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Hierarchical Auction-based Mechanism for Real-Time Resource Retrieval in Cloud Mobile Robotic System

Lujia Wang[1], Ming Liu[2] and Max Q.-H Meng[1]

***Abstract*— In order to share information in the cloud for multi-robot systems, efficient data transmission is essential for real-time operations such as coordinated robotic missions. As a limited resource, bandwidth is ubiquitously required by applications among physical multi-robot systems. In this paper, we proposed a hierarchical auction-based mechanism, namely LQM (Link Quality Matrix)-auction. It consists of multiple procedures, such as hierarchical auction, proxy scheduling. Note that the proposed method is designed for real-time resource retrieval for physical multi-robot systems, instead of simulated virtual agents.**

We validate the proposed mechanism through real-time experiments. The results show that LQM-auction is suitable for scheduling a group of robots, leading to optimized performance for resource retrieval.

I. INTRODUCTION

Nowadays, mobile robotics evolves rapidly along with the social development. They provide heterogeneous services for humans. Not surprisingly, robotic services are more complicated than ever before. Despite the diversity of robotic services, it is impossible to develop a universal robot which is capable of all expected services due to various limitations, such as power consumption, payload, sensory and kinematic constraints. As for a typical robotic system, a mobile robot equipped with various sensors, is usually expensive and power consuming. Benefiting from the highly developed network, all primary information can be stored and retrieved from online data centers such as a cloud, by which the requirements on local infrastructures are alleviated.

Nevertheless, there are still drawbacks and challenges to be further addressed. For instance, limited network bandwidth and communication range in robotic system are the primary hold-backs, since most of the robotic applications need real-time data transmission, e.g. navigation and localization generally require a large bandwidth to transmit the raw sensor measurements. Moreover, some applications involving cooperative control of a robot team have hard real-time communication requirements. Recently, the real-time wireless multi-hop protocol (RT-WMP) [1] has been proposed on top of IEEE 802.11, which provides real-time communication among multiple robots. RT-WMP is capable of managing the message priority and mobility for both outdoor and indoor environments. Adopting this facility, we propose an auction-based resource retrieval strategy. In this paper for real-time data transmission among mobile robots.

Auction, a market-based approach, is one of the most effective solutions for resource allocation and assignment problems. As a primary strength of these approach, they only rely on local information and self-interest of agents to arrive efficient solutions for large-scale, complex problems. The flexibility of the auction model allows agents to necessarily cooperate and compete to accomplish resource allocation efficiency. Therefore, auction-based mechanisms are widely applied in multi-agent systems. Especially, multi-robot task allocation [2] utilizes auction-based strategy, where tasks are treated as commodities and auctioned to agents. The agents can bid for a particular task regarding their own requirement. Several related works have been reported in this direction, e.g. loosely coupled tasks like exploration [3], [4] and surveillance [5], and tightly coupled tasks like box pushing [6] and robot soccer [7].

Auction mechanisms proposed for multi-robot task allocation mainly focus on coordinating robots for the completion of a single complex task [8] or a bundle of tasks [9], Moreover, bidding strategies [10] are proposed for different objective optimization [11]. However, most aforementioned mechanisms are validated among a large number of virtual agents or only via simulated scenarios. Only few of them have been evaluated on physical systems. For instance, the MURDOCH [6] and TraderBot [12] have 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, we aim at solving the resource competition among robots for providing services in the cloud robotic system.

Furthermore, for distributed systems, hierarchical structures have been extensively studied in the domains of artificial intelligence [13] and robotics [14]. The reason is that the hierarchical methods usually decrease the undetermined complexity for some NP-hard problems, such as Traveling Salesman Problem (TSP) [15], ST-SR-TA problem [2] which involves determining a schedule of tasks for each robot, as an instance of a machine scheduling problem.

Considering the efficiency and fairness, we propose a hierarchical auction mechanism based on link quality for real-time resource retrieval in the cloud robotic system. Specifically, this paper addresses the following aspects:

- A general hierarchical framework for real-time communication is proposed, regarding efficient resource retrieval. It is validated by a typical network topology.

[1]L. Wang and M. Meng are with Faculty of Electronic Engineering, The Chinese University of Hong Kong, Shatin N.T. Hong Kong {ljwang, qhmeng}@ee.cuhk.edu.hk

[2]M. Liu is with Department of Electronic and Computer Engineering, Hong Kong University of Science and Technology, Hong Kong {eelium@ust.hk}

- A resource retrieval mechanism called LQM-auction is proposed for local optimization of bandwidth allocation.
- A co-localization scenario is adopted for the evaluation of the proposed mechanism in a typical real-time cloud robotic system.

The remainder of this paper is organized as follows. In the next section, we introduce the problem formulation for resource retrieval for a real-time cloud robotic system. In Section III, we propose the hierarchical LQM-auction mechanism and corresponding theoretical proof. After that, as a use-case, a co-localization experiment using multiple mobile robots is introduced in Section IV, followed by the analysis and discussion. At the end, we summarize this work.

II. Problem Formulation

In the target system, each client retrieves data objects from a central repository where the data are maintained by all other clients. However, due to the distributed connection among robots is a multi-hop network, an unmanaged resource retrieval system can easily overload the limited communication capability [16]. In this section, we introduce a general framework for real-time communication environment.

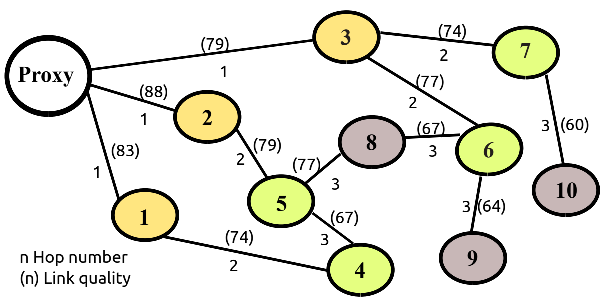

Fig. 1. A hierarchical network graph of the proposed robotic multi-hop architecture and the corresponding link quality. Nodes in the same layer are drawn in the same color, e.g., v_1, v_2, v_3 are in layer $l = 1$.

A. Network Topology

We use the aforementioned protocol RT-WMP [1] as the routing protocol, which is on top of the IEEE 802.11, and can manage the message priority in a cloud robotic system.

As an example shown in Fig. 1, 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 $E = \{lqm_{ij} | v_i, v_j \in V\}$. The distributed network topology is a hierarchy at time t, which is determined by the inherent multi-hop mechanism.

Definition 2.1 (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 2.2 (Link Quality Matrix): The link quality matrix (LQM) of the graph is denote by a $E := [lqm_{ij}(t) | v_i, v_j \in V]$. The entry lqm_{ij} is the received signal strength between pairs of nodes. All the nodes update their LQM whenever a new frame is received. Each lqm_{ij} is given by the following function:

$$lqm_{ij} = k \cdot P_i \cdot (d_{ij})^{-\iota} \tag{1}$$

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]

B. Problem Objective

In the above mentioned robotic multi-hop network, efficient frame transmission and power utilization should be achieved in order to optimize the resource retrieval. Due to the lack of global information in our network topology, we define the objective as maximized the sum transmission rate at each relay node in the following form:

$$\max \sum_{i}^{n_r} \gamma_i - c_i \tag{2}$$

where n_r is the number of children of relay node v_r, c_i is the cost of child v_i.

The achieve rate of data from node v_i to the relay node v_r is defined as

$$\gamma_i = \frac{Bw_i}{2} log_2(1 + \Gamma_{ir}) \tag{3}$$

where Bw_i is the allocated bandwidth for v_i. Assuming that additive noise is Gaussian distributed with concentration parameter σ^2 in each channel. When a frame is transmitted from node v_i to a relay v_r, the signal-to-noise ratio (SNR) obtained at relay v_r is

$$\Gamma_{ir} = \frac{lqm_{ir}}{\sigma^2 d^2} \tag{4}$$

where d is a physical distance that hops to the relay node.

Note that the local optimization of the transmission rate at each relay node, may not necessarily guarantee the fairness. For instance, some of them may be transmitting at a very low rate, while others may occupy most of the bandwidth. Therefore, in the next section, we propose an auction mechanism, which ensures that rate for any node cannot be further increased without decreasing the rate for others.

III. Hierarchical Auction Mechanism

A. Definitions and Assumptions

Related terminologies and the algorithm introduced in this section are illustrated in Fig. 2. At first, several *roles* of topological nodes in a multi-hop network are defined as follows.

- **Proxy**: A proxy distributes the resources in the cloud according to the final results of auctions.
- **Client**: The node that being part of the system, who potentially has the needs for resource.
- **Relay node**: The **client**s that maintain the connectivity of the network.

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

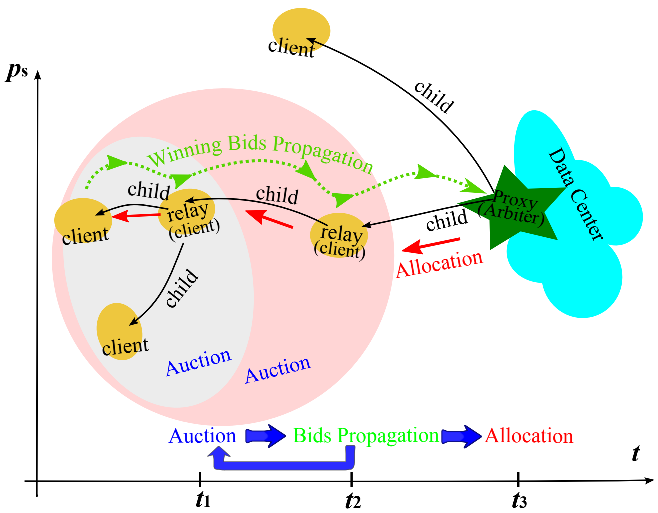

Fig. 2. Bidding information propagation in the topology of a typical network that conducts the proposed auction mechanism. Brown eclipses represent clients. The green star represents the access proxy to the data center, who manages the data retrieval for this local network. The shaded regions, which are the communication reachable for nodes in it, indicate the competition (auction) among clients.

- **Parent/Child**: The **client**s that rely on a certain relay node to get connectivity to the rest of the network are the **child**ren of a **relay node**. Conversely, the relay node is the **parent** of its **child**ren.

Considering the multi-hop network characteristics, we emphasize the following **assumptions** for the hierarchical auction mechanism:

- The relay nodes maintain connectivity by passing the data frame of its children. Therefore, the relay selects the client who bids the highest in each auction round.
- All children compete for the transmission opportunity through relay node, and they don't bid with children of other relay nodes, even for those in the same layer.
- The connectivity cost is related to request bandwidth for transmission of each node. The less of bandwidth query, the lower cost it pays.

B. LQM-auction Strategy

The **auction rules** are described as:

- *Known Information:* The LQM of a network graph $\mathcal{G}(V, E, t)$, and a set of price π ($\pi > 0$) of a unit bandwidth announced by each relay node to its children before the bidding start.
- *Bids:* b_i is the bid of v_i submits to the relay node v_r, we utilize the link quality as the bid where $b_i = lqm_{ir}$.
- *Allocation:* The proxy allocates bandwidth in terms of

$$Bw_i = \frac{b_i}{\sum_{j \in V} b_j} Bw \tag{5}$$

where Bw is the total bandwidth of the link and Bw_i is the bandwidth allocated to node i for transmission.

- *Reward:* node v_i's reward function equals to the achieved rate γ_{ir} as (3).
- *Cost:* node v_i's cost function is defined by its payment, and the formula is as

$$c_i = \pi Bw_i \tag{6}$$

Given the vector of bids $\mathbf{b} = (b_i, \mathbf{b}_{-i})$, the bid vector of node i's opponents $\mathbf{b}_{-i} = (b_1, \ldots, b_{i-1}, b_{i+1}, \ldots, b_n)$, and resource price π_i for node i, then its payoff is defined as

$$U_i(b_i; \mathbf{b}_{-i}, \pi) = \gamma_i(b_i; \mathbf{b}_{-i}) - c_i(b_i; \mathbf{b}_{-i}, \pi) \tag{7}$$

Then the node v_i's *best response* is defined as

$$\mathcal{B}_i(\mathbf{b}_{-i}, \pi) = \{b_i | b_i = arg \max_{b \geq 0} U_i(b_i; \mathbf{b}_{-i}, \pi)\} \tag{8}$$

To derive the *best response*, we only need to get an optimal price π_r^* by relay node v_r. Substituting (3) and (6) into (7), we can rewrite the payoff function as

$$U_i(b_i; \mathbf{b}_{-i}, \pi) = \frac{b_i Bw}{b_i + \mathbf{b}_{-i}} [log_2(1 + \Gamma_{ir}) - \pi] \tag{9}$$

In terms of (8), we can derive the optimal price π_r^* by differentiating (9) with respect to b_i. Then the π_r^* is as

$$\pi_r^* = \frac{1}{2ln2} \frac{b_i}{\mathbf{b}_{-i}} [ln(1 + \frac{b_i}{\sigma^2 d^2}) + \frac{b_i + \mathbf{b}_{-i}}{\sigma^2 d^2 + b_i}] \tag{10}$$

With the π_r^*, *best response* defined in 8 is achieved.

C. 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 proxy based on the result of the final auction. Given the above notations, let $b_i(t)$ further denote the bid of client i at time t. The auction process is triggered by the request for resource. Then an LQM-auction is executed for a local neighborhood (including the clients and relay) as shown in Fig. 2. After each local auction, the parent relay node represents the winning child for next round auction. The detailed process is explained as follows, and depicted in Fig. 3.

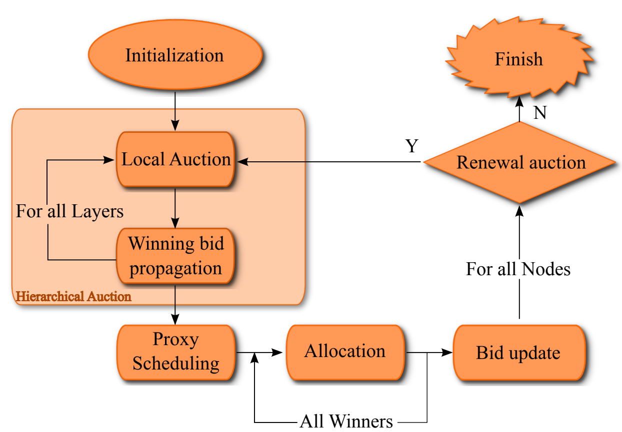

Fig. 3. Flowchart of the auction-based resource retrieval

- **Initialization:** Each relay node announces its particular price π_r. Each client sets its own reward value regarding

the price, and bid with its link quality which demonstrates its connectivity status in the network. 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 layer with maximum hop number is L.
- **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 the launched among the nodes in a set $B := \{a_i\} \cup \{b_i | children\_of(a_i)\}$. After auctions are made in this layer, the winning node is represented by its relay node to a higher layer. Suppose a_i is the relay node, then it uses the link quality to its parent as the bid for next the auction, while keep tracking the real winner in set B.
- **Proxy Scheduling:** The final result of the auction is assessed by the proxy. The winners (in the case that multiple clients have the same winning bids) are stored in the buffer. The proxy publishes a priority rank of winners in this round. Then it sends back the queried resource via network topology.
- **Renewal Auction:** Another round of the auction may be deployed after each successful allocation. The bid list 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.

IV. Experimental Validation

In this section, we validate the proposed LQM-auction in a real experiment, which is introduced in detail in [17].

A. Experiment Design

In a dynamic environment, the map is usually not known as a prior. In our test, there are two kinds of robots: the first one is the well-equipped leading robot, which combines various kinds of sensors: a laser scanner mounted on rotation unit for 3D scans, Ladybug camera and an inertial unit (IMU) with a GPS module. Sufficient information can be retrieved for mapping and localization problems; the second type is the so-called poor-equipped robot. It is a mobile robot that equipped only with a camera and wireless connector. The raw database is built before other clients can query the information they need. We define a co-localization scenario is shown as follows, with further depiction in Fig. 4.

- Relation database containing sensor and other perception data that is constructed before the operation of poor-equipped robots. All the data can be queried by any client to uncover the details of the environment.
- The data flow in the proposed system framework has been established in [17], and asynchronous access by `python-twisted` library [18] is utilized. The only update is a multi-hop token network configuration [19] that used in throughout this study. Each poor-equipped robot sends requests of image to the proxy. Upon the request, the proxy accesses the database and fetches the target data.
- The related requests are to be negotiated with the predefined hierarchical auction mechanism before handling.
- Time of Response (ToR), Reliability of Response (RoR), and usage of CPU and bandwidth are logged on every robot to evaluate the experiment results. The definition of ToR and RoR are as follows:
  Definition 4.1 (Time of Response (ToR)): the period from a request sending to its response receiving on a client.
$$ToR = T_{Data\_received} - T_{Request\_sent} \tag{11}$$
  Definition 4.2 (Reliability of Response (RoR)): the confidence that the retrieval data are accurate received.
$$RoR = \frac{\#_{Succeeded\_Requests}}{\#_{Total\_Requests}} \tag{12}$$

As the instance shown in Fig. 4, we put several Augmented Reality (AR) markers in a typical indoor environment, poses of which can be estimated using ARToolkit [20]. The well-equipped robot builds a full 3D map with marker locations registered on it as shown by active client 1 of Fig.4. All information on the map is stored in the data center and subscribed by poor-equipped robots that are winners of previously introduced auction-based autonomous scheduling. In the aspect of poor-equipped robots, each uses its camera to take pictures of AR markers as depicted by active client 5, 8 and 9 in Fig. 4.

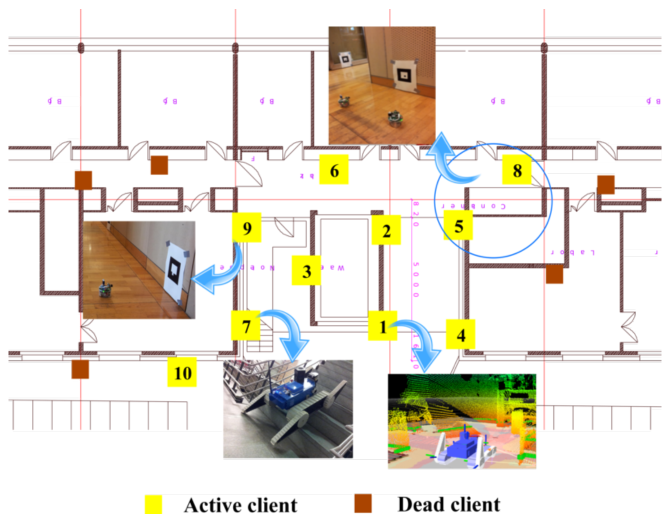

Fig. 4. A map of typical indoor environment for multi-robot co-localization (10 active robots are in a multi-hop network which has a topology as shown in Fig. 1.)

B. Experiment Analysis and Discussion

In the co-localization scenario of Fig. 4, we performed 100 trials for 10 active clients who attempt to localize themselves by sending image queries to the proxy. Assuming that these client robots have a graph connectivity of Fig. 1, when all the robots transmit their requests in parallel, it is a dense task for the limited network bandwidth. Since the relevant work on physical robots is scarce, we implemented two classical auction algorithms for validation and benchmark, which are parallel auction (P-auction) [21] and naive auction (N-auction) [22]. The following experiments are carried out accordingly.

TABLE I

COMPARISON OF *response ranking (defined in Section V.B)*

Method	LQM-auction			P-auction			N-auction		
Client	Hi.	Lo.	Avg.	Hi.	Lo.	Avg.	Hi.	Lo.	Avg.
1	3	4	3.63	1	4	3.42	1	1	1.00
2	10	11	10.63	2	8	7.16	5	5	5.00
3	3	17	9.45	6	18	14.49	3	3	3.00
4	1	1	1.00	1	4	1.36	4	7	5.05
5	4	5	4.63	2	8	4.06	2	2	2.00
6	9	14	11.27	21	23	21.74	15	18	15.21
7	9	14	11.21	3	17	9.59	21	24	23.43
8	2	2	2.00	2	8	3.19	8	11	9.62
9	3	8	5.15	3	18	7.66	33	36	34.53
10	3	8	6.33	3	17	6.71	33	36	34.47

We first compare the *response ranking* of each client with different auction algorithms as shown in table I, where "Hi." is Highest Rank, "Lo." is Lowest Rank, and "Avg." is Average Rank. It shows the highest, lowest and average priority of ten clients for each column respectively. For each row, it also shows the effects of three different auction mechanisms on each client. For example, the worst average priority for any node is 11.27 with LQM-auction, while it's 21.74 (about 2 times as bad) for P-auction, and 34.53 (about 3 times as bad). The reason of the remarkable differences is: The N-auction leads to the lowest ranks because it starts with any assignment and any set of prices. If any assignment is not the optimal one, it exchanges the assignment with the assigned node at the beginning of the iteration. The process repeats until all nodes are optimal. Compare with P-auction, LQM-auction achieves higher ranks since the bidders in an auction are selected based on P-auction.

Second, we compare the CPU load and bandwidth usage in cases of without and with the different auction mechanisms. As shown in Fig. 5, the average of network bandwidth has a flat usage when 10 clients are bidding for location retrievals. It experiences several peaks of bandwidth usage when they arbitrarily send requests without management. If they request resources at the same time, it would result in massive packet dropping, network congestion and unstable responses. There is no big difference among cases of utilizing the three auctions, since the quantity of total data transmission is the same. In Fig. 6, the proxy avoided system halt by benefiting from auction among clients. As depicted by the straight curve in red, the proxy gets fully loaded on CPU capability which would dramatically slow down the operations on it. Three auction mechanisms have quite similar CPU load since they have identical computational complexity.

Third, we compare the ToR including auction periods with different auction mechanism. As shown in Fig. 7, four blocks depict arbitrary query and three auction approaches. It illustrates that the response time is much longer when many clients arbitrarily query resources than they use the proposed LQM-auction. Among the three auctions, the LQM-auction has a least ToR than the others. It reveals the similar tendency

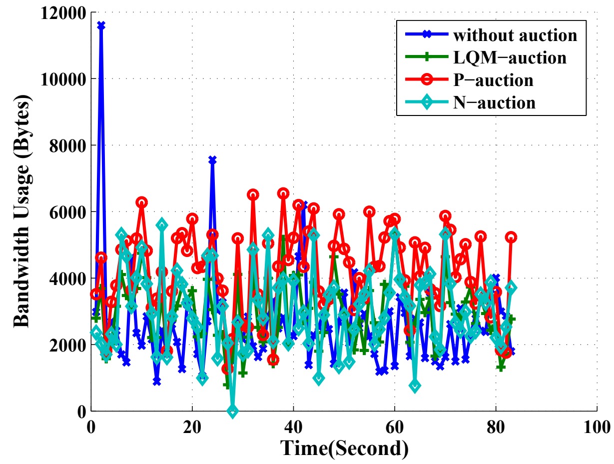

Fig. 5. Comparison on bandwidth usage when the access to proxy is in a random fashion, or controlled by LQM-auction, P-auction, or N-auction

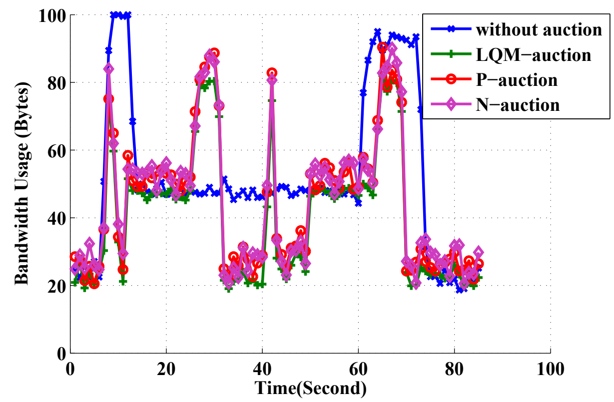

Fig. 6. Comparison on CPU load of proxy when the resource retrieval is in a random fashion, or controlled by LQM-auction, P-auction, or N-auction

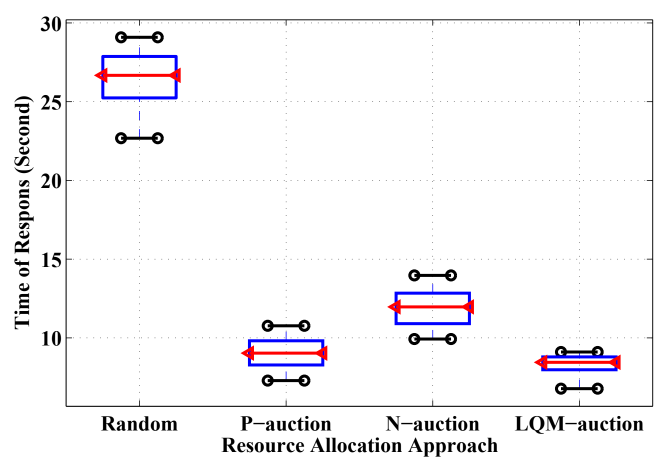

Fig. 7. Time-of-Response comparison among different auction mechanisms approaches using boxplots. Red lines (with triangle ends) mark the mean of ToR. The edges of the blue box are the 25th and 75th percentiles, Black lines (with circle ends) mark some extreme data points. This representation applies for figure 8.

as table I, i.e. N-auction needs more iterations than others because of the aforementioned flaw.

Last but not least, we calculate the RoR as shown in Fig. 8 when the bandwidth limitation is 2Mb/s for each client in the distributed network. For each test, we setup a timeout ξ as tolerance for resource retrieval missions. For instance, if send the package size q will be 93.6MByte in total, the transmission time is ideally $q/(2Mb/s) = 46.875s$. We observe that when ξ is small, the RoR is greatly affected. However, with the LQM-auction mechanism, clients negotiate with their neighbours through an auction which is organized by a relay client. The results demonstrate that the average RoR has increased from 52%, 1% and 0.3% to 100%, 50% and 35% respectively. (In boxplot of Fig. 8, the two signs of "$+$" are 1% and 0.3% for LQM-auction for timeouts 10s and 20s) Therefore, LQM-auction is validated to increase the efficiency of resource retrieval greatly.

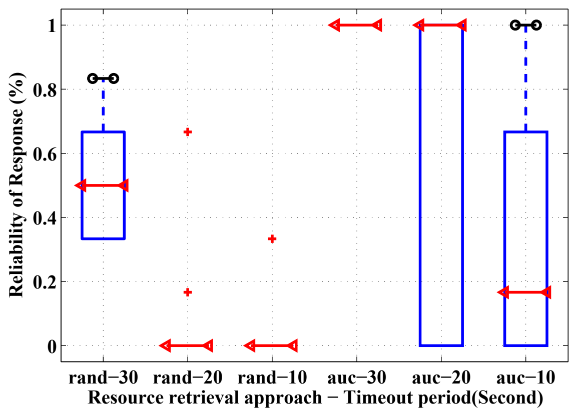

Fig. 8. Comparison on RoR of clients using boxplots for the cases of with/without auction mechanisms. "rand-ξ" is the resource retrieval without management, using a timeout of ξ seconds. "auc-ξ" indicates the hierarchical auction-based resource retrieval with a timeout ξ seconds.

V. Conclusion

In this paper, we proposed a hierarchical auction-based mechanism called LQM-auction for autonomous negotiation among robots in a cloud robotic system. We aimed at solving fair and efficient resource retrieval for real-time data transmission among robots in a distributed multi-hop network. We specified the proposed mechanism with auction taxonomy, and theoretically verified that LQM-auction can achieve the *best response*. Furthermore, we validated the proposed LQM-auction using a real-time co-localization scenario. The conducted results, including comparisons in the CPU/bandwidth usage, the time of responses and the reliability of responses confirmed the good performance of LQM-auction.

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