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CONCEPTUAL SEMANTIC NETWORK KNOWLEDGE REPRESENTATION FOR HUMAN-ROBOT TASK ASSIGNMENT AND EXECUTION IN MOLD ASSEMBLY

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Abstract. *Human-robot collaboration (HRC) systems combine abilities of human and robot to achieve a certain level of automation with flexibility. This paper focuses on the application of HRC in a mold assembly operation to improve human working condition with the robot assistance. Besides, human existence in the HRC system provides adaptability to cope with the wide variety of tasks and parts in the mold assembly. An efficient mold assembly task execution by the HRC depends on the task assignment and real-time status monitoring. This paper proposes a semantic knowledge representation conceptual framework for the dynamic human-robot task assignment and execution. The HRC mold assembly includes three modules, which are task assignment, status monitoring and task execution modules. Task assignment module performs assignment of tasks to resources based on considerations of task characteristics, processing time and agent's capability. Status monitoring module monitors and estimates the progress of the executing tasks. Then, the task execution module carries on the tasks and feeds back the status to task assignment module via status monitoring module for re-assignment if necessary. The proposed knowledge representation describes the relationships between the modules and components within each module to develop an efficient and practical HRC mold assembly operation. The conceptual knowledge representation presented is based on the one human with two cobots collaboration environment.*
Keywords: Human-robot collaboration, Task assignment, Task execution, Status monitoring, Semantic network

1. **Introduction.** Human-robot collaboration (HRC) systems become a potential solution to improve flexibility of automated systems with the integration of advanced collaborative robots (cobots) [1]. An HRC system is a system where a human and robots work together on the same task within a shared workspace. The rapid development in the artificial intelligence algorithms during the Industry 4.0 promotes the implementation of the HRC systems in the manufacturing environments especially in the assembly operations [2-4]. This paper focuses on the application of HRC system in the mold assembly operation. The HRC mold assembly must be flexible in reconfiguration to cope with all types of molds. Besides, the wide variety of weights and shapes of mold parts require use of various tools during the assembly operation. Therefore, this paper proposes use of two cobots instead of a cobot with high payload for the mold assembly operation.

Knowledge representation was applied to providing information from a real-world situation in a data structure that is understandable by a decision-making system to solve problem in the related domain [5]. In this paper, semantic network technique is applied to gathering all the information about the resource, mold, task and related considerations and requirements for the user to understand and enable the HRC mold assembly

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operation. Until now, the mold assembly is performed manually. In other words, all the knowledge related to the mold assembly operation is based on the human intelligence that may not be expressed in symbolic processing system. It is necessary to structure and represent the human knowledge in the form that is understandable by the robot or the intelligent system. Hence, this paper presents the knowledge representation conceptual semantic networks in the HRC mold assembly operation modules. The proposed HRC mold assembly consists of three resources which are the human, and two cobots (Cobot 1 and Cobot 2). In this paper, we define an agent as the combination of either of two resources. Hence, besides the semantic networks for the main modules, we also include semantic networks that represent the characteristics of the agent alternatives in the task assignment module and other sub-modules that link to the main modules. In our previous study, we developed task assignment [6] and status recognition models [7]. The developed task assignment model included analysis on mold assembly operation to identify potential resources in HRC systems with two cobots and assignment of tasks to these resources. Status recognition was developed to recognize the status of manual tasks based on actions that are to be used to update the state of HRC assembly. However, these models are individual and not linked to each other. Therefore, this paper aims to express relations between modules using semantic network-based knowledge representation as a basis to connect and integrate each module for developing an efficient and practical HRC mold assembly operation.

The background and related research of this paper is presented in Section 2. Section 3 explains three main modules in the HRC mold assembly operation, and Section 4 presents the semantic knowledge representation of the modules. Finally, Section 5 concludes this paper and discusses the future research.

2. **Related Research.** For an intelligent system to be able to process and make decision, we need to input a large amount of information and knowledge that exist in real world. However, it is impossible for a designed intelligent system to perform efficiently without an accurate and proper structure or representation of knowledge that is related to the domain of the targeted problem [8]. Humans gain the ability to tackle and solve difficult real-world problems through the knowledge resources within the problem domain that is obtained from their experience and training. For example, a human-robot interaction based on visual communication where the robot received command from a human to pick required parts. The robot captured and sent the images at working site to the human to make decision on next task [9]. However, we need to transfer the information used by the human into a structured knowledge so that the robot can make decision without receiving command from the human. A way to provide such ability to an intelligent system is through knowledge representation that represents information from the real world. The created knowledge representation makes expert knowledge explicit and accessible, is often based on logic and can explain their conclusions, and hence, it enables an intelligent system to make decision about the targeted problem [10]. Semantic network-based knowledge representation is easy to visualize, and the related semantic knowledge can be easily clustered and clearly identifiable from the labels. Semantic networks can represent factual knowledge about classes of objects and their properties with declarative, static representations of relations [11,12].

In this paper, we focus on semantic networks-based knowledge representation technique in the manufacturing and HRC applications. A knowledge representation model using semantic networks was proposed to represent the knowledge in the manufacturing process that included product characteristics, technology available and tasks required [13]. The model was based on the concept of "situation" that implied the state of process to decide the corresponded actions and tasks. Besides, semantic networks have been applied to constructing knowledge in the production planning control domain [14]. The proposed semantic networks covered four main functions in the production control, which are process capacity planning, shop flow control, purchasing and marketing requirement. The semantic networks of the functions presented the linkage to the related information and connections to other functions. The expanding applications of the HRC concept in the manufacturing industry encouraged the application of semantic networks to gather and organize the human and operation knowledge. The semantic network framework for the HRC manufacturing process was proposed to represent different aspects of assembly process that included knowledge of the process, objects, human and robot capabilities and the environment [15]. The proposed framework was expanded to include knowledge representation of process state, constraints, and relations with robot skills. The expanded knowledge representation of assembly process was connected to the object tracker and action recognition systems to deal with HRC operation and enable interactive learning in the HRC environment [16,17]. A high-level ontology that contained two structures: semantic event chain related to a skill and human to robot communication handling was proposed for dynamic planning in human-robot teams [18]. The proposed ontology transformed the human knowledge into an action plan to allow human to teach and communicate with the robot. A knowledge engineering environment (KEE) was implemented in the timeline-based task planning for a safe HRC operation. The functions of the proposed architecture included support domain experts to coordinate human and robot tasks, generate temporal flexible plan and task execution with control and feedback functions [19]. Besides, an architecture of a cognitive semantic network consisting of four modules: user interface, semantic network representation, knowledge representation and reasoner modules was presented. These modules were developed to enable cognitive decision making in electrical motor domain [20]. In the application of activity recognition in a smart home environment, a framework comprised of semantic knowledge base and activity recognition module was proposed. The semantic knowledge base included common sense knowledge base and domain-specific knowledge base that provided descriptive knowledge related to the environment [21].

Various knowledge representation techniques were used in the existing studies to enable decision making and communication in HRC applications. However, these studies focused on the decision-making during operation execution. Besides, the HRC systems considered in the existing studies were only based on assembly of simple prototypes using one human and one robot. This paper focuses on using semantic networks to represent comprehensive knowledge from operation planning and feedback during execution stages, which include three modules: task assignment, status monitoring and task execution by considering two cobots in mold assembly.

3. **Modules in HRC Mold Assembly Operation.** Most assembly operations begin with task assignment and scheduling, followed by operation monitoring and execution. In this paper, we focus on three main modules: task assignment, status monitoring, and task execution for an HRC mold assembly operation (see Figure 1). Before we proceed to the semantic networks of each module (Section 4), we explain the functions and events in every module and the corresponding sub-modules. This paper decomposes the mold into cavity and core sub-assemblies, and then each assembly contains its main and supporting parts based on the bill of material (BOM). For the task assignment purpose, we decompose the tasks of the mold assembly operation according to the BOM into sub-tasks. Every sub-task handles a main part and/or necessary joining parts such as screws or pins. Tasks of the mold assembly operation are executed sequentially, which means only one task is executed at a time. To simplify the analysis on the task, we decompose the tasks into sub-tasks and the sub-tasks are categorized into nine categories based on actions, part types and tolerance. The main role of the task assignment module is to generate an initial assembly plan that is to be input into the task execution module. The task assignment

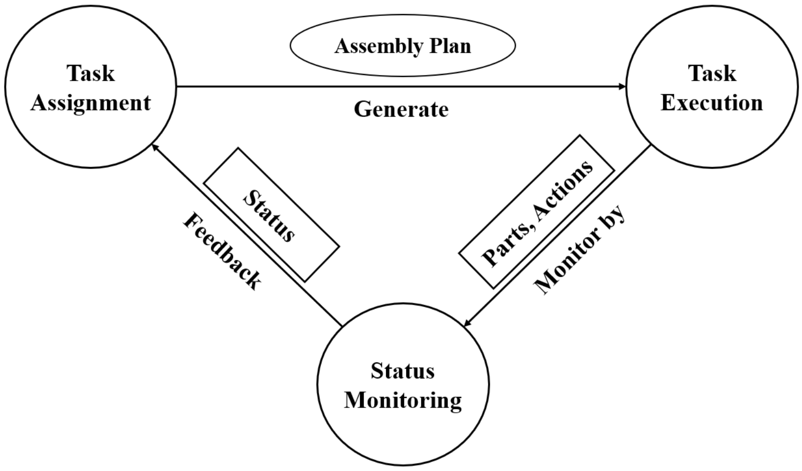

Figure 1. Three modules in HRC mold assembly

module assigns assembly sub-tasks to an agent based on the task characteristics, agent's capability, and processing time. We analyze task characteristics and agent's capability based on two main criteria: part and skill. The part criteria include part weight and tolerance, and the skill criteria include ergonomics, force and support requirement. The objective of the task assignment module is to optimize processing time, capability of agent assigned to execute the task and the ergonomics score.

As shown in Figure 1, the initial assembly plan generated from the task assignment module is input into the task execution module. The assembly plan includes the sequence of assembly tasks, the agent assigned to every sub-task, part to be assembled and tool required. In this paper, we exclude the generation of robot programming for the task execution. We assume all the parts and tools are located within the robot reachability. Besides, the payload of the robot has been considered in the task assignment module as one of criteria for the agent's capability. During the task execution, status monitoring module takes the role of assembly progress monitoring and feeds back the statuses to the task assignment module. Three types of statuses are included in the status monitoring module: assembly state, process state, resource states such as agent and tool states. Assembly state indicates the progress of the whole assembly operation. Resource state gives us the status of each agent and tool, either idle or busy. Assembly and resource states can be input from the task execution module. Process state represents the status of a sub-task during the task execution. The status monitoring module estimates the process state by recognizing the parts and actions based on the images captured during the execution. Results from the status monitoring module are fed back to task assignment module to update the status of agent and tool. Based on the feedback, the task assignment module can re-assign the subsequent tasks in case of any delay during the execution.

4. **Semantic Networks of Modules in HRC Mold Assembly.** A mold assembly operation can be described as a series of tasks decomposed to sub-tasks and actions based on the BOM that is executable by agents using the specified tools. From the description, the mold assembly operation plan consists of a set of tasks (T), a set of agents (A), a set of tools (E) and a set of mold parts (P). These basic components connect to each main module to enable the events within the modules and express the relationships between basic components and modules. Assembly tasks can be decomposed into sub-tasks, that can be represented by $\textit{Sub-tasks} \subseteq \textit{Tasks}$. The set of tasks $= \{T_1, T_2, \ldots, T_m\}$, where T_1 is the first task and so on, with total m number of tasks. Every task defines the main part to be assembled and its sub-tasks. The set of sub-tasks of a task is defined as $T_i = \{V_{m1}, V_{m2}, \ldots, V_{mn}\}$, where V_{mn} is the nth subtask of task T_m. Figure 2 illustrates

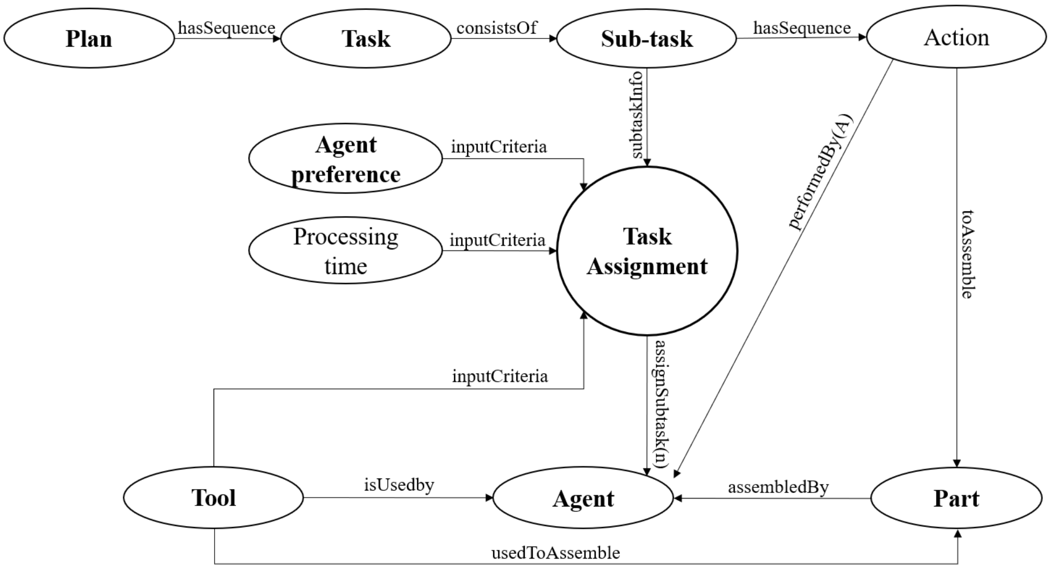

FIGURE 2. Semantic network of task assignment and execution modules

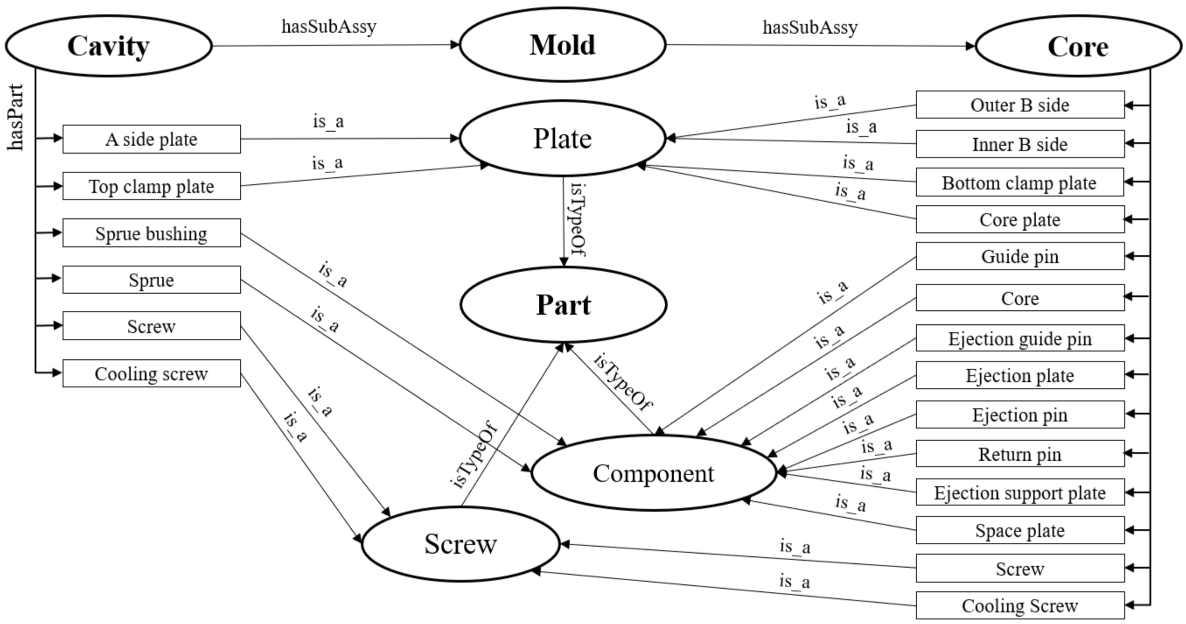

FIGURE 3. Semantic network of the mold and parts

the semantic network of task assignment and execution modules. The top part shows the decomposition of mold assembly plan.

The task assignment module considers three input criteria which are agent preference, processing time and tool to assign an agent to every sub-task. The right and bottom parts of Figure 2 show the execution of a sub-task that is assigned to an agent. The sequence of actions of a sub-task is performed by agent A by using a tool that is defined to be used to assemble a part.

Figure 3 presents the decomposition of a mold into cavity and core sub-assemblies and the list of parts in each sub-assembly. The mold parts are categorized into three types of part: Plate, Component and Screw based on the shape and weight of parts. Parts categorized into Plate and Component are considered as the main part to be assembly in a sub-task. As mentioned previously, this paper focuses on the HRC configuration that consists of resources: one human and two cobots (1H:2R), where *Resource* =

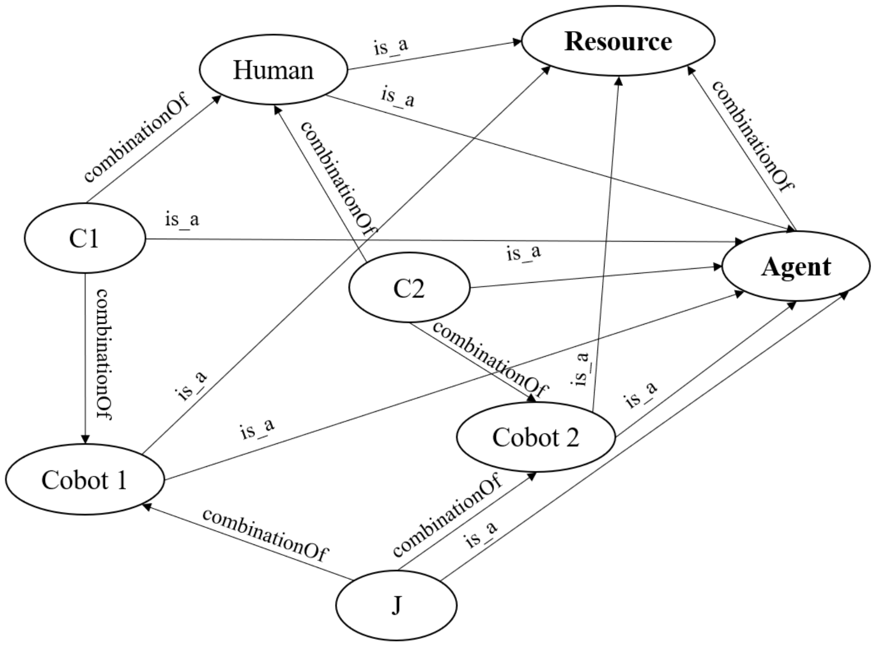

FIGURE 4. Semantic network of resources and agents

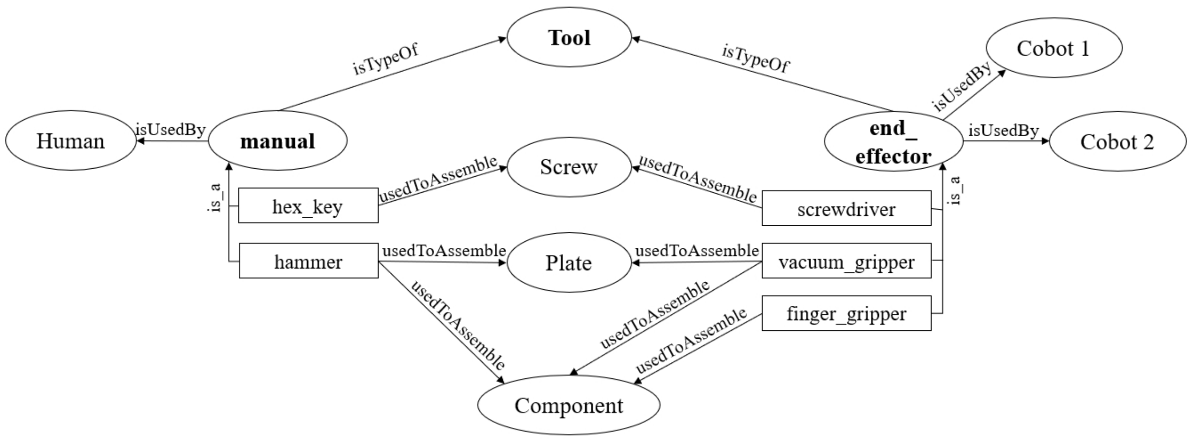

FIGURE 5. Semantic network of the tools used in the mold assembly

$\{Human, Cobot\ 1, Cobot\ 2\}$. Figure 4 illustrates the semantic network of resources and agents in this paper. Each resource is able to work independently or collaborate with each other. We define an agent as a resource or combination to perform a sub-task. Hence, we have six alternative agents: $Agent = \{Human, Cobot\ 1, Cobot\ 2, C1, C2, J\}$. $C1$ and $C2$ are combination of *Human* and *Cobot* 1, and *Human* and *Cobot* 2, respectively. J is the combination of both cobots. Since we have human and cobot as agents to perform sub-tasks, we need manual tools and end-effectors that are attached to the cobot.

Figure 5 shows the sub-class of tools and relations of tools and part types. For manual tools and end effectors for cobots, we define $manual = \{hex\_key, hammer\}$, and $end\_effector = \{finger\_gripper, screwdriver, vacuum\_gripper\}$, respectively. In the semantic network of the tools, we include relations of which tool is used to assemble a part that is categorized in a specific part type. For example, to assemble a screw, we need to use a hex-key if it is assigned to the human or use a screwdriver if it is assigned to a cobot. In this paper, we categorize sub-tasks into nine categories based on the actions, tolerance and the part types (see Figure 6), where Sub-task = $\{LPR, LPF, LPT, GCF, GCT, GST, HPT,$

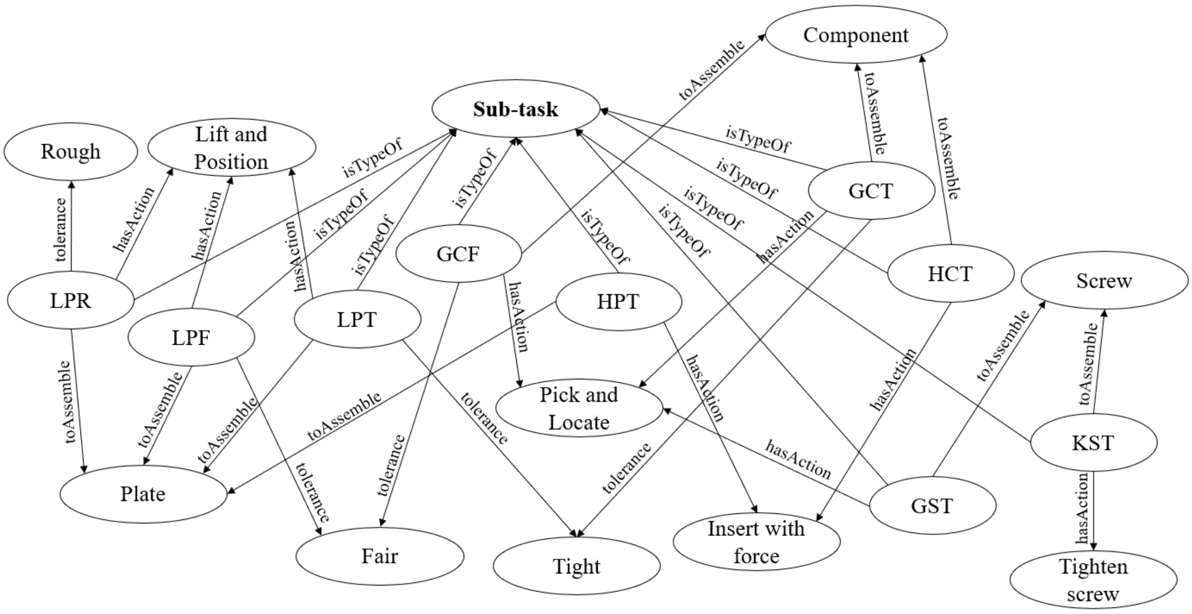

FIGURE 6. Semantic network of types of sub-tasks

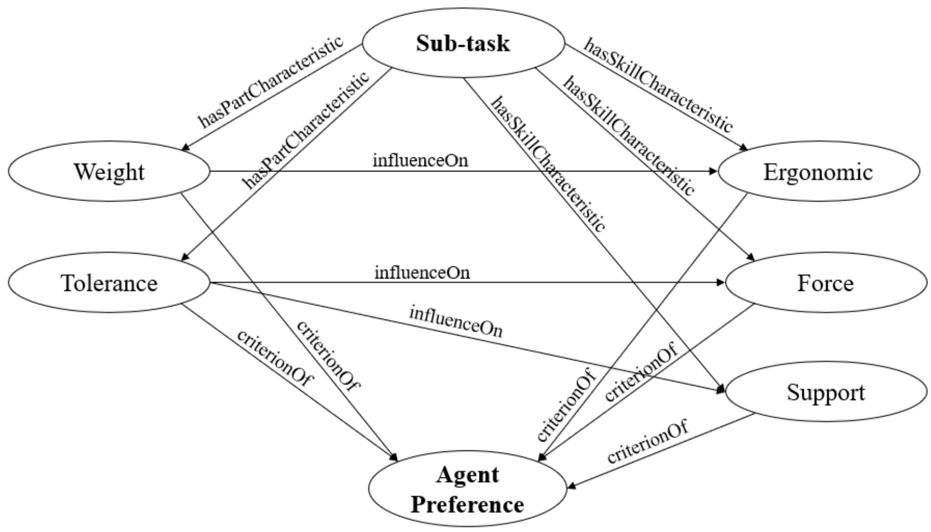

FIGURE 7. Semantic network of criteria used to generate agent preference

$HCT, KST\}$. The first character of the sub-task type indicates the actions: "*lift and position* (L)", "*pick and locate* (G)", "*insert with force* (H)", and "*tighten screw* (K)". Then, the second character indicates the same part types as presented in Figure 3: *Plate* (P), *Component* (C), *Screw* (S). The last character defines the levels of tolerance: *Tight* (T), *Fair* (F) and *Rough* (R). We categorized the sub-tasks into nine types to simplify the analysis of the task characteristics and the capabilities of the agents. Each sub-task type has part and skill characteristics which are also the criteria to generate the agent preference. In Figure 7, the weight and tolerance have influence on the ergonomic, force and support criteria. We used analytic network process (ANP) to generate the agent preference in our previous study [7], so the details of the ANP are not included in this paper.

Figure 8 illustrates the semantic network of the status monitoring module. Four different statuses are included in the module: assembly state (B), process state (Q), tool state (D) and agent state (J). The set of assembly state $= \{B_1, B_2, \ldots, B_m\}$, where each assembly state B_i corresponds to a task, and m defines the number of tasks. Process

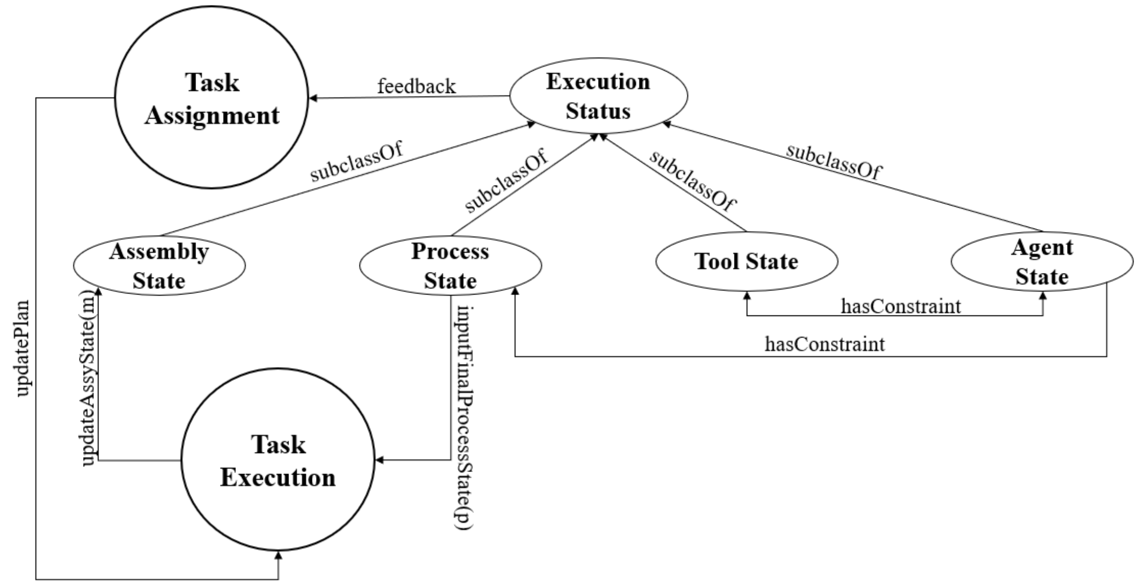

FIGURE 8. Semantic network of status monitoring module

states are the state of the sub-tasks of a task, $Q_{ij} = \{Q_{i1}, Q_{i2}, \ldots, Q_{in}\}$, where n defines number of sub-tasks in task T_i. Initially, all assembly states and process states equal 0 (non-complete), and then B_i change to 1, indicating task is completed when all process states Q_{ij} of task T_i are completed. Once assembly state B_i changed from 0 to 1, the task T_{i+1} will start. The update of status continues until all the assembly tasks are completed. An agent and the defined tool are required to execute a sub-task. When no task is assigned to agent, all agents, and tools states equal 0, once tasks are assigned to agent, and if the agent required a tool, then both states of the agent and the specific tool will change to 1. Both tool and agent states have a constraint on the process state, where a sub-task can start only when the assigned agent and tool of the task are available.

5. **Conclusions.** This paper presented semantic networks to represent knowledge of three main modules in the HRC mold assembly operation: task assignment, task execution, and status monitoring modules. Besides, we also included the semantic networks of the mold, tasks, tools, and agents that were acted as the basic components. The proposed semantic networks presented the information related to all the basic components and how they are connected to each module. The semantic networks presented were based on the task assignment model and status recognition that was developed in our previous study [6,7]. Although the presented semantic networks are at the conceptual stage, these networks acted as the basis and are expected to contribute to integrating the three modules to develop a complete and practical HRC mold assembly operation.

The proposed semantic networks require further effort to realize the practical HRC mold assembly using artificial intelligence (AI) approaches. AI helps us transfer human knowledge expressed in the semantic networks into an intelligent system that enables real-time decision-making via interaction between humans and cobots during the HRC mold assembly operation. In the future, we will connect the developed modules based on the semantic knowledge framework by applying the reinforcement learning technique.

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