A formalization for distributed cooperative sensor resource allocation

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Abstract. Distributed sensor resource allocation problem is an important research area of multi agent systems. In this paper we propose a model of distributed resource allocation problem for distributed sensor networks. Several models based on constraint network and another model based on concept of agency, are compared. Then, constraint network formalization which are similar to resource allocation problem of agency model, is shown.

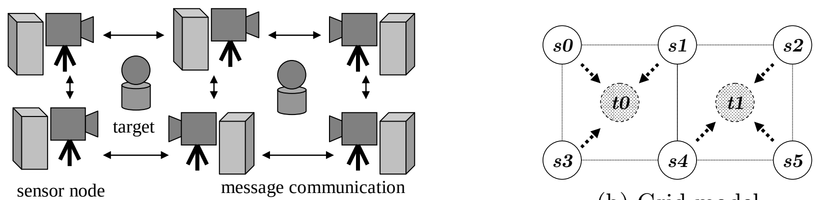
1 Introduction

Distributed sensor network is studied as an application domain of multi-agent system. In this paper, we focus on a distributed observation system shown in Figure 1(a). In the observation system, sensor nodes have its sensor and processor that are connected with message communication link. Intrusion detection, target tracking and scheduled observation are included in tasks of the system. The observation tasks are performed as distributed cooperative processing using sensor node's processors and communication link.

In the observation systems, resource allocation, which allocates sensors to targets, is an important problem. In generally, the resource allocation problem contains optimization problems. Therefore, consideration of applying distributed optimization algorithm is useful to understand the problems and to design the cooperative protocols. Distributed constraint satisfaction/optimization problems, which is a fundamental formalism for multi-agent cooperation, have been studied [1], [2], [3], [4], [5], [6] . Formalizations which represents distributed sensor networks as distributed constraint networks have been proposed [7],[8].

On the other hand, a distributed cooperative observation system using agency model has been developed [9],[10]. The agency model has been applied to practical environment consists on autonomous camera sensor nodes, which own pan-tilt-zoom controlled cameras, computers and local area network. In this model, total processing, including camera input and pan-tilt-zoom output, are integrated as a hierarchical distributed processing.

In this paper, a DCOP formalization is applied to a cooperative sensor resource allocation problem. Formalizations using DCOP and agency model are compared. Furthermore a cooperative formalization is proposed intend to integrate DCOP approach into agency model.



(a) Sensor nodes and targets (b) Grid model

Fig. 1. A model of sensor network

2 Background: Modeling for sensor allocation

2.1 Sensor allocation problem

In this paper, we focused on a resource allocation problem such that observation resources of sensor nodes are allocated to targets. For the sake of simplicity, the sensor resource allocation problem is represented using grid model shown in Figure 1. The grid models are used in related works [8]. In Figure 1(b), s_i and t_j represent a sensor node and a target respectively.

The goal of the problem is an optimal allocation of sensor resources for all targets. The allocation have to satisfy conditions for as follows.

– Sensors have limited observation area. For example, each sensor observes targets which is inside of neighbor grids. Other targets are invisible.
– Sensors have limited observation resources. For example, each sensor simultaneously observes one target in observation area.
– There are requirements of sensor resources for observation of targets. For example, three sensors are required for a target to estimate coordinate of the target in enough accuracy.

In Figure 1(b), an optimal solution is shown as arrows.

Sensor nodes solve the problem using distributed cooperative processing. In this paper, two approaches for the cooperation are focused. In 2.2, 2.3 and 2.4, formalization using distributed constraint satisfaction/optimization problem [7],[8] is shown. In 2.5 another model using concept of agency [9],[10] is shown.

2.2 DCOP

Distributed constraint optimization problem (DCOP) [1], [2], [5], [6], is a fundamental formalism for multi-agent cooperation. In the DCOP, multi-agent systems are represented as variables and constraints. Definition of DCOP is as follows.

– A DCOP is defined by a set A of agents, a set X of variables, a set C of binary constraint and a set F of binary functions.
– Agent i has its own variable x_i. x_i takes a value from discrete finite domain D_i. The value of x_i is controlled by agent i.

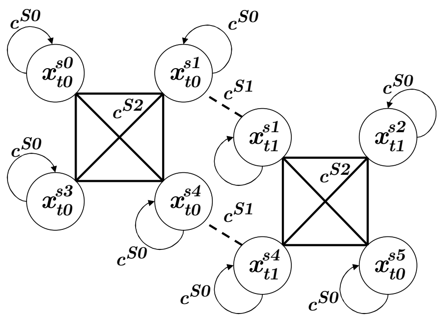


Fig. 2. STAV

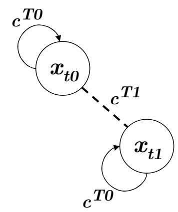


Fig. 3. TAV

- Relation of an assignment $\{(x_i, d_i), (x_j, d_j)\}$ is defined by a binary constraint $c_{i,j}$.
- Cost for $c_{i,j}$ is defined by a binary function $f_{i,j}(d_i, d_j) : D_i \times D_j \rightarrow \mathbb{N}$.
- The goal is to find global optimal solution $\mathcal{A}$ such that it minimizes the global cost function: $\sum_{f_{i,j} \in F,\ \{(x_i,d_i),(x_j,d_j)\} \subseteq \mathcal{A}} f_{i,j}(d_i, d_j)$.

Agents cooperatively search the optimal solution using distributed constraint optimization algorithms. In recent years, a number of algorithms are proposed for DCOP[1] [2], [3], [4], [5], [6] . These algorithms are categorized into exact solution methods and inexact solution methods. In sensor network, inexact methods will be useful because of its scalability. However, the methods frequently obtains local optimal solution.

2.3 STAV (Sensor Target As Variable)

In this section, a DCOP formalism, in which variables are defined for sensors and targets, is shown. The example of sensor network shown in Figure 1 is formalized as a STAV shown in Figure 2.

Variable $x^{s_i}_{t_j}$ is defined for sensor s_i and target t_j which is inside of observation area of sensor s_i. The variable $x^{s_i}_{t_j}$ takes a value which represents an allocation of sensors for target t_j. For example, if target t_j is inside of observation area of sensors $s_0, \cdots, s_n$, The variable $x^{s_i}_{t_j}$ takes a value which represents $\{\phi, \{s_0\}, \cdots, \{s_n\}, \{s_0, s_1\}, \cdots, \{s_0, \cdots, s_n\}\}$.

Constraints which are defined for each variables are as follows.

- $c^{S0}(x^{s_i}_{t_j})$: A unary constraint which represents requirement of sensor resource for target t_j.
- $c^{S1}(x^{s_i}_{t_j}, x^{s_i}_{t_{j'}})$: A binary constraint which represents limitation of sensor resource. It is disallowed that a sensor s_i is multiply allocated to different targets $t_j and t_{j'}$.
- $c^{S2}(x^{s_i}_{t_j}, x^{s_{i'}}_{t_j})$: A binary constraint which represents consistency of decision of sensors. Two sensor allocations, which are decided in s_i and $s_{i'}$ for a target t_j, must be equal.

In this example, it is disallowed that one sensor is multiply allocated to different targets. Therefore, the constraint c^{S1} is formalized as a binary constraint. If one sensor is multiply allocated to targets, the constraint is formalized as a n-ary constraint.

Moreover, constraint c^{S2} is defined for each two variables which are related to t_j. As another formalization, these constraints are integrated into a n-ary constraint.

In the STAV, variables are distributed into sensor nodes, and agreement of sensor nodes is explicitly formalized. However, this detailed formalization increases number of variables and constraints.

2.4 TAV

In this section, a DCOP formalism, in which variables are defined for targets, is shown. The example of sensor network shown in Figure 1 is formalized as a TAV shown in Figure 3.

Variable x_{t_j} is defined for t_j. The variable x_{t_j} takes a value which represents an allocation of sensors for target t_j. The domain of the variable are same as STAV.

Constraints which are defined for each variables are as follows.

- $c^{T0}(x_{t_j})$: A unary constraint which represents requirement of sensor resource for target t_j.
- $c^{T1}(x_{t_j}, x_{t_{j'}})$: A binary constraint which represent consistency of sensor allocation for $t_j, t_{j'}$. This represents each sensor is allocated to at most one target.

In the TAV, agreement of sensor nodes is not considered. STAV is translated to TAV as follows.

1. Constraints of c^{S0} for same target t_j are integrated into a constraint c^{T0}.
2. Constraints of c^{S2} for same target t_j are removed.
3. Constraints of c^{S1} for same pair of targets (t_i, t_j) are integrated into a constraint c^{T1}.

In the TAV, number of variables and constraints are less than one in SAV. However, in practical problem, variables can not be processed in targets. In this paper, we assume that available resources for computation is only contained in sensor nodes. Therefore, solving another problem, that distributes the variables and constraints on sensor nodes, is necessary.

2.5 Agency based cooperative model

As another approach different form DCOP formalization, distributed cooperative observation system using agency model has been proposed [9],[10]. The agency model has been applied to practical environment consists on autonomous camera sensor nodes, which own pan-tilt-zoom controlled cameras, computers and local

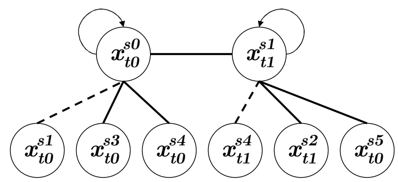


Fig. 4. A constraint network similar to agency model

area network. In this model, total processing, including camera input and pan-tilt-zoom output, are integrated as a hierarchical distributed processing. The outline of the system is as follows.

- The observation system is consist on sensor nodes which are called AVA. The hardware of each AVA consists on pan-tilt-zoom controlled camera, computer and local area network interface.
- When each AVA discovers targets, AVAs form a group (agency) for each target.
- One of AVAs in a agency performs as a manager of the agency. Other AVAs follow decision of the manager. The managers negotiate to share sensor resources (AVAs) among agencies.

In this paper, our discussion is focused on sensor resource allocation of the agency model. Important points as the sensor resource allocation problem is as follows.

- Similarly to TAV, information is gathered for each target.
- The gathered information is allocated to a manager node.
- Other nodes which are related to same target follow its manager node's decision.

From these points of view, the agency model is considered as an integrated model which partially contains STAV and TAV. A constraint based formalization, which is similar to the agency model, is shown in Figure 4. In this formalization, variables are defined same as STAV. However, for target t_0, a variable which is contained in sensor s_0 is prioritized. Similarly, for target t_1, a variable which is contained in sensor s_1 is prioritized. Other values of variables follow the variable which is prioritized for the target.

In some cases, variables which, are related to same sensor node, are follow different variables. For example, in figure 4, x_{t0}^{s4}, x_{t1}^{s4} are follow different variables. Similarly, $x_{t0}^{s1} and x_{t1}^{s1}$ are follow different variables. In this case x_{t1}^{s1} follows itself.

The agency model has been successfully demonstrated in practical environment. On the other hand, sensor resource allocation problem and its solver is implicitly contained. The solver is basically considered as hill-climb based method.

3 Cooperative model using constraint network

In TAV, it is necessary that variables are allocated to sensor nodes in processing. On the other hand, in the agency model, this variable allocation and sensor resource allocation using the variables are integrated. For practical model, this integration is useful. However, representation of sensor allocation problem and its solver is implicitly contained. Our purpose is to represent these problems as constraint formalization. In this section, a formalization which hierarchically integrates two problems as follows.

- Variables of STAV are prioritized for each target. The prioritization is considered as an allocation of computation resources.
- Then the most prioritized variables are used to solve for sensor resource allocation which is based on TAV.

3.1 Allocation of computation resources

Allocation of computation resources is as follows. STAV is translated to TAV. Then variables of TAV are allocated to sensor nodes (computation resources). In actually, this is done by solving a leader election problem which satisfy constraints as follows.

- At least one STAV variable for each target must be the manager of the target.
- At most one STAV variable for each sensor must be the manager. This constraint represents limitation of computation resources. We assume that only one target is processed in one sensor node. This limitation may generalized to handle multiple targets.

Allocation of computation resources is a basis of allocation of sensor resources. Unless allocation of computation resources is not solved, allocation of sensor resources is not solved. Therefore these constraints must be immediately satisfied to solve problem. In this paper, we assume that the allocation of computation resources is always solved.

3.2 Allocation of sensor resources

After computation resources are allocated, allocation of sensor resources is solved as TAV using most prioritized variables. Other variables must take same value as the corresponding most prioritized variable.

3.3 TAV+SAV (Sensor As Variable) — Gathering of decision making

Constraint c^{T1} for TAV variables is related to multiple variables. Therefore, communication between variables is necessary to evaluate the constraint. For example, when variable x_{t_i} takes a value from its domain $\{\phi, \{s_0\}, \{s_1\}, \{s_0, s_1\}\}$, verifying exclusive assignment is necessary for each other variable which is related to sensor s_0 or s_1.

To reduce this communication, domains of variables are modified. The modified domain consists on tuple of assignments of sensors. The assignment of each sensor represents a target which is allocated to the sensor. For example, domain of x_{t_i} consists on tuple of assignment of s_0 and s_1. The assignment for $s0$ represents a target in $\{\phi, t_k, \cdots, t_{k'}\}$ which are inside observation area of $s0$. Here ϕ represents that no target is allocated. In this translation, resource constraint of sensor is considered.

As a result of the translation, information about targets and sensors is gathered into sensor nodes which own most prioritized variables. This is considered as gathering of decision making into agency managers.

When a sensor is related to multiple most prioritized variables (agency managers). Assignment for the sensor is decided by one agency manager using tie-break. A cooperative method using the similar concept of multiple agency is shown in [10].

3.4 Formalization

A cooperative model shown in above subsections is formalized as follows. Each agent knows information as follows.

- T_s : A set of target which is inside observation area of sensor s.
- N_s : A set of neighbor sensors of sensor s. Information including T_s and resource constraint of sensor s is shared with other sensors in N_s.

According to these information, each sensor generates variables and constraints. Variables are defined as follows.

- $x^T_{s,t}$: A variables which represents manager or member of agency. $x^T_{s,t}$ takes a value form its domain $D^T_{s,t} = \{0, 1\}$. $x^T_{s,t} = 1$ represents that sensor node s is manager of agency for target t. Otherwise s is member of the agency.
- x^S_s : A variable which represents allocation of sensor s for targets. X^S_s takes a value from its domain D^S_s. D^S_s represents a subset of tuple of T_s or nothing to allocate. In our example problem definition, sensor s is allocated to only one target in T_s. Therefore D^S_s=$T_s \cup \{\phi\}$.
  Each sensor node s has variables of related sensor nodes in N_s. The copy of other neighbor node's variables are necessary when s performs as a manager.

Constraints are defined as follows.

- $c^{A0}_{s,t}$: A constraint which prohibits confliction of multiple agency manager between two sensor nodes. The constraint is defined as follows. Number of variable such that $x^T_{s,t} = 1$ for all $s \in N_s$, must be 1. Only one sensor node performs as an agency manager for a target.
- $c^{A1}_{s,t}$: A constraint which prohibits confliction of multiple agency manager for own targets. The constraint is defined as $\neg(x^T_{s,t} = 1 \wedge x^T_{s,t} = 1)$ for all $t \neq t'$. In our example problem definition, a sensor node performs as a agency manager for only one target.
- $c^{A2}_{s,s',t}$: A constraint which represents membership of agency. If $x^T_{s',t} = 1$ then $x^S_s = x^S_{s'}$ must be satisfied. If $x^T_{s',t} = 1$ in multiple sensors s' then one of those is prioritized using tie-break of sensor identifier.

- $c^{A3}_{s,t}$: A constraint which represents requirement of sensor resources for target t. This constraint is relaxed using cost function if it is necessary. The cost is evaluated using number of variables such that $x^S_s = t$. Cost value of constraints is defined as follows.

$$f^{A3}_{s,t}(n+1) \ll f^{A3}_{s,t}(n), \\ \text{where } n \text{ denotes number of variables such that } x^S_s = t. \tag{1}$$

Additionally, we also use tie-break using priority of variables identifier to avoid confliction of decisions between nodes.

3.5 Problem solving

In 3.4, a cooperative model, which is similar to agency model, is formalized as DCOP. However, solving this problem ignoring hierarchy structure contained in that, is obviously inefficient. Therefore search processing is pruned using the hierarchy.

Priority of constraints

A priority relation between constraints is defined from hierarchy structure of problem. The priority relation is shown as follows: $c^{A0} \succ c^{A1} \succ c^{A2} \succ c^{A3}$. Here $c \succ c'$ denotes that constraint c is prior to c'. Constraints are satisfied according to the priority.

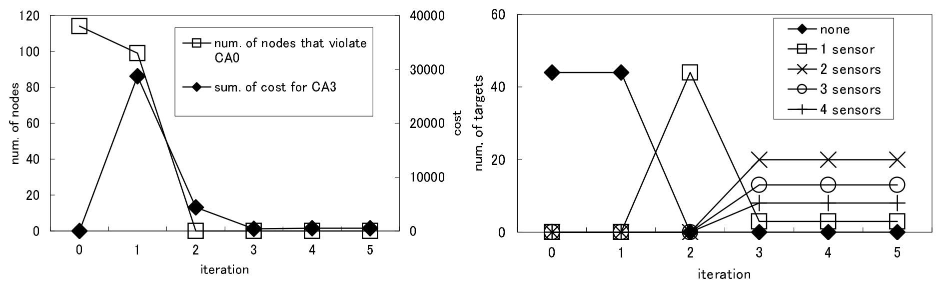
c^{A0} and c^{A1} are the constraints for leader (manager) election problem. These constraints are related to set of variables $x^T_{s,t}$. Therefore, in first step of search processing, partial solution for the set of variables. Then other constraints related to x^S_s are satisfied. This prioritization is done using a variable ordering such that $x^T_{s,t}$ is prior to $x^S_{s,t}$.

Gathering decision

In member (non-manager) sensor node, search processing to satisfy c^{A2} and c^{A3} is redundant. Therefore, the member nodes only receive the assignment of variables. Search processing of the assignment is not performed in the member nodes.

4 Experiment

As first experiment, proposed model is applied to a grid sensor network problem. The problem is generated using parameters w, h, c. w and h determines width and height of grids. c determines a degree of constraint network. Each target is added to grids such that, number of targets inside 8 neighbor of the grid, is more than 1 and less than c. The cost of c^{A3} is set to $\{0, 1, 10, 100, 1000\}$ for number $\{4, 3, 2, 1, 0\}$ of allocated sensor nodes respectively. In the experiment basic hill-climb based method using variable ordering is applied. The outline of the processing is as follows. Each node sends its assignments to neighbor nodes. Messages are exchanged by simulator. In this experiment, processing of nodes is synchronized to global message cycles. When each node receives neighbor node's assignment, the node modifies its assignment. These processing is iteratively



(a) Constraint and cost (b) Allocation

Fig. 5. An example of execution

Table 1. Error rates to optimal cost

w, h	c	num. of targets	error
3	3	7.6	2.74
3	4	8.5	0.94
5	1	11.7	1.63
5	2	15.5	2.57
10	1	43.1	1.42

repeated until assignment is converged. An example of execution is shown in Figure 5. In fast step of the execution, constraints c^{A0} and c^{A1} are solved. Then, sensor allocation, represented as c^{A2} and c^{A3}, are solved. In these problems, assignments are converged within 5 iterations. However, most assignments are converged into local optima. Error rates to optimal cost are shown in Table 1. It is considered that the sensor allocation problem is rather complicated problem. Therefore applying DCOP algorithms is necessary to improve solution.

5 Conclusion

In this paper, DCOP formalization is applied to a cooperative sensor resource allocation problem. Formalizations using DCOP and agency model are compared. And a cooperative formalization is proposed intend to integrate DCOP approach into agency model.

Integration of distributed algorithms including construction of constraint network, applying other solver for DCOPs and extension for practical observation problems will be included in our future work.

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