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Distributed artificial capital market based planning in 3D multi-robot transportation

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Abstract. Distributed planning and decision making can be beneficial from the robustness, adaptability and fault tolerance in multi-robot systems. Distributed mechanisms have not been employed in three dimensional transportation systems namely aerial and underwater environments. This paper presents a distributed cooperation mechanism on multi robot transportation problem in three dimensional environments. The cooperation mechanism is based on artificial capital market, a newly introduced market based negotiation protocol. In the proposed mechanism contributing in transportation task is defined as asset. Each robot is considered as an investor who decides if he is going to invest on some assets. The decision is made based on environmental constraint including fuel limitation and distances those are modeled as capital and cost. Simulations show effectiveness of the algorithm in terms of robustness, speed and adaptability.

Keywords: multi-robot transportation; multiagent cooperation; market mechanism; artificial capital market

1. Introduction

Distributed planning, control and decision making in multi-robot systems have attracted much attention in recent years. One of the motivations in this field is limitations of single robot systems in performing some complicated tasks. Another motivation is more efficient performance of distributed multi-robot systems in comparison with systems with centralized control. Reusability Iñigo-Blasco 2012), scalability (Cunningham and Wurm 2012), reliability and fault tolerance (Parker 2012, Pereverzeva *et al.* 2012) are among advantages of distributed multi-robot systems that have encouraged researchers to design new systems and develop new ideas in this area. Despite above advantages, some new challenges are encountered in multi-robot systems.

Cooperation and cooperation of robots (Lau *et al.* 2011), communication among robots (Hoog *et al.* 2011) and task allocation (Gerkey 2003, Lee *et al.* 2010) are among these challenges. In addition, structure of robots in a multi-robot system is different from that of single robot systems.

One of the interesting frameworks in multi-robot systems is transportation problem where

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So far transportation problem has been defined with different assumptions over articles, robots and environment. The articles can be static or dynamic, small or big, homogenous or heterogeneous, etc. The robots can be homogenous or heterogeneous, limited or unlimited in resources, with or without communication etc. Finally the environment can be dynamic or static, stochastic or deterministic, discrete or continuous, etc.

Despite many different studies with different assumptions in transportation problem, three dimensional environments have attracted less attention. Three dimensional environments are interesting in underwater and aerial robotics. Although being different in dynamics and control, aerial and underwater robots are similar from the planning and decision making point of view as 3-dimensinal planning is required in both. In the last decade, researchers have significantly studied underwater and aerial robots (see for example Barrett *et al*. 1999, Terada 2000, Kim 2003, Yu *et al.* 2005, Yu and Wang 2005, Vandapel *et al*. 2006, Bachmanna *et al.* 2009, Zarafshan *et al*. 2010, Bernard *et al.* 2011, Dimg and Yu 2013).

Most of existing researches in the field of aerial and underwater robots have focused on dynamic and kinematic modeling and control of aerial and underwater robots; however a few works in cooperative planning in multi-robot environments can be found in the literature. Shao *et al.* (2006) investigated multiple robotic fish coordination problem in context of a disk-pushing task. Sang *et al.* (2005) studied the system of the patrol control mechanism and algorithm of multiple robot fish. Fink *et al.* (2011) studied three-dimensional planning and control of multiple aerial robots while manipulating a payload using a cable mechanism. In their work, individual robot control laws and motion plans as well as desired trajectory were devised.

In the work of Shao *et al.* (2006), Sang *et al.* (2005) and Fink *et al.* (2011) distributed planning and decision making were not applied, hence aforementioned advantages of distributed multi-robot systems were not anticipated. Work of Acevedo *et al.* (2013) proposed a distributed approach to coordinate unmanned aerial robots in patrolling task where low communication ranges and memory storage were available. Carlési *et al.* (2011) employed an organizational model to facilitate and regulate interactions between heterogeneous autonomous underwater vehicles for limiting communication. Transportation issues were not taken into consideration in works of Acevedo *et al.* (2013) and Carlési *et al.* (2011).

Coordination, cooperation, competition and communication are requirements in multi-robot systems that make them similar to human societies from some aspects. Therefore some ideas are borrowed from human societies to develop planning and decision making algorithms in multi-agent systems. Artificial market mechanisms are among these algorithms. Work of Smith (1980) is known as the earliest market-based multi-robot mechanism. So far plenty of papers have been published in the frame work of using market mechanisms in multi-robot systems. An excellent review can be found in *Dias et al.* 2006. However, all of these works can be categorized in two general paradigms including auction mechanisms and contract nets. Works of Dias *et al.* (2011) and Loue *et al*. (2012) are examples of recent research published in the field of auction mechanisms and works of Sun and Wu (2009) and Lili and Huizhen (2012) are examples of recent research published in the field of contract nets.

Artificial capital market as a new paradigm in market mechanisms was introduced in our previous work (Simzan *et al.* 2011). In that work a centralized method for cooperation of robots was proposed.

This paper is an extension of Simzan *et al.* (2011) from centralized mechanism to a distributed one and from 2-dimensional environment to 3-dimensinal one. More detailed evaluations and discussions are also provided in this study. In this paper, three-dimensional multi-robot transportation problem is studied and cooperative planning algorithm based on artificial capital market is proposed.

In the next section the problem is defined and corresponding assumptions are devised. In section 3 the proposed distributed cooperation algorithm is proposed. In the froth section simulation results are illustrated and the last section includes conclusions.

2. Problem description

Assume that R robots are located in different positions of a three-dimensional environment as it is shown in Fig. 1. We denote the position of i^{th} robot by $\boldsymbol{P}_i = (X_i,Y_i,Z_i)$. It is desired that the robots transport an object from its initial position $\boldsymbol{P}_O = (X_O,Y_O,Z_O)$ to a goal position $\boldsymbol{P}_G=(X_G,Y_G,Z_G)$. The object can be carried by a single robot or by a team of robots. The robots initially have limited fuel and F_i stands for amount of initial fuel of i^{th} robot. Fuel consumption rate of robots, while carrying no object, is E_f unit per meter. If a single robot carries the object it will consume E_c unit of fuel per meter and if n robots cooperate in carrying a single object, rate of fuel consumption will be decreased to E_c/n unit per meter for each robot. There is a fuel station located at $\boldsymbol{P}_F = (X_F,Y_F,Z_F)$. Each robot knows its own position and the positions of the object, the fuel station and the goal. It does not know the positions of the other robots.

The main question is: "Which robots should contribute in carrying the object toward the goal?". Answering this question is not straightforward. The complexities are originated from the following facts:

1. It is obvious that only the robots those have enough fuel can contribute in carrying the object. Nevertheless decision of a robot in contributing or not contributing in task will affect fuel consumption rate of other participant robots as it was explained above. Then it is not easy to find out which robots have enough fuel for doing the task.
2. Decision making in the society is made in a distributed manner i.e. each robot make its own decision. However, the robots are considered as self-interested agents and their decisions are not necessarily beneficial for the society. Here we need a mechanism to force self-interested robots to make decisions those are good for the society.
3. A criterion is needed to evaluate "beneficial decisions for the society". In this paper we define total fuel consumption of the society as the decision criterion. However, in a distributed decision making mechanisms (like our system), there is no central planning unit with full information of whole system. Then global optimization methods are not applicable.
4. The robots need to communicate in order to make a collective decision. Amount of transmitted data will affect decision speed. Therefore, the decision making protocol should not require high data transmission.

In this paper we answer abovementioned main question with the aim of reducing total fuel consumption in the presence of the fuel constraints and with no central decision making unit. We introduce a distributed mechanism that is able to address the issue. We will propose a negotiation mechanism in the form of an artificial capital market by which the agents can come to agreement about the combination of the robots contributing in transportation of the object. The mechanism is designed such that the final solution is as beneficial as possible for whole society. In the proposed mechanism amount of transmitted data among the robots is reduced as well.

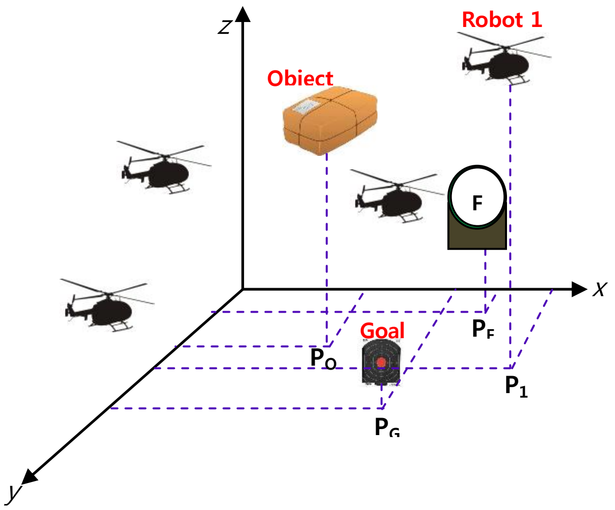

Fig. 1 A 3D multi-robot transportation system with an object, a goal and a fuel station

3. Distributed decision making mechanism

3.1 Artificial capital market

We model our transportation problem as a simple artificial capital market. Artificial capital market, introduced by Simzan *et al.* (2011) is a new paradigm in market based distribution artificial intelligence. Components of the artificial capital market are defined as the following:

Investors: The robots are considered as investors in artificial market.

Assets: Covered distances by the robots − carrying or not carrying the object − is considered as assets.

Cost of assets: Fuel consumption in a distance is considered as price to be paid for an asset. If a robot covers a distance it has to pay the corresponding cost. The costs are function of three factors: covered distance, carrying or not carrying the object and the number of robots contributing in task.

Asset Bundles: "Participation in transportation" is assumed as an asset bundle. A participant tobot should cover three distances: achieving from initial location to the object, carrying the object to goal and returning from the goal to fuel station. Hence, each bundle is composed of tree probable assets: **A**chieving the object, **C**arrying it to the goal and **R**eturning to the fuel station. If we show the cost of these assets as C_A, C_C and C_R, then the cost of bundle will be $C= C_A+C_C +C_R$.

Initial capital: Initial fuel of i^{th} robot is considered as its initial capital and is shown by F_i.

Outcomes: After carrying out the transportation task, the contributing robots would be allowed to fuel. A limited amount of fuel S is available at the station that would be shared among n participant robots. Then outcome of each agent would be S/n .

Payoffs: Payoff of agent i is defined as difference between its outcome and its costs:

$$P_i = \begin{cases} \dfrac{S}{n} - C_i & \text{if the agent cantributes in task} \\ 0 & \text{if the agent does not cantribute in task} \end{cases} \quad (1)$$

where P_i and C_i stand for payoff and costs of robot *i*.

3.2 Negotiation mechanism

In the transportation problem, described in section 2, it should be decided which robots are contributing in transportation task. The decisions are made in a distributed manner and there is not a central processing in the society. Each robot individually decides if it is interested in contributing in transportation or not. This issue can be interpreted that in artificial capital market each investor individually decides if it is interested to investment on asset bundle or not.

Decision making of each robot is done based upon some information. The robot can obtain local information including its distances from the object, the goal and the fuel station. Obviously the agent cannot make efficient decision with only local information and it needs to obtain some information about other robots in the environment. From the viewpoint of distributed decision making it is desired that amount of information transmitted among the robots be as small as possible. In our proposed mechanism, the only information that each robot gets from the other robots is their "decisions". On the other words each robot only knows which robots are interested on contributing is task. Before we devise our negotiation mechanism, we explain how the agents share this information. We encode decisions of the society by a binary string $D = b_1 b_2 .. b_R$.

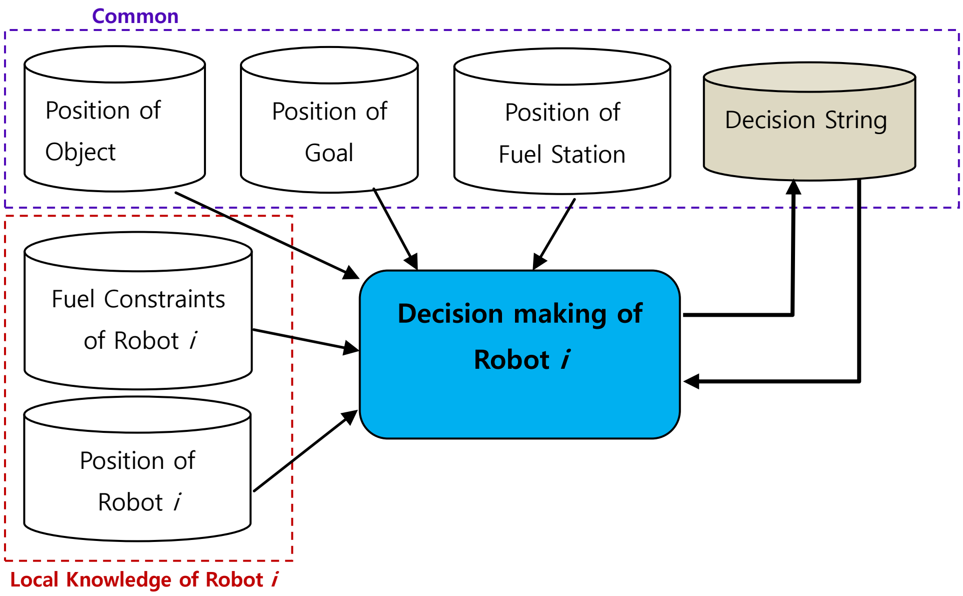

Fig. 2 Knowledge base of robots. Decision of each robot is made based on local and common knowledge

where b_i represents decision of i^{th} robot. If i^{th} robot decides to contribute in carrying the object we have $b_i = 1$, otherwise $b_i = 0$. For example in a five robot system D = 10010 means that agents 1 and 4 have decided to participate in the manipulation task. This decision string is common knowledge for robots.

In summary each investor agent (robot) has local and common knowledge about the environment (see Fig. 2). Local knowledge of agent includes its fuel constraint and its position. Common knowledge includes abovementioned decision string as well as positions of the object, fuel station and goal. Based on this knowledge base, decision making process of an agent is very simple. Investor agent i takes following steps to make decisions (see Fig. 3):

1. Calculates the cost of asset bundle if it invests (contributes in transportation task). The cost is equivalent to fuel consumption and is given as $C_i = C_{A,I} + C_{C,i} + C_{R,i}$ which is the aggregation of **A**chieving, **C**arrying and **R**eturning costs as it was explained earlier. In order to find these costs the agent i needs to have its own position $\boldsymbol{P}_i$, position of object $\boldsymbol{P}_O$, position of goal $\boldsymbol{P}_G$, fuel consumption rates E_f and E_c and the number of robots contributing in transportation (denoted by n). All of these values are available in knowledge base of the object.
2. Obtains its payoff ($\frac{S}{n} - C_i$) if it participates in task.
3. If the agent does not have enough capital ($C_i > F_i$) or the investment is not beneficial ($\frac{S}{n} - C_i < 0$) then it declines the investment and sets corresponding bit in decision string to zero ($b_i = 1$).
4. If the agent has enough capital and the investment is beneficial then it accepts the investment and sets corresponding bit in decision string to one ($b_i = 1$).

FUNCTION D=INVESTOR(D)

// THIS FUNCTION IF FOR INVESTOR i

// D=($b_1 b_2 \ldots b_n$) is decision string which is a common knowledge

n = **sum** (D) *// number of robots participated in task is number of 'one's in decision sting*

$C_{A,i} = E_f \left\| \mathbf{P}_i - \mathbf{P}_O \right\|$ *//Cost of Achieving*

$C_{C,i} = \frac{E_c}{n} \left\| \mathbf{P}_O - \mathbf{P}_G \right\|$ *// Cost of Carrying*

$C_{R,i} = E_f \left\| \mathbf{P}_G - \mathbf{P}_F \right\|$ *//Cost of Returning*

$C_i = C_{A,i} + C_{C,i} + C_{R,i}$

IF $C_i > F_i$ or $\frac{S}{n} - C_i < 0$ **THEN** $b_i = 0$ *// Decline investment*

ELSE $b_i = 1$ *// Accept investment*

Fig. 3 Decision making algorithm of robot i

This decision making process is illustrated in Fig. 3. It should be noted that the decisions of agents are made in a distributed manner; that is each agent individually executes algorithm of Fig. 3 in a loop. There is no specific order or priority among the agents. An agent, at each iteration of its loop, reads and employs current decision string D to make decision. The market is initiated with a random decision string D^0 and the computations are continued until decision sting converges to a fixed string.

4. Simulations and discussions

We considered a $2\times2\times2\text{m}^3$ area with 10 robots as test environments. Initial locations of robots are shown in Table 1. The rate of fuel consumptions with and without carrying the object is assumed $E_f = 0.07$ and $E_c = 0.7$ respectively.

4.1 Simulations with static object

In the first stage of simulations it is assumed that the object is stationary and the robots have the same amount of initial fuel. ($F_i = 5$ I $=1,...,10$). Available fuel at fuel station is set to $S = 4$. To verify performance of the algorithm, it should be tested in different conditions. We applied the proposed algorithm for two problem cases with different locations for object, goal and fuel station shown in Table 2. The results of applying the proposed algorithm for different choices of initial decision string D^0 are shown in Tables 3 and 4. In these tables the final decisions are denoted by D^f. The final solutions are also graphically illustrated in Figs. 4 and 5. From Tables 3 and 4 it is obvious that the final solution is not sensitive to initial string which shows the robustness of algorithm to the initial guess.

Number of changes in decision string to reach from D^0 to D^f are also provided is Tables 3 and 4. Among six runs shown in Tables 3 and 4, the maximum changes in decision string are 10 which corresponds to Run 1 in Table 4. For other runs changes of decision string are less than 10. This implies on fast convergence of the decision making process.

We can compare fuel consumption of society corresponding to obtained solutions with the optimal solution. To do this, in each case we found the optimal decision using a brute force search, i.e. calculating the fuel consumption in all possible decisions:

Table 1 Initial position of robots. $\mathbf{P}_i = (X_i, Y_i, Z_i)$ is position of i^{th} robot in meters

	$\mathbf{P}_1$	$\mathbf{P}_2$	$\mathbf{P}_3$	$\mathbf{P}_4$	$\mathbf{P}_5$	$\mathbf{P}_6$	$\mathbf{P}_7$	$\mathbf{P}_8$	$\mathbf{P}_9$	$\mathbf{P}_{10}$
X_i	0.2	1.8	0.6	1.9	1.9	0.1	1.6	0.4	1.6	0.3
Y_i	0.3	1.9	0.2	0.1	1.9	1.9	0.1	0.1	1.9	1.9
Z_i	0.1	1.5	0.5	1.4	0.6	0.7	0.1	0.2	1.7	1.5

Table 2 Positions of goal, object and fuel station (in meters) in two problem cases studied in simulations

CASE	Goal position $\mathbf{P}_G = (X_G,Y_G,Z_G)$	Object position $\mathbf{P}_O = (X_O,Y_O,Z_O)$	Fuel station position $\mathbf{P}_F = (X_F,Y_F,Z_F)$
1	(0.2,0.7,1.2)	(1,1,1)	(1.6,1.4,0.3)
2	(1.7,0.5,0.8)	(0.8,1.4,1.6)	(1.2,1.5,0.5)

- In problem case 1, optimal decision is obtained as D^{opt} = 0010000011 and corresponding optimal fuel consumption of society is 1.24248. In this case the proposed algorithm has converged to D^f = 0010000101 with fuel consumption of 12.5079. It can be seen that the value is very close to optimal solution.
- In problem case 2, optimal decision is obtained as D^{opt} = 010010011 and corresponding optimal fuel consumption of society is 1.65858. This is exactly equal to the solution found by the proposed algorithm.

In order to verify reliability of the algorithm, we performed an statistical analysis by running the algorithm for 1000 problem cases with random selection of goal, object and fuel station positions and fixed values for initial positions of robots (given in Table 1) and fuels ($F_i = 5$ and $S = 4$). In each case the results are compared with optimal solutions (obtained by brute force search).

Number of problem cases converged to the optimal value, average deviation from optimal value and average number of changes in decision string are illustrated in Table 5. One can see that in 58.2 percent of cases optimal value is achieved by the proposed procedure and deviation from

Table 3 Results of the proposed decision making process for problem case 1 in three different runs

	Run 1	Run 2	Run 3
D^0	1010010011	1110111000	1000011010
D^f	0010001001	0010001001	0010001001
Number of changes in D	5	6	9

Table 4 Results of the proposed decision making process for problem case 2 in three different runs

	Run 1	Run 2	Run 3
D^0	1001001001	0011011001	1111100000
D^f	0100010011	0100010011	0100010011
Number of changes in D	8	7	10

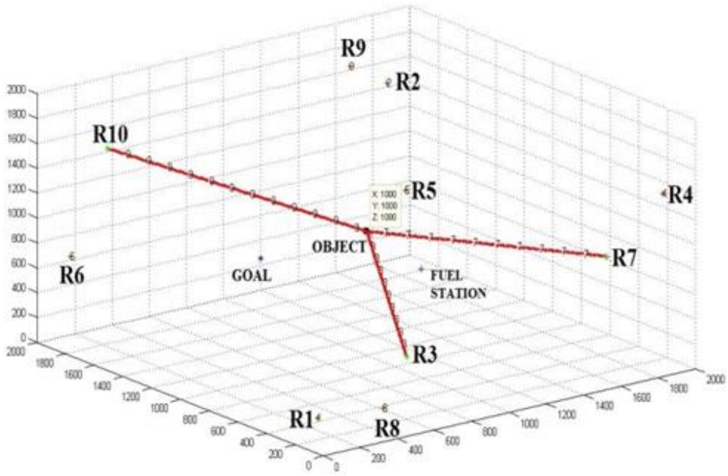

Fig. 4 Final solution of problem case 1. X, Y and Z axis are in mm

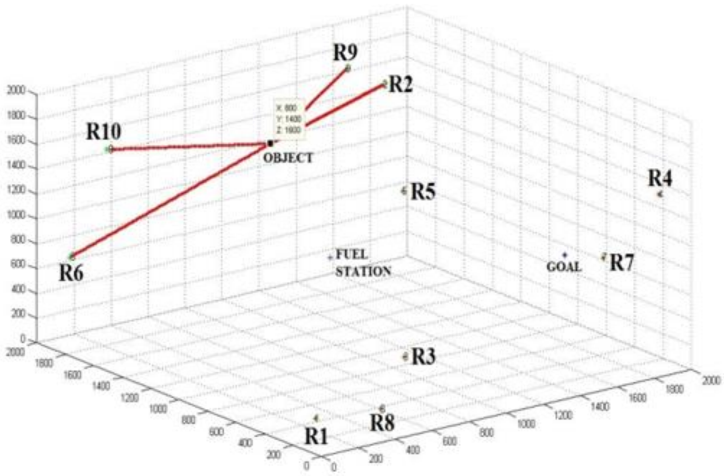

Fig. 5 Final solution of problem case 2. X, Y and Z axis are in mm

Table 5 Results of statistical analysis of proposed decision making process by running 1000 times with different goal, object and fuel station positions

Number of optimal solutions achieved	*Average deviation from optimal value*	*Average number of changes in decision string*
582	% 1.91	7.2

optimal value in other cases is less than 2 percents. Moreover average change in decision string during decision making process is 7.2.

From above analysis it can be concluded that the proposed algorithm converges to near optimal decisions (sometimes optimal decisions) which is acceptable for a distributed algorithm wherein the agents do not have access to full information of the environment. It can also be concluded that the decision process is very fast and the solution is found in less than 10 changes in decision string.

4.2 Real time implementation of decision making process

To evaluate real time speed and performance of the decision making process, we set up a real time test where ten PIC18F6520 microcontroller systems are considered as ten agents. The agents were physically located in a 2×2×2m room. Their locations are selected according to values of Table 1. Other parameters of the system are considered as abovementioned problem case 1. For each agent, its position, its initial fuel, available fuel at fuel station and positions of goal, object and fuel station are loaded in agent's memory as its database. Decision string is saved in a ground server and each agent can communicate with the ground server via a Bluetooth Class II device that has a range of over 100 m. The devices operate in the 2.4 GHz frequency range and include band hopping and error correction. They also have automatic retransmission at a maximum rate of 115.2 kbps. Agents use this communication channel to read decision string from the ground server and change it if required. Each agent executes independently algorithm of Fig. 2. With different initial values of decision string the real time system generated final decision as $D^f = 0010001001$ which is the same as simulations results given in Table 3. The average decision making time with this system is about 8ms which is appropriate for real time applications.

4.3 Simulations with moving object

To investigate how the proposed mechanism would act in transportation of a moving object, we apply the algorithm for an environment with a moving object. It is assumed that the object moves according to the following equation:

$$P_o^{t+1} = \begin{cases} X_{t+1} = X_t + 0.12 \\ Y_{t+1} = Y_t - 0.35 \\ Z_{t+1} = Z_t - 0.35 \end{cases} \tag{2}$$

We run two simulations where in the first one the initial position of the object is $\boldsymbol{P_G}$ = (0.2,0.7,1.2) and in the second one initial position of the object initial position of the object is $\boldsymbol{P_G}$ = (1.7,0.5,0.8). These initial positions are selected equal to object positions of two problem cases of Table 2. The object moves according to (2) and stops when it is caught by one of the robots. The robots run the proposed negotiation algorithm every T = 3 time steps. Then the winning robots move toward the object for 3 time steps until the next decision is made. Parameter T can be different according to dynamics of the object. More fast objects would require smaller valued for T.

For problem cases 1 and 2, the progress of the algorithm and corresponding motions of the robots and the object are depicted in Figs. 6 and 7. In Fig. 6, robots *R3*, *R7*, *R10* start moving toward the object in earlier steps of simulation. However after some time steps (by moving the object away from *R10* and close to *R1*, *R8*), *R10* gives up chasing the object and *R1*, *R8* start moving toward object. In Fig. 7 robots *R2*, *R6*, *R9*, *R10* start moving toward the object and *R3* joins them afterwards. These two examples show that the decision made by the proposed algorithm can be adapted according to changes of the environment.

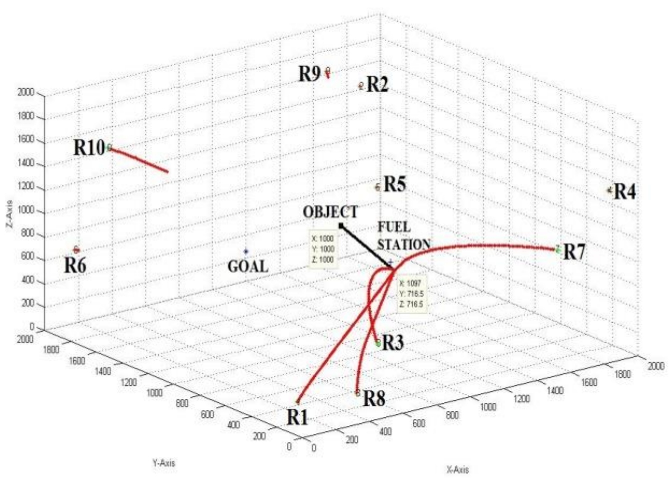

Fig. 6 The robots, starting from locations of problem case 1, chase a moving object using the proposed algorithm. X, Y and Z axis are in mm

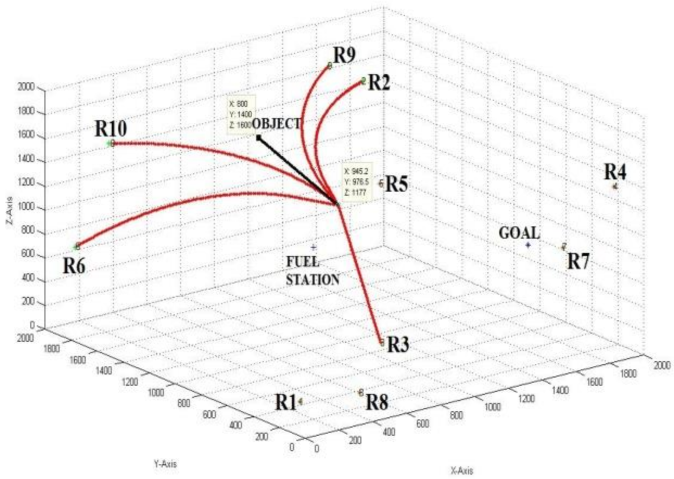

Fig. 7 The robots, starting from locations of problem case 2, chase a moving object using the proposed algorithm. X, Y and Z axis are in mm

5. Conclusions

A capital market based cooperative planning and decision making algorithm was introduced for multi-robot transportation task in three-dimensional environments. In our transportation problem, some robots with limited fuel negotiate to come to an agreement about carrying an object to its goal. The robots who contribute in the transportation task are rewarded by predefined value of fuel. The problem was modeled as an artificial capital market wherein the robots were modeled as investors with limited capital. A negotiation protocol was proposed to support the society to come to agreement. In the negotiation algorithm only small piece of information is exchanged among the robots. Simulations were performed with static and dynamic objects. Statistical simulations were also performed. A real time implementation was provided to test speed of the decision making process. From the simulations and implementations it can be concluded that the:

1. The mechanism is robust to initial decision of the robots.
2. The solutions are close to optimal solution in terms of fuel consumption of the society.
3. The convergence of the algorithm is fast. Decision is made in less than 10 steps in simulations and less than 8ms in real time for a 10 robot system.
4. The algorithm can be easily extended to dynamic environments and shows good adaptability to environment changes.

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