of v_i that is submitted to the relay node v_r. We utilize the link quality as the bid where $b_i = \boldsymbol{e}_i^r$.
3) *Allocation:* The relay node allocates the bandwidth to its according to their bids, which is calculated by

$$\mathrm{Bw}_i^r = \frac{b_i}{\sum_{j\in v_r} b_j}\mathrm{Bw}^r \tag{6}$$

where Bw^r is the total bandwidth of the link through the relay node v_r and Bw_i^r is the bandwidth allocated to node v_i. Additionally, the vector of bids $\mathbf{b} = \sum_{j\in v_r} b_j = (b_i, \mathbf{b}_{-i})$, where the bid vector of node v_i's opponents $\mathbf{b}_{-i} = (b_1, \ldots, b_{i-1}, b_{i+1}, \ldots, b_{n_r})$.
4) *Reward:* Node v_i's reward function equals to the achieved rate γ_i^r in (3).

5) *Cost:* Node v_i's cost function is defined by its payment (after winning an auction) as

$$c_i^r = \pi_i \mathrm{Bw}_i^r. \tag{7}$$

Please note that each auction is bidding among a group of child nodes of the same relay node. Given the vector of bids $\mathbf{b} = (b_i, \mathbf{b}_{-i})$ and a unit of resource price π_i for node v_i, the payoff of a node v_i is defined as

$$U_i(b_i; \mathbf{b}_{-i}, \pi_i) = \gamma_i^r(b_i; \mathbf{b}_{-i}) - c_i(b_i; \mathbf{b}_{-i}, \pi_i). \tag{8}$$

Then the node v_i's best response at the relay node v_r is defined as

$$\mathcal{B}_i(\mathbf{b}_{-i}, \pi_i) = \left\{ b_i | b_i = \operatorname*{argmax}_{b_i \geq 0} U_i(b_i; \mathbf{b}_{-i}, \pi_i) \right\}. \tag{9}$$

To derive the best response, an optimal price π_i^* by relay node v_r is required. Substituting (3) and (7) into (8), the payoff function is

$$U_i(b_i; \mathbf{b}_{-i}, \pi_i) = \frac{b_i \mathrm{Bw}^r}{b_i + \mathbf{b}_{-i}} \left[\ln\left(1 + \Gamma_i^r\right) - \pi_i \right]. \tag{10}$$

According to (9), the optimal price π_i^* can be derived by differentiating (10) with respect to b_i. The π_i^* is thus given as

$$\pi_i^* = \frac{1}{2 \ln 2} \frac{b_i}{\mathbf{b}_{-i}} \left[\ln\left(1 + \frac{b_i}{\sigma^2 d^2}\right) + \frac{b_i + \mathbf{b}_{-i}}{\sigma^2 d^2 + b_i} \right]. \tag{11}$$

After obtaining the optimal price π_i^* from the above equation, the best response defined in (9) can be computed. In other words, the payoff can be maximized by selecting the optimal price using the bids of all child nodes of relay node v_r. Note that a bid indicates the communication capability of the corresponding node.

Thereafter, the global convergence of the proposed auction strategy are proved, after deriving the optimal at each relay node as follows.

1) Proposition (Convergence of the LQM Auction): Given a connected graph, the LQM-auction algorithm terminates in a finite number of auction iterations with an upper bound

$$K^{\max} = \sum_{l=1}^{L-1} \left(n_l \times \frac{\gamma_l^{\max}}{\varepsilon_l^{\min}} \right) \tag{12}$$

where

n_l number of nodes in layer l;
$\gamma_l^{\max}$ maximum reward of nodes in layer l;
$\varepsilon_l^{\min}$ minimum increment of bid of layer l.

Proof: Assuming that the network structure of robotic system is in a multihop pattern. For each resource, the reward and bidding increment of each client is a finite value. For a certain iteration of auction, the client v_i, who once won, updates its payoff by $\gamma_i - \pi_i$, where γ_i is the reward of client v_i and π_i is the price paid by client v_i when its request was accepted in the last iteration. For the next iteration, some other client will win. After adequate iterations of auctions, all clients will be served. The worst case is as follows: when the last winner is in the layer of the maximum hop number from the proxy, it needs to win $L-1$ auctions for its $L-1$ relay nodes. The largest number of iterations that makes it to win is $\gamma_l^{\max}/\varepsilon_l^{\min}$. Please note that the $\varepsilon_l^{\min}$ is the minimum increment of LQM value between layer l and layer $l-1$. Therefore, the upper bound of iterations is $K^{\max}$ as (12). ■

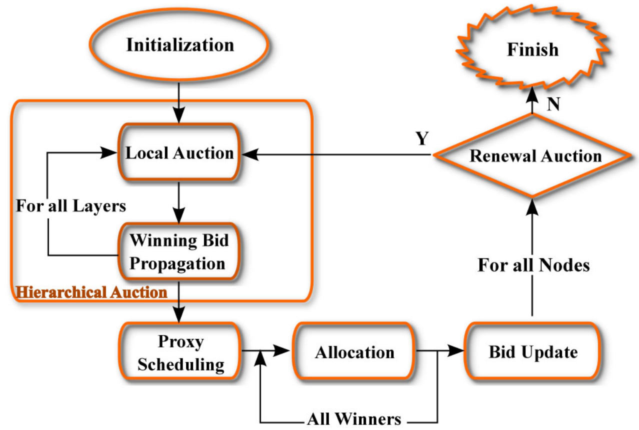


Fig. 4. Flowchart of the auction-based resource retrieval.

D. Implementation of LQM Auction Algorithm

The auction mechanism can provide an optimal response ranking, which is the response order of requests from clients. This response ranking is scheduled by the proxy based on the result of the final auction. Given the above notations, let $b_i(t)$ denote the bid of client i at time t. The auction process is triggered by the request for the resource. Then an LQM auction is executed for a local neighborhood (including the clients and relay) as shown in Fig. 3. After each local auction, the parent relay node represents the winning child for a next round auction. The process in Fig. 4 is explained as follows.

1) *Initialization:* Each relay node announces its own particular price set Π for its children. Each client collects its reward regarding the price and the bid with its link quality that demonstrates its connectivity to the parent layer. At the same time, according to the network topology $\mathcal{G}(V, E, t)$, the relay nodes and layer l for each client are assigned. The deepest layer is L.
2) *Hierarchical Auction:* The auction process starts from the relay nodes lie on layer $L - 1$, denoted as a set $A := \{a_i\}$. For each a_i, a local auction process is launched among the nodes in a set $B := \{a_i\} \cup \{b_i | \text{children\_of}(a_i)\}$. After all auctions are completed in this layer, the winning node is forwarded to a higher layer by its relay node. Supposing a_i is a relay node, it uses the link quality to its parent as the bid for the next the auction, while keeps tracking the real winner in set B.
3) *Proxy Scheduling:* The proxy assesses the final result of the auction. The winners (multiple clients may have the same winning bid) are stored in the buffer. The proxy publishes a priority rank of winners at this stage. Then the proxy sends back the queried resource via network topology.
4) *Renewal Auction:* A second round of auction may be deployed after each successful allocation. The bid list

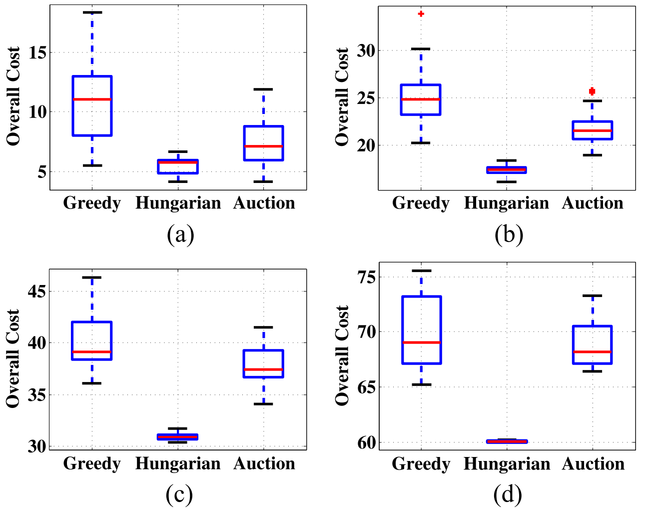


Fig. 5. Cost comparison among three algorithms with different size of nodes. Red lines mark the median value. The edges of the blue box are the 25th and 75th percentiles. Black lines mark the maximum and minimum values. The red cross points are extreme values. This representation applies for Fig. 6. (a) 10 nodes. (b) 50 nodes. (c) 100 nodes. (d) 200 nodes.

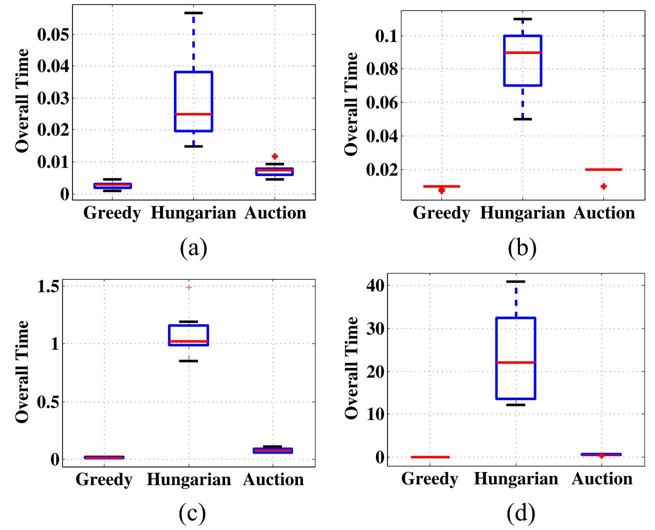


Fig. 6. Time comparison among three algorithms with different size of nodes. (a) 10 nodes. (b) 50 nodes. (c) 100 nodes. (d) 200 nodes.

is required to initialize for the next round of auction according to their LQM. The process will end if all requests from clients are fulfilled.

V. Simulations

We have compared our method with two other popular and classical assignment algorithms: 1) Hungarian algorithm and 2) greedy algorithm. The Hungarian algorithm is a deterministic and centralized algorithm that always yields the global optimum [35] of an assignment problem in polynomial time. We choose the greedy algorithm because it heuristically solves the assignment problem with locally optimum at each stage [35]. Besides, the greedy algorithm, in general, does not produce an optimal solution, but may figure out a local optimum that approximate a global optimal solution in a reasonable time. Therefore, the effectiveness of the proposed method can be verified by comparing our proposed mechanism with a global optimum and a local optimum.

In this simulation, we implemented the greedy algorithm and the Hungarian algorithm for benchmarking and evaluation. Two comparisons are conducted in the simulations. First, the overall cost and time are used to evaluate the performances of the greedy algorithm, the Hungarian algorithm, and the proposed auction algorithm. Second, three auction algorithms are compared by a scheduling metrics.

A. Overall Cost and Time Comparison

Cost is the effort that a robot needs to take to obtain the required resource. For example, distance traveled or runtime consumed [23]. We defined the cost of each node (robot) as the distance traveled (hops). The value of the cost is a random number in the range of {0, 10}. Then, the overall cost is a sum of distances to query N resources, which are allocated to N nodes. As shown in Fig. 5, the Hungarian algorithm always performs the best among the three algorithms when the number of nodes is 10, 50, 100, and 200, respectively. The proposed algorithm performed better than the greedy algorithm since its overall cost is lower than the result of the greedy algorithm and closer to the result of the Hungarian algorithm.

Runtime reflects the computation complexity of an algorithm as shown in Fig. 6. The Hungarian algorithm took much longer time to dispose of the solution and the overall time increases largely with the number of nodes (from 25 ms to 20 s in average). The greedy algorithm spent trivial time, and the number of nodes has a minor effect on it (from 2 to 20 ms in average). The proposed auction algorithm needed marginally more time than the greedy algorithm, and its overall time did not change much when the number of nodes increases from 10 to 200.

According to the above overall cost and running time results, the auction algorithm can achieve the optimal results more quickly.

TABLE I
Comparison of Response Ranking (Defined in Section V-B)

Method	LQM auction			PSIA			RSSIA		
Client	H	L	A	H	L	A	H	L	A
1	3	4	3.63	1	4	3.42	1	2	1.10
2	10	11	10.63	2	8	7.16	2	6	3.10
3	3	17	9.45	6	18	14.49	2	7	4.10
4	1	1	1.00	1	4	1.36	1	5	2.30
5	4	5	4.63	2	8	4.06	4	10	6.70
6	9	14	11.27	21	23	21.74	9	22	13.10
7	9	14	11.21	3	17	9.59	5	13	9.40
8	2	2	2.00	2	8	3.19	13	37	20.00
9	3	8	5.15	3	18	7.66	19	44	31.30
10	3	8	6.33	3	17	6.71	3	10	5.20

B. Response Ranking Comparison

To evaluate the scheduling performance, the simulation implements two classical auction algorithms, namely

TABLE II
CONFIGURATION OF NODES INVOLVED IN THE EXPERIMENTS

Nodes	System Configuration			Requests	
	System	WiFi Device	Max Transmission Power	Scale State	Video Sequence
Proxy Node R0 (Receiver)	Intel-based laptop running Linux Ubuntu 12.04 LTS	A built-in Centrino Advanced-N 6205 wireless network card running IEEE 802.11b/g/n	$15dBm$	Receiving request topics from all other nodes	
Transmitting Nodes R1 and R2 (Sender)	ARM-based E-pucks running a lean version of Linux Ubuntu 10.10 LTS	A WiFi dongles running IEEE 802.11b/g mode	$15 \pm 1.5dBm$	Hundred bytes data sent via ROS at a rate of 1.0 Hz	• Images of 160×120 pixels sent via ROS at a frame rate of 8.0 Hz • 18.75 KB/s of bandwidth taken up
Transmitting Nodes R3, R4, R5, and R6 (Sender)	Intel-based laptop running Linux Ubuntu 12.04	A built-in TL8188CE wireless network card running IEEE 802.11b/g/n	$15dBm$	Hundred bytes data sent via ROS at a rate of 1.0 Hz	• Images of 320×240 pixels sent via ROS at a frame rate of 8.0 Hz • 75 KB/s bandwidth taken up

PSIA [26], and RSSIAs [25]. The comparison of the two algorithms in the simulation is because relevant works on physical robots are scarce and with various uncontrollable conditions.

The response ranking of each client is compared with different auction algorithms as shown in Table I. “H” is the highest rank, “L” is the lowest rank, and “A” is the average rank, where the rank represents the priority of ten clients for each column, respectively. For each row, it shows the effects of three different auction mechanisms on each client. For example, the worst average priority for any node is 11.27 for LQM auction, having 21.74 (about two times as bad) for PSIA, and 31.30 (almost three times as bad) for RSSIA. The reason of the remarkable differences is: the RSSIA leads to the lowest ranks because it depends on the resource of robots. If the unassigned robots do not have enough resource to complete the rest of tasks, it will repeat the auction till some robot can refill. The process repeats until all nodes are globally optimally ranked. Compared with PSIA, the proposed LQM auction achieves higher ranks since the bidders in an auction are selected based on PSIA.

VI. EXPERIMENTAL VALIDATION

In this section, the proposed LQM auction is validated in a real experiment. The experimental design is first introduced. Then the outcomes of the experiments are presented and discussed.

A. Experiment Design

The goal of this case study is to realize a joint surveillance for several poorly-equipped robots. The navigation goal of these poorly-equipped robots can be retrieved from a database by sending both video sequences and scale state information (i.e., battery voltage in this scenario) to the proxy. Whereas resource competition among requested robots can affect the efficiency of data retrieval greatly.

The infrastructure implementation of the system is introduced in the previous work [36]. Based on different types of requests, experiments for unconstrained resource allocation and constrained resource allocation cases are both conducted with and without the resource allocation strategy. The results not only validate the improvements made when the proposed mechanism is applied but also indicate how the mechanism works, when there are an increased load and the resource becomes constrained.

1) Devices: The devices shown in Table II are used to fulfill the various roles in the experiment. All of them had the `ros-rt-wmp` node running in the user space at 2.412 GHz (or channel 1). This channel is selected because it is applied in most devices.

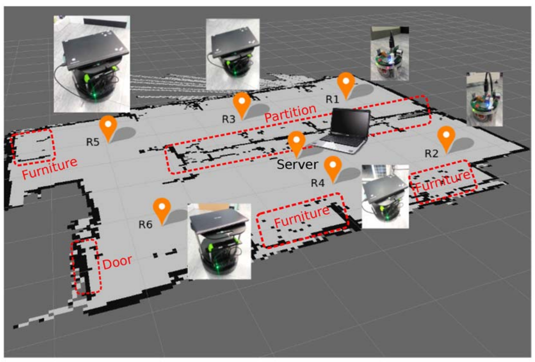
2) Placement of Nodes: Fig. 7 demonstrates the placement of all the nodes in the experiments. The test area is an indoor environment, which is surrounded by concrete walls and a door, and has partitions and some types of furniture inside the room. A simple WiFi sweep is performed and the trace revealed that there are not many other WiFi signals present at the desired operating frequency at 2.412 GHz (or channel 1 [37]) as shown in Fig. 7(b). Thus, WiFi interference is expected to be minimal in this area. Detailed benchmark work has been presented in [34]. The nodes are initially placed in these positions such that they are forced to hop through each other. They are moving around at the maximum speed of 0.5 m/s regarding their navigation goals during the experiment.

3) Scenarios: In most exploration cases such as robot surveillance, robots have to know their location or navigation information. Several poorly-equipped robots send requests in the local neighborhood to the proxy that accesses the data center. The proxy matches the images and scale state with the information stored in the data center and sends navigation goals back to the robots. The corresponding requests are managed by the proxy with predefined auction-based management mechanism with scheduling algorithm and protocol. For instance, the proxy responses the request from the poorly-equipped robot winner in each auction round. Based on the request types, we analyze the following two conditions.

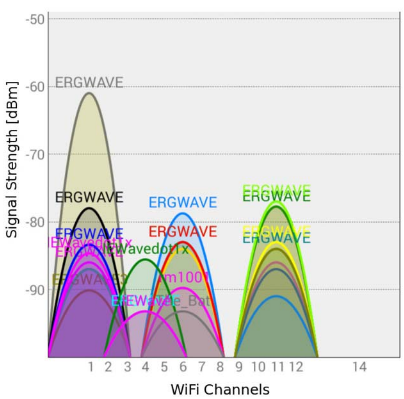
1) *Unconstrained Resource Allocation:* When only scale state requests are sent to the proxy, the bandwidth resource can be regarded as unconstrained, since the conducted requests are with trivial bandwidth requirement.

TABLE III
COMPARISON ON PACKET LEVEL PERFORMANCE FOR SCALE STATE REQUESTS

Nodes	Received Number of Messages		Message Delivery Delay (ms)						Bandwidth (Kbps)	
			Average		Max		Min			
	No Strategy	With Strategy	No Strategy	With Strategy	No Strategy	With Strategy	No Strategy	With Strategy	No Strategy	With Strategy
R1	815	783	4.046	2.538	105.173	100.864	0.033	1.051	0.23	0.22
R2	792	763	3.428	2.61	202.476	17.995	0.013	0.034	0.24	0.22
R3	732	1053	1138.469	2.295	826315.604	9.179	0.039	0.424	0.23	0.3
R4	647	725	239.069	4.406	653.223	102.02	7.019	0.284	0.23	0.24
R5	691	709	2.914	3.057	101.913	101.54	0.011	0.09	0.23	0.24
R6	657	978	2.259	2.616	104.021	104.839	0.015	0.408	0.23	0.29



(a)



(b)

Fig. 7. Typical indoor environment for multirobot joint surveillance. (a) Indoor map with initial placement of nodes. (b) WiFi trace.

2) *Constrained Resource Allocation:* In the system, the images captured by the poorly-equipped robots are used to retrieve the perception data such as location and location-related data. As shown in Table II, video sequence requests from two different types of nodes take up 18.75 and 70 Kb/s bandwidth, respectively. Transmission of JPEG images in the robotic network is a dense task. Therefore, the bandwidth is a constrained resource.

4) Node Configuration: The RT-WMP allows the priorities of nodes to be dynamically changed during runtime. The following configurations are conducted.

1) *Transmission With No Strategy:* Before the start of each experiment, all the priorities of requests are configured to be equal to each other. No changes are made at runtime. In principle, messages with the same priority are transmitted in an FIFO manner.
2) *Transmissions With Resource Allocation Strategy:* Initially, the priority of nodes are randomly configured. During the runtime, the priorities are then adjusted by the strategy dynamically.

B. Evaluation Metrics

Received message number, message delivery delay, bandwidth usage, and CPU load are used as evaluation metrics in this paper. Especially, a calculation of the frame-rate is done each time when a new image is received by a client. The definition is as follows.

Definition 4 (Instantaneous Frame Per Second): The instantaneous frame per second (IFPS) formula used was a simple moving average of the K most recent images, which is

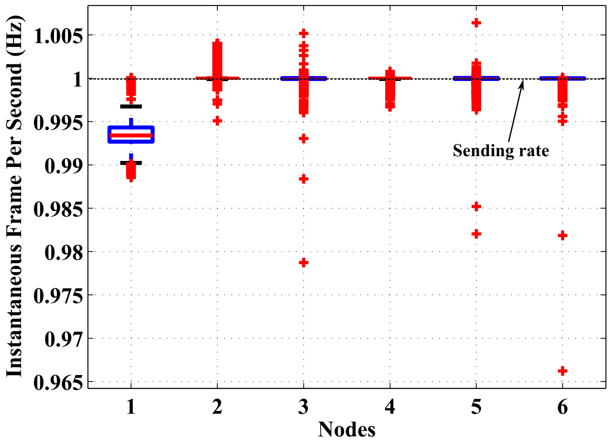
$$\mathrm{IFPS} = \left(\frac{\sum_{i=1}^{K} \tau_i}{K}\right)^{-1} \quad (13)$$

where τ_i represents the duration taken for the ith image to arrive at a client after the $(i-1)$th image. The result of this calculation gives an indication of the amount of network resource allocated to a particular client at that point. A higher IFPS value of a client represents a greater amount of network resource has been allocated to it with a higher capacity for data payload. If a series of IFPS values are recorded and observed, the spread of IFPS value also indicates the performance of the network.

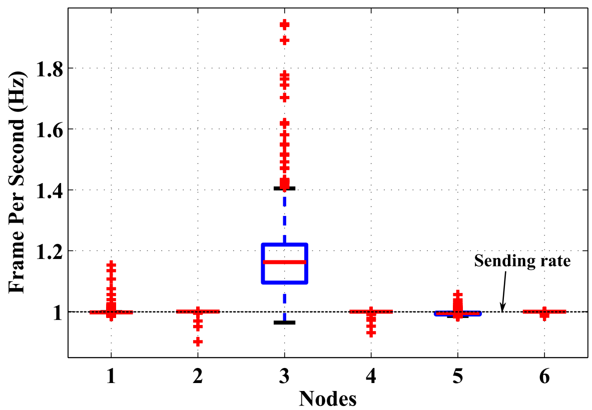
C. Experimental Results

IFPS, received message number, message delivery delay, bandwidth usage, and CPU load are used as the evaluation metrics for FRT in the experiments.

1) Unconstrained Resource Allocation: Experiment is conducted for six nodes transmitting scale state requests which are not a dense task for the network bandwidth. Two cases with and without the resource allocation strategy are carried out. The message delivery performances in packet level are shown in Table III. For received number of messages, $R3$–$R6$ transmit more messages with the resource allocation strategy while $R1$ and $R2$ transmit a bit fewer messages. It is because the resource

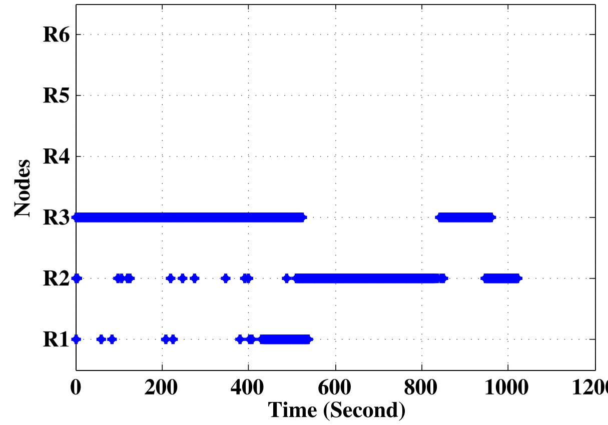


(a)

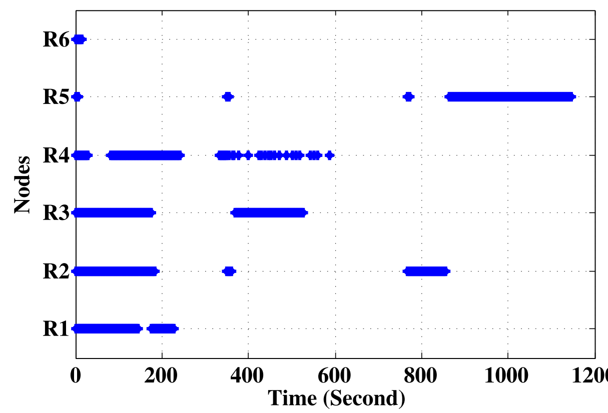


(b)

Fig. 8. Boxplots of IFPS values under unconstrained resource conditions. Red lines mark the median value. The edges of the blue box are the 25th and 75th percentiles. Black lines mark the maximum and minimum values. The red cross points are the extreme values. This representation applies for Fig. 10. (a) No strategy. (b) With strategy.



(a)



(b)

Fig. 9. Traces of images received at proxy. (a) No strategy. (b) With strategy.

allocation strategy optimize all request transmission in the network to let node $R3$–$R6$ have got more chances to transmit their requests using the LQM auction strategy. Additionally, the total number of received messages are increased from 4334 to 5011. On the other hand, when no resource allocation strategy is applied, all requests of six nodes with the same priority are queued in a buffer and transmitted based on the FIFO principle. If the earlier come nodes occupy the network, then other nodes cannot transmit their requests. For the message delivery delay, it can be observed that $R3$ and $R4$ decrease a lot with respect to the messages delivery delay, which are around 600 and 50 times, respectively. But other nodes do not change much of the delay. Although the bandwidth is sufficient to handle this transmission when no strategy is applied, some of the nodes have much longer delivery delay because other nodes occupy the network bandwidth. For the bandwidth usage, there are not big differences between the two cases since the requests are for the unconstrained resource.

As shown in Fig. 8, the results of IFPS analysis demonstrate that the proposed strategy increases the median rate of receiving requests a bit and decreases the lower extreme data. When no resource allocation strategy is applied, the median IFPS values of nodes are 1 Hz except $R1$, which is 0.99 Hz as shown in Fig. 8(a). With the resource allocation strategy incorporated, $R1$ and $R3$ have improved their IFPS values to 1 and 1.18 Hz, respectively, as shown in Fig. 8(b). Note that a lot of extreme IFPS points from $R3$ are higher than the transmit frame rate. It is caused by the data packets queued up in the buffer for a period when the $R3$ is not allowed to transmit. Once $R3$ is permitted to transmit, these queued up data packets are transmitted as quickly as possible. Besides, the minimum values are quite straight forward, they are caused by the data packets queued up in the buffer for transmission when the node has the opportunities to transmit. Therefore, some of data transmission are delayed.

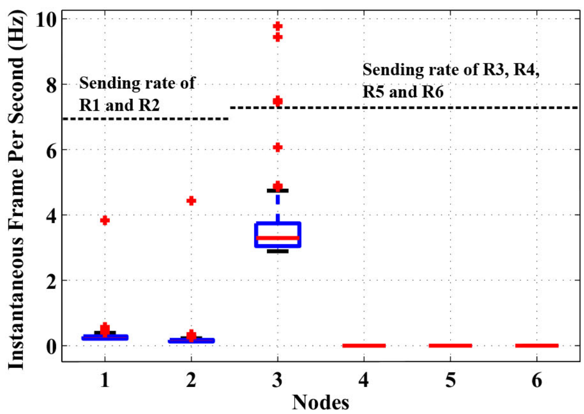
Therefore, the average delay of received requests is not obvious even when no resource allocation strategy is applied in the case of unconstrained resource. However, the maximum delay value is greatly reduced with the proposed strategy, which makes the data retrieval meet the FRT requirement.

2) Constrained Resource Allocation: Assuming that these client robots have a graph connectivity as Fig. 2 when all the robots transmit requests with video sequence in parallel. This is a dense task for the constrained network bandwidth.

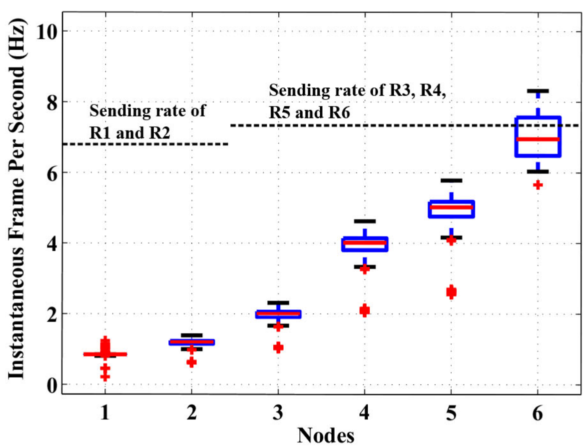
First, traces of video sequence received at the proxy from each node are compared. When no resource allocation strategy is applied, only $R1$–$R3$ transmit messages throughout the whole transmission session as shown in Fig. 9(a). On the other

TABLE IV
COMPARISON ON PACKET LEVEL PERFORMANCE FOR VIDEO SEQUENCE REQUESTS

Nodes	Received Number of Messages		Message Delivery Delay (ms)						Bandwidth (Kbps)	
			Average		Max		Min			
	No Strategy	With Strategy	No Strategy	With Strategy	No Strategy	With Strategy	No Strategy	With Strategy	No Strategy	With Strategy
R1	813	3991	10.05	10.005	105.606	112.701	0.064	0.047	9.40	57.38
R2	1420	4978	11.808	12.156	123.751	4160.363	0.121	0.074	18.23	61.67
R3	7482	3835	101.764	10.424	448327.871	97.799	1.237	1.008	185.17	50.69
R4	0	4495	∞	10.508	∞	123.983	∞	3.428	0	61.68
R5	0	3798	∞	10.906	∞	126.021	∞	0.982	0	53.97
R6	0	217	∞	10.443	∞	26.715	∞	0.119	0	2.26



(a)



(b)

Fig. 10. Boxplots of IFPS values under constrained resource conditions. (a) No strategy. (b) With strategy.

hand, when the resource allocation strategy is applied, the priority is dynamically changed in terms of the LQM value of the node. Thereafter, the priority is used to bid in an auction. Winners in the response ranking list get the permission to send images. The LQM values of nodes are changing while they are moving around; their bids are thus changing. Therefore, all nodes get certain permissions to transmit the requested images as shown in Fig. 9(b). Besides, a comparison of IFPS is presented in Fig. 10. When no resource allocation strategy is applied as shown in Fig. 10(a), the median IFPS values for $R1$–$R3$ are 0.25, 0.16, and 3.25 Hz, respectively, while not many frames are transmitted for $R4$–$R6$. When the resource allocation strategy is applied as shown in Fig. 10(b), the median IFPS values have improved ($R1$: 0.85, $R2$: 1.21, $R3$: 2.01, $R4$: 4.02, $R5$: 5.02, $R6$: 8.68).

These results clearly indicate that the proposed strategy improves the chance and rate of transmission of all nodes. The reason is that the proposed strategy combined with RT-WMP protocol handles different data flows and optimizes the transmission. There are two situations that the corresponding data streams are still permitted to be transmitted simultaneously. One is the data flow with the highest priority in the response ranking does not saturate the bandwidth, the other is there is sufficient amount of bandwidth available to accommodate the rest data streams of a lower priority.

Second, message delivery performances of video sequence requests at the packet level are compared between the cases where the strategy is applied or not, as shown in Table IV. For message transmission, the proposed resource allocation strategy increases the received number of messages on average. When no strategy is applied, only some requests from $R1$–$R3$ are received. After incorporating the strategy, all the six nodes transmit thousands of messages except $R6$, which transmits hundreds of messages. For message delivery delay, the average value, maximum value, and minimum value are compared. The proposed strategy decreases the delay such as $R3$ decreases the average about ten times and the maximum value about 4000 times. Also, it balances the transmission among the six nodes since all nodes have similar average outcomes in the message delivery delay with the applied strategy. For bandwidth usage, $R3$ occupies most of the network bandwidth, and $R1$ and $R2$ have got little opportunities to transmit when no strategy is applied. On the other hand, the bandwidth is distributed to each node according to the auction results when the strategy is applied. Especially, it can favor some nodes when they win the auction with a higher priority, which makes their resource allocation meet the FRT requirement under constrained resource conditions.

Third, the bandwidth usage and CPU load on the proxy are compared in cases of with and without the proposed auction mechanism when mixed requests are conducted. As shown in Fig. 11(a), the standard deviation (std) of network bandwidth is lower when six clients are in the auction for resource retrievals. It fluctuates when they arbitrarily send requests

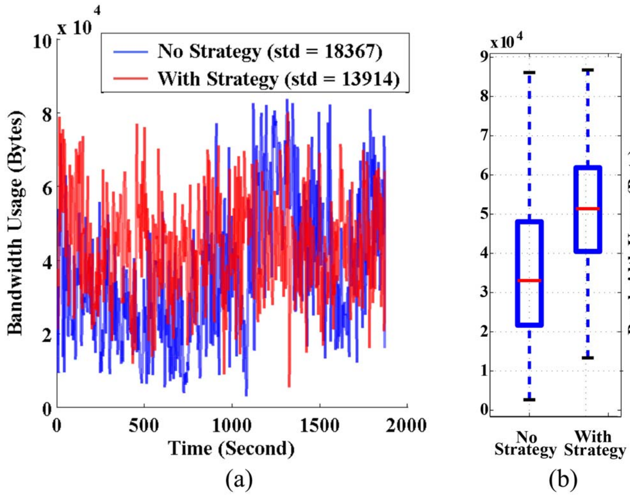


Fig. 11. Bandwidth usage comparison of the accesses to the proxy. (a) Line plot. (b) Boxplot.

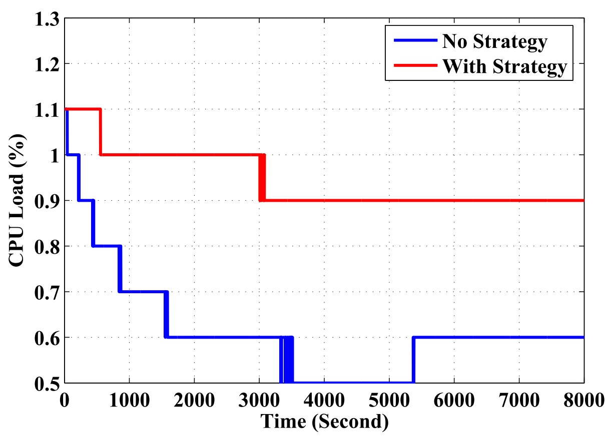


Fig. 12. Comparison on CPU load of the proxy when the resource retrieval is in a random fashion or controlled by LQM auction.

without management. If all nodes request resources at the same time, it will result in massive packet dropping, network congestion, and unstable responses. There is no big difference between the cases with and without management since the quantity of total data transmission are the same in our scenario. However, the stable bandwidth usage without congestion can provide more efficient transmission. As shown in Fig. 11(b), the median value of bandwidth usage has increased from 33 050 to 51 390 bps, which rises 35.9%.

Compared to the case where no resource allocation strategy is applied, the proxy is running for sending video sequence stably using marginally higher CPU load as depicted by the red curve in Fig. 12. With acceptable increased CPU load, the proposed strategy greatly improves the performances of resource allocation as proved here.

VII. Conclusion

This paper proposed a hierarchical auction-based mechanism called LQM auction for autonomous negotiation in a cloud robotic system. Aiming at solving fair and efficient resource retrieval for efficient data transmission among robots in a distributed multihop network, the auction taxonomy of the proposed mechanism is specified. We theoretically proved that the proposed LQM auction can achieve the best response as well as its convergence. The simulation results indicated the proposed approach outperforms the classical local and global optimization approaches—the greedy algorithm and the Hungarian algorithm. Besides, we validated the proposed LQM auction using an FRT joint surveillance scenario. The experimental results, including comparisons in the CPU/bandwidth usage, the time of responses, and the reliability of responses, validated the high performance of the proposed LQM auction. Note that the proposed mechanism does not specifically deal with dynamics of the network topology changes that may occur during the auction process. These dynamics usually rarely happen during the cycle of the transmission. Once it happens, the system will drop out the bid automatically due to the change of connectivity. We will try to solve these detailed issues in our future work. Despite this limitation, the proposed mechanism demonstrated its outperforming features against the state-of-the-art in both response time and the fairness of resource allocation for cloud robotic systems.

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