Cyber Physical System Considering Physical Contacts in Robotic Manipulation for Improving Automation in Food Industry

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Abstract—**Population aging in Japan is exacerbating the labor shortage problem in food industry, agriculture, and other labor-intensive industries. Recently, automation and IoT technologies become highly demanded in such industries for improving productivity and labor-saving. This article reviews the challenges of introducing automation in food industry and proposes a cyber physical system framework for applications in food industry. For facilitating the application of IoT technologies, we propose a module integrated with multiple sensors for monitoring the environment and the robotic system conditions. Further, a network platform is proposed to connect the physical space (robotic system) and the cyber space (cloud). Two examples of robotic systems for automatic tempura plating and presentation and chopped green onion topping are presented to demonstrate the capabilities of applying such technologies in food industry.**

Index Terms—**Cyber physical system, Node-Red, Json format, automation, food industry, robotic manipulation**

I. INTRODUCTION

Comparing with automotive and electrical industries, automation and IoT technologies are not widely applied in food industry, agriculture, the forestry and fisheries industry due to the lack of effective robotic end-effectors, the complexity of the products in geometry, size, surface condition, and so on [1]. On the other hand, along with the population aging in Japan, automation and IoT technologies are highly demanded in food industry, agriculture, the forestry and fisheries industry to improve their productivity and reduce labor cost.

IoT technologies have been applied in logistic information system [2], supply chain [3], and quality monitoring [4] in food industry, but have not been utilized for robotic handling tasks. According to Vermesan *et al*. [5], the main characteristics that an IoRT (internet of robotic things) should involve are sensing, actuating, control, planning, perception, and cognition. Cloud-based robot grasping has been proposed using the

google object recognition engine [6]. Cloud robotics, as an emerging field of robotics, has been receiving attentions and applied to industries for improving energy efficiency, real-time performance, and reducing costs. The major driving forces behind the development of cloud robotics are the cloud computing technology, the big data, the spirit of open source, the robot cooperative learning, and the network connectivity [7]. Typical applications of cloud robotics can be mainly categorized into SLAM (simultaneous localization and mapping), grasping, and navigation [8]. The content of this article is focusing on the applications of grasping.

In the current state of food factories, grasping tasks are mainly performed by human laborers. In the automated production lines, suction cups are widely used for grasping/handling packaged food products. However, there are many food products that are not able to be handled by suction cups, such as many raw foods, vegetables, fruits, fishes, seafoods, and so on. In such cases, human laborers must perform the handling tasks. To automate these tasks, effective robotic end-effectors must be developed.

In recent years, along with the emerging of the soft robotics field, many soft and flexible robotic hands and grippers were proposed to handle food products. A soft gripper using the effects of magnetorheological fluid was proposed to cope with the differences in shape and softness of vegetables and fruits, such as apples, carrots, strawberries, broccolis [9]. A robotic end-effector was developed based on the Bernoulli principle for handling sliced vegetables and tested on sliced tomato and cucumber for assembling sandwich [10]. Li et al. proposed an origami 'magic-ball' soft gripper and it could grasp objects much heavier than the gripper itself [11]. The gripper has been tested for grasping 12 food items. A lightweight kirigami gripper was also developed by Ma et al. for food grasping [12]. The gripper weighs only 4 g and can handle an object of 25 g. Gafer et al. proposed a cable-driven quad-spatula gripper and experimentally demonstrated the capability of grasping food ingredients [13]. Wang et al. proposed a series of

grippers for handling food and agricultural products, such as the 3D printable soft gripper and the prestressed gripper for packaging lunch box [14], [15], the wrapping gripper for handling granular foods [16], the circular shell gripper for grasping and twisting [17], the soft gripper equipped with suction cups [18], the needle gripper for eliminating defective products [19], and the parallel shell gripper for packaging multiple cucumbers [20].

Other than research works, some soft grippers have also been commercialized for improving automation in food industry and agriculture, such as the mGrip gripper from Soft Robotics, Inc. [21], the adaptive shape soft gripper from Festo [22], soft gripper from OnRobot A/S [23], the SOFTmatics gripper from Nitta Co. Ltd. [24], the modular designed soft gripper from SoftGripping [25], and the flexible gripper for picking tomato from Root AI, Inc. [26]. These grippers are showing potentials for handling various kinds of food agricultural products.

The article is organized as follows. Section 2 introduces the system configuration, followed by the explanation of the proposed multi-sensor module in Section 3. Section 4 presents two examples of robotic systems for automating food operation tasks. Section 5 discusses the current system performances and Section 6 concludes the article and suggests some future work.

II. System Configuration

A. Overall System
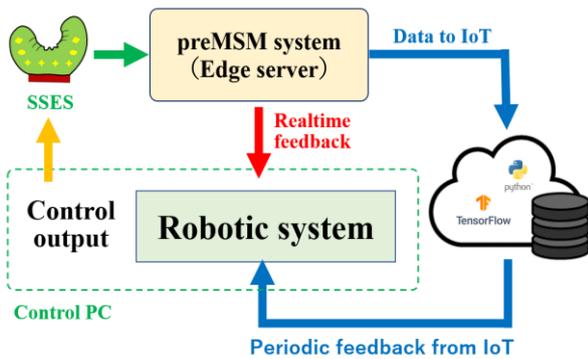
Figure 1. The concept of the cyber physical system.

The system concept is shown in Fig. 1. The SSES denotes the soft sensor-rich end-effector system, which is responsible for performing the grasping/handling tasks. The SSES consists of sensors and robotic hand or gripper fabricated using soft materials to cope with the variations in shape, size, and softness of the targets in food industry applications. The preMSM is the short for preliminary multi-sensor module, in which different sensors are integrated together as an individual module to facilitate the multiple sensing tasks simultaneously. The preMSM system is attached to the robotic system directly and measuring different signals from the robotic system during actual operations. The system also takes the role of an edge server and conducts edge computing to extract useful data and send them to the cloud IoT network. At the same time, the preMSM system also provides real-time feedback directly to the robotic system if necessary.

After data processing in cloud computing, periodic feedback will be sent back to the robotic system to update the control strategy for improving the task performances. This closes the control loop for the entire system.

B. Local Network

To mimic the food factory, we established an experimental field in Ritsumeikan University as shown in Fig. 2a. Six SCARA robots are arranged alongside the belt conveyor to simulate the production line of lunch box packaging in food factory. To validate the above-mentioned cyber physical system, a local network was constructed as shown in Fig. 2b. The sensor data are collected by the micro controllers through analog/digital circuit. The data are further transmitted to the gateway through serial or USB communication. The gateways are connected to a local edge server through USB or Wi-Fi and the server then access to the cloud using Node-Red. In addition, real-time feedbacks are sent to the robotic system from the micro-controller and gateway depending on necessity.

(a)

(b)
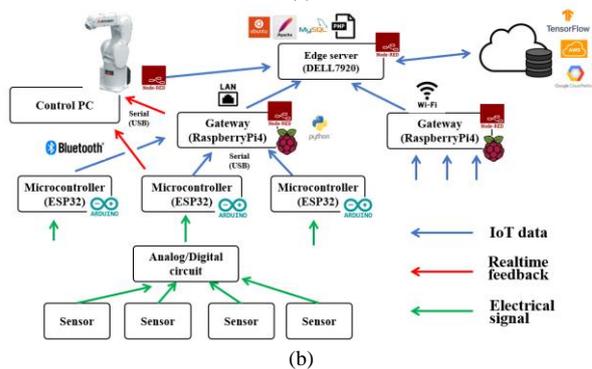
Figure 2. (a) The experimental field and (b) the local IoT network.

III. Multi-Sensor Module

In a handling task using robot, there are many physical information that may affect the handling performance. For instance, when grasping an apple using a robotic hand as shown in Fig. 3, image sensor is usually used to recognize the apple and obtain the position and size of the apple. When the robot hand touches the apple, information of force, slippage, and surface condition sensed by the robotic fingers become available and play a role for successful grasp. At the same time, the vibration

and force information on the robot hand/gripper and even the robotic manipulator may also affect the grasping performance. The temperature and humidity of the environment also play an important role. Therefore, it would be helpful to know such information beforehand for better controlling the robotic hand/gripper. However, measuring all such information with a single sensor is usually impossible and it is also a challenging task to measure them using multiple sensors separately due to the synchronization and wiring issues. Therefore, we propose a preliminary multi-sensor module (preMSM) to solve this problem.
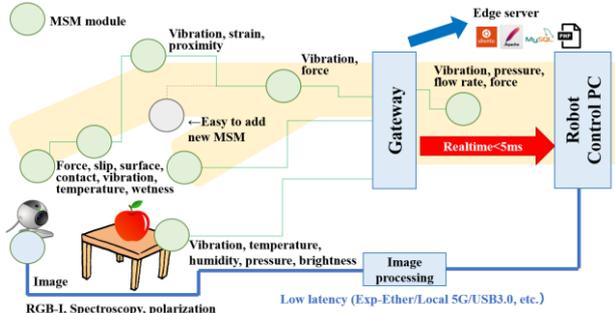
Figure 3. The concept of multi-sensor module for grasping an apple with a robot.

(a)

(b)
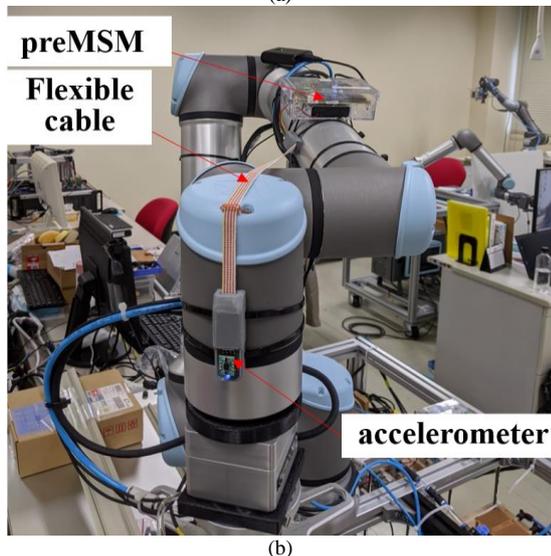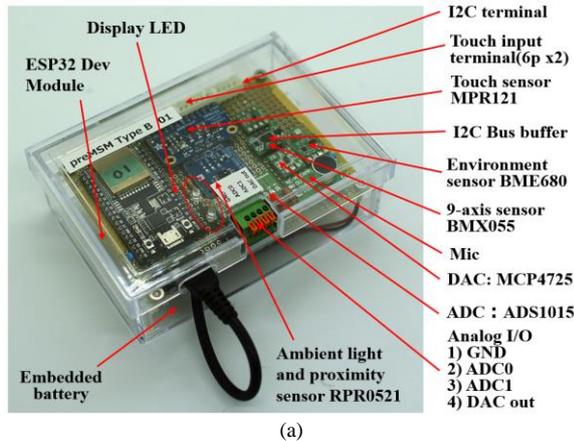
Figure 4. (a) The developed prototype of preliminary multi-sensor module (preMSM) and (b) the attachment of the preMSM and an accelerometer addon on a robot manipulator

The prototype of the preMSM is shown in Fig. 4a. It integrated a proximity capacitive touch sensor (MPR121), an ambient light and proximity sensor (RPR0521), a 9-axis absolute orientation sensor (BMX055), a temperature, humidity, pressure and gas sensor (BME680), and a high sensitivity microphone (AE-MICAMP), an onboard embedded battery, and several input and output terminals. These sensors are low cost and easily available. The measured data are collected using the micro controller (ESP32) and then sent to the RaspberryPI for data processing. All components are encapsulated in a transparent box for facilitating the attachment on robotic system. An example of attaching the preMSM on a robotic manipulator (UR10e) is shown in Fig. 4b. The preMSM can be easily extended by adding other sensors. For instance, as shown in Fig. 4b, an accelerometer was additionally extended to the manipulator end by using flexible cable. Finally, by using the preMSM, we can monitor most physical data that are available and may affect the performances of robotic grasping.

IV. ROBOTIC SYSTEM FOR FOOD AUTOMATION

A. Robotic System for Tempura Plating and Presentation

For actual applications in food industry, we developed a robotic system for automating the tempura plating and presentation operation. In restaurants, the tempura plating and presentation operations are usually performed by human chef. The task is to pick the tempura items from a tray or container and then place them into a dish plate with a predetermined order. To well present the arrangement, special cares must be taken when choosing the place positions and orientations of the tempuras. The developed robotic system, as shown in Fig. 5a, is constructed by a robot manipulator (UR5e), a robotic hand (Robotiq 2F-85), and a depth camera (RealSense D435). The tempuras are prepared in several trays and the camera recognizes the tempuras and extracts the boundaries of the tempuras by eliminating the background using the depth information from the camera, as shown in Fig. 5b (top). Then, by fitting the boundary of the tempura with ellipsoid, we can calculate the center position and the posture of the tempura. In addition, the tail of the shrimp tempura must be placed upward based on the tempura presentation regulation. Therefore, the image processing algorithm recognizes the shrimp tail by color information as shown in Fig. 5b (bottom left). Similarly, the orientation of the pumpkin tempura must be placed towards a certain direction. To this end, we recognize this orientation using the curvatures of the curved edges of the pumpkin tempura as shown in Fig. 5b (bottom right). After knowing the above information, the robotic system could automatically perform the tempura plating and presentation, and the finished tempura presentation results are shown in the in-set view of Fig. 5a. The current operation takes approximately 1 minute per plate, and it will be sped up by improving the speed of image recognition and the robot motion.

(a)

(b)
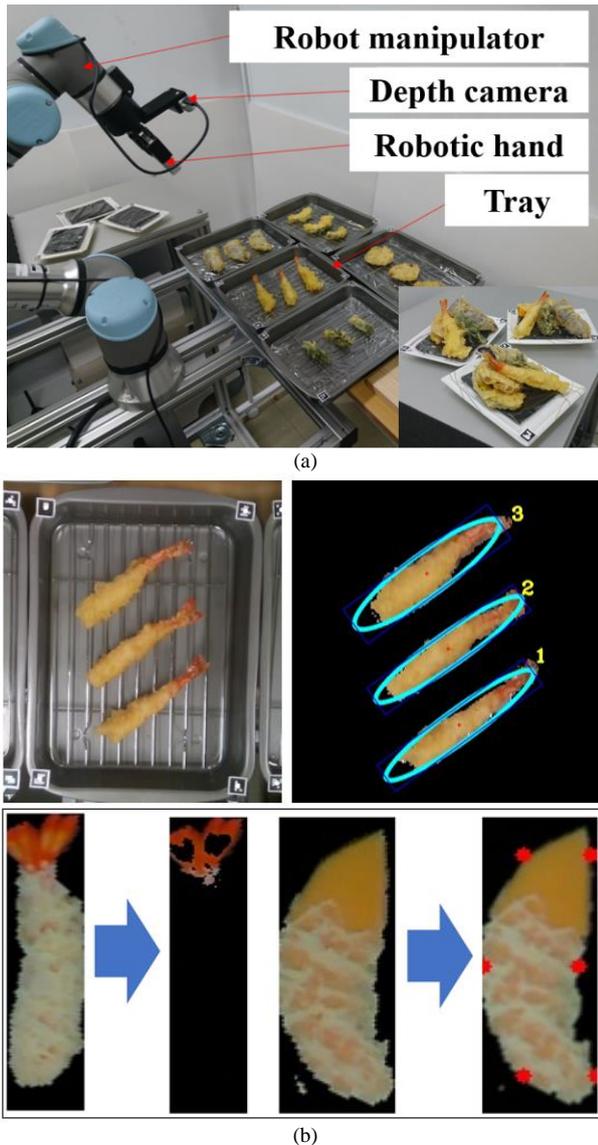
Figure 5. (a) The robotic system for automatic tempura plating and presentation, and (b) the recognition of the tempuras and determination of tempura postures.

B. Robotic System for Green Onion Topping

The second example of robotic system for improving automation in food industry is a robotic system for automating the green onion topping operation. In Japanese lunch boxes, chopped green onion often appears as an important ingredient, and the topping operation is mostly performed by human laborers. The task is to pick approximately 15 g green onion from a container and place it into a desired location in a lunch box. The tolerance in onion mass is approximately ±20%.

For automating this operation, we developed a robotic system as shown in Fig. 6a. A SCARA robot (HSR065, DENSO WAVE) is used to perform the pick-and-place motion because of the high-speed of the robot. A depth camera (RealSense D435) was used to measure the roughness of the surface of the chopped onion inside the container. A soft wrapping gripper [16] is attached on the SCARA robot to perform the grasping task. An electric scale is used to measure the mass of the grasped onion. The robotic system is constructed using ROS (Robotic

Operating System) and all sensor data are collected by the control PC and sent to a local server.

In order to determine the grasping position, we measured the depth information of the surface of the chopped onion and then calculated the normal vector of the point cloud, as shown in Fig. 6b. Based on the normal vectors, we can determine the convex and concave areas and experimental results have shown that grasping at the convex areas yields better performances in terms of the grasped mass of the chopped onion. Therefore, we employed this strategy for grasping the chopped onion. The robotic gripper used in the experiments is a pneumatically driven soft wrapping gripper, which is capable of grasping granular objects using four soft fingers. Once the gripper is pressurized, the soft fingers deform and form a closed cavity and therefore can hold granular objects without dropping. A total of 42 trials of grasping were conducted and the grasped onion mass is shown in Fig. 6c for comparison.

We found that the averaged mass grasped by the robotic system is approximately 16.9 g. There is no trial that the grasped onion mass was less than the −20% limit. On the other hand, there are 14 trials that the grasped onion masses were over the +20% limit. Fortunately, no complain will occur on the products with more chopped onion according to the food factory manager.

(a)

(b)

(c)
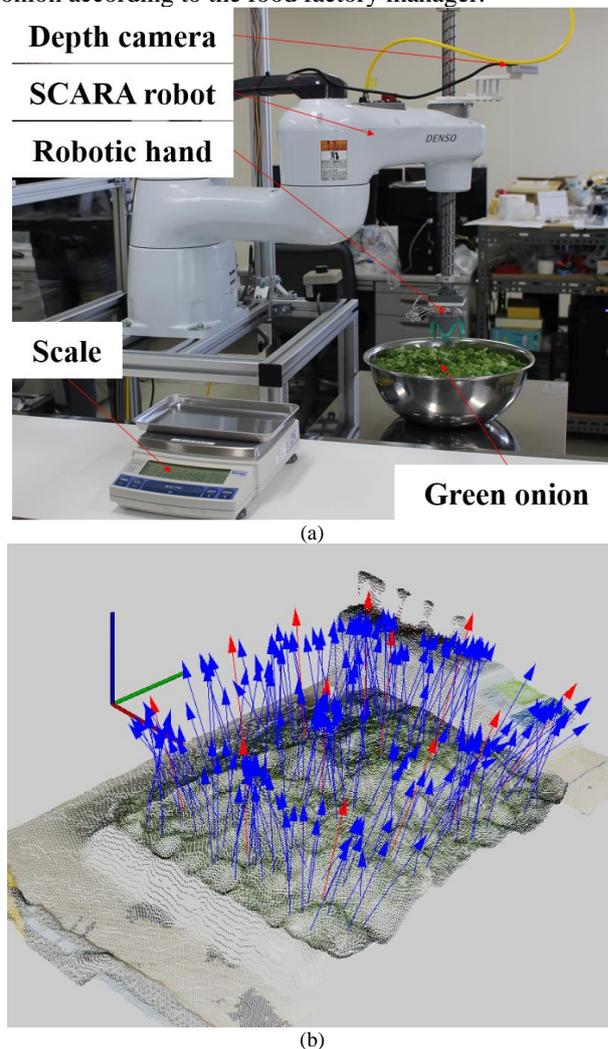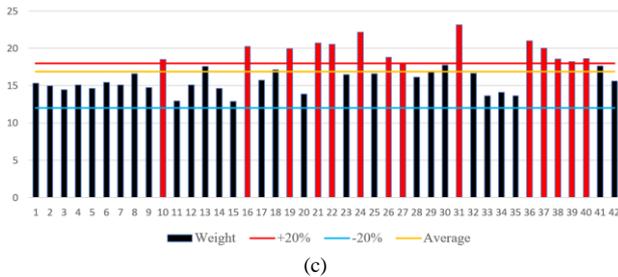
Figure 6. (a) The robotic system for automating green onion topping operation, (b) the recognition of the roughness of the chopped green onion in a container using the depth information, and (c) the weight comparison of grasped green onion.

V. DISCUSSIONS

The current system provides possibilities to use cloud computing to improve the system performances in food handling tasks. Useful data related to the physical contacts and environment conditions can be collected using the preMSM and then sent to a local edge server, at which edge computing can be conducted. After necessary edge computing, the corresponding data can be further transmitted to the cloud where high-level processing and machine learning can be performed. The resulted model or useful parameters can be then sent back to the local physical system for improving the system performances.

For the case of automatic tempura plating and presentation task, the tempura positions and orientations of the arrangement can be related to the desired presentation from experts and these relationships can be determined through cloud computing. For the case of green onion topping task, the relationships between the grasped onion mass and parameters of green onion condition, robotic gripper insertion depth, the environment humidity can be also learned through cloud computing. To do so, data from different food factories can be fused together at the cloud side to achieve better predictions at a macro scale.

Except for the two robotic system introduced in this article, we are also working on several other robotic system for automating dishwashing operation, packaging operation of agricultural products, and operations of handling seafood.

VI. CONCLUSION

This article presents a cyber physical system framework, a preliminary multi-sensor module (preMSM), and two robotic systems for improving the automation in food industry. The cyber physical system framework consists of a robotic system and a local network. The preMSM integrated with multiple low-cost sensors can collect useful data related with the physical tasks. The robotic system performs the actual physical tasks, particularly the food handling tasks in this work. The sensor data were then transmitted to a local edge server for edge computing, after which the processed data can be further sent to the cloud for performing cloud computing. Finally, guidance from the cloud side was feedback to the local physical system for improving the task performances.

Examples of a tempura plating and presentation system and a green onion topping system were detailed. Both systems showed promising potentials for applications in food industry to improve the productivity and save human laborer.

Future work includes the machine learning algorithms for tempura plating and presentation and green onion topping tasks. Cloud computing will also be investigated to finally close the cyber physical loop.

CONFLICT OF INTEREST

The authors declare that this study received funding from the Cabinet Office of Japan. The funder was not involved in the study design, collection, analysis, interpretation of data, the writing of this article or the decision to submit it for publication. Author S. Kawamura is a co-founder of the company Chitose Robotics Inc. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

All authors contributed to the conception and design of the study. SK proposed the idea of the cyber physical system for robotic system and supervised the research process for the robotic system of the tempura plating and presentation. MS constructed the local network and proposed and manufactured the multi-sensor module. ZW proposed and constructed the robotic system for green onion topping operation and wrote the draft of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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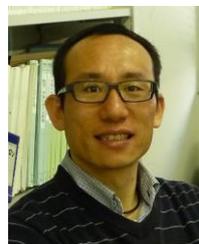
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