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An Auction-based Resource Allocation Strategy for Joint-surveillance using Networked Multi-Robot Systems

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***Abstract*—Networked multi-robot systems benefit from a large amount of heterogeneous online data on the server, and enable poor-equipped robots to fulfill complex tasks. However, as a major bottleneck of practical network, the limited bandwidth is lack of consideration. In the matter of fact, resource competition is pervasive for practical networked robotic applications. We propose a multi-robot *negotiation* mechanism in this paper. It includes a game theory based auction for allocating resources that are shared among robot clients, such as the network bandwidth. We validate the proposed strategy by a joint-surveillance scenario. Experimental results demonstrate that the proposed framework achieves excellent Quality of Service (QoS) performance under the condition of resource competition, where a shared network with limited bandwidth is optimized.**

I. Introduction

Robots have become an integral part of human life. There is a growing need for service robots in the society. Therefore, requirements of services are more complicated than ever before. It is impossible to develop a universal robot that covers all possible services due to the limitations of power consumption, payload, sensory and kinematic constraints, among many others. As for a classic robot system, various sensors are utilized on mobile robots. However, these sensors are usually expensive. By adopting the paradigm of networked robots, all primary information can be retrieved from the data center so that the requirement on equipments is relieved. A typical networked multi-robot system is shown as Fig 1. Nevertheless, the competition of data retrieval is inevitable and optimal solutions are required.

In this paper, we introduce an auction-based strategy to solve the resource allocation problem over multiple clients using game theory. As a case study, a joint-surveillance experiment scenario is demonstrated as follows: A well-equipped robot online generates and shares the available information over the network, whereas a host server can aid the inspection of several poor-equipped robot clients. The proposed scenario is conducted with several challenges. For instance, network bandwidth for transmitting image data, CPU occupancy for parallel computation, as well as available number of hosts (proxy) in multi-robot systems are limited. Several applications also require reliable network connections, for example, urban search and rescue in [1], [2], [3], and topological navigation [4], and synchronized data retrieval for multi sensor fusion [5]. Therefore, how to maximize the utility of available resources on demand is a quite challenging problem. Especially, when multi-robot clients request the same kind of resource or service in an asynchronous manner. Above all, optimization of the allocation strategy and negotiation among client robots are managed, regarding the computational and facility constraints of all the clients on the network.

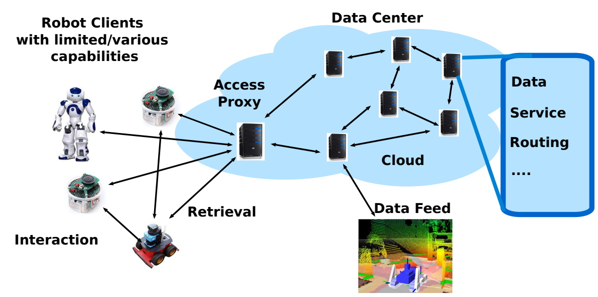


Fig. 1. Resource allocation framework for networked multi-robot systems

A. Game Theoretic Resource Allocation

Game theory has a long history in the decision making and resource allocation. Authors [6] verified that even quite simple negotiation protocols can be efficiently implemented by game-theoretic techniques. Among the state-of-the-art algorithms in game theory, market-based negotiation plays an important role. The mechanism is applied in grid resource management [7]. K.M. Sim et al [8] adopted genetic algorithms in order to filter best-response strategies for market-driven clients. R. Ariel [9] discussed the equilibrium of sequential bargaining mechanisms. Although it can produce optimal solutions, sequential bargaining has more communication and computation requirements in fully distributed environments. Generally, the core algorithm of market-based negotiation is referred as auction-based method. *Auction* [10], derive from economic research, is a typical quick and concise strategy for multi client system to make decisions on distribution of resources.

B. Auction-based Resource Allocation in Robotics

For robotic system, there are several works have been done. M.G. Lagoudakis et al [11] introduced single task-centric iterated auctions. Their experimental results are very close to the theoretical optimal when bidding rules are appropriatdly designed. Vickery auction [12] is applied for solving real-time task and path planning problems in multi-robot systems. Combinatorial auction [13] is utilized to allocate multi-task in a multi-robot system. They got good results with limited number of task bundles. The above works solved the problem by emphasizing feasible implementation of tasks.

C. Challenges

There are several advantages of the market-based resource allocation mechanism. Firstly, it is the ability to deal with the uncertainty in the real-time environment. This ability is essential for information exchange among client robots. Therefore, the host is able to respond faster than heuristic approaches which are conducted with higher computational complexity. Secondly, it is the scalability of the negotiation system. Since the computation is distributed among the robot clients, the system can handle large-scale problems.

However, when adopting a market-based resource allocation mechanism in networked multi-robot systems, most problems are to achieve individual objectives of clients and to perform an integrated task at the same time. It is composed of the following subtle difficulties:

- Data synchronization is hard for distributed systems, especially when asynchronous tasks are performed[14].
- Resource allocation is low-efficient, when multiple sensor data or information are distributed in the network.
- For strategy design, involving protocol and decision making model design, several properties are desired to be satisfied, such as Nash equilibrium and Pareto-efficient solutions, individual rationality, stability, simplicity and guaranteed convergence.
- Practical applications on real-time systems are not well reported, although multi-client negotiation is extensively applied for distributed systems.

D. Contributions

In this paper, we study the following characteristics, which are deployed in physical devices and embedded systems.

- A negotiation strategy with incomplete information based on game theory is proposed. It can relieve the competition among client robots.
- A real-time experiment is implemented to integrate the proposed strategy in order to balance the resource allocation for joint-surveillance.
- A set of criteria are designed, which represents empirical QoS. They evaluate the feasibility of online resource allocation for networked multi-robot systems.

E. Arrangement

The rest of the paper is organized as follows. Section II introduces the data flow of the proposed networked multi system, followed by auction mechanism design in section III which includes both decision making model and protocol strategy. Section IV analyzes the proposed mechanism and a set of QoS. The implementation of experiments scenarios and the evaluation results of the auction strategy is demonstrated in section V. Finally, section VI concludes the paper and introduces our future vision.

II. Data Flow of the Proposed System

Hereby we introduce the data flow and functionalities of the proposed system. We demonstrate the details of auction-based resource allocation at different phases in the network communication. Fig. 2 depicts the proposed system architecture which enables automatic launching of new threads for each client. Generally, each client attempts to connect to the network with an approved address and a specific port. As a major feature, we deploy a negotiation mechanism which can maximize the utility of each robot client and the revenue of resource in the data center. We define the specific functionalities in the host and clients separately, as follows.

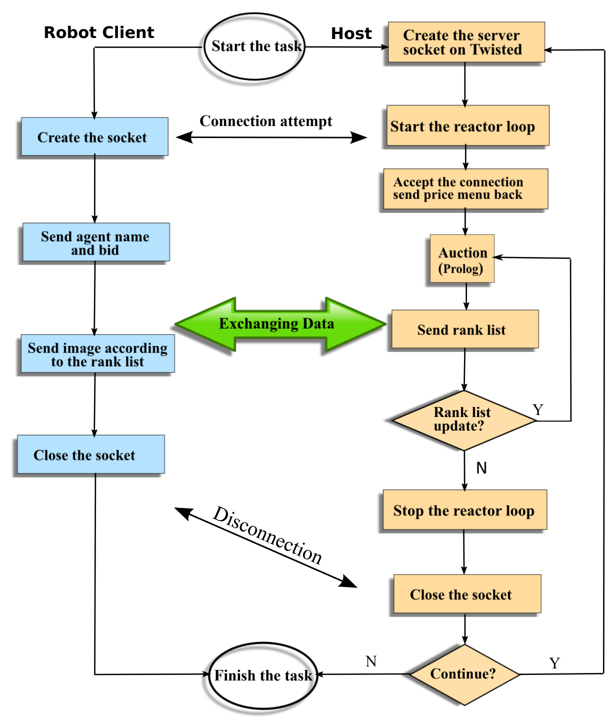


Fig. 2. Data flow of communication and negotiation in networked multi-robot systems

1) Information query in the data center: This functionality is launched and managed by the host. It is the basis of other operations. The data exchanging is an asynchronous socket communication process. Moreover, `rostopics` are utilized for an online service lookup and a real-time constraint communication. By fusing these two aspects, the data access is more efficient than solely accessing of a relation database.

2) Auction-based negotiation: This function is embedded with a logic programming module, which results in a priority list of the response order by ranking all connected robot clients using logical regulation. After robots are connected to the network, the host publishes a resource price menu of auction bids. Clients send their bids according to the price menu and their computational ability. E.g. when a client has high local CPU usage, the price that it can afford will be limited accordingly.

3) Scheduling management: For each client, the interval of retrievals to query responses is differently due to the priority. For example, the higher priority of the client, the less waiting time. In addition, a local data buffer is embedded for storage of the frequently requested data. Since activities of robots are usually routine, the same resource may be queried repetitively. Therefore, the scheduling mechanism help to alleviate the database access bottle-neck effect to a certain extent.

III. System Model and Mechanism

We model the interaction between the host and robot clients as a Vickrey-Clarke-Grove (VCG) auction [15] game, which is also called the second-price auction (SPA). The mechanism tries to optimize both the total revenue of resource provider and utility of each robot client.

A. The Auction Mechanism

Let $N = \{1, \ldots, n\}$ denotes a set of robot clients, who share a fixed bandwidth. For k parallel and dependent requests, one unit bandwidth has a fixed price p. Each robot is selfishly motivated and comes up with rational in order to make their bids. As a bidder, the robot client does not know the bid values of others. Each of them calculated their total cost as:

$$c_i(t_i) = \omega_t t_i - p t_i \tag{1}$$

where t_i is the time slot that solely completes requests of client i, ω_t is a reward weight for request completion.

Different from [16], the exponent utility function of robot i is a convex completion function calculated as:

$$u_i(t_i) = \omega_i \log(1 + t_i) - p t_i \tag{2}$$

where ω_i is the weight derived from the equation (1).

Without loss of generality, we assume: the capacity of each resource is inelastic and undividable; all resources use time-sharing policy to schedule tasks in the data flow.

At the heart of the negotiation mechanism in the proposed system lies a simple distributed protocol that allocates the resources via a sequence of SPA one-round auctions. Based on the above assumptions, the object function in clients' side is given by

$$\max_{t_i \geq 0} \sum_{i=1}^{K} u_i(t_i) \tag{3}$$

where $\sum_i \omega_i = 1$. On the other hand, the revenue of resource provider is defined as

$$L = \sum_{i=1}^{K} p t_i \tag{4}$$

The constraint is the deadline of execution time T_0:

$$\sum_{i=1}^{K} t_i \leq T_0 \tag{5}$$

Lemma *For each robot client i, the utility u_i is increasing, strict concave, and twice continuously differential in t_i.*

From the first order necessary conditions, which are also sufficient, the optimal completion time of client i is derived from (3) as

$$t_i^* = 1 - \frac{\omega_i}{p} \tag{6}$$

Since each robot client could get an optimal value, then the summation are optimal. Please note that the time constraint must hold equality, by plugging (6) into (5), we have

$$\sum_{i=1}^{K} (1 - \frac{\omega_i}{p}) = T_0 \tag{7}$$

Assuming that $\omega_1 \leq \omega_2 \leq \cdots \leq \omega_N$, then the number of admitted robot clients K is optimized, thereby optimizing the resource provider revenue in equation (4). As proved in [16], the proposed mechanism gets a Nash equilibrium as the following theorem.

Theorem *Nash equilibrium of the auction game always exists when each request solves its optimal problem independently without considering the multiplexing resources.*

B. Implementation of the Mechanism

1) Bidding Rules: Inspired by [11], we define the bidding rules for comparison as follows:

$$\begin{aligned} \text{MinMax} : b_i &= c_i^* = c_i(t_i^*) && (8) \\ \text{MinSum} : b_i &= c_{\Delta i} = c_i(t_i^*) - c_i(t_i) && (9) \\ \text{MinMix} : b_i &= c_i^* + c_{\Delta i} && (10) \end{aligned}$$

where c_i^* denotes the optimal cost of request x_i, and $c_{\Delta i}$ is the extra cost. Note that the MinSum is correspond to the above optimal utility in equation (3).

2) Auction Rules: Several functions for negotiation are defined, such as auction rules: spa_rule, priority rank: rank_bidder_value, allocation rules: allocate_rule, payments rule; payments_rule. The inputs and outputs are shown as Table I, where the clients are participants in the current game, allocate are the preference of each client.

TABLE I
Configuration of Host and Clients in Experiment

Function	Inputs	Outputs
spa_rule	bids, winner, topPirce, secondPrice, allocate	rank_bidder_value
rank_bidder_value	clients, bids, allocate	priority_rank_list
allocate_rule	clients, rank, allocate	allocation
payments_rule	clients, rank, prices	bids

3) Auction Implementation: The process is triggered by the introduction of a task to the system as shown in Fig. 2. In every case, the auction proceeds in five steps:

- Task announcement: the host publishes the price menu $\mathbf{P} > 0$.
- Bid submission: after observing the price menu, robot client i submits their bids $b_i \geq 0$.

- Winner list publishing: the host sends a response priority rank list according to the bids and preference of clients.
- Auction renewal: the auction starts another round, since the previous one reached a deadline. Players and priority rank list are generated and updated.

Basic operation policy of the request negotiation is demonstrated in Table II. The primary objective of the policy is to provide an index for ranking candidate requests. It can be made by considering the quantity of free CPU, bandwidth and willingness payment of each request, etc.

TABLE II
NEGOTIATION ALGORITHM USING PROLOG PSEDOCODE

Inputs: clients I, price:T, bids:P, profile L
Outputs: RANK_list, Winner, payments

```
BEGIN
    rank_bidder_value_pairs(clients:I, bids:P,rank:RANK):-
        findall(B-A, (nth1(K,I,A),nth1(K,P,B)),PA),
        sort(PA,SPA),
        reverse(SPA,RANK),
    allocate_rule(clients:I,rank:RANK,allocate:L):-
        RANK=[_TopPrice-Winner—_],
        findall(LA, (member(A,I),win_price(Winner-1,A-LA)),L),
    payments_rule(clients:I,rank:RANK,price:T):-
        RANK=[_TopPrice-Winner—[SecondPrice-_—_]],
        findall(TA, (member(A,I),win_price(Winner-SecondPrice,A-TA)),T),
    spa_rule(bids:P,win:Winner,by:TopPrice,price:SecondPrice],allocate:L,
            prices:T):-
        clients(I),
        rank_bidder_value_pairs(clients:I,bids:P,rank:RANK),
        allocate_rule(clients:I,rank:RANK,allocate:L),
        payments_rule(clients:I,rank:RANK,prices:T),
        RANK=[TopPrice-Winner—[SecondPrice-_—_]].
    return RANK
END
```

IV. ANALYSIS AND DISCUSSION

We analyze the integration of auction strategy and data exchange in the communication interfaces, and followed by the QoS criteria are defined for its evaluation.

A. Data Flow Analysing

The communication interfaces relation in the proposed system is shown in Fig. 2. We emphasize the following features of the conducted data flow:

1) Compatibility: We use TCP socket as the major communication interface in order to facilitate the generalization. Its protocol is built on top of the twisted framework which is deploying asynchronous, event-driven and multi-thread supported network system in Python [17]. Therefore, it is easy to compose complex applications in various pattern.

2) Diversification: The proposed mechanism can fit various robots since several different robots are deployed in it [18]. This is the most obvious characteristic for current networked multi-robot systems. The resource sharing can be shared by robots equipped with different sensors. Moreover, robots can be allocated to an integrated task by utilizing sensors without the expensive cost.

3) Reliability: As there are multiple robots in the system, the reliability needs to be guaranteed when some robot clients lose connection or new clients join the network. Therefore, we define a set of QoS to do the evaluation.

B. Quality of Service (QoS)

Generally, QoS is used to assess the performance of a Service Oriented Architecture. It advertises performance quality levels of service which are provided by service providers; at the same time, clients use it to select an optimal candidate data/service, which could be at least in part fulfill the request. Therefore, a well-defined set of QoS's could greatly help the assessment of the quality of a resource allocation mechanism. In common cases, CPU usage is one of the most important factors to support high level performance , since the responses of request are also depend on it. Several properties are essentially satisfied behind the QoS, such as Nash equilibrium, Pareto-efficiency, stability and nationality.

- Time-to-Response (ToR)
  ToR is defined as a period time for a client to received a response after a request has been sent:

$$ToR = T_{Data\_received} - T_{Request\_sent}$$

- Reliability-of-Response (RoR)
  RoR is defined as a ratio that the retrieval data is successfully received. It is calculated in percentage as:

$$RoR = \frac{\#_{Succeeded\_Requests}}{\#_{TotalRequests}}$$

- Complexity
  Since the case study is joint-surveillance in this paper, it is important to evaluate computation complexity of auction-based negotiation. When considering trade-offs between scalability and solution quality in networked multi-robot systems, it is also important to consider the problem domain. For the robot system, there are hard real-time constraints when several robots perform task online.

V. EXPERIMENTAL VALIDATION

The goal of this case study is to realize a joint-surveillance for several poor-equipped robots by using video sequences captured by on-board cameras. The regional appearance and video sequences that can be retrieved by these poor-equipped robots through a database with all information registered on it. Whereas the resource competition among requested robots can affect the efficiency of online information retrieval greatly. In this section, we set up the following scenario for evaluating the resource allocation strategy.

A. Design of the Experiment

The system hardware includes two kinds of robots. On one hand, a high level robot, which is equipped with various kinds of sensors like kinect, infrared, audio and inertial unit (IMU), should provide sufficient mapping and localization information. On the other hand, several poor-equipped robots with only cameras and wireless connectors, which performs as a user. It requests data, such as video sequences in the local neighbourhood. The software of the system is based on the socket communication protocol and ROS communication interface which publish and subscribe `rostopic`. The negotiation between poor-equipped robots and the host utilizes socket framework as we discussed in section III.

In this test, several poor-equipped robots send images or video sequence in the local neighbourhood to the host who could access the data center. The host matches the image with the information stored in the data center, and sends the request information back to the poor-equipped robots. Details of experiment setup are introduced as follows.

- Build a map of a typical indoor environment around it as shown in Fig. 3. All information on the map is stored in a data center, and can be queried by any user to uncover such structure, for instance, the poor-equipped robot who is the winner in the auction-based negotiation.
- Provided with the ROS topic, each poor-equipped robot can send several requests by the captured images or video sequence in the local neighbourhood depicted in (A) and (B) of Fig. 3 to the host.
- Each request is managed by the host with predefined auction-based management mechanism with scheduling algorithm and protocol.

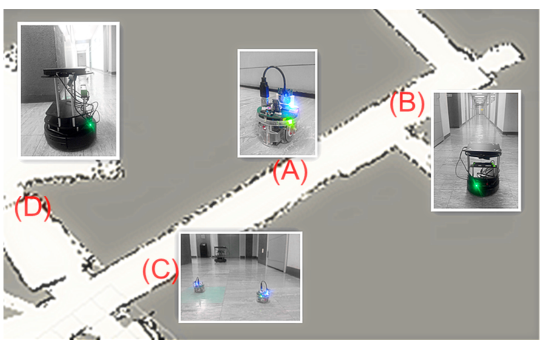


Fig. 3. A map of the typical indoor environment for multi robots joint-surveillance

B. Results and Analysis of the Experiment

In the online joint-surveillance scenario, several robots attempt to update the global representation by sending video sequence in parallel. Such operations are computationally heavy for the network.

At first, we compare the ToR of different resource allocation approaches. As shown in Fig. 4, the response time is greatly reduced when bidding rules are applied. MinSum performs better than the other two, and MinMax is the worst among the three bidding rules. This is consistent with our theoretic results in section III, since MinSum is equivalent to sum utility maximization of all requests.

Second, we calculate the average RoR as shown in Table III. The bandwidth limitation is 2Mb/s for each client. For each resource retrieval mission, we setup a timeout as a transmission tolerance. The results demonstrate more requests get responses from the host, when auction strategy is applied. Our conclusion fit the simulation results in [19].

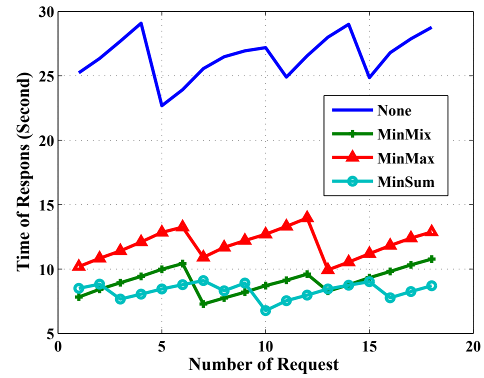
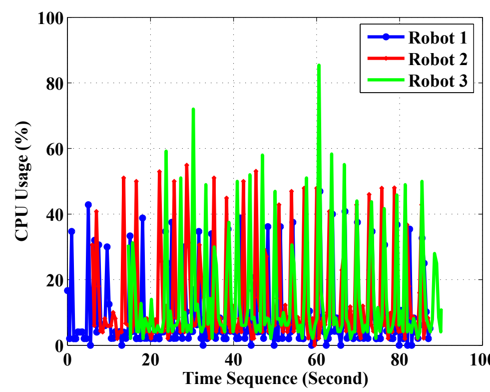


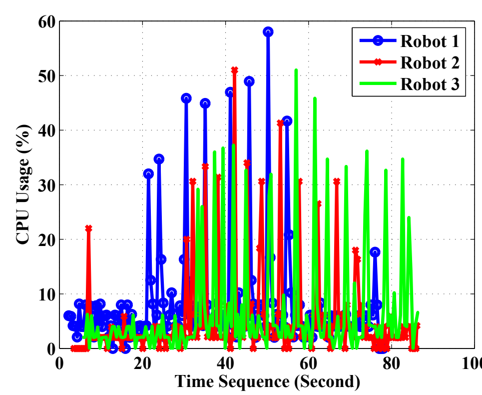
Fig. 4. Time-of-Response comparison of different bidding rules

TABLE III
RoR COMPARISON AMONG DIFFERENT BIDDING RULES UNDER VARIOUS TIMEOUT PERIOD

Timeout Period (Second)	Bidding Rules			
	None	MinMax	MinSum	MinMix
10	0%	8.27%	13.34%	11.67%
20	0%	66.78%	71.65%	76.20%
30	56.31%	100%	100%	100%



(a) Without resource allocation strategy



(b) With resource allocation strategy

Fig. 5. Comparison of CPU usage for 3 robot clients

Third, computation complexity is evaluated by CPU usage for each client robot as shown in Fig. 5. We could see that they are evidently reduced, since clients would decide not to query redundant information when the ranking on the resource allocator is low. Fig. 6 depicts that with the control strategy. CPU cost from the host side is reduced. This is an important feature, since we aim at realizing the information retrieval with minimized cost.

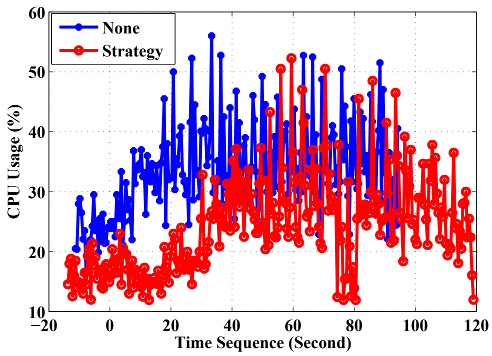


Fig. 6. Comparison of CPU cost of the host

VI. Conclusion

In this paper, we have presented the design, implementation and evaluation of an auction-based negotiation and scheduling strategy for resource allocation problem in networked multi-robot systems. A dynamic priority scheduling method and an auction mechanism are proposed, which are implemented by logic programming. The experimental results demonstrate a significant improvement in terms of ToR, CPU usage etc. In addition, the system computational complexity is low, by which the extra burden on the real-time tasks is limited. Given that a flexible and less computational auction strategy is utilized, future work will address experiments on a multi-hop networked robot system.

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