IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 6, 2021, accepted August 22, 2021, date of publication September 13, 2021, date of current version October 15, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3112614

Generalization Capability of Mixture Estimation Model for Peristaltic Continuous Mixing Conveyor

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This work was supported in part by JSPS KAKENHI Grant-in-Aid for Scientific Research on Innovative Areas through MEXT of Japan under Grant 18H05465, and in part by Chuo University Research and Development Initiative.

ABSTRACT We propose herein a method for estimating the mixing state of the contents of a peristaltic continuous mixing conveyor simulating the intestine, developed for mixing and conveying powders and liquids. This study serves to improve a previously proposed method for estimating the mixing state using a logistic regression model with the pressure and flow rate sensors installed in the device as inputs. Moreover, the estimation accuracy of the proposed method is better than that of the previous method. The generalizability of the proposed method is evaluated for four conditions in which the feeding order of the contents, powder, and liquid are changed. The feeding order is as follows: powder first, liquid first, and powder and liquid alternately. As a result, a highly accurate estimation of mixing is achieved under the condition wherein the powder component is in the unit adjacent to the lid, but not under the condition wherein the liquid component is fed first. It is speculated that this is because the movement of the powder component inside the device is more easily reflected by the pressure and flow rate sensors installed in the device than in the liquid component.

INDEX TERMS Soft robotics, robot sensing systems, machine learning, predictive models, data acquisition, product safety, transportation.

I. INTRODUCTION

Mixing and conveying technologies for solid-liquid mixtures and highly viscous fluids are required as intermediates in the manufacturing process to obtain the final products in various industries, such as soil, cement, food, and medicine. Currently, separate equipment is used for mixing and conveying, and a batch process is followed throughout. This leads to increased production costs, such as increased labor costs, and decreased yields. Moreover, mixing via a rotating mixer generates large frictional and shear forces between the material to be mixed and the mixer blades. The heat consequently generated, and the impact thereof may destroy the structure of the object. This also limits the operating conditions of the mixer.

As a solution to these problems, focus has been laid on intestinal motility [1], involving continuous mixing and transport with low shear force. The intestinal tract transports food masses, and mixes food masses and digestive juices by opening and closing flexible ducts with a small force. Further, the intestine is known to have an autonomous nervous system, called the enteric nervous system [2]. The enteric nervous system consists of a network of sensory nerves that detect mechanical and chemical stimuli, interneurons that transmit information, and motor nerves that control muscle movement. Within this network, all elements are necessary for the generation of muscle movements. The intestine can be regarded as being driven by axial units [3]. Signals generated by stimuli are exchanged between adjacent units, and the signals are used to generate complex intestinal movements by contracting or relaxing the muscles. The neural network in the intestinal wall enables the intestine to sense the state of its contents and control intestinal motility autonomously and in a decentralized manner.

Previously, we developed a device that functioned similar to the intestine (Fig. 1 [4]) using pneumatic artificial

The associate editor coordinating the review of this manuscript and approving it for publication was Mehul S. Raval.

muscles [5] composed of soft rubber material. Through application of compressed air, the inside of the device expands, and the contents can be mixed or transported by pushing the contents. There exists a similar device commonly known as a peristaltic pump, however, it is designed to continuously transport fluids and cannot mix powders and liquids [6]. This developed device has been successfully used to transport highly viscous fluids and solid-liquid mixtures. It also has been used to produce solid rocket fuel by mixing powder components with highly viscous fluids [7], [8]. In these studies, the device operation pattern was based on sequence control with periodic inputs determined experimentally. There is however much room for improvement regarding the motion pattern of the device. Therefore, we aimed to construct an efficient mixing and conveying control system based on autonomous control by sensing the contents of the intestinal tract. The generation of intestinal peristalsis [9], [10] and autonomous intestinal motility via neural oscillators [11] have been studied previously. These studies are based on simulations and are not applicable to the complex physical behavior of the device. Although there are methods to analyze the phenomena of only fluids or only powders, the behavior of their mixtures is very complex and difficult to predict. Therefore, reproducing intestinal motility via the device functioning similar to the intestine can lead to a better understanding of intestinal function. Our system is designed to determine the mixing state in each unit from the sensor values installed in the device [12], [13]. In the future, we aim to control the driving pattern of the device autonomously based on the estimated mixing degree to achieve efficient device driving. In addition, this device is designed for safe and continuous mixing and conveying of powders and highly viscous fluids. By realizing an efficient mixing and conveying system, it is expected to reduce the cost of manufacturing food and medicine, which consist of a mixture of powder and liquid. The purpose of this study is to improve the accuracy of the mixing degree estimation of the contents.

For example, there exists a method to determine the state of an object in the mixing process by collecting a sample of the object and using a viscometer. Since the peristaltic continuous mixing conveyor continuously mixes and conveys, stopping and opening the device to determine the mixing state proves disadvantageous. Therefore, in this study, we aimed to determine the mixing state from the sensor values attached to the device without removing the contents. As mechanical stimuli for intestinal input, pressure and dilatation of the intestinal wall due to the contents have been suggested [14]. Therefore, a sensing system using the pressure and flow rate sensors was developed, focusing on the air pressure applied to the device [12]. The system could estimate the degree of mixing via machine learning from the time-series information of the sensors [13]. On the other hand, the quantity of both training and testing data was small, so the results of the proposed estimation method were not evaluated sufficiently. The relationship between the estimation results and the sensor values was unclear. Moreover, the method of assigning labels to the training data in the estimation method was problematic.

In this paper, the previously proposed mixture estimation method was improved, and the generalizability thereof was evaluated. To improve the method, the approaches for acquiring training data and assigning labels in the training model were changed. For the generalizability evaluation, the degree of mixing was estimated when the mass fed into the device was kept constant, and the feeding order was changed. Furthermore, we attempted to clarify the complicated relationship between the sensor data, the state of the contents, and the estimated values, which had not been focused on in the previous study.

The remainder of the paper is organized as followed. Section II describes the mixing conveying device, and Section III describes the proposed mixing estimation method and evaluation policy. In section IV, the estimation results are presented, and the relationship between the sensor value, and in section V, the estimation result is considered. Section VI describes the summary and future prospects.

II. MIXING AND CONVEYING DEVICE BASED ON INTESTINAL MOVEMENT

A. OVERVIEW OF PERISTALTIC CONTINUOUS MIXING CONVEYOR

The muscular layer of the intestine is composed of circular and longitudinal muscles [15]. The circular muscle is arranged in a ring in the intestine, and the longitudinal muscle is arranged axially. Each muscle layer mutually contracts and expands to perform peristalsis and transport the food mass. The developed peristaltic conveyor has a structure that imitates that of the intestine. The conveyor unit and cross-sectional views are shown in Fig. 2(a) and (b), respectively. This unit consists of an axial fiber-reinforced pneumatic artificial muscle (in the following referred to as ''artificial muscle''), a rubber tube, a shaper ring, and a flange. When air pressure is applied to a chamber between the rubber tube and artificial muscle, the rubber tube expands to close the inside of the tube. At the same time, the artificial muscle expands in the radial direction and contracts in the axial direction, contributing to the occlusion of the inside of the tube and the improvement of the transport performance of the contents (Fig. 2(c)). The shaper ring promoted the stable occlusion of the rubber tube. After exhaustion, the artificial muscle returns to its initial state before the air is applied. If the device is empty, the rubber tube also returns to its initial state. However, if there are contents in the device, the initial state is not necessarily the same. This is because the rubber tube is a flexible material and can be deformed by the contents. This each unit was equipped with a pressure sensor in the chamber and flow rate sensors, such as the air supply and exhaust flow to the chamber.

B. PROBLEMS WITH PREVIOUS ESTIMATION METHOD

Machine learning-based mixture estimation using compressed air sensing on the subject of mixing powders and liq-

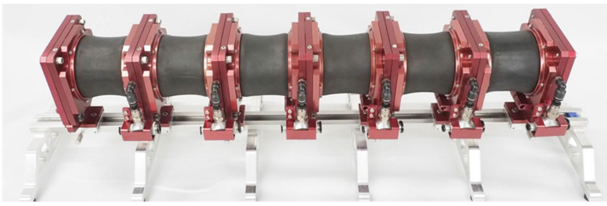


FIGURE 1. Overall view of peristaltic continuous mixing conveyor.

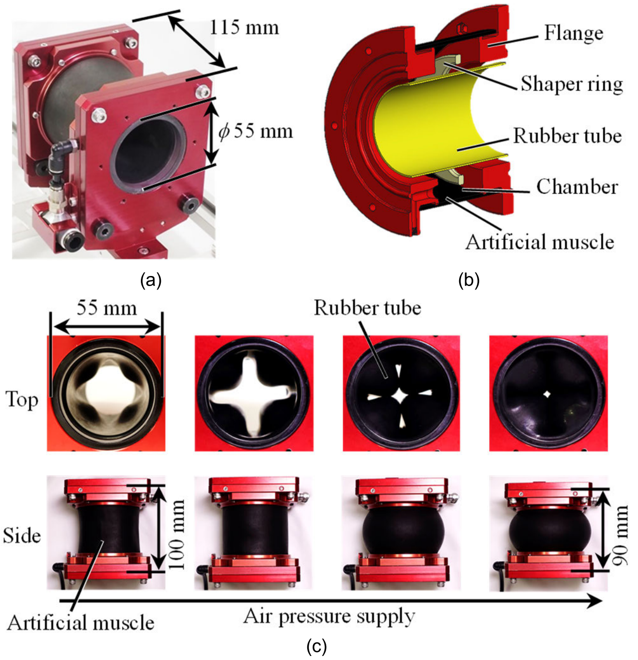


FIGURE 2. Details of peristaltic continuous mixing conveyor: (a) Overview of one unit of the device. (b) The cross-sectional view of the unit (c) Movement of the unit when compressed air was applied.

uids has been conducted previously [13]. A machine learning model was constructed using three different air pressure and flow rate sensor values attached to three units. Considering the fact that the driving state of each unit switches with respect to the input given to the device at random (state transition), the degree of mixing can be estimated. However, there was a problem with the proposed estimation model. The training data were the data obtained from the time when the unit started to drive and was operated for a certain duration after the mixing was complete. In this set of time-series data, the training data were labeled as either unmixed (0) or fully mixed (1) before and after a certain time. In such a case, even data acquired in the middle of mixing are labeled as unmixed or complete, which is the problem. In addition, the labeling depends on the specified time, which significantly affects the estimation results. It is difficult to determine the specified time. Therefore, in this study, we changed the method to acquire training data. The data collected in the first 30 minutes of mixing, which can be considered as the time before mixing, was set as unmixed (0). The complete mixed (1) data were set as the data that were completely mixed by hand before being fed into the machine.

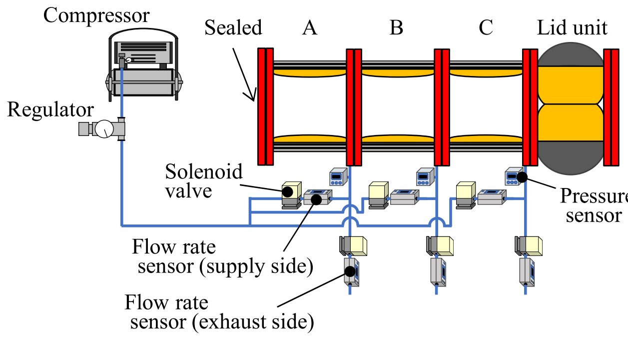


FIGURE 3. Experimental environment with the pressure and flow rate sensors.

In addition, the results of the previous study were obtained under a certain type of experimental conditions. There are many possible feeding orders of powder and liquid into this device. For example, the powder is fed after the liquid, or reverse order, or the powder and liquid are fed alternately. However, in the previous study, only the method in which powder is added and then liquid is added was studied, and the other methods were not investigated. Therefore, it is unknown as to whether the mixture degree estimation can be performed under other experimental conditions. The relationship between the selected training dataset and the estimation results is not clear. Hence, it is necessary to verify the adaptive range of the learning model, including these factors. In this study, we evaluated the proposed estimation model by performing mixture estimation for the case in which the mass of the feeding materials is kept constant, and the order of the feeding materials is changed. The accuracy of the estimation is affected by the final mixing state. If the mass or ratio of the contents is changed, the final mixing state will differ from the training data, and the accuracy of the estimation is expected to decrease. In this paper, as the first step of the generalizability verification, the case in which the mass of the feeding materials is kept constant, and the feeding order of contents is changed is verified. The verification of other feeding conditions will be future work.

III. PROPOSED METHOD AND GENERALIZABILITY EVALUATION POLICY

This section describes the proposed mixed estimation method and the generalizability evaluation policy when the feeding order of the contents is changed.

A. DEVICE DRIVE METHOD AND CONTENTS TO BE FED

Fig. 3 shows the experimental environment. In this experiment, the three pump units shown in Fig. 2 were connected horizontally. The units were named A, B, and C, respectively, for convenience. At the right end, another unit was connected as a lid that could be opened and closed separately from the referred three units. The left end was sealed with a lid plate. The values of the pressure and flow rate sensors were obtained when the device was driven by the object to be mixed.

Two two-port solenoid valves (VDW20JA, SMC Co., Japan), one for the air supply and the other for the exhaust, were installed in one unit. These solenoid valves were turned on and off with signals controlled by a microcontroller (Arduino MEGA 2560). Each unit was independently controlled. When the solenoid valve for the air supply of each unit is turned on, compressed air is supplied from the compressor to the chamber of the unit through the regulator up to the set value of the applied pressure (60 kPa). When the solenoid valve for the exhaust air of each unit is turned on, the air in the unit is exhausted. An air pressure sensor (ZSE30AF C6H-C-MGA1K, SMC Co., Japan) was installed in each unit to measure the pressure in the chamber, and two flow rate sensors (PFM750-C6-C-A, SMC Co., Japan) were installed to measure the flow rate on the air supply and exhaust sides. The sampling period of the sensors was set to 100 Hz.

In this experiment, two states were prepared as inputs (state signal) to each unit: (1) air supply state and (2) exhaust state. (1) The air supply state is when the air supply valve is open, and the exhaust valve is close; (2) the exhaust state is when the air supply valve is close, and the exhaust valve is open. Even with the same state signal, the sensor values are different owing to the effect of the previous signal. For example, suppose that at a certain time t [s], the sensor value is acquired when the state signal is 211. At this time, the sensor value not only depends on the state signal 211, but also depends on the state signal at previous time t-2 [s]. In short, the sensor value is different when the state signal of t-2[s] to t[s] is 112 to 211 and when it is 111 to 211. This is because the movement and shape of the contents, as well as the mixing degree, depend on the state transition of the device. Therefore, we also focused on the state transitions. Fig. 4 shows an example of sensor data measurement in the state transition (112 to 211). At this time, unit A transitions from the air supply to the exhaust, and unit C transitions from the exhaust to the air supply. Unit B remains in the air supply state and does not transition; however, its sensor value changes owing to the changes in the left and right units. In this manner, nine sensor data points can be obtained according to the state transition every two seconds.

In this experiment, the powder and liquid components were determined as Table 1. These are the same as those in the previous study [12]. The powder concentration, which is a criterion for the object to be mixed and the actual degree of mixing, is determined as follows:

Powder Concentration: Percentage of the weight of the powder component in the total weight of the contents [wt%], which is 76 wt% for the complete mixture of powder and liquid used in this study.

B. PROPOSED MIXING ESTIMATION MODEL

The structure of the proposed learning model is shown in Fig. 5. Logistic regression model was used to discriminate between the two unmixed (0) and mixed (1) states. Logistic regression model is used for binary classification to determine between 0 and 1. There are other types of classification

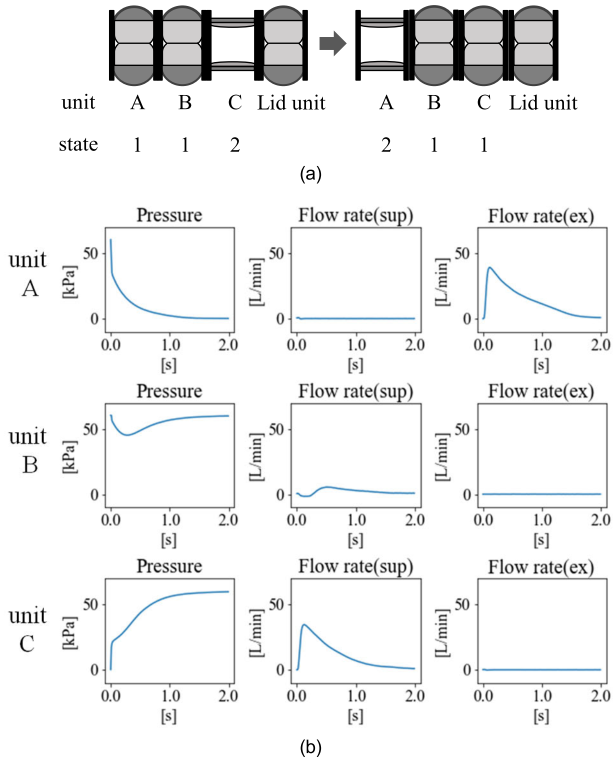


FIGURE 4. (a) The state of peristaltic continuous mixing conveyor, and (b) Example of sensor value in a state transition: 112→211.

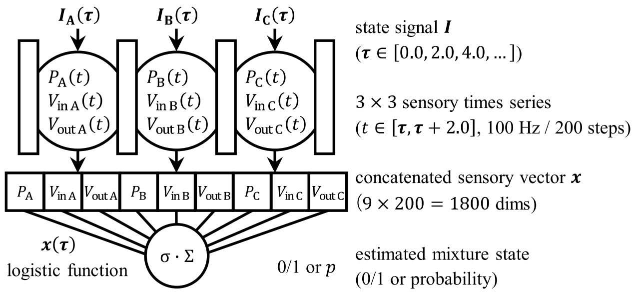
TABLE 1. The powder and liquid components.

	component	weight
powder	Glass beads with a diameter of 0.350–0.500 mm (GB-0.4, Kennis Co.)	627g
liquid	Sodium polyacrylate (SAP) in an aqueous solution temperature ; 22 °C viscosity ; 20 Pa·s	198g

models such as decision tree, random forest, and support vector machine. Logistic regression model is most used and whose results are easy to understand. In this paper, it was selected as the initial study because it deals with the complex phenomenon of mixing powders and liquids.

The time at which the state signal switched was used as the delimiter. Nine sensor data acquired between the delimiter were used as explanatory variables. To obtain a stable output, the transition pattern of the state signal is focused, regression model is constructed according to the transition pattern before and after the state signal. The final mixed estimation is calculated by the weighted average of the estimates of the model. This model is based on the mixture estimation model [13] proposed in the previous study with some improvements, such as the labeling method. The method used to obtain the training data is described in the next section.

The time at which the state signal switches were defined as $\tau \in \{0, 2, 4 \cdots\}$ [sec] and the state signal at time τ were



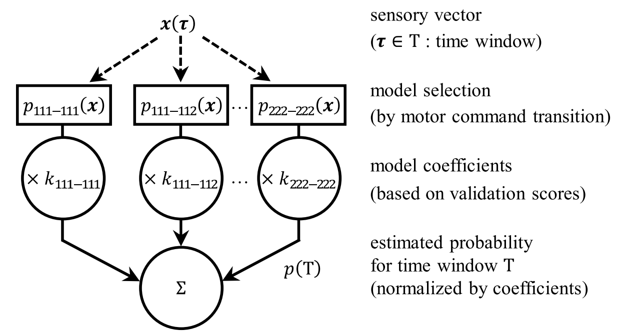


FIGURE 5. Schematic graphs of machine learning model. (a) Logistic regression model used in our method. (b) Integrated model composed of multiple logistic regression models conditioned by state signal pattern ($I(\tau$-2), $I(\tau)$).

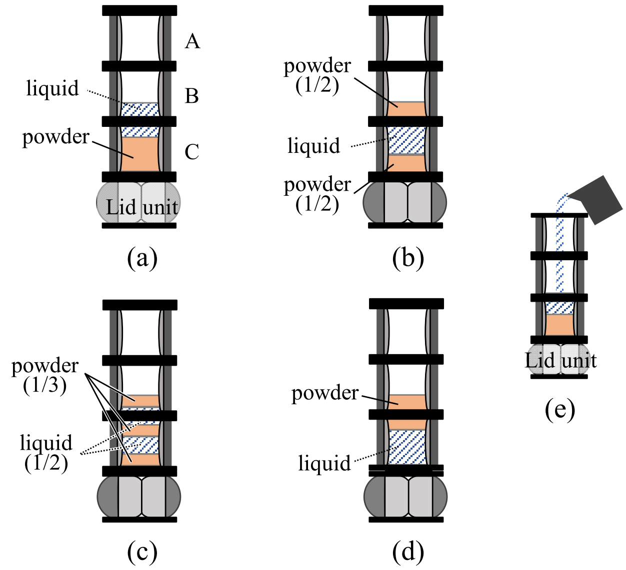


FIGURE 6. Feeding order of objects into the device: (a) LP: Basic feeding order in which the liquid component is fed into device A side and powder component into device C side. Only this feeding order was used as training data. (b) PLP: The weight of the powder was divided into halves and fed alternately with the liquid. (c) PLPLP: The weights of the powder and the liquid were divided into 1/3 and 1/2 respectively, and they were fed alternately. (d) PL: reverse feeding order of (a). The powder component is fed to the A side and the liquid component is fed to the C side. (e) Method of feeding. The objects were fed from the top with the lid unit down. After feeding, the air in the device was removed and the unit was leveled.

defined as $I(\tau) \epsilon M (M := \{``111", ``112", \cdots, ``222"\}, |M| = 2^3)$. M is a set of motor commands. The state of each unit is randomly input as 1 or 2. The experimental device consists of three units. This means that M has 2^3 elements, one of which is input to the device as a motor command. The internal state $x(\tau) \epsilon \mathbb{R}^{1800}$ was defined as a vector that combines the nine sensor time series data during the two seconds that the state signal $I(\tau)$ is maintained. Next, a total of 64 ($2^3 \times 2^3$) logistic regression models for each transition pattern of the two state signals before and after the state signal was built.

A weighted average of the outputs of these models yields an estimate for the time window T. The coefficients k_m corresponding to the regression model for each transition state $m(\tau)(:= (I(\tau-2), I(\tau)) \epsilon M \times M)$ are defined by the following equation:

$$k_m := \{\max(v_m - v_{th}, 0)\}^{\alpha}. \quad (1)$$

Here, v_m is the correct answer rate of the model in the accuracy verification data ($0 \leq v_m \leq 1$) (hereinafter, v_m is called the validation score). To evaluate generalizability of mixing estimation, k-fold cross-validation was used to create the model from multiple data to calculate the parameters of equation (1). The training data were divided into five parts, accuracy verification was performed using the cross-validation method, and v_m was obtained. v_{th} is the threshold of the validation score and can be set any value in the range of values that v_m can take. The higher this value, the higher priority is given to the model that obtains a high score in the validation test. α (>0) is a constant for emphasizing a model with a higher correct answer rate. In this experiment, $v_{th} = 0.95$ and $\alpha = 4.0$ was adopted.

Finally, the estimated probability $p(T)$ for a certain time window T can be obtained from the following equation:

$$p(T) := \frac{\sum_{\tau \in T} k_{m(\tau)} p_{m(\tau)}(x(\tau))}{\sum_{\tau \in T} k_{m(\tau)}}. \quad (2)$$

In this case, $T = 600$ s, and the mixing degree was estimated every 10 minutes.

C. METHODS FOR OBTAINING DATA FOR TRAINING AND EVALUATION

1) TRAINING DATA

For the training data, data in the unmixed (label 0) and mixed (label 1) states were prepared. The unmixed data are the data obtained when the objects were placed into the device in the order shown in Fig. 6(a) and the device was randomly driven for 30 minutes. Fig. 6(e) shows method of feeding objects. The mixed data are data obtained when the objects are mixed by hand in advance and then fed into the device and driven. In these data, the objects were placed into the device, and the device was driven randomly for 180 minutes. The data for 90 minutes in the second half was used for learning as the data in which the contents were completely dispersed in the device. The unmixed data were obtained in four trials and the mixed data in two trials. These data are used to train the mixture estimation model.

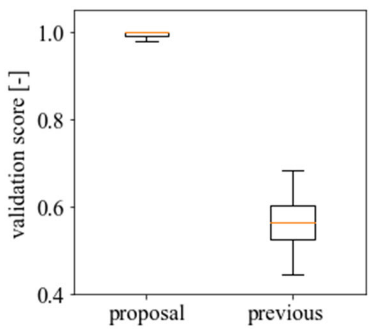


FIGURE 7. Boxplots of validation scores in the regression model for all state transitions of the proposed method and the previous method (n = 64).

2) DATA FOR EVALUATION

The evaluation data were obtained by randomly driving the object for 180 minutes after feeding. To evaluate the generalizability of the estimation model, two sets of four different data sets with different feeding orders were prepared, as shown in Fig. 6. Considering the initial state of the contents, it is presumed that feeding orders LP and PL take the longest time from the start of the system drive to the completion of mixing while feeding orders PLP and PLPLP result in faster completion of mixing.

To understand the actual mixing degree, we obtained the mass % concentration of only the feeding order LP. The system was run randomly for 180 minutes, and the mixture inside the unit was sampled every 20 minutes. The lid unit was opened, and small samples (approximately 3 g) were taken from three locations to determine the mass % concentration. The sensor data at this time were not used as the evaluation data.

IV. ESTIMATION RESULTS

A. COMPARISON WITH THE PREVIOUS METHOD

Fig. 7 shows boxplots of the validation scores of each regression model for all state transitions of the proposed method and the previous method. The proposed method improves the accuracy of the regression model in each state transition compared with the previous method. In the previous method, there was a large variation in the score among the low. In contrast, the proposed model is more stable and accurate. From this result, the v_{th} in equation (1) was set to 0.95 in the proposed method, while that of the previous method is 0.5. The larger the v_{th} is, the higher the priority of the model with the highest percentage of correct answers. In other words, the adoption rate of data becomes more severe in the proposed method than in the previous method. Therefore, it is expected to improve the estimation accuracy.

Fig. 8 shows the comparison results with the previous method under feeding order LP. The horizontal axis shows the elapsed time from the start of mixing (min), and the vertical axis shows the estimated mixing degree. The higher the estimated value of the mixing degree, the closer it is to the completion of mixing. For the estimation using the previous method, two new datasets acquired in the same way as the data acquisition method for evaluation in this study were prepared and used as training data. For the evaluation data of two trials of the feeding order LP, the mixing transition was estimated using the previous method and the proposed method. Fig. 8 shows that in the proposed method, the mixing time increased from the start of mixing to approximately 60 minutes in both trials, and then remained constant. This indicates that the proposed method completes mixing in approximately 60 minutes. However, the previous method did not converge to a constant value and continued to increase slowly until the end of mixing. The difference between the two trials in the previous method was large, so it was difficult to judge from this graph that the mixing was completed.

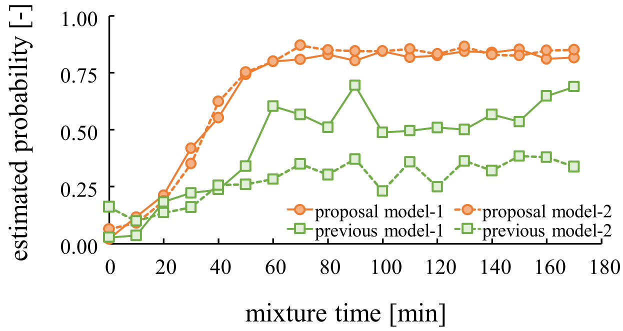


FIGURE 8. Mixing estimation results of the proposed method and the previous method: These are the results of the two methods for two trials in the input condition LP. In the previous method, the model from the previous study was used, the mixing completion time in the training data was set to 60 minutes, and v_{th} in equation (1) was set to 0.5.

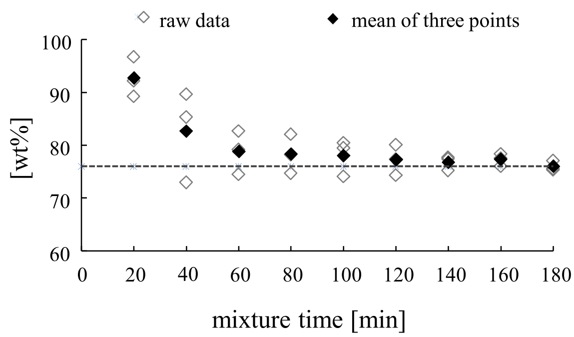


FIGURE 9. Mass% concentration of unit C in the feeding order (a) LP.

Fig. 9 shows the trend of mass% concentration in the feeding order LP, which converges to a constant value after 60 minutes. This graph shows that unit C is close to complete mixing after 60 minutes. This is the same trend as that of the mixing estimates for the feeding order LP by the proposed method in Fig. 6, indicating that the proposed model can estimate the feeding order LP with high accuracy. This is because this mixture estimation model is constructed using only sensor data in the case of the feeding order LP as training data.

B. ESTIMATION RESULTS FOR EVALUATION DATA WITH DIFFERENT FEEDING ORDER

The results of the mixing degree estimation are shown in Fig. 10. The estimated values of the mixing degree increased monotonically and converged to a constant value,

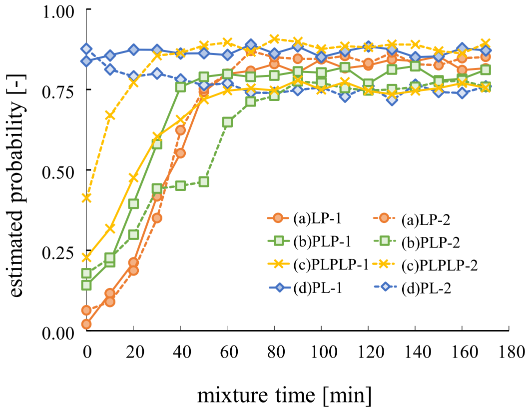


FIGURE 10. Results of mixture estimation: The results of two trials for each feeding order are shown.

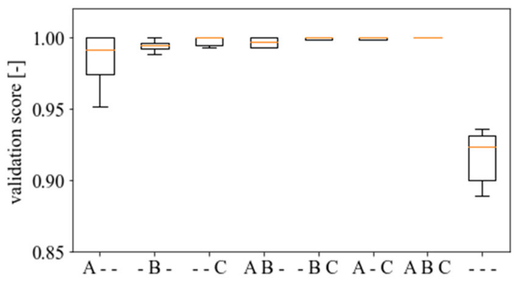


FIGURE 11. Results of validation score: All motor patterns (64 types) were divided into eight sets according to the unit that changed the motor pattern (from 1 to 2 or from 2 to 1), and the validation score for each transition state is displayed. The letter at the bottom of each graph indicates the unit that changed, and - indicates the unit does not change. For example, "A–" stands for the motor pattern of only unit A (left side unit) is changed. "- - -" has the same driving pattern as the previous state, so the previous state is maintained, and the device is not moving.

except for the feeding order PL. On the other hand, for PL, the estimated value remained high at the start of mixing and then leveled off. The mean $\pm$ standard deviation of the convergence values for all feeding orders were 0.81 ± 0.05. In the case of the feeding orders PLP and PLPLP, the convergence was the same or faster than that of the feeding order LP, so it can be concluded that the estimation was generally successful except for the feeding order PL.

Fig. 11 shows the results of the validation scores (v_m in Equation (1)) for all state signals in the proposed model, aggregated by the units that are in transition. The value of the validation score was higher in the transition condition where unit C changed. Additionally, the validation score tended to be higher when multiple units changed than when a single unit changed. In the case where nothing changed or only unit A changed, the validation score decreased. In this estimation model, a validation score of 0.95 or higher was used. It was found that the degree of mixing was estimated mainly using motor patterns that included changes in unit C, which had multiple units changing.

V. CONSIDERATION

Based on this result, the convergence value of the mixing completion state, mixing completion time using time series data, and mixing initial state were investigated in detail. In the following sections, we focus on the time series data of unit C during state transition 212-221. The data with transition 212-221 has a high validation score, and the change in the sensor time series is easy to understand.

Fig. 12 shows the time series data of the sensor values in the evaluation data during state transitions 212-221 and the sensor values in the data after mixing for training. The average values every 30 minutes from the start were calculated for one trial of the evaluation data for each feeding order. For comparison, all the average sensor values of the training mixed data from the same state transition were plotted. As shown in Fig. 12(a), the pressure in the feeding order LP instantly rose to a value of nearly 20 kPa immediately after 0 second when the unit state switched from 2 to 1 (from the exhausted state to the air supply state), and then slowly reached 60 kPa set as the supply pressure. The increase in pressure after mixing was slower than that of the feeding order LP at 0-30 minutes. As time passed, the sensor values of the feeding order LP approached those of the mixed condition, and after 60-90 minutes, the sensor values were almost the same. The flow rate at air supply showed a similar trend, although the directions of increase and decrease were opposite to that of pressure. From the previous study [12], it is known that when the contents are only powder, they are not pushed out by the pump drive and tend to remain in the unit, resulting in a rapid rise in pressure and a rapid decrease in the air flow rate. As the flowability of the contents increased, the pressure rise slowed and the air flow rate decreased faster. In the feeding order LP, a large number of powder components existed in unit C at the beginning of mixing and as the mixing progressed, they mixed with the liquid components, creating fluidity in the mixture, and facilitating the movement of the mixture. The sensor values after 60-90 minutes were almost the same as those after mixing, indicating that the mixing was completed within 90 minutes from the start of mixing. This is consistent with the mass % concentration in unit C in Fig. 9 and the result of LP mixing estimation in Fig. 10. It is suggested that the time series of the sensor values in unit C is strongly reflected in the learning.

Comparing the feeding orders for 0-30 minutes, the increase in pressure value was faster in the order of LP, PLP, PLPLP, and PL. For PLP and PLPLP, the sensor values approached those after mixing as time progressed, as in LP. It can be assumed that PLP and PLPLP showed this tendency because the powder component in unit C was lower in the initial stage of mixing compared with LP. The higher the amount of initial powder component in unit C, the faster the pressure value rises, and the faster the flow rate at air supply decreases. In the feeding order PL, the values were similar in all periods and almost the same as those after mixing. This is because, under feeding order PL, unit C contains only the liquid component in the initial stage of mixing. The liquid component has high fluidity and is close to the fluidity after mixing. The pressure and flow rate sensors used in this system can discriminate powder that are

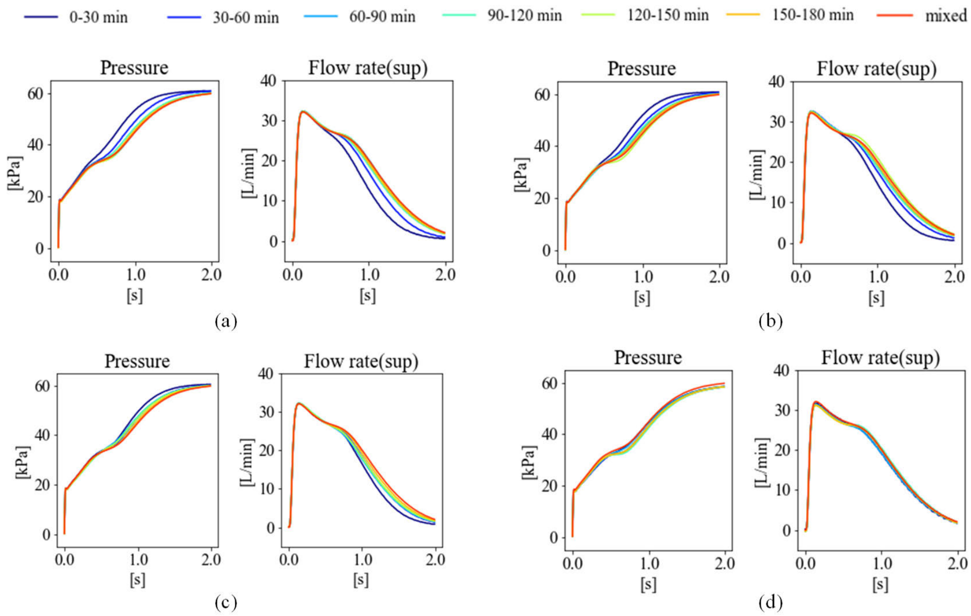


FIGURE 12. **Time series data of sensor values in the evaluation data during state transition 212-221 and sensor values after mixing for training data during same state transition. Pressure and flow rate at air supply of unit C under the feeding orders LP to PL are shown.**

different in fluidity, but it is known that there are limits to the detailed discrimination of contents that have some fluidity. As mentioned above, the learning model has been likely formed based on the behavior of the unit that contains much powder component, which causes many differences in the sensor information as the mixing progresses. This has a significant impact on the differences in the feeding order used in this evaluation. Accordingly, the initial values of the mixture estimation results in Fig. 10 are higher for LP, PLP, PLPLP, and PL. It can be suggested that the estimated mixing degree of the feeding order PL, which is the opposite of the training condition, does not show a monotonically increasing trend when compared with the other feeding orders, and is estimated to be close to the mixed state from the beginning of mixing.

A. ADDITIONAL VALIDATION: EVALUATION OF THE TRAINED MODEL USING DATA FROM THE FEEDING ORDER PL

Through the verification so far, it was found that the change in sensor values due to the movement of the powder component is important in the evaluation data for the estimation method. In the training data, the feeding order PL was set as the unmixed data. However, it is unclear how the position of the powder component in the training data affects the estimation. As an additional validation, the proposed model was trained using the unmixed data with feeding order PL and evaluated in the same way as before. Fig. 13 shows the estimation results of the model when the feeding order of the unmixed data in the training data is changed to PL. The mixed data and the evaluation data were the same as in the estimation shown in Fig. 10. The threshold of v_{th} in Equation (1) was set to 0.95. The mean $\pm$ standard deviation of the convergence values for the eight trials was 0.39 ± 0.22. Because the final mixed state is the same for all feeding orders, the estimated values should converge to a single value; however, this was not the case. When PL was used as the training data, it was difficult to estimate the degree of mixing. Next, the validation score of the training model was focused on determining the reason for the decrease in the estimation accuracy. Fig. 14 shows the results of the validation score when the condition of unmixed data in the training data is changed to the feeding order PL. The aggregation method is the same as that shown in Fig. 11. The validation score for the case where the unit is unchanged ("- - -") is larger than that of Fig. 10, but the variation in the validation score is generally larger. This is because the powder component is located in the central unit, and there is no regularity in whether the powder component moves to the left or right in the initial stage of mixing. Therefore, when using this estimation method, the initial feeding position is the position where the powder component moves in the mixing progress direction, that is, the powder component should be at the end unit when initially fed.

B. LIMITATIONS OF THIS METHOD

In the proposed estimation model, when the feeding volume was constant and the feeding orders were changed, mixing estimation was possible under the condition that the powder component was present in the right-hand unit, as in the training data. When the right-hand unit was mostly filled with liquid component, mixing estimation was not possible. Also, when the position of the powder component in the training data was changed, the degree of mixing could not be estimated. It can be inferred that the estimation is possible under the condition that the proportion of powder component is changed by keeping the feed volume constant and the powder

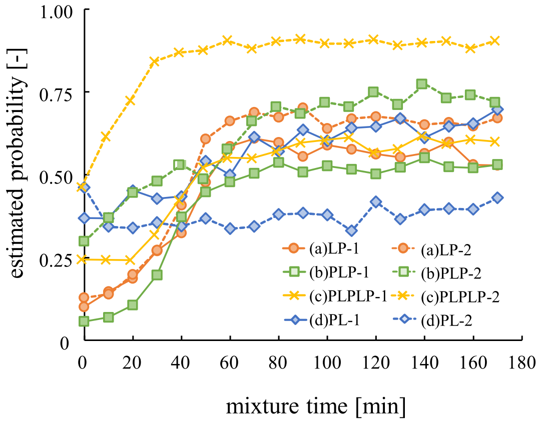


FIGURE 13. Mixed estimation results when the feeding order of unmixed data in the training data is changed to PL.

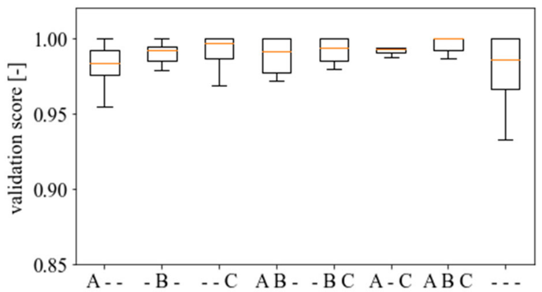


FIGURE 14. Result of the validation score when the feeding order of unmixed data in the training data is changed to PL.

feed position at the end unit. Because the estimation accuracy was high under the condition that the powder component moved in one direction as the mixing process progressed, it was necessary to set the unit adjacent to the lid as the initial powder feed position for both training and evaluation data to improve the accuracy. The estimations in which LPL or LPLPL are used as training data were not tested. In those cases, we can expect that the mixing estimation will not work as well as PL because the initial state in the unit adjacent to the lid is similar to the mixing completion.

In the future, we will obtain data for different proportions of powder components and verify the results. In addition, the sensor pattern of the pressure and flow rate sensors was almost the same for liquids and mixtures with different flowabilities, which means that the sensor cannot discriminate fine differences in the flowability of the contents. This shows a limitation in estimating the mixture using the values of the pressure and flow rate sensors. To improve the accuracy of mixture estimation due to differences in feeding conditions and amounts, it is necessary to introduce new sensors.

VI. CONCLUSION

In this paper, we proposed a method for estimating the mixing state of powder and liquid contents using the pressure and flow rate sensors in the peristaltic continuous mixing conveyor that simulates intestines and evaluated its generalizability. The proposed model consists of an additive logistic regression model that takes into account the state transition of the device, using unmixed data as the data from the start of mixing until 30 minutes after that and mixed data as the data after mixing. The generalizability of the model was evaluated under four conditions in which the feeding order of the powder and liquid contents was changed. When the powder component was included in the end unit, as in the training data, the model was able to estimate with high accuracy. However, when only the liquid component was present in the end unit, the estimation was not possible. When the learner was constructed using unmixed data, where only the liquid component was present in the end unit, estimation was not possible under all conditions. This indicates that the presence of powder component in the end unit is important for this method.

In the future, we will evaluate the generalizability of the method when the feeding conditions are changed, for example, when the components of the powder and liquid are changed. Additionally, we will introduce sensors other than the pressure and flow rate sensors to improve the accuracy of the mixing estimation.

ACKNOWLEDGMENT

(Sana Oshino and Rie Nishihama contributed equally to this work.)

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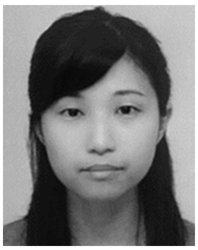

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