

# From Robot to Universal Robotics

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## Abstract

System-Informational Culture (SIC) ergonomics is based on Artificial Intelligence (AI) applications. The latter becomes the decisive factor of innovations. Robotics is developing in the direction of universality which can be accomplished in the paradigm of cooperative approach. Robots' system can make decisions autonomously distributing control over its behavior. Autonomous robotics emerges attracting achievements of AI. Robots are able to perform individual parts of the overall task together. They form a single Multiagent System (MAS) with intelligent actors pursuing their own objectives and interacting by messaging. The MAS is simulated as a relational cooperative game. Its formulation uses a variety of relationships. In order to jointly perform a universal task, robots have to solve effectively a scheduling problem. The optimal networking communications structure is built by them with the help of coalitions forming. The equilibrium scheduling can be obtained by means of polynomial distributive algorithm. Becoming of universal robotics takes place in the way.

**Keywords:** Multiagent system; Cooperative robotics; Intelligent agent; Scale of universal task; Scheduling; Monoidal category of binary relations; Preorder; Relational game; Equilibrium; Pareto effective solution; communications network

## Introduction

An important role in the up-to-date SIC ergonomics plays robotics [1,2]. Robots' team simulation needs to be made in the most general terms in order to provide universality of the discussed technology. A language of binary relations suits to the aims [3]. Robots are described by means of their preferences relations  $\rho_i, i \in I$ , given on the set of all tasks  $A$  to be provided. They are operations to be made and robots' locations in the working space. The overall task is ordered by means of a precedence relation  $\tau$ . It means that all subtasks are to be completed according to the ordering  $(A, \tau)$ . Allow the object  $(A, \tau)$  to be named the universal task. Robots are able to study their system configuration and make rational decisions [2]. Their awareness is based on messaging. They form an AI-powered multiagent system [4]. Agents themselves endeavor to choose the most suitable subtasks leaning on their preferences relations. The latter preorder the set  $A$  in different ways. In particular, the smallest elements of the preordered set  $(A, \rho_i)$  answer to requirements that cannot be at all accomplished by robots  $i \in I$ . It is supposed that every subtask  $A_j \in A$  can be performed by any robot  $i \in I$ . Agents may have heterogeneous capabilities. In the competition to choose tasks, those robots must win that can do the tasks better. For the purpose, robots are compared with the help of the given relationship  $\varphi \subset A \times R \times R, R = \{\rho_i, i \in I\}$ . Artificial intelligence can be applied to the discussed MAS. It leads to some relational gaming problem solution [2,5,6]. Intelligent robots are players which apply acceptable strategies depending on their awareness. The classes of their strategies are defined according to the used information exchange [5].

Earlier, the contributed simulation was carried out in case of more general game problems [6]. Now, it's about relational cooperative game having a special kind. Anyway, robots' system universality attainment is reduced to a scheduling problem solution [7]. It is grounded on the game principles of optimality [5]. The needed scheduling to be built must be stable and Pareto effective [8]. Based on the scheduling, robots' team functioning is similar to the trading and load balancing control method applied to distributed systems [9-11].

## Problem Formulation

So, there are intellectual players that have preferences relations  $\rho_i \subset A \times A, i \in I$ . The set  $A$  does not include tasks impossible to be executed. Relationship  $(A, \tau)$  graph defines time scale of the universal task  $A$  [6]. The agents are to select and complete the subtasks  $A_{j(i,t_k)}$  in the moments  $t_1 \leq t_2 \leq \dots \leq t_s$  which obey the ordering  $(A, \tau)$ . Thus, robots  $i \in I$  will serve requirements in the following sequences:

$$\tilde{A}_i = \{A_{j(i,t_1)}, \dots, A_{j(i,t_s)}\}, i \in I,$$

The scheduling must form a partition of the set  $A$ :

$$A = \bigcup_{i \in I} \tilde{A}_i, \forall_{i \neq j} \tilde{A}_i \cap \tilde{A}_j = \emptyset.$$

For the aims of the scheduling optimization, the relationships  $\rho_i, i \in I$ , should be laid out from the set  $A$  on the sequences set  $\{\tilde{A}_i, i \in I\}$ . The continuations are denoted  $\tilde{\rho}_i$  [3].

Robots' specialization is to be also taken into account expressed with the help of 3-ary suitability relation  $\wp$ . Its meaning is presented by its binary sections

$$\Psi_j \equiv \Psi(A_j) = \{(\rho_k, \rho_l) : (\rho_k, \rho_l, A_j) \in \wp\}, j \in J.$$

Robot  $l$  is more suitable and more effective to perform the subtask  $A_j$  than his partner  $k$  if  $(\rho_k, \rho_l, A_j) \in \wp$ .

It is worth mentioning that all binary relations  $\tau, \rho_i, \Psi_j$  are preorders [3] known to all players.

Corresponding dynamic game is to be solved in which the players might maximize their continued preferences relations:

$$\tilde{\rho}_i \rightarrow \underset{\{A_k, k \in I\}}{MAX}$$

The agents' goal is to find an optimal scheduling [7,9,11]. In the given case, this is understood as the game solution which is equilibrium and Pareto effective simultaneously [8]. The classes of acceptable strategies are defined by players themselves. They depend on the players' awareness acquired through messaging [2, 4-6]. The needed equilibrium can be achieved due to communications exchange [5]. The players operate autonomously. Messaging ensures their cooperation. Multiobjective optimization for scheduling in networked systems and decentralized control are contemporary manifestation of AI [9-11]. More detailed description of the corresponding relational dynamic game is given in the following section.

## Cooperative Scheduling

Distributed decentralized control adds uncertainty to decision making. To diminish it, agents might coordinate their activity by messaging. Corresponding classes of strategies usage may guarantee existence of the game equilibrium solution [2,5,6].

The game communications network  $\Gamma$  building is also the result of agents' cooperation and part of agents' strategies application. It can be optimized autonomously by robots themselves [2]. In the process, a set of robots' coalitions  $C_k, k = 1, 2, \dots, r$ , emerges. Due to it, players' moves become partially ordered [3,5,6]. If a task

is chosen by an agent who informs some partners about it, the latter make their decisions later than the former on the base of the data. The coalitions are formed on the basis of consistency of agents' interests and suitability relation. Coalitions have their own characteristic preferences relations  $\rho^{C_k}$ . Coalitional strategies are also intended for needed scheduling optimization. A reduction of the problem is allowed in which coalitions are treated as players. Moreover, the networking relational game has a compositionality expressed by means of the monoidal category of binary relations [3]. The tools are monoidal operations such as disjunctive sum  $\rho_1 \amalg \rho_2$  and superposition  $\rho_1 \circ \rho_2$  of relations correspondingly.

Example 1. Allow parallel  $C_p = C_1 \cup C_2$  and hierarchical  $C_h = C_1 \rightarrow C_2$  coalitions be made up of previously formed coalitions  $C_1, C_2$ . They have the following characteristic relations:

$$\rho^{C_p} = \rho_1 \amalg \rho_2, \rho^{C_h} = \overline{\rho_1 \circ \rho_2}.$$

(Here,  $\bar{\rho}$  is transitive closure of  $\rho$  [3].) This is how all coalitions are built.

Every game can be gradually reduced up to receiving only one coalition  $C = C(\Gamma)$  representing the whole game. The latter has resulting preferences relation  $\rho^g = \rho^{C(\Gamma)}$ . Players' communications structure  $\Gamma$  depends on the system of built coalitions [2, 6].

Initial dynamic game can be presented in the form of a sequence of static subgames connected by the scale  $(A, \tau)$ . They can be solved by generalized relational Bellman's method [6]. For the aim, dynamic relationships  $\tilde{\rho}_i(t), i \in I$ , are to be built and optimized. Sequential solution of the static subgames:

$$\tilde{\rho}^g(t) \rightarrow MAX, t = t_k, k = 1, 2, \dots, s,$$

allows to build needed equilibrium scheduling  $\tilde{A}_i^*, i \in I$ .

Coalitional strategies usage gives additional optimization options to perfect the scheduling. Every coalition  $C_k(t), k = 1, 2, \dots, r(t)$ , knows the tasks  $A_{j(i)}, i \in C_k(t), A_{j(i)} \in \tilde{A}_i^*$ , to perform. They can be reassigned among partners  $i \in C_k(t)$  to find Pareto optimal scheduling regarding the order  $\Psi_1 \times \dots \times \Psi_J$  [8]. So, robots' team can solve autonomously any universal task  $(A, \tau)$  using distributive control. The problem of optimal communications networking has polynomial complexity allowing for its scalability [2].

Messaging in the optimal network  $\Gamma^*$  occurs only within effective [2] or stable coalitions [5]. The notion of coalitions stability is also defined leaning on robots' preferences and suitability relations. A variety of types of stable coalitions gives the structure  $\Gamma^*$  augmentation. This reduces uncertainty in the process of decision making.

## Conclusion

In system-informational culture, artificial intelligence develops human tools in the direction of universality. It can be achieved by means of specialized intellectual robotic systems cooperation. Based on messaging, the latter allows to solve the overall universal task autonomously and under decentralized control. The problem under discussion boils down to the subtasks relational scheduling.

The approach is based on the relational game solution. The simulation shows that equilibrium scheduling can be found using relational Bellman's method. Corresponding distributive algorithm has polynomial complexity.

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