**Advances in Robotics Research**, *Vol. 2, No. 3 (2018) 247-257*
DOI: https://doi.org/10.12989/arr.2018.2.3.247


# A combined auction mechanism for online instant planning in multi-robot transportation problem

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*(Received April 26, 2017, Revised December 12, 2018, Accepted December 13, 2018)*

**Abstract.** Various studies have been performed to coordinate robots in transporting objects and different artificial intelligence algorithms have been considered in this field. In this paper, we investigate and solve Multi-Robot Transportation problem by using a combined auction algorithm. In this algorithm each robot, as an agent, can perform the auction and allocate tasks. This agent tries to clear the auction by studying different states to increase payoff function. The algorithm presented in this paper has been applied to a multi-robot system where robots are responsible for transporting objects. Using this algorithm, robots are able to improve their actions and decisions. To show the excellence of the proposed algorithm, its performance is compared with three heuristic algorithms by statistical simulation approach.

**Keywords**: multi-agent system; multi-robot coordination; multi-robot transportation; task allocation; auction mechanism

## 1. Introduction

Transportation by robots is one of the significant challenges in today's modern world (Wawerla 2010). For much of aspects, this task can be considered as a distributed task (Zheng 2009). Hence, nowadays use of a group of robots has attracted much attention in this field. Exploiting group of robots can facilitate transportation of goods, which is a complex problem and sometimes can be impossible to be performed by a single robot (Ljesnjanin 2009). Multi-robot systems are interpreted as multi-agent systems (MAS) those have got advantages such as fast responsibility, reliability, low cost, high levels of flexibility and extensibility (Sycara 1998). According to these advantages, it is obvious why nowadays in many applications, single-agent systems have been replaced by multi-agent systems (see Zlot and Stentz 2005, Kalra 2006, Gerkey 2003, Lee 2010, Jonban 2015) as examples). Nevertheless, there are some difficulties in this context that the most of them is related to allocate task in order to create coordination among agents (Gerkey 2003). Various methods have been proposed to solve these challenges. One category of these methods is

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http://www.techno-press.org/?journal=arr&subpage=7 ISSN: 2287-4976 (Print), 2287-4984 (Online)

multi-agent machine learning methods (Wu 2011) those necessitate large memory to perform learning algorithms. Moreover these algorithms, in most cases, have large convergence time. Other category is optimization based methods (Parker 2012, Cerquides 2014) those require exact mathematical model of system which is not available in many cases. In the face of these methods, third category of methods is model-free methods with instant decision making mechanisms. These methods would provide advantages of low memory systems with low complexity in modeling; hence they are interested in online application. Among them, one may consider auction mechanisms (Cramton 2006, Hoos 2000, Koenig 2006, Sandholm 2002) and local heuristics (Dasgupta 2011). Dasgupta (2011) has listed three local heuristics:

**Closest Task First (CT):** In this heuristic, task is selected by an agent that is closest to it.

**Most Starved Task First (MST):** Any agent in this heuristic prefers to select a task from its list that has minimum agent in its vicinity.

**Most Proximal Task First (MPT):** In this heuristic, status of task and other agents are crucial factor and any agent selects a task that has least number of agents closer to the task than itself and also is the nearest towards being completed.

Auction algorithms can be implemented as centralized or as a distributed one (Koenig 2007). In centralized auction algorithm, an agent as team leader is responsible to assign tasks (Dias 2002). The main purpose of this type of auction is to minimize total cost function. The main determinant in this auction is the team leader which performs all the calculations. Hence, in this type of auction, it is not needed to create communication between the auctioneer and others. Disadvantage of this type of system is that if the auctioneer is faced a failure, system will not able to respond properly. Hence, we need a system with a distributed algorithm where every agent can make decision. With this capability, the multi-agent system would be fault tolerant (Aarts 1997).

Local heuristics are other model free instant task allocation techniques in multi agent systems.

The idea of coordination of agents according to the market protocol and suitable distribution of tasks among the agents was initially presented by Smith (1980). However, methods of coordination among agents in multi-agent systems have been improved in recent years. Nowadays, market mechanisms are used in various fields such as transportation, providing maps of planets and exploration of unknown areas (Michael Zlot 2005, Kalra 2006). Various mechanisms those are based on artificial market algorithm have been used for solving transportation problem. In 2009, Garcia allocated tasks among agents by the market mechanism for a multi-robot system in a collection of industrial robots which were responsible for cleaning a ship's tank (Garcia 2009). Dias (2004) could allocate tasks among agents in a dynamic environment by market-based coordination approach where each agent with increasing its own payoff would take whole team toward an optimal solution. Simzan (2011) used artificial capital market as a mechanism for deciding among competing agents to solve problem of transportation. In this mechanism, a number of agents, as capitalists that have limited amount of budget, want to increase their payoffs by investment on goods.

Auction algorithms are classified among market algorithms and are used to solve transportation problems. For example Song (2009) used distributed bidirectional auction algorithm for coordinating agents where auctioneer and bidder make decision for tender. At first, auctioneers invite bidders to the tender, then receive their offers for each sub-task and accept the minimum offer for each task, as each bidder can only do one of subtasks. Nanjanath (2006) assigned tasks by reverse auction. In this mechanism, auctioneer agent is a bidder which assigns tasks by a priority. Matarić (2003) used four strategies for allocating tasks where tasks have been allocated among team members with combination of commitment and coordination levels. Zhang (2013) used cooperative auction method, called stochastic clustering auction for allocating tasks among agents. Two algorithms have been introduced including Gibbs Sampler Stochastic Clustering Auction (GSSCA) and Swendsen Wang Stochastic Clustering Auction (SWSCA). It was shown that GSSCA algorithm is appropriate for allocating tasks those need to transfer and exchange individual tasks among heterogeneous agents (Barbu 2005) and GSSCA algorithm is suitable for complex transfers and classifying interconnected tasks those need for greater cooperation among homogeneous agents (Geman 1984).

In this paper a new auction mechanism is presented for task allocation among transportation agents that is an extension of method which used by Akbarimajd (2014) from transforming one object to two objects by multi-robot and operation of the algorithm will be compared with 3 heuristic algorithms. In this work, in comparison with previous work, all agents have to cooperate in carrying objects and choosing appropriate agents for transferring an object by auction agents is known as a main challenge. The model expectedly has inherent advantages of auction mechanisms in being model free instant technique. It is not needed to implement complex model and any agent has a low memory that it is just used in auction moment (agents do not need to save the past states). Moreover, in this algorithm any agent can perform the auction, and if an agent is unable to act in the environment for any reason, other agents complete the mission. The presented technique is compared with above local heuristics in a statistical approach.

## 2. Problem definition

Assume that there are $m$ robots and $n$ objects in an environment as shown in Figure 1, and object $i$ is initially in $a$ point with $P_i$= ($X_i$, $Y_i$) coordinates and robot $j$ is in a point with $P_j$=($X_j$,$Y_j$) coordinates. After finding the objects, robots have to transfer them to their target point i.e. $Pg_i$= ($Xg_i$,$Yg_i$). As shown in Fig. 1, objects are statics and can be transferred to the target point by one robot or more.

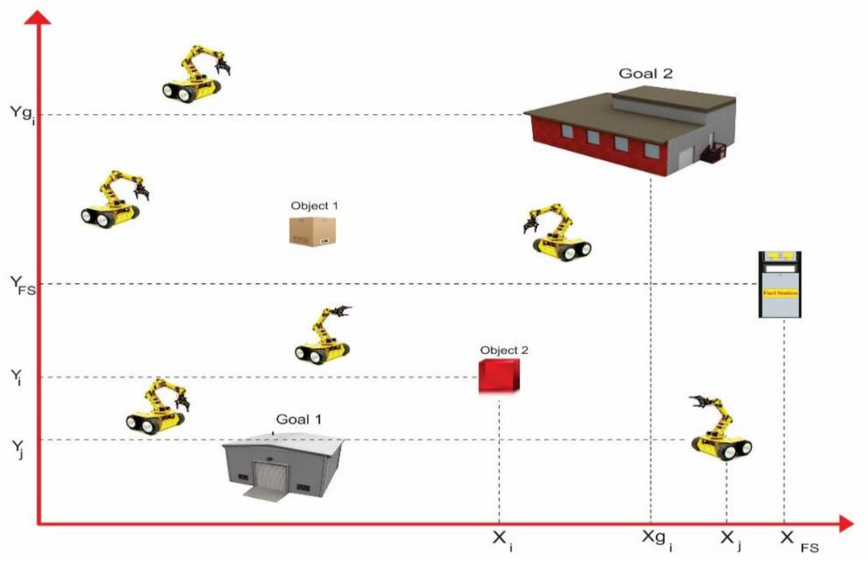



Fig. 1 An environment of multi-robot transportation problem

Initially, robot *j* has $f_j$ amount of fuel. The rate of fuel consumption when it is not loaded is $C_j$ unit per meter. If a single robot carries an object the rate of fuel consumption will be $C_j^i$ unit per meter and if the robot carries an object by cooperating other robots then the rate of fuel consumption will be $a \times C_j^i$ unit per meter where *a* is *a* positive coefficient smaller than 1 $(0 < a < 1)$ . There is a fuel station located in $P_{FS}=(X_{FS}, Y_{FS})$ coordinate and if an agent's fuel reaches to less than a certain predefined value, it returns to this station and pays the fee according to its required fuel. Each robot receives some amount of money for transporting the object to the target point. If the robot takes the object *i* alone, this amount for each unit will be $R_i$ *$* and if n robots cooperate to carry this object, this amount for each unit will be $^{R_i}/_n$ *$*. Initially, *M $* is awarded for each robot that can be used for fueling.

## 3. Combined auction algorithm

### *3.1 Components of the auction*

In this section, we present an algorithm for decision-making and allocation tasks. In this algorithm, auctioneer agent intends to take some decisions to increase payoff. Components of this mechanism are:

**Auctioneer agent:** is responsible for holding auction and its decisions are based on social payoff. This agent is not determined before implementation of the algorithm and any one of agents can take this responsibility.

**Good:** An object which auction is held about. In our approach, good is moving task of objects to target points.

**Capital:** Each agent needs to have a capital to be able to participate in auction. In this study, fuel of agents is considered as their capital.

**Price of good:** The winner agent in an auction must pay price for transporting of object. Here, fuel consumption during transportation is considered as price.

**Outcome:** The agents those are involved in an auction take amount of money with related to amount of work they have done. This amount of money is considered as outcome.

**Payoff:** Net payoff for each agent is the difference of outcome and cost of consumed fuel

$$P_j^i = O_j^i - C_j^i \qquad (1)$$

where $P_j^i$ , $O_j^i$ , $C_j^i$ are payoff, outcome, and cost, respectively that the agent *j* receives from transporting the object *i*.

### *3.1 Auction algorithm*

In the aforementioned mechanism, auctioneer agent should make the best decision for transporting of goods. This decision is made in distributed manner and any agent that has found object first, is responsible for organization auction and should make its decisions according to social profit. The auctioneer agent should be able to adopt the best possible decision by receiving position and fuel of agents. When object found, two options are available for agent. Either the agent decides to carry object alone or it decides to perform in cooperation with others. If agent carries object alone, it will receive whole outcome and if it performs in cooperation with others, outcome will be divided among them. The difference is that in the first case, fuel consumption will be higher than the latter and for this reason, in most cases; auctioneer will try to cooperate others.

When agent is an auctioneer, at first it takes position and fuel of agents; then it generates all possible states in a form of binary codes by Eq. (2)

$$S^i = \begin{bmatrix} s^i{}_{11} & s^i{}_{12} & & & s^i{}_{1m} \\ s^i{}_{21} & s^i{}_{22} & & & s^i{}_{2m} \\ . & & . & & . \\ . & & & . & . \\ . & & & . & . \\ s^i{}_{s1} & & & & s^i{}_{sm} \end{bmatrix} \tag{2}$$

where $S^i$ is the possible states for transportation of object $i$. $S^i{}_{sm}$ is participation status of agent m in transportation of object i in state $s$. $S^i{}_{sm}=1$ means agent m contributes in carrying object $i$ in state $s$ and $S^i{}_{sm}=0$ means disaffiliation of agent m in transporting object $i$ in state $s$.

After generating these states, auctioneer agent calculates distance between each object and related target point as well as distance between each robot and object by using Eqs. (3) and (4)

$$D^i = \sqrt{\left( (Xg_i - X_i)^2 + (Yg_i - Y_i)^2 \right)} \tag{3}$$

$$d^i_j = \sqrt{\left( \left( X_i - X_j \right)^2 + \left( Y_i - Y_j \right)^2 \right)} \tag{4}$$

where $(X_{gi}, Y_{gi})$ is target position of object. $(X_i, Y_i)$ is position of object $i$. $(X_j, Y_j)$ is position of robot $j$. $D^i$ is distance from object to target point. $d^i_j$ is distance from robot $j$ to object $i$.

Using above mentioned equations, auctioneer agent calculates social profit in each state according to Eqs. (5)-(7)

$$P^i_k = O^i_k - C^i_k \tag{5}$$

$$O^i_k = \Sigma^m_{j=1} S^i_{kj} D^i R_N \tag{6}$$

$$C^i_k = \Sigma^m_{j=1} S^i_{kj} \left( 0.6 d^i_j + D^i C_N \right) \tag{7}$$

where $P^i{}_k$ is payoff function that robots earns in carrying object $i$ in state $k$. $O^i{}_k$ is amount of money that they take to carry object in state $k$. $C^i{}_k$ is cost function that robots expend in transporting object to its target in state k.

An auctioneer agent selects that state in which $P^i$ is maximized. Then it informs object position to agents that have won the auction. These agents start moving toward the object in order to transport it. Besides payoff, another factor which is involved in winning the auction is fuel. If fuel of a robot is less than needed fuel to carry the object, then auctioneer deprives that robot. Therefore, instead of carrying object, the excluded robot returns to the fuel station. During auction, auctioneer evaluates each agent's capability for carrying object by following function

$$E = f_j - \left( d^i_j + D^i \ fc^i_j \right) - L_i \tag{8}$$

where $f_j$ is fuel of robot *j*. $fc_j^i$ is amount of fuel that robot *j* needs to carry object *i*. $L_i$ is distance from target point of object *i* to the fuel station. If value of this function is negative for an agent, auctioneer does not let it to participate in the auction.

## 4. Simulation

We intend to organize simulation in two sections. At first, result of applying proposed algorithm to the system will be devised. In second subsection, from a statistical viewpoint, performance of algorithm will be compared with three heuristic methods that were mentioned in section 2.

### *4.1 Simulation results*

In order to test our proposed algorithm, we assume a 100×100 area with 5 robots, *n*=5, and 2 objects, *m*=2. The environment consists of a fuel station and two target points for the objects. It is assumed that each robot knows only its own situation and position of the fuel station in the environment and has no information about objects and position of others. The initial position of each robot is given in Table 1. The robot's fuel consumption when it is foraging the object is $fc_j=1$ and when it is carrying the object, with respect to number of robots participated in the auction, is given in Table 2. In this table, it is obvious that there is no linear relation rates of fuel consumption in different modes like the real case. Each robot consumes fuel for moving, transferring object and communication. Initially, fuel of each robot is considered 1000 units ($f_i=1000$, $j=1,2,\ldots,5$).

This amount of fuel is the maximum possible amount which could be placed in robot's fuel

Table 1 Initial position of robots

| Robot | 1 (White) | 2 (Red) | 3 (Violet) | 4 (Black) | 5 (Yellow) |
|---|---|---|---|---|---|
| Position | (95,5) | (5,5) | (95,95) | (5,95) | (50,50) |

Table 2 Fuel consumption, cost and reward for each agent in carrying objects in contribution with N agents

| N | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Fuel consumptions | 8.33 | 3.92 | 2.5 | 1.83 | 1.5 |
| Reward (RN) | $6 | $3 | $2 | $1.5 | $1.2 |
| Cost (CN) | $5 | $2.35 | $1.5 | $1.1 | $0.9 |

Table 3 Positions of objects, targets and fuel station

| | Position |
|---|---|
| Object 1 (Blue rectangle) | $P_1$=(67,72) |
| Object 2 (Green rectangle) | $P_2$=(18,67) |
| Goal 1 (Blue star) | $P_{g1}$=(40,5) |
| Goal 2 (Green star) | $P_{g2}$=(95,95) |
| Fuel station (Triangle) | $P_{FS}$=(95,70) |

Table 4 Position and fuel of all robots when objects are being detected

| Robot | 1 (White) | 2 (Red) | 3 (Violet) | 4 (Black) | 5 (Yellow) |
|---|---|---|---|---|---|
| Position | (90.8,60) | (15.8,60) | (78.8,32) | (60,70.1) | (5,44.5) |
| Fuel | 945 | 945 | 945 | 945 | 945 |

Table 5 Possible states for transporting objects and payoff function of each one

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| State | For object1 | 00010 | 00011 | 00110 | 00111 | 10010 | 10011 | 10110 | 10111 |
| | For object2 | 11101 | 11100 | 11001 | 11000 | 01101 | 01100 | 01001 | 01000 |
| P | For object1 | \$68.3 | \$49.8 | \$64.5 | \$38.8 | \$74.6 | \$48.9 | \$63.6 | \$30.7 |
| | For object2 | \$26.3 | \$33.5 | \$60.3 | \$59.3 | \$61.6 | \$60.5 | \$87.4 | \$78.1 |

Table 6 Fuel consumption of robots in arriving to the objects position

| Robot | 1 (White) | 2 (Red) | 3 (Violet) | 4 (Black) | 5 (Yellow) |
|---|---|---|---|---|---|
| Fuel consumptions (Liter) | 21 | 3 | 12 | 5 | 12 |

Table 7 Money and fuel of robots after object transformation

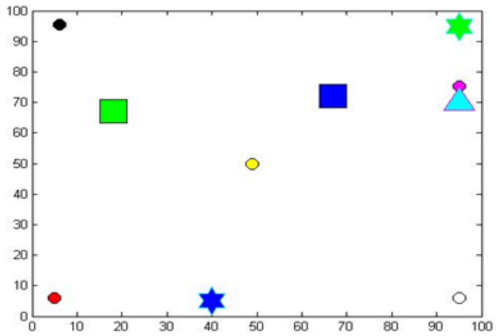
| Robot | 1 (White) | 2 (Red) | 3 (Violet) | 4 (Black) | 5 (Yellow) |
|---|---|---|---|---|---|
| Money (\$) | 1054 | 1231 | 1054 | 1054 | 1231 |
| Fuel (Liter) | 856.5 | 640.4 | 865.5 | 872.5 | 631.4 |

tank. At first, \$1000 is considered for each robot in which robot can use it for fueling. The money which each robot needs to pay for each unit of fuel is \$0.6. The algorithm is applied to the system when positions of objects and their target are in accordance with Table 3. Initially, agents start to forage objects in the environment, randomly. When distance between a robot and an object becomes less than 7 units, the robot detects the object. During search, each robot consumes one unit of its fuel. In this simulation, robots No.2 and No.4 in step q=55 simultaneously detect objects No.2 and No.1, respectively.

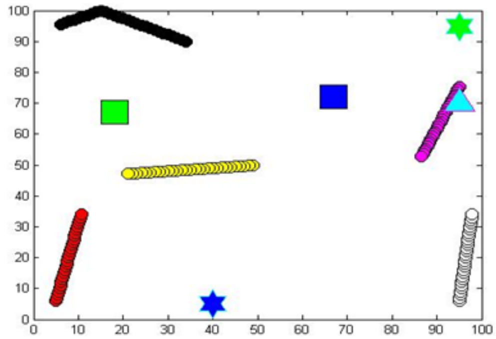
Robots No.2 and No.4 inform others that they have found objects and ask their position and fuel capacity (Table 4). Then robots No.2 and No.4 as auctioneer agents generate all possible states which could be carried. In such case, it is clear that robots No.2 and No.4 are included in possible options to transfer objects No.1 and No.2, respectively. These agents calculate payoff function for each state according to equation 5 (see Table 5). According to Table 5, robot No.4 announces to robots No.1 and No.3 that they have won carrying object No.1 and robot No.2 announces to robot No.5 that it has won to transfer object No.2. Robots afterwards move toward their corresponding object and consume some fuel in this motion. Their fuel consumption when robots reach to objects is given in Table 6.

Robots No.2 and No.5 consume 3.92 units for transporting object No.2, whiles, receive \$3 reward. Similarly, Robots No.1, No.3, and No.4 consume 2.5 liter for carrying object No.1, and receive \$2 reward. Table 7 shows assets of each robot after transportation.

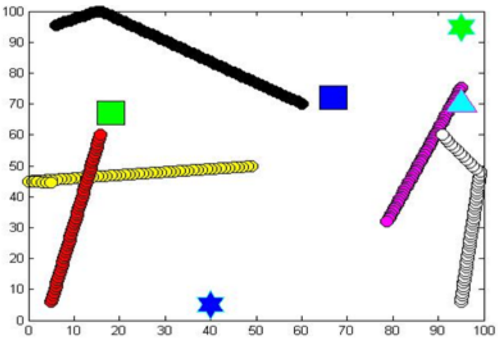
Five steps of simulation include position of robots and objects in initial moment, random search of agents for finding objects in the environment, detecting object by robots, holding the auction and moving winner robots toward objects and transporting it to goals, are given in Fig. 2.



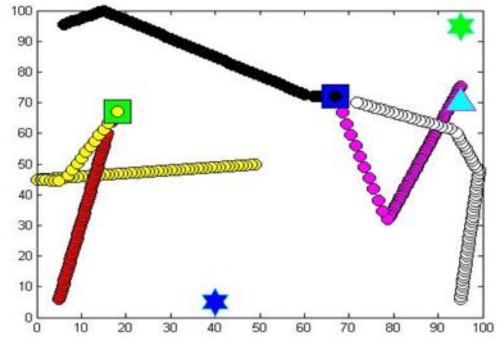
(a) Placing robots and objects in their initial positions



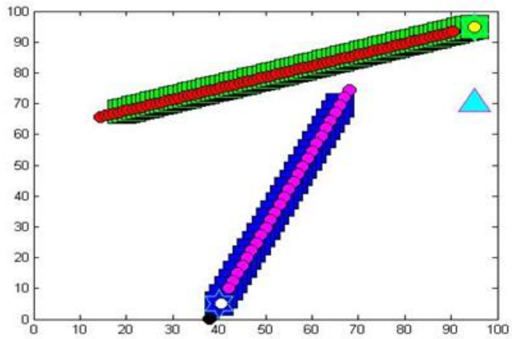
(b) Stochastic movement of robots in the environment



(c) Object detection by robots and holding time of the auction



(d) Movement of winner robots toward objects



(e) Transferring objects

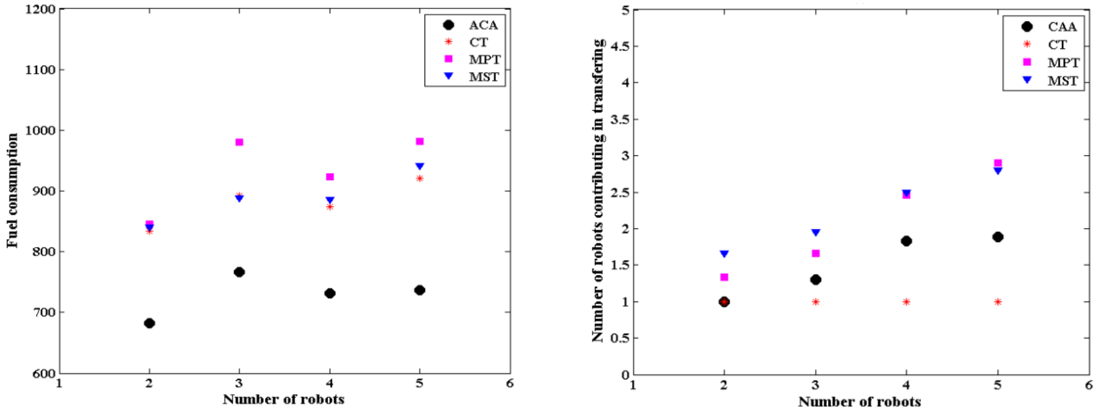
Fig. 2 Results from five steps of simulation

### *4.2 Comparative simulations*

In this subsection, the presented algorithm is compared with local heuristics CT, MST and MPT (mentioned in section 1) using a statistical simulation approach. These heuristics for our specific problem are interpreted as:

**CT:** Every robot found object carries object by itself.

**Most Starved Task First (MST):** Objects are transferred by robots those have less distance with robots.




(a) (b)

Fig. 3 The compared results ACA with 3 heuristic algorithms. Simulations have run for R=2,…,5 robots for 200 times with random selection of initial position of robots

**Most Proximal Task First (MPT):** Robots try to transport objects that have less distance with their target.

To estimate performance of the algorithm, an environment was considered with a 100×100 area. Position of objects, their target, robots and fuel station are shown in Tables 1-3. The fuel consumption without transferring object is presumed 1 unit. This value as well as reward of any robot in carrying object is shown in Table 2. The initial fuel of robot is considered 1000 units.

We assume that robots transfer objects after finding them in the environment. The proposed Combined Auction Algorithm (CAA), CT, MPT and MST methods are run on the system 200 times for $i$=2,…,5 robots in the environment with randomly selecting initial positions of robots. The "average number of robots contributing in carrying" and "average fuel consumption" are shown in Figure 3. In the presented CAA method, average of fuel consumption (Fig. 3(a)) and number of robots contributing in transferring (Fig. 3(b)) are less than CT, MPT and MST methods. Also, by raising number of robots, fuel consumption and number of robots contributing decrease in CAA, as fuel consumption with 4 and 5 robots is less than 3 robots. These results verify effectiveness of the algorithm and its superiority over compared heuristic method.

## 5. Conclusions

In this study, we solved a multi-robot transportation problem as well as coordination among agents by using a combined auction algorithm. The algorithm was applied for a set of homogeneous robots that were responsible for finding and transporting some objects in the environment. The simulation results showed with using this algorithm, agents have had better decisions in the environment. Additionally, thanks to coordination and appropriate allocation of tasks among themselves, agents could transport objects by spending less number of robots and energy. Moreover, they had an improvement in their overall payoff. The results of the proposed algorithm was compared with three local heuristics, namely, closest task first (CT), most starved task first (MST) and most proximal task first (MPT). This comparison study showed that a superior result for the proposed algorithm in term of fuel consumption and number of robots contributing in transferring.

In applying the algorithm in real world, some challenges may be encountered. Some challenges are technical ones corresponding to implementation of the system. The way of picking and placing goods, mechanism of fueling at fuel station, tools and protocols of communication are examples of implementation challenges. Such issues essentially do not affect the planning algorithm that is the subject of this paper. Some other challenges are related to constraints on motion of robots. For example, robots and goods may not be homogenous, some obstacles may exist in the environment or nonholonomic constraint may be imposed on motion of robots. In such cases some modifications on the algorithm would be required however fundamentals of the algorithm will not be changed. Dealing with this kind of issues are recommended as subjects of future works of this research.

## References

Aarts, E.H. and Lenstra, J.K. (1997), *Local Search in Combinatorial Optimization*, John Wiley and Sons, London, U.K.

Akbarimajd, A., Lotfi, A., Jonban, M.S. and Hassanpour, M. (2014), “A combinatorial auction algorithm for a multi-robot transportation problem”, *Proceedings of the 3rd International Conference on Machine Learning and Computer Science (IMLCS’2014)*, Dubai, UAE, January.

Barbu, A. and Zhu, S. (2005), “Generalizing swendsen-wang to sampling arbitrary posterior probabilities”, *IEEE T. Pattern Anal. Machine Intell.*, **27**(8), 1239-1253.

Cerquides, J., Farinelli, A., Meseguer, P. and Ramchurn, S. D. (2014), “A tutorial on optimization for multi-agent systems”, *Comput. J.*, **57**(6), 799-824.

Cramton, P., Shoham, Y. and Steinberg, R. (2006), *Combinatorial Auctions*, MIT Press, Cambridge, Massachusetts, U.S.A.

Dasgupta, P. (2011), *Multi-Robot Task Allocation for Performing Cooperative Foraging Tasks in an Initially Unknown Environment*, in *Innovations in Defence Support Systems-2*, Springer, Berlin, Heidelberg, Germany, 5-20.

Dias, M.B. and Stentz, A. (2002), “Opportunistic optimization for market-based multirobot control”, *Proceedings of the 2002 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS ’02)*, Lausanne, Switzerland, September-October.

Dias, M.B. and Stentz, A. (2004), “Traderbots: A new paradigm for robust and efficient multirobot coordination in dynamic environments”, Robotics Institute, Carnegie Mellon University, Pittsburg, Pennsylvania, U.S.A.

Garcia, P., Caamano, P., Bellas, F. and Duro, R.J. (2009), “A behavior based architecture with auction-based task assignment for multi-robot industrial applications”, *Proceedings of the International Work-Conference on the Interplay Between Natural and Artificial Computation*, Santiago de Compostela, Spain, June.

Geman, S. and Geman, D. (1984), “Stochastic relaxation, gibbs distributions, and the bayesian restoration of images”, *IEEE T. Pattern Anal. Machine Intell.*, **6**(6), 721-741.

Gerkey, B.P. (2003), “On multi-robot task allocation”, Ph.D. Thesis, University of Southern California, Los Angeles, California, U.S.A.

Hoos, H. and Boutilier, C. (2000), “Solving combinatorial auctions using stochastic local search”, *Proceedings of the 7th National Conference on American Association for Artificial Intelligence (AAAI)*, Saint Paul, Minnesota, U.S.A.

Jonban, M.S., Akbarimajd, A. and Javidan, J. (2015), “Intelligent fault tolerant energy management system with layered architecture for a photovoltaic power plant”, *J. Solar Energy Eng.*, **137**(1), 011004.

Kalra, N., Zlot, R.M., Dias, M.B. and Stentz, A. (2006), “Market-based multirobot coordination: A survey

and analysis”, *Proc. IEEE*, **94**(7), 1257-1270.
Koenig, S., Tovey, C.A., Lagoudakis, M.G., Markakis, V., Kempe, D., Keskinocak, P., Kleywegt, A.J., Meyerson, A. and Jain, S. (2006), “The power of sequential single-item auctions for agent coordination”, *Proceedings of the AAAI Conference on Artificial Intelligence (*AAAI), Boston, Massachusetts, U.S.A., July.
Koenig, S., Tovey, C.A., Zheng, X. and Sungur, I. (2007), “Sequential bundle-bid single-sale auction algorithms for decentralized control”, *Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI)*, Hyderabad, India, January.
Lee, D.H., Na, K.I. and Kim, J.H. (2010), “Task and role selection strategy for multi-robot cooperation in robot soccer. Trends in intelligent robotics”, *Commun. Comput. Inform. Sci*., **103**(3),170-177.
Ljesnjanin, M. and Velagic, J. (2009), “A market based approach for complex task allocation for wireless network based multi-robot system”, *Proceedings of the 22nd International Symposium on Information, Communication and Automation Technologies*, Bosnia, Serbia, October.
Matarić, M.J., Sukhatme, G.S. and Ostergaard, E. (2003), “Multi-robot task allocation in uncertain environments”, *Autonom. Robots*, **14**(2-3), 255-263.
Nanjanath, M. and Gini, M. (2006), “Auctions for task allocation to robots”, *Proceedings of the International Conference on Intelligent Autonomous Systems*, Tokyo, Japan, March.
Parker, L.E. (2012), “Decision making as optimization in multi-robot teams”, *Proceedings of the International Conference on Distributed Computing and Internet Technology*, Bhubaneswar, India, February.
Sandholm, T. (2002), “Algorithm for optimal winner determination in combinatorial auctions”, *Artif. Intell*., **135**(1-2), 1-54.
Simzan, G., Akbarimajd, A. and Khosravani, M. (2011), “A market based distributed cooperation mechanism in a multi-robot transportation problem”, *Proceedings of the International Conference on Intelligent System Design and Application*, Cordoba, Spain, November.
Smith, R.G. (1980), “The contract net protocol: High-level communication and control in a distributed problem solver”, *IEEE T. Comput*., **C29**(12), 1104-1113.
Song, T., Yan, X., Liang, A., Chen, K. and Guan, H. (2009), “A distributed bidirectional auction algorithm for multirobot coordination”, *Proceedings of the International Conference on Research Challenges in Computer Science*, Shanghai, China.
Sycara, K. (1998), “Multiagent systems”, *AI Mag*., **19**(2), 79-92.
Wawerla, J. and Vaughan, R.T. (2010), “A fast and frugal method for team-task allocation in a multi-robot transportation system”, *Proceedings of the International Conference on Robotics and Automation (ICRA)*, Anchorage, Alaska, U.S.A., May.
Wu, J., Xu, X., Wang, J. and He, H.G. (2011), “Recent advances of reinforcement learning in multi-robot systems: A survey”, *Control Decision*, **26**(11), 1601-1610.
Zhang, K., Collins Jr, E.G. and Barbu, A. (2013), “Efficient Stochastic Clustering Auctions for Agent-Based Collaborative Systems”, *J. Intell. Robot. Syst*., **72**(3-4), 541-558.
Zheng, X. and Koenig, S. (2009), “Negotiation with reaction functions for solving complex task allocation problems”, *Proceedings of the 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, Missouri, U.S.A., October.
Zlot, R. and Stentz, A. (2005), “Market-based multirobot coordination for complex tasks”, *Int. J. Robot. Res*., **25**(1), 73-101.

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