Motion Measurement and Segmentation Toward Automated Sewing Operations

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***Abstract* - In this study, we developed a system that acquires the operation skills of a human operator in a sewing task and a data-processing method to utilize the skills in automating sewing tasks. We propose a force sensor that measures the force at the fingertip of the operator based on changes in the width of the finger. We employed the proposed sensor in measuring a system without losing the sensation of the finger pad during a sewing task. Further, we established a method to automatically divide sewing tasks into a combination of simple motions. We also established a method to classify the motions of the hands using the force data acquired from the proposed force sensor. To verify the effectiveness of the proposed system and methods, we experimented with a simulated sewing task and applied the proposed methods to the data acquired by the system.**

Index Terms – Cloth manipulation measurement, operation segmentation, motion classification, automated sewing operation

I. Introduction

With the progress of technology, automation in the manufacturing industry is advancing. However, many operations, including sewing of cloths, still require human skills. In textile-manufacturing industries, flexible objects are manipulated by various fingering techniques. The manipulation is influenced by not only the appearance of the desired product but also the force applied by the fingertips. In other words, to analyze professional sewing operations, it is necessary to evaluate both the movement of worker's fingers and the force applied to them.

We focused on automating flexible-object manipulations, such as sewing clothing parts, and streamlining the manufacturing process. To automate the sewing process, Lee et al. [1] proposed a method for measuring sewing processes using sensors on the sewing machine. However, the method does not consider the skills of trained sewing workers, but the skills may enhance the sewing operation. Here, we established a method for measuring human skills in sewing operations, which we consider the first step for automating sewing operations. Several studies that measure human behavior for skill extraction have been reported. Dillmann [2] used human behavior recorded by a camera and data gloves to demonstrate the automation of tasks, such as putting dishes into a dishwasher. Yang et al. [3] recorded muscle force information with a sensor attached to the upper arm of a person and achieved cutting-task learning by a robot using the recorded force information. Amaro et al. [4] trained a robot to learn cooking skills using positions of human hands and tools extracted from recorded videos. Demura et al. [5] trained a robot to imitate skills based on the time series of the positions of the tools held by a human. These studies mainly focus on rigid object manipulation; however, we focus on sewing processes, which require precise manipulation of deformable objects. Thus, it is undesirable to attach sensors to the part where the finger touches the cloth for measurement. This is because the worker's senses would be out of order; therefore, he/she may not be able to work appropriately. Therefore, it is necessary to devise a measurement method that does not interfere with the sewing process.

In this study, the behavior data of workers are considered to be available for robot motion generation. The movement of a human hand in sewing processes is complicated, and it is difficult to code the movement directly for a robot. However, the process can be divided into several steps. Thus, the coding of each procedure can be automated after dividing it appropriately, thereby reducing the burden on robot developers. On this basis, we consider a method for segmenting the acquired time-series data.

The contributions of this study are as follows:

- We constructed devices that can measure the movement of a worker's hand and the force applied to the fingertip during sewing processes.
- We propose a sensor that measures the amount of deformation of the finger width without losing the sensation of the finger pad.
- We simulated the sewing process to validate the measuring accuracy of the proposed method. We employed time-series data analysis to analyze the measurement results to confirm the availability of the data.

The rest of this paper is structured as follows: Section II reviews related studies; Section III presents the requirements for measuring sewing processes and describes the approach of this study; Section IV describes the sensor systems used and measurement methods; Section V explains the analysis method for the acquired time-series data; Section VI presents the results of actual data measurement and processing; Section VII presents the conclusions.

II. Related Studies

A. Measurement of hand movements and application

In the sewing process, the operator's fingers make various movements. It is vital to measure those movements appropriately. Data gloves are often used to record finger movements. Ekvall et al. [6] used data gloves to extract hand

movements and grasp-state information. They classified grasp work for objects with different shapes and sizes. They used data gloves to acquire grasping states; however, for more precise operations, such gloves might affect the feel of fingers, reducing the accuracy of the work. Therefore, data gloves are inappropriate for measuring finger movement in sewing operations. In some studies, the measured hand movement data are divided into significant data and used for some tasks. Some studies have extracted specific hand movements by dividing the time series of hand movements extracted from videos [7, 8]. By extracting meaningful hand movements, we can communicate with robots and collaborative work between human beings and robots can be conducted [9]. However, since the manipulation targets here are cloth products, which are flexible, we measure not only the movement of the hand but also the force of the fingertip, considering the deformation of the flexible object.

B. Fingertip force measurement and its application

Okuyama et al. [10] installed a load cell under an object to measure the force applied to the fingertips, and Kim et al. [11] proposed a cylindrical finger-force-measuring system equipped with a sensor. These methods are useful for stable force measurement. However, it is necessary to provide a place to install a load cell or to make or replace a sensor each time the object is changed. Park et al. [12] measured the force on fingertips by wearing a thimble glove-type sensor, and Cerveri et al. [13] measured the force by wearing a finger sack-type sensor. These methods can accurately determine the force the wearer exerts and posture of the hand. However, since sack-type sensors are pinched between the fingertips and the objects and may cover most parts of the hand, it could hinder the movement of the fingers, preventing the operator from working as usual if the senses at the fingertips are significant to the task.

III. Requirements and Approach

A. Requirements

We assume a task that an operator feeds cloth parts to a sewing machine and sews them together. We aim to measure the behavior of the operator and use the data for automation. Therefore, we consider the kind of information necessary.

One of the pieces of information is the movements of fingers. Fingertips play a significant role in sewing operations, and it is necessary to know where fingertips are located on the sewing machine and cloth parts, as well as the direction the fingertips move. However, data gloves and the likes may interfere with the original movements of the fingers during sewing operations. Another important information is the movement of the hand. In sewing operations, it is necessary to consider the process of taking out new cloth parts from the storage area and placing them on a sewing-machine table. When placing the cloth part on the stand, it is expected that a robot can place the cloth part on the sewing-machine table in the same shape as a human operator does. The idea is to let the robot reproduce the motion trajectory of a human operator holding a cloth part in the process of placing a cloth part. To acquire the trajectory accurately, we utilize the trajectory of the hands in the sewing operation, which has less unavailable information for the cloth-placing process than finger positions, such as the information of picking-up motion or cloth-feeding motion. Therefore, in placing cloth parts, we consider that the trajectory of the operator's hands is more important than the movement of the fingertips.

Further, in the process of feeding cloth parts to a sewing machine, the cloth parts are picked up and pulled or moved in a certain direction while being pressed on the sewing-machine table. It is vital to measure the force employed in this process. However, if the sensor covers parts of the fingers that touch the cloth part, tactile information for operators, which is essential for manipulating flexible parts, might be lost.

In summary, the requirements for constructing the sensor system here are as follows:

1. Measurement of the fingertip and hand positions. However, fingers should be able to bend and open without resistance.
2. Measurement of the force applied to the fingertips. However, the sensation of the fingertips touching the cloth parts should not be lost.

Next, we consider the processing policy for the acquired data. In sewing operations, there are several steps, such as picking up cloth parts, placing them on the sewing-machine table, and feeding them to the sewing machine. Several complex hand movements are made to achieve these steps. The forces applied to the fingertips vary among the steps. It is desirable to use the force information on the fingertips to classification every step appropriately.

On this basis, the requirements for sensor data processing in this study are summarized as follows:

3. The time-series change of hand positions during the whole sewing process can be divided into a combination of simple trajectories.
4. The force applied to the fingertips during the sewing process can be appropriately used to classify actions.

If the segmentation process described in item 3 is properly performed, an approach that solves the action generation for every divided motion as a subproblem and combines the results can be employed. Also, if we can solve the force application as a pattern recognition problem, it can help motion generation by an automated device.

B. Our Approach

Our approaches are summarized as follows. Each item number corresponds to the number in the previous section.

1. Small markers are attached to the fingernails and back of hands to measure the overall position of hands and fine movement of fingers by a motion-capturing device. Since data gloves are not used, we can measure finger movements with minimal discomfort caused by the sensors.
2. Instead of directly measuring the force applied to the finger pad, we measure the change in the finger width. We shall develop a sensor for this purpose. This makes it possible to process the cloth with less discomfort without losing the sensation of the finger pad.

Fig. 1 Motion capture system V120: Trio (A) and its markers (B)

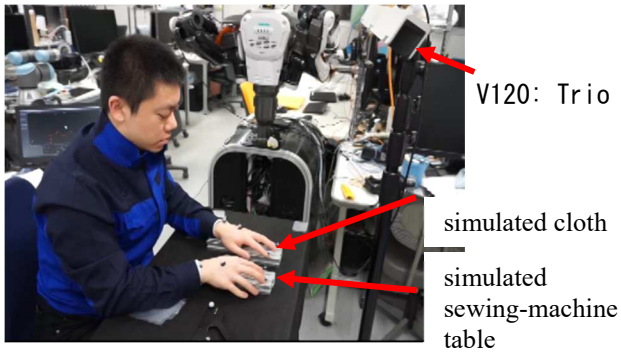

Fig. 2 Motion-capturing system in the experiment environment

3. We apply a time-series data segmentation algorithm to the positional information of the hand and other objects obtained from motion capture. Using a method that can consider the length and motion class of every segment simultaneously, a time-series manipulation trajectory can be divided into a combination of simple trajectories.
4. We introduce a method that can measure the similarity of data, and apply the method to time-series data of the fingertip force. This method detects repetitive motions, and combined with a classifier, it can classify motions.

Each item is explained in detail in subsequent sections.

IV. Sewing Task Measurement System

A. *Hand-motion measurement using a motion-capturing system*

To record the movements of an operator during sewing operations, it is desirable to measure the movement of the hand until the cloth part is taken out and placed on the sewing-machine table. This reveals the trajectory to stably place a flexible cloth on the sewing-machine table. It is also desirable to measure the movements of the fingertips during sewing manipulation. If we combine the movements of the fingertips and the force measurement data, we can obtain appropriate data when an expert feeds cloth to the sewing machine. However, as described in Section III-A, the measuring device should not interfere with the work in any case. Thus, we attach small markers are attached to several parts of the hand, and their positions are measured.

We chose a motion-capturing system V120: Trio manufactured by OptiTrack [14]. The main parts of V120: Trio are shown in Fig. 1 (A). V120: Trio is a motion-capturing system that emits infrared light to retroreflective markers and acquires infrared images with three infrared cameras for three-dimensional (3D) reconstruction. The 3D position can be measured within an error of 1 mm at 120 Hz. The retroreflective markers are attached to the tip of fingers and back of hands as the measurement target areas. The scene is shown in Fig. 1(B). The markers attached to fingertips have a radius of 7.9 mm, and those attached to the back of the hands and wrists have a radius of 9.5 mm. Since the markers are light and small, they do not restrict fingertip movements during the sewing process.

Fig. 2 shows the experimental environment for measuring the 3D positions during sewing work. We attach markers to the operator's hands, and the operator moves simulated cloth parts on a simulated sewing-machine table. The sewing process is observed by the V120: Trio, which is set diagonally above, and the 3D positions of the hand and fingertips are measured.

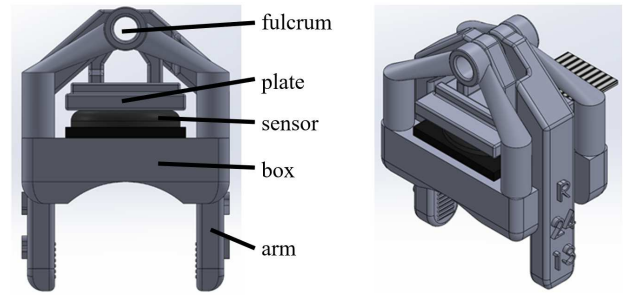

Fig. 3 Configuration of a wearable fingertip contact-force sensor

B. *Force sensor measuring finger width*

To measure the force applied to the fingertip without anything inserted between the finger and the object, we focus on the deformation of the finger width. According to Aizawa et al. [15], when a finger presses against a circular hole, the displacement of the skin that enters the circular hole increases with the load. As the load increases, the displacement increases more slowly. In other words, there is a relationship between the displacement and the deformation of the finger width. For example, when the pad of a finger is pressed against a table, the cross-section of the finger becomes flat. Converting this shape change into force data, we can measure the magnitude of the contact force.

Based on this idea, we propose a wearable contact-force sensor (Fig. 3) consisting of three parts formed in resin using a 3D printer and a three-axis tactile sensor. The tactile sensor is a Shokac Chip [16] manufactured by Touchence Corporation. The box part is configured as an axis, and the plate part is inserted between the arm and the three-axis tactile sensor to accurately transmit force from the arm part. In this device, the force generated, accompanied by the deformation of the fingertip width, is measured using the three-axis tactile sensor installed on the nail side. In other words, the changes in the finger side are transmitted to the tactile sensor through the arm. When attaching the sensor to the fingertip, the bridge part of the box and the nail are attached with double-sided tape, and both sides of the finger are clipped between the arms. All parts, except the tactile sensor, are detachable so that individual differences in finger size can be accommodated by replacing the arm parts.

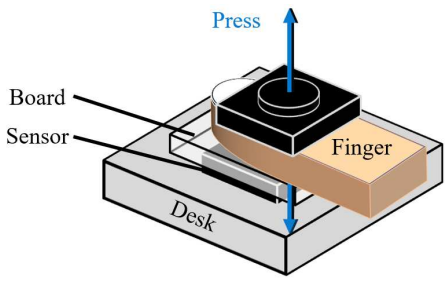

Fig. 4 Calibration setup

The force measured by the device described above is different from the value of the force originally applied to the fingertip. Therefore, it is necessary to calibrate the measured force in advance. The measurement method for the calibration is depicted in Fig. 4. First, we set the output of the sensor at the time the sensor device is installed to 0. A hard and thin board is attached to the surface of the three-axis tactile sensor and fixed on a desk. Then, the sensor is pressed vertically to a finger, and the pressing force is gradually increased until the output value of the sensor on the desk exceeds the specified value. The offset added to the value of the fingertip sensor should be determined so that the values of the two sensors match. As described in Section VI, the relationship between the two sensor values is not linear. Thus, curve fitting is employed.

V. Data Segmentation And Classification

A. Data segmentation and clustering

When we measure a task by motion capture, as described in Section IV, we can obtain time-series data of hand movements in a continuous task. To use this data for automation, the task is considered to comprise a combination of several simple motions, and the motions can be divided and classified appropriately. However, it is time-consuming to do this work manually. Here, we employ the Gaussian process hidden semi-Markov model (GP-HSMM) [17], which is a segmentation algorithm based on a hidden Markov model.

In GP-HSMM, time-series data can be segmented into unit series, and simultaneously, the unit series is generated, from which the motion class can be estimated. The flow of the segmentation process is depicted in Fig. 5. First, the operator performs sewing work several times to acquire a set of trajectories for each hand. For initialization, every trajectory is randomly segmented, the segments are randomly labeled, and segments with the same label are assumed to be generated from the same motion class. Then, every trajectory is resegmented so that every trajectory can be segmented into every motion class, and the segmentation is repeated until the segments belonging to every motion class are stable. Then, the learning process is considered to have converged, and the segmentation process is terminated.

When every trajectory is resegmented, we use the forward filtering-backward sampling algorithm reported in [16] to determine the motion class from which the newly obtained segment is generated. During the segmentation, the segment that ends at time step t and has a length k is denoted as $\mathrm{s}_{t-k:t}$, and the probability that $\mathrm{s}_{t-k:t}$ is generated from motion class c is calculated using the following equation:

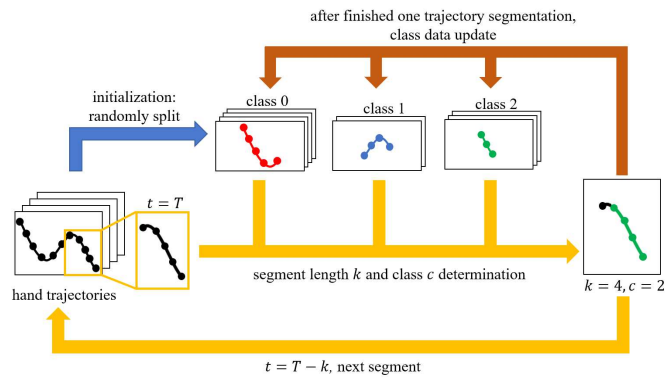

Fig. 5 Schematic representation of the segmentation

$$a[t][k][c] = GP(\boldsymbol{s}_{t-k:t}|c) \times \sum_{k'=1}^{K} \sum_{c'=1}^{C} p(c|c')\alpha[t-k][k'][c'], \quad (1)$$

where K is the maximum length of the segment, C is the number of motion classes, and $GP(\boldsymbol{s}_{t-k:t}|c)$ is the probability that the samples from the time step $t-k$ to t belong to motion class c, calculated as follows:

$$GP(\boldsymbol{s}_{t-k:t}|c) = \prod_{i=t-k}^{t} p(a_i|s_i, X_c), \quad (2)$$

where a_i is the difference $s_{i+1} - s_i$, which represents the amount of hand activity at time step i. X_c is the set of segments labeled with motion class c, and $p(a_i|s_i, X_c)$ is the likelihood function. Unlike the method introduced in [17], which only employs paired data (s_i, i) to calculate $GP(\cdot)$, we introduce a_i into (2), which makes the segment points of the trajectory close to the switching points of motions where $s_{i+1} - s_i = 0$. Therefore, we can obtain the separated segments, which indicate each motion close to the ground truth in the trajectory. Further, $p(c|c')$ in (1) represents the probability of transition from class c' to c in all trajectories, and it is calculated using the following equation:

$$p(c|c') = \frac{N_{c'c} + \epsilon}{N_{c'} + \epsilon}, \quad (3)$$

where $N_{c'c}$ is the number of transitions from class c' to c in all trajectories, $N_{c'}$ is the number of transitions from c' to other classes in all trajectories, and ϵ is a constant. Calculating $a[t][k][c]$ for every time step of every trajectory, we can calculate the probability that a segment of length k is generated from every class c.

Next, according to the probability distribution $a[t][k][c]$, k and c are sampled simultaneously from the tail time step $t = T$ to time step $t = 0$ of every trajectory, the segment trajectories generated from every motion class. Then, we employ the forward filtering-backward sampling algorithm again, and when the segment trajectories belonging to every motion class are stable, the calculation is terminated and the segmentation is completed.

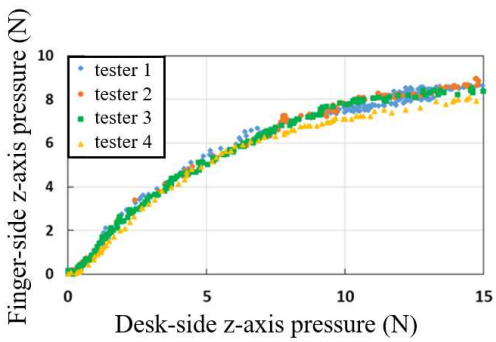

Fig. 6 Sensor output value for each subject

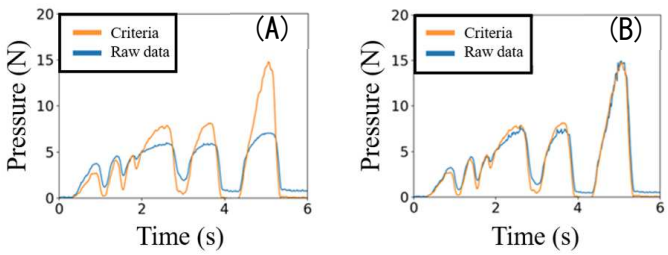

Fig. 7 Estimation result, (A): before estimation; (B): after estimation

B. *Motion classification based on force data*

Using the force sensor device described in Section IV, we can obtain time-series data of the force applied to the fingertip during continuous work. To utilize this data for automation and data analyses, the motion data should be classified according to the action being performed, the success or failure of the action, and the skill level of the operator. Therefore, the classification can be done manually or using the method that divides closer sample data into one motion class by comparing the similarity of the sample data. Another method is to use the Euclidean distance to calculate the similarity. However, manual classification is time-consuming, and for the method using Euclidean distance, the similarities between two time-series data can only be calculated when the number of samples is the same. To avoid these problems, we employ dynamic time warping (DTW) [18], which is an algorithm that can calculate similarities using distance, even when the number of samples is different.

DTW is used to calculate the similarity between two time-series data. It calculates all the distances between a point in time-series data and all points in another time-series data. It then calculates the similarity from those distances. Therefore, it is possible to calculate the similarity between two time-series data with different numbers of samples. Here, we measure the time-series data obtained from human operator actions, such as sewing-machine operations. Hence, the time spent to complete a task and the speed of the operation are considered different for each operation. Further, DTW can be employed even when the number of samples, phase reference, period, etc. are different, and it can discriminate in a way that is consistent with human intuition. Therefore, in our experiment, we used DTW, which is adaptable to time-series data pairs with a different number of samples, to calculate the similarity and classify the actions from the similarity.

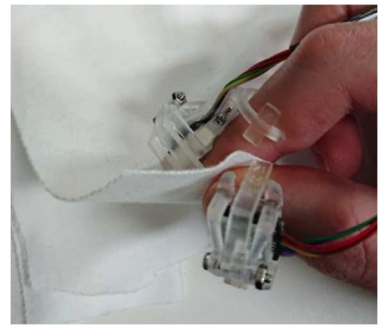

Fig. 8 Movement for turning a cloth

VI. Experiments

A. *Calibration of the fingertip sensors*

Fig. 6 shows the graph of the z-axis output of the proposed sensor described in IV-B and the sensor on a desk for four people. The vertical axis is the output value of the sensor, and the horizontal axis is the force applied to the fingertip obtained from the sensor on the desk. In all operations, as the force applied to the fingertip increases, the cross-section of the finger becomes flatter, the arms of the sensor pushed out reduces, and thus, the rate of change of the output value from the sensor decreases. There, the output value of the sensor changes in a step function of a linear delay system in response to the change in the force applied to the fingertip.

To compensate for this difference, we first describe the relationship between the output value of the sensor and the force applied to the fingertip, expressed as follows:

$$F_d = a\left(1 - e^{-\frac{F_f}{b}}\right), \tag{4}$$

where F_d is the force applied to the fingertip, F_f is the output value from the sensor, and a and b are parameters determined for each operator being measured.

Next, as a method of force estimation, we used the method depicted in Fig. 4 to measure the output of the sensor by gradually increasing the pressing force until the output value of the desk sensor became 15 N. After that, we selected two arbitrary points among the values and estimated the parameters a and b in (4) to minimize the root-mean-square error between the estimated and output values of the desk sensor. Then, F_d in (4), which is the force applied to the fingertip, could be estimated.

Fig. 7 (A) shows the relationship between the measured z-axis value obtained from the sensor and the force applied to the finger obtained from the desk sensor, and Fig. 7 (B) shows the relationship between the estimated force applied to the fingertip and that obtained from the desk sensor. From the estimation results, in the range of 0–10 N, where the output value of the desk sensor shows, the root-mean-square error before and after estimation is 1.33 and 0.59 N, respectively. In the range of 0–15 N, the root-mean-square error before and after estimation is 2.70 and 1.35 N, respectively. These results indicate that the fingertip force can be estimated in a wide range, and there is an improvement in both ranges stated above.

B. *Motion discrimination using the fingertip sensor*

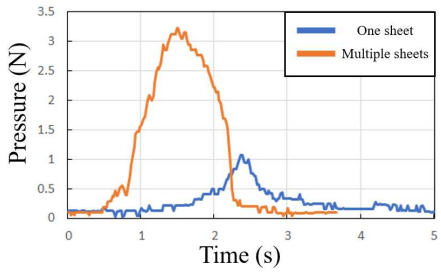

Fig. 9 Measurements when picking up cloth

TABLE I

DISCRIMINATION ACCURACY WHEN TURNING OVER CLOTH

thumb	index finger	both fingers
90%(9/10)	80%(8/10)	90%(9/10)

We experimented to discriminate movements based on time-series force data obtained by the fingertip sensor. The sensors were attached to the thumb and index finger of the dominant hand, as shown in Fig. 8, and the operator performed a motion to pick up a cotton cloth with the thumb and index finger. Then, we confirmed the discriminability between picking up one piece and multiple pieces of cloth.

First, we acquired the data from the sensor once for each motion of picking up one piece and multiple pieces of cloth, respectively, as sample data. We also acquired the data of each motion five times as test data. The data were acquired a total of 12 times. After acquiring all data, a low-pass filter with a cutoff frequency of 4 Hz was applied to all acquired data, and DTW was employed to discriminate the motions each test data belong to according to the sample data. DTW was implemented using the tslearn library [19] in Python.

Fig. 9 shows the graph of the z-axis output of the sensor for each motion described above, and Table I lists the discrimination accuracy. The accuracy of discrimination when using only the output value from the thumb was 90%, and the accuracy when using only the output value from the index finger was 80%.

C. *Motion capture accuracy measurement*

The accuracy of the V120: Trio was evaluated using the system described in IV-A. We used a transparent cutting mat (Fig. 10 (A)) to measure the accuracy. An operator affixed retroreflective markers to the index fingers of both hands (Fig. 10 (B)), and the movement of the retroreflective markers was measured as errors when the transparent cutting mat was moved 30 mm horizontally and vertically and rotated 30° without shifting the fingers and the cutting mat. The measured accuracies are listed in Table II. The positional errors in the cloth-feeding direction and the vertical component of the feeding direction were less than 5 mm, and the rotational error was less than 10°. Therefore, the measurement of position and rotation using V120: Trio has good recognition accuracy.

D. *Segmentation of simulated sewing task*

Using the time-series data acquired from V120: Trio, we performed a simulated sewing task and conducted a segmentation experiment using the method described in V-A. We segmented a simulated hand motion to feed a cloth part to a sewing machine. This task consists of the following three motions, which are repeated in a series.

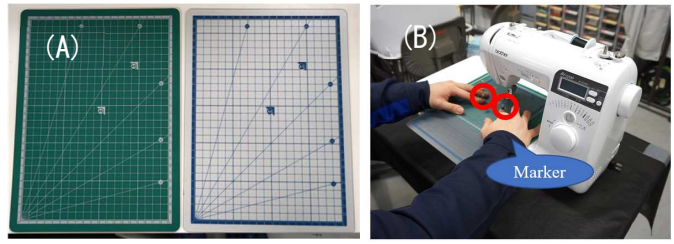

Fig. 10 (A): transparent cutting mat with scale used in experiment; (B): retroreflective markers pasted on index fingers

TABLE II

ERRORS OF RETROREFLECTIVE MARKERS

	Left index finger marker	Right index finger marker
positional error in feeding direction	1.23 mm	1.65 mm
positional error in direction perpendicular to feeding direction	0.82 mm	0.91 mm
angle error	3.68 deg	

1. The motion of the hands from the sewing-machine table to the position where cloth parts are stored, and then, picking one cloth part (Motion 1).
2. The motion to moves the cloth part to the sewing-machine table (Motion 2).
3. The motion to adjust the position of the cloth part and feed it to the sewing machine (Motion 3).

We used aluminum frames as a sewing-machine table and transparent films as cloth parts. The positions of retroreflective markers attached to the wrists, back of the hands, index fingers, and middle fingers were recorded by V120: Trio throughout the operation period. The setup is shown in Fig. 11. The task was completed when motions 1–3 were performed in order. The operator repeated the task five times, and the position of each marker was recorded as time-series data for each task. After that, the time-series data of the marker positions on the back of both hands were segmented. As a preprocessing step, the 3D coordinates of each marker were reduced to 2D coordinates on a horizontal plane, and then, the segmentation was implemented on the five processed data for four dimensions.

The segmentation result of the trajectory in the first simulated task is depicted in Fig. 12. Classes 1, 4, and 0 in Fig. 12 correspond to Motions 1–3, respectively. The segmentation result confirms that the series of hand movements are classified into three simple motions. In Fig. 12, Class 0 appears twice because the hand was almost standstill when performing Motion 3, which could result in an unintended false segment point. However, since the motions before and after the mis-segment point both belong to Class 0,

Fig. 11 An operator performing simulated sewing

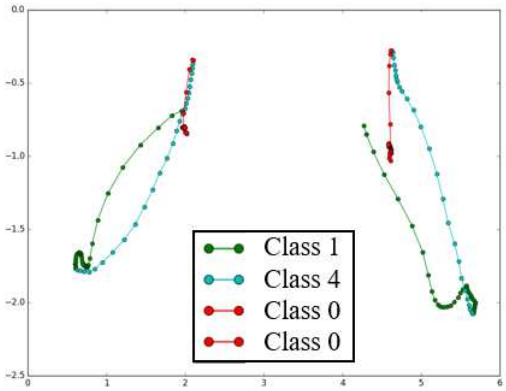

Fig. 12 Segmentation result for trajectory 1

the classification of the motions is correct, and it is possible to eliminate such mis-segment points by postprocessing, which merges adjacent simple motions belonging to the same class. Thus, the mis-segmentation result is not affected. In the segmentation experiment, for all five task trajectories, the result of segmenting each trajectory into simple motions was 100% (Fig. 13). These verify the effectiveness of the proposed segmentation method.

VII. Conclusions

Here, we propose a measurement system that acquires the positions of the fingers and hands of a sewing-machine operator and the force on the fingertip, which are required for automating sewing operations. The data are acquired without the operator losing the sense of feeling flexible objects. Further, we established classification and segmentation methods for the motions obtained from a human operator so that a robot can learn human operating skills. Finally, we validated the proposed method by applying it to time-series data obtained from a simulated sewing operation performed by a human operator. For future studies, we shall develop a method for generating the motions of sewing processes for a robot based on the system and methods proposed here. Thus, we can automate the sewing process.

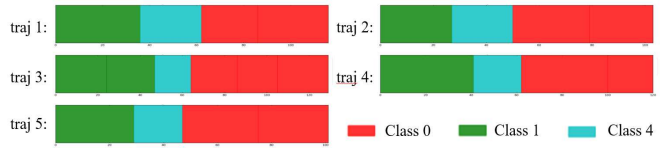

Fig. 13 Segmentation results for all trajectories

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