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Quantitative Assessment at Task-level for Performance of Robotic Configurations and Task Plans

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Abstract Given a robotic manipulation task, decision on which robotic configuration (robotic system and necessary peripherals, including assistant tools, sensor systems, and so on.) to use and evaluating performance of the solution remains as an open, challenging but a meaningful problem. This work attempts to address this problem by defining the concept of task-level performance and developing an approach for systematic assessment based on a proposed task representation for performance quantification of different task plans and robotic configurations. Starting from productivity which is one of the main concern for manufacturers, this work introduces a methodology for quantitative assessment of any given robotic configuration and task handling. Such a method is useful for comparing the productivity of different robotic configurations and evaluating the worthiness of updated solution of a sub-task through observing improvements in productivity. Implemented and tested on a peg-in-hole task with the different level of difficulty through single-arm and dual-arm manipulation on a dual-arm robot, the methodology has demonstrated encouraging results. Finally, the connection of performance assessment from task-level to economy-level is presented.

Keywords Industrial robot · Task planning · Performance evaluation

1 Introduction

In manufacturing, the common problem of identifying suitable robotic configuration (the type of robot, actuators, sensors, etc.) for a given task is a

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difficult issue for manufacturers. Different robotic configurations and corresponding task plans lead to huge differences in performance. Furthermore, these differences are further magnified due to repetition. Performance study of a robotic system (or configuration) in handling a task has been an important but not well-addressed issue in the community. A quantitative assessment allows robot manufacturer or potential operator to make an objective decision based on results of the assessment, such as deciding on the choice of a robotic system to purchase and possible return on investment. This would lead to improved efficiency and effectiveness in the deployment of robotic systems in the industry.

Research in performance assessment at economy-level and robot-level has been well explored in recent years, as listed in Table 1. In general, performance study at robot-level tends to focus on the design of the robotic mechanism, repeatability and resolution [1][2] while analysis at economy-level tends to focus on investment driven considerations such as cash flow, risk, and capital recovery factor [3]. To connect economy-level and robot-level, assessment at task-level is necessary. Criteria at task-level bridges the gap by looking at factors which cover perspectives of both sides. For example, improving productivity at task-level through selecting a more suitable type of robot at robot-level for a given task may bring manufacturer higher capital recovery factor at economy-level.

This work presents an approach to quantify the performance of a set of robotic configurations and their corresponding task plans proposed from manufacturers. In addition, a systematic assessment method is provided to cross-analyze the performance at task-level of given set of deployments by manufacturers. Proposed steps of performance assessment at task-level are shown in Figure 1.

1.1 Selection of robotic configurations

This step focuses on the selection of suitable robots based on requirements of a given task, such as range of workspace, accuracy (task tolerance), payload (weight of tools and workpieces), lifetime and reliability, etc. Once the performance criteria at robot-level of the considered robot satisfy all requirements in the given task, then the robot can be integrated into a system for subsequent task planning.

1.2 Consideration of task plans and strategies

Based on features of robotic configuration and given task, different task plans and test strategies are considered. A task plan can be decomposed into a set of achievable actions based on proposed task representation. Augmented by different strategies, the performance of the task plan executed by studied robotic configuration may vary.

Table 1 Performance criteria at robot-level and economy-level.

Robot-Level	Economy-Level
Type of structure	Cost
Payload	Value
Joint speed and range	Interest rate
Repeatability	Risk
Resolution	Capital recovery factor
Lifetime	Payback period
etc.	etc.

Fig. 1 Steps of performance assessment at task-level.

1.3 Establishment of assessment model

After determining specific task plans, corresponding assessment models can be established by a set of sub-plans which are the combination of the actions decomposed from given task plans.

1.4 Performance quantification

Using information vectors obtained from conducted experiments to calculate the Average Product Rate (APR) which serves as a quantitative measure of performance of the robot on this task, this achieves the purpose of performance quantification for a specific task. Such measurement further provides manufacturers an objective standard of evaluation on different robotic configurations as well as corresponding task plans and adopted strategies for a better solution in a specific task.

1.5 Cross-Analysis

This analysis involves verification, estimation, and further optimization:

- 1 Data verification: In order to make experimental results consistent, experimental data should be verified.
- 2 Influence of strategies: Identify strategies with significant effect under different tasks and robot configurations, for further optimization of task planning and strategy selection.
- 3 Performance estimation of a new strategy: Experimental data is reused to estimate the effect of change or addition of a new strategy in task plans.
- 4 Dominance of robotic configurations: Dominance of robot configuration on performance at task-level can be informative.

The remainder of the work is organized as follows: first of all, a discussion on closely related works is presented. Then, task representation is proposed to implement the decomposition of a task plan. Based on the representation and continuous time Markov Chains (CTMC), this work develops a performance assessment model to quantify the performance of robotic systems at task-level. Later, an experimental study on a peg-in-hole task is carried out, where multiple groups of experiments are provided to validate the effectiveness of the proposed approach among different robotic configurations, corresponding task plans, and adopted strategies. Quantitative results are obtained through the proposed approach, the results of which are comparable with each other and valid to be further cross-analyzed for providing better decisions on selecting robotic configurations and updating strategies in task plans. Lastly, an example of further performance assessment at economy-level by using the experimental data is given in this work.

2 Related works

Vast amount of literature exists in performance study of hardware, including dexterity [4], positioning [24], manipulability [5] and dynamic capability [6][7][8].

In the domain of robotic motion, the comparison of the re-grasping algorithms for single-arm and dual-arm robots has been performed [9]. Performance of path planning for a mobile robot has also been studied [10].

For performance assessment of Human-Robot Interaction (HRI), an overview of common performance metrics has been presented [25][26], providing researchers a comprehensive view on performance assessment of task-oriented HRI. Besides, prediction [11] and assessment method [12] have been developed for cooperation between a human and multiple robots. For performance assessment of multi-robot coordination, a set of performance criteria for rescue robots has been proposed [13].

Literature also exists on performance study of task execution. For example, quantification of mobile robot autonomy in a different environment has been

performed [14]. Performance in flight operations [15] and a pick-and-place task among different gripper solutions [16] has been studied.

To authors' best knowledge, there appears to be a lack of mention in the literature about a generalized assessment approach for performance study of robotic systems in manufacturing. This leads to a situation where decisions on the deployment of robotic systems in factories are often made by experience instead of scientific approaches, which may alienate manufacturers to the possibility of better solutions for their factories.

3 Representation of robotic task

In this work, a representation of a robotic task is proposed to illustrate the relationship among tasks, robotic configuration, action, strategy and plan in a task. This provides an approach for practitioners to represent any robotic task in a structured environment. Definitions and descriptions of each key term are provided below.

3.1 Task

A task T comes with a given goal, initial state, and final state.

- 1 A goal refers to expected results of a task.
- 2 Initial state is pre-determined based on the conditions of its workspace.
In general, considering that a production line consists of several various robotic systems, it is recommended to make a number of assumptions according to neighboring robotic systems (or mechanisms) of the studied task.
- 3 Final state refers to the state that achieves the goal. Operation of the robotic system after this state will enter a new episode of the task.

3.2 Robotic Configuration

A robotic configuration set R is a set of robotic systems that can implement a given task. Each robotic configuration consists of a robot (including corresponding control system), end-effectors, sensors, and other peripherals.

All components in a robotic configuration are needed to implement a given task. For instance, if a task T is accomplished by using cameras only in a robotic configuration $R_1 \in R$ as sensors, then the used cameras belong to this robotic configuration. However, if there is also a tactile sensor mounted on the robots end-effector, then the tactile sensor does not belong to R_1 as it is not used in the task. Similarly, if a dual-arm robot is prescribed to accomplish a task by only one manipulator, then the dual-arm robot is regarded as a single-arm robot.

Note that there are specific definitions for a dual-arm robot, a single-arm robot, and two single-arm robots in this work.

- 1 Dual-arm robot: A dual-arm robot is a robot with two serial manipulators. On each manipulation, the robot can either simultaneously move the two manipulators to an assigned pose of each end-effector or move only one manipulator to an assigned pose. The robot must finish a manipulation command first so that it can execute the next manipulation command. This definition can be extended and adapted to a multi-arm robot.
- 2 Single-arm robot: A single-arm robot is a robot with only one serial manipulator.
- 3 Two single-arm robots: Two single-arm robots are different from a dual-arm robot. It can execute manipulation command of one manipulator before completion of the previously executed manipulation command on another manipulator. This means that a robotic system with two single-arm robots possesses more flexibility on task planning than a robotic system with a dual-arm robot because it can do synchronized and synchronized planning. This definition can be extended to multiple single-arm robots.

3.3 Action

An action set A refers to a set of behaviors that the studied robotic configuration can perform. Executable action sets vary based on the capabilities of different robotic configurations. Each action $A_k \in A$ carries an information vector $\mathbf{I}_k = (t_k, r_k)$, which contains information on execution time t_k and success rate r_k . Note that the success rate of action is assumed to be 100% if the action is unable to detect success rate through perception. If an action is able to detect the success rate through perception, this action is known as a detection action.

- 1 Setup: Setup action refers to initialization of a robotic system, including loading of planning programs, adjustment of robot's pose to initial pose, etc. This is a necessary preparation before manipulation.
- 2 Manipulation: Manipulation actions are the most important ones in a task plan and what practitioners pay more attention to, such as realistic pose change of robot and perception. They are designed by practitioners based on the given robotic configuration and workspace. Each robotic configuration has a set of actions they can perform. These sets can be overlapped (partially or fully) or disjoint.
- 3 Troubleshooting: When the robotic configuration fails to achieve the expected result of an action before the final state, for preventing the robotic system and the workpiece from damaging due to the consequent actions, the troubleshooting action ensures the safety of robotic system and workspace and resets the task to the initial state of a new episode.

3.4 Strategy

A strategy refers to the change or addition of functions, algorithms, and parameters to a certain action. This may affect the success rate or execution

time in a specific action. The ideal goal of a proposed strategy is to increase the success rate (i.e. increase in robustness) or decrease execution time (i.e. increase in efficiency).

3.5 Plan and sub-plan

Theoretically, there are unlimited solutions for a task under a given robotic configuration, and those feasible solutions form a plan set P . A plan $P_i \in P$ is a weakly connected digraph with several manipulation actions to implement the given task.

A sub-plan sP_{jk} is a weakly connected subgraph of P_i . There must be an action as a sink vertex in this subgraph, with the capability to detect the success rate of this sub-plan through perception, or a terminated manipulation action as a sink vertex in this subgraph.

Figure 2 shows an example of model under the proposed representation, where A_5 is the detection action. In task T , a robotic configuration set $R = \{R_1, R_2, R_3\}$ where each robotic configuration belonging to this set that can implement this task is considered. Take R_1 as an example, the designed action set for this robotic configuration is $A = \{A_1, \dots, A_9\}$. Therefore, one would have a possible plan set $P = \{P_1, P_2\}$, where plans can be expressed by a graph $P_1 = (V_1, E_1)$ with $V_1 = \{A_1, A_2, A_5, A_3, A_6, A_9\}$ and $E_1 = \{(A_1, A_2), (A_2, A_5), (A_5, A_3), (A_3, A_6), (A_6, A_9)\}$, and a graph $P_2 = V_2, E_2$ with $V_2 = \{A_1, A_4, A_5, A_8, A_9\}$ and $E_2 = \{(A_1, A_4), (A_4, A_5), (A_5, A_8), (A_8, A_9)\}$. A sub-plan is a subgraph of its plan. For example, a sub-plan $sP_{11} = (sV_{11}, sE_{11}) \subseteq P_1$, with $sV_{11} = \{A_1, A_4, A_5\}$ and $sE_{11} = \{(A_1, A_4), (A_4, A_5)\}$ is also a subgraph of P_2 . A subgraph, however, may not be a sub-plan of its subgraph. For example, $sP_{11} \cup (\{A_8\}, \{(A_5, A_8)\})$ is a subgraph of P_2 , but it is not a sub-plan of P_2 as the sink vertex A_8 is not a detection action.

4 Performance quantification

Challenges of task-level performance assessment for an integrated robotic system exist. First of all, integrated systems and corresponding task plans are difficult to be expressed in analytical forms. Besides, most motion planning algorithms are of probabilistic nature, leading to the existence of uncertainties in robotic motions [17]. Furthermore, due to uncertainties in the realistic world, results of task planning cannot be predicted in advance, meaning that successful implementation of tasks must be established based on experiments.

In view of these challenges, the proposed performance assessment model must be compatible with the probabilistic nature discussed and is expected to be able to quantify integrated robotic configurations, task plans, and adopted strategies. Furthermore, the outputs from the analysis should allow performance assessment at economy-level. Therefore, the probabilistic graph model (PGM) is a more appropriate tool to cope with this issue [18]. This kind of

Fig. 2 Example of a model under proposed representation.

model can clearly express the probabilistic dependencies of every pair of vertices (actions) in a graph model (task plan).

4.1 Continuous time Markov Chains

In this work, the model for performance assessment is established based on Markov Chains [19]. The most remarkable characteristics of Markov Chains is its memoryless property, defined as follows [20]:

Definition: (Markov Chains) Given a temporally homogeneous stochastic process $X = (X_t, t \in T)$ in a probability space (Ω, F, Pr) , for a totally ordered index set T , Markov Chains is a stochastic process on a measurable finite state space $S \in \Omega$ satisfying

$$Pr(X_t = j \in S \mid F_s \in F) = Pr(X_t \in S \mid X_s \in S), \quad (1)$$

where $s, t \in T$ with $s < t$, and $F_s = \sigma(X_0, \dots, X_s)$ is a collection of known events considered. This indicates that the future can be predicted by availability of present event without past events, if the stochastic process is a Markov Chains. The transition probability of a Markov Chains from state i to state j , between index s and index t , can be formulated by [20]:

$$Pr(X_t = j \in S \mid X_s = i \in S) = p_{ij}(s, t). \quad (2)$$

Based on the memoryless property of Markov Chains, the idea of this work is that result of a sub-plan depends on the transition probability from the

previous sub-plan. Therefore, it is proposed that a robotic task can be decomposed into various actions by the aforementioned representation. In addition, each sub-plan consists of part of these actions with a measurable result. This is to presume that a robotic system is able to process various kinds of jobs, which is like a small-scale production line with multiple machines. In this small-scale production line, multiple inspection mechanisms exist in a special way to check manufacturing results of the previous machine. Once an unexpected result occurs, the robotic system will enter an under-recovery mode and wait for the workspace clearance from other mechanisms, and then start a new episode of its task. However, as this research focuses on performance assessment of an individual robotic system at task-level, the queues of workpieces before entering the robotic system are regarded as transmission processes, which are addressed by assumptions and not discussed in this research.

As the operation of a robotic system is under a continuous time-space, the probabilistic graph of Markov Chains is generally expressed by a transition rate derived by Kolmogorov differential equations [21]:

$$\begin{cases} \mathbf{P}(s, t) = [p_{ij}(s, t)] = \exp\{\int_s^t \mathbf{Q}(\xi) d\xi\} \\ \mathbf{Q}(t) = [q_{ij}(t)] = \lim_{h \rightarrow 0} \frac{\mathbf{P}(t, t+h) - \mathbf{I}}{h} \end{cases}, \quad (3)$$

where $\mathbf{P}$ is so-called transition probability matrix and $\mathbf{Q}$ is transition rate matrix. The relationship between elements of $\mathbf{P}$ and $\mathbf{Q}$ is determined through infinitesimal property formulated by little-o notation as follows.

$$\begin{cases} q_{ii}(t) = p_{ii}(t, t+h) - 1 + o(h) \\ q_{ij}(t) = p_{ij}(t, t+h) + o(h), i \neq j \end{cases}, \quad (4)$$

where h is an infinitesimal time increment. The relationship indicates following property in a transition probability matrix $\mathbf{P}(t)$ and $\mathbf{Q}(t)$.

$$\begin{cases} \sum_j p_{ij}(s, t) = 1, & \forall i, s \leq t \\ \sum_j q_{ij}(t) = 0, & \forall i \end{cases}, \quad (5)$$

4.2 Probabilistic dependencies in task plan

Combining information vector and proposed task representation on the PGM which is with characteristics of Continuous Time Markov Chains (CTMC), a linear equation to formulate any existed arc (probabilistic dependency) among its end vertices (sub-plans) is given by

$$q_{ij}(t) \sum_{A_k \in sP_i} t_k = \begin{cases} \prod_{A_k \in sP_i} r_k, & j = i + 1 \\ 1 - \prod_{A_k \in sP_i} r_k, & otherwise \end{cases}. \quad (6)$$

4.3 Mapping task plan to CTMC model

After establishing probabilistic dependencies between each ordered pair of vertices in PGM, one can subsequently construct a mapping from a task plan P to a CTMC model with a state space $\mathcal{S}$. Firstly, assumption that a studied task plan consists of n manipulation actions assigned $A_1, \dots, A_n$ is made. Then, action A_0 and A_{n+1} are set to be the setup and the troubleshooting action, respectively. Hence, there is an action set $A = \{A_0, \dots, A_{n+1}\}$ with $|A| = n+2$ and a default action set $A_{default} = \{A_0, A_{n+1}\} \subset A$. Secondly, it is assumed that there are l detection actions among these actions, where maximum number of ideal sub-plans is taken. Every ideal sub-plan $sP_j(sV_j, sE_j)$ is disjoint with each others and chosen by

$$sP_j = \underset{sP_{jk}}{\operatorname{argmax}} |sP_{jk}| \quad s.t. \quad P_i = \bigcup_{j=1}^{l+1} sP_j. \quad (7)$$

This means that there is a sub-plan set $sP = \{sP_1, \dots, sP_{l+1}\}$ with $|sP| = l+1$ (l detection actions and a terminated manipulation action) in a plan P_i . The mapping is constructed by three functions: $f : A_{default} \rightarrow \mathcal{S}$, $g : A/A_{default} \rightarrow sP$ and $h : sP \rightarrow \mathcal{S}$, satisfying following properties.

- 1 $f : A_{default} \rightarrow \mathcal{S}$ is injective-only.
- 2 $g : A/A_{default} \rightarrow sP$ is surjective-only.
- 3 $h : sP \rightarrow \mathcal{S}$ is injective-only.

Finally, one can use these three functions to construct the mapping by:

- 1 $f(A_0) = \mathcal{S}_0$ and $f(A_{n+1}) = \mathcal{S}_{l+2}$.
- 2 $g(A_i) = sP_j$, if $A_i \in sP_j$.
- 3 $h(sP_i) = \mathcal{S}_i$.

The mapping above implies that no matter how many actions there are in a task plan, it will eventually lead to $|\mathcal{S}| = |sP| + 2$. Figure 3 shows an example of this mapping with $n = 4$ and $l = 1$. The detection action is A_2 and the state space of this mapping is with $|\mathcal{S}| = |sP| + 2 = 4$.

4.4 Performance assessment model

Based on this mapping method, a generalized CTMC model with a state space $\mathcal{S} = \{\mathcal{S}_i\}, i = 0, \dots, l+2$ can be established, where each state has physical meaning:

1. $\mathcal{S}_0$: The robotic system is being set up.
2. $\mathcal{S}_{l+2}$: The robotic system is under troubleshooting.
3. $\mathcal{S}_i, 1 \leq i \leq l+1$: The robotic system is executing task normally.

Figure 4 shows the generalized CTMC model. Note that there is no failure in the last sub-plan because no matter what result of this sub-plan returns, the

Fig. 3 An example of mapping from a task plan $(n, l) = (4, 1)$ to a state space for CTMC model. A_2 is a detection action.

manufactured product will be transmitted out of the studied robotic system by the assumptions made previously, thereby nothing will influence the next sub-plan which will be executed in the new episode of the task. Based on (6), the transition rate matrix $\mathbf{Q} = [q_{ij}]_{(l+3) \times (l+3)}$ can be expressed by:

$$\left\{ \begin{array}{ll} q_{1,2} = \frac{1}{t_1}, & q_{1,1} = -\frac{1}{t_1}, \\ q_{(l+3),1} = \frac{1}{t_{l+3}}, \\ q_{(l+3),(l+3)} = -\frac{1}{t_{l+3}}, \\ q_{(l+2),2} = \frac{1}{\sum_{A_k \in sP_n} t_k}, \\ q_{(l+2),(l+2)} = -\frac{1}{\sum_{A_k \in sP_n} t_k}, \\ q_{i,i+1} = \frac{\prod_{A_k \in sP_{i-1}} r_k}{\sum_{A_k \in sP_{i-1}} t_k}, & 2 \leq i \leq l+1, \\ q_{i,(l+3)} = \frac{1 - \prod_{A_k \in sP_{i-1}} r_k}{\sum_{A_k \in sP_{i-1}} t_k}, & 2 \leq i \leq l+1, \\ q_{i,i} = -\frac{1}{\sum_{A_k \in sP_{i-1}} t_k}, & 2 \leq i \leq l+1, \\ q_{i,j} = 0, & otherwise \end{array} \right. \quad (8)$$

In order to assess the performance (i.e. the information vector), one needs to conduct a steady state analysis based on proposed CTMC model. A vector $\boldsymbol{\pi} = (\pi_0, \dots, \pi_{l+2})^T$, with properties $\pi_i \geq 0, \forall i$ and $\|\boldsymbol{\pi}\|_1 = 1$, is said to be the probability of each state of a CTMC. Furthermore, if $\boldsymbol{\pi}$ is under steady state,

Fig. 4 The proposed CTMC model.

then π is unique and can be calculated as follows [22]:

$$\frac{d\pi(t)}{dt} = \pi Q = 0 \quad (9)$$

For each element in (9), one would have:

$$\pi_i q_{ii} + \sum_{i \neq j} \pi_j q_{ij} = 0, \forall i \quad (10)$$

By solving (10), probability of each state in proposed CTMC can be obtained. This indicates that one can calculate APR by:

$$APR = \pi_{l+1} q_{l+2,2} \prod_{A_k \in sP_n} r_k = \pi_{l+1} \frac{\prod_{A_k \in sP_n} r_k}{\sum_{A_k \in sP_n} t_k} \quad (11)$$

Output of proposed approach can be defined as:

- 1 APR: The APR indicates the production capability of a robotic system under a certain task plan. Intuitively speaking, the higher the APR is, the better the system and the corresponding plan is.
- 2 Information vector: The information vector does not only provide the necessary parameters for CTMC model, but also for performance assessment at economy-level.

5 Experimental study

This experimental study validates the effectiveness of the proposed approach on performance assessment of robotic configurations and plans at task-level

from three aspects. The first aspect is the validation of the proposed approach among different tasks. This work considers a simple peg-in-hole (PIH) task with the different level of difficulty in this study, where T_1 is a task with the clearance of 0.25 (easy) and T_2 is a task with the clearance of 0.1 (hard). The second aspect is to test the generality of the proposed approach in performance quantification on different robotic configurations. A dual-arm robotic system is used where two robotic configurations, dual-arm R_D and single-arm R_S , are taken into this study [27]. To simulate the robotic configuration of single-arm, the right arm of the robot is disabled. The third aspect takes a different combination of strategies to verify the usability of the proposed approach. Details of the experiment study are provided as follows.

5.1 Setup

Details of the experimental setup are presented in this section.

5.1.1 Task

The goal of this task is to pick up round peg and hole on a table and insert the round peg into the round hole within an assigned assembly region.

The initial state of this task is pre-determined by some assumptions. First of all, the robotic system is a workstation in a production line, receiving given assembly parts under a certain degree of uncertainty such as various positions (2 degrees of freedom on the table) and orientations (1 degree of freedom along the normal vector of the table). This is to simulate disturbance in transportation. In addition, assembly parts are assumed to be presented by a transportation system without delay, allowing parts to be presented with a given spatial distribution. The given spatial distribution is to simulate transportation from various directions, meaning that each assembly part is assigned to be presented within a fixed region.

Final state utilizes the mechanism of the adopted transportation system, which is able to transport all assembly parts out of the robotic system without delay to terminate the episode of the task once the goal is achieved.

Figure 5 shows the initial state and final state of this task. Based on manual assembly tasks, workers generally possess knowledge on how to accomplish the given assembly task. Therefore, information of assembly parts and corresponding processes is provided to the robot as prior knowledge.

5.1.2 Robotic configuration

Robotic system used in this work consists of a dual-arm industrial robot (KAWADA NEXTAGE Open), a pair of 3-D printing two-jaw grippers based on DYNAMIXEL MX-28-T motors, a pair of two-million-pixel industrial cameras mounted on the grippers for local detection, a Microsoft Kinect 2 sensor

Fig. 5 The initial state (a) and the final state (b) of the task.

mounted on head of the robot for global detection, and a working plane to support the manipulation.

Figure 6 shows the robotic system used in this work. The robotic configurations are defined as follows.

1 Dual-arm configuration R_D :

- (a) Robot: Two arms of KAWADA NEXTAGE Open (12 D.O.F.).
- (b) Sensor: A Microsoft Kinect 2 sensor and two two-million-pixel industrial cameras mounted on the robot.
- (c) End-effector: A pair of two-jaw grippers mounted on the robot.

2 Single-arm configuration R_S :

- (a) Robot: Left arm of KAWADA NEXTAGE Open (6 D.O.F.).
- (b) Sensor: A Microsoft Kinect 2 sensor and a two-million-pixel industrial camera mounted on the robot.
- (c) End-effector: A two-jaw gripper mounted on the robot.

Fig. 6 The setup of the robotic system.

5.1.3 Task Plan and Action

Task plans for R_D and R_S are shown in Figure 7.

In Figure 7, every block refers to a robotic action. Blocks with dash outlines are detection actions. GD refers to "Global detection"; LD refers to "Local detection"; Pic(X) refers to "Pick X"; Pla(X) refers to "Place X"; Ins(X) refers to "Insert X"; Res(X) refers to "Release X and move to initial pose". P and H inside the brackets refer to "Peg" and "Hole", respectively. L and R before the underline refers to "using left arm" and "using right arm", respectively.

Fig. 7 Task plans for R_D and R_S . Action with dash border refers to the detection action. In this work, the detection action is not necessary the action with detection function. Practitioners can select the detection actions based on their needs. In this work, we select GD, Pic and Ins as detection actions due to the possibility of failure of these actions.

For R_D , there are three detection actions, namely $|sP| = 4$ and $|\mathcal{S}| = 6$, while for R_S , there are four detection actions, namely $|sP| = 5$ and $|\mathcal{S}| = 7$.

5.1.4 Strategy

For an integrated robotic system, sources of uncertainties include but are not limited to variations in the initial pose of assembly parts, modeling errors, sensor noises, and truncation errors. To implement a given task, practitioners often need to think about what strategies are needed to cope with these uncertainties? The adopted strategies need to have a higher level of robustness. However, from the manufacturer's perspective, the chosen strategies need to

be cost-effective. This indicates that, sometimes, a strategy set producing the highest success rate may not be the best choice. Strategies considered in the tasks are as follows:

- 1 Strategy S_A : Assembly detection employed before peg insertion can increase success rate but also increases the execution time of adding action. However, for different assembly clearances (task difficulties), one cannot estimate whether the effectiveness of this strategy is significant. For example, if the clearance is large enough for more error tolerance, the robot can insert the peg into the hole without detection. Figure 8 shows the strategy in this task. For further detail of implementation can refer to [28]
- 2 Strategy S_B : Assembly point is assigned to be located at assembly region, but the best location within this region is unknown. In this paper, two different assembly positions were chosen to conduct an experimental study.
- 3 Strategy S_C : In spite of the lack of force/torque sensor for impedance control, discretization of fine motion enables the robot to generate vibration during peg insertion and improves the success rate of putting the peg into the hole. However, this strategy causes longer execution time in adding action.

Fig. 8 The scenario of execution of Strategy S_A .

5.2 Results

In experimental study of this work, execution time of the troubleshooting action was uniformly estimated at 5 seconds. There were 50 replicates for each run, average of the execution time of each action was taken. Performance quantification of experimental results are provided in Table 2 and Table 3, where the descriptions of experiment labels are given in Appendix. Figure 9 shows part of the task execution scenes.

Table 2 Experimental results of R_D on T_1 and T_2 .

T_1	#1	#2	#3	#4	#5	#6	#7	#8
$\sum t_i$ (s)	37.39	29.81	36.94	29.49	35.87	27.77	35.58	27.44
$\prod r_i$ (%)	100	100	98	98	86	86	94	92
APR (1/s)	0.0314	0.0413	0.0313	0.0423	0.0287	0.0389	0.0315	0.0422
T_2	#9	#10	#11	#12	#13	#14	#15	#16
$\sum t_i$ (s)	36.90	29.62	36.90	28.96	35.87	27.34	35.34	27.40
$\prod r_i$ (%)	96	88	94	88	86	64	74	74
APR (1/s)	0.0305	0.0364	0.0302	0.0377	0.0287	0.0294	0.0250	0.0339

Table 3 Experimental results of R_S on T_1 and T_2 .

T_1	#17	#18	#19	#20
$\sum t_k$	46.77	37.31	44.69	35.06
$\prod r_k$	100	98	100	96
APR (1/s)	0.0240	0.0305	0.0253	0.0320
T_2	#21	#22	#23	#24
$\sum t_k$	47.00	37.12	44.90	35.02
$\prod r_k$	96	94	96	96
APR (1/s)	0.0229	0.0294	0.0241	0.0321

Fig. 9 Part of the task execution scenes. (a) Picking action A_3 of R_D . (b) Assembly action A_5 of R_D . (c) Picking action A_6 of R_S . (d) Assembly action A_7 of R_S .

6 Cross-Analysis

This section analyzes the experimental results from the previous section. First of all, data validation is analyzed through a statistical method, t -test, to prove that the experimental data is reasonable for performance quantification and subsequent analysis. Secondly, quantitative performance, the APR, of each

group of the experiment is obtained by the proposed approach, where the differences and explanations among these results are also provided. Finally, a method for estimation of the cost-effectiveness of additional strategy in a task plan is given, providing manufacturers a quick solution to determine the update of new strategy without time-consuming experiments.

6.1 Data validation

According to Table 4 and Figure 10, it can be seen that the strategy affects execution time significantly as the situation between two sets of sP_3 (under R_D and R_S) is different with two sets of sP_4 . Based on proposed task representation, experimental results from two sets of identical sub-plans can be considered that they are from one population. Here, two examples are given for the validation, sP_3 and sP_4 . Firstly, p -value from calculation of t -test on comparison of two samples of sP_3 is less than 10^{-5} , which is smaller than 0.01, meaning that we have 99% confidence that two samples of sP_4 are not from one population, which also implies that the execution time is influenced by adopted strategy. Another comparison on two samples of sP_4 shows the p -value calculated from t -test is 0.411407, which is greater than 0.01, meaning that we have 99% confidence that two samples of sP_2 are from one population, which implies that the same sub-plans from different groups of experiments are identical.

Table 4 Results of sP_3 and sP_4 from experiment #12 and #16.

#12	sP_3	sP_4	#16	sP_3	sP_4
M (s)	6.791	8.211	M (s)	1.798	1.801
SD (s)	0.202	0.241	SD (s)	0.074	0.065

6.2 Influence of strategy

Based on the APR calculated, a comparative study to investigate the effect of each strategy can be conducted through Analysis of Variance (ANOVA) [23]. As an example, performance of R_D on T_1 and T_2 with different combination of adopted strategies are shown in Table 5.

According to Table 5, one can know that:

- 1 Strategy S_A : Obviously, S_A can improve the success rate of assembly tasks. In the experiment of R_D on T_1 , although strategy A increases the success rate of peg insertion, incremental improvement does not seem largely due to high error tolerance of assembly parts. For example, the APR of experiment #4 and #8 are almost the same, indicating that if rework cost is not considered, the option of S_A will not have a significant effect on

Fig. 10 Data visualization of experimental results between experiment #12 and #16.

Table 5 ANOVA for R_D on T_1 and T_2 .

R_D on T_1 with $\alpha = 0.5$			
Source of Variation	Sum of Squares	Degrees of Freedom	F_0
S_A	1.12E-06	1	9
S_B	6.13E-06	1	49
S_C	2.10E-04	1	1681
$S_A S_B$	3.13E-06	1	25
$S_B S_C$	1.25E-07	1	1
$S_A S_C$	1.25E-07	1	1
Error	1.25E-07	1	
Total	2.21E-04	7	$F_{0.05,1,1} = 161.4$

R_D on T_2 with $\alpha = 0.5$			
Source of Variation	Sum of Squares	Degrees of Freedom	F_0
S_A	4.05E-05	1	324
S_B	2.00E-06	1	16
S_C	7.20E-05	1	576
$S_A S_B$	5.00E-07	1	4
$S_B S_C$	1.80E-05	1	144
$S_A S_C$	4.50E-06	1	36
Error	4.50E-06	1	
Total	1.42E-04	7	$F_{0.05,1,1} = 161.4$

task performance. Nevertheless, the practical strategy set is still #4 which possesses a higher success rate.

- 2 Strategy S_B : Effect of S_B is not significant in both groups of experiments.
- 3 Strategy S_C : According to experimental results, strategy with highest APR is not always the strategy with the highest success rate. This result is caused by different execution time based on options of S_C .

This analysis provides practitioners some useful information. For example, we know that the strategy S_A does not affect T_1 anymore, then we can assert that it would not affect those tasks easier than T_1 . Therefore, we do not need to consider S_A in easier tasks, vice versa.

6.3 Estimation of a new strategy

Sometimes practitioners would like to know whether there is another strategy which could also improve the performance of the robotic system. The experimental data could be reused to provide them with quantification metrics for the addition of a new strategy. Experimental data is taken into consideration without using strategy as a reference. If a practitioner is curious about how performance of a new strategy added into the assembly motion (in the sub-plan sP_4) is, one can replace $\sum_{A_k \in sP_4} t_k$ with $\Delta t + \sum_{A_k \in sP_4} t_k$ (Δt is the increased execution time of new strategy in an adding action or sub-plan, often obtained through new experiments) to calculate the relationship between APR and Δt , as shown in Figure 11. The answer can be obtained that only at $\Delta t \leq 7.576$ (s), 100% success rate achieved by the new strategy is acceptable (the new APR is no less than original one). If one has an estimation of the increased success rate about the new strategy, the cost-effectiveness (the success rate of sP_4 without strategy is 74%) can be verified by the location of the point in Figure 11 (must be within the cost-effective area).

Fig. 11 The relationship between APR and Δt .

6.4 Dominance of robotic configuration

According to the experimental results, the strategy set with highest APR is considered the best selection of its corresponding configuration. The APR ratio of R_D to R_S is 1.322 on T_1 and 1.174 on T_2 , which means the dual-arm configuration is more dominant among the alternatives on easier PIH task (just in this experimental study). This analysis gives practitioners a simpler guide to deploying their robots if he/she possesses the knowledge about the cost ratio of the two configurations. For example, if a practitioner estimates that the cost of dual-arm is double of the single-arm, then the single-arm is more cost-effective because the APR ratio of R_D to R_S is less than 2.

6.5 Discussion

As shown in Figure 12, for different tasks executed by the same robotic configurations and corresponding plan, the APR of R_D on T_1 is obviously higher than on T_2 (14.22%), while the APR of R_S on T_1 is slightly higher than T_2 (3.04%). This result shows that the easier task (T_1) brings higher APR than harder task (T_2) under the same robotic configurations and corresponding task plans. Besides, the reason that there is merely the difference of APR between T_1 and T_2 under R_S is that the motion of the hole part is not constrained by another arm, making the hole part movable during the peg insertion action. Therefore, the hole part is endowed with a certain degree of compliance, leading to improvement of the success rate. This improvement leads to the decreased difference of success rate and APR between T_1 and T_2 .

Fig. 12 The comparison of APR between T_1 and T_2 .

As shown in Figure 13, for different robotic configurations and the corresponding task plans, due to the capability of simultaneous picking of multiple objects by dual-arm robots, an expectation that dual-arm configuration

is more efficient in this task than single-arm configuration can be validated, improving about 28.62% of APR on T_1 and 16.03% of APR on T_2 .

Fig. 13 The comparison of APR between R_D and R_S .

The results of different strategy sets of the same robotic configuration are provided in Figure 14-16, where the pluses and minuses below the bars refer to the adoption status of another two strategies. The following conclusions can be drawn:

1. The task plans with S_A lead to a higher APR value can be drawn, where this strategy averagely improves R_D about 3.53% and 15.21% of APR on T_1 and T_2 , respectively. This shows that S_A benefits the productivity though it takes more execution time.
2. For strategy S_B , the average variations of APR performed by both configurations are less than 5%, implying that taking S_B or not in task plan is equivalent in performance.
3. Task plans with S_C greatly reduce the performance of R_D by 25.4% and 16.7% on T_1 and T_2 , respectively. Experimental results show that S_C provides the robotic system higher success rate on peg insertion action, but it considerably extends the execution time of in peg insertion, leading to a lower APR. Therefore, S_C is not a good strategy for manufacturers.

With the requirement of production and related cash flow, further justification at economy-level can be made based on these quantified results by manufacturers, if necessary.

6.6 Summary

The experimental study demonstrates how to use the proposed approach to quantify the performance of a robotic configuration and the corresponding task plans and strategies on a task. Given a task, all components for the proposed representation should be given first. Next, based on the representation, a task plan can be decomposed for the modeling of the CTMC. With the conducting

of experiments, the resulting information vectors play an important role in the calculation of APR. Finally, the obtained APR plays an important role in the performance quantification, providing essential information for the cross-analysis and further assessment at economy-level.

Fig. 14 The comparison of APR on adoption of S_A .

Fig. 15 The comparison of APR on adoption of S_B .

7 Connection to assessment at economy-level

This section presents a discussion on assessment at economy-level, providing manufacturers with methods to select solutions among available options. Manufacturers can refer to this regarding determining a suitable robotic configuration, corresponding plan, and strategy for higher cost-effectiveness. Assuming the estimated profit of an accomplished task is M and the estimated cost per second of the studied robotic system (this value depends on the robot, including installation, operation, maintenance, etc.) is C_R . Combining the result of

Fig. 16 The comparison of APR on adoption of S_C .

APR and information vector, the estimated cash flow $\hat{F}$ can be measured by:

$$\hat{F} = APR \cdot M - (C_R + \sum_{i=1}^n \prod_{A_k \in sP_i} (1 - r_k) C_i) \quad (12)$$

where C_i is estimated rework cost per second for sP_i .

Once the cash flow is estimated, manufacturers can further estimate the present value PV about this robotic system by [3]:

$$PV = \sum_{t=0}^{n_t} \frac{\hat{F}(t)}{(1 + \bar{r})^t} \quad (13)$$

where $\hat{F}(t)$ refers to the estimated cash flow $\hat{F}$ in period t , depending on the estimated unit profit and other costs in (12); n_t is the total number of considered time periods; $\bar{r}$ is fractional interest rate due in each studied period.

8 Conclusion

This work has developed an approach for quantitative performance assessment at task-level, which can assist manufacturers in performance evaluation of a task plan under a specific robotic system while adopting various strategies. Given alternatives of tasks for specific robotic configurations, manufacturers can compare multiple task plans under selected robotic configurations by proposed approach.

Based on the proposed task representation, manufacturers can decompose a task plan into a set of actions. The information vectors of these actions are then used for the establishment of performance assessment model by CTMC. After conducting series of experiments, the performance assessment model

can quantify performance for all of the alternatives proposed by manufacturers. According to experimental results, this approach has made it feasible to quantify the performance of multiple task plans under given tasks and robotic configurations as APR. In addition, this work also provides a methodology for cross-analysis of the APR, which can assist manufacturers to validate experimental data, evaluate influences of strategies, estimate performance of a new strategy and judge the dominance of given robotic configurations. Furthermore, the connection between the APR at task-level and performance metric at economy level can be built, allowing manufacturers to study their cash flow based on this approach. Finally, an extension of proposed task representation for multi-robot coordination in industrial scenarios is provided for manufacturers to decompose task plans executed by multiple robotic configurations.

In the future, more elaborated experiments will be conducted on the evaluation of multi-robot coordination for performance study and contribute to the optimization of solutions in robotic automation. In addition, task representation for performance study of robotic task plans in the unstructured environment will be discussed in future work.

Appendix

Table 6 Descriptions of experiment labels. Here, $\neg S$ indicates "without the adoption of strategy S ".

		T_1					T_2				
R_D		S_A		$\neg S_A$			S_A		$\neg S_A$		
		S_B	$\neg S_B$	S_B	$\neg S_B$		S_B	$\neg S_B$	S_B	$\neg S_B$	
		S_C	#1	#3	#5	#7	S_C	#9	#11	#13	#15
	$\neg S_C$	#2	#4	#6	#8		$\neg S_C$	#10	#12	#14	#16
R_S		S_A		$\neg S_A$			S_A		$\neg S_A$		
		S_B	$\neg S_B$	S_B	$\neg S_B$		S_B	$\neg S_B$	S_B	$\neg S_B$	
		S_C	#17	#19	-	-	S_C	#21	#23	-	-
	$\neg S_C$	#18	#20	-	-		$\neg S_C$	#22	#24	-	-

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Table 7 Descriptions of symbols in this work.

Symbol	Description
T	Task
T_1	PIH Task with 0.25 clearance (Experiments)
T_2	PIH Task with 0.1 clearance (Experiments)
R	Robotic configuration
R_D	Dual-arm configuration (Experiments)
R_S	Single-arm configuration (Experiments)
P	Task plan
sP	Sub-plan
A	Action
$\mathbf{I}$	Information vector
t	Execution time
r	Success rate
S_A, S_B, S_C	Strategy A, B, C (Experiments)
S	State
APR	Average product rate
M	Estimated profit of an accomplished task
C_R	Estimated cost per second of studied robotic system
$\hat{F}$	Estimated cash flow
PV	Present value about the robotic system
n_t	Total number of considered time periods
$\bar{r}$	fractional interest rate due in each studied period

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