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RESEARCH ARTICLE

Construction of Motion Mode Switching System by Machine Learning for Peristaltic Mixing Conveyor Based on Intestinal Movement

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ABSTRACT The high frequency of rocket launches requires low-cost solid rocket fuel. Currently, the fuel manufacturing process faces increased launch costs caused by the risk of ignition from rotary mixers and increased equipment and labor costs from batch processes in which mixing and conveying are separated. Therefore, this paper proposes and verifies an automatic switching system between mixing and conveying modes for a peristaltic mixing conveyor that enables safe and continuous mixing and conveying of solid fuel. In a previous study, peristaltic mixing conveyor with low shear force was developed and successfully produced solid fuel. However, there was room for improvement for more efficient fuel production because the device was controlled by pre-determined driving pattern. The actual intestine generates movement autonomously by enteric nerves. Therefore, the development of a sensing function that imitates the enteric nervous system and generates movement patterns based on the acquired data is expected to improve manufacturing efficiency. In this study, the sensor data of a mixed solid fuel simulant packaged in a bag were acquired, and the degree of mixing (unmixed and mixed completely) was discriminated using supervised learning (the k-nearest neighbor method). Furthermore, a system was constructed to continue the mixing mode when unmixing and automatically switch the motion to the conveying mode when the mixing was complete. The experiment showed that the motion mode automatically switched to the conveying mode at almost the same time as the labeled training data, and mixing and conveying of the simulated material was successfully performed.

INDEX TERMS Solid fuel, soft robotics, robot sensing system, machine learning, predictive, data acquisition, product safety, mixing, conveying.

I. INTRODUCTION

This paper presents a fuel manufacturing process that facilitates a high frequency of rocket launches by cost-saving. Recently, there have been more demands for more frequent rocket launches to send numerous satellites into space. Solid fuel is expected to reduce launch costs because of its small size, inexpensive, and easy to handle characteristics [1], [2]. The fuel can also be further reduced in cost by improving the efficiency of the solid fuel manufacturing line. Solid fuel is manufactured by mixing and conveying a powder of metal and other materials with a viscous fluid. Generally, a rotary mixer is used for mixing solid fuel [3]. The automated manufacturing and mass production is difficult because mixing with a mixer generates frictional heat due to high shear force. After completing mixing, the fuel is conveyed by manual operation causing increased equipment and labor costs. Therefore, the developing a method of continuous manufacturing solid fuel with low shear force is expected to costs-saving of solid fuel.

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To realize the costs-saving of a fuel manufacturing low shear force, the authors focused on intestinal movements. The intestine is constructed of two different muscle layers, the longitudinal muscle, and the circular muscle [4]. The intestinal tract mixes and conveys food masses and digestive juices through repeated contraction and relaxation of these two muscle layers. Because the intestinal wall is flexible, mixing and conveying by the intestine is performed continuously and with low shear force [5]. In addition, the intestine has enteric nerves, which control intestinal movements by mechanical and chemical stimuli from the contents, independent of commands from the brain. By controlling muscle movements this way, the intestine autonomously determines the movements for mixing (segmental movements) and conveying (peristaltic movements) the food mass and digestive juices. The development of a device and control system that can reproduce the motion of the intestine's small force of mixing and conveying is expected to realize a safe and continuous manufacturing method. Furthermore, the introduction of the intestinal movement generation mechanism into the device automates a series of processes from mixing to conveying, which is expected to improve the manufacturing efficiency.

In this study, we aim to develop a device that imitates the intestinal tract and a system that autonomously determines the mixing or conveying motion and switches the motion, like an enteric nervous system, to realize a safe and efficient solid fuel manufacturing method. Specifically, we develop a device that can reproduce the segmental and peristaltic movements of the intestinal tract. The device has a sensing function and uses a machine learning model built based on data acquired from the sensors to determine the degree of mixing of solid fuel. The construction of a system that switches to a segmental movement for mixing if unmixed, and to a peristaltic movement for conveying if the mixing is complete. The realization of this system is expected to establish an efficient manufacturing method for solid fuel and to lower the cost of solid rocket launches.

Therefore, we developed a peristaltic mixing conveyor based on the intestine's mixing and conveying function as shown in Fig. 1. This device uses pneumatically driven rubber artificial muscles to imitate the muscular layers of the intestines [6], [7]. When the device is supplied with air pressure, the inside rubber tube is occluded, and the contents of the device produce a squeezed flow. The device is constructed as a unit, and multiple units can be connected and driven independently to reproduce peristalsis and segmental movements of the intestine. Solid fuel was successfully produced using this device [8], [9]. In addition, the device was able to mix the materials even when the materials were packed in bags and input into the device [10]. This has the practical advantages of enabling mixing under quantitatively controlled conditions, ensuring stable physical properties, and facilitating maintenance. Since all these studies were based on sequence control using experimentally determined drive patterns, there was room for improvement toward more efficient fuel manufacturing. On the other hand, to reproduce a control system that autonomously determines the appropriate motion for the contents, such as an enteric nervous system, it is necessary to develop a system that detects the mixing state of the contents based on information obtained from the sensors mounted on the device and automatically generates a driving pattern according to that state. Therefore, we partially developed a sensing function [11] and system with a distributed arrangement like that of the intestinal tract. The two issues of estimating the mixing state of the contents [12], [13] and automatic switching of the drive pattern according to the state of the contents [14] were verified, respectively. For the estimation of the mixing state, machine learning was used to successfully estimate the mixing state of powder and liquid in the device [12], [13]. In addition, the state of mixing of fuel simulants packed in bags has been successfully estimated [15]. Both studies were able to estimate mixing completion at some level under certain conditions. In a study on switching the drive pattern [14], a rigid rod was detected based on sensor data mounted on the device, and the movement was successfully switched from random drive to peristaltic movement. Currently, a system that simultaneously estimates the mixing state and switches driving patterns for highly fluid contents has not yet been developed.

In this paper, we construct and verify a system that automatically switches the motion mode of a peristaltic mixing conveyor after the contents have been mixed. Specifically, the following is a list of the following.

1) The device mixes the solid fuel simulant, which is a highly fluid content. For practical use, the contents of the device should be packaged in bags, so this paper focuses on bagged simulants.
2) Determine whether the mixture is unmixed or completed using machine learning based on sensor data acquired during mixing.
3) If the discrimination result is unmixed, the mixing mode is continued, and if the mixing is complete, the motion is automatically switched to the conveying mode.

In a previous study, switching of the motion mode was verified by detecting the presence or absence of a rigid rod, but this is the first verification of switching of the motion mode from a mixing determination for a fluid content. Previous studies have already shown that a mixed decision is possible in certain environments. Since the purpose of this paper is to validate the entire system, a simple machine learning model that can make decisions with high accuracy only in the current environment was constructed, as in the previous study.

The contributions of this paper are as follows.

- Regarding intestinal motion, which performs an appropriate action according to the state of the contents, we constructed a system that automatically switches the motion mode when the solid fuel simulant is mixed.

TABLE 1. Comparative table of devices capable of reproducing the peristaltic movement of a living body.

Name	Development Purpose	Summary	Comparison with Peristaltic Mixing Conveyor
Tube pumps[17]	Medical Infusion Pumps Conveying small volumes of fluids, such as for hemodialysis devices Etc…	Two rollers periodically press against the tube to generate peristaltic waves within the tube, enabling liquid conveyance. Already used in various medical devices	・Difficult to convey over long distances because of the rotary mechanism ・Difficult to mix because of the purpose of conveyance ・Difficult to measure the internal condition of the tube ・Sequence control
Biomimetic swallowing device[18][19]	Reproduction of fluid conveyance during esophageal swallowing in humans	Created by stacking 12 pneumatically driven actuators that close the esophagus, this device is equipped with a sensor that generates continuous peristaltic movement and enables measurement of pressure and shear forces during peristaltic movement of the esophagus.	・Not intended for industrial use ・Conveying is possible, but mixing is uncertain. ・Sequence control
Pump capable of bending motion using a balloon[20]	Conveying liquids and other materials in confined spaces with obstructions, such as operating rooms and medical facilities	This peristaltic pump utilizes ballooning, and its simple design can reproduce peristaltic motion with only one control signal. The device itself can be bent to save space for conveyance.	・Difficult to use in industrial applications due to its small size ・No sensing function, making it difficult to estimate the state of the device's contents ・Conveying is possible, but mixing is not. ・Sequence control
Peristaltic Mixing Conveyor[7]	Solid propellant manufacturing	Independently pneumatically driven devices can be connected for mixing and conveying Each unit is equipped with a sensor to estimate the condition of the contents in the device.	

This paper is organized as follows: Chapter 2 describes related research, Chapter 3 outlines the peristaltic mixing conveyor for solid fuel production, and Chapter 4 describes the selection of a suitable machine learning model for the estimation of the mixing degree of bagged solid fuel. In Chapter 5, we describe the operational experiments using the device and system for switching from the mixing mode to the conveying mode using the training model we created.

II. RELATE WORKS

A. PERISTALTIC PUMP

Several devices have been developed to reproduce the peristaltic motion of living organisms, such as intestine, esophagus, etc. [16]. Table 1 lists the purpose of developing the peristaltic pump, a summary, and a comparison with the regarding the function in hardware and software of the peristaltic mixing conveyor proposed in this paper. Table 1 compares three devices to peristaltic mixing conveyor devices: a tube pump that uses two rollers to generate peristaltic waves [17], a swallowing device that imitates the digestive tract of a living body [18], [19], and a pump using ballooning [20]. These compared devices are not intended for industrial use, such as the production of solid fuel. In addition, the device is primarily intended for fluid conveyance. The performance of mixing the fuel is not described. Other devices that can reproduce peristaltic motion include a linear pump using magnetic fluid [21] and a device with a rotating helix drive mechanism [22]. Pneumatic pumps also include flexible pumps made of silicon [23], [24] and micropumps [25] that are mounted in microfluidic modules. Furthermore, we developed a peristaltic pump (Fig. 1) that simulates the muscular layer of the intestinal tract using pneumatic artificial muscles made of rubber material [6], [7]. This device is intended for industrial applications such as the manufacture of solid fuel and is capable of mixing and conveying the contents in one device. Therefore, this paper focuses on peristaltic mixing conveyor.

However, all these devices that reproduce the peristaltic movement of the digestive tract are sequence-controlled, in which a predetermined driving pattern is input to the device to generate the movement while the actual digestive tract is driven autonomously by a neural network as shown in the next section.

B. THE SYSTEM AND SIMULATION BY ENTERIC NERVES

The intestinal tract, also known as the "second brain," has a nervous system (enteric nervous system) that constructs the reflex arches without involving the reflex centers [26]. Therefore, intestinal muscular movements are controlled independently of brain commands by mechanical and chemical stimuli from the contents. In addition, simplifying the intestinal mechanism, the intestinal tract can be thought of as a unit separated by a certain length [27]. The complexly constructed nervous system determines not only the movement

of the stimulated unit but also the movement of muscles in neighboring units as the stimulus propagates. By controlling muscle movements in this way, the intestine autonomously determines the movements for mixing (segmental movements) and conveying (peristaltic movements) the food mass and digestive juices. Simulations include intestinal models using neural circuit models such as motoneurons [28], [29] and two-dimensional intestinal models using neural oscillators [30]. These models show that, assuming that the intestine is divided into units, when one unit is stimulated, peristalsis and other movements can be reproduced by the coordination between neighboring units. In general, it is difficult to control a soft robot such as this device delicately because of the complex behavior of hyperelastic materials, such as nonlinearities, large strains, and deformations. However, applying high-precision sensing and control to a soft robot and allowing it to operate autonomously will eventually allow the robot itself to acquire autonomous behavior under various environments and for various tasks [31], [32].

Based on the above, the development of a control system that autonomously generates mixed conveyance motion in response to stimuli, as in the case of the intestinal tract, is possible for this device.

C. OUR APPROACH

In our previous study, we aimed to develop a system to control a peristaltic mixing conveyor by sensing stimuli caused by changes in the contents of the device, like the enteric nervous system. In this paper, we developed a sensing function using a distributed arrangement like that of an intestinal tube [11] and verified two issues: estimation of the mixing state of contents [12], [13] and automatic switching of driving patterns according to the state of contents [14], respectively. For the estimation of the mixing state, logistic regression was used to successfully estimate the mixing state of the powder and liquid in the device [12], [13]. In addition, GMM has been successfully used to estimate the mixing state of bagged fuel simulant [15]. Both studies were able to estimate mixing completion at some level under certain conditions. In a study on switching the drive pattern [14], the volume of the rigid rod in the unit was detected from the air flow sensor data mounted on the device, and the operation was successfully switched from random drive to peristaltic movement. However, this method makes it difficult to detect fluid contents and the conveyance of fluid contents has not yet been investigated. Currently, a system that can estimate the mixing state and switch the drive pattern accordingly has not yet been developed. The construction of an autonomous decentralized system that simulates the enteric nervous system has not yet been achieved. The introduction of such a control system into this device will automate a series of processes from mixing to conveying and is expected to improve the efficiency of solid fuel production, which is the objective of this research.

In this paper, we aim to construct a system that automatically switches the motion mode of a peristaltic mixing conveyor after the contents have been mixed, based on our previous research. The system acquires pressure and flow sensor data during the mixing of solid fuel simulants and determines the degree of mixing by machine learning. If the discrimination result is not yet mixed, the system continues in the mixing mode, and if the mixing is complete, the system automatically switches the motion to the conveying mode.

III. PERISTALTIC MIXING CONVEYOR FOR THE PRODUCTION OF SOLID FUEL

A. SOLID FUEL

Solid fuel is manufactured by mixing and conveying oxidizers, metallic fuels, binders, plasticizers, and hardeners. Existing solid fuel production methods are batch processes in which mixing and conveying are separate. Mixing uses a planetary mixer that rotates metal blades inside a metal container to mix the materials [3]. After that, the mixed fuel is conveyed to the rocket and cast by hand. The mixing and conveyance of the product are the two main issues. Mixing with a mixer involves the risk of ignition due to high shear forces, and it is difficult to mix a large amount of fuel at the same time. In addition, manual conveyance involves thorough safety control, equipment costs, and labor costs in the manufacture of solid fuel. Therefore, the rocket launch costs increase and the launch frequency decreases.

Related studies [33], [34] have attempted to reduce the cost of continuous production of solid fuel. However, the risk of combustion cannot be eliminated because the mixing and conveying paths are composed of metals. We focused on a mixing and conveying method for the intestinal tract that mixes and conveys food mass and digestive juice with a low shear force.

B. OVERVIEW OF PERISTALTIC MIXING CONVEYOR

The muscular layer of the intestinal tract is constructed from the circular and longitudinal muscles. Circular muscles are arranged in an annular pattern in the intestinal tract, whereas longitudinal muscles are arranged axially. Each muscle layer contracts and relaxes to generate peristalsis and convey food masses. Fig. 1 (a) shows the overall view of the device that was developed to simulate the intestinal structure. The device consists of units, and a single unit is shown in Fig. 1 (b). As shown in Fig. 1 (c), The device consists of an outer axial fiber-reinforced artificial muscle (hereinafter referred to as "artificial muscle") and an inner rubber tube. The material to be mixed and conveyed is input into the rubber tube. When compressed air is applied to the chamber between the outer artificial muscle and the inner rubber tube, the device is axially contracted by the outer artificial muscle and the inner rubber tube is occluded as shown in Figure 2. The contents inside the device move between the neighbor units because of the squeezing flow caused by the closure of the rubber tubing.

This device is constructed as a unit and reproduces the movement of the intestine by selecting the unit to which air

is applied by turning the solenoid valve attached to each unit on or off.

Segmental motion, which is the motion of the intestine during mixing, can be reproduced by switching the units to which air is alternately applied, as shown in Fig. 3(a). Peristaltic motion, which is the movement of the intestine during conveyance, can be reproduced by applying air to each of the two units sequentially in the direction of the desired conveyance, as shown in Fig. 3(b). The flange of the device has a curved flow channel, and it is possible to control temperature inside the flange by flowing warm water to heat the flange. Each unit was equipped with two types of sensors (pressure and flow sensors). The pressure sensor measures the pressure in the chamber, and the flow sensor measures the air flow rate applied to the device.

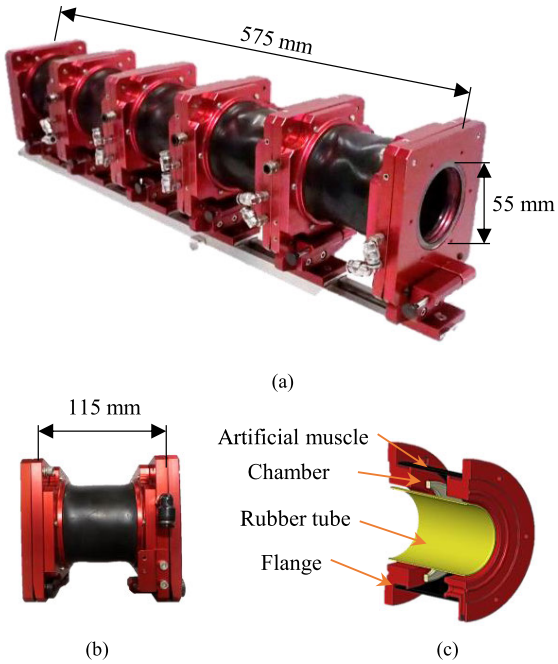

FIGURE 1. (a) Overall view of the peristaltic mixing conveyor, (b) single unit, (c) cross-section of the single unit.

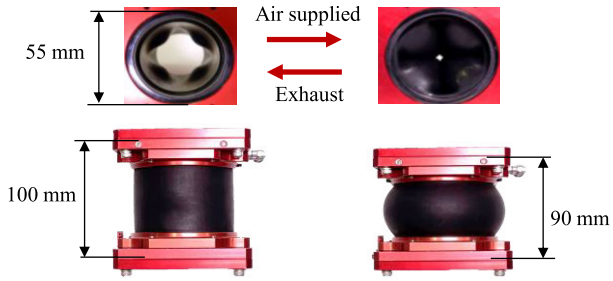

FIGURE 2. Motion when air is supplied to a single unit.

Using these sensors, the volume and viscosity of the device can be detected [28]. Moreover, machine learning models constructed from sensor data can be used to determine the mixing state of device content [29], [30]. A system was also constructed to switch motion to peristaltic motion by detecting a rigid rod input into the device [31].

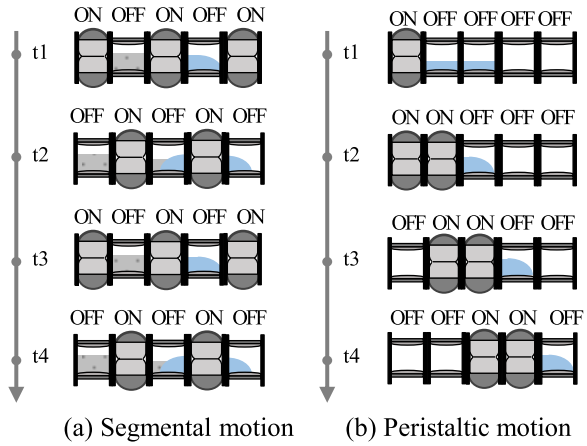

FIGURE 3. Segmental and peristaltic motion of a device coupled to 5 units.

C. AUTONOMOUS DECENTRALIZED SYSTEM SIMULATING ENTERIC INNERVATION

In the manufacture of solid fuel, it is important to efficiently maintain stable physical properties of the fuel because the degree of fuel mixing affects the combustion speed. The realization of a method that enables continuous mixing and conveying will enable the construction of a safe and low-cost fuel manufacturing system. In contrast, in the intestinal tract with enteric innervation, appropriate movement patterns are generated according to the state of the contents. The degree of mixing of the fuel inside the peristaltic mixing conveyor was estimated by machine learning constructed from sensor data, referring to the intestinal tract system, and the switching between the mixing and conveying modes of motion was automated. In addition, an autonomous decentralized system is constructed to convey the contents of the device when they are inside the device.

The procedure for switching from mixing to conveying mode is described below. A flowchart of this process is shown in Fig. 4. While the device is in operation, pressure and flow sensor data are constantly acquired and motion patterns are generated.

1) Start mixing bagged materials (powder + high viscosity fluid) input into the device tube.
2) Discriminate the degree of mixing by machine learning using pressure and flow sensor data.
3) While the estimated mixing degree is unmixed, the mixing mode (segmental motion, Fig. 3 (a)) continues. When the mixing is completed, the motion is switched to the conveying mode (peristaltic motion, Fig. 3 (b)), and conveying starts.
4) In the conveying mode, if a unit detects the content, the peristaltic motion continues.
5) After completion of content conveyance, switch to the mixing mode and prepare for a new degree of mixing discrimination.

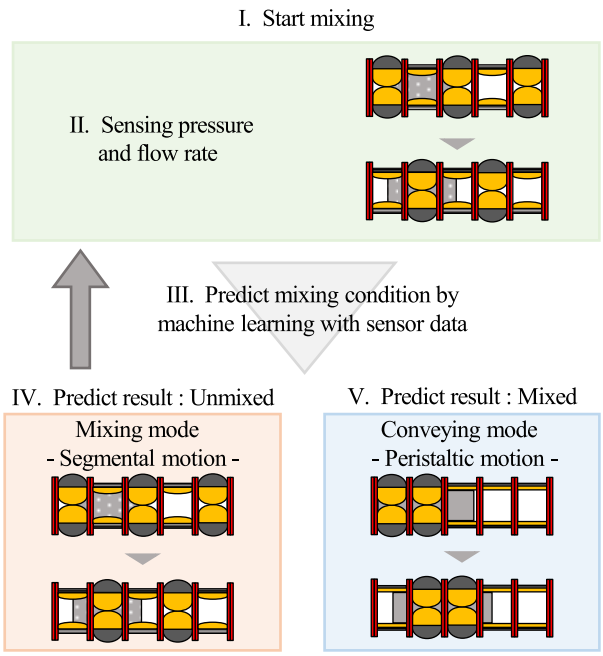

FIGURE 4. **Automatic switching system of motion mode according to contents condition. While the mixing prediction is unmixed, the mixing mode (segmental motion) is continued, and when the mixing is completed, the motion is switched to conveying mode (peristaltic motion).**

In this study, the first step was to construct a system that automatically switched exercise modes (steps 1-3).

IV. MIXTURE DISCRIMINATION BY SUPERVISED LEARNING

Pressure and flow sensors were installed in each unit of the device, and mixing experiments were conducted with powders and highly viscous fluids, which were bagged solid fuel simulants. Furthermore, a machine learning model is required to estimate mixing was constructed from the acquired sensor values and evaluated, and a learning model was selected for use in the mixing and conveying switching system. Previous studies [12], [13], [15] have shown that mixing degree discrimination is possible in certain environments. Therefore, in the next phase, a simple machine learning model that enables highly accurate mixture discrimination in this environment was applied to the device in the same way as in the previous study to construct a motion-switching system.

A. OUTLINE OF EXPERIMENT

The purpose of this experiment was to verify the change in the state of the simulant during the mixing process and its mixing completion time to label the unmixed and mixed states of the simulant for use in supervised machine learning. The experimental setup is shown in Fig. 5. There are connected five unit of peristaltic mixing conveyor in the experimental environment. There are two types (pressure and flow sensors) of 15 sensors in the experimental environment. The pressure sensors (SMC ZSE30AF-C6H-C-M) measure air pressure in the chamber of the unit. The flow sensors (SMC PFM750-C6-C) measures flow rate for air supply and exhaust air on the device. Three sensors are mounted on each unit. Supply air to the device is supplied from the compressor via the regulator and the solenoid valve (SMC VDW20JA) on the air supply side. Exhaust from the device is discharged into the atmosphere by opening the solenoid valve on the exhaust side. The device is driven by a microcontroller (Arduino MEGA 2560) that switches the air supply and exhaust every 2 s (4 s from air supply to exhaust is called one cycle). The pressure is set at 60 kPa by the regulator and the sampling frequency is 20 Hz. As in previous studies [29], [30], the device was driven by a segmented motion that alternately switched the units to which air was applied every 2 s. The device consisted of several powder components and a liquid component consisting of a premixed metal powder and a highly viscous fluid. They were used as simulant for solid fuel and were based on recipes in a previous study [19] (hereafter referred to as simulant). The materials were sealed in polyethylene bags (90mm × 300 mm, 0.08 mm thick)

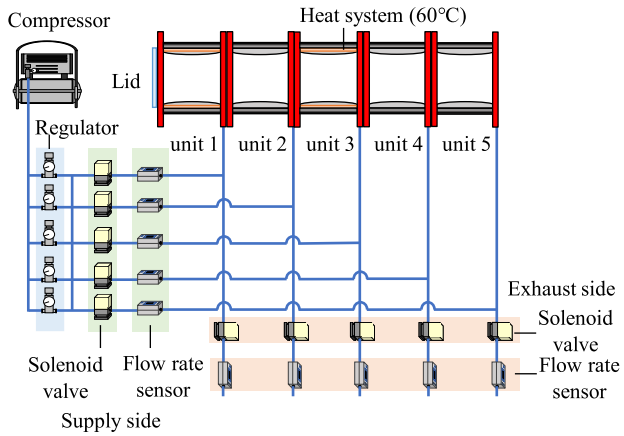

FIGURE 5. **Experimental environment. All sensors and valves are connected to Arduino Mega 2560.**

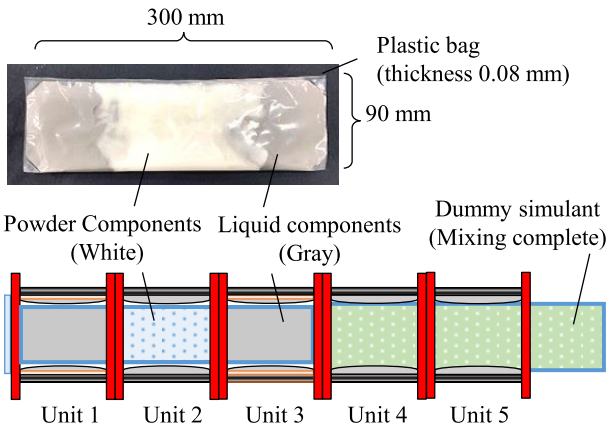

FIGURE 6. **Upper side: Packaged solid fuel in a plastic bag. The total amount of material is 270g, Under side: Sample input method for the solid propulsion simulant mixing experiment.**

large enough to be mixed by the three units of the device for the experiment. The total weight was 270 g, which is 90% of the maximum amount packed in bags and input into the device. Although it is possible to mix and convey the maximum amount of material, this is difficult because the simulant clogs up in the device during conveying. The actual bagged simulated material is shown in the upper part of Fig. 6.

As shown in Fig. 6, unmixed simulated materials packed in three unit-sized bags were input into Units 1–3, and the mixing process was acquired from the sensor data. Dummy simulant was placed in units 4 and 5 in the same volume, in a completely mixed state, and packaged in bags with a size of three units. These bags were connected to bags of the simulated material in units 1-3. The dummy simulant in Units 4-5 was installed to convey the simulated material, and mixing experiments were conducted only in Units 1-3, which were inputted with unmixed simulant. If there are no dummy simulant in units 4–5, the simulant is not conveyed from units 3 to 4, and the simulant in unit 1 are conveyed in the bag, causing the simulant to accumulate in unit 2 and risking bag breakage. The dummy simulant could be connected to a pull. The completed mixed sample from unit 3 to unit 4 for smooth conveyance.

To promote mixing, a heating system was installed in units 1 and 3, where the liquid component was present, and 60 °C hot water was run through the flange so that the temperature in the device tube was warmed to around 55 °C.

B. RESULTS OF THE EXPERIMENT

Fig. 7 shows the simulated material photographed every 5 min from the start of mixing to 20 min later. At 0 min before mixing, the grey liquid and white powder components were completely separated. After 5 min of mixing, the liquid began to penetrate the powder, and a white powder was observed at the center. After 10 min of mixing, the liquid almost completely penetrated the powder. The center of the product is slightly uneven (light gray), and the human touch confirms the feeling that there is slightly more powder at the center than at the edges. After 15 min, the mixture was almost complete, although a very slight powder unevenness was observed at the lower edge of the center. After 20 min, the mixture was determined to be complete because there was no uneven texture. Based on the above, mixing was defined as unmixed for 15 min or less from the start of mixing and as complete for 20 min or more.

C. ACQUISITION OF TRAINING DATA IN MACHINE LEARNING

The experimental environment was the same as that described in Section A. Based on the results described above, the mixing data from the start of mixing to 10 min were considered unmixed, and the mixing data of the simulated material after mixing for 1 h were considered mixed. From the data obtained with reference to previous studies [32], the pressure value was

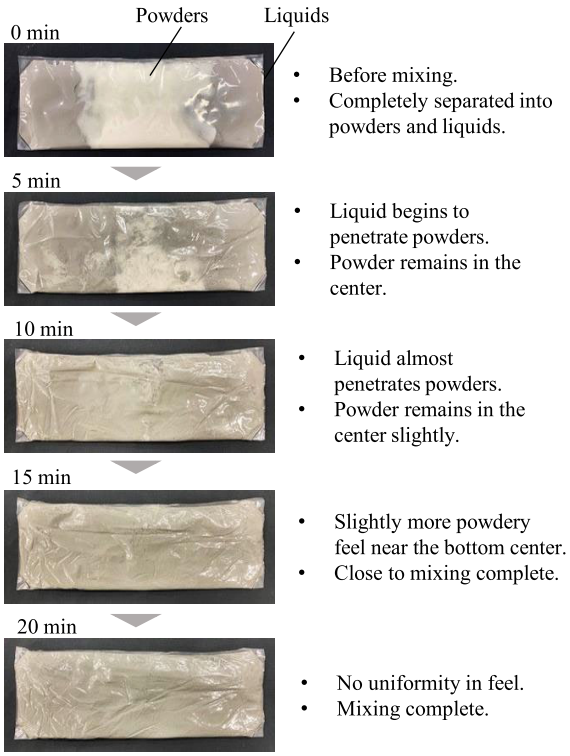

FIGURE 7. The mixing process of simulant from before mixing to the mixing complete.

calculated at 0.05 s from the start of the air supply for each cycle, and the flow rate was calculated as the integrated flow rate for 2 s of air supply and 2 s of exhaust air, respectively. Data were prepared for 1510 pressure values, and integrated supply and exhaust flow values for unmixed and completed mixing (two conditions × three variables × 1510 values). Of the total data, 80% were divided into training data (used to build the learning model) and 20% into test data (used to evaluate the model).

D. CONSIDERATION OF THE BEST MACHINE LEARNING ALGORITHM FOR MIXING DEGREE DISCRIMINATION

The objective of machine learning in this study was to clearly distinguish between the unmixed and mixed contents of a device to construct an automatic switching system for the motion mode. Thus, two classifications were established: unmixed and mixed. To improve the accuracy of mixture discrimination, we compared the discrimination accuracies of 7 popular 2-class classification methods in supervised learning. The models in the Python Scikit-learn library were used for machine learning. This method is described as follows:

- Logistic Regression: Probability prediction between zero and one using a nonlinear sigmoid function.
- Support Vector Machines (SVM): classification by linear discriminant function
- AdaBoost generates more accurate models by repeatedly training them on the same data.

- Random Forest: Multiple decision trees are used to make predictions by majority vote.
- k-nearest neighbors (k-NN): estimates the class to which the data belongs by the majority vote of k training data close to the unknown data.
- Decision Tree: Classification by repeated conditional branching using a tree structure.
- Naive Bayes makes predictions based on the probability of the category to which the data belong.

For each method, a model was constructed using the training data (80% of all the data) described in Section C. of this chapter, and the correct response rate for each method was calculated using the test data (20% of all the data). Table 2 presents the results for each unit. For each unit, the results showing the top three correct responses for the seven methods are colored. Table 2 shows that k-NN has the highest correct response rate among the seven methods for all units. Based on the above, k-NN, which was expected to discriminate the degree of mixing with the highest accuracy, was adopted for mixing discrimination. Mixing degree discrimination was performed for k-NN, which was adopted as the mixing degree discrimination model. The results are presented in Fig. 8. The upper row of Fig. 8 shows a plot of the original data, and the lower row shows the discriminant prediction of the test data. From (a) to (c) in Fig. 8, for all units, although the red unmixed data are slightly misclassified as blue mixed data near the border between the unmixed and mixed data, the trend of the plots for the original and discriminated data and the results were almost the same. Therefore, as shown in Table 2, the test data exhibited a high percentage of correct responses, and the trend of the predictions of the test data was almost the same as that of the original data, indicating that k-NN can discriminate mixtures with a high degree of accuracy.

V. MIXED CONVEYING EXPERIMENT WITH MOTION MODE SWITCHING SYSTEM

A. PROPOSAL AND OVERVIEW OF SWITCHING METHOD TO CONVEYING MODE

In Chapter 3, it was shown that k-NN could discriminate the degree of mixing for Units 1 to 3 with more than 95% correct answers. However, there is a tendency for unmixed data to be misclassified as completely mixed data. The actual simulated material from the start of mixing to 10 min can be visually confirmed to have unmixed powder components; however, it is also close to the clay-like texture of the complete mix

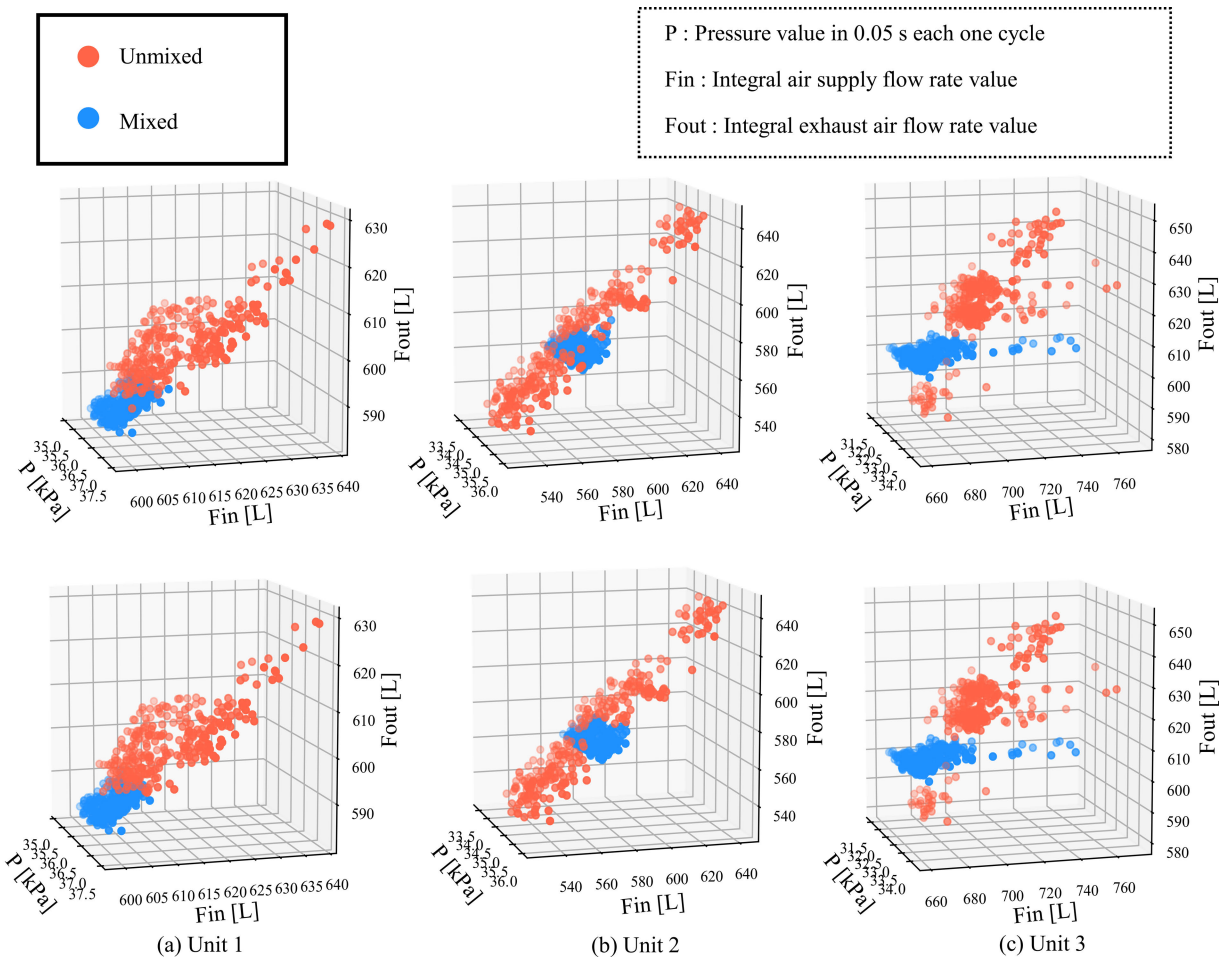

FIGURE 8. Prediction results from k-NN Upper row: Acquired data Lower row: Predicted values by model.

TABLE 2. Comparison of the accuracy rate to test data in each unit when two or three variables are used and colored for the top results in each unit.

	Unit 1	Unit 2	Unit 3
Logistic Regression	0.828	0.728	0.904
SVM	0.881	0.573	0.907
AdaBoost	0.955	0.965	1.00
Random Forest	0.954	0.965	0.997
Nearest Neighbors	0.950	0.969	0.998
Decision Tree	0.944	0.969	1.00
Naive Bayes	0.934	0.929	0.960
k-NN	0.950	0.969	0.998

to the human touch. It is difficult to acquire this difference in texture from sensor data.

Accordingly, we propose a system that switches to the conveying mode only when all units 1–3 are determined to be completely mixed. This method prevents misclassification more effectively than discrimination using a single unit. As previously noted, the degree of mixing of the solid fuel affects the combustion speed. If the material is conveyed without mixing, it will be difficult to maintain stable physical properties; therefore, it must be conveyed when mixing is completed. Consequently, the proposed method was adopted.

As shown in Fig. 9, a microcontroller (Arduino MEGA 2560) acquired the sensor data and switched the motion mode, and a PC (Python) determined the mixing degree and motion mode. The system continues in the mixing mode (segmental motion) if the mixture is unmixed, and switches to the conveying mode (peristaltic motion) when the mixing is complete. After the mixing starts, the motion mode is automatically switched when the mixture changes from unmixed to mixed by discriminating the degree of mixing using machine learning. The model (k-NN) constructed in Section III was used for machine learning. The procedure for the motion-mode switching system is as follows.

1) After the device's contents are input, communication between the microcontroller and the PC is initiated.
2) The PC sends the first motion mode (mixing mode) to the microcontroller.
3) The microcomputer starts driving the device in the mixing mode received from the PC.
4) Sensor data were acquired at a sampling frequency of 20 Hz using a microcomputer, and the data were transmitted to a PC.
5) After acquiring one data cycle (80 data points for 4 s), a machine-learning model (k-NN) was used to determine the degree of mixing.
6) If Units 1–3 are not mixed, send the mixing mode to the microcontroller and repeat Step (4).
7) When all units 1–3 have completed mixing, the conveying mode is sent to the microcontroller, and communication between the microcontroller and PC is terminated.

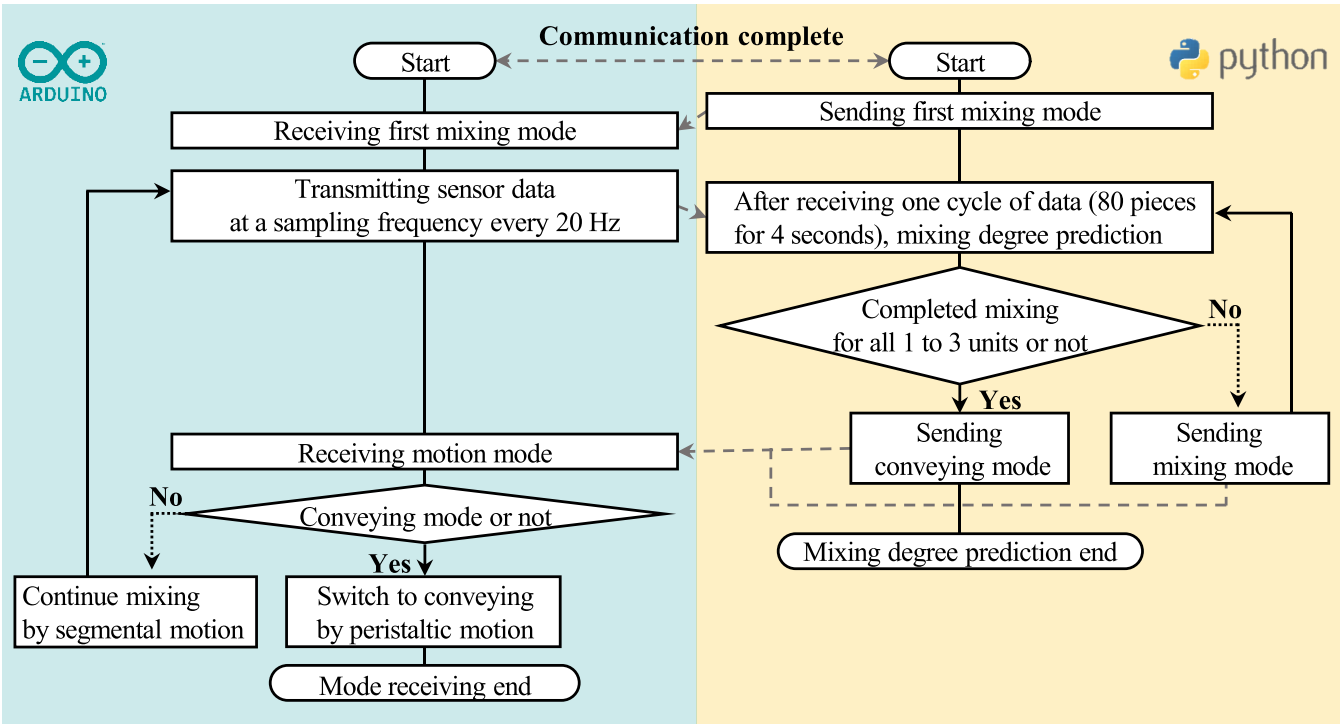

FIGURE 9. Automatic motion mode switching system communication flow between microcontroller (Arduino MEGA 2560) and PC (Python).

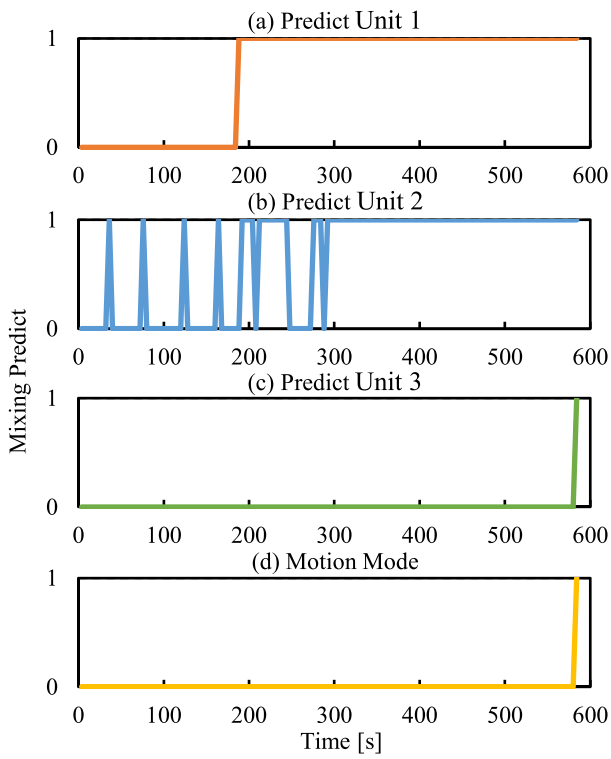

FIGURE 10. Time-series results of mixing predict. Mixing predicts (unmixed: 0, mixed: 1) and motion mode (mixing: 0, conveying: 1) for each unit.

8) The peristaltic motion of the device continued until the microcomputer completely conveyed the content.

B. OVERVIEW OF MIXING AND CONVEYING EXPERIMENTS

The experimental environment was the same as that used in the mixing experiment (Fig. 5) described in Section III. During mixing, the material is mixed via segmental motion, and during conveying, the mixed simulant is conveyed via peristaltic motion. In both exercises, the unit to which air was applied was switched every 2 s. The experiments were started with the same initial conditions as in Chapter 3 (unmixed in Units 1-3 and mixed simulant in Units 4-5), and the system described in the previous section was used to verify whether the motion mode automatically switched when the simulant changed from unmixed to mixed.

C. RESULTS OF THE EXPERIMENT

1) MIXING AND CONVEYING TIME

A mixing and conveyance experiment was conducted using the constructed system. The results of the time-series prediction of the mixing degree discrimination are shown in Fig. 10. Fig. 10 (a)–(c) show the mixing degree discrimination (unmixed:0, mixed:1) and (d) the motion mode (mixed:0, conveyed:1) for each unit. The actual device is shown in Fig. 11. The device after receiving the first mixing mode (mixing start of approximately 4 s) is shown in Fig. 11 (a) and (b). From this 4-second data, the degree

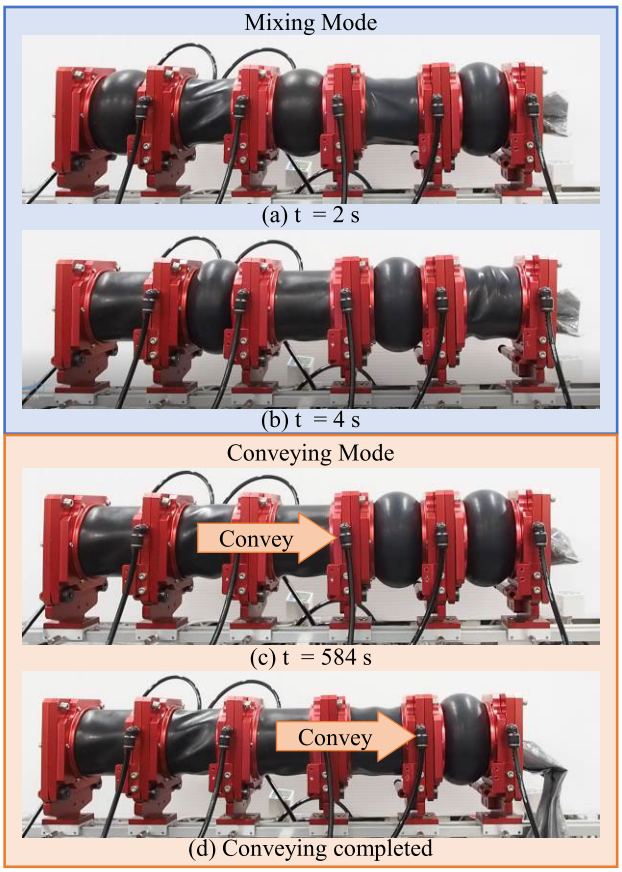

FIGURE 11. Switching of the motion mode of the peristaltic mixing conveyor.

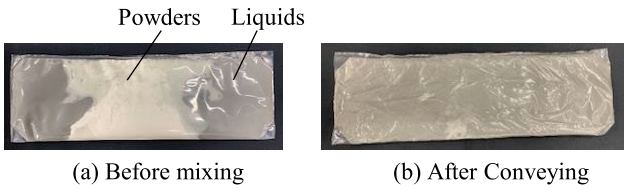

FIGURE 12. Simulant before mixing and after conveying in the switching experiment.

of mixing was calculated for every cycle, and the segmental motion was conducted similarly. Four seconds after that shown in Fig. 10, the motion automatically switched from the mixing mode to the conveying mode at 9 min 40 s (580 s) from the start of mixing. Fig. 11 (c) shows the device immediately after the motion was switched to conveyor mode. Approximately 20 min after the start of conveying, the simulant mixed in units of 1–3 was conveyed (Fig. 11 (d)). Fig. 12 shows the simulated materials before and after the experiment. As mentioned above, mixing in the three units was completed within 15–20 minutes. As a result of the experiment, conveying occurred earlier than mixing, and as shown in Fig. 12(b), a small amount of unmixed powder was observed near the center of the bag. Although the mixing was not complete, the mixed simulant had almost

no texture unevenness, except at the center, and was difficult to distinguish even by human texture. The unmixed state was defined as the start of mixing at less than 10 min, and the model was constructed to discriminate the degree of mixing, which switched to the conveying mode at approximately the same time. Thus, we succeeded in constructing a system that automatically switched motion modes.

The simulated material in Unit 1 moved to Unit 5 in about 20 minutes (1200 seconds) after the start of the conveying mode, and the conveying of the simulated material was completed. The conveyor speed was 0.38 mm/sec. Although the device was confirmed to convey the fuel from this verification, the conveyance speed is slow for efficient solid fuel mixing and conveying, and there is still room for improvement in the current conveyance speed.

2) DISCRIMINATION OF THE DEGREE OF MIXING OF EACH UNIT

As shown in Fig. 10, the motion switched to conveying mode at 9 min and 40 s from the start of mixing. As described in Section A of this chapter, the system switches to the conveying mode when all units 1 to 3 are completely mixed. Fig. 10 shows that mixing was never determined to be complete for Unit 3 during the 580 s from the start of mixing. However, Unit 1 was discriminated as mixed complete once, and Unit 2 was discriminated as mixed complete several times. The plot of the training data and trajectory of the experimental data (green) in each unit from 4 s after the start of mixing to the switching of the motion mode (9 min and 40 s) are shown in Fig. 13. Fig. 13 shows the start of the mixing degree calculation (t = 4 s, Fig. 11 (b)) and the mixing completion point (t = 580 s, 2 s before Fig. 11 (c)), which are marked with yellow stars. Fig. 13 (a) show that, for Unit 1, much of the experimental data differed from the training data. From Fig. 13 (b), the green trajectory repeatedly approaches the blue mixing completion for unit 2, which is repeatedly discriminated against as complete mixing during the mixing mode. However, Fig. 13 (c) shows that for Unit 3, which has never been discriminated as mixing complete, the green trajectory passes through the red unmixed data and approaches the blue mixing complete trajectory at the mixing complete point. Fig. 13 shows that the trends of the trajectories of the experimental data and plots of the training data roughly correspond for both units.

Fig. 13 shows that in unit 3, the experimental data closely follow the trend of the training data, whereas in units 1 and 2, the experimental data trace the area where the training data do not exist. It can be predicted that there is a lack of data regarding the construction of the learning model used in this system. In addition, in supervised learning, the more data used in the model, the greater is the number of correct answers, and thus, the better is the accuracy. From the above, it is necessary to increase the training data to improve the accuracy of mixture discrimination.

D. CHALLENGES AND FUTURE WORKS OF THE CONSTRUCTED SYSTEM

The degree of mixing of the flowing solid fuel simulant was estimated from Section C of this chapter, and the switching

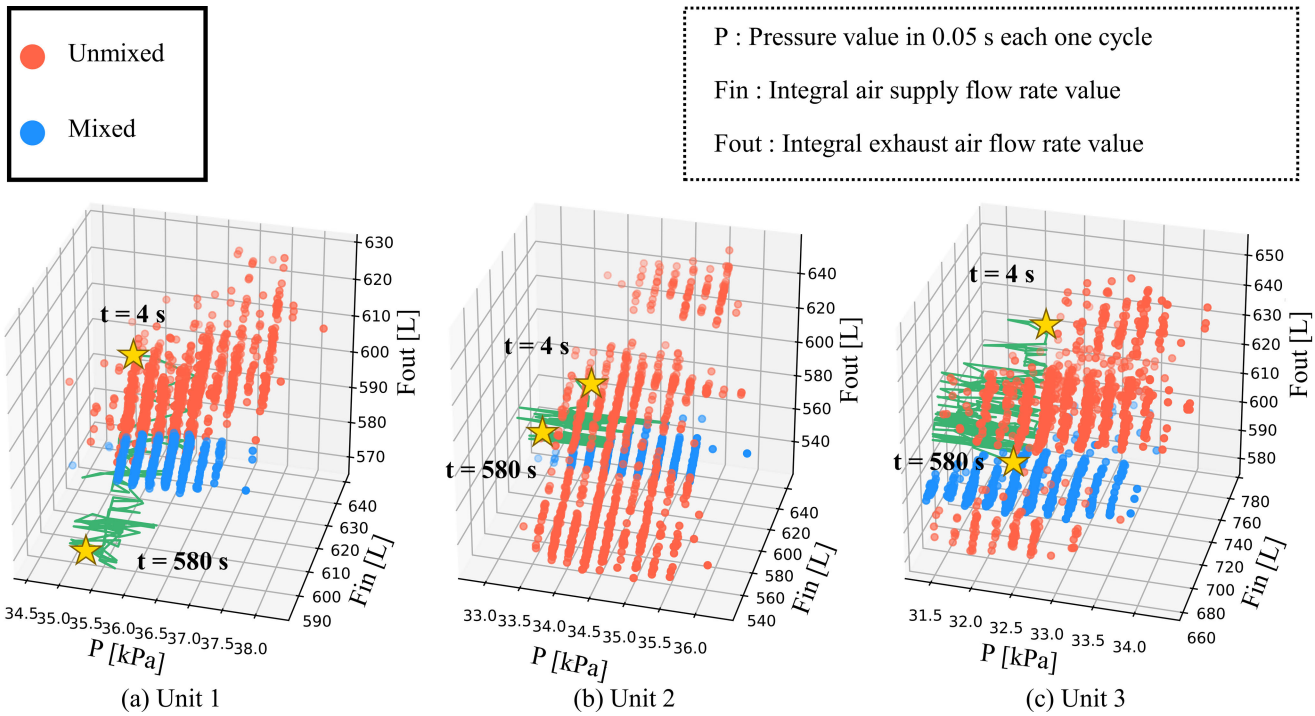

FIGURE 13. Plot of the training data and the trajectory of the experiment data (green color) in each unit from 4 s after the start of mixing to the switching of the motion mode (9 min 40 s). The mixing predict start point (t = 4 s) and the mixing completion point (t = 580 s) are marked with yellow stars.

of motion suitable for the state of the contents was realized. However, in order for this device to be used for fuel production, the accuracy of mixing estimation needs to be improved and the conveyor speed needs to be increased.

The challenge in estimating the degree of mixing was that some of the conveyed simulated material was unmixed. Although this experiment was conducted in a limited environment, reconstruction of the model using sensor data at 15 to 20 minutes after the start of mixing to unmixed data can be used to improve the estimation of the degree of mixing in this experimental environment, preventing conveyance that leaves unmixed portions. Sensor data from the start of mixing to less than 10 minutes were used for the unmixed data in this experiment's mixing discrimination model. This was selected based on previous studies [13]. From the experimental results, since the time from the start of mixing to switching to the exercise mode (9 min 40 sec) was almost the same as that of the labeled training data, more accurate discrimination of the degree of mixing may be possible by reexamining the unmixed data.

In the future, fuel production will need to be estimated with high accuracy in complex environments. In this experiment, the mixing estimation used a limited set of data: the values of three different sensors at a specific time. In the case of a change in the experimental environment, such as a change in the weight or composition of the contents to be mixed or an increase in the number of units, the accuracy of the mixing estimation is difficult to maintain in its current state, and it lacks generalizability. Considering the actual fuel manufacturing process, the environment is expected to be more complex than this experiment. In the future, the machine learning model, including the type of data to be used, needs to be reconstructed to enable highly accurate mixture estimation even in complex environments.

On the other hand, the simulated material in Unit 1 moved to Unit 5 in about 20 minutes (1200 seconds) after the start of the conveying mode, and the conveying of the simulated material was completed. The conveyor speed was about 0.38 mm/sec. The conveyor speed depends on the time the air is applied and the pressure set to the device. These set values are experimentally pre-determined values. Currently, each unit is set to move discretely in a constant rhythm. In the actual intestine, the amount and duration of intestinal contractions vary according to the amount and hardness of the contents, and the intestinal wall is continuously deformed. Reproducing such intestinal movements may improve the speed of conveyance. In the future, we will verify whether increasing the degree of freedom in setting up each unit will improve the conveyor speed.

VI. CONCLUSION

This study aimed to incorporate a control method that imitates the autonomous motion generation mechanism of the intestinal tract and an automatic motion-mode switching system between mixing and conveying in a peristaltic mixing conveyor. In this study, we acquired experimental data on the mixing of bagged solid fuel simulant and used supervised learning (the k-nearest neighbor method) to determine the degree of mixing (unmixed and completed mixing). In addition, the system continues in the mixing mode when the results of the mixing degree discrimination indicate that the mixture has not been mixed, and automatically switches the motion to the conveying mode when the mixing is complete. The experimental results showed that the motion mode automatically switched to conveyance at almost the same time as the unmixed labeled training data (mixing started at 10 min), and the mixed simulant was successfully conveyed.

The future prospect is to improve the accuracy of mixture discrimination by rebuilding the machine learning model. In addition, there is still room for improvement in the speed of fuel conveying for practical use. Adjust parameters such as drive pattern of conveyance, air application time, and set pressure.

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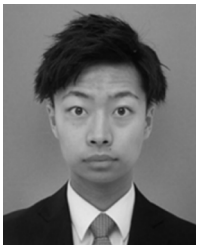

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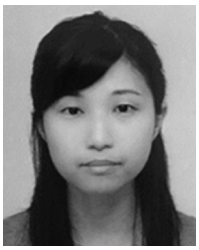

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