

# Using Self-learning RPA to Automate a Greater Range of Business Tasks

A variety of companies are adopting RPA for the purposes of eliminating workforce shortages and improving labor productivity. RPA is a technology that automates back-office work by using software robots that emulate human work processes in the same manner as conventional robots. Hitachi is researching “self-learning RPA” that uses a software robot to process multiple inquiries and sort inquiries by confidence score. The low-confidence inquiries are processed manually to enable the software robot to learn from the results, thereby enabling a greater range of business automation. Using the Hitachi Group’s businesses as fields for testing, Hitachi has conducted proof-of-concept trials on automating tasks including accounts documentation checking and inquiry handling. The trials achieved manual process substitution rates of 74% and 72% respectively for these business tasks.

Yoshiyuki Kobayashi, Ph.D.

Yasufumi Suzuki, Ph.D.

Masahiro Motobayashi, Ph.D.

Makoto Iwayama, Ph.D.

Yu Asano, Ph.D.

## 1. Introduction

Robotic process automation (RPA) is a technology that uses software robots to automate back-office work. It is being adopted by a variety of companies for the purposes of eliminating workforce shortages and improving labor productivity. A software robot is a software program that emulates human work processes in the same manner as a conventional robot (the term robot is used only metaphorically).

Hitachi is currently working on adopting level 1 RPA, which is automation of tasks that can be clearly defined by rules. In the future, level 2 RPA, which

refers to automation of tasks that require intelligence, such as recognition and decision-making, is expected to attract increasing interest in the years ahead.

To achieve level 2 RPA, Hitachi has recently developed and trialed “self-learning RPA” that can incrementally acquire knowledge from work results, enabling a growing range of business tasks to be automated over time. This article reports the findings of these trials.

## 2. Self-learning RPA

Self-learning RPA receives unstructured data such as images and natural language as input and attempts to

use knowledge acquired from past tasks to automate tasks for appropriate processing. Automating tasks involves the following challenges:

- (1) Being able to extract the data needed for the task from unstructured data
- (2) Systematizing the task and being able to adjust the rate of automation in response to the allowable error level
- (3) Being able to provide the system with knowledge used to appropriately process tasks by a non-rule based method

To address these challenges, Hitachi's self-learning RPA technology uses the following methods to automate tasks:

- (1) Extracting data using artificial intelligence (AI) that recognizes unstructured data
- (2) Classifying the recognition AI's processing results by confidence score
- (3) Manually processing input data that could not be processed automatically, and having the recognition AI learn task knowledge from the processing results

Figure 1 shows a conceptual configuration of RPA. After receiving the input data, the recognition AI uses the processing result and various attribute values to

output a confidence score. If the confidence score exceeds a preset threshold value, the recognition AI ends processing with the output result. Otherwise, the input data is processed manually and the manual processing result is used as the correct response data for learning by the recognition AI. The recognition AI uses correct response data to gradually learn, enabling a growing range of business tasks to be automated over time.

### 3. Automating Accounts Documentation Checking

#### 3.1

##### Accounts Documentation Checking

This research examined automation of the accounts documentation checking done by Hitachi Management Partner Corporation. Figure 2 illustrates the flow of this task. The user enters/applies for a payment request in the system in accordance with the information in the bill received from a trading partner or other payee. At the same time, the user sends the original copy of the paper bill to Hitachi Management Partner as corroboration. For each payment request, the original copy of the bill is converted to image data and sent to the data entry clerks. Two independent data entry clerks read and enter the billing amount and other information on the bill from the image data.

Figure 1 — Self-learning RPA Conceptual Diagram

The result recognized by the AI is output with a confidence score appended, and processed automatically if the confidence score is high. If the confidence score is low, the process is done manually and the result is learned by the AI to expand the range of tasks it can process.

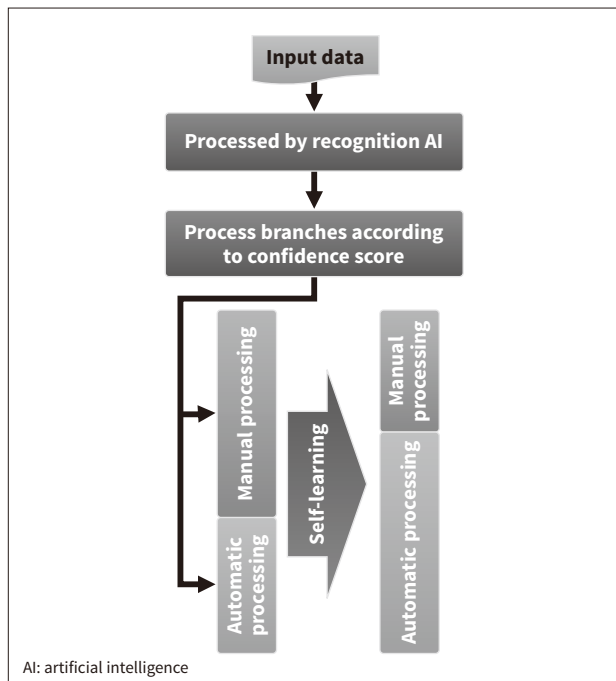
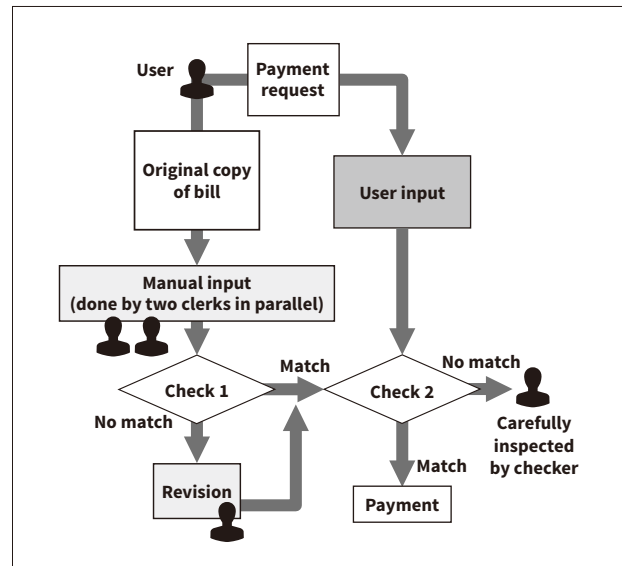


Figure 2 — Accounts Documentation Checking Flow

Human workers check whether the payment claim data entered by the user matches the information in the original copy of the bill.



The payment process is executed if the data entered by the two clerks matches, and also matches the data entered/applied for by the user. Otherwise, the data is sent to a checker for checking/revision. Ideally, this series of checking tasks should be automated since they require a workforce of two data entry clerks and one checker.

### 3.2

#### Challenges

The challenges involved in automating accounts documentation checking are as follows:

- (1) Automatically reading information such as monetary amounts and bank account numbers from bills in tens of thousands of different formats sent from inside and outside the Hitachi Group
- (2) Being able to process initially unprocessable bills the next time a bill is sent in the same format
- (3) Being able to automate accounts documentation checking with a lower error rate than the error rate for manual processing

### 3.3

#### Solution

Hitachi used the self-learning RPA system and the method below to address the challenges of 3.2 above.

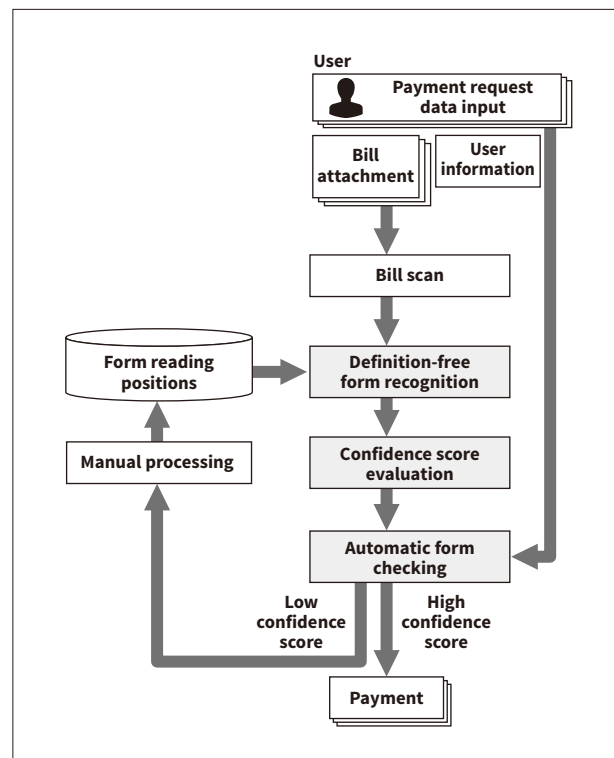
- (1) Apply template-free form recognition technology. This technology eliminates the need for defining coordinates for each bill format that conventional form recognition methods require, enabling processing of bills in tens of thousands of different formats.
- (2) If the data in a bill cannot be read correctly, learn form-specific reading positions as task knowledge, and apply the newly accumulated knowledge the next time a bill arrives in the same format.
- (3) Calculate confidence scores from feature values such as the form recognition result and the match rate with the application data. Set a threshold value for process branching that results in an error rate no higher than the manual processing error rate.

**Figure 3** shows the task flow of accounts handling after automation of documentation checking.

This accounts documentation checking automation system was used to carry out trials on Hitachi data in FY2016, and on Hitachi Group data in FY2017. At the end of FY2017, Hitachi demonstrated that

**Figure 3 — Task Flow after Accounts Documentation Checking Automation**

The template-free form recognition technology reads the data from the bill and checks the information entered by the user.



the technology is capable of automating 74% of the tasks done to check tens of thousands of forms every month. It started to apply the technology to actual business tasks in FY2018.

## 4. Automating Inquiry Handling

### 4.1

#### Handling Inquiries

Among the inquiries handled by Hitachi Management Partner, Hitachi's research examined automation of the responses to inquiries on year-end adjustments.

Currently, call center operators respond to user inquiries by phone. The operators respond using their personal business knowledge and the information in the business manual. Responses should ideally be provided as quickly as possible to prevent users from waiting. Operators therefore need to have prior knowledge of the business, and training operators incurs costs.

But handling inquiries involves responding to some inquiries that arise frequently, so ideally a system

should be used to respond automatically to these inquiries with previously prepared responses.

#### 4.2

##### Challenges

The challenges involved in automating inquiry handling are as follows:

- (1) Recognizing inquiries expressed in natural language and responding appropriately
- (2) When unable to appropriately respond to an inquiry, being able to efficiently acquire the required business knowledge (the relationship between inquiry and response in this case)
- (3) Answering only inquiries for which it can respond appropriately, and responding to unanswerable inquiries by switching to another process such as escalation to an operator

#### 4.3

##### Solution

Hitachi used the self-learning RPA system and the method below to address the challenges in 4.2 above.

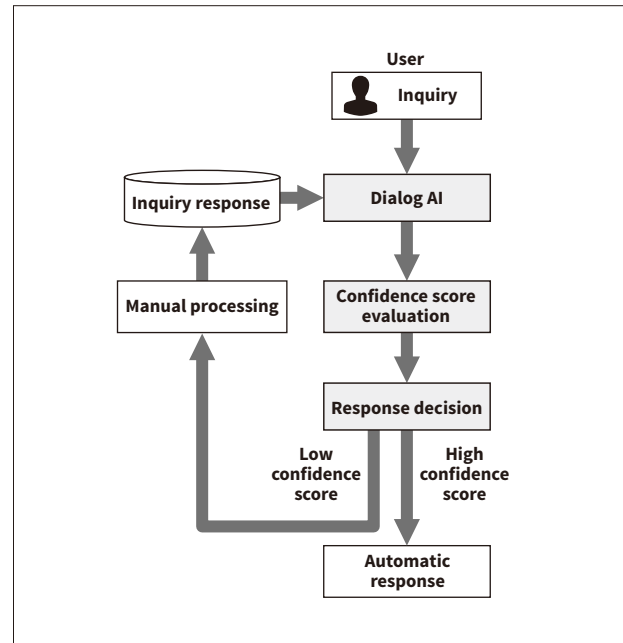
- (1) Apply dialog AI (chatbot) technology. This solution used a question-answering dialog AI, prioritizing the ability to respond correctly. Pairs of inquiries and responses were collated in a dialog AI database. The dialog AI responded to each user inquiry by searching for a highly similar inquiry in the database and outputting the response registered for that inquiry.
- (2) For inquiries that the dialog AI was unable to answer appropriately, a request was sent to a manager to add the inquiry/response to the dialog AI database. The added knowledge was then used to answer the inquiry the next time it was received.
- (3) Confidence scores for answer correctness were calculated from feature values such as the similarity between the inquiry/response in the database and the user's inquiry, and the inquiry character string length.

**Figure 4** shows the task flow used after automating inquiry handling.

To use dialog AI, a sufficient volume of inquiries/responses needs to be registered in the database before starting to use the system. For the trials, Hitachi used the business manual and past inquiry response history (operator response reports) to enable efficient collation of inquiries/responses in the database.

**Figure 4— Inquiry Handling Automation Task Flow**

If the confidence score of a response to a user is high, the response is given. If the confidence score is low, a manager adds the missing knowledge.



This system was used to conduct a trial on inquiry handling related to Hitachi Management Partner year-end adjustments. The trial was conducted from October 2017 to January 2018. As a result, call center inquiries about topics unrelated to changes due to legal revisions were reduced by about 72%. The past inquiry/response history was used to add question wordings to the inquiry section of the database. When the cost-cutting benefits needed for adding these question wordings were assessed, Hitachi found that it could cut costs by about 60% from the previous level.

## 5. Conclusions

Hitachi is researching self-learning RPA technology as a way to automate office work that has traditionally required human recognition or judgement. Automation of actual accounts documentation checking started in April 2018. Automation of inquiry handling for inquiries on year-end adjustments was trialed in FY2017, and benefits were demonstrated. In FY2018, Hitachi plans to expand the kind of tasks to which the technology can be applied, and will continue automating business in the years ahead, while widening the range of self-learning RPA applications.

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## Authors

**Yoshiyuki Kobayashi, Ph.D.**

Media Intelligent Processing Research Department, Center for Technology Innovation – Digital Technology, Research & Development Group, Hitachi, Ltd. *Current work and research:* Managing the Natural Language Research Team. *Society memberships:* Association for Computing Machinery (ACM), the Japanese Society for Artificial Intelligence (JSAI), The Association for Natural Language Processing (NLP), and the Information Processing Society of Japan (IPSJ).

**Yasufumi Suzuki, Ph.D.**

System Productivity Research Department, Center for Technology Innovation – Systems Engineering, Research & Development Group, Hitachi, Ltd. *Current work and research:* Researching design and verification of system architecture. *Society memberships:* IPSJ.

**Masahiro Motobayashi, Ph.D.**

Intelligent Information Research Department, Center for Technology Innovation – Digital Technology, Research & Development Group, Hitachi, Ltd. *Current work and research:* Researching business process automation. *Society memberships:* The Institute of Electronics, Information and Communication Engineers (IEICE).

**Makoto Iwayama, Ph.D.**

Media Intelligent Processing Research Department, Center for Technology Innovation – Digital Technology, Research & Development Group, Hitachi, Ltd. *Current work and research:* Researching natural language processing. *Society memberships:* ACM, JSAI, NLP, and IPSJ.

**Yu Asano, Ph.D.**

Media Intelligent Processing Research Department, Center for Technology Innovation – Digital Technology, Research & Development Group, Hitachi, Ltd. *Current work and research:* Researching dialogue systems. *Society memberships:* JSAI and IPSJ.